Next Generation Earth System Prediction: Strategies for Subseasonal to Seasonal Forecasts

DETAILS

290 pages | 7 x 10 | PAPERBACK
ISBN 978-0-309-38880-1 | DOI: 10.17226/21873

AUTHORS

Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting; Board on Atmospheric Sciences and Climate; Ocean Studies Board; Division on Earth and Life Studies; National Academies of Sciences, Engineering, and Medicine

PREPUBLICATION COPY

NEXT GENERATION EARTH SYSTEM PREDICTION

STRATEGIES FOR SUBSEASONAL TO SEASONAL FORECASTS

Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting

Board on Atmospheric Sciences and Climate
Ocean Studies Board

Division on Earth and Life Studies

This prepublication version of Next Generation Earth System Prediction: Strategies for Subseasonal to Seasonal Forecasts *has been provided to the public to facilitate timely access to the report. Although the substance of the report is final, editorial changes may be made throughout the text and citations will be checked prior to publication. The final report will be available through the National Academies Press in spring 2016.*

The National Academies of
SCIENCES · ENGINEERING · MEDICINE

THE NATIONAL ACADEMIES PRESS
Washington, DC
www.nap.edu

THE NATIONAL ACADEMIES PRESS 500 Fifth Street, NW Washington, DC 20001

This study was supported by the Heising Simons Foundation under contract number 2014-72, the Office of Naval Research under contract number N00014-14-1-0194, and the National Aeronautics and Space Administration under contract number NNX08AB07G, with additional support from the National Academy of Sciences' Arthur L. Day Fund. Any opinions, findings, conclusions, or recommendations expressed in this publication do not necessarily reflect the views of any organization or agency that provided support for the project.

International Standard Book Number-13:
International Standard Book Number-10:
Digital Object Identifier: 10.17226/21873

Additional copies of this report are available for sale from the National Academies Press, 500 Fifth Street, NW, Keck 360, Washington, DC 20001; (800) 624-6242 or (202) 334-3313; http://www.nap.edu.

Printed in the United States of America

Suggested citation: National Academies of Sciences, Engineering, and Medicine. 2016. *Next Generation Earth System Prediction: Strategies for Subseasonal to Seasonal Forecasts*. Washington, DC: The National Academies Press. doi: 10.17226/21873.

The National Academies of
SCIENCES · ENGINEERING · MEDICINE

The **National Academy of Sciences** was established in 1863 by an Act of Congress, signed by President Lincoln, as a private, nongovernmental institution to advise the nation on issues related to science and technology. Members are elected by their peers for outstanding contributions to research. Dr. Ralph J. Cicerone is president.

The **National Academy of Engineering** was established in 1964 under the charter of the National Academy of Sciences to bring the practices of engineering to advising the nation. Members are elected by their peers for extraordinary contributions to engineering. Dr. C. D. Mote, Jr., is president.

The **National Academy of Medicine** (formerly the Institute of Medicine) was established in 1970 under the charter of the National Academy of Sciences to advise the nation on medical and health issues. Members are elected by their peers for distinguished contributions to medicine and health. Dr. Victor J. Dzau is president.

The three Academies work together as the **National Academies of Sciences, Engineering, and Medicine** to provide independent, objective analysis and advice to the nation and conduct other activities to solve complex problems and inform public policy decisions. The Academies also encourage education and research, recognize outstanding contributions to knowledge, and increase public understanding in matters of science, engineering, and medicine.

Learn more about the National Academies of Sciences, Engineering, and Medicine at **www.national-academies.org.**

PREPUBLICATION COPY

COMMITTEE ON DEVELOPING A U.S. RESEARCH AGENDA TO ADVANCE SUBSEASONAL TO SEASONAL FORECASTING

RAYMOND J. BAN (Chair), Ban and Associates, LLC, Marietta, GA
CECILIA M. BITZ, University of Washington, Seattle
ANDY BROWN, UK Met Office, FitzRoy Road, Exeter, UK
ERIC CHASSIGNET, Florida State University, Tallahassee
JOHN A. DUTTON, Prescient Weather Ltd., State College, PA
ROBERT HALLBERG, NOAA Geophysical Fluid Dynamics Laboratory, Princeton, NJ
ANKE KAMRATH, National Center for Atmospheric Research, Boulder, CO
DARYL KLEIST, University of Maryland, College Park
PIERRE F.J. LERMUSIAUX, Massachusetts Institute of Technology, Cambridge
HAI LIN, Environment and Climate Change Canada, Dorval, Quebec
LAURA MYERS, University of Alabama, Tuscaloosa
JULIE PULLEN, Stevens Institute of Technology, Hoboken, NJ
SCOTT SANDGATHE, University of Washington, Seattle
MARK SHAFER, University of Oklahoma, Norman
DUANE WALISER, NASA Jet Propulsion Laboratory, Pasadena, CA
CHIDONG ZHANG, University of Miami, FL

National Academies of Sciences, Engineering, and Medicine Staff:
EDWARD DUNLEA, Senior Program Officer
CLAUDIA MENGELT, Senior Program Officer
ALISON MACALADY, Associate Program Officer
SHELLY FREELAND, Financial Associate
ROB GREENWAY, Program Associate

BOARD ON ATMOSPHERIC SCIENCES AND CLIMATE

A.R. RAVISHANKARA (*Chair*), Colorado State University, Fort Collins
GERALD A. MEEHL (*Vice Chair*), National Center for Atmospheric Research, Boulder, CO
LANCE F. BOSART, University at Albany-SUNY, NY
MARK A. CANE, Columbia University, Palisades, NY
SHUYI S. CHEN, University of Miami, FL
HEIDI CULLEN, Climate Central, Princeton, NJ
PAMELA EMCH, Northrop Grumman Aerospace Systems, Redondo Beach, CA
ARLENE FIORE, Columbia University, Palisades, NY
WILLIAM B. GAIL, Global Weather Corporation, Boulder, CO
LISA GODDARD, Columbia University, Palisades, New York
MAURA HAGAN, National Center for Atmospheric Research, Boulder, CO
TERRI S. HOGUE, Colorado School of Mines, Golden
ANTHONY JANETOS, Joint Global Change Research Institute, College Park, MD
EVERETTE JOSEPH, University at Albany-SUNY, NY
RONALD "NICK" KEENER, JR., Duke Energy Corporation, Charlotte, NC
JOHN R. NORDGREN, The Climate Resilience Fund, Bainbridge Island, WA
JONATHAN OVERPECK, University of Arizona, Tucson
ARISTIDES A.N. PATRINOS, New York University, Brooklyn
S.T. RAO, North Carolina State University, Raleigh
DAVID A. ROBINSON, Rutgers, The State University of New Jersey, Piscataway
CLAUDIA TEBALDI, Climate Central, Princeton, NJ

Ocean Studies Board Liaison
DAVID HALPERN, Jet Propulsion Laboratory, Pasadena, CA

Polar Research Board Liaison
JENNIFER FRANCIS, Rutgers, The State University of New Jersey, Marion, MA

National Academies of Sciences, Engineering, and Medicine Staff
AMANDA STAUDT, Director
EDWARD DUNLEA, Senior Program Officer
LAURIE GELLER, Program Director
KATHERINE THOMAS, Program Officer
LAUREN EVERETT, Program Officer
ALISON MACALADY, Associate Program Officer
AMANDA PURCELL, Associate Program Officer
ALEX MORGAN, Christine Mirzayan Fellow
RITA GASKINS, Administrative Coordinator
ROB GREENWAY, Program Associate
SHELLY FREELAND, Financial Associate
MICHAEL HUDSON, Senior Program Assistant
ERIN MARKOVICH, Program Assistant

OCEAN STUDIES BOARD

Acknowledgments

This report has been reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the institution in making its published report as sound as possible and to ensure that the report meets institutional standards for objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the process. We wish to thank the following individuals for their review of this report:

John Wallace, University of Washington, Seattle
Douglas C. Marble, Metron Scientific Solutions, Inc., Reston, VA
Andrew Robertson, Columbia University, Palisades, NY
Julie Demuth, National Center for Atmospheric Research, Boulder, CO
Frederic Vitart, European Center for Medium-Range Weather Forecasting, Reading, UK
James L. Kinter III, George Mason University, Fairfax, VA
Gregg A. Jacobs, Naval Research Laboratory, Stennis Space Center, MS
James G. Richman, Naval Research Laboratory, Corvallis, OR 97330
Randal Koster, National Aeronautics and Space Administration, Greenbelt, MD
Robert Weller, Woods Hole Oceanographic Institution, Woods Hole, MA
Gianpaolo Balsamo, European Center for Medium-Range Weather Forecasting, Reading, UK
Nadia Pinardi, University of Bologna, Italy

Although the reviewers listed above have provided many constructive comments and suggestions, they were not asked to endorse the report's conclusions or recommendations, nor did they see the final draft of the report before the release. The review of this report was overseen by Robert E. Dickinson, University of Texas at Austin, and Marc Levy, Center for International Earth Sciences Information Network, Columbia University; they were responsible for making certain that an independent examination of this report was carried out in accordance with institutional procedures and that all review comments were carefully considered. Responsibility for the final content of this report rests entirely with the authoring committee and the institution.

The Committee would also like to thank numerous members of the community who provided input to the Committee throughout the study process, including Robert Bertram, Julie Demuth, Lisa Dilling, Stephen Eckermann, Gina Eosco, Fern Gibbons, Sara Gonzalez-Rothi Kronenthal, Jennifer Henderson, Paul Higgins, Wayne Higgins, William Hooke, Susan Jasko, Christopher R, Johnson, Jeanine Jones, James Kinter III, Benjamin Kirtman, Randal Koster, William Lapenta, Richard Loft, Rohit Mathur, Rebecca Morss, David Randall, Andrea Ray, Carolyn Reynolds, Suranjana Saha, Richard Stumpf, David Titley, and Huug Van den dool.

Preface

Today, millions of people tune to their favorite TV meteorologist or check the newspaper or their smart phones to get the latest weather forecast. Knowing what the weather will likely be for the next few hours and the next several days has opened up incredible opportunities for society as a whole—for individuals making decisions about what they will do in their daily lives, for industry planning and risk management, and for governments making critical life and property protection decisions.

What if there were similar use of forecasts for two weeks, three weeks, or even three or six months from now? It is easy to envision the potential value of high-quality predictions two weeks to 12 months ahead for any number of industries—for example, energy, water resource management, and agriculture. There are undoubtedly potential benefits to other sectors that we cannot even imagine today. Even if such information never matches the level of confidence associated with tomorrow's weather forecast, it could still be used by individuals, businesses, and governments to plan and make a large array of important decisions. In this study, our Committee puts forward a vision that subseasonal to seasonal forecasts (S2S)—i.e., forecasts of environmental conditions made approximately two weeks to twelve months in advance—will be as widely used a decade from now as weather forecasts are today. The path to realizing this vision and its inherent value will require focused effort on S2S processes and predictions by both physical and social scientists. Today, this type of commitment largely exists on both the weather timescale and on the scales in which climate change is expected. S2S falls in a "gap" between these two areas, and in general, has not received the same level of dedicated effort and support. This report presents research strategies for dealing with this "in-between" space over the next decade.

Although the overall quality and use of products in the S2S time frame have been growing over the past decade, increasing the predictive skill of coupled Earth system models in S2S forecast ranges will be essential to increasing the benefits and expanding the number of end users of these products. The benefits of S2S forecasts will be further enhanced if the scope of operational S2S forecasts were extended beyond the traditional weather variables to include more Earth system variables and events. Opportunities for improvements and expansions to existing forecasts include, for example, enhanced predictions of the ocean state, sea ice fields, aerosols and air quality, and water management. A focus on developing better information on the likelihood of specific and disruptive environmental events, in addition to improving the skill of currently available forecasts of temperature and precipitation anomalies, has great potential to further enhance the value of S2S predictions.

This report presents a research agenda that provides the framework for the physical and social science communities to collaboratively advance the skill, breadth and value of S2S predictions. Our Committee held five in-person meetings between October 2014 and May 2015, and received broad and diverse input from experts in both physical and social science as well as from end users of S2S forecasts. We would like to thank all of those who provided their time and insight. The contributors are listed in the Acknowledgments section above. The Committee is also greatly indebted to Study Directors Edward Dunlea and Claudia Mengelt and to Associate Program Officer Alison Macalady. This report would not have been possible without their tireless efforts and expert support. Finally, I would like to thank the Committee members for their hard work and dedication to excellence. I particularly want to thank the Committee for their patience with me as I learned so much from them. It was indeed a true pleasure to work with this talented group of professionals.

Raymond J. Ban, Chair
Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting

Contents

Summary

The use of weather forecasts by governments, businesses, and individuals is ubiquitous in the United States: Should a school system be closed due to cold or snowy conditions on a given day? How much power should an electric utility plan to produce in order to meet demand for air conditioning during a summer week? Is a weather-sensitive military sortie likely to be effective on a particular afternoon? Making these and myriad other decisions across virtually all sectors of the economy has been transformed by the availability of skillful forecasts with lead times of a few hours to a few days. The value and importance of weather and other environmental forecasts will increase as the nation's economic activities, security concerns, and stewardship of natural resources become increasingly complex, globally interrelated, and affected by longer-term climate changes.

While short-term forecasts already play a vital role in shaping societal decision-making, many critical decisions must be made several weeks to months in advance of potentially favorable or disruptive environmental conditions. For example, it can take weeks or months to move emergency and disaster-relief supplies, but pre-staging resources to areas that are likely to experience extreme weather or an infectious disease outbreak could save lives and stretch the efficacy of limited resources. Similarly, emergency managers responding to unanticipated events such as nuclear power plant accidents or large oil spills face the task of communicating the ramifications of such events on timescales that stretch well beyond a few days. There are many more such examples: naval and commercial shipping planners designate shipping routes weeks in advance, seeking to stage assets strategically, avoid hazards, and/or take advantage of favorable conditions; with improved knowledge of the likelihood of precipitation or drought, farmers can purchase seed varieties that are most likely to increase yields and reduce costs; and depending on the year, water resource managers can face a multitude of decisions about reservoir levels in the weeks, months, and seasons ahead of eventual water consumption.

A frontier in forecasting involves extending the capability to skillfully predict environmental conditions and disruptive weather events to several weeks and months in advance, filling what has long been a gap between today's short-term weather and ocean forecasting capabilities (within the next 14 days) and a growing ability to project the longer-term climate (on scales of years to decades or more). Seasonal—and more recently subseasonal—predictions (defined in Box S.1) have improved over the last decade, but there is great opportunity to further improve the skill of S2S forecasts, as well as the breadth of forecasted variables and routinely available forecast products. Doing so could dramatically increase the benefits of the environmental prediction enterprise: saving lives, protecting property, increasing economic vitality, protecting the environment, and informing policy choices.

Despite their large potential, Earth system predictions on subseasonal to seasonal timescales remain challenging for researchers, modelers, and forecasters. While it is increasingly recognized that many sources of predictability exist in the Earth system on S2S timescales, representing these sources of predictability in Earth system models is challenging. Models must adequately capture the initial states of the atmosphere, ocean, land surface and cryosphere, as well as the interactions, or coupling, of these different components. Furthermore, the longer lead times associated with S2S predictions make the representation of uncertainty and the verification process more challenging and more computationally intensive than numerical weather

BOX S.1—Definition of Subseasonal to Seasonal (S2S) Forecasts

Seasonal forecasts often refer to outlooks of oceanic and atmospheric conditions averaged over a season, or about 3 months, issued with lead times ranging from a month to multiple seasons. Subseasonal forecasts often project average conditions over a week or more, often with lead times of 2-6 weeks or more. In this report, "subseasonal to seasonal" or "S2S" includes environmental predictions with forecast ranges from 2 weeks to 12 months (see also Box 1.1).

prediction. Nonetheless, potential advances both in technology—satellites, computing, etc.—and in science—model parameterizations, data assimilation techniques, etc.—make advances in S2S forecasting feasible within the next decade.

Another key challenge is making S2S forecasts more applicable to users. S2S forecasts are generally less skillful than shorter-term predictions, are issued at lower spatial and temporal resolutions, and may involve the communication of probabilistic information that is unfamiliar to many users. These barriers have the potential to be overcome through research about and engagement with users.

Given the opportunities associated with improved S2S forecasts, but also the many challenges associated with developing them, the Office of Naval Research (ONR), the National Aeronautics and Space Agency (NASA), and the Heising-Simons Foundation asked the National Academies of Sciences, Engineering, and Medicine to undertake a study to develop a 10-year U.S. research agenda to increase S2S research and modeling capability, advance S2S forecasting, and aid in decision making at medium and extended lead times (see Appendix A for the study's Statement of Task). The Academies convened the Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting to meet this request.

VISION AND RESEARCH STRATEGIES FOR THE NEXT DECADE

The Committee believes that there is great potential to advance S2S forecasting capability and rapidly increase the benefits of S2S predictions to many sectors in society. However, overcoming the challenges to developing S2S forecasting will take sustained effort and investment.

Encouraged by its sponsors to be bold, the Committee puts forward a vision that **S2S forecasts will be as widely used a decade from now as weather forecasts are today** and identifies four research strategies and 16 recommendations to guide progress towards that vision. The research strategies for improving the use of S2S forecasts in the next decade (see Figure S.1) are:

1. Engage Users in the Process of Developing S2S Forecast Products
2. Increase S2S Forecast Skill
3. Improve Prediction of Extreme and Disruptive Events and Consequences of Unanticipated Forcing Events
4. Include More Components of the Earth System in S2S Forecast Models

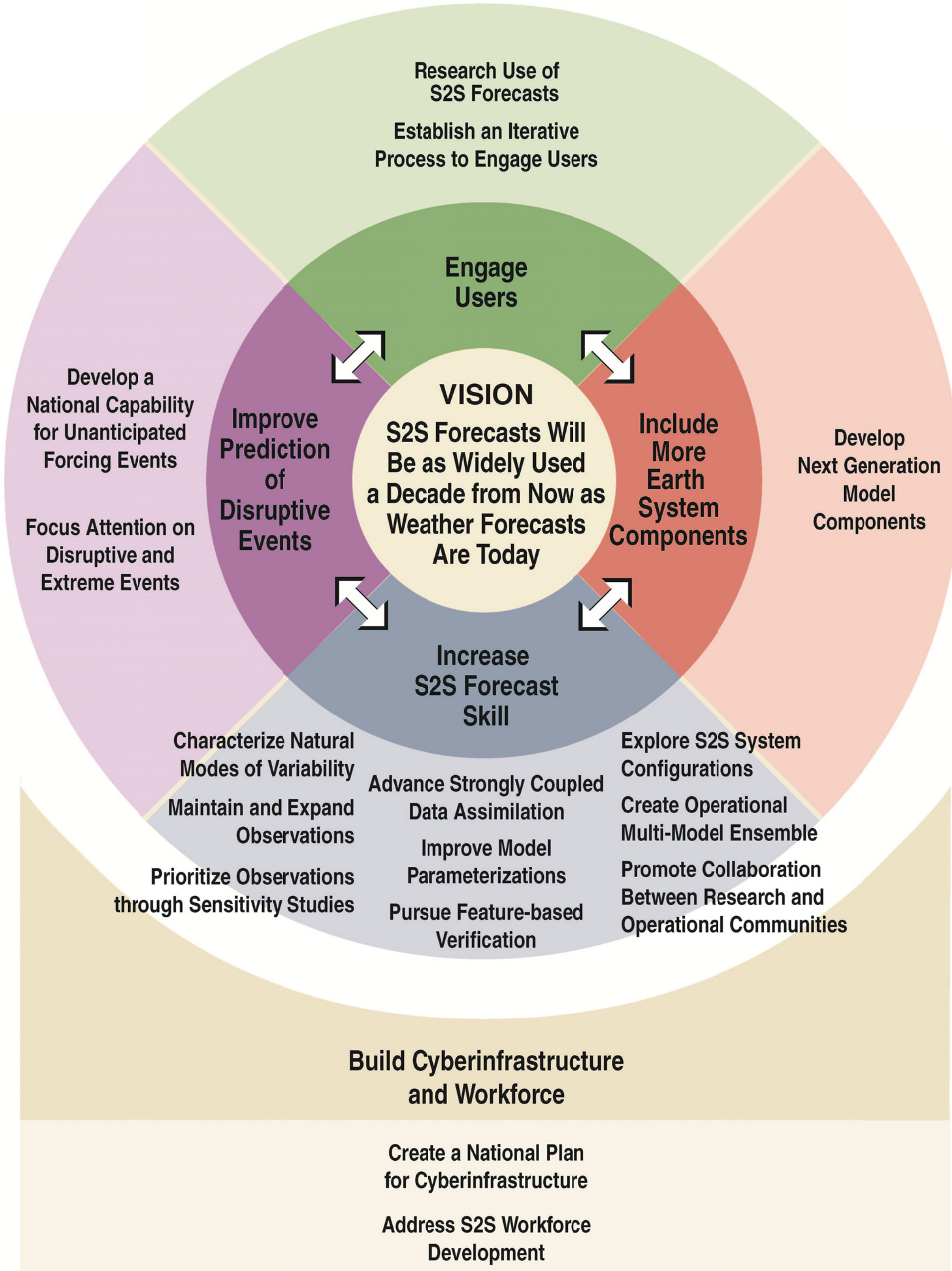


FIGURE S.1 This schematic illustrates the relationship between the Committee's vision, strategies, and recommendations for advancing subseasonal to seasonal forecasting. The Committee's vision (center) serves as the target for the research agenda. Four research strategies are intended to organize actions to advance towards the vision, but are not mutually exclusive (indicated by the white arrows). The outer most layer of the circle contains paraphrases of the individual recommendations for more research activities, aligned with the strategy that they most closely support (although recommendations can support more than one strategy—see Table S.1). The base of the circle shows activities necessary to support the research agenda.

RECOMMENDED ELEMENTS OF A RESEARCH AGENDA

Implementing the four strategies above will require research in the physical and social sciences, as well as improved coordination among user, research, and operational forecast communities. The Committee's recommendations collectively constitute an S2S research agenda for the nation. Given the fluid technological, political, and financial environment in which the research agenda will be implemented, the Committee decided it was more important to identify the most important areas where progress can be made without overly prescribing the sequence or priority in which they should be addressed. While most recommendations support more than one research strategy, they are described in the following sections under the primary strategy with which they are associated.

To help agencies and others within the weather/climate enterprise select specific parts of the research agenda to pursue, Table S.1 and Table 8.1 in the report provide additional detail about the recommendations: whether they involve basic or applied research; which are expected to have short-term benefits; which might require a new initiative; and which have a scope that calls for international collaboration. The chapters contain additional recommended activities that fall under each main recommendation, which add further specificity and breadth to the research agenda. While it might not be possible to pursue all of these actions simultaneously, the more that is done to implement these recommendations, the more advances in S2S forecasting can be made.

Research Strategy 1: Engage Users in the Process of Developing S2S Forecast Products

Many barriers hinder the use of existing S2S forecast information, including increasing demand for a wider variety of forecast variables and formats that are not readily available. An important first step in providing more actionable S2S forecast information is to develop a body of social and behavioral science research that leads to more comprehensive understanding of the current use and barriers to use of S2S predictions (Recommendation A). This will involve research to uncover the specific aspects of products—forecast variables, spatial and temporal resolutions, necessary levels of skill, etc.—that make S2S products more useful to decision-makers across multiple sectors.

Beyond such assessments, engaging the S2S research and operational prediction community in an iterative dialogue with user communities is necessary to help ensure that forecast systems, forecast products, and other model output, are designed from the outset to be useful for decision making (Recommendation B). Ongoing efforts will be needed to match what is scientifically predictable and technological feasible at S2S timescales with what users find actionable, as both scientific skill and user needs continually evolve. Launching such a dialogue requires bringing decision makers into the research and development process sooner rather than later. Private industry and 'boundary organizations' within academia and the public sector (such as the National Oceanic and Atmospheric Agency's [NOAA] Regional Integrated Sciences and Assessments program and the International Research Institute for Climate and Society at Columbia University, and many others) have already started such discussions. Leveraging the entire weather and climate enterprise—not just the public sector—will be necessary for further developing such an iterative approach to the development of S2S products and services.

Research Strategy 2: Increase S2S Forecast Skill

The skill (i.e., the quality) of S2S forecasts has been increasing, but is still limited, even for traditional weather and climate variables (temperature, precipitation). Improving the skill of S2S forecasts is fundamental to increasing their value to society. Enhancing skill begins with understanding sources of and limits to S2S predictability within the Earth system. Current research indicates that a large portion of S2S predictability originates from:

- Natural modes of variability (e.g., El Niño-Southern Oscillation [ENSO], the Madden-Julian Oscillation [MJO], and the Quasi Biennial Oscillation [QBO]—see Box 1.3);
- Slowly-varying processes (e.g., involving soil moisture, snow pack and other aspects of the land surface, ocean heat content, currents and eddy positions, and sea ice); and
- Elements of external forcing (e.g., aerosols, greenhouse gasses) that can result in a systematic and predictable evolution of the Earth system.

Basic research on these phenomena and their interactions is fundamental to identifying and understanding the processes that must be included in Earth system models in order to increase S2S forecast skill (Recommendation C).

In addition to extending knowledge about sources of S2S predictability, efforts are needed across every part of the forecast system, including improved observations and data assimilation methods, advances in Earth system models, and improved methods for uncertainty quantification, calibration, and verification.

Observations

Routine observations are essential for accurately initializing models, validating model output, and improving understanding of the physical system and its predictability. The ocean, land surface, and cryosphere remain significantly under-observed compared to the atmosphere, despite being major sources of S2S predictability. Maintaining and in some cases bolstering the network of observations across all components of the Earth system is critical to advancing S2S prediction skill (Recommendation E).

While it would be beneficial to expand the geographic coverage and resolution of many types of observations, cost and logistics will continue to demand an identification of the most critical priorities. Observing system simulation experiments (OSSEs) and other sensitivity studies are powerful tools for exploring the importance of specific observations on estimation of the state of the Earth system and overall model performance, and could be better used to prioritize improvements to observation networks for S2S prediction systems (Recommendation F).

Data Assimilation

Data assimilation is the process of initializing and updating Earth system models with observations, and is also important for uncertainty quantification, calibration, and validation of forecasts. Integrating tens of millions of observations into the different components of an Earth system model presents many challenges, including ensuring that initializations are dynamically consistent and that they minimize the growth of errors. Given that coupling between the multiple, dynamic components of the Earth system (e.g., atmosphere, ocean, ice, land) is central to S2S prediction, developing and implementing coupled data assimilation methods is at the forefront of S2S model development. “Weakly-coupled” data assimilation is one existing method that is increasingly implemented in weather prediction, and also holds promise for improving S2S prediction systems. “Strongly-coupled” data assimilation allows observations within one component of the Earth system to affect state estimates in other components (with constraints). This technique is still in its infancy but has the potential to spur a more dramatic leap forward. Realizing the method’s potential will require significant research and testing that should be explored while continuing to pursue weakly-coupled methods (Recommendation G).

Models

Systematic errors are numerous within the Earth system models used for S2S forecasting—many global models produce an unrealistically strong Pacific equatorial cold tongue, a spurious double Inter Tropical Convergence Zone (ITCZ), wet or dry biases in rainfall in many parts of the world, among other issues. These model errors can be large compared to the predictable signals targeted by S2S forecasts. Thus taking steps to reduce systematic errors within coupled Earth system models is one of the most important steps in improving the skill of S2S predictions.

Modest increases in model resolutions hold potential for reducing model errors and such improvements should continue to be studied. However, given the computational costs of increasing model resolution, many critical Earth system processes will need to be parameterized—i.e., represented using simplified physics schemes rather than being explicitly resolved in models—for the foreseeable future. Thus improving physical parameterizations will remain fundamental to reducing model errors and increasing S2S forecast skill, even as the capability to resolve more and more processes expands (Recommendation H). Coordinated, coupled field campaigns, process-targeted satellite missions, and long-term collaborations between research and operational scientists are essential for developing the understanding required to improve models and model parameterizations.

Calibration, Combination, Verification, and Optimization of S2S forecasts

Some model errors will remain even with major improvements in models and increased resolution. Using multi-model ensembles (MMEs) is likely to remain critical for S2S prediction as one of the most promising ways to account for errors associated with Earth system model formulation. However, current MMEs are largely systems of opportunity (i.e., basing the MME design on expediency). Research is required to more systematically develop MME forecast systems. Careful optimization of the configurations of a multi-model prediction system will include systematic exploration of the benefits and costs of adding unique models to an MME and evaluation of other S2S forecast system design elements (“trade space”), including calibration methods, model resolution, number of ensemble members, averaging period, lengths of lead and retrospective forecasts, and options for coupled sub-models (Recommendation K). Exploring this trade space will be a complicated and expensive endeavor, but determining how performance depends on system configuration is a key task in the S2S research agenda.

Verification metrics are important for tracking and comparing model improvements, and are also a critical part of building user trust in S2S forecasts. Improving verification should be done in collaboration with user groups, along with research on feature-based and two-step verification methods and consideration of how the design of retrospective forecasts and reanalyses can influence the ability of some users to directly evaluate the consequences of acting on forecasts at various predicted probabilities (Recommendation J).

Moving research to operations

Finally, transitioning new ideas, tools, and other technology between the S2S research community and operational centers is challenging but essential to translating research discoveries into better informed decision-making. The use of MMEs in research settings, for example the North American Multimodel Ensemble program (NMME), has demonstrated the potential for improving the skill of S2S forecasts and has produced many lessons for developing an operational MME. Operationalizing the current NMME, which relies on non-operational institutions supported by research funding, is not necessarily recommended, but there would be great value in the development of an operational MME forecast system that includes the operational centers of the United States (Recommendation L).

To make the rapid improvements to operational S2S prediction systems that are envisioned by the Committee, it will be generally important to speed the flow of information between scientists with research and operational foci (Recommendation M). This includes promoting and expanding existing mechanisms to facilitate knowledge transfer—such as NOAA's Climate Process Teams—and developing new mechanisms to enhance researcher access to operational forecast data, including access to archives of ensemble forecasts, retrospective forecasts, and initialization data. Additionally, allowing researchers to conduct or request specific experiments on operational systems would provide an additional boost to the flow of discoveries and technical advances.

Research Strategy 3: Improve Prediction of Extreme and Disruptive Events and of the Consequences of Unanticipated Forcing Events

To improve the overall skill of S2S forecasts and provide more actionable information to users, the Committee identifies two areas that deserve special attention, and to that extent we promote them to our third and fourth Research Strategies. Research Strategy 3 involves an increased focus on discrete events, and includes two sets of recommendations. The first is to emphasize the prediction of weather, climate, and other Earth system events that disrupt society's normal functioning (e.g., major winter storms, excessive rainfall events, monsoon onset and breaks, tropical storms, heat waves). Thus, in contrast to the forecasts of specific weather events on a scale of days, improved S2S forecasts would identify situations with high probabilities of disruptive consequences, especially for subseasonal forecast ranges (approximately 2-12 weeks). A coordinated effort to improve the forecasting of these events could allow communities more time to plan for these events and mitigate damages. Improved forecasting of disruptive events may also involve developing "forecasts of opportunity"—identifying windows in time when expected skill is higher than usual at a particular place because of the presence of certain features in the Earth system, certain phases of large-scale climate patterns (e.g., seasonal cycle, ENSO, or MJO), or certain interactions of these modes, slowly-varying processes, and external forcing. Studying these interactions and ensuring they are represented in models will be important for S2S prediction and for identifying forecasts of opportunity (Recommendation D).

The second part of this research strategy involves using S2S forecast systems to predict the consequences of disruptive events caused by outside forces. Such outside forces include volcanoes, meteor impacts, and human actions (e.g., aerosols, widespread fires, large oil spills, certain acts of war, or climate intervention). Even though these events themselves are not predictable, their consequences may be—in particular the consequences on S2S timescales. A national system for projecting the consequences from these unanticipated events on S2S timescales would aid emergency response and disaster planning (Recommendation N). With improved coordination between government agencies and academics, it would be possible to assist in recovery efforts by quickly generating S2S forecasts of the consequences of such unanticipated events shortly after they take place.

Research Strategy 4: Include More Components of the Earth System in S2S Forecast Models

The other area that the Committee believes needs more focused attention is the utilization and further development of advanced Earth system model components beyond the troposphere, which has been the traditional focus of numerical weather prediction. The S2S prediction problem is inherently a problem of capturing the coupled processes operating at the interface between various components of the Earth system, including the troposphere, stratosphere, ocean, cryosphere, biosphere, and land surface.

Progress in recent decades has extended the coupling of more model components and more comprehensive representation of processes within these components in operational S2S forecast systems (see also Research Strategy 2). However, there is an increasing need to accelerate the development of model components outside the troposphere and to improve their coupling within S2S forecast systems. In particular, it will be important to rapidly advance towards next-generation ocean, sea ice, and land surface modeling capability within coupled Earth system models, in addition to preparing for cloud-resolving capability in atmospheric models. This will include moving towards eddy-resolving resolutions in the ocean, inclusion of ocean surface wave effects, and developing better representation of sea ice, land surface, and surface hydrological processes. Other strong candidates for improvements to existing practices for operational S2S forecasting systems include advancing prediction capabilities of aerosols and air quality, soil-state and seasonal vegetation growth, and aquatic and marine ecosystems. Research is also required to better understand which added components have significant interactions with the weather and climate system as a whole, pointing to the need for dynamic integration into operational forecasting systems (Recommendation I).

Improving these model components may also be important for better predicting a wider array of Earth system variables on S2S timescales (e.g., sea ice, ocean productivity, hydrology, air quality), even if they do not feedback strongly to the coupled system. Iterative interaction with forecast users (Research Strategy 1) can help determine what processes and variables are most important to include in coupled S2S systems as these systems evolve.

Supporting the S2S Forecasting Enterprise

The research strategies outlined in the report will require advances in computational infrastructure to support S2S forecasting, and the development and maintenance of a workforce ready to realize potential advances in S2S forecasting. These challenges are not unique to the S2S enterprise—they are also important in the weather prediction and climate modeling communities, among other technical enterprises.

Similar to weather forecasting and climate modeling, S2S prediction systems test the limits of current cyber-infrastructure. The volume of observational data, data assimilation steps, model outputs, and reanalysis and retrospective forecasts involved in S2S forecasting means that the S2S modeling process is extremely data intensive. Advances in S2S forecast models (such as higher resolutions, increased complexity, the generation and retention of long retrospective forecasts) will require dramatic increases (likely 1,000-fold) in computing capacities, together with similar expansions in storage and data transport. Earth system models are not taking full advantage of the complexity of current computing architectures and improving their performance will likely require new algorithms that process more data locally and new algorithms to exploit even more parallelism. The transition over the next decade to new computing hardware and software that is not necessarily faster, but is more complex, will be highly disruptive. Future storage technology will also be more complex and varied than it is today, and leveraging these innovations will require fundamental software changes. Facing these challenges and uncertainties about the future, the United States would benefit from developing a national plan and investment strategy to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all stages of the prediction process (Recommendation O).

There are numerous barriers to training and retaining talented workers in the S2S enterprise. S2S is complex and involves working across computing and traditional Earth science disciplinary boundaries to develop and improve S2S models, and across science-user decision boundaries to better design and communicate forecast products. From the limited workforce data available, the Committee surmises that the pipeline of workers for the S2S enterprise is not growing robustly in the United States and is not keeping pace with this rapidly evolving field. Given the importance of S2S predictions to the nation, a concerted effort is needed to entrain, develop, and retain S2S professionals. This involves gathering quantitative information about workforce requirements and expertise base to support S2S forecasting, improving incentives and funding to support existing professionals and attract new professionals, and expanding interdisciplinary programs to train a more robust and diverse workforce to employ in boundary organizations that fill the space between S2S modelers and forecast user communities (Recommendation P).

CONCLUSION

This report envisions a substantial improvement in S2S prediction capability, and the Committee expects valuable benefits to flow from these improvements to a wide range of public and private activities. It sets forth a research agenda that describes what must be done—observations, basic research, data management, and interactions with users—to advance prediction capability and improve societal benefits. Despite the specificity in recommending what should be done, the report does not address the challenging issues of how the agenda should actually be pursued—who will do what and how the work will be supported financially. Given that this research agenda significantly expands the scope of the current S2S efforts, the Committee believes that some progress can be made with current levels of support and within current organizational structures, but achieving even a considerable fraction of the S2S vision will likely require additional resources for basic and applied research, observations, forecast operations, and user engagement. The scope of the research agenda will also require closer collaboration between federal agencies and international partners, better flow of ideas and data between the research and operational forecasting communities, and engagement of the entire weather and climate enterprise.

Again, the Committee acknowledges that addressing the challenge of dramatically improving the skill and use of S2S forecasts will require many different actions, but the Committee reiterates that these are the actions that will need to be pursued to achieve the full potential for S2S forecasting. The more that can be pursued within this research agenda, the closer the nation can be towards realizing the full potential of S2S forecasting and the more benefits can be produced for a wide range of users and the nation as a whole.

TABLE S.1 These 16 recommendations—lettered in the order they appear in the report—comprise the Committee's research agenda (a similar table that also contains the more specific recommendations from the chapters is in Table 8.1). The second column indicates the research strategy that each recommendation primarily supports (colors are the same as in Figure S.1). Additional research strategies (1-4) supported by each recommendation are indicated by numbers. The Committee specifically did not prioritize these recommendations. However, this table presents the Committee's opinion on whether each activity will involve mainly basic or applied research/operational activities, or both; whether a short-term return-on-investment is likely (≤ 5 years); and whether a new initiative or program, or a significant expansion of a program, may be necessary to implement each recommendation. The last column indicates recommendations for which the Committee believes that international collaboration and coordination is particularly important.

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Critical
Chapter 3						
A: *Develop a body of social science research that leads to more comprehensive and systematic understanding of the use and barriers to use of seasonal and subseasonal Earth system predictions.*	1, 4	■	■	■		
B: *Establish an ongoing and iterative process in which stakeholders, social and behavioral scientists, and physical scientists co-design S2S forecast products, verification metrics, and decision-making tools.*	1, 4	■	■	■		
Chapter 4						
C: *Identify and characterize sources of S2S predictability, including natural modes of variability (e.g., ENSO, MJO, QBO), slowly varying processes (e.g., sea ice, soil moisture, and ocean eddies), and external forcing (e.g., aerosols), and correctly represent these sources of predictability, including their interactions, in S2S forecast systems.*	2, 3	■		■		■
D: *Focus predictability studies, process exploration, model development and forecast skill advancements on high impact S2S "forecasts of opportunity" that in particular target disruptive and extreme events.*	3, 2	■		■		■
Chapter 5						
E: *Maintain continuity of critical observations, and expand the temporal and spatial coverage of in situ and remotely-sensed observations for Earth system variables that are beneficial for operational S2S prediction and for discovering and modeling new sources of S2S predictability.*	2, 3, 4	■	■	■	■	■
F: *Determine priorities for observational systems and networks by developing and implementing OSSEs, OSEs, and other sensitivity studies using S2S forecast systems*	2, 3, 4	■	■	■	■	
G: *Invest in research that advances the development of strongly-coupled data assimilation and quantifies the impact of such advances on operational S2S forecast systems*	2, 3, 4	■	■	■	■	■
H: *Accelerate research to improve parameterization of unresolved (e.g., subgrid scale) processes, both within S2S system submodels, and holistically across models to better represent coupling in the Earth system.*	2, 3, 4	■		■	■	■
I: *Pursue next-generation ocean, sea ice, wave, biogeochemistry, and land surface/hydrologic as well as atmospheric model capability in fully-coupled Earth system models used in S2S forecast systems.*	4, 2, 3	■	■	■	■	

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Criticial
J: *Pursue feature-based verification techniques in order to more readily capture limited predictability at S2S timescales, as part of a larger effort to improve S2S forecast verification.*	2, 1, 3	■	■	■	■	■
K: *Explore systematically the impact of various S2S forecast system design elements on S2S forecast skill. This includes examining the value of model diversity, as well as the impact of various selections and combinations of model resolution, number of ensemble perturbations, length of lead, averaging period, length of retrospective forecasts, and options for coupled sub-models.*	2, 3, 4	■	■	■	■	■
Chapter 6						
L: *Accelerate efforts to carefully design and create robust operational multi-model ensemble S2S forecast systems.*	2, 3		■		■	■
M: *Provide mechanisms for research and operational communities to collaborate, and aid in transitioning components and parameterizations from the research community into operational centers, by increasing researcher access to operational or operational mirror systems.*	2, 1, 3, 4		■	■		■
N: *Develop a national capability to forecast the consequences of unanticipated forcing events.*	3, 1		■		■	
Chapter 7						
O: *Develop a national plan and investment strategy for S2S prediction to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all stages of the prediction process, including data assimilation, operation of high-resolution coupled Earth system models, and storage and management of results.*	Supporting	■	■	■	■	
P: *Pursue a collection of actions to address workforce development that removes barriers that exist across the entire workforce pipeline and in the diversity of scientists and engineers involved in advancing S2S forecasting and the component and coupled systems.*	Supporting		■	■	■	

Chapter 1: Introduction

As the nation's economic activities, security concerns, and stewardship of natural resources become increasingly complex and globally interrelated, they become ever more sensitive to environmental conditions. For the past several decades, forecasts of weather, ocean and other environmental phenomena made a few days ahead have yielded invaluable information to improve decision making across all sectors of society (Lazo et al., 2011). Enhancing the capability to forecast environmental conditions outside the well-developed weather timescale—e.g., extending predictions out to several weeks and months in advance—could dramatically increase the societal value of environmental predictions, saving lives, protecting property, increasing economic vitality, protecting the environment, and informing policy choices. Indeed, forecasts in the subseasonal to seasonal (S2S) time range (defined in this report 2 weeks to 12 months; see Box 1.1) have the potential to inform activities across a wide variety of sectors as many important decisions are made weeks to months in advance.

The potential of S2S forecasting has advanced substantially over the last few decades, as improvements in numerical modeling, in the Earth observing network, and in understanding of sources of Earth system predictability in the so-called "gap" between short-range weather and climate timescales (see below) have enabled the development of extended-range weather and seasonal climate forecasts. As the availability and skill of seasonal climate forecasts—and more recently subseasonal predictions—has improved, S2S forecasts are increasingly being used in sectors like agriculture, energy, and water resources management. But there is enormous potential to further increase the benefits of S2S predictions. Many sectors have yet to exploit even the S2S information that is currently available. The user base could expand dramatically if the skill of S2S forecasts improves, if more variables of the Earth system are explicitly forecast (for example, a wider range of conditions of the ocean, cryosphere, and land surface), and if users' awareness of and ability to apply S2S information to important decisions and actions increases. Because so many critical planning and management decisions are made in the subseasonal to seasonal time frame, it might be argued that the benefits of the longer range predictions has the opportunity to meet or exceed the current value of 0-14 day weather predictions if the quality, scope, and utilization of the forecasts can improve from their current state. S2S predictions may become even more valuable under anthropogenic climate change, as improved S2S forecasts could allow for the development of early warning systems that are becoming even more of a societal imperative in a warming world.

MOTIVATION FOR THIS STUDY

This report develops a vision for realizing the potential benefits of S2S Earth system predictions within the next decade. It identifies key strategies and proposes a research agenda with specific recommendations to guide progress towards that vision. There were four main motivations for initiating this study:

- The need to develop a research agenda to close the "gap" between efforts to improve numerical weather prediction (NWP) and climate modeling;

BOX 1.1—Definitions of Subseasonal and Seasonal Forecasts

This Committee's charge was to develop a research agenda for improving forecasting on subseasonal and seasonal timescales, and for the purposes of this report, the Committee defined "Subseasonal to Seasonal" as a forecast range from 2 weeks to 12 months. There is no consensus on the precise meaning of a given forecast time. Often the forecast "range" is a combination of a lead time and an averaging period, where lead time refers to the period between when a forecast is initialized and when the forecast is first valid, while the averaging period is the time window the forecast is applicable. Similarly, terminologies and definitions of forecast times related to subseasonal and seasonal forecasting vary across research groups and initiatives.

The Committee's S2S definition reflects common usage in the community, but it differs slightly from the definition of "Intraseasonal to Interannual (ISI)" used in the 2010 NRC report *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability* , which covers similar scientific topics. ISI predictions are defined as ranging from 2 weeks to several years. Thus the terms intraseasonal and subseasonal are virtually interchangeable both literally and in practice. However, the terms "seasonal" and "interannual" do have literal differences. The term "interannual" implies forecasts of year-to-year variability, and thus brings to mind a forecast of an annual mean one or two years in the future or perhaps a seasonal mean a year in advance, whereas the term "seasonal" in a forecasting context usually refers to a forecast of a seasonal mean one or more seasons in the future, or a monthly mean a season in advance.

This Committee's definition of "Subseasonal to Seasonal" and the accompanying acronym "S2S" also differs from the WCRP/WWRP's S2S Project (Box 2.3), which defines "Subseasonal to Seasonal (S2S)" as ranging from two weeks out to a single season (e.g., approximately 2-12 weeks). The Committee made a conscious choice to avoid introducing a new acronym and terminology to cover the time period from 2 weeks to 12 months, and chose to use the S2S acronym to refer more broadly to subseasonal and seasonal forecasts. This is because the acronym "S2S" is now used rather loosely across the community to refer to both subseasonal and seasonal timescales.

- The need to expand and improve S2S forecast capabilities beyond dynamical predictions of the atmosphere (i.e., to improve or develop S2S predictions of the oceans, land surface and cryosphere, as well predictions of atmospheric variables such as aerosols);
- A desire to develop a more global S2S forecasting capacity, especially to meet needs related to national security and humanitarian response; and
- A changing computing environment that may open up both new opportunities and challenges for Earth system prediction.

As noted above and in the 2010 NRC report, *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability* (hereafter NRC, 2010b; or ISI Report; see Box 1.2), subseasonal and seasonal forecasting fall in a "gap" between the current modeling capabilities used for short and medium term prediction and those used in climate projections. Because of the short lead times involved with numerical weather prediction, efforts to improve weather forecasting have been focused on enhancing the accuracy of atmospheric and surface data for specifying initial conditions and on representing the short-term evolution of the atmosphere from this initial state. Earth system models that were first developed for making long-term climate projections have focused, in contrast, on representing Earth system processes that evolve more slowly (such as large-scale atmosphere and ocean circulation, the cryosphere, the state of land surface, and feedbacks between components) and how these processes are influenced by external

BOX 1.2—Progress Since the NRC 2010 IRI Report

The 2010 NRC report on *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability* report and this report address much of the same phenomena and timescales, with the intent of improving ISI/S2S forecasts. However, this report provides an important update on the science and potential of S2S forecasts, especially on the subseasonal timescale, and the two reports further differ in areas of emphasis. The 2010 report focused attention on the sources and gaps in our understanding of ISI predictability, "building blocks" in the development and evolution of ISI forecast systems, an assessment of the performance of (then) current ISI forecast systems, and recommendations for strategies and best practices for future improvements to ISI forecasts. Three case studies—ENSO, MJO, and soil moisture—were presented to highlight end-to-end considerations of ISI forecast systems. For each case study, the report described the scientific basis for the variability and predictability, the manner in which forecast "building blocks" were developed and implemented to realize the forecast potential, and the gaps in understanding and treatment of each phenomenon. Considerable attention was given to "best practices" for ISI forecasts, focusing on four important aspects, including the production, reproduction, evaluation, and dissemination of prediction information.

This report addresses all of these same areas but does not address predictions beyond 12 months, and places significantly more attention on widening the consideration of S2S-relevant phenomena and associated Earth system processes—and by extension on Earth system modeling and prediction. The aim of this expansion is to consider a wider range of sources of predictability, impacted quantities, and processes, including extreme weather and other disruptive events. The latter dovetails with another significant focus of this report, which is the need to highlight the value proposition of S2S forecasts, in part through better engagement with the potential stakeholder community. Finally, in its targeted effort to develop a U.S. research agenda to advance S2S forecasting, this report gives consideration to the infrastructure and programmatic elements required for advancement, including workforce, cyberinfrastructure, and interactions between the research and operational forecasting communities.

climate drivers (e.g., greenhouse gas emissions, volcanic activity, other aerosols, and solar variability).

Although there is a traditional separation between research on weather and climate timescales, the boundaries between short-term and climate prediction are largely artificial (Shapiro et al., 2010). Because both fast and slower-evolving aspects of the climate system are important to conditions that develop in the 2 weeks to 12 month forecast range, S2S forecasting systems require both close attention to initial conditions and high-fidelity representation of coupling and feedbacks between more slowly varying aspects of the Earth system. The potential to close this "gap" is now supported by a body of research indicating predictability in the Earth system at all timescales (e.g., Hoskins, 2013). In the S2S time range, this predictability arises in part from coupled ocean-atmospheric phenomena such as the El Niño -Southern Oscillation (ENSO) and the Madden Julian Oscillation (MJO), and in stratosphere-troposphere interactions associated with the quasi-biennial oscillation (QBO) (see Box 1.3). Further S2S predictability may exist in other climate oscillations and their teleconnections, and in the Earth system response to slowly varying conditions in the ocean, land, and cryosphere, among other phenomena. Efforts are already underway in the United States and internationally to exploit these sources of S2S predictability, stretching the lead time of weather timescale models forward and climate models backward, in part through the development of improved and more highly coupled Earth system models.

BOX 1.3—Examples of Modes of Variability

There are a number of natural modes of variability that have widespread effects on the weather and climate, including the El Niño-Southern Oscillation (ENSO), the Madden-Julian Oscillation (MJO), and the Quasi Biennial Oscillation (QBO), among others. ENSO and MJO are prime examples of modes of variability that provide predictability at S2S lead times. ENSO is a coupled atmosphere-ocean mode of variability that involves slow variations in the equatorial Pacific that impact sea surface temperatures in the central and eastern Pacific, and associated changes in surface pressure and wind in the atmosphere that extend over most of the tropical regions. MJO exhibits planetary-scale features along the equator in pressure, winds, clouds, rainfall, and many other variables, with the strongest anomalies in precipitation propagating from the Indian to central Pacific Oceans over a period of about 30 to 50 days. The MJO has traditionally been described as primarily an atmospheric phenomenon, but recent research highlights the importance of interactions with the upper ocean in its propagation.

The continued development of coupled Earth system models also presents an opportunity to expand and improve S2S forecasts of environmental conditions well beyond the traditional weather variables, which represents a second major motivation for this report. There is a strong desire to develop more reliable S2S forecasts of conditions in the ocean, cryosphere, and on the land surface, and meeting these needs is becoming more important as the financial and societal implications of managing environmental risk become more evident and larger in magnitude. Reliable ocean forecasts on S2S timescales, for example, could improve the safety and effectiveness of commercial, military, and humanitarian operations at sea, in part by improving planning and ship routing by indicating ice-free and freeze-up likelihood as well as other ice and ocean eddy hazards. The desire for this type of S2S forecast highlights the importance of high-fidelity representation of ocean, sea ice, and land surface conditions in S2S forecast systems, in many cases for reasons beyond whether they feed back to influence the atmosphere.

A third major motivation for this report is the increasing desire for an enhanced forecasting capability globally. In particular, the Department of Defense and State Departments desire S2S forecasting capability that can best support U.S. engagement anywhere in the world. In addition, commerce, agriculture, and civilian hazard warnings that are at the national level could be expanded to cover more of the world. Developing a comprehensive and skillful global forecasting capability poses an additional challenge because in many areas, only limited in situ weather data are publically available for use in evaluating and improving forecasts.

Finally, accelerating computer and software capabilities could allow S2S prediction systems to operate with greater spatial and temporal resolution, more complete representation of interacting components of the Earth system, and more ensemble members for calculating uncertainties. Together with improved understanding of the physical process governing the Earth system's dynamics and potential advances in the ability to assimilate data into more sophisticated models, new computing capabilities could allow for significant gains in S2S predictions over the next decade.

Despite these needs and opportunities for enhanced Earth system forecasts in the S2S time range, a coordinated national research agenda aimed at strengthening the contributions of S2S forecasts to public and private activities has not yet emerged. For all of these reasons, the Heising-Simons Foundation, the National Aeronautics and Space Agency (NASA), and the Office of Naval Research (ONR) asked the National Academies of Sciences, Engineering, and Medicine to undertake a study aimed at outlining a ten-year research plan to advance the nation's capacity to provide more skillful, comprehensive, and useful S2S predictions. The statement of task that guided the study (see Appendix A) asked the authoring Committee to develop a strategy to accelerate progress on extending prediction skill for weather, ocean, and other Earth system forecasts from meso/synoptic scales to higher spatial resolutions and longer lead times, thereby increasing the nation's research capability and aid in decision making at medium and extended lead times.

In order to meet this request, the current study reviews present S2S forecasting capabilities and recommends a national research agenda to advance Earth system predictions at lead times of 2 weeks to 12 months. The study builds on previous reports that have described a grand vision to significantly advance forecasting accuracy, lead time, and prediction of non-traditional environmental variables (NRC, 1991b, 2008), as well as reports that have discussed opportunities and best practices for intraseasonal-to-interannual prediction (NRC, 2010b). In the years to come, the research agenda proposed here and the efforts that follow could produce increasingly accurate numerical models of the Earth system by describing its coupled interactions and future evolution, thus enhancing the value of weather, climate and other Earth system forecasts to society.

THE REPORT ROADMAP

This report addresses the Committee's charge in seven subsequent chapters. Chapter 2 provides context for discussions in the remainder of the report by presenting an overview of the history and recent evolution of the field of S2S forecasting, descriptions of recent and ongoing research activities, and a summary of the current status and skill of operational subseasonal and seasonal forecasting systems.

Chapter 3 covers decision-making contexts, applications for S2S forecasts, the potential benefits of S2S predictions, attributes of effective forecasts, and user sensitivity to forecasting accuracy. The chapter also contains case studies, including western U.S. water management, public health, and national security and defense, that provide more in-depth discussions of needs for and applications of S2S predictions.

Chapter 4 introduces sources of S2S predictability from natural modes of variability and teleconnections, as well as from the ocean, soil moisture, terrestrial snow, and sea ice and external forcing. The chapter includes recommendations to further predictability research in the S2S context.

Chapter 5 discusses in detail recent advances and activities needed to accelerate the improvement of S2S prediction systems, including discussions of gaps and research needs related to routine observations, data assimilation, and models, as well as calibration, combination, validation, and assessment of S2S forecast skill.

Chapter 6 covers research-to-operations in the context of current operational and research S2S prediction systems.

Chapter 7 presents findings and recommendations on infrastructure for computing, storage, programming models, shared software, and data cyberinfrastructure. The chapter also discusses institutional and workforce capacity building for S2S forecasting and decision support.

Chapter 8 concludes the report by presenting the Committee's vision for the future of S2S forecasts, as well as a summary of the research strategies and research agenda the Committee proposes to advance S2S forecasting over the next decade.

Chapter 2: History and Current Status of S2S Forecasting

Providing useful weather and ocean forecasts, as well as predicting other aspects of the Earth system, have significantly improved national capabilities for decision making in sectors including energy, agriculture, transportation, insurance and finance, defense, emergency preparedness and response, and public security including health, water, and food. As discussed in Chapters 1 and 3, the ability to foresee environmental changes and disruptive events weeks and months in advance could have tremendous additional value because of the broad range of decisions that are made weeks to months in advance. As a prelude to developing a U.S. research agenda for advancing subseasonal to seasonal forecasting, this chapter lays out the history and evolution of the S2S forecast endeavor and briefly summarizes current operational capabilities and research activities.

EVOLUTION OF THE FORECAST ENTERPRISE

Short to Medium Range Forecasts (Up to 14 Days)

Modern weather prediction evolved from the global weather observations obtained during World War II, the computers that followed in the wake of the war, and a working knowledge of equations that model the typical variations in the mid-latitude atmosphere. Earth-sensing satellites, starting with the Television Infrared Observation Satellite Program (TIROS) in the 1960s, provided striking views of Earth's changing weather patterns and contributed to the understanding of weather systems and to the improvement of routine weather forecasts.

With these improved data sources and modeling capabilities, purely subjective forecasts based on atmospheric synoptic maps, experience, and intuition gave way to a combination of computer-generated atmospheric and marine forecasts based on physics equations and a statistical interpretation of the forecast information. This know-how developed into highly capable systems operated by the civil and defense weather services. In the latter part of the 20th century, consumer interests in weather and the wide demand for specialized forecasts stimulated a vigorous private sector operating alongside the public weather services (NRC, 2003). Similar trends are also occurring for ocean forecasting and applications.

Moving into the 21st century, the combination of greatly improved atmospheric and oceanic observations and accelerating computer power has produced increasingly accurate and reliable atmospheric forecasts. Computer-calculated forecasts of global and regional weather patterns are now as accurate at 72 hours as they were at 36 hours in the 1990s (Figure 2.1). Although this might suggest that lead times for useful forecasts could continue to increase indefinitely with further improvements in observations, understanding, and computer capability, the discovery of mathematical chaos in nonlinear physical systems in the early 1960s by Edward N. Lorenz (Lorenz, 1963) challenged this assumption. Instead, Lorenz showed that unavoidable small errors in initial conditions will amplify during the computation, bringing a natural limit to the lead time that the "weather"—or any given natural environmental phenomenon—can be

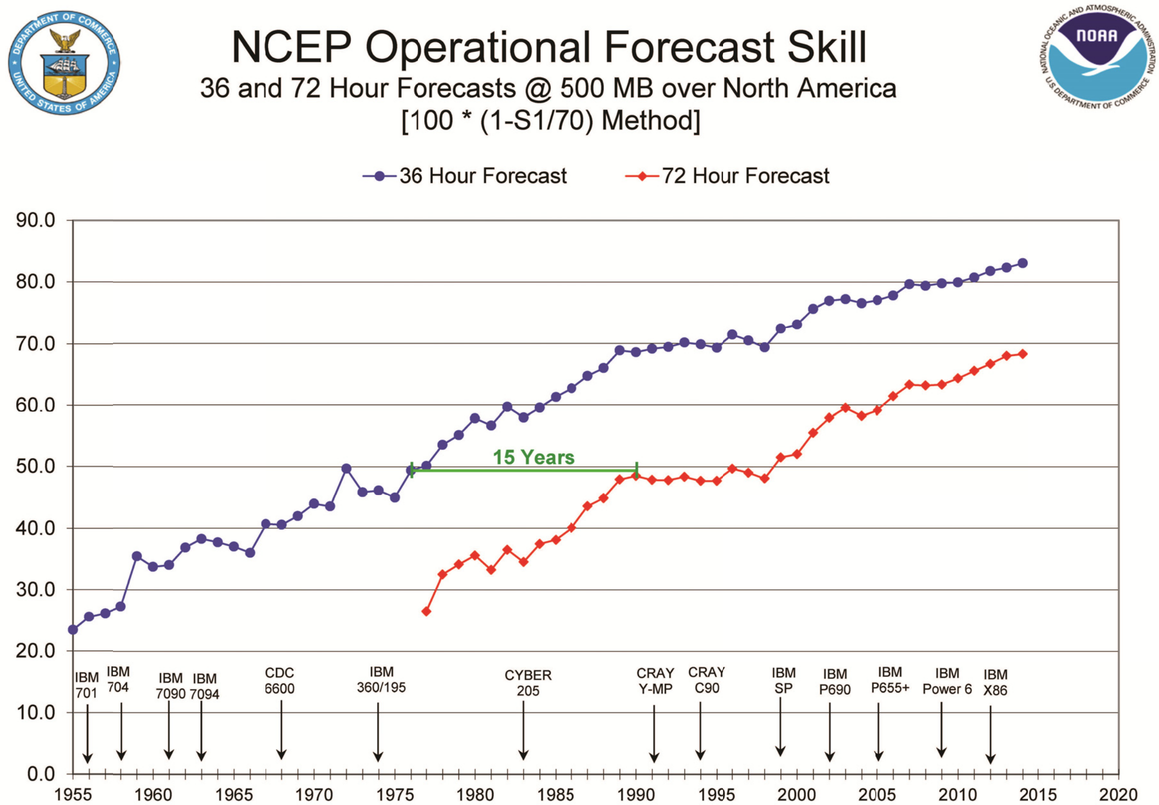


FIGURE 2.1 Forecast verification for 36 and 72-hour forecasts for the Global Forecast System (GFS) model. The skill (S1) is based on the mean error of the 500 mb heights in the forecasts relative to radiosonde measurements over North America. This quantity is shown as 100*(1-S1/70). A perfect forecast is 100. Dates of computer hardware upgrades are shown with arrows along the x-axis. SOURCE: National Center for Environmental Prediction, http://www.nco.ncep.noaa.gov/sib/verification/s1_scores/s1_scores.pdf, accessed July 20, 2015.

predicted, at least deterministically. Today, the emphasis is on improvement and extension of lead times through probability forecasts, created by averaging over space and time and running multiple cases to create ensembles of forecasts that reflect probabilities of variables or events at future times. Along with probabilistic ensemble forecasts, recent advances in weather prediction accuracy have come from improved understanding of the underlying processes and more realistically incorporating them into the forecast models, in part by increasing model spatial resolution and in part through better parameterization of unresolved processes. Further, improved measurements and assimilation of those measurements to more accurately reflect the initial state of the environment have also greatly advanced the skill of weather forecasts.

Following the atmospheric community, short- to medium-range (up to 7 days) ocean forecasts have been routinely available for the past 10 years and provide predictions of ocean currents, temperature, and salinity (GODAE, 2009). These predictions are used by national agencies (e.g., Navy, National Oceanic and Atmospheric Administration, Coast Guard), the oil industry, and fisheries, among others, for various applications such as ship and submarine routing, search and rescue, deep ocean drilling, oil spill drift application, monitoring of open ocean ecosystems, fisheries management, coastal and near-shore resource management (e.g., Jacobs et al., 2009). The development of these ocean forecast systems has been critical to the development of high-resolution coupled ocean-atmosphere-ice-land prediction systems for improving short- to medium-range forecasts, and they are being used by the ocean community to develop subseasonal ocean forecasts (Brassington et al., 2015). With the addition of aerosol chemistry and biogeochemistry, such models are often referred to as Earth prediction systems. Advances in coupled model systems are central to extending lead times and furthering accuracy of short and medium-term forecasting capabilities in the ocean and atmosphere, are the basis for advancing S2S forecasts, and are critical for developing a more expansive set of routinely forecast Earth system variables.

Seasonal Forecasts (3 to 12 Months)

Long-range and seasonal forecasts began in the mid-1950s as Weather Bureau forecasters noticed some identifiable large-scale patterns and relations between atmospheric and ocean temperature anomalies in various locations (Hoskins and Karoly, 1981; Namias, 1953; Roads, 1999; Walker, 1924; Wallace and Gutzler, 1981). These early seasonal forecasts were made based on statistical methods. Dynamical seasonal predictions started in the early 1980s (Reeves and Gemmill, 2004), using atmosphere-only models with prescribed surface conditions. Often, the latest observed ocean anomalies persisted during the forecast, but other surface conditions, like sea ice, snow cover, and soil moisture, were proscribed from climatology (e.g., average historical conditions). Such systems treated the surface as a fixed boundary condition, and generally ignored the coupled dynamics with the surface that evolve over the forecast period (two-tier system). Focused on El Niño-Southern Oscillation (ENSO; see Box 1.3) prediction, the first coupled atmosphere-ocean forecasts were generated with simple dynamical or statistical models of tropical surface temperatures (Cane et al., 1986; Graham et al., 1987; NRC, 1986, 1991a, 1994; Shukla, 1998).

In contemporary seasonal forecast systems, many aspects of the Earth system are predicted in a coupled model involving the atmosphere, ocean, land, and cryosphere. These seasonal forecasts systems seek to better exploit ENSO as a source of predictability, while also representing more recently discovered predictability sources originating from other natural modes of variability of the coupled ocean-atmosphere system; stratosphere-troposphere interactions; the slow evolution of the ocean, ice, land hydrology and biosphere; and radiative forcing from GHG and aerosols and land use changes (see Chapter 4). In dynamic seasonal prediction systems, modeled Earth system components (atmosphere, land, ocean, and sea ice) are increasingly coupled numerically to represent the rapidly varying atmosphere exchanges of energy, water, and momentum, which give the system much of its predictability on timescales longer than a few days. Additional progress could be made: some components, such as the ocean, are more realistically coupled with the atmosphere, while aspects of coupling to the cryosphere and land are widely recognized to be oversimplified in today's forecast systems (Doblas-Reyes et al., 2013). Recent research indicates that much of the seasonal predictability in some parts of the world derives from trends associated with GHG warming superimposed on natural variability, thus more realistic representation of atmospheric chemistry and biogeochemistry (GHG forcing, land use changes, aerosols, etc.) in seasonal prediction systems is also increasingly common (Doblas-Reyes et al., 2006).

Seasonal forecasting has improved over the last decade with efforts to reduce systematic model errors and with better understanding and representation of sources of predictability within the coupled Earth system. There are two other notable strategies for advancing the skill and utility of seasonal forecasts. One is the inclusion of quantitative information regarding uncertainty (i.e., probabilistic prediction) in forecasts and probabilistic measures of forecast quality in the verifications (e.g., Dewitt, 2005; Doblas-Reyes et al., 2005; Goddard et al., 2001; Hagedorn et al., 2005; Kirtman, 2003; Palmer et al., 2004; Palmer et al., 2000; Saha et al., 2006, among many others). This change in prediction strategy naturally follows from the fact that Earth system variability includes a chaotic or irregular component, and, because of this, forecasts must include a quantitative assessment of this uncertainty. More importantly, the prediction community now understands that the potential utility of forecasts is based on end-user decision support (Challinor et al., 2005; Morse et al., 2005; Palmer et al., 2000; Chapter 3), which requires probabilistic forecasts that include quantitative information regarding forecast uncertainty or reliability.

The use of perturbed parameter ensembles represents a second strategy that is now commonly used to quantify uncertainty in the initial conditions of seasonal prediction systems, though the number of such ensembles in both the forecast and the retrospective forecast vary widely across different operational centers (Appendix B). Other techniques have been implemented to account for uncertainty in model formulation. Most prominent among these is the development of multi-model ensembles (MMEs). By combining the predictions from more than one model, MMEs quantify some of the uncertainty associated with individual model formulations, and also tend to improve the forecast, probably because errors in one model may not appear in the others. With a few caveats, MMEs that include multiple operational and/or research models appear to achieve a better skill than individual models, by combining different approaches to data analysis, data assimilation, model parameterizations and resolutions (Weigel et al. 2008; Kirtman, 2014; Kirtman et al., 2014). Other techniques, such as perturbed physics ensembles or stochastic physics (e.g., Berner et al., 2008; Berner et al., 2011) have now also been developed and appear to be quite promising for representing some aspects of model uncertainty (e.g., Weisheimer et al., 2011). Chapter 5 covers these developments in more detail.

Subseasonal Forecasts (2-12 Weeks)

A prevailing expectation is that subseasonal prediction in the 2-12 week range between short and medium-range and seasonal prediction poses serious challenges. This expectation arose because of the perception that the subseasonal atmospheric forecast problem does not fit neatly into the simplistic paradigms of an initial-value weather forecast problem (because the lead times are too large and initial-value information can be lost) or the so-called “boundary-value climate prediction problem,” terminology associated with the early seasonal climate forecast systems that were driven by prescribed surface temperature anomalies. However, recent work indicates the potential for predictability across all timescales (Hoskins, 2013; WMO, 2015a). There is evidence to indicate that the existing coupled ocean-atmosphere-ice-land Earth system forecast models, mentioned above, integrate the information from the initial conditions across the coupled system, including the slowly varying components (e.g., ocean, sea ice, and land hydrology), to produce subseasonal forecasts with realized skill in traditional weather variables often comparable to that of the seasonal forecasts (Dutton et al., 2013; Dutton et al., 2015).

Predictability and prediction studies on intraseasonal tropical variability and the Madden Julian Oscillation (MJO; see Box 1.3) have further advanced the prospects of subseasonal forecasting (e.g., Lin et al., 2008; Vitart et al., 2007b; Waliser et al., 2006). However, it is important to note that within the subseasonal timescale, predictability and prediction in sub-monthly timescale is still relatively underexplored and underdeveloped compared to forecasts with lead times of a month to a season (Doblas-Reyes et al., 2013; Vitart et al., 2012). An important goal for subseasonal (and seasonal) forecasting is to move beyond multi-day averages of typical meteorological variables to prediction of the likelihood of important and disruptive events in all components of the Earth system, such as heat and cold waves, unusual storminess, ice cover, sea level, Gulf of Mexico Loop current position, etc.

CURRENT STATUS OF ACTIVITIES AND RECENT PROGRESS

This section provides a brief survey of current capabilities and ongoing activities in both seasonal and subseasonal prediction, along with recent progress at operational centers. This is a prelude to establishing a U.S. research agenda that will lead to improved S2S forecasts and better-informed decisions in both the public and private sectors.

Seasonal

Most operational centers have produced routine dynamical seasonal predictions for more than a decade. A majority of the centers utilize global atmosphere, ocean, land, and sea ice coupled models (one-tier systems) to predict climate anomalies out to lead times of 6-12 months. There are a few centers, such as the International Research Institute for Climate and Society (IRI[1]), that use so-called two-tier systems, in which the ocean component is predicted first, and then those predicted sea surface temperatures are used as boundary conditions for an atmospheric forecast with lead times out to 3-4 months. IRI has been issuing seasonal climate forecasts from this system since 1997 (Barnston et al., 2010). Examples of one-tier systems include the U.S. National Weather Service's Climate Forecast System (Saha et al., 2010; Saha et al., 2006), which produces operational predictions with lead times of up to nine months, and the European Centre for Medium-Range Weather Forecasts' (ECMWF) seasonal climate prediction system, which is soon to be in its fourth generation[2]. Other nations have similarly developed seasonal prediction systems that include models developed specifically for this purpose, and the WMO Lead Centre for Long-Range Forecast Multi-Model Ensemble[3], coordinated by the Korea Meteorological Administration and NOAA, collects seasonal forecasts from 12 such seasonal prediction systems (Global Producing Centers) and combines them into multi-model seasonal forecasts that are used by regional and local climate centers around the world (see Box 2.1).

Seasonal prediction has been increasingly prominent at national and international operational centers for several decades. Almost all operational centers produce seasonal predictions at least once per month. Usually, deterministic and probabilistic forecasts of seasonal mean anomalies of surface temperature (atmosphere and ocean) and precipitation are issued for above, below, and near normal values. Seasonal outlooks and ENSO index predictions are also

---

[1] http://www.wmo.int/pages/prog/wcp/wcasp/clips/outlooks/climate_forecasts.html, accessed January 27, 2016.
[2] http://www.ecmwf.int/en/forecasts/documentation-and-support/evolution-ifs/cycles/technical-description-seasonal (accessed February 3, 2016).
[3] https://www.wmolc.org/, accessed January 27, 2016.

issued based on a combination of dynamical predictions, statistical models, and expert knowledge of teleconnection patterns.

In addition to the ensemble of model integrations into the future, seasonal forecasts require a historical series of model integrations over past decades (these are also called retrospective forecasts, reforecasts or hindcasts). To create retrospective forecasts, the model configuration is integrating over a large sample of historical cases (forecasts with known outcomes). These are then used to calibrate future forecasts for biases and reliability as well as to evaluate model skill. An average (or another statistic such as an anomaly) over time is also required for the forecast to be meaningful. For seasonal prediction, this averaging period is usually a season (three months). A common practice is to produce categorical (e.g., above normal, below normal, or near normal) probabilistic forecast of seasonal mean anomalies of some basic variables such as surface air temperature and precipitation at monthly lead times (see Figure 3.2).

In addition to seasonal forecasts from operational centers throughout the world, collaborative international efforts aimed specifically at improving seasonal predictions have been critical for advancing forecasting capabilities. Many of these efforts have a focus on studying predictability and improving forecast skill via multi-model approaches. In addition to the MME seasonal forecasts issued by IRI, the Asia-Pacific Economic Corporation Climate Center (APCC) provides routine seasonal MME forecasts to member countries, and the aligned Climate Prediction and its Application to Society (CliPAS) developed a database of retrospective forecasts for prediction and predictability research (Box 2.1). The North American Multi-Model Ensemble (NMME) is a demonstration project for S2S prediction involving universities and laboratories in the United States, the National Centers for Environmental Prediction (NCEP), and the Canadian Meteorological Center (CMC). NMME started producing seasonal multi-model ensemble forecasts in 2011 (Kirtman et al., 2014), and these are now issued in a quasi-operational mode (Box 2.2).

In Europe, the Development of a European Multi-model Ensemble system for seasonal to interannual predictions (DEMETER) produced a comprehensive set of seasonal retrospective forecasts in order to evaluate MME skill (Palmer et al., 2004). The ENSEMBLES Program[4] has built on DEMETER to assess how advances in individual seasonal forecast systems translate into reductions in ensemble mean error (Weisheimer et al., 2009). ENSEMBLES has attempted to objectively evaluate uncertainty in MME and other ensemble predictions at seasonal through decadal and longer timescales, including the relative benefits of different model and system configurations. Several model intercomparison efforts, including, the WCRP Seasonal Prediction Model Intercomparison Project (SMIP-2),[5] have also provided valuable insights into model predictive skill and predictability.

Subseasonal

Building on a number of research and experimental efforts over the last decade, subseasonal predictions began in earnest with the establishment of an MJO prediction metric and

[4] http://www.ecmwf.int/en/research/projects/ensembles, accessed January 27, 2016.
[5] Seasonal Prediction Model Intercomparison Project-2.

BOX 2.1—The Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) Climate Outlook

The Asia-Pacific Climate Center (APCC[6]) is a joint activity of Asia-Pacific Economic Cooperation involving 17 operational and research centers from nine APEC member countries, including the United States. Along with Climate Prediction and its Application to Society (CliPAS)[7] the aim of the APCC is to produce a well-validated multi-model seasonal prediction system to support the Asia-Pacific region. APCC has been collecting dynamic ensemble seasonal prediction data from affiliated centers since 2006, and it produces one month and three-month forecasts of precipitation, temperature at 850hPa, and geopotential height at 500hPa with lead times ranging from one month to six months. These forecasts are disseminated to APEC members, and verification is conducted in compliance with the WMO guideline on verification of long-range forecasts. APCC also produces routine forecasts of several climate modes including ENSO and Indian Ocean Dipole (IOD) on seasonal timescales, as well as the Boreal Summer Intraseasonal Oscillation (BSISO), which is an important modulator of Asian monsoon onset and breaks on subseasonal timescales. APCC also provides multi-model output-based statistical downscaling results for Taiwan, Philippines, Thailand, South Korea, and Japan. As examples, the output of these forecasts has been useful for predicting the electricity demand in Japan and the local level forecasts in South Korean and Taiwan are being applied to drought forecasting to manage water resources. As part of the research activities of the APCC, CliPAS assembled a database of retrospective forecasts (1980-2004) to gain a better understanding of the factors that limit seasonal prediction (e.g., Wang et al., 2008; Wang et al., 2009a) and to foster research on improving MME methodologies (e.g., Kug et al., 2008; Min et al., 2014).

BOX 2.2—The North American Multi-Model Ensemble (NMME)

The North American Multi-Model Ensemble (NMME[8]) is a demonstration project for S2S prediction involving universities and laboratories in the United States, NOAA NCEP, and the Canadian Meteorological Center (Kirtman, 2014). NMME has multiagency support from the NOAA, the National Science Foundation (NSF), National Aeronautics and Space Administration (NASA), and the Department of Energy (DOE). The Phase 1 experimental real-time system started issuing forecasts in August 2011 (Kirtman, 2014). The Phase 2 system (NMME-2), with a slightly different suite of systems, began operations in August 2014 and is being used in a demonstration mode as part of the NOAA NCEP Climate Prediction Center (CPC) seasonal forecast system. NMME-2 participating centers, climate projection systems, and ensemble members are shown in Appendix B. Real-time data are provided to users on an NCEP server system, while retrospective forecast data are provided by IRI and archival data are passed to the National Center for Atmospheric Research (NCAR) as time and funding allow for research access.

The first phase of NMME focused on seasonal-to-interannual timescales and only monthly data were collected. Due to the growing interest in forecast information, there is a strong emphasis in NMME-2 to focus on the 2-4 week timescale. The requirements for operational S2S prediction are used to define the parameters of a rigorous retrospective forecast experiment and evaluation regime. An additional focus of Phase 2 will be the hydrology of various regions in the United States and elsewhere in order to address drought and extreme event prediction.

---

[6] http://www.apcc21.org/, accessed January 27, 2016.
[7] http://iprc.soest.hawaii.edu/users/jylee/clipas/, accessed January 27, 2016.
[8] More information on the National Multi-Model Ensemble is available at http://www.cpc.ncep.noaa.gov/products/NMME/NMME_description.html and https://www.earthsystemcog.org/projects/nmme/ (both accessed January 27, 2016).

its uptake by a number of forecast centers (e.g., Gottschalck et al., 2010; Vitart and Molteni, 2010; Waliser, 2011). As of 2009, the outputs from 10 operational centers have been used in an operational manner to provide ensemble predictions of the phase and magnitude of the MJO.[9] These systems all produce daily ensemble forecasts (sizes range from 4 to 51) with lead time of 7 to 40 days. Some centers also produce single deterministic forecasts using high-resolution versions of their models. NCEP CPC receives the daily forecasts of zonal wind and outgoing longwave radiation (OLR) from these centers and calculates the predicted MJO index. The forecast products are delivered as plume phase diagrams of the predicted MJO index for each center. APEC's BSISO forecasts are produced similarly (see Box 2.1).

Many operational numerical weather prediction centers have also recently implemented extended-range (10-30 day) prediction systems that provide building blocks for more useful subseasonal prediction systems (Brassington et al., 2015). Such forecasts are developed in three basic ways: (1) by using forecasting systems designed for seasonal climate predictions, but utilizing only the first 30 to 60 days of the forecast, and paying more attention to the daily or weekly variations rather than the mean monthly or seasonal variations within the forecast; (2) by running an air-sea-ice-land coupled model with a higher resolution than the seasonal system; and (3) by extending the lead times of an ensemble medium-range weather forecast using a Numerical Weather Prediction (NWP) model out to lead times of 30 days or more. Methods 2 and 3 produce systems that are independent of the seasonal system. Current operational systems include a 4-times-per-day, 4 member, 45-day lead ensemble from the U.S. National Weather Service (NWS), a 2-times-per-week, 51 member, 46-day lead ensemble from the European Centre for Medium-range Weather Forecasts (ECMWF), a once-per-week, 21 member, 32-day lead ensemble from Environment Canada, and at least eight others. See Appendix B, Table B.2 for more detail on forecasts and the configuration of subseasonal forecast systems.

Many of the same statistical considerations and associated trade-offs cited above for seasonal forecasting (e.g., forecast lengths and averages, ensemble sizes, multi-model ensembles [MMEs], verification periods) are relevant for subseasonal forecasting, although the shorter lead times for subseasonal prediction allow for increased verification instances for a given size observation period. A number of operational centers now compute retrospective forecasts (also known as forecast histories or reforecasts) as part of the operational forecast process and provide them along with the forecast itself. Frequently computing retrospective forecasts has allowed for continuous improvement of some aspects of forecast systems and permits the calibration to take account of recent events in the current weather/climate regime.

As for seasonal forecasts, an important component of subseasonal forecasts is the retrospective forecast, which is performed over a few years to decades in order to calibrate the real-time forecasts. In contrast to operational medium-range weather prediction, there is lack of standardization among the centers in producing subseasonal forecasts. For example, some centers produce the forecast once a month, some once a week, some twice a week, and some every day. Some centers start all the ensemble members from the same initial time, whereas others use a time-lagged method where they start with different initial times and therefore different initial analyses. The retrospective forecasts are also produced very differently, e.g., some on-the-fly, and some with a fixed model version which may not represent the latest operational configuration. These differences can make it difficult for data exchange, performance

[9] http://www.cpc.ncep.noaa.gov/products/precip/CWlink/MJO/CLIVAR/clivar_wh.shtml, accessed January 27, 2016.

inter-comparison, and research. Further details of current subseasonal forecast systems' resolutions, lead times, ensembles, etc., can be found in Appendix B.

Common targets for subseasonal prediction beyond intraseasonal tropical variability (e.g., the MJO and BSISO forecasts mentioned above) include tropical cyclones and extratropical weather. A number of centers provide long-lead information for one and two week outlooks depicting the probability of United States-based hazardous weather, as well as tropical cyclone frequency, tropical-midlatitude teleconnection impacts, etc. (e.g., the National Centers for Environmental Prediction [NCEP]/Climate Prediction Center's [CPC's] Global Tropical Hazards and Benefits Outlook and U.S. Hazards Outlook[10]). These products are graphically highlighted areas with expected persistent above- or below-average rainfall and regions favorable or unfavorable for tropical cyclogenesis in weeks 1 and 2. The outlooks are based on expert combination of various statistical and dynamical forecasts, including the MJO forecast mentioned above. More recently, the private sector has also become active in developing commercial subseasonal forecasts; for example, the NWS and ECMWF subseasonal forecasts have been combined in a commercial MME by the World Climate Service (Dutton et al., 2013; Dutton et al., 2015). Many centers produce forecasts at various lead times of the mean values and probabilities of anomalies averaged over periods of a week or a month. Research efforts to support the further development of subseasonal forecasts are also beginning to develop. The WMO's World Climate Research Program (WCRP) and World Weather Research Program (WWRP) have jointly developed a new initiative on Subseasonal to Seasonal Prediction (the S2S Project) (Robertson et al., 2015; Vitart et al., 2012; see Box 2.3 and Chapter 6 for additional information). The thrust of the S2S Project is on improving the subseasonal prediction of extreme weather, such as droughts, heat waves, tropical cyclone development, monsoon precipitation, and also subseasonal prediction in polar areas. To do so, the project is collecting forecasts and retrospective forecasts from a number of operational modeling centers into a common database and disseminating them in delayed mode for research purposes to the science and applications communities.

In addition to the seasonal forecasts discussed in the previous section, NMME (Box 2.2) is also focusing on a second phase of effort to issuing in demonstration mode and further developing subseasonal forecasts and retrospective forecast databases (see Chapter 6 for more details). These forecasts are issued in real time in near-operational mode, and are already used by NCEP Climate Prediction Center (CPC) to inform subseasonal hazards outlooks, as well as being available to other users and for the purposes of predictability research and model and forecast system improvement.

Recent Progress in Advancing S2S Forecast Skill

There has been substantial progress in improving the skill of both subseasonal and seasonal forecasts in recent years. Generally, forecast skill for traditional atmospheric variables is still low (see discussion below), but the skill of forecasts of indices of coupled ocean-atmosphere modes of variability is often higher. For seasonal prediction, the Niño 3.4 index, a major indicator of the ENSO, shows useful skill up to one year in some models (e.g., Jin et al., 2008; Stockdale et al., 2011). ECMWF System 4 and NCEP CFSv2 also capture the year-to-year

[10] http://www.cpc.ncep.noaa.gov/products/predictions/threats/threats.php and http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ghazards/index.php, both accessed January 27, 2016.

BOX 2.3—The Subseasonal to Seasonal Prediction Project

The World Weather Research Programme (WWRP) and World Climate Research Programme (WCRP) started a joint research project, S2S Project[11], in January 2013. The S2S Project has three primary objectives: (1) to improve forecast skill and understanding on the subseasonal to seasonal timescale; (2) to promote its uptake by operational centers and exploitation by the applications community; and (3) to capitalize on the expertise of the weather and climate research communities to address issues of importance to the Global Framework for Climate Services. Specific attention will be paid to the risk of extreme weather, including tropical cyclones, droughts, floods, heat waves, and the waxing and waning of monsoon precipitation.

The central activity of the S2S Project is the establishment of a multi-model data base consisting of ensembles of subseasonal (up to 60 days) forecasts and supplemented with an extensive set of retrospective forecasts following THORPEX Interactive Grand Global Ensemble (TIGGE) protocols. As of January 2016, nine operational centers (i.e., BoM, CMA, ECMWF, HMCR, JMA, Météo-France, UKMO, CNR-ISAC, and NCEP) have begun to send retrospective forecast and forecast data to the S2S Project archive (see Appendix B for details on these centers), with a total of eleven centers expected to be contributing by the end of 2016. Note that while this project leverages operational systems, the forecasts are disseminated with a three-week delay, and thus at present there is a focus on leveraging operational model output for research that can improve subsequent forecast systems, rather than on issuing MME forecasts in demonstration mode. However, there are plans to provide the forecasts in near real-time to the WMO Lead Center for Extended Range Prediction (WMO, 2015b).

A major research topic will be evaluating the predictability of subseasonal events, including identifying windows of opportunity for increased forecast skill with a special emphasis on events that have high societal or economic impacts. Attention will also be given to the prediction of intraseasonal characteristics of the rainy season that are relevant to agriculture and food security in developing countries. The Project's research implementation plan (WMO, 2013) calls for six subprojects that focus on key S2S research and application areas, including the MJO, Africa, extreme weather, verification, stratospheric link, and teleconnections. The project will last five years, after which the opportunity for a five-year extension will be considered.

ENSO variability with fair accuracy, and both capture the main ENSO teleconnection pattern in the tropical and extratropical regions (e.g., Kim et al., 2012).

Prediction skill of extratropical modes and patterns such as the North Atlantic Oscillation (NAO) has also recently improved. Scaife et al. (2014a) show good prediction skill of the winter NAO from the UKMO system, with a correlation in excess 0.6 between ensemble mean and observed NAO index for December-February for forecasts from the start of November (Figure 2.2). They also show that the model is capable of capturing at least qualitatively the observed influence of ENSO on the NAO, as well as the influence of Atlantic heat content, sea ice from the Kara Sea, and the QBO on NAO seasonal predictability. The performance of this model relative to what was possible a few years ago was likely achieved primarily through reducing biases in the model atmosphere and ocean, leading to an improved model climate (Scaife et al., 2011). Increases in model resolution were also likely important.

Similar progress in forecasting indices has also been made on subseasonal timescales. About 15 years ago, dynamical models had some MJO forecast skill out to 7-10 days (Waliser, 2011), but performed worse than empirical models that use statistical methods to predict MJO

[11] Details of the S2S Project, including the database, contributing centers / forecast systems, descriptions of the subprojects, project organization can be found at s2sprediction.net.

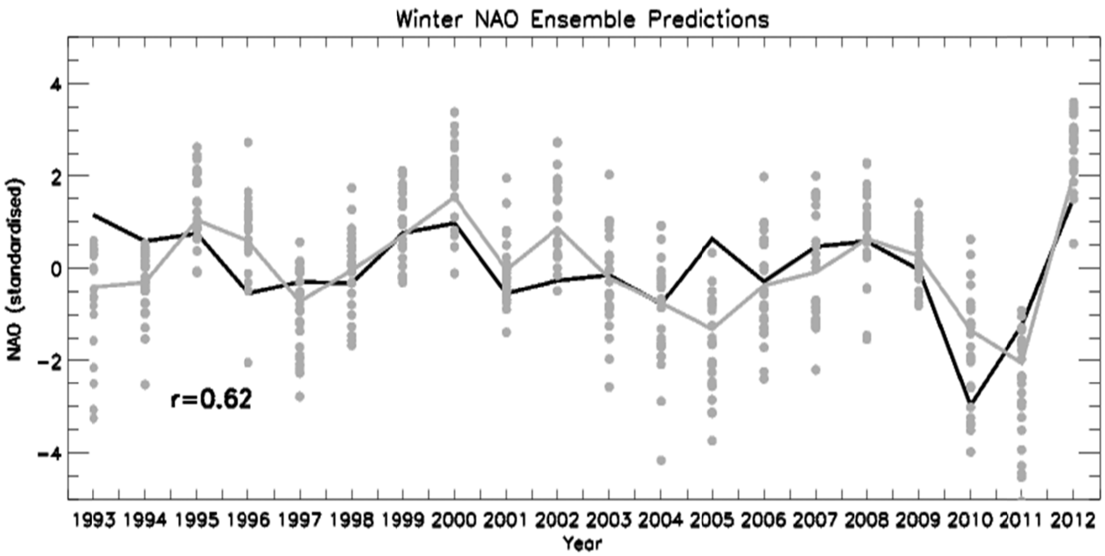


FIGURE 2.2 Predictability of the winter (December-February) NAO in the UKMO seasonal forecast system. Time series of the NAO in observations (black line), ensemble mean forecasts (grey line), and individual ensemble members (grey dots) in winter retrospective forecasts are shown. The correlation score of 0.62 is significant at the 99% level according to a t test and allowing for the small lagged autocorrelation in forecasts and observations. SOURCE: Figure and caption modified from Scaife et al., 2014a.

(e.g., Hendon et al., 2000; Jones et al., 2000). Recently, skillful MJO forecasts have been achieved beyond 20 days (e.g., Kang and Kim 2010; Rashid et al. 2010; Vitart and Molteni 2010), and the ECMWF in particular has made substantial strides its MJO forecast (particularly at longer lead times) (Figure 2.3). These advances are due largely to improvements in the representation of physical processes and coupling in the models, better initial conditions, and the availability of better quality and longer periods of retrospective forecast data to calibrate the forecast (e.g., Vitart, 2014; Vitart et al., 2014). Through better model representation of the teleconnections (i.e., vertical profile of tropical heating and better stratospheric processes and stratosphere/troposphere interactions), improvements in the prediction of tropical phenomena such as MJO and ENSO have also led to some increase in skill in the extratropics and also the prediction skill of ocean variables and phenomena such as tropical cyclone counts (e.g., Vitart et al., 2007a).

Despite this progress, traditional measures of S2S forecast skill such as anomaly correlation and root mean square error when applied to systems such as NCEP's CFSv2 (Climate Forecast System) or GEFS (Global Ensemble Forecast System) indicate little skill from week 2 and beyond, even with the application of temporal averaging. As mentioned above, multi-model ensemble forecasts have improved forecast skill of such traditional atmospheric variables in some cases, but even for seasonal forecastss, large gaps persist across specific regions and seasons, especially for precipitation. For example, skill of ENSEMBLES multi-model forecasts of boreal winter conditions is good in the tropics and over oceans, particularly for temperature; however, skill over land, especially outside of the tropics, is limited (Figure 2.4). Although the quality is slightly better over land areas with strong ENSO teleconnections (e.g., North America in boreal winter), skill is still low in certain areas, for example, over most of Europe during the winter (Doblas-Reyes et al., 2013).

.

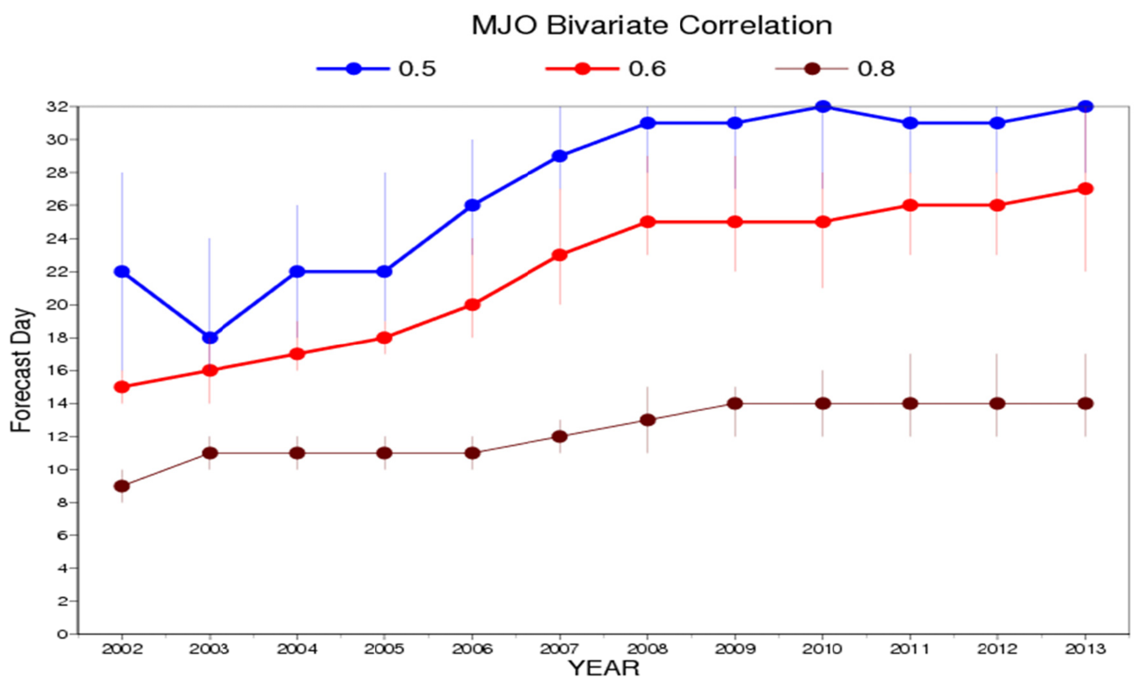


FIGURE 2.3 Evolution of the MJO skill scores since 2002, calculated as bivariate correlations applied to the Real-time Multivariate MJO (RMM) index of Wheeler and Hendon (2004). The MJO skill scores are computed on the ensemble mean of the ECMWF retrospective forecasts produced during a complete year. The blue, red, and brown lines indicate respectively the day when the MJO bivariate correlation skill drops to 0.5, 0.6, and 0.8. SOURCE: Modified from Vitart, 2014.

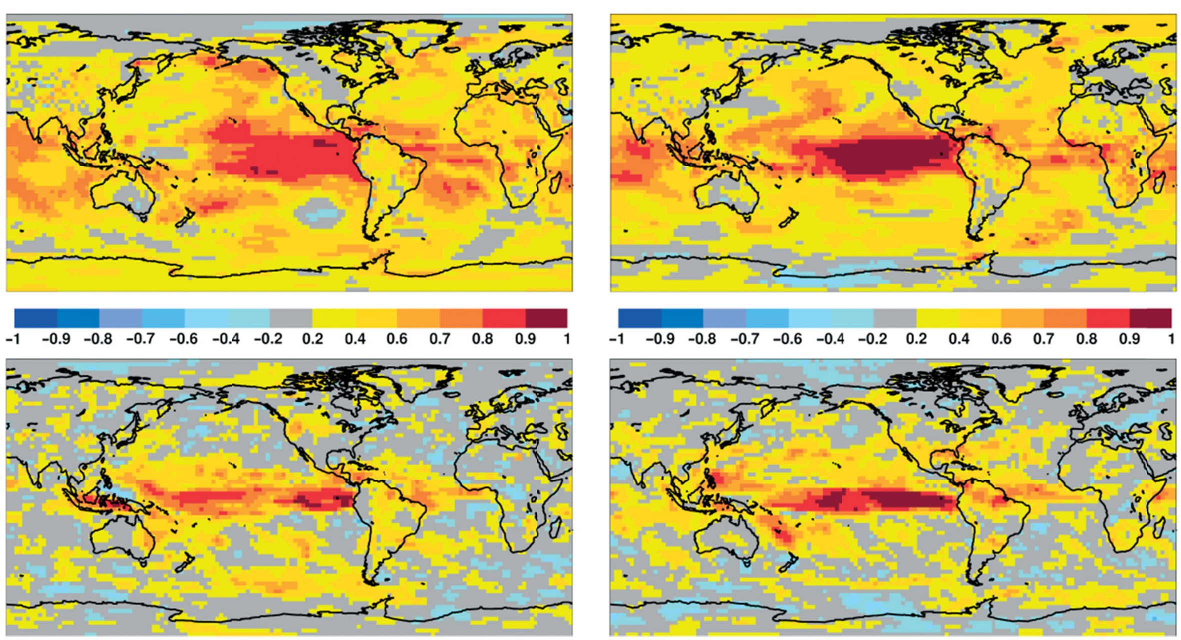


FIGURE 2.4 Correlation of the ensemble mean of one-month lead surface air temperature (top row) and precipitation (bottom row) from the ENSEMBLES multi-model seasonal predictions in boreal summer (June to August, left column) and winter (December to February, right column). The predictions have been performed over the period 1980-2005 with five different forecast systems, each one running nine-member ensembles. The reference data are taken from ERAInterim79 for temperature and GPCP116 for precipitation. SOURCE: Figure and caption from Doblas-Reyes et al., 2013.

Enhanced forecast skill is sometimes possible during specific windows of time in specific regions. Skill to 20 days is possible, for example, during specific MJO phases (Lin et al., 2010; Rodney et al., 2013). Such contingent improvements in forecast skill, along with generally low skill for traditional atmospheric forecast variables over large areas and time windows, highlights the importance and promise of so-called forecasts of opportunity (see Chapter 4).

The recent extreme low sea ice extent in summer in the Arctic prompted the Sea Ice Outlook[12] to begin gathering seasonal forecasts in 2008. The first published skill of a retrospective forecast of sea ice extent appeared soon after, in 2013 (Wang et al. 2013; Sigmond et al, 2013; Merryfield et al, 2013). Dynamical models exhibit skill at these lead times, but their skill is still substantially below estimates of perfect-model forecast skill (see also Figure 4.2). Further, no study has yet published an evaluation of S2S forecast skill at the regional or local scale for sea ice variables such as concentration, thickness, or ice-type, which are likely to be useful to forecast users.

In summary, over the past two decades substantial progress has been made understanding some of the physical drivers for S2S prediction, and operational centers have made some progress in improving S2S forecast skill. While prediction skill for indices of climate modes such as the MJO and ENSO has improved more dramatically, current operational skill is low for many traditional weather and climate variables. S2S forecasts for Earth system variables outside traditional weather and climate forecasts are less well developed, but have also been advanced by the development of coupled Earth system prediction systems.

The growing interest by the science community and operational forecast centers to develop and implement many of the projects and experiments described above, in addition to recent progress in S2S predictability research and operational predictions, illustrates the research priority and expectations associated with S2S timescales. However, an associated U.S. national research agenda aimed at strengthening the contributions of S2S forecasts to public and private activities has not yet emerged.

Finding 2.1: Although there has been considerable progress in S2S forecasting over the past several decades, there are still many opportunities for improvements in S2S forecast skill.

[12] http://www.arcus.org/sipn/sea-ice-outlook, accessed January 27, 2016.

Chapter 3: Enhancing the Value and Benefits of S2S Forecasts

Determining the economic value of climate and weather forecast information remains challenging (Dutton, 2002; Morss et al., 2008; Lazo et al., 2011; Letson et al., 2007; U.S. Department of Commerce, 2014). Some work indicates that a significant portion of annual U.S. gross domestic product (tens of billions or even trillions of dollars) may be sensitive to the weather (Dutton, 2002). Regardless of forecasts' exact economic value, there is growing recognition that subseasonal to seasonal (S2S) predictions could play an important role in reducing society's exposure to weather, climate, and other environmental variability, both in the United States and globally (e.g. Thiaw and Kumar, 2015;World Bank, 2013).

Realizing potential benefits of S2S predictions will require physical science research to advance understanding of the many complex interactions at play within Earth system and to overcome the many technical hurdles associated with translating such research into improved S2S forecast systems (see Chapters 4 through 7). However, a crucial aspect of realizing the value of S2S forecasts involves generating and applying knowledge about the many social and behavioral dynamics, as well as the legal and equity issues that are associated with using such forecasts to improve decision making (NRC, 1999, 2010a, c). While addressing the latter set of issues in their entirety is beyond the scope of this report, the Committee believe that it is important both to highlight in more detail the value proposition of S2S forecasts and to outline critical steps that the S2S research community can take to ensure that investments made in current and future S2S forecast systems are leveraged to maximize the ability to inform choice, action, and social and economic benefit.

This chapter presents the context in which S2S forecasts are or could be used by a diverse set of decision makers, highlights some barriers to use, and presents findings and recommendations to help ensure that future S2S forecast systems and forecast products realize their potential to benefit society.

THE POTENTIAL VALUE OF S2S FORECASTS TO DECISION MAKERS

A number of federal, state and private users presented information to the Committee about how they make decisions for which S2S Earth system information is or has the potential to be a factor. Building on these presentations, the Committee developed information on a large set of sectors and decisions for which S2S forecasts are or have the potential to inform decisions (Figure 3.1, and Table 3.1). Case studies later in this chapter expand upon some of these examples, including applications to water management, public health, emergency response and national defense. As the case studies make clear, some of the potential value of S2S forecasts lies in their ability to inform decision processes that begin months or even years in advance of a potential event. Often, the long-term average or climatology of a particular phenomenon—such as assumptions for the seasonal volume of water held in a reservoir—are incorporated into decision making as a first step. As the decision point draws nearer, adjustments are made as additional information becomes available. In this context, S2S forecasts can inform the process

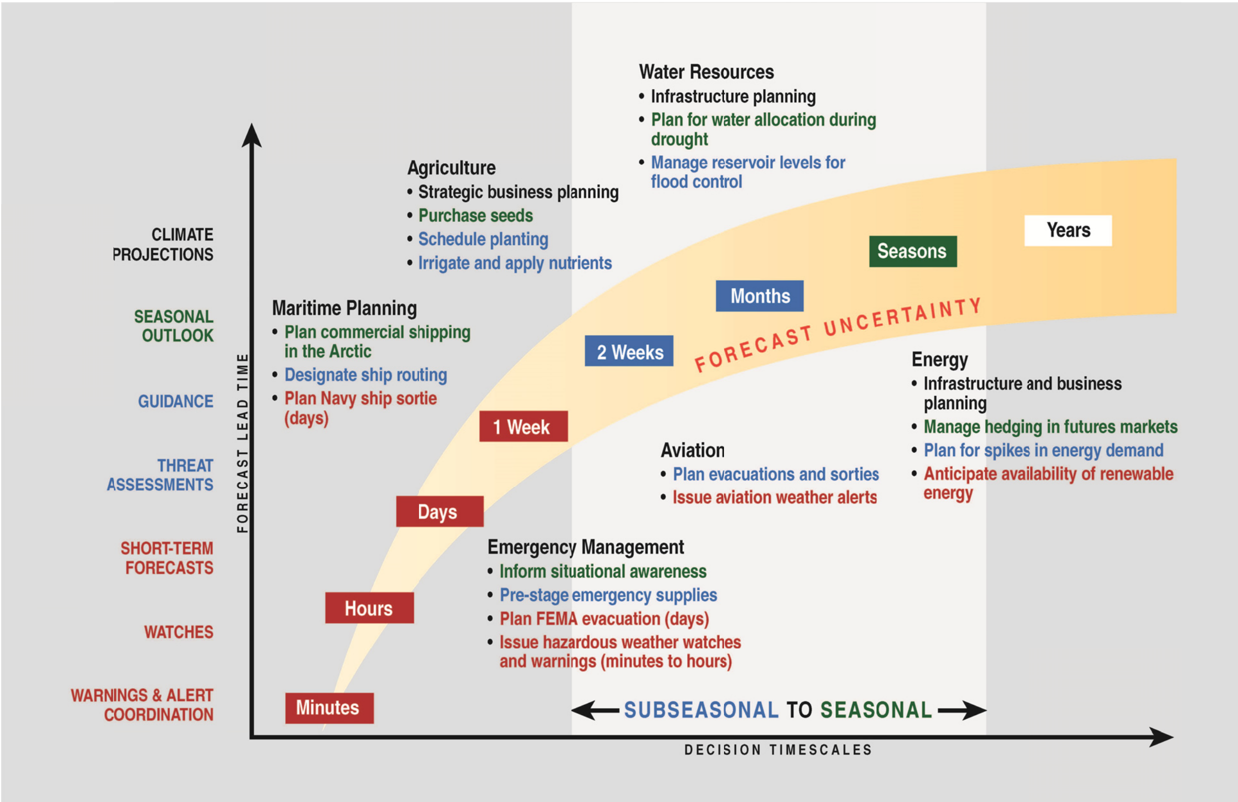


FIGURE 3.1 S2S forecasts (shown in blue and green) fill a gap between short-term weather and ocean forecasts (shown in red) and longer-term Earth system projections (shown in black). They inform critical decisions (also shown in blue and green) across many different sectors by providing information about likely conditions in between these more established prediction times. SOURCE: Modified from the Earth System Prediction Capability Office.

of adjusting decision making between the timescale of long-term planning and short-term response to events across a wide range of sectors within the economy (Table 3.1).

Finding 3.1: There is a broad range of sectors and decision-making contexts in which S2S forecasts provide value or have great potential to provide value to society.

TABLE 3.1 Example decisions from a range of sectors that can be informed by S2S and longer forecasts. Variables needed to make these decisions are shown in parenthesis. The examples are based upon presentations to the Committee, examples of use solicited from the State Climatologists and other climate services providers, and from published research.

Sector	Decision Process	Weeks-Months	Seasonal-Annual	Longer-Term
Water Resources Management (see case study for more detail)	Water Supply Management (including flood control and drought)	Probability of heavy rainfall or runoff; probability of unusually high demand (precipitation; temperature; snowpack; runoff; likelihood of atmospheric river events)	Allocation of water supply; water transfer requests; assuring minimum flows for endangered species (accumulation of winter snowpack; timing of seasonal snowmelt; summer water demands; precipitation; temperature; snowfall; evapotranspiration)	Storage capacity and sources; conservation programs (changes in mean annual temperatures, precipitation, snowfall accumulation, runoff, evapotranspiration)
	Hydropower Scheduling	Available water supply in reservoirs; anticipated demand (lake levels; stream flow; evaporation; temperatures for demand estimates)	Probability of reaching target elevation levels in reservoir (snowmelt / inflow; evaporative loss)	Changes in demand and supply (changes in mean seasonal and annual temperature across basin and service area; changes in snowmelt patterns; changes in precipitation, changes in evapotranspiration)
	Recreation Budgeting	Reservoir/Lake levels and temperature—e.g., high temperatures may increase probability of algal blooms or fish kills (inflow; evaporative loss; temperature departures)	Probability of reaching target elevation levels in reservoir / lake (snowmelt/inflow; evaporative loss)	Probability of maintaining seasonal target elevation levels (net water supply to reservoir / lake; changes in evaporative loss)
National Security (see case study for more detail)	Anticipating disruptive events / deployment of resources (aid, security, evacuation)	Pre-deploy resources to areas that are at greatest risk of high-intensity events (probability of disruptive events, especially flooding and drought)	Anticipate staffing and resource needs; identify timing of Arctic shipping lanes open (sea ice; probability of disruptive events including flooding and famine)	Identifying areas that may become at-risk from natural disasters- e.g., climate change, famine (regional changes in temperature and precipitation patterns; sea-level rise)
	Food and water security	Emerging areas of food or water shortage that may require transport of large quantities of food (precipitation departures; monsoon)	Areas at risk of famine or flood during coming months to year (monthly to seasonal precipitation; drought forecasts; temperatures exceeding critical thresholds for major crop areas)	Areas undergoing desertification or decline in water quantity and/or quality (changes in precipitation patterns; salinity; changes in jet stream, monsoon, or ITCZ)
	Tactical planning	Shipping routes and operations planning (wind; wave height; sea ice; ocean currents)	Projected dates of Arctic ice breakup and thawing permafrost rendering ice roads and runways unusable (sea ice; monthly temperatures)	Inundation of coastal facilities from sea-level rise and storm surge (sea-level rise; changes in hurricane intensity)

Sector	Decision Process	Weeks-Months	Seasonal-Annual	Longer-Term
Energy	Energy generation, trading and hedging	Potential spikes in demand; availability of renewable energy (heat waves / cold outbreaks; mean daily wind speed; daily solar radiation; adverse weather impacts such as ice storms, wind storms, hurricanes)	Seasonal supplies of natural gas and renewable energy sources; trading with other producers, hedging in futures markets and over the counter trades; fuel adjustment clauses (winter and summer temperatures; probability of heat waves or cold outbreaks; projected runoff from snowmelt)	
	Operations and Maintenance scheduling	Potential disruptive events / damage to infrastructure or supply chain (severe storms; hurricanes; floods; heat waves; wind)	Taking units off-line (probability of heat waves or cold outbreaks leading to unusually high demand)	Building, upgrading, and relocating new facilities (summer and winter temperatures; sea-level rise; changes in snowpack / spring runoff)
Agriculture	Crop production	Susceptibility to disease; application of nutrients, pesticides & herbicides (temperature; precipitation; wind speed; relative humidity; soil temperature)	Projected yields; food production and distribution (precipitation; soil moisture; temperature; projected dates of first/last freeze; probability of disruptive events—flood, drought, heat waves, freeze)	Types of crops that can be grown in a changing climate; trees and vine varieties (changing ecoregions; changes in monthly and seasonal precipitation; evapotranspiration; length of growing season)
	Commodity trading in grains and other high-value crops	Protect profit, anticipate market movement	Protect profit, anticipate market movement	
	Ranching	Forage management strategies; altering stocking rates (probability of abnormally wet or dry weeks; extreme temperatures; abrupt changes in temperatures)	Herd size, pasture availability (total rainfall; vegetation health)	Long-term changes in viability of operations in semi-arid areas (precipitation; evapotranspiration; frequency of drought)
	Fisheries	Stocking, fish kills (water temperatures; stream flow; salinity)	Migratory patterns-e.g., salmon (snowpack; streamflow)	Viability of species-appropriate habitats in lakes and rivers (temperature; water temperature; streamflow; snowpack)

Sector	Decision Process	Weeks-Months	Seasonal-Annual	Longer-Term
Severe Weather / Event Management	Event Management	Pre-deploy resources to areas most likely to be impacted (probability of disruptive events-storms, hurricanes, floods, fire)	Seasonal outlooks for number and intensity of hurricanes, storm outbreaks, or flooding (weekly to monthly precipitation accumulation; patterns favorable for development of storms; ENSO phase and intensity)	Areas likely to become more or less at-risk from disruptive events (changes in wildfire frequency or magnitude; changes in extreme precipitation; changes in drought; changes in storm tracks; changes in hurricane frequency or intensity)
	Risk Awareness	Encouraging people to stock sufficient supplies (probability of disruptive events)	Initiate public awareness and preparedness campaigns (probability of an active season-hurricane, storm, flood)	Changes in patterns or timing of severe weather (changes in frequency or magnitude of disruptive events)
	Wildfire Management	Pre-deploying resources, wildfire management (temperature; wind; humidity)	Seasonal outlooks (precipitation; temperature; wind; fuel load)	Changes to fire susceptibility (expansion of pine bark beetle habitat; changes in seasonal water balance; changes in temperature)
Environmental Impacts	Oil spill	Loop currents (e.g., tracking where oil is likely to go)	Dispersion and dilution; impacts on fisheries	Changes in natural habitats
	Coastal Zone Management	Hurricane / wave impacts	Beach erosion and re-nourishment	Loss of wetland habitat due to sea-level rise; Changes in shoreline habitat and wildlife (e.g., conversion of salt marshes to mangroves)
Transportation	Shipping & Navigation	Disruptions to surface transportation systems; preparing evacuation routes for hurricanes (probability of flooding; periods of active tropical activity)	Timing of opening shipping lanes in the Arctic (sea ice; summer temperatures; streamflow on major waterways)	Susceptibility of ports to inundation; transit routes (sea-level rise; storm surge; ice-free Arctic)
	Maintenance of highways, railroads, waterways, airports	Positioning equipment and assets-e.g., salt for roads, barges and railcars for transportation, de-icing equipment and supplies for airports (probability of adverse weather, including snowfall or ice, heavy rainfall, drought)	Positioning equipment and assets for repairs of infrastructure and equipment; seasonal supplies of road salt, de-icing supplies, fuel; (probability of favorable, adverse, or severe weather; number of freeze/thaw cycles; first and last frost; seasonal snowfall; ice storms)	Re-sizing bridges and culverts to handle flood flows; selection of materials to handle extreme temperatures (projected number of days exceeding critical temperature thresholds; changes in maximum probable precipitation)

Sector	Decision Process	Weeks-Months	Seasonal-Annual	Longer-Term
	Maintenance	Positioning equipment and assets-e.g., salt for roads (probability of winter weather including snowfall or ice)	Planning for pothole repairs; seasonal supplies of road salt; possible repair of flooded roadways and bridges (probability of extreme rainfall; number of freeze/thaw cycles; first and last frost; seasonal snowfall; ice storms)	Re-sizing bridges and culverts to handle flood flows; selection of materials to handle extreme temperatures (projected number of days exceeding critical temperature thresholds; changes in maximum probable precipitation)
Construction		Probability of weather-related delays-e.g., staffing (precipitation; temperature; snowfall; humidity; wind)	Timing of materials delivery; contract incentives and penalties (probability of disruptive events; consecutive days of hot/cold or wet weather)	Annual number of days with suitable work conditions (changes in temperature and precipitation patterns; length of frost-free season)
Business	Retail	Supply chain decisions-e.g., promoting products in response to weather events (probability of heavy rainfall; extreme temperatures; snowfall)	Production and purchase of seasonal items-e.g., umbrellas, outdoor activities, snow sports; possible disruption of supply chains (seasonal snowfall, number of rainy days, extreme temperatures; probability of disruptive events)	Probability of disruptive events
	Insurance & Financial Management	Hedging / risk management; shifting funds in anticipation of large payouts from widespread events such as flooding or active period of extreme events such as hurricanes (probability of disruptive events)	Potential demand for energy; potential crop yields; contracts for insurance or reinsurance; setting premiums (above or below normal number of hurricanes; large-scale patterns favoring flooding or drought; extended periods of abnormally hot or cold temperatures)	Insurability of coastal property; changes in regional patterns of risk (sea-level rise; storm surge; storm patterns; frequency and intensity of hurricanes and droughts; changes in maximum daily rainfall events)
Public Health (see case study for more detail)	Potential disease outbreaks	Conditions conducive to development of disease vectors (temperature; precipitation; easterly waves; extratropical cyclones)	Seasons that may have above-average number of cases—e.g., meningitis, malaria (sea-surface temperatures; cumulative rainfall; temperature variability; strength of Indian Monsoon)	Changes in regions susceptible to spread of disease—e.g., areas where viruses and bacteria can survive due to warming temperatures (changes in regional temperature and precipitation patterns)
	Extreme temperatures, heat waves, cold spells	Likelihood of a significant event (maximum and minimum daily temperatures; humidity)	Likely number of events during a season (probability of occurrence of consecutive days with temperatures above or below critical thresholds)	Changes in the frequency of extended periods of abnormally hot or cold weather (daily temperature)

Sector	Decision Process	Weeks-Months	Seasonal-Annual	Longer-Term
	Heat waves	Likelihood of a significant event (maximum and minimum daily temperatures; humidity)	Likely number of events during a summer (probability of occurrence of consecutive days above temperature thresholds)	Changes in the frequency of extended periods of abnormally hot weather (daily temperature)
	Algal blooms / release of neurotoxins in water	High temperatures with relatively stagnant water and abundant sunshine (air and water temperature; precipitation; cloud cover)	Probability of extended periods (weeks) of hot, dry weather (temperature; precipitation; runoff)	Changes in conditions conducive to algal blooms (summer water and air temperatures; changes in cloud cover; changes in frequency of drought and runoff)

CHALLENGES TO THE USE OF S2S PREDICTIONS

Despite the wide range of potential sectors in which S2S forecasts are or have the potential be valuable, there are many challenges and barriers to their uptake by decision makers. For example, many water managers can see the potential application of seasonal and subseasonal forecasts to their work, and in some cases such information has provided valuable context for planning (see case water management case study below). However, the outcomes of forecast use have not always been positive; currently available products do not always fit easily into institutional decision-making frameworks, and managers are eager for forecasts of variables and at resolutions that are more directly relevant to their contexts. These points are broadly consistent with published research on applications of S2S predictions to decision making, which to date focuses on the use of seasonal predictions in the agricultural, energy, or water management sectors (e.g., Breuer et al., 2010; Hansen et al., 2006; Lemos, 2008; Mase and Prokopy, 2014; Pagano et al., 2002). For example, Patt et al. (2007) document how use of a seasonal forecast in Ethiopia enabled an emergency management team to identify specific relief actions with months of lead time, alleviating food shortages in 2002. In contrast, seasonal forecasts prompted the restriction of credit for seed in Zimbabwe in 1997, which prevented planting and led to food shortages even though seasonal rainfall ended up at near-normal levels.

Beyond the experience of negative consequences of seasonal forecast use, one important set of documented barriers to the use of S2S forecast products relates to mismatches between currently available products and the stated needs of end users. Forecast products currently available from organizations such as NOAA's Climate Prediction Center (CPC) or the seasonal MME forecasts from the APCC (see Chapter 2), for example, are issued in the form of low-resolution depictions of the probabilities of departure from mean temperature and precipitation over a 3-month period (Figure 3.2), or as forecasts of climate indices such as ENSO.

These forecasts, and text discussions that accompany them, provide general guidance on future temperature and precipitation, but they do not readily translate into operational decision support for many applications. In agriculture, S2S information could be used to assist in determining planting dates, irrigation needs, crop types, fertilization, expected market conditions, pests and disease, livestock management, and the need for insurance (Breuer et al., 2010; Mase and Prokopy, 2014). However, these decisions are dependent on the timing, magnitude, frequency, and duration of weather events within the three-month forecast window, not departures from seasonal average conditions (Vitart et al., 2012; Srinivasan et al., 2011).

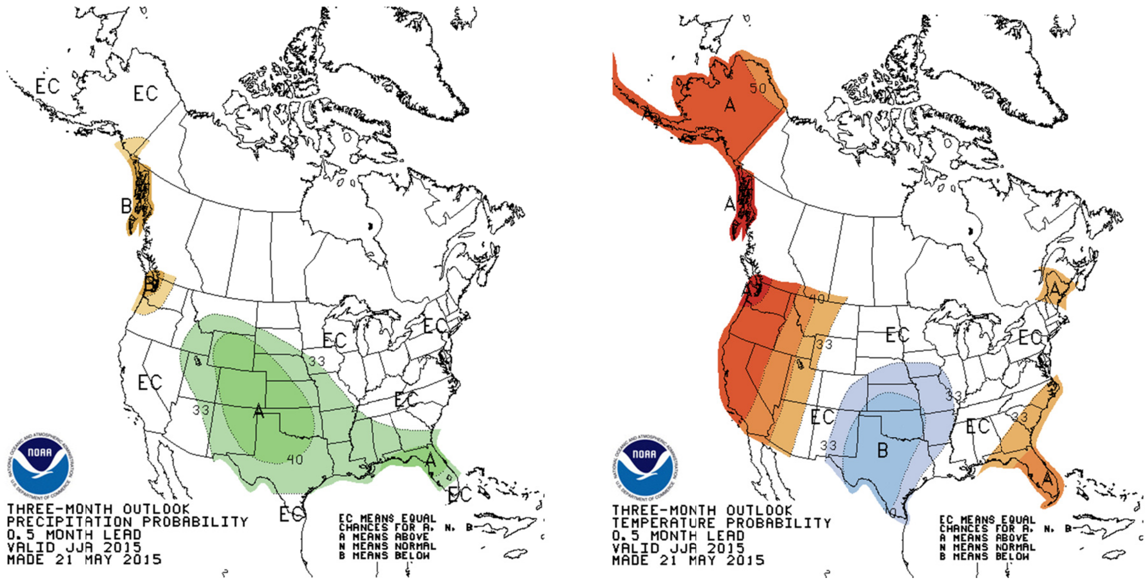


FIGURE 3.2 Three-month outlooks issued by the NOAA Climate Prediction Center for June-July-August 2015, issued 21 May 2015 (0.5 month lead time). Contours indicate probability of above (A) or below (B) normal precipitation (left) and temperature (right). EC indicates equal chances, where probability is evenly distributed across the three categories (above, normal, or below). SOURCE: NOAA.

Mase and Prokopy (2014) studied seasonal forecast use in the agricultural sector and identified four barriers to the uptake of current seasonal forecasts, including mismatches between desired and available products:

1. Decision contexts rarely involve direct use of information about temperature and precipitation anomalies or climate indices. Instead, tailored, sometimes derived forecast variables, have proven to be much more useful. It is not immediately clear what actions a farmer can make with the information that there is a 40% probability of above-normal precipitation (compared to a climatological probability of 33%). Variables such as the date of first or last frost might better inform the agricultural sector with specific decisions, such as determining when resources are needed to inform decisions related to harvesting or planting.
2. Forecasts of average conditions or anomalies from average conditions are not always immediately useful for many types of decisions. Decision makers often must respond to conditions that are out of the normal realm of climate variability, such as extremes of heat waves, drought, or floods, or the impacts of a volcanic eruption. A forecast of "above normal" conditions does not necessarily describe whether critical thresholds such as reservoir capacity may be exceeded or plant die-off may occur. For these types of decisions, the probability of exceeding critical thresholds is more important than the departure from the mean (see Pulwarty and Redmond, 1997; Vitart et al., 2012).
3. Spatial and temporal forecast scales are often mismatched to decision making. Decisions are rarely made for a 3-month period across a large spatial domain; rather, decisions are based on discrete events occurring within a specific time frame and often for a very specific location. A product providing only above- or below-normal or normal conditions over a very large domain may not be immediately useful to a water manager trying to regulate water usage or flow for several watersheds contained within that large domain or

spanning several different forecast domains (see also water management case study; Srinivasan et al., 2011; Robertson et al. 2014). For example, seasonal forecast skill is enhanced by a strong El Niño-Southern Oscillation (ENSO) signal, but by the time forecasters have confidence of likely impacts from the event, many decisions on crops, water storage, or other resources have already been made. Furthermore, different combinations of forecast lead times and averaging period may be more or less useful in different contexts (see also Chapter 5).

4. There is often a lack of understanding in and trust of forecasts. Many users do not understand the process by which forecasters come to their conclusions, and existing forecast verification metrics are often not directly relevant to users' contexts (Morss et al., 2008). Consequently, users often have little confidence in the forecast (Mase and Prokopy, 2014). Familiarizing users with the processes by which forecasts are produced often requires direct interaction over a sustained time period. Such interactions are expensive, resulting in fewer communication pathways between the producers and users. Thus a lack of resources issue often exacerbates this issue and hampers delivery of information to end users (see also Hansen et al., 2011; Klopper et al., 2006; Lemos and Morehouse, 2005).

Such examples extend beyond agriculture. For example, forecasting events such as heat waves for the public health sector, or environmentally caused anomalous electromagnetic propagation and mirages for ocean communications applications, have the potential to provide much greater value to decision makers than information about departures from average temperature and precipitation across a wide region (see also case studies below). Contextual factors, such as lack of trust or inflexible personal or institutional operations, also impede forecast use in water management and public health sectors. In water management in the United States, for example, some institutions may even have policies that designate certain sources as official information, posing a barrier to the use of new products (Lemos, 2008; Pagano et al., 2002; J. Jones, personal communication, January 2015). Differences in perceptions of risk and bias, fear of bearing personal responsibility for making decisions based on probabilistic forecasts that are still less familiar to the public are also barriers to use in some cases (e.g., Suarez and Tall, 2010). Lack of resources can also influence the ability to access decision support. Although some private companies and research laboratories produce higher temporal or spatial resolution and tailored forecasts for their clients (e.g. IRI tailored products, and see case study on national security and defense), these are not necessarily widely available to the public. Beyond specific barriers to use, many decision makers (and even entire sectors) may not be fully aware of S2S forecasting efforts and the potential to apply such information to decision making (Buontempo et al., 2014; public health case study below).

To summarize, the current use of S2S forecasts at present is primarily limited to general guidance, although there are emerging sectors and businesses that make more in-depth use of forecasts. Reasons for the slow adoption of and demand for S2S forecasts into operational environments include: (1) a poor fit between aspects of the forecast (skill, scale, and lead time—e.g., salience and credibility [Hansen et al., 2011; Klopper et al., 2006]); (2) contextual factors such as lack of trust, inflexible operations, market fluctuations, and lack of resources; and (3) lack of awareness.

That said, the number of studies that address the role of S2S forecasts in decision making across important sectors, including transportation, infrastructure, or heath and humanitarian crises, is still limited (though studies within humanitarian and health contexts are growing—see Braman et al., 2013 and Coughlan de Perez and Mason, 2014). The relative paucity of analysis about the use (or lack of use) of S2S forecasts—particularly subseasonal forecasts—across multiple sectors and regions inhibits the understanding of the potential value of S2S predictions and the development of strategies to maximize the benefits of S2S predictions to society.

Finding 3.2: Research about the demand for and utilization of S2S predictions across multiple sectors is still limited. Studies that have been conducted often indicate significant barriers to using S2S forecasts in decision making, including mismatches between available and desired forecast products, barriers associated with policy and practice, and lack of understanding of what could be provided.

Finding 3.3: Decision makers generally express a need for a wider range of skillful model and forecast variables—particularly information about the likelihood of disruptive or extreme events—that are valid at finer spatial and temporal scales to inform management practices.

Some of the issues highlighted above are not new or unique to S2S forecasts. The weather forecast community, for example, faces many similar challenges, and a developing body of social and behavioral science research on forecast use is beginning to increase understanding about how to overcome challenges associated with increasing forecast use in decision making (Brunet et al., 2010; NRC, 2010c). Learning from experiences on both the shorter-term weather forecasts, as well as leveraging existing knowledge about the use of seasonal forecasts, can provide guidance to maximize the use of subseasonal and seasonal forecasts across many more sectors of society. As an example, findings about the barriers to use of seasonal forecasts above are broadly consistent with previous research on the use of weather forecasts, which identified similar types of information that users generally consider to be the most relevant to decision making (Pielke and Carbone, 2002):

- Extreme events, including droughts, hurricanes, floods, blizzards, tornadoes, and thunderstorms (including hail);
- The benefits of good weather, meaning favorable conditions for a particular activity;
- Routinely disruptive weather, defined as not extreme, but significant enough to warrant behavioral adjustments; and
- Forecast impacts, particularly associated with misses and false alarms (including over-warning).

Finding 3.4: Building on experience related to increasing the usability and use of weather and seasonal forecasts will be important for rapidly broadening the role of S2S forecasts in decision making.

Uncertainty and Lead Times

In addition to user-relevant forecast output variables and scales, there are key attributes of forecasts that must exist before a prediction can make a value-added contribution to decision processes. Forecasts must be available in a timely manner, be provided in a readily understandable format with known accuracy, and be accepted as an available tool by the users and policy makers (Hartmann et al., 2002; Pagano et al., 2002).

Different users have different tolerances for how accurate a forecast must be before it becomes useful to them. Some users need high confidence before they can take action, while others may be more tolerant of incorrect forecasts (Lemos and Rood, 2010; Mase and Prokopy, 2014). According to a cost-loss model, if the probability of occurrence of an event exceeds the ratio of the cost of mitigation action to the losses that would be expected to occur without mitigation then the mitigation actions are considered worthwhile. Consequently, if the costs of action are high, then the user would require a higher level of certainty that the forecasted event will occur (Murphy, 1977). Such specific probability thresholds are usually unknown to forecasters, however, as they are situationally and geographically dependent.

Decision makers always operate under uncertainty; even a 24-hour forecast has uncertainties. Such uncertainty is now frequently and more appropriately presented in terms of probabilistic forecasts. However, as has been shown by notable errors in weather forecasts, such as predictions of winter precipitation, when decisions have significant associated costs, people are more critical of forecast errors (Joslyn and Savelli, 2010; Roulston and Smith, 2004; Savelli and Joslyn, 2012). Furthermore, seasonal forecast information, when presented at finer spatial and temporal scales, increasingly has larger bounds of uncertainty. Thus, there may be a higher likelihood of an outcome that is different than the forecast at the particular location where the decision is made. When presented on a value or cost/loss basis, this may make decision makers reluctant to invest in actions based upon generally lower-skill, highly probabilistic S2S forecasts. For example, a 53% probability of greater than normal snow fall may not justify contracting for additional snow removal availability. However, in order to make valid value decisions and actions, decision makers need established reliability measures. If preventive action requires steep costs, and reliability measures are not well developed, policy-makers are less likely to adopt (especially experimental or new) forecast products and are more likely to resort to a wait-and-see position (Lemos and Rood, 2010). When confronted by crisis, however, such as reservoirs operating above or below their capacities, the willingness to use S2S forecast information may increase significantly (Lemos, 2008).

Thus creating more skillful forecasts does not necessarily guarantee that the forecasts will be useable or used. To be useful, a user must also have confidence in the prediction. Confidence is typically established by evaluating the success of the forecast against a large number of previous occurrences. However, S2S predictions have a number of major challenges in establishing such confidence. For example, because forecasts are typically averaged over weekly or longer time intervals, there are fewer data points against which to verify the forecasts. Furthermore, if users are interested in a prediction of a weather-driven event such as severe flooding, then multiple forecast variables are involved, including precipitation amount and intensity, soil moisture, snow pack, and temperature. Errors in any one of these variables will lead to errors in the projected outcome. The issue of developing confidence in forecasts is of central importance to users, but also links centrally to S2S forecast systems, and is therefore covered in greater detail in Chapter 5(see the section on Calibration, Combination, Verification, and Optimization)

Finding 3.5: Assessing tolerance for uncertainty and developing user-oriented verification metrics are important to building confidence in the use of forecasts among decision makers. At the S2S timescales this aspect has been generally under-developed.

IMPROVING THE USABILITY AND USE OF S2S FORECASTS

Given the current barriers to use highlighted in the section above, this section highlights potential avenues for increasing forecast uptake into decision making. Decision makers have a range of capabilities, from those able to apply statistical techniques to extract useful information from forecasts, to those with less ability to modify or interpret probabilistic forecasts. Tailored and interpreted forecast information has the potential to increase the value of S2S forecasts by expanding the range of forecast variables and outputs that are available to specific users. Some tailored product variables may be obtained through the development of statistical models or correlation fields for relating existing forecast variables and spatial scales, such as regional temperature and precipitation averages, to other, more useful variables (Mase and Prokopy, 2014). For example, extension agents in the agricultural sector prefer derivative information over simple climate predictions (i.e., forecasting impacts instead of seasonal departures of temperature and precipitation). Here, forecasts of the probability of receiving sufficient precipitation during crop maturation or sufficient soil moisture for seed germination can help the agricultural sector anticipate the amount and timing of irrigation needs.

Creating some tailored products is possible using currently available forecast output. Developing other tailored forecast variables will require advances in the S2S forecasting system itself, particularly through an expansion of the capabilities of coupled Earth system models that enable, for example, new forecast variables such as the occurrence of unusual surf or extreme waves, mean cloud cover, and likelihood of harmful algal blooms. Similarly, some progress on predicting the less probable but high-impact events, so-called extreme events, can be made through tailoring existing forecasts. Such events may include a very hot week in an otherwise near-normal summer. Because these are part of a continuous distribution, there is potential to predict the probability of such events occurring within a forecast period. However, improvements in coupled model forecast systems are likely also needed to meet user demands for predictions of such extreme or disruptive events, especially since the noteworthy nature of extremes is typically sector specific. For example, uncharacteristically low winds might not represent a problem for water, transportation, or agriculture sectors, but would be significant for the wind energy and air quality sectors.

Qualitative interpretation of forecasts can also increase their uptake and value. For example, simplified forecast discussions that accompany National Hurricane Center public advisories provide the explanations behind the forecast that increases many users' trust of such forecasts. Thus increasing the use of such simplified forecast discussions in other routinely issued forecasts could yield almost immediate benefits. However, careful thought needs to be given to how such information is integrated into decision-making processes (NRC, 2009).

The multitude of potential applications, driven by a multitude of different decision makers with different needs requiring different formats, increases the complexity of production and dissemination of forecast information. To some extent, private sector providers may develop products that meet this need, but on a large, advisory scale it is likely that the producers of information will need to consider multiple formats, along with broader scale efforts to develop tailored, sector-specific products.

Finding 3.6: Many forecast products that have the potential to provide greater benefit to society could be developed from existing modeling technology. Developing other important forecast variables and uses will require advances in modeling technology. These variables are

likely to be sector or decision-specific and their provision is likely to involve derivative products and/or other decision support.

The Need for Social and Behavioral Sciences

As highlighted in the paragraphs above, developing a system that supports use of S2S information requires more than increased understanding of sources of predictability and improved prediction skill. Advances in use and value require consideration of the decision-making context, which often requires complementary research in the social and behavioral sciences. Specifically, social science research can help to address many of the barriers to use previously highlighted in this chapter, including increasing understanding users' confidence in the accuracy of forecasts, understanding users' decision-making contexts and how to best integrate forecast information, and understanding decision making in contexts of high uncertainty and limited skill (see also NRC, 2010c). This includes research into how users react to false alarms and the costs associated with incorrect forecasts, and how probabilistic information can be better communicated to fit into users' operations (R. Morss, G. Eosco, S. Jasko, J. Demuth, personal communication, March 2015). Social science research on perceptions of quality—e.g., at which point users will make an investment of time and resources to integrate forecasts in their operational contexts and what types of products are needed to mesh into existing decision-making infrastructures—will also be important to understanding the potential value of S2S forecasts. As much of S2S information is probabilistic, research will be needed on the interface between probabilistic forecasts and decision maker applications to determine new ways of translating forecasts to mesh with common usage of other Earth system information. This may involve setting more nuanced decision limits, particularly around low probability predictions (e.g., 51-55%). Additional research is also needed on the role that social networks may play in the dissemination of information and practice (e.g., Mase and Prokopy, 2014).

Finding 3.7: Understanding decision contexts for a wide array of users in both sectoral applications and technical capacities is essential for increasing use of S2S forecasts. Such understanding cannot be advanced without social and behavioral science research.

Integrating Users into the Process of Developing Forecast Products

Perhaps even more critical than improving forecast products and access is building trust in the S2S forecast process. Scientists and operational forecasters who create the information are often disconnected from how that information is being applied, at least outside of agency operations (Lemos et al., 2012). Broader use of S2S forecasts will be encouraged by creating systems of integrated actors and organizations that initiate, modify, import, and diffuse science and technology, identifying information pathways, relating new information to prior experience of the users, and creating toolkits to enable application of information to various decision contexts (Lemos et al., 2012; Vitart et al., 2012). This requires integration of users in decisions relating to the research and development process, from defining relevant research questions to the process of production and dissemination of products (Lemos and Morehouse, 2005). Developing a mechanism for integration may be informed by existing mechanisms used for integration of NWP forecasts with a variety of users, but will need to be adjusted for different circumstances related to the production of S2S forecasts. Model developers and operations in NWP interact with a variety of forecast centers around the country and with the media in annual meetings and routine correspondence. To the extent practical, expanding this existing stakeholder network to include mechanisms for collaboration with S2S model developers and operations would be beneficial as compared to developing a separate network from scratch.

The discussion of opportunities and limitations involved in producing S2S forecasts highlights potential trade-offs and risk of using the products that enhances the users' confidence in adopting new products or practices (Lemos et al., 2012). Such discussions are facilitated, in many cases, by boundary organizations, such as NOAA's Regional Integrated Sciences and Assessments (RISA) Program and the IRI. These organizations conduct interdisciplinary research on decision-making processes with the goal of better coupling the production and use of climate information (Goddard et al., 2014; Lemos and Rood, 2010; Pulwarty et al., 2009). The growing experience of these organizations points to the considerable effort and long-term relationships that are needed to help users understand what types of forecasts are available, the process of producing the forecasts, and to engage them in the design of forecast products and aligned decision-making frameworks to take advantage of currently available forecast technology. For example, IRI has found that seasonal climate forecasts of relatively low skill can still be successfully applied to water management problems in Brazil and Chile, but only through coupling climate forecasts with streamflow projections and working with managers to explicitly link such tailored forecasts to their reservoir management decision-making process (Robertson et al., 2014). Similarly, malaria early warning systems based on S2S forecasts have been successful through extensive efforts to forge relationships between end users and physical and social scientists who manage the technical aspects of designing forecast products (see case studies below). Growing experience among interdisciplinary researchers has resulted in a similar set of conclusions relating to the benefit of 'co-producing' forecast products and information together with the end users of such information (Meadow et al., 2015).

Finding 3.8: An ongoing, iterative process between the developers, the providers, and potential users facilitated by the relevant social science researchers improves the use and value of S2S predictions.

Ongoing engagement between decision makers and scientists involved with producing forecasts can facilitate the development of iterative or multi-step decision-making processes, such as the "ready, set, go" framework. Here, warnings, preparation, and action are keyed to increasing probabilities of adverse events (e.g., Coughlan de Perez and Mason, 2014). Preliminary planning may be initiated when an extended S2S prediction indicates the possibility, perhaps at a small probability, of a significant event. This would be followed by preparatory actions (such as prepositioning emergency supplies) if subseasonal predictions indicated increasing probabilities of the event. Finally, action (such as evacuation) would be initiated based on a deterministic or short-range ensemble prediction with a high level of certainty. This scenario assumes a reliable transition of the predicted probabilities between the seasonal climate system, the subseasonal system, and the short range deterministic or ensemble systems—all with their own statistical characteristics and skill levels. Blending the probabilities on these diverse timescales (and possibly spatial scales as resolution improves) into a coherent chain of predictions for a user is a difficult post-processing challenge.

As mentioned above, the decision makers will be concerned with some measure of risk and consequence based on a combination of the evolving probability of the adverse event and the costs of mitigating compared to those of not mitigating. The more quantitative the model of risk and consequence, the more meaningful will be the estimates derived from the evolving probabilities of the adverse event. Not all organizations will necessarily participate in all three stages. Certain organizations may enter the process at different points and levels of certainty.

The set of actions taken and the probability thresholds that act as triggers are usually dependent upon users' unique circumstances and institutional landscapes. Developing models for applying S2S information in these types of scenarios represents an opportunity for growth in the private sector. For example, applications requiring acquisition of resources, such as power poles in advance of an expected ice storm, may require more lead time than others for which resources are already available, such as frost protection for an orchard. Such decisions are not static; they are revised as new information becomes available, including reduced uncertainty as the forecast lead time shortens. Decision processes on weather timescales could be instructive, such as how public safety officials change their decisions from the timescales of outlooks several days before an event to watches and then warnings.

Finding 3.9: Successfully aiding users with a multi-step decision model for mitigating the effects of adverse events is a difficult challenge and one not yet considered carefully in the S2S prediction community.

Resources Required to Encourage Use

Developing interactive, transparent processes is a time-consuming and expensive process. It is constrained by limited resources of research, forecasting and many user communities. As forecasting capabilities improve, the demands users place upon providers of forecast information will only increase. Forecasters and researchers need to be careful not to over-promise the capabilities of improved systems. Especially if they are unable to also address the translation process, the demand for services and interpretation of products may exceed the level that can be met, resulting in disenchantment and abandonment of forecasts (Meinke et al., 2006).

As mentioned above, boundary organizations can play an important role in facilitating transparent dialogs and processes that can help overcome many barriers to forecast use. There are many existing structures that are engaged as boundary organizations at the weather and climate change scales, including the NOAA RISA Program, IRI, National Weather Service Forecast Offices, the Department of Interior's Climate Science Centers, the Department of Defense Climate Services, the emergent USDA Climate Hubs, and other programs within academia. All of these programs and offices engage with decision makers and possess expertise in social science methodology coupled with a physical understanding of weather or climate. They often work in interdisciplinary teams and with those intermediaries who ultimately reach the individual decision makers.

Finding 3.10: Growth in the use of S2S products will place more demands upon operational agencies and boundary organizations to explain reasoning employed in producing forecasts, and in developing a suite of products that meet the needs of a diverse user community.

CASE STUDIES WITH EXAMPLE APPLICATIONS OF S2S FORECASTS

Water Management in the Western United States

Improved forecasting capability on S2S timescales is an oft-stated goal of water managers, especially in the drought-prone basins of the western United States (e.g., NIDIS Program Implementation Team, 2007; WGA, 2008). Federal, state, and local water managers in California, for example, seek improved forecasts in order to stretch their ability to balance the needs of 38 million residents (representing 12% of the U.S. population), the needs of an agriculture sector that farms over 9 million irrigated acres and leads the nation in production, and demands for hydroelectricity from the state's 13,765 MW of capacity.[13] The state's recent, severe drought (e.g., Griffin and Anchukaitis, 2014) has only heightened awareness of the challenges associated with meeting these needs (Figure 3.3).

In California, winter precipitation makes up the majority of the annual water budget, and estimates of spring run-off from winter snowpack are currently used to help manage and coordinate the in- and outflow from the state's vast system of reservoirs, aqueducts, and groundwater storage facilities. A primary tool used for making decisions about reservoir levels, water allocations, and water transfers is the California Department of Water Resource's forecast of total April - July river runoff. These forecasts are issued beginning in February, and are updated monthly through May. Water-year (i.e., September - August) based indices are also issued based on historical analogs. In other western states, similar forecasts are issued by the USDA Natural Resources Conservation Service in partnership with NOAA/National Weather Service (NWS). The skill of these forecasts is currently derived entirely from a sparse network of snowpack measurements, which means they are not readily disaggregated by month.

In contrast to forecasts derived from observations of the winter snowpack, water managers have not relied heavily on the current array of operational S2S weather and climate forecast products. When used, the forecasts tend to be assessed qualitatively and used as a 'tie-breaker' in higher-stakes, scarcity situations (M. Crimmins, personal communication, March 2015). There are a number of barriers to use of currently available S2S forecast products. First, users may not be aware of times when forecast products have higher skill, such as during a strong ENSO event. This potential variability of skill from month-to-month is critically important in the California context. Second, the spatial resolution of current S2S forecasts is often inadequate for quantitative use. Finally, institutional barriers can sometimes limit the use of experimental information. For example, state and federal water managers are sometimes restricted to using only forecasts that are operationally issued by federal agencies in their decision-making process (J. Jones, personal communication, January 2015).

Water managers are in broad agreement that better S2S forecasting could improve the basis for a number of their decisions. On the subseasonal timescale, efforts to incorporate quantitative precipitation and temperature forecasts from existing numerical weather and climate predictions may help improve the temporal resolution of river run-off forecasts and allow for better decisions about, for example, flood control. For example, anticipating atmospheric river events with several weeks' notice would allow managers to assure capacity to contain excess runoff. During dry winters, the likelihood that drought will persist into late winter and spring is information that is also consistently sought, but is not yet reliably available. This might again be achieved through better anticipation of the likelihood of extreme precipitation events associated

[13] http://www.energy.ca.gov/hydroelectric/, accessed January 27, 2016.

FIGURE 3.3 Recent drought has a severe impact on water availability in California, and water levels are exceedingly low in many CA reservoirs. Here, water levels over a section of Lake Oroville near the Bidwell Marina are shown on July 20, 2011 (left) versus on January 16, 2014 (right). Such scarcity has heightened the desire for more skillful and useable S2S forecasts. SOURCE: California Department of Water Resources.

with atmospheric rivers arriving from the Pacific (e.g., Dettinger, 2013), which have recently been shown to contribute the majority of annual precipitation and snowpack in CA (Dettinger et al., 2011; Guan et al., 2010). Such capacity is likely to occur through improving advance knowledge about the state of the Madden-Julian Oscillation (MJO), Pacific/North American teleconnection pattern (PNA), or Arctic Oscillation (AO) (e.g., Guan et al., 2013; Guan et al., 2012).

More accurate seasonal forecasts of winter precipitation, issued in the previous summer and fall, could substantially improve decision making about allocations to water project contractors, planning for reservoir water and power operations, anticipation of the number of water transfer requests, and whether to plan emergency flows for endangered species management. Developing more accurate seasonal forecasts may also spur the development and implementation of novel economic instruments such as reliability contracts to spread risk and improve allocation choices during drought (e.g., Hartmann, 2005; O'Donnell and Colby, 2009).

On seasonal to longer lead times, information about the likelihood of drought continuing for multiple years is needed to inform funding decisions for drought response, conservation programs, and the initiation of programs such as water banking. Improved understanding of natural climate variability could improve analog year analysis. A focus on producing forecasts at the scale of California and Colorado River Basin through statistical or dynamical MME could be particularly useful. More generally, there is a desire for tailored forecasts that fit individual water project/agency location and timing needs. Managers would benefit most from focused research driven by policy that is in-tune with their specific needs (e.g., Hartmann et al., 2002).

Public Health

It has long been recognized that variability in weather, climate, oceanic conditions, and vegetation can influence the emergence of epidemic diseases (e.g., Kelly-Hope and Thomson, 2008; Kuhn et al., 2005). Yet the use of climate information to inform decision making in the public health sector remains relatively limited (Jancloes et al., 2014). Currently, barriers to unlocking the potential of climate-inclusive frameworks for disease prevention and control relate less to a lack of climate information and more to a need for sustained, multi-disciplinary research efforts and institutional collaborations between climate information providers and the public health community (Jancloes et al., 2014; Thomson et al., 2014; Roger Nasci, personal communication, March 2015). However a few emerging efforts provide a glimpse into how improvements in Earth system forecasting could enable important advancement in the management of disease and other public health risks.

Meningitis

Improved subseasonal (in particular for 2-4 weeks) forecasts of relative humidity have the potential to improve response to meningococcal meningitis epidemics, particularly those in the so-called meningitis belt of central Africa (Pandya et al., 2015; Thomson et al., 2006b). Meningitis, a bacterial infection, has a history of devastating impact in this region, with large outbreaks affecting hundreds of thousands of people. Untreated infections lead to death 50% of the time (WHO 2012). Epidemics in the Sahel region emerge during the dry season, and correlations between low humidity and meningitis cases were first noted more than 30 years ago (Greenwood et al. 1984). Further research revealed strong relationships between meningitis and dusty, dry conditions (Sultan et al., 2005; Thomson et al., 2006b), and abrupt cessations of epidemics with increases in humidity (Molesworth et al., 2003). However, environmental conditions are only one of many factors, including demographic, behavioral, and ecological conditions, which can precipitate infection. Specifically, in many regions, lack of disease surveillance limits the potential to develop accurate disease transmission models of any kind. This can make translating correlations between disease and environmental conditions into actionable information very challenging (Pandya et al., 2015; M. Hayden, personal communication, March 2015).

The MERIT (Meningitis Environmental Research Information Technologies) initiative was launched in 2007 by the World Health Organization (WHO) as a multi-sector partnership between climate and environmental scientists, social scientists, and the public health community to encourage collaboration and the development of innovative solutions for controlling meningitis epidemics (Thomson et al. 2013, Garcia-Pando et al. 2014). Years of subsequent data collection, climate data and forecast output analysis and collaboration with public health officials in Ghana has led to the development of relative humidity thresholds that can readily be incorporated into existing public health frameworks. Forecasts of relative humidity and storminess up to two weeks in advance, coupled with the observed two-week lagged relationship between humidity and meningitis, have led to a prototype decision-support tool that issues meningitis predictions at lead times of up to one month—enough time to influence positioning of vaccines (Pandya et al., 2015). The end of the dry season is paced by the annual northward migration of the Intertropical Convergence Zone, but rainfall events can modulate the timing of seasonal change on local-to-regional scales (Figure 3.4). Knowledge generated in developing the prototype early warning system is now driving research into the dynamics of west African monsoon onset and retreat that is specific to meningitis-prone regions (e.g., Broman et al., 2014). Rainfall events are usually associated with African easterly waves, equatorial Kelvin Waves and Rossby Waves, extra-tropical cyclones, and/or the MJO (Mera et al., 2014). Better representation of these phenomena in forecasts may thus increase predictability of the end of the dry season and of meningitis risk.

FIGURE 3.4 S2S_forecasts of the end of windy, dusty conditions, such those conditions depicted at the height of the dry season in Naimey, Niger (left), can be used to help direct vaccination campaigns for meningitis across the Meningitis belt in Africa (right). SOURCE: Francesco Fiondella/IRI and Gabe Bienczycki.

Malaria

Malaria is the most widespread parasitic infection in humans, with approximately 500 million cases and over a million deaths yearly (Greenwood et al. 2005). A substantial subset of these cases are linked to malaria epidemics (as opposed to endemic infections), and development of early warning systems to reduce the incidence and impact of these epidemics is a key goal of the world health community (WHO, 2001, 2015). In vulnerable semi-arid and highland areas of Africa, malaria prevention programs target the control of malarial mosquitoes through spraying of pesticides during epidemics, prophylactic drug therapy for target groups during malaria season, and the positioning of resources to ensure timely and effective medical care for infected individuals. Current early warning systems of epidemic malaria rely primarily on disease surveillance, with epidemic alerts issued and repositioning of resources triggered by thresholds in weekly caseloads. There is the possibility for developing more advanced warnings through increased knowledge of climate and oceanic conditions ahead of the malaria season.

Transmission and infection rates of malaria have been linked to rainfall and temperature variation. In Botswana, for example, epidemics usually emerge in the two months after the November-February rainy season, and research linking emergence of epidemics to December-February seasonally averaged rainfall and sea surface temperatures has allowed for forecasts of epidemic risk with a month lead time (Thomson et al, 2005). Although this represents a potentially large improvement in time available for public health officials to mount a response, early warning systems may be most useful when case numbers can be predicted two to six months ahead of risk—enough time to allow for tactical positioning of resources (Myers et al., 2000). A growing body of research suggests that integrating monthly to seasonal forecasts of sea-surface temperatures, cumulative rainfall, and temperature variability—especially from multimodel ensembles shown to have skill in regions of interest—will likely allow for the development of malaria early warnings at longer (4-6 month) lead times (Jones and Morse, 2010, 2012; Lauderdale et al., 2014; MacLeod et al., 2015; Thomson et al., 2006a; Tompkins and Di Giuseppe, 2015). In the short term, skill and geographic reach of such malaria predictions would increase with improved representation of ocean-atmosphere processes associated with the West African and Indian Monsoons, along with the better representation of the Indian Ocean Dipole and ENSO, both of which influence rainfall amounts and temperature variation in critical areas.

Other Diseases

Sixteen additional climate-sensitive diseases have been identified as targets for research and other investments to promote the development of climate-inclusive early warning systems (Kuhn et al., 2005). This list contains some of the world's most devastating diseases, such as cholera, dengue fever, and West Nile virus. In many cases, non-traditional forecast output variables, such as ocean nutrient forecasts in addition to ocean temperature information for cholera (e.g., Jutla et al., 2011), daily temperature fluctuations instead of average temperature for dengue virus and malaria (Lambrechts et al., 2011; Paaijmans et al., 2010), and extreme rainfall and temperature events instead of average conditions for a variety of other public health disasters (Coughlan de Perez and Mason, 2014), are likely to be important. Close collaboration between the forecasting and applications communities is critical to develop research agendas that will support the identification and development of new forecast products that maximize benefits to the public health sector (Buontempo et al., 2014; Morse et al., 2005).

National Security and Defense

One specific area where S2S forecasting could prove particularly beneficial on a routine basis is global ocean and ice predictions, particularly as the Arctic warms. In addition, disaster preparations in advance of catastrophic tropical cyclones and other severe events where the military may be called to respond could benefit from pre-staging of relief efforts around the world. Food and water security will be important areas where S2S prediction can contribute key information to national security, and having insight into possible famine due to drought or flood conditions will be crucial to economic and stability concerns in the future.

There are important decisions that the defense sector makes regarding military operations which involve advance warning of environmental conditions on S2S timescales include: vessel routing; military exercise planning; war games; tactical planning; disaster relief; search and rescue advance planning (e.g., in the Arctic). In addition, there are serious threats posed by extreme events to military facilities in vulnerable locations. For example, military facilities on the remote Indian Ocean island of Diego Garcia house the Air Force Satellite Control Network which serves as an essential GPS command and control hub (Vedda, 2011). Other installations vulnerable to extreme weather and ocean events include Bahrain, Guam, Eglin Air Force Base, FL, and Norfolk, VA.

The Department of Defense (DOD) currently uses standard public climate data sets, forecast model products, and specialized data sets, models, and methods developed by DOD (Fleet Numerical Meteorology and Oceanography Center [FNMOC], Naval Oceanographic Office [NAVO], Air Force Weather Agency [AFWA]). DOD has, and continues to develop, advanced and tailored products to aid decision making. These include predictions about performance of equipment and people/organizations given environmental conditions. DOD has many downstream decision-support tools into which the predictions feed. For example:

1. Commander Third Fleet ship operation planning in the eastern North Pacific utilizes seasonal forecasts of NE Pacific winds and waves, by month based on both standard climatologies and statistical predictions derived from multiyear model reanalyses as a basis to revise/update the timing of the operations.

2. For tropical cyclone/hurricane predictions, 2-4 week timescales and below are essential for avoiding adverse impacts to sea operations before, during, and after cyclone passage. Military exercises, supply chains, and ship movements are vulnerable to tropical cyclones. DOD currently issues monthly tropical cyclone formation probability forecasts based on dynamical-statistical ensemble forecasts (Navy statistical module attached to the NOAA dynamical model output Climate Forecast System version 2 (CFSV2), which are 1-2 week Climate Prediction Center (CPC)-issued forecasts of above and below average probability of cyclogenesis and rainfall).
3. Piracy activity predictions (Figure 3.5) are based on forecasts of wave height and surface winds in the Indian Ocean, and a statistical module relating operations/behavior to environmental conditions and similar models for disaster relief operations, etc. Versions of this methodology are also used by agencies involved in migrant and drug interdictions.
4. Forecasts of beach and amphibious landing conditions for planning are based on high-resolution air, ocean, wave, and surf model predictions from historical reanalyses and statistical/analog techniques.

To summarize, for this type of decision making, the DOD has a well-developed capacity to utilize and ingest the type of tools/specialized forecasts that users often demand. But areas for improvement abound. In the short-term, improvements in observations for setting initial conditions (especially in areas with insufficient observations like oceans and geographic regions like Africa and the Western Pacific), and in forecast skill covering the global oceans are especially needed (see Chapter 5). On slightly longer time horizons, improvements in S2S predictions will be vital for future tactical and operational planning under climate change. For example, there is great need for better-integrated predictions of sea ice in a changing Arctic. The Navy and Coast Guard have focused attention on Arctic via their 2014 Roadmap and 2013 Strategy, respectively (US Navy Task Force Climate Change, 2014; USCG, 2013). Indeed, Arctic installations are some of the most vulnerable.

> "The combination of thawing permafrost, decreasing sea ice, and rising sea level on the Alaskan coast have led to an increase in coastal erosion at several Air Force radar early warning and communication installations. According to installation officials, this erosion has damaged roads, utility infrastructure, seawalls, and runways…..As a result, only small planes or helicopters are able to land in this location, as opposed to larger planes that could land on the runway when it is fully functional.
> Daily operations at these types of remote radar installations are at risk due to potential loss of runways, and such installations located close to the coastline could be at risk of radar failure if erosion of the coastline continues. Air Force headquarters officials noted that if one or more of these sites is not operational, there is a risk that the Department of Defense early warning system will operate with diminished functionality." (GAO, 2014)

For the Coast Guard, there is an acute need to engage in medium-range (subseasonal) response planning in the event of an accident in Arctic seas (for example an oil spill or a cruise ship evacuation). Navy forces are also much more likely to be engaged in the Arctic to assist Coast Guard search and rescue and other civil support operations (US Navy Task Force Climate Change, 2014). Within this context, there is a need for better forecasts now, but the need will be

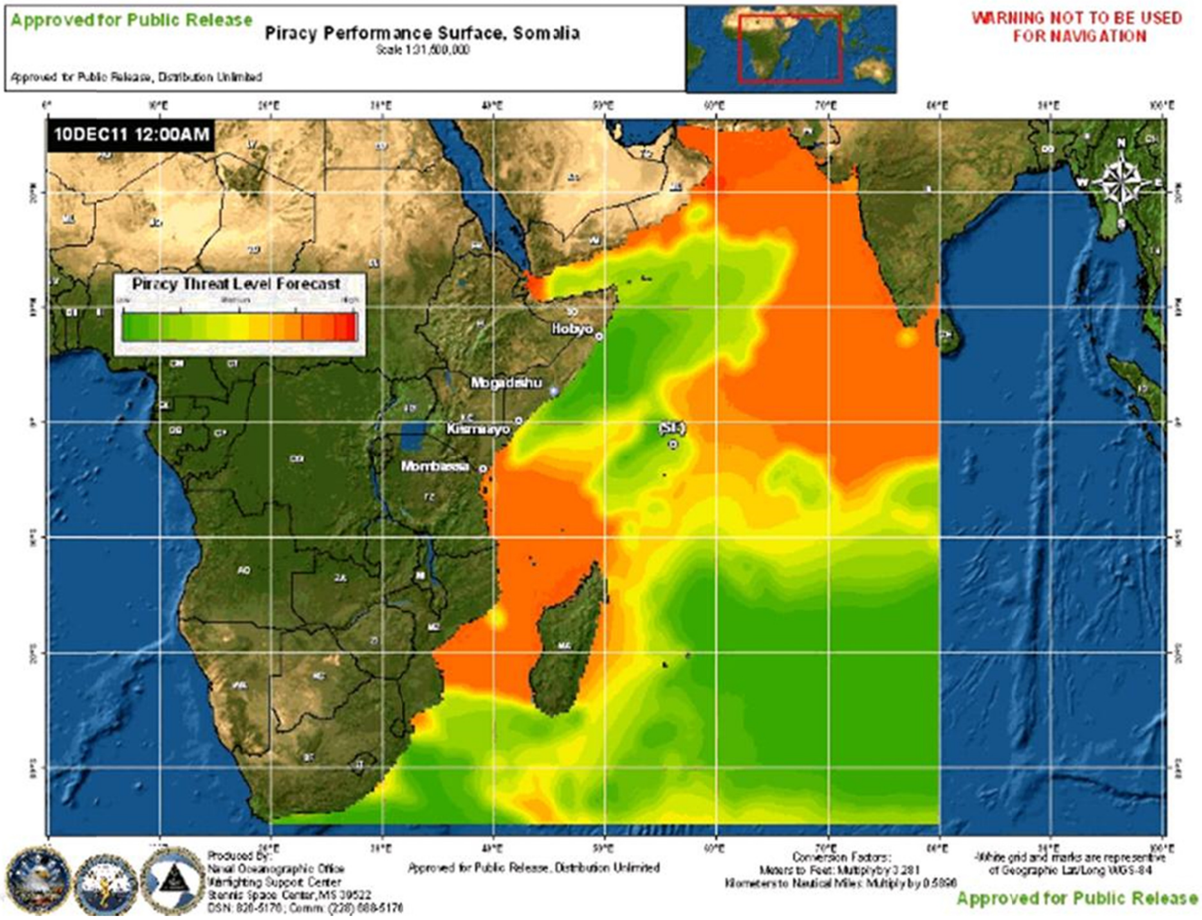


FIGURE 3.5 A piracy threat-level forecast issued by Naval Oceanographic Office, Warfighting Support Center. Real-time parameters—including intelligence information, shipping information, and forecasts of ocean currents, waves, and wind—are combined with historical correlative analysis between environmental conditions and pirate attacks to provide a forecast of pirate threat levels. Warm colors indicate a higher probability of attack. SOURCE: Naval Oceanographic Office, Warfighting Support Center.

particularly great as climate change begins to initiate ice free passage through the Arctic Ocean and activity related to shipping/tourism and energy extraction begins to increase.

The *Deepwater Horizon* Oil Spill

On April 20, 2010, an explosion aboard the Deepwater Horizon (DWH) drilling rig killed 11 workers and triggered a massive spill of oil and natural gas into the deep waters of the Gulf of Mexico that lasted for 87 days before it was finally capped off (Graham et al., 2011; Lubchenco et al., 2012). For the purposes of this report, DWH provides an instructive case study regarding the response on S2S timescales to a large, unexpected forcing event.

Oil spill trajectory forecasting systems in 2010 were well-suited for responding to surface spills, even beyond the scale of the 1989 Exxon Valdez oil spill, and worked well for predicting where surface slicks moved for the following 72 hours for which weather forecasts were sufficiently accurate. However, the vast volume and depth of spilled hydrocarbons associated with the DWH, the extended duration of the spill, and the spatial extent of its impacts presented unique challenges for projecting of the consequences of the spill to an alarmed public.

To help meet this challenge, there was a massive mobilization of the relevant scientific community to document the event observationally and understand its consequences (e.g., Lubchenco et al., 2012). This response included model forecasts and predictions, with three additional near-term ocean forecast systems being added to the initial three member ensemble used for 72-hour surface slick predictions (Lubchenco et al., 2012). For S2S timescales, both National Center for Atmospheric Research (NCAR)/ Los Alamos National Laboratory (LANL) (Maltrud et al., 2010) and NOAA/Geophysical Fluid Dynamics Laboratory (GFDL; Adcroft et al., 2010) adapted existing regionally eddy-permitting (1/10° and 1/8° horizontal resolution respectively) global Earth system models to explore the long-term transport and dilution of hydrocarbons or the resulting oxygen drawdown from the spill.

Despite the mobilization of the climate and ocean modeling community to address the consequences of the DWH, a frenzy of popular media activity during the spill created a particularly challenging environment for clearly communicating credible scientific guidance regarding what could be expected on S2S timescales. There was at times a particular focus by the official sources on defending the government's scientific integrity, especially after the first official estimates placed the flow rate as at least 5,000 barrels per day based on observed surface slicks, but subsequent analysis by academics revealed the true rate to be an order of magnitude larger (McNutt et al., 2011). During the event, there was also extensive speculation by scientists from a wide range of backgrounds about the implications of the spill, often going directly to the media without first passing through peer review. For example, one widely covered NCAR press release on June 3, 2010 with vivid animations (Figure 3.6A) was based on scientifically correct ocean model simulations, but was widely misinterpreted in the popular press as suggesting the impending arrival of harmful concentrations of oil along the entire east coast of the United States (McNutt et al., 2011). About the same time, NOAA scientists developed projections of the regional spreading and dilution of dissolved oil and the possibility of significant oxygen drawdown in the deeply submerged plumes of oil that took into account the estimated spill rates and the biological consumption of oil (Adcroft et al., 2010). These projections were based on a prototype high-resolution climate model and extensive input from NOAA's oil-spill projection team. An animation from this study (Figure 3.6B) correctly depicted the localization of dissolved oil from the spill to the Northern Gulf of Mexico, but as a new government product, it was only publicly released after being published in a peer-reviewed journal, about two weeks after the well had been capped.

These two early studies illustrate some of the specific challenges of using innovative modeling tools to provide insights during an emergency. The particular challenges of communicating across scientific disciplines and using scientific expertise to inform the public awareness during a high-profile incident like DWH has led to calls for the development of a "community of disaster science" (McNutt, 2015), with expertise that can be applied to responding to a wide range of high-profile events.

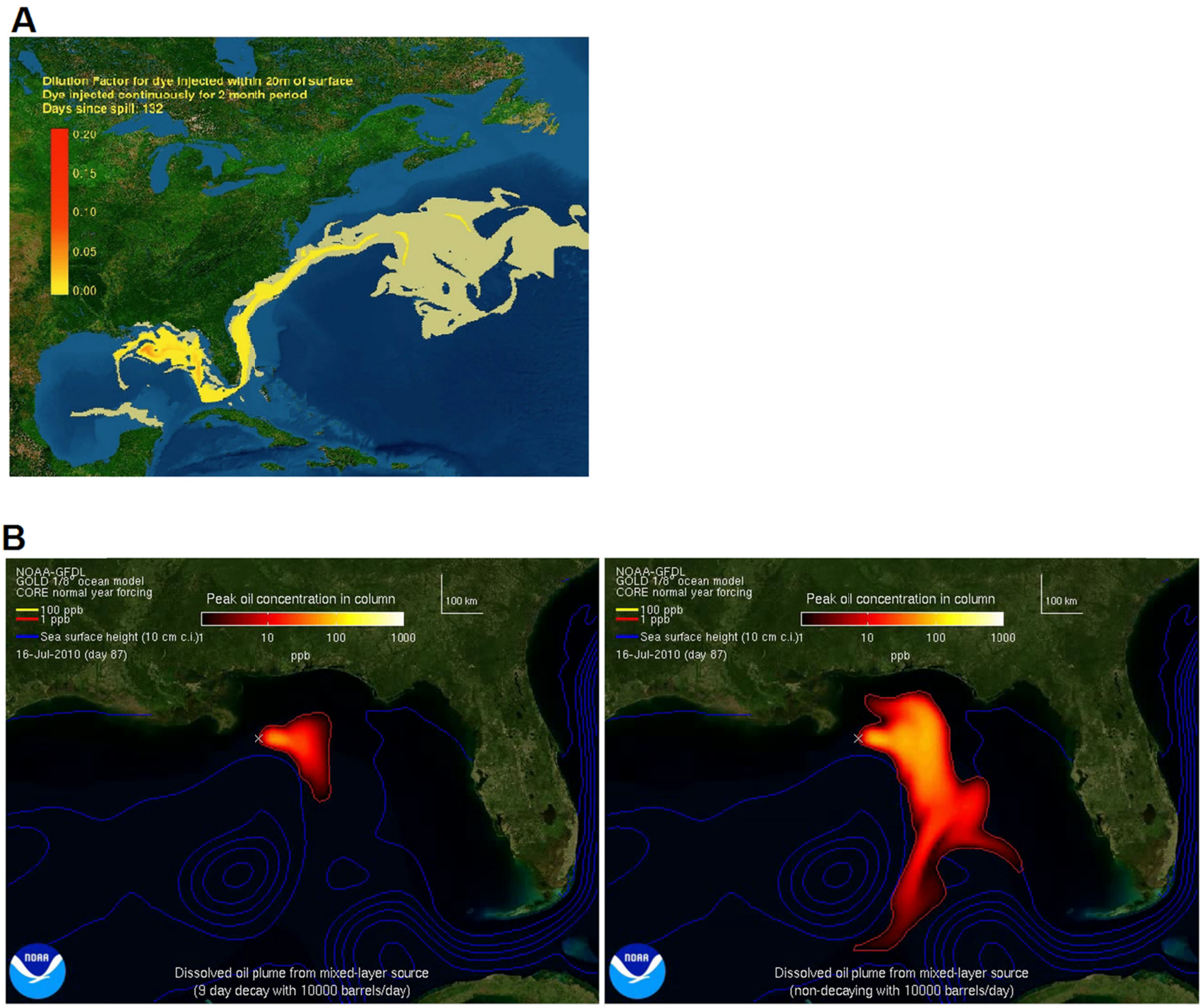


FIGURE 3.6 (A) A frame from a June 3, 2010 animation depicting the dilution and transport after 132 days of a dye released at the location of the *Deepwater Horizon* oil spill. This animation was widely shown on national television (Maltrud et al., 2010). SOURCE: https://www2.ucar.edu/atmosnews/news/2154/ocean-currents-likely-carry-oil-along-atlantic-coast, accessed January 27, 2016. (B) A frame from a NOAA animation of dissolved oil concentrations that include (left) or omit (right) the biological consumption of oil and only contour the oil concentrations that exceed EPA limits in drinking water to avoid creating misleading interpretations (Adcroft et al., 2010). Although this animation was available in June, 2010, while the DWH was near its peak flow, NOAA only released it publicly after the paper describing it had gone through peer review and been accepted for publication in early August, 2010, two weeks after the well had already been capped off. SOURCE: NOAA.

Sufficiently accurate and well-validated S2S forecasting of the weather and ocean currents could have helped better target the response to DWH. For example, the likelihood of DWH oil impacting the beaches along the west coast of Florida and in the Florida Keys was unclear using the climate models described above. Specifically, these projections did not take into account the position and strength of the Loop Current, a current that exerts strong control on the direction of ocean waters. As a result, the projections over-estimated the geographic extent of impacted shoreline. Had there been a skillful and validated forecast of the Loop Current structure on S2S timescales during the summer of 2010, it may have been unnecessary to deploy as many Local Incident Command Posts and oil response equipment to Florida. A portion of these resources was never used, and with more skillful S2S forecasts, could have been sent to alternate locations where they would have been of much greater value (D. Payton, personal communication, June 2015).

There is a high cost to incorrect projections of the direction of an oil spill, and in an emergency there is little time to identify the sources of incorrect current directions or other model biases. For use in official government guidance, therefore, it is important that models are observationally validated or have their quality otherwise established. For an unprecedented forcing event, observational validation may be impossible, and scientific journals' peer-review and embargo may be inconsistent with the time constraints of the situation. Thus alternate approaches may be required for establishing legally required quality assurance.

As result of the challenges in coordinating the broad participation of the scientific community to DWH, a number of the leaders in the response to DWH joined together to found the Scientific Partnerships Enabling Rapid Response (SPERR) to promote rapid communication and coordination of efforts and sharing of expertise during disasters. This was a one-year pilot project that ended in 2015, but such efforts provide a forum for developing the expertise and frameworks necessary to build capacity on forecasting the consequences of unanticipated events. This is an important step towards developing a "community for disaster science" in advance of an incident (McNutt, 2015).

Nuclear Events

Catastrophic/unprecedented (unusual/infrequent) events include nuclear power plant accidents that could distribute radioactive material over wide areas and impact many nations (e.g., Chernobyl and Fukushima), and intentional nuclear detonations affecting large populations (e.g., Nagasaki and Hiroshima). Accidental radiological release events have the potential to impact the air/sea over S2S timescales. Linked modeling systems encompassing the Earth system components can provide important benefits in forecasting the scope of impacts (Pullen et al., 2013).

Nuclear weapon scenarios in the current geopolitical context include limited nuclear exchanges. The range of possible scenarios transcends the "mutually assured destruction" envisioned during the Cold War where nuclear winter was an assured outcome (NRC, 1985). Recent simulations of a regional nuclear exchange (100 15-kt yield) with a comprehensive Earth system model including atmospheric chemistry, ocean dynamics, and interactive sea ice and land components have revealed significant impacts at S2S timescales (Mills et al., 2014). Under this scenario, black carbon injected into the stratosphere would deliver global ozone losses of 20-50%, reduced sunlight, and catastrophic effects on global crop yields.

In the immediate aftermath of such rare events, emergency response-focused simulations would be conducted through the Department of Homeland Security (DHS) Interagency Modeling and Atmospheric Assessment Center (IMAAC) utilizing DOD Defense Threat Reduction Agency (DTRA) for national consequences. (Separately, the Department of Energy [DOE] National Atmospheric Release Advisory Center [NARAC] and DOD DTRA consequence assessment assets can be mobilized for international events, as in Fukushima.) However, these simulation tools were not designed to provide forecast information on S2S timescales.

The DHS National Exercise Division engages in major emergency exercises every year—gaming out the response to such events as pandemics and earthquakes. They utilize the National Infrastructure Simulation and Analysis Center (NISAC) at Sandia National Laboratory as an extensive tool set to examine the impacts from catastrophic events. But these tools do not encapsulate real-time prediction out to S2S timescales. We need to be prepared as a nation to anticipate, prepare, and react to such impactful events at the appropriate timescales. A framework that could encompass multiple temporal scales of impacts, while exercising state-of-the-science models, could prepare agencies to collaborate and respond in the event of a catastrophic/unprecedented incident. Such incidents that could produce sustained regional-to-global impacts beyond several weeks duration include volcano eruptions and forest fires/biomass burning.

THE WAY FORWARD FOR REALIZING THE POTENTIAL OF S2S PREDICTIONS

Even though user needs are not fully articulated at this point and reside mostly in case studies and anecdotal information, it is clear that there is much potential value in developing S2S forecasts. However, decision makers need a wider range of model and forecast variables than what is generally available at present. Producing forecast products that are valid at finer spatial and temporal scales, and generating event- and impact-based information, are some of the most commonly expressed needs. For example, knowing the probability of receiving an abnormally high number of heat events during a summer can help local and state emergency management officials prepare resources to minimize impacts.

Advances in S2S predictions, which will be described in Chapters 4 and 5, will provide opportunities to advance from basic products and provide both finer spatial and temporal resolution and additional variables that are not presently available to most end users. Some of these specialized products will continue to be created off-line, through techniques such as downscaling of S2S forecasts, coupling S2S forecasts with sector-specific dynamic or decision models, such as in the case of predictions of piracy activity (Figure 3.5), or seasonal hydrology forecasts to inform water management. Such specialized products do already provide some of the needed capabilities, but access to such products is limited, as developing derived products can be costly.

Decision makers may also benefit from an ability to run on-demand simulations to respond to unanticipated events. This could be useful in responding to an event or it may be useful in generating scenarios that can be used in a planning context. A capability of using similar models to those used to make operational predictions can allow decision makers the flexibility of generating a range of scenarios. For example, forecasts of a range of ocean currents and surface winds can help decision makers anticipate where to deploy resources for containing an oil spill, or possible outcomes of a volcanic eruption.

However, advancing effective use of S2S information requires both "knowledge of" and "knowledge in" the process (c.f., Lasswell (1971) discussion of the policy process). Knowledge *in* the process focuses on mechanisms that promote the use of S2S information, including understanding product requirements as described above, evaluation metrics, and integration into operational systems. Knowledge *of* the process includes research on decision-making processes and contexts that promote or inhibit the use of information. These can roughly be thought of as a need to understand use and a need to promote use.

An essential first step is improving understanding of what stakeholders view as actionable information. S2S information has transformative potential but the path forward towards application of such information is unclear due to lack of study and synthesis of existing information. More generalized information on what end users want, which is important to help inform advances in S2S forecasts, requires more than *ad hoc* case studies of particular decision contexts, such as water managers' use of information in a particular basin. Case studies need to be broadened to include more sectors, the interaction between sectors, and more regions of the country, in order to develop a more systematic assessment of user needs across sectors. Such an assessment will be particularly important for developing forecasts of variables such as sea ice or harmful algal blooms that are not as readily available at the present time. Furthermore, quantification of the value of use of seasonal forecasts is needed to establish a baseline against which improvements in use can be measured.

The S2S community also needs to learn more about decision makers' tolerances for use of products with limited skill. Under what conditions are decision makers willing to accept limited skill and still use the products? Are they more willing to accept limited skill in the context of general guidance as compared to concrete decisions? How do they respond to failed forecasts? A more thorough examination of decision makers' tolerance for forecasts with lower skill will reveal some sectors or applications that can make effective use of present and near-term products, as well as identifying longer-term opportunities and targets for new products as skill improves.

S2S information may be used to consult, consider, incorporate, or engage in dialogue about risks (A. Ray, personal communication, March 2015). Examining the decision-processes in each of these applications will enable development of new products, and also drive improvements to the dissemination of such products by both the public and private sectors. It is likely that targeted products will need to be developed for a range of different sectors and decision-making contexts.

Recommendation A: Develop a body of social science research that leads to more comprehensive and systematic understanding of the use and barriers to use of seasonal and subseasonal Earth system predictions.

Specifically:

- Characterize current and potential users of S2S forecasts and their decision-making contexts, and identify key commonalities and differences in needs (e.g., variables, temporal and spatial scale, lead times, and forecast skill) across multiple sectors.
- Promote social and behavioral science research on the use of probabilistic forecast information.
- Create opportunities to share knowledge and practices among researchers working to improve the use of predictions across weather, subseasonal, and seasonal timescales.

Realizing the full value of improvements in S2S predictions will also require engagement of end users throughout the process of developing and disseminating forecast products. Just as the retail sector places consumers at the center of their research and development, decision makers who are the likely consumers of S2S information should be integrated into the research and development process. Integrating developers, providers, and users in the context of strategic planning for the S2S enterprise assures the growth of S2S applications and helps push the boundaries of the science of S2S prediction. An iterative engagement with users is required in part because the diversity of applications of S2S forecasts is large, and the science of S2S forecasting is rapidly advancing. Ongoing work will be necessary to continually match and integrate what is technologically feasible with what is most actionable for decision makers. In particular, it will be important to: 1) understand what variables and timescales provide the most value and opportunities; 2) understand how decision makers might operate within the context limited skill or high uncertainty predictions; and 3) determine the formats and message content for products in partnership with those using those products. Such iterative engagement will also provide guidance to the operational community on the critical research challenges, such as forecasting extreme events, and the way in which information can be most effectively delivered.

As with weather forecasts, most decision makers are likely to acquire information via an intermediary (Breuer et al., 2010; Lemos and Rood, 2010; Mase and Prokopy, 2014; Pagano et al., 2002). There are opportunities to utilize existing programs, such as NOAA's Regional Integrated Sciences and Assessments, which actively engage decision makers in co-production of knowledge related to needs for climate information and services. There are also numerous academic programs that promote inter-disciplinary research related to the use of climate and scientific information in societal applications. These present existing avenues that should be built upon to examine decision making, generate decision-support tools, and provide guidance on future S2S research priorities, operational forecast products, and services.

As demand for S2S products grows, there will be new opportunities for research and applications, necessitating changes in the workforce. Blended research between the physical and social sciences will facilitate the transfer of knowledge between forecasts, outlooks and predictions of the physical environment, and their social applications. Growing the number of "extension agents" or other boundary roles and institutions should also be considered to improve the outcomes of S2S forecast use, and to better integrate decision makers into the process of developing S2S forecasts. Changes in the structure of the workforce are discussed further in Chapter 7.

Although it is important to bolster the capabilities of operational centers to produce useful forecasts, it is also important not to neglect the private sector's role in delivering new products. S2S forecasts offer an obvious opportunity for private sector providers to transform forecasts of conventional variables into new, value-added products focused on user needs and preferences. There is an emerging private sector already providing detailed analyses needed for specialized applications. Thus private sector providers should be closely involved in any program for engaging stakeholders, and should be informed of the results and conclusions of such efforts. The U.S. Small Business Innovation Research (SBIR) program is one such a mechanism for the weather and climate research agencies to engage the private sector in developing improvements for operational commercial offerings and to more effectively target specific user groups. Continued growth of both the private sector and the array of products in the public sector are thus required to meet the growing demand for services.

Recommendation B: Establish an ongoing and iterative process in which stakeholders, social and behavioral scientists, and physical scientists co-design S2S forecast products, verification metrics, and decision-making tools.

Specifically:

- Engage users with physical, social, and behavioral scientists to develop requirements for new products as advances are made in modeling technology and forecast skill, including forecasts for additional environmental variables.
- In direct collaboration with users, develop ready-set-go scenarios that incorporate S2S predictions and weather forecasts to enable advance preparation for potential hazards as timelines shorten and uncertainty decreases.
- Support boundary organizations and private sector enterprises that act as interfaces between forecast producers and users.

Chapter 4: Sources of Subseasonal to Seasonal Predictability

INTRODUCTION

This chapter will:

- Outline important concepts in the consideration of predictability and its relation to practical aspects of prediction and prediction skill;
- Identify important sources of subseasonal to seasonal (S2S) predictability and highlight recent progress in understanding and modeling these sources;
- Recommend research in these areas that will further our understanding of sources of predictability and allow us to better exploit them to extend and improve S2S forecast skill.

During the early developments of seasonal to interannual climate prediction, weather prediction was often described as an “initial-value” problem and seasonal orlonger-term climate prediction as a “boundary-value” problem (Box 4.1). However, as our aspirations and capabilities for providing skillful predictions across timescales and Earth system components has increased, the value of such distinctions has become limited.

The schematics in Figure 4.1 are meant to further illustrate the above considerations and the complexities in estimating predictability across a range of timescales and phenomena (e.g., S2S) and implementing them in a forecasting system. The top schematic shows time series depicting variations in an arbitrary quantity (e.g., temperature, precipitation) that are typical of weather, subseasonal, and seasonal variability over a roughly six-month period, with an indication of what processes might be associated with the given variation and timescale (e.g., green ~ Madden-Julian Oscillation [MJO], soil moisture). The bottom schematic is similar but for longer timescale variations. For weather forecasting, the forecast proceeds from an observed initial state (solid blue circle) out to lead times of a few days. For subseasonal or seasonal forecasts, the same is true out to a few weeks or months, respectively. Along the lines of the discussion above, the influence on weather or S2S forecasts from the sorts of (long timescale) phenomena indicated in the lower schematic could feasibly be provided as a fixed boundary value. However, this practical separation between processes and timescales is not always possible or straightforward, particularly as the different timescales become closer. In fact, filling the forecast capability gap between the weather (initial value) and the seasonal (previously referred to as boundary value) problems with subseasonal capabilities has served to strongly blur the perception that they are separate sorts of forecast “problems” and helped to instigate the desire for “seamless” forecasting systems (e.g., Palmer et al., 2008, see Box 5.2).

BOX 4.1—"Initial Value" Versus "Boundary Value" Modeling Problems

The distinction in the application of these two terms—"initial-value" and "boundary-value"—does not arise from the inherent nature of the weather/climate phenomena, but rather from the practicalities of the prediction framework. Put another way, virtually every prediction problem of the natural weather/climate system is, in its purest and most comprehensive form, an "initial-value" problem. However, the practicalities of producing a forecast nearly always also include the application of the "boundary-value" paradigm in one form or another, which arises from one of three practical reasons. In one case, an incomplete knowledge or model of the state or evolution of a given process necessitates that the representation of that component/process be specified (or approximated) as a fixed boundary condition to the part of the system that is being modeled and forecasted. An example of this might be how sea ice was treated in the first global weather forecasts. Although there was reason to think that sea ice could evolve and influence weather patterns over the course of the forecast, there did not exist the process knowledge, associated models, and observations to accurately include it in a manner that would improve the forecast. Thus, it was of necessity in that case to provide a fixed specification (i.e. a "boundary value") for the distribution of sea ice and not explicitly include its interaction in the forecast. The influence/interactions of vegetation in today's weather forecasts, are often treated similarly, i.e., there is reason to think they influence key water and energy processes relevant to the weather and climate, but the process models and associated observations for initialization are too incomplete to include in an operational forecast setting. The above considerations are important because as long as a process is relegated to a boundary condition, the estimate of the predictability of that phenomenon is incomplete or at least compromised, even though it might be key to the fidelity of a modeled or forecast phenomenon.

In the second case, there may be a skillful and efficient model of a process relevant to a forecast and even observations that could be utilized to initialize the relevant quantities. However, because of a relatively slower evolution of that component of the system, it is both feasible and advisable to simply specify the values for that part of the system from observations, leaving them as constant "boundary-values" for the forecast period. Examples of this case might be the specification of the solar forcing, greenhouse gas concentrations, aerosols, ice sheet and glacier coverage, etc. Note that a skillful prediction of any of these quantities is in itself an "initial-value problem." But when it comes to a shorter timescale forecast (e.g., weather or S2S forecasts) or an associated estimate of predictability, it is an excellent approximation to simply consider them as "boundary-values."

The third case is a hybrid of the first two. For cases where the coupled interaction between two Earth system components or processes is weak, the knowledge of the coupling between the two is incomplete, or there are technical challenges yet to be overcome in fully coupling the two working component models, it is often the case that a forecast model for one of the components will be produced and the values from it supplied as "boundary-values" to the forecast model of the other component. The most salient example of this was the use of dynamical seasonal forecasts first developed from the growing knowledge that El Niño Southern Oscillation (ENSO)-related tropical sea surface temperature (SST) variations. The SST variations had a substantive impact on the seasonal climate anomalies in the tropics and some mid-latitude regions. In this case, our early dynamical ocean model forecasts of tropical SSTs were initialized and run to lead times of 3-12 months to produce future estimates of tropical SST anomalies. These SSTs—forecast as an initial value problem—were in turn used as the SST boundary conditions to global atmospheric forecast models run over the same lead times to produce a seasonal climate forecast. In this case, the atmospheric initial condition information that strongly influences 5-day weather forecast outcomes become irrelevant after the first month and only the SSTs, provided as "boundary values", dictated the climate forecast outcome. This particular example is when/where the short-term climate prediction problem became strongly equated to a "boundary-value" problem, whereas in actuality the underlying and evolving tropical SST (i.e., ENSO) portion of the forecast is an "initial-value problem" of an ocean model (e.g., a "two-tier" forecast system—see Chapter 2). A related example is air quality forecasting, which often utilizes the temperature, humidity, pressure, and flow fields from a weather forecast to drive an atmospheric chemistry model. The desired forecast comes from the atmospheric chemistry model with the weather forecast model, and surface emission specifications, providing evolving, yet uncoupled, boundary information.

Even when considering only the timescales associated with the S2S forecast range, there is a spectrum of phenomena and processes that contribute to the observed variations. This is schematically indicated in Figure 4.1 by the rainbow of colors equated from high (purple) to low (red) frequency phenomena. Within this spectrum of phenomena/processes are some, highlighted by the individual colored lines, that dominate the variability and provide valued sources of predictability. The study of predictability is to answer the question of whether a prediction of a phenomenon is possible given all antecedent observations.

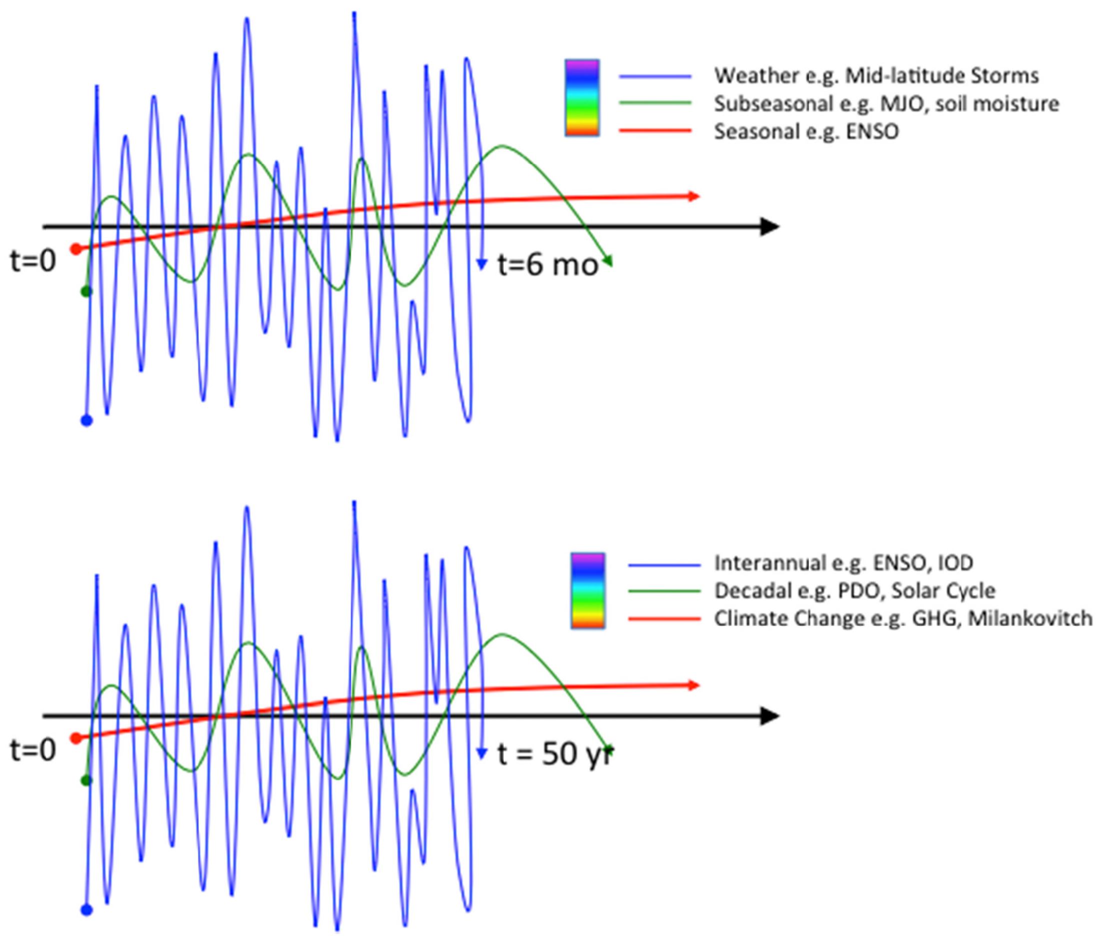


FIGURE 4.1 Schematic illustration of time series depicting variations in an arbitrary quantity relevant to weather/climate with variations typical of (top) weather (blue), subseasonal variability (green) and seasonal variability (red) over a 6 month period starting from t=0. The bottom panel is similar to the top, but for interannual, decadal, and longer-term century scale variations. The line colors and spectrum of colors from which they are draw are mean to illustrate that there are a continuum of phenomena/processes across these indicated timescales (i.e., frequencies) with notable peaks in the spectrum highlighting a subset of the continuum that typically are found to be sources of predictability.

DEFINING PREDICTABILITY

In this report, predictability refers to a phenomenon's potential, i.e., its upper limit, for being predicted. Theoretically, this is inherent to the phenomenon itself and its limit comes from inevitable errors in initial conditions, which are amplified through nonlinear processes in a perfect model. Practically, predictability can only be estimated through various means using empirical or numerical models that are not perfect (NRC, 2010b). Such models can lead to over or under estimates of predictability. For example, by not adequately accounting for "noise" relative to the specific phenomenon (i.e., the "signal"), models will often over estimate predictability. Similarly, if the specific phenomenon is only weakly represented, models will often underestimate its predictability. A firm estimate of the lower bound of predictability is the upper limit on the observed forecast skill of operational systems. Achieving the upper limit of predictability with a prediction system is hindered by practical factors. In addition to a lack of accurate specification of the initial conditions (typically due to inadequate observation sampling in space, time, and physical quantity), there are shortcomings in forecast systems (typically limited by models with too coarse spatial resolution and incomplete or inaccurate physical process representations) and shortcomings in the data assimilation systems (see Chapter 5). For the purposes of this report and the associated research agenda, it is critical to explore and quantify the predictability of various components of the Earth system, especially weather and climate. The estimated upper bounds of predictability for the various phenomena and processes discussed in this chapter are key to identifying unexploited or underexploited prediction capabilities and providing a quantified means to measure our progress in practical forecast skill against our predictability (i.e., upper limit) estimates (e.g., Figure 4.2). Together these help to prioritize areas of research and model development across the range of sources of predictability to pursue.

PREDICTIBILITY RESEARCH

Research on predictability and its sources is a central part of carving a path to new and improved forecast capabilities (e.g., S2S). Advancements in this research critically hinge on observations, a variety of models, forecast system analogs, and ensemble retrospective forecast datasets. Such research typically begins with theoretical considerations or empirical analysis based on observations (Figure 4.3, Facet I; e.g., a lagged correlation analysis between two or more variables) that point to a process or phenomena that exhibits predictability. From this perspective, it is essential to have long-records of multi-variate observations for both the predicted and the potential predictor(s). Often predictability of a particular observed phenomenon is investigated through process-oriented studies using a hierarchy of models (Figure 4.3, Facet II). Models used for this purpose may be reduced order or idealized. In other cases researchers may create a series of sensitivity experiments in complete Earth system models or make intercomparisons across models.

Further advancement (Figure 4.3, Facet III) is made by the development of robust models that incorporate the physical relationships underlying the phenomena or coupled interactions that yield the predictability, as demonstrated by simulation or retrospective forecast experiments that are evaluated against observations. Such model development generally requires additional targeted process observations, research and analysis in order to properly understand the

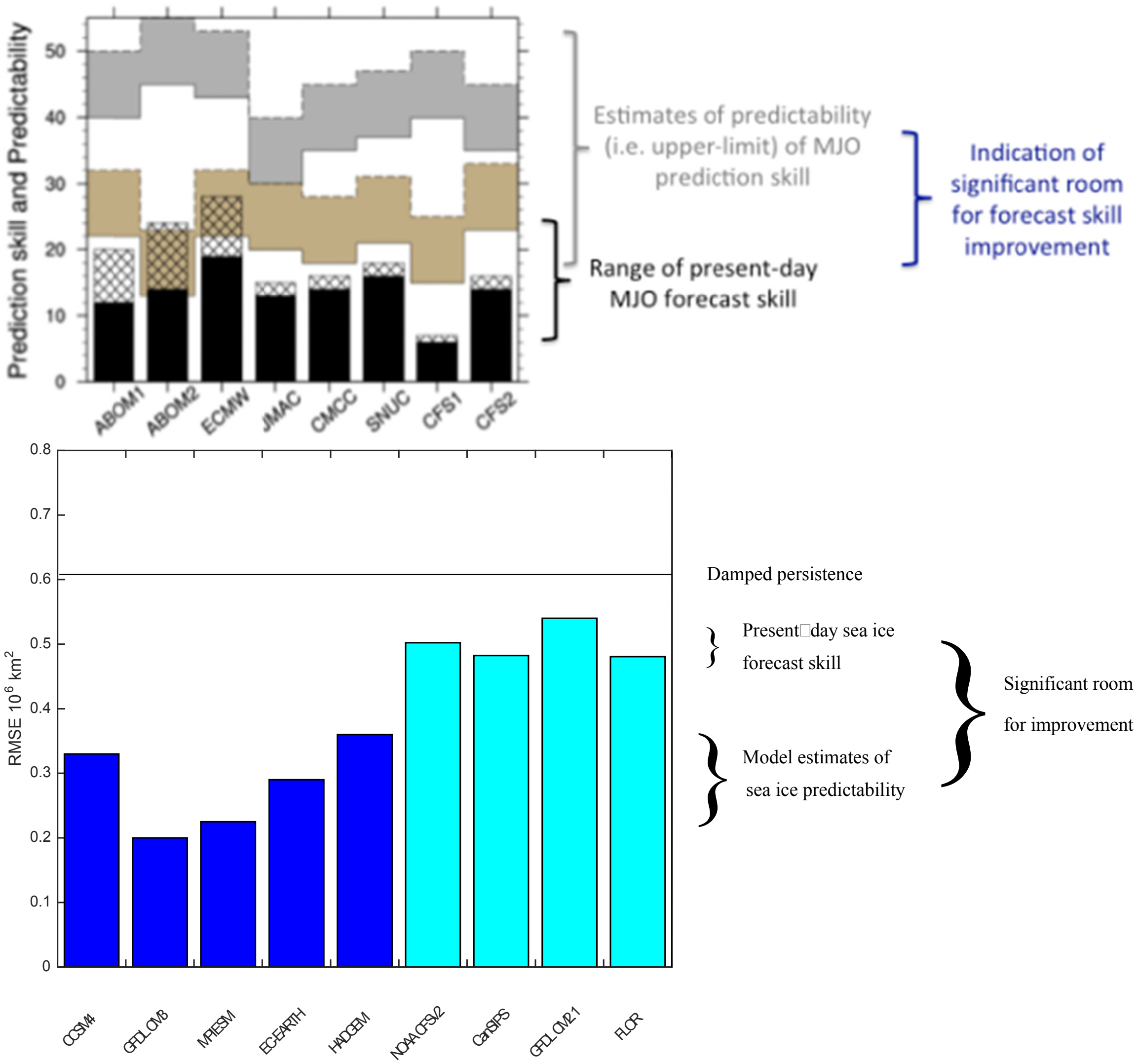


FIGURE 4.2 Prediction skill values versus estimates of predictability—i.e., an estimate of practical present-day skill versus estimates of the potential upper limits of skill—for the MJO (upper) and Arctic September sea ice extent at two-month lead times (lower). For the MJO, predictability is measured in terms of lead time in days. Each bar is based on one of eight ensemble-prediction systems with varying numbers of members depending on the forecast system, or calculated from approximately 20 years of retrospective forecasts. The black bars denote retrospective forecast skill based on single-member forecasts, while the hatched bar shows the improvement based on the ensemble forecast system—i.e., using the ensemble mean of all the forecast system's members. The tan and gray bars show two different estimates of predictability using the "perfect model" (sometimes called "idealized twin experiment") approach. For the predictability estimates, one member is designated to represent the "observed" case and another single members (tan bars) or the mean of the remaining members (grey bars) is used to predict it. The sea-ice panel is similar, except error increases with height of the bars, and the dark-blue bars are estimates of predictability and light-blue bars are retrospective forecast skill. SOURCE: Top panel adapted from Neena et al., 2014. Bottom panel based on results in Blanchard-Wrigglesworth (2015).

Facet	Predictability Research	Requirements
I.	Exploratory research based on empirical and/or theoretical relations of observed variability	Long records of multivariate observations
II.	Process-oriented studies using a hierarchy of models ranging from low-order models to Earth system models and including "ensembles of opportunity"	Development of low-order and Earth system models and archives of model output
III.	Studies to assess reliability of forecasts and retrospective simulations to capture empirical and/or theoretical relationships, including exploring the number of ensembles needed to represent probability	Development and/or coupling of accurate models and observations to use for initial conditions and validation
IV.	Predictability experiments to estimate upper limits of predictive skill and explore coupled influences, scale interaction, and identify regimes of high/low expected skill	Development and/or coupling of accurate models

FIGURE 4.3 Four facets of, and associated requirements for, predictability research.

underlying processes, and significant effort to encapsulate and validate them in the models. Because S2S forecasts are inherently probabilistic, an ensemble of simulations is usually needed to tests if relationships that give rise to predictability are accurately simulated. The number of ensemble members needed to capture the probability is a research question that can be explored either theoretically or practically.

With the dynamical/coupled models developed in Facets II and III, carefully designed experiments can be performed to estimate the predictability and assess sources of skill (Figure 4.3, Facet IV). To identify the contribution of a process to forecast skill, numerical retrospective forecasts are usually performed and compared using model configurations with and without the process. In an example with such an approach, it was found that seasonal forecast skill is enhanced following stratospheric sudden warmings (Sigmond et al., 2013). Roff et al. (2011) assessed the effect of stratospheric resolution on extended-range forecast skill.

Another approach involving relaxation retrospective forecast experiments—where, for example, atmospheric fields in one region are relaxed towards analysis fields—has been used to assess the impact of teleconnections and to identify the origin of skill. With this approach, Ferranti et al. (1990) found important contribution of tropical subseasonal variability on the forecast skill in the North Hemisphere middle latitudes. Vitart and Jung (2010) assessed the influence of the Northern Hemisphere extratropics on the skill in predicting the MJO.

In summary, research on predictability and its sources is critical for helping to identify and prioritize advancements between the various phenomena and Earth system components that might impact/offer S2S predictability. Such research is also critical guiding model and forecast system development and helping identify observing systems for sustained observations.

A useful technique to estimate predictability is the analysis of variance (ANOVA). An atmospheric variable, such as air temperature or precipitation, may be decomposed into a predictable component (signal) and an unpredictable component (noise), Z = Zs + Zn. The predictable signal comes from sources of predictability such as those discussed in the next section, and the unpredictable noise comes from chaotic processes with respect to S2S, such as high-frequency eddies. The total variance is then the sum of the signal variance and the noise variance i.e., Var(Z)=Var(Zs)+Var(Zn). The extent to which the signal variance, Var(Zs), exceeds the noise variance, Var(Zn), determines the potential predictability. Thus potential predictability can be defined as the ratio of signal variance to the total variance, Var(Zs)/Var(Z), or the ratio of signal to noise, Var(Zs)/Var(Zn). In S2S, forecasts averaged over a period of a week, a month or a season, are usually produced. Such time averaging can increase the signal-to-noise ratio, as it reduces high-frequency noise variance while keeping most of the slow-varying signal variance, and thus improve predictability. Estimates of predictability with ANOVA can be performed using observational data (Facet I of Figure 4.3) or with ensemble model integrations (or retrospective forecasts) (Facet II of Figure 4.3). For example, Madden (1976) estimated weather noise variance of seasonal means by extrapolating the power spectrum derived from observed daily time series in a season. In the case of dynamical ensemble retrospective forecast, the ensemble mean represents the "predictable signal component", as it is independent of the uncertainties (in initial condition or model parameter). On the other hand, the difference among the members of the ensemble retrospective forecast (spread) represents the "unpredictable noise component". This ANOVA approach has been applied in many previous studies to assess predictability (e.g., Quan et al., 2004; Straus et al., 2003; Zwiers, 1996).

Estimates of predictability of a given process or phenomenon when accounting for (unavoidable) uncertainties in the initial conditions and model configurations can also be done from "twin experiments" or an ensemble of experiments where one of the ensemble members is considered truth (or the "observed" state) and the other member(s)—which only differ by some small perturbation in the initial conditions and/or model parameters—are used to predict it. These predictability estimates can then be put into the same context as retrospective forecast experiments that instead compare the same predictions to observations in order to quantify forecast skill. This is the type of prediction skill and predictability experimentation that is shown in Figure 4.2. One of the main messages from this figure is that the practical forecast capabilities are still far from what might be achieved given the associated estimates of predictability (i.e., at least 2-3 weeks of additional lead time might be possible). An additional message is that predictability estimates are model dependent, as stated earlier. Further research and exploration can be performed with this type of system of experimentation through categorizing results by season or the conditions of other portions of the climate system (e.g., warm or cold ENSO state). In summary, predictability research is critical for helping to identify and prioritize advancements between the various phenomena and Earth system components that might impact/offer S2S predictability, as well as guiding model and forecast system development and helping identify observing systems for sustained observations.

Finding 4.1: Predictability research is critical for identifying predictable phenomena and providing lead time dependent upper limits on prediction skill. These serve to guide model and forecast system developments with practical targets for forecast skill. Further research on predictability is needed to more completely identify sources and quantify levels of predictability, including interactions across scales and phenomena and how these impact predictability of extreme events.

SOURCES OF PREDICTIBILITY

As illustrated in Figure 4.1, predictability derives from a number of processes and phenomena that exhibit a wide range of timescales. For the purpose of this discussion, these sources will be generalized into three types.[14] The first occurs in the form of recurring and/or quasi-oscillatory patterns of variability—often referred to as *"modes" of variability*—that vary with S2S timescales. When a space-time pattern of variability tends to reoccur in the observed record, particularly when it includes positive and negative phases and/or space-time propagation of the given pattern, it is often referred to as a *natural "mode" of variability.* Attempts are made to understand the physics behind the pattern(s) and the evolution of a typical event life cycle for such modes. Examples include ENSO, Madden-Julian Oscillation (MJO), Quasi-Biennial Oscillation (QBO), and Indian Ocean Dipole (IOD). Referring to Figure 4.1, this type of S2S predictability would be exhibited as a quasi-oscillatory phenomena with a period ranging somewhere between about two weeks to a year (based on this report's definition of S2S).

The second source of predictability occurs from an anomaly in the initial state of one of the components of the Earth system whose typical timescale of evolution (i.e., persistence time) is similar to the target forecast. For the S2S timescale, this might be large-scale anomalies in upper ocean heat content, sea ice, snowpack, soil moisture, etc. Given their relatively slow variation compared to weather, such anomalies are said to retain *"memory"* of the initial state and impart "inertia" to the system's subsequent evolution. They typically have a systematic or recurring manner of evolving on timescales much longer than the forecast. For the purposes of this discussion, we refer to these as "slowly varying processes."

The third type of predictability stems from anomalous external forcing that is extensive or strong enough to have an impact globally or regionally for weeks to months (such as cyclic or anomalous solar output, anthropogenic factors, and events such as volcanoes). In this case, its predictability in relation to S2S is derived from a combination of being able to specify the anomalous external forcing and the forcing evolving relatively slowly or in a well-defined way over the forecast lead times (for example the annual cycle of solar radiation).

Understanding and being able to model the dynamics of each of these three types of predictability sources, as well as their interactions and teleconnections, is essential to generating S2S forecasts. Although much progress has been made in recent years in furthering understanding of how some of these sources of predictability, such as the MJO or soil moisture, influence environmental conditions or events that forecasters would like to be able to predict (e.g., precipitation anomalies, heat waves, or tropical cyclones), more work is needed and continued progress in this area remains fundamental to advancing S2S predictions (e.g., NRC, 2010b; Vitart et al., 2014). Indeed large gaps remain in our understanding of sources of

[14] Using an analog from basic physics, these three types can very loosely be equated to a harmonic oscillator, a strongly damped harmonic oscillator and a forced harmonic oscillator.

predictability and how they may interact, and discoveries of new sources of predictability for forecasts of different phenomena remain likely. Each of the sub-sections below describes progress and gaps in understanding the three types of predictability important for S2S prediction—natural modes of variability, slowly varying processes, and external forcing.

Predictability from Natural Modes of Variability

Natural modes of variability display distinct and organized patterns that are typically oscillatory or cyclic in some fashion, or at least bimodal with the given "mode" having a tendency to occur with an anomaly pattern of one sign or its opposite (e.g., see Figure 4.4). The "modes" are typically identified in a given field (e.g., SST, 500 hPa heights, 200 hPa zonal winds) but are correlated to impacts on, or interactions with, other features in the Earth system, such as temperature, precipitation, drought, bio-productivity, ozone, etc. These modes of natural variability are characterized by dynamical interactions within or across Earth system components. A canonical example of a coupled mode of variability is ENSO. When these modes have life cycle lengths similar to S2S forecasts(e.g., 2 weeks to 12 months), their characteristic evolution offer a source of S2S predictability (Figure 4.1). For such cases, it is imperative that the forecast system be able to accurately represent the mode of variability and its life cycle. If the life cycle is much longer than the S2S timescale, then practically speaking for the purpose of the S2S forecast, the mode's variation would likely be considered a "slowly varying process". Natural modes of variability are often associated with teleconnection properties that relate variability at one location to conditions in another. For example, the mechanisms that produce ENSO occur and evolve in the tropical Pacific Ocean, yet influence mid-latitude variability through atmospheric dynamics. As a result, the sign, strength, and frequency of occurrence of known patterns of extratropical atmospheric circulation (such as the Pacific North America pattern, PNA) partly depend on ENSO (e.g., Zhang et al., 1997). Atmospheric patterns are in turn important drivers of winter weather and climate over North America. Some of the more well recognized natural modes of variability already found to or expected to be important for S2S predictability are discussed in more detail below, with specific attention to areas that are ripe for or in need of further research.

A large part of the signal for S2S weather and climate predictions have tropical origins (NRC, 2010b). Through relatively long-lived SST anomalies (e.g., ENSO, IOD) and/or systematic dynamic flows (e.g., wave-like motions, MJO, Kelvin waves), large-scale storm systems become highly organized and produce systematic variations in atmospheric heating. This excites circulation anomalies that have local impacts on rainfall and temperature in the tropics but that also "propagate" to the extra-tropics via sequences of circulation anomalies of alternate sign, often referred to as "waves" (Horel and Wallace, 1981; Trenberth et al., 1998). The remote impact is referred to as a teleconnection, in this case connecting variability in the tropics to middle- and high-latitude weather.

ENSO

ENSO, treated in detail in the NRC (2010b) ISI report, is a coupled atmosphere-ocean mode of variability that involves slow equatorial waves in the ocean that impact SST,

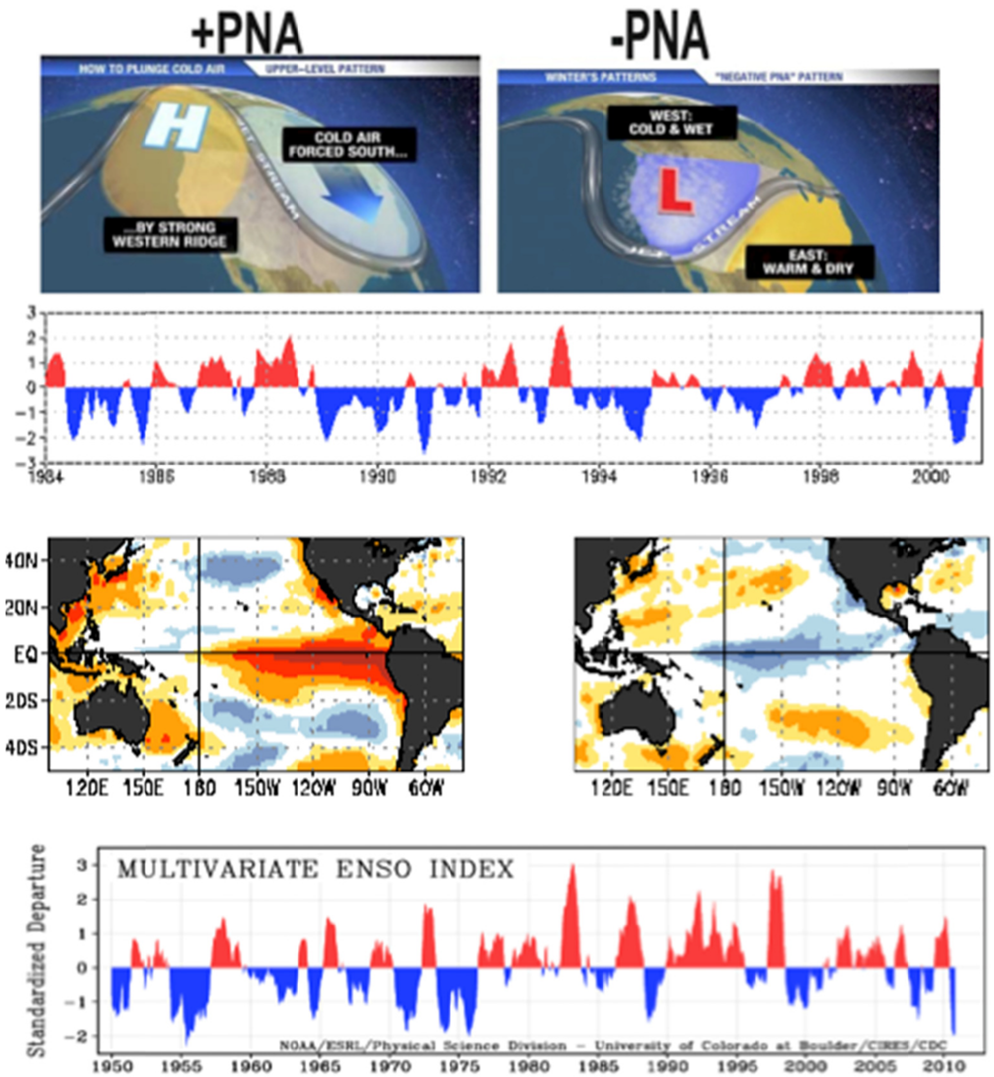


FIGURE 4.4 Two examples of common and impactful "natural modes of variability". Top panels illustrate the atmospheric circulation anomalies associated with the Pacific North America (PNA) pattern in its positive (left) and negative (right) phases. Bottom panels illustrate the SST anomalies associated with the ENSO phenomenon, showing both El Niño (left) and La Niña (right) phases. SOURCE: From top panel from njweatherblogs.com, other panels from NOAA.

particularly in the central and eastern Pacific, and associated changes in surface pressure and wind variations in the atmosphere that extend over most of the tropical regions. The SST variations in the Pacific and associated circulation changes result in strong modulations of organized convection and precipitation in this region, which in turn influence the extra-tropical circulation via teleconnections as described above. For seasonal prediction, ENSO's coupled dynamics provides a major source of skill (e.g., NRC, 2010b; Shukla et al., 2000), while for subseasonal predictions, the relatively slowly varying SST anomalies provide a relatively persistent tropically forced atmospheric circulation anomaly. Because the evolution of ENSO is anchored to the seasonal cycle, it is often described as an event, with terms El Niño for warm events and La Niña for cold events (e.g., Figure 4.4). The signature of an ENSO event first emerges during boreal spring or summer, and the associated SST anomalies peak the following fall or winter, and then typically decay in spring.

The normal progression of ENSO and its impacts on the tropics and elsewhere through teleconnections are relatively well studied (e.g., Hoerling and Kumar, 2000; Latif et al., 1998; Rasmusson and Mo, 1993). Recent work has advanced our understanding of ENSO's impact on predictability, the impacts of a number of distinct types of ENSO events, and ENSO's decadal and longer timescale change. For example, there are lagged impacts of ENSO on predictability of the Indian Ocean in summer. In the summer after a positive ENSO first emerges, the tropical Pacific SST returns to normal, but the Indian Ocean SST is anomalously high, with a strong suppression of tropical cyclones and impacts on temperature and precipitation across Southeast Asia and Japan (Chowdary et al., 2011; Kosaka et al., 2013). Despite the large body of existing work on ENSO, there are important gaps related to understanding both ENSO and its influence on S2S predictability (McPhaden, 2015). For example, there is neither consensus on a theory nor agreement on the predictability limit of ENSO. Recent work shows that variations in the structures and seasonal timing of ENSO strongly affect the persistence and predictability (Lee et al., 2014), as well as ENSO teleconnections (Capotondi et al., 2014). In recent decades, the SST anomalies in El Niño events have often peaked in the central Pacific rather than the more typical location of the past in the eastern Pacific. Whether such ENSO diversity is a consequence of greenhouse warming, and hence the recent shift can be expected in the future, is also unclear (Cai et al., 2015; Capotondi et al., 2014).

MJO

The MJO, also discussed in detail in the NRC (2010b) ISI report, is the dominant mode of intraseasonal variability in tropical convection, precipitation, and circulation. Through its local influences in the tropics and its teleconnections to higher latitudes, it represents a primary source of predictability at the subseasonal timescale (e.g., Waliser, 2011). The MJO is mainly an atmospheric phenomenon, but it also exhibits some modest interactions with the upper ocean—both in forcing and responding to coupled SST anomalies and exciting ocean currents and waves. It exhibits planetary-scale structures along the equator in pressure, winds, clouds, rainfall, and many other variables, with its strongest anomalies in precipitation propagating from the Indian to central Pacific Oceans over a period of about 30 - 50 days. An eight phase index for MJO, referred to as the Real-time Multivariate MJO (RMM1 and RMM2) indices of Wheeler and Hendon, are usually used to describe the east-west location and amplitude of the MJO (Wheeler and Hendon, 2004). See NRC (2010b), Lau and Waliser (2011), and Zhang (2005) for further description.

The MJO has been shown to have significant connections to a number of important global weather and climate phenomena, including high impact events (e.g., see reviews in Lau and Waliser, 2011; Zhang, 2005, 2013). This includes a strong influence on the onset and breaks of the Asian and Australian summer monsoons and on the modulation of synoptic variability—including tropical cyclones—and even the triggering of ENSO variations. Improving representation of the MJO in global models has led to better prediction on S2S timescales at high latitudes as well as in the tropics (e.g., Ferranti et al. 1990; Vitart, 2014). For example, North American wintertime surface temperatures are found to be anomalously warm 10-20 days after MJO-related convection occurs in the Indian Ocean (Lin and Brunet, 2009) (Figure 4.5). Such a lagged relationship implies predictability of North American temperature anomalies up to about three weeks given knowledge of the initial state of the MJO. Forecasts using statistical models

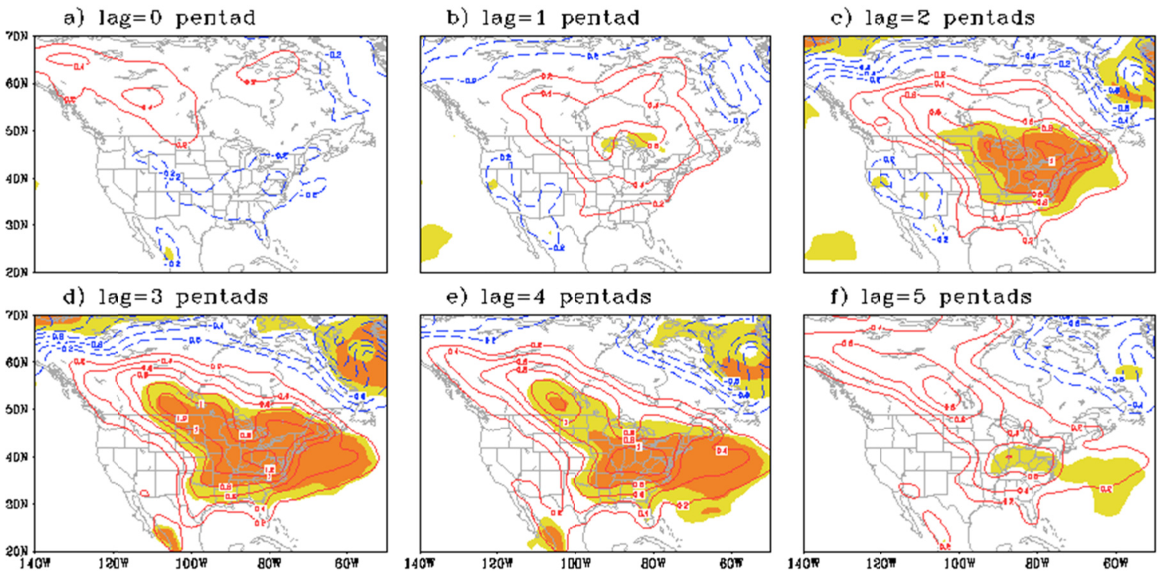


FIGURE 4.5 Lagged regressions of surface air temperature (SAT) in the North American region onto −RMM2. Lag n means that the SAT anomaly lags −RMM2 by n pentads (5-days). The sign of RMM2 is reversed so that it represents enhanced convection in the Indian Ocean and corresponds to MJO phases 2-3. The magnitude corresponds to one standard deviation of the RMM2. Yellow (orange) areas represent those where the regression is statistically significant at a 0.05 (0.01) level according to a Student-t test. Contour interval is 0.2°K. The zero contour is not plotted, and contours with positive and negative values are in solid red and dashed blue, respectively. RMM2 is the second component of RMM, which corresponds to anomalous convection activity in the tropical Indian Ocean. SOURCE: Figure courtesy of Hai Lin.

have demonstrated that it may be possible to extend the forecast range of North American temperature anomalies beyond 20 days, especially for strong MJO cases (Johnson et al., 2014; Rodney et al., 2013; Yao et al., 2011).

Quasi-Biennial Oscillation

The stratosphere is a potential source of S2S predictability because of its persistent and slowly varying circulation anomalies (NRC, 2010b). In boreal winter, such persistent circulation anomalies in the lowest part of the stratosphere interact vigorously with the upper troposphere and influence prediction of tropospheric circulation (Baldwin et al., 2003; Gerber et al., 2012). The quasi-biennial oscillation (QBO) is an easterly-to-westerly reversal of tropical stratospheric winds driven by stratospheric waves originating from the troposphere. The QBO has a mean period of about 28 months, and its phase is predictable a few years ahead. The QBO influences the strength of the mid-to-high latitude westerly winds in the stratosphere, or the polar vortex. Prominent strengthening or weakening of the wintertime stratospheric polar vortex tends to be followed, with a lag of about a month, by similar variations in the large-scale tropospheric circulation patterns known as the annular modes (Baldwin and Dunkerton, 2001; Thompson and Wallace, 2000). Variability in the annular modes have in turn been associated with episodes of extratropical surface air temperature anomalies (warm spells or cold surges) and sea ice anomalies (Rigor et al., 2002; Thompson et al., 2002) (see below).

Extratropical Modes

Extratropical weather is frequently dominated by recurring circulation patterns, often referred to as weather regimes or extratropical modes of variability. Because of their large-scale and low-frequency nature, these circulation patterns can contribute to atmospheric S2S predictability. For example, it has long been recognized that the Pacific - North American pattern (PNA), has a significant impact on the North American surface air temperature and precipitation (e.g., Wallace and Gutzler, 1981). Although the state of the PNA and its predictability on S2S timescales is influenced by ENSO (Zhang et al., 1997) and MJO (Mori and Watanabe, 2008) variability, it is unclear how interactions between these coupled modes and/or additional drivers may influence PNA variability and its associated weather patterns.

The North Atlantic Oscillation (NAO) is another major circulation pattern that influences weather from eastern North America to Europe, and it is highly correlated with the Northern Annular Mode (NAM). The NAO/NAM exhibits predictability on S2S timescales because its variability is linked to other components of the Earth system that are more predictable, such as the stratospheric polar vortex. Observational studies also show a robust lagged connection between the MJO and NAO (Cassou, 2008; Lin et al., 2009), and indeed a higher level of skill in predicting the NAO on a subseasonal timescale can be achieved when a strong MJO signal occurs in the initial condition (Lin et al., 2010). Similarly, skillful seasonal NAO predictions have been made by improving the initialization procedure to more realistically capture the initial state of the QBO and ocean and sea ice conditions (Scaife et al., 2014b). It follows that forecasts of the NAM have also been found to be skillful on seasonal timescale and that this skill was improved through more realistic initialization (Riddle et al., 2013).

Understanding and correctly representing phenomena like the NAO/NAM, the PNA and the Southern Annual Mode (SAM) in the southern hemisphere are additionally important for S2S predictions because their state can influence the development of strong and persistent anomalies in midlatitude atmospheric circulations that are sometimes caused by blocking events. Blocking can be exploited as a source of predictability (Hoskins and Woollings, 2015) and has been linked to high impact weather such as severe cold spells in winter and droughts in summer. Variability in the NAO has been related to blocking episodes (Woollings et al., 2008), and as the NAO has proved to be more predictable than previously thought, so has blocking (Athanasiadis et al., 2014).

Future Directions on how Modes of Variability Influence Predictability

Natural modes of variability represent key sources of S2S predictability. Although much progress has been made in understanding these modes, in particular ENSO and MJO, less is known about the how the interactions between coupled modes and slowly varying processes influence the development of specific environmental conditions. Continued research into variability in coupled modes, and their interactions across timescales, is necessary in order to fully exploit their predictability for S2S forecasting. Important questions that need to be addressed include: How does the MJO influence rainfall over southeast Asia during El Niño vs. La Niña, or in different phases of the Indian Ocean Dipole? How do tropical Kelvin and other atmospheric waves influence the initiation, amplitude, or decay of the MJO? Under what conditions can the various modes of tropical variability ensure the high or low occurrence probability of tropical cyclones in a given region? These sorts of investigations fall under Facet I in Figure 4.3. Moreover, as correlations between these modes and impactful weather/climate are discovered, it is essential that our models can re-create such variability and its impact in simulations and retrospective forecast experiments (i.e., Facet II and III in Figure 4.3). For example, some models do quite well at representing intraseasonal variability in the eastern Pacific—which has a strong impact on tropical cyclones in that area—while others perform relatively poorly (Jiang et al., 2012a; Jiang et al., 2012b). Many such examples are evident from the literature where empirical analysis has indicated potential relationships that can be exploited for S2S predictability, yet models still struggle to represent the variability and relationships correctly. These include IOD and boreal summer monsoon interactions (Ajayamohan et al., 2009), Kelvin wave and MJO interactions (Guo et al., 2015), and many others. Of particular challenge are those modes of variability that stem from coupled processes, including ENSO, but that could also include land-atmosphere or cryosphere-atmosphere coupling.

Finally, as our models become more capable of representing these processes, it is critical to carry out the predictability experimentation described above and highlighted as Facet IV in Figure 4.3. Such experimentation can point to forecasting system research and development avenues that would yield the greatest benefits and help to identify and/or characterize forecasts of opportunity based on specific modes of variability being in a particular phase (e.g., when the MJO is in phase 4-5 there is a strong enhancement of tropical cyclones to the west of the maritime continent and a suppression of them to the east).

Finding 4.2: Natural modes of variability represent key sources of S2S predictability, and it is essential that S2S models accurately represent them. Further research is needed especially to understand the interaction of natural modes across timescales, associated impacts on teleconnection patterns, and the formation of extreme environmental conditions. Long and sustained observational records are essential for such research.

Predictability from Slowly Varying Processes

As discussed briefly above, S2S predictability can stem from persistence in the initial state of various components of the Earth system. For example, anomalous conditions in the stratosphere or ocean can persist for several months owing to their vertical stability and slowly overturning circulation. In addition, persistence in anomalous environmental conditions often stems from storage of anomalous energy, typically in the form of heat or water in a given phase, such as in snow, sea ice, soil moisture, or ocean heat content. For example, the heat capacity of the entire atmosphere column is about the same as just the top 2.5 m of the ocean, and the melting of a global 25 cm shell of ice would take as much energy as warming the entire atmosphere by 10°C. When these anomalous stores of heat occur on large spatial scales (e.g., greater than ~1,000s of kilometers), their evolution/dissipation typically occur on timescales of several days, weeks, or months and thus provide predictability to the Earth system. Smaller anomalies may also provide predictability for important ocean and coastal properties that are of interest to predict in their own right. Similarly, anomalies in momentum (e.g., ocean currents or atmospheric circulation patterns), aerosols and chemical species, and phytoplankton can also instill slow and anomalous variations on the coupled Earth system, impacting the ability to make skillful S2S forecasts.

Sometimes persistence is used as a threshold for predictive skill, which does not preclude considering persistence as a source of predictability. By the Committee's definition, a phenomenon can exhibit predictability even if it is can be predicted with an idealized model or theoretical means. Furthermore, the threshold for predictive skill must itself have a source of predictability. Even so, the probability of a phenomena occurring due to persistence in a system with many interacting processes may not be possible to predict with an idealized model or theoretical means, and may require a predictive system, even though the mechanism for predictability at some level appears basic and might not be considered "dynamical." Additional details of a number of slowly varying processes within the coupled Earth system that provide predictability on S2S timescales are provided below.

Ocean

Given the ocean's relatively larger heat capacity compared to other components of the Earth system and the persistence of its temperature, salinity, and currents, the ocean represents a key source of predictability on S2S timescales in a number of ways (NRC, 2010b). Here we focus on mechanisms involving the ocean surface conditions owing to their relevance for humans (e.g., fisheries, harmful algal blooms, controls on the atmosphere and sea ice, etc.), rather than those that primarily affect the deep ocean. These mechanisms include large- and small-scale ocean dynamics in the tropics (e.g., Alexander 1992) and the extratropics (e.g., Hartmann 2015), as well as ocean interactions with the atmosphere and sea ice through surface exchange of energy, moisture, and momentum, yielding both one-way influences and coupled feedbacks.

The persistence of surface anomalies depends primarily on the depth of the upper ocean mixed layer. Other secondary factors include the net surface energy and freshwater fluxes, upwelling rates (via Ekman pumping and entrainment), and the properties of upwelling subsurface waters. Anomalous upwelling driven by persistent wind regimes associated with atmospheric modes of variability can lead to predictable anomalous surface conditions because subsurface waters generally also have longer-lived properties, including concentrations of nutrients that can drive biological productivity (e.g., Waliser et al., 2005). Subsurface anomalies may even lie "dormant" (unrelated to the mixed layer properties) until one or more storms with high winds mixes the upper ocean, transporting the anomaly vertically to the surface (Alexander et al., 1999).

Small-scale (10s-100s of kilometers) surface ocean features, such as circular motions known as eddies and regions of strong gradients known as fronts, can also exhibit persistence for months to years (Chelton et al., 2004; Chelton and Xie, 2010). These small-scale variations in SST cause divergence and convergence in the surface wind and vertical motions that link the small-scale ocean features to cloud properties and other atmospheric features (e.g., Chelton and Xie, 2010). Ocean eddies also have an association with ocean biogeochemistry through their influence on upwelling or downwelling, horizontal advection, and isolation of nutrients and ecosystems (Gaube et al., 2014). Because of their persistence and coupling with the atmosphere (20% of the heat flux between the atmosphere and ocean is related to the ocean eddy field [Boas et al., 2015]), these eddies represent a potential source of S2S predictability for the ocean and even the entire Earth system if feedbacks to the atmosphere are prominent.

Soil Moisture and Vegetation

Soils have the capacity to hold substantial amounts of water relatively close to the surface (e.g., centimeters to meters), depending on soil texture, structure, and vegetation. This water-holding capacity lends predictability to the atmosphere up to several weeks or months by influencing surface energy budgets (e.g., heat and moisture fluxes to the atmosphere) (Koster et al., 2010; NRC, 2010a). For example, given soil moisture's influence on heat flux, the number of hot days over land in many regions has been found to correlate highly with precipitation summed over a preceding period (Figure 4.6 and Mueller and Seneviratne, 2012). Soil moisture's influence on surface temperature is coupled with a direct impact on the surface moisture flux to the lower atmosphere, which together influence subsequent precipitation anomalies (e.g., Guo et al., 2012; Koster et al., 2011; Roundy et al., 2014). It follows that soil moisture is also strongly associated with drought predictability (e.g., Kumar et al., 2014; Roundy and Wood, 2015; Thomas et al., 2015). This predictability may be especially pronounced during boreal spring and summer, when coupled Earth system models often exhibit lower predictive skill due to weaker links between mid-latitude climate systems and the oceans and an increase in land-atmosphere interactions. Along with its coupling to atmospheric conditions, the slow variations of soil moisture are also important for predicting quantities such as runoff to rivers, lakes, and the ocean, as well as plant growth—and thus land cover, albedo, and flood potential. For example, there is increasing evidence that vegetation states and anomalies can be sources of weather and climate predictability on S2S timescales (Koster and Walker, 2015).

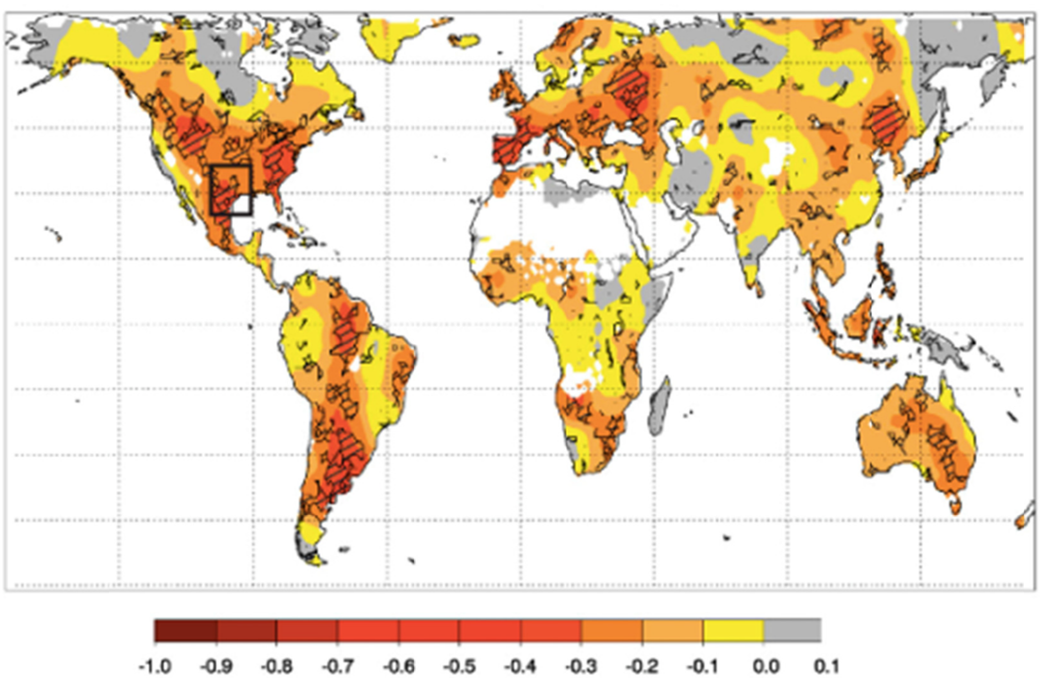


FIGURE 4.6 Correlation between number of hot days in the hottest month of each year and preceding three months precipitation deficits. Red areas indicate where dry periods from preceding three months correspond with more hot days. SOURCE: Mueller and Seneviratne, 2012.

Terrestrial Snow

Snow also contributes to predictability of atmospheric and land conditions due to its storage of surface water and its influence on surface energy budgets. The latter occurs due to its high albedo relative to snow-free areas; it acts as a significant surface heat sink via the latent heat required to melt the snow, and in changing the interface conditions it influences the fluxes of heat and moisture between the land and atmosphere. Knowledge of anomalous snow conditions, particularly the snow water equivalent as opposed to just snow cover, can improve forecasts of air temperature and humidity, runoff, and soil moisture during the winter and spring seasons (NRC, 2010b; Jeong et al., 2013; Peings et al., 2011; Thomas et al., 2015). For large-scale anomalies in snow conditions, there is also some evidence that snow can influence remote atmospheric conditions by altering large-scale atmospheric circulation features (e.g., Rossby waves) (also see section below on Sea Ice and Polar Land Surface). For example, correlations have been documented between autumn anomalies in Eurasian snow and the large-scale northern hemisphere atmospheric circulation a few weeks to months later through the influence of snow cover on the vertical propagation of wave energy into the stratosphere and the NAO (Brands et al., 2012; Fletcher et al., 2007; Orsolini et al., 2013; Orsolini et al., 2015). Snow cover and snow water can have a profound influence on the evolution of the local, regional, and even large-scale weather patterns as well as a number of Earth system components. This influence places a high priority on ensuring observations of snow are available for process understanding and forecast initialization (e.g., Orsolini et al., 2013) and that our terrestrial hydrology and atmospheric models properly represent snow and related processes (see Chapter 5).

Sea Ice and Polar Land Surface

Sea ice lends predictability to the Earth system because its presence strongly reduces heat and moisture fluxes from the ocean to the atmosphere, it serves as a significant reservoir of freshwater within the upper ocean, and it is an excellent reflector of solar radiation. The persistence of sea ice anomalies has several important timescales (Figure 4.7). There is an initial persistence of anomalies in the sea ice cover that varies from 2-4 months (Lemke et al., 1980), depending on the season (Blanchard-Wrigglesworth et al., 2011a; Day et al., 2014) and location (Bushuk and Giannakis, 2015). After this initial period of persistence, there is a reemergence that occurs in some seasons owing to sea ice internal dynamic and coupled interactions between sea ice and SST. Modeling studies suggest anomalies of sea ice thickness are far more persistent and about as important as SST in controlling the persistence characteristics of the sea ice cover (Bitz et al., 1996; Blanchard-Wrigglesworth and Bitz, 2014; Blanchard-Wrigglesworth et al., 2011b; Chevallier and Salas-Melia, 2012; Holland et al., 2013; Lindsay et al., 2008). The lack of long-term sea ice thickness measurements forces researchers and forecasters to turn to models to estimate these quantities. When models factor in transport, sea ice thickness anomalies can persist for almost two years and exhibit typical length scales of about 500-1,000 km (Blanchard-Wrigglesworth and Bitz, 2014).

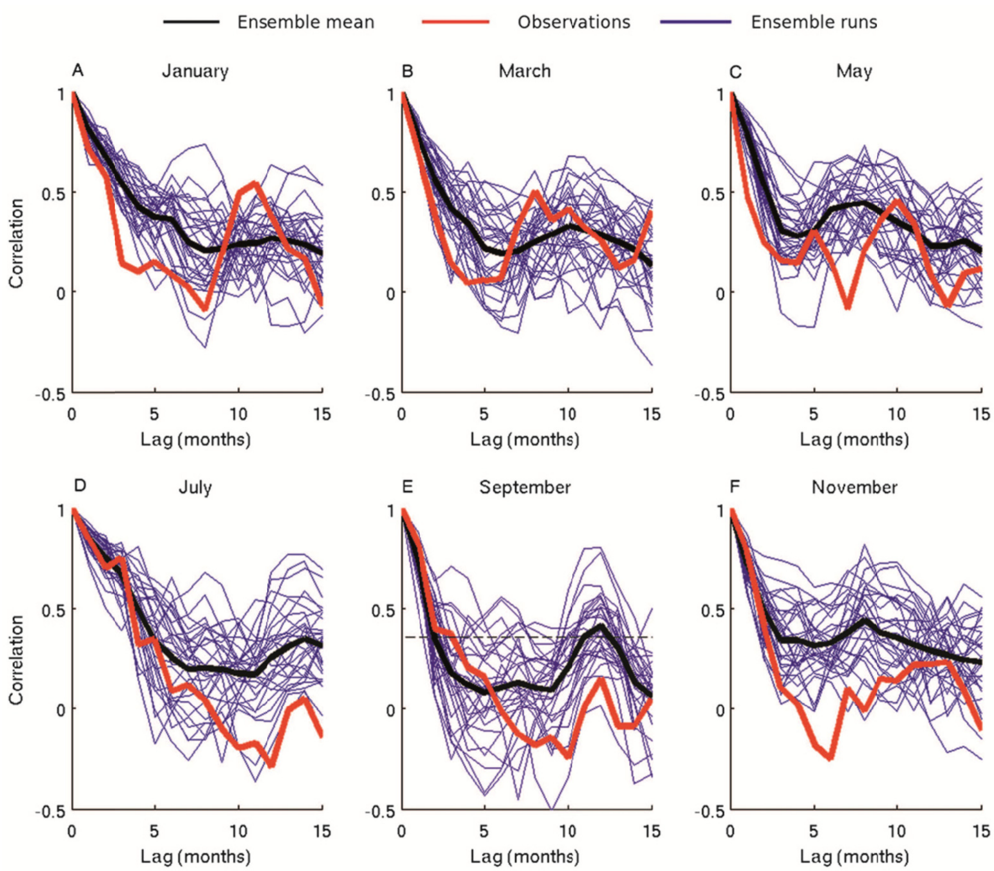


FIGURE 4.7 Monthly lagged correlation of Arctic sea ice area in an ensemble of early 21st century simulations with the Community System Model Version 3 (blue lines are ensemble members and black lines are ensemble mean) and observations from passive-microwave satellites (red lines). For the first panel, the autocorrelation for January is shown at lag 0, the correlation of January with February is shown at lag 1, and so forth. The figure shows that sea ice extent anomalies initially persist for 2-4 and then, after a period of low correlation, anomalies reemergence at lags of about 6-12 months, depending on the season. The data were detrended by removing the ensemble mean from the model and a linear fit to the observations. SOURCE: Blanchard-Wrigglesworth et al., 2011a.

Through coupling to the atmosphere, the presence and persistence of sea ice affects the trajectories of atmospheric storms and ocean circulation (Balmaseda et al., 2010; Bitz et al., 2006; Screen et al., 2011), and has considerable impacts on coastal erosion (Barnhart et al., 2014), marine and terrestrial biology (Post et al., 2013), and shipping (Khon et al., 2010). Researchers are actively exploring the extent to which sea ice anomalies and polar conditions in general can influence the lower latitudes, with longer lasting cold air outbreaks in years with an anomalously warm Arctic surface as one possibility (Francis and Vavrus, 2012). A proposed mechanism stems from polar controls on atmospheric meridional temperature gradients and the subsequent coupled interactions among temperature gradients, the mid-latitude jet stream, and storms. However, the multitude of interactions involving the mid-latitude jets has made it difficult to find conclusive evidence of Arctic-mid-latitude weather linkages (Figure 4.8; Cohen et al., 2014). Though the mechanisms remain obscure, when global forecast models include more realistic Arctic sea ice and other Arctic variables, forecasts improve in lower latitudes (Jung et al., 2014; Scaife et al., 2014a). Because of the persistence of sea ice and arctic snow cover, it is

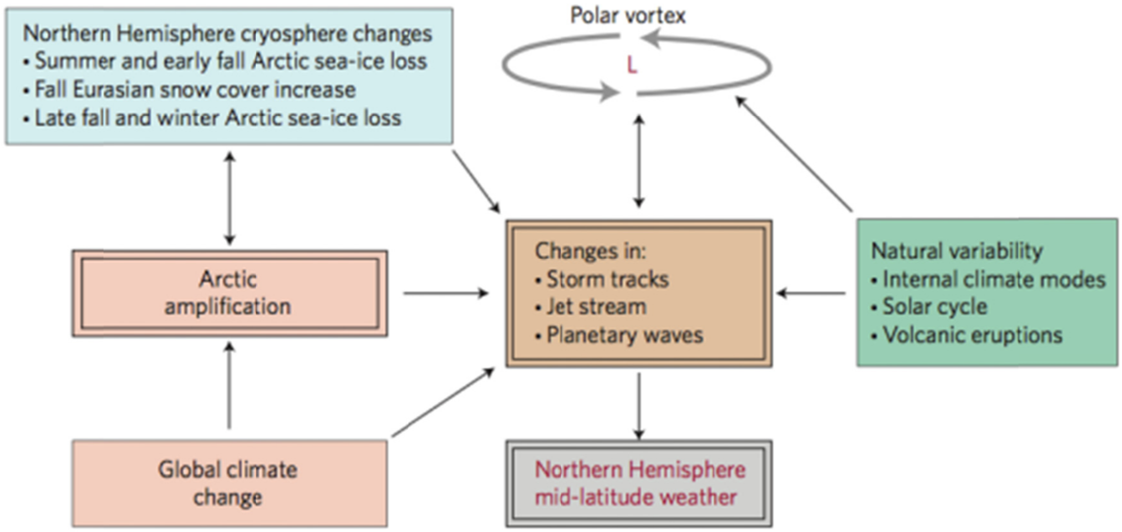


FIGURE 4.8: Schematic of ways to influence Northern Hemisphere mid-latitude weather. Three major dynamical features for changing Northern Hemisphere mid-latitude weather—changes in the storm tracks, the position and structure of the jet stream, and planetary wave activity—can be altered in several ways. Arctic amplification directly (by changing the meridional temperature gradient) and/or indirectly (through feedbacks with changes in the cryosphere) alters tropospheric wave activity and the jet stream in the mid- and high latitudes. Two other causes of changes in the storm tracks, jet stream and wave activity that do not involve Arctic amplification, are also presented: (1) natural modes of variability and (2) the direct influence of global climate change (that is, including influences outside the Arctic) on the general circulation. The last two causes together present the current null hypothesis in the state of the science against which the influence of Arctic amplification on mid-latitude weather is tested in both observational and modelling studies. Bidirectional arrows in the figure denote feedbacks (positive or negative) between adjacent elements. Stratospheric polar vortex is represented by 'L' with anticlockwise flow. SOURCE: Figure and caption from Cohen et al., 2014.

important to improve our understanding of sea ice and related processes and the mechanisms linking Arctic and mid-latitude conditions, as well as to incorporate these processes and mechanisms into models used for S2S predictions.

Sudden Stratospheric Warmings

Occasions of rapid slowdown of the stratospheric Arctic vortex are usually accompanied by sudden stratospheric warmings (SSWs) and a subsequent negative phase of the Northern Annular Mode (NAM). However, experimentation with models that have adequate resolution in the stratosphere to capture the relevant dynamics is a relatively new endeavor. Recent studies show that SSWs can be predicted only a week or two in advance (Gerber et al., 2009; Marshall and Scaife, 2010). Yet for several months following an SSW, enhanced forecast skill has been found in extratropical surface temperatures and sea level pressure (Sigmond et al., 2013). More recent work has found multi-scale/mode interactions between the MJO, SSWs and the QBO (Liu et al., 2014).

Finding 4.3: A number of slowly varying processes impart predictability to the Earth system in the S2S time range, including processes and interactions related to sea ice, the thermal and dynamic evolution of the upper ocean, and soil moisture, surface water, snow and vegetation on the land surface.

Finding 4.4: It is essential to maintain and increase observations of the slowly varying components of the Earth system relevant to S2S (e.g. snow, soil moisture, sea ice and near-surface ocean) for the purpose of process understanding, model development, and to improve the initial conditions in forecast system. Further studies are needed to understand the relative importance of these processes as sources of S2S predictability.

Predictability from External Forcing

Variability on S2S timescales may also be driven by external forcing, such as from anomalies in solar forcing, anthropogenic emissions of pollution or aerosols, or the episodic input of aerosols from volcanoes. Advanced knowledge of changes in the radiative, thermal, biogeochemical, or hydrological forcing of some part of the Earth System can lead to skillful predictions of other quantities of interest such as surface temperature or precipitation. Two leading cycles in the Earth system, the diurnal cycle and seasonal cycle, are very predictable precisely because they are driven by highly repeating patterns in the incoming shortwave radiation at the top of the atmosphere. While these timescales are very relevant to S2S variations, particularly when considering interactions across scales, it has not been a trivial matter to represent their impacts in global weather/climate forecast models.

Over the last decade or so, numerical weather and climate models have started to be able to better reproduce credible seasonal variability through careful representation of the relevant processes. However, there are still significant shortcomings in representing the effects from these very well defined external forcings that are highly relevant to S2S prediction, such as the diurnal cycle. For example, there is potential influence of the diurnal cycle over the maritime continent on the MJO as it propagates eastward from the Indian Ocean into the western Pacific Ocean. Observations exhibit a relative minimum in the MJO-driven subseasonal variability over the maritime continent, possibly because of the relatively stronger diurnal cycle in this region relative to the open ocean to the east and west. Representing this scale interaction in models has been challenging and has represented a barrier to producing accurate forecasts of MJO amplitude and propagation in this region (e.g., Weaver et al., 2011)

Aerosol variability in a number of forms holds the potential to influence variability on S2S timescales and represents an important source of S2S predictability in some cases.[15] A volcanic eruption has the potential to loft significant ash and dust into the troposphere and stratosphere, which can result in substantial anomalies in both incoming solar radiation and outgoing infrared radiation. Depending on the magnitude of the mass injection and its altitude, the anomalous aerosol forcing can last for days to a couple of weeks in the troposphere and months to a year in the slow, stable circulation of the stratosphere. Accurate representation of the

---

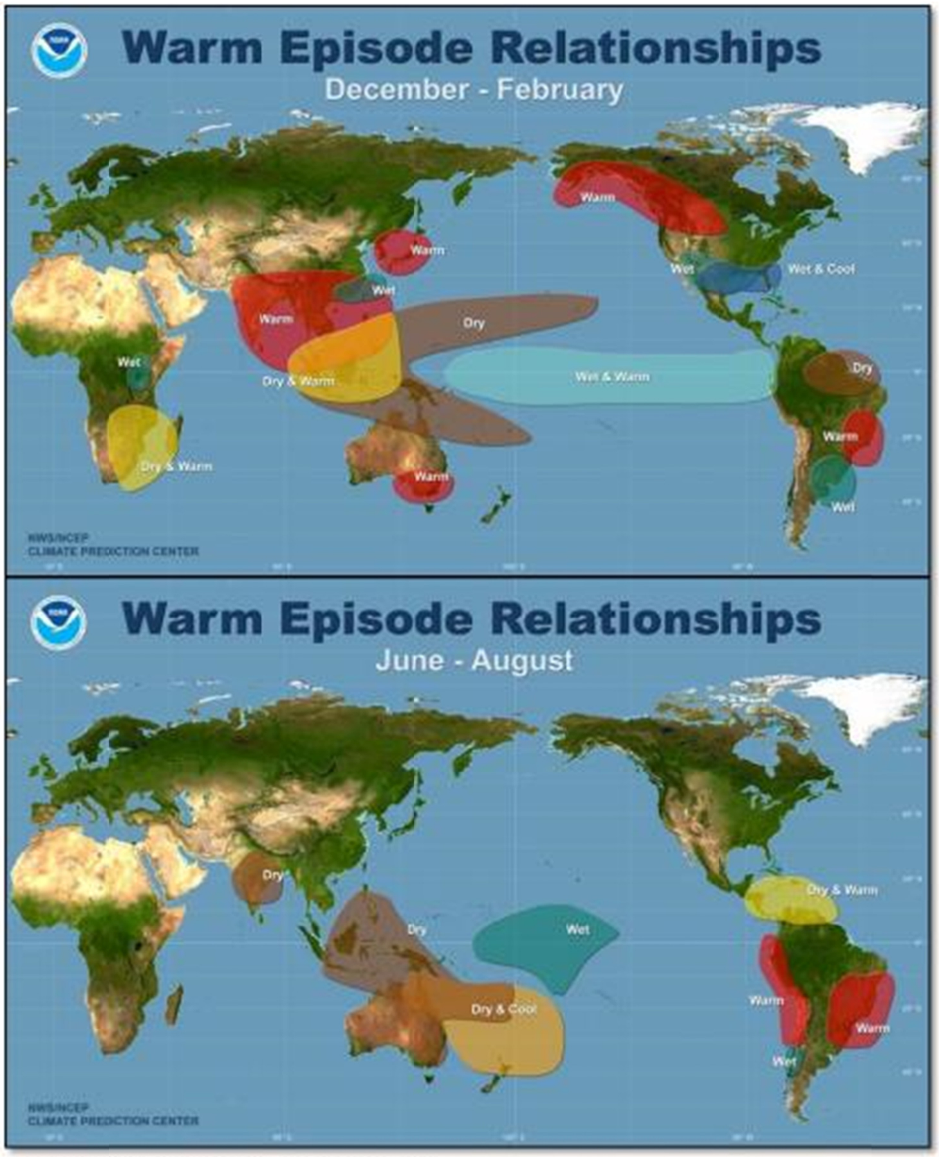
[15] Aerosols also play a key role in cloud formation and the development of precipitation. Understanding and modeling this process accurately is critical to producing high fidelity models of the atmosphere for nearly all forecast timescales. Given its place as a key physical process, rather than a source of predictability, aerosol-cloud interactions are treated in Chapter 5.

aerosol content, types, and interactions with clouds and radiation provides a potential source of predictability. Demand for realizing this forecast potential stems from the needs to better represent and forecast its influence on weather and short-term climate as well as to better understand and predict the lifetime of the aerosol anomaly itself and its societal impacts (e.g., how long will the ash plume last, will it affect air traffic?).

In some cases, ash, dust, and other aerosols can influence the Earth system even after they are removed from the atmosphere, most notably when they are deposited on ice or snowpack. In this case, they can have a substantial influence on the subsequent evolution of the surface, producing considerably faster melting than would otherwise be the case. This has both hydrological implications (Qian et al., 2009) via the change in the runoff and implications for the evolution of the snow pack and the manner it influences weather and short term climate (see section above on Slowly Varying Processes). Aerosols can also impart predictability on near-surface ocean biology by providing input of key nutrients, namely iron, that can facilitate the development of widespread phytoplankton blooms (Langmann et al., 2010), which have life cycles of days to weeks. Such blooms influence the vertical profile of solar absorption in the upper ocean, typically leading to greater warming of SST and a more stable surface mixed-layer than would otherwise occur (Siegel et al., 1995). The latter can have considerable implications for large-scale variations and spatial structure of SST anomalies, which in turn can influence weather and short-term climate.

While the lifetimes of other atmospheric constituents can be much longer, it is still critical that they be accounted for in S2S forecast systems. Notable examples for this are the concentration of anthropogenic greenhouse gases (GHGs, e.g., carbon dioxide, methane, etc.). The typical lifetime of anthropogenic greenhouse gas anomalies is on the order of a decade to centuries, and fluctuations and trends in the emissions of greenhouse gases also tend to occur on timescales that are long relative to the S2S forecast. These long timescales imply that, for a given forecast, the GHG concentration can be specified to be a constant. However, because multi-decade retrospective forecast datasets are a crucial component of a S2S forecast system for bias correction (see Chapter 5), it is imperative that the values of impactful constituents be specified to the forecast system as time-varying boundary condition over the time period of the retrospective forecasts. This type of slowly varying forced signal can lead to systematic shifts in the probability distributions of variables (e.g., temperature and precipitation) that can be predicted given the known value of the forcing. Furthermore, such external forcing has caused the seasonal minimum of Arctic sea ice extent to decline by over 40%, radically changing the probability of where the sea ice edge lies at the end of summer in recent years compared to the beginning of the satellite record in 1979. As S2S forecast systems encompass more Earth system components and coupled processes that are influenced by such external forcing, it is important to have an accurate representation of GHG forcing and other slowly varying external forcing (e.g. solar constant, surface albedo).

Finding 4.5: Given the requirement that S2S forecasts have for multi-decade retrospective forecast datasets for the purposes of bias correction, is it imperative that the model forecast system account for all slowly varying external forcings that influence the frequency, spatial distributions, and temporal distributions of S2S forecast quantities (e.g., temperature, precipitation). Such external forcing includes the influences from natural and anthropogenic aerosol emissions, GHG concentrations, variations in the solar constant, and surface albedo, where the latter may derive from snow/ice cover or land use/land cover changes.



High Resolution Images can be found at:
http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ENSO/ENSO-Global-Impacts/

FIGURE 4.9 Global climate impacts associated with warm ENSO conditions (i.e. El Niño) during boreal winter (top) and summer (bottom). "Wet" areas indicate a higher likelihood of floods, particularly when occurring in a given region's normal wet season (e.g., winter for California or summer in Argentina), and "dry" areas may be subject to a greater likelihood of drought conditions. SOURCE: CPC/NCEP/NOAA.

Prediction of Disruptive and Extreme Events and "Forecasts of Opportunity"

A strong motivation for developing and improving S2S forecasts is to provide guidance on the likelihood, magnitude, and impacts of disruptive events (see also Chapter 3), which could be severe rain or wind storms (e.g., tropical or extra-tropical cyclones, large mesoscale convective systems, tornado outbreaks), Santa Ana or Chinook wind conditions, severe rain or snow events, drought, prolonged cold surge or heat wave conditions, etc. These types of events

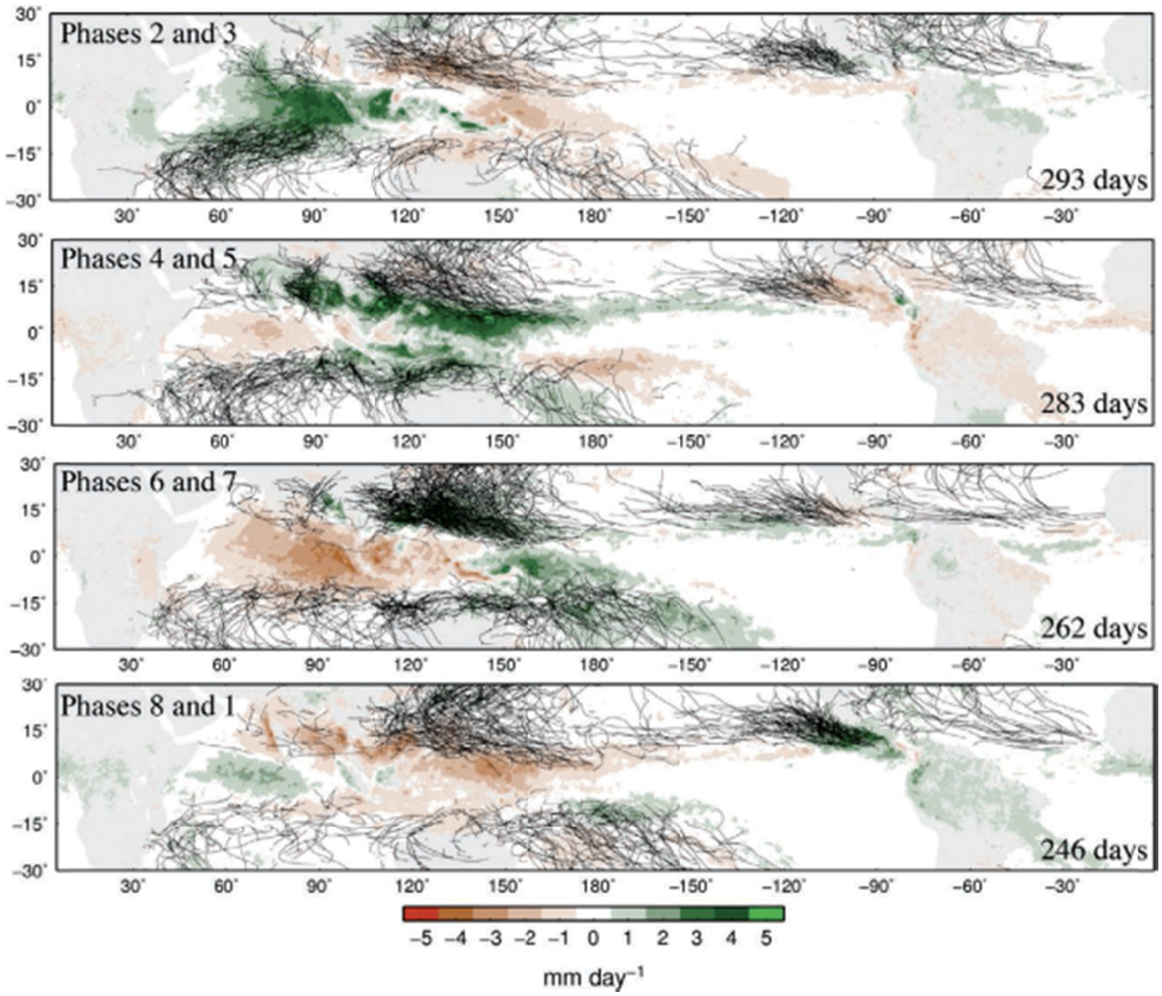


FIGURE 4.10 Composite of tracks of tropical cyclones (1975-2011) and rainfall anomalies (colors) based on Tropical Rainfall Measuring Mission (TRMM) data (1998-2011) for different phases of the MJO represented by the Wheeler and Hendon (2004) Real-time Multi-Variate MJO (RMM) index. Total number of tropical cyclone days in each composite is given at the lower right corners. SOURCE: Zhang, 2013.

may exhibit predictability, but usually only when they are associated with other phenomenon, such as the MJO and ENSO, that are predictable (e.g. Pepler et al., 2015). For example, Figure 4.9 illustrates the impacts, typically felt through one or a series of extreme weather events, from El Niño conditions (or "warm episodes"). Similarly, Figure 4.10 illustrates the impact of the MJO on the frequency and spatial variability of tropical cyclones.

Indeed ENSO and the MJO have remarkable impacts on the modulation of the frequency, spatial distribution, and types of extreme environmental events that occur in a number of regions around the globe. Other sources of variability discussed above can similarly impact the occurrence of extreme or disruptive events. Particularly important for disruptive events is the additive effect of the various sources of predictability. As a simple consideration of this effect, both the cool phase of ENSO (i.e., La Niña) and phases 4-6 of the MJO increase the likelihood of precipitating conditions over the Maritime continent region. These two phenomena then work in concert to facilitate the development of more frequent, longer, and/or more severe precipitating events, one operating on a timescale of months (i.e., ENSO) and the other weeks (i.e., MJO; also see Figure 4.1). Similarly, an El Niño condition along with MJO phases 8 and 1 will produce subsidence and thus dry conditions over the same region. On top of modes of variability, other processes lending predictability can act on the given anomaly to further exacerbate the condition. For example, wet conditions will produce positive soil moisture anomalies, which can in turn positively influence the further development of precipitation in the given region. Such timescale and process interactions, in terms of their additive or in some cases counter-acting influences, can occur in a number of places around the globe depending on the phenomena, region and season. These multi-scale interactions of an inherent, albeit intermittent, source of S2S predictability, represent "forecasts of opportunity"—a foundational consideration in S2S forecasting. Better understanding these interactions will make it possible to develop more forecasts of opportunity, e.g., forecasts that take advantage of windows of time in which higher predictability are possible. This will be particularly important for the prediction of events that are of interest to decision makers.

Finding 4.6: The nature of sources of S2S predictability, namely intermittent natural modes of variability, wide and often disaggregated variations in anomalous conditions in a number of slowly varying processes/quantities, and varied natural and anthropogenic external forcings, liken the S2S prediction challenge to the identification and successful prediction of a series of "forecasts of opportunity." Identifying such windows of predictability will be particularly important for forecasts of extreme and disruptive events.

THE WAY FORWARD FOR RESEARCH ON SOURCES OF PREDICTABILITY

The relative value of predictability sources is dependent on location of the forecast and time of the year. While some processes have a stronger local impact, others influence the climate through teleconnections and have a far-reaching effect. For example, initial anomalies in soil moisture can influence the local forecast precipitation and surface air temperature through changes in surface energy budget associated with evaporation. Anomalies of tropical convection associated with ENSO and the MJO influence the middle latitude climate through teleconnections related to Rossby wave energy propagation, and thus a large impact is usually observed along the path of Rossby wave train. In the Northern Hemisphere extratropics, the wintertime westerlies provide a more favorable background for Rossby wave propagation than in summer, thus the teleconnection contribution is stronger in winter. On the other hand, the influence of soil moisture becomes relatively more important in summer than in winter.

Our understanding of the source of S2S predictability is still lacking. The relative value of predictability sources has not yet been established. The approaches that have been used in predictability study may not be appropriate to separate the contributions of different sources. For example, the specification of soil moisture in the initial condition in the retrospective forecast experiment that is designed to identify the contribution of soil moisture may contain information of ENSO or other sources of predictability. In the relaxation experiment that is designed to identify the origin of skill source, the analysis fields that are relaxed to in a given region may already contain variability propagating from other regions. The combined effect of several different sources of predictability may not be a simple sum of individual processes. More studies are needed to understand how different sources of predictability interact.

Climate models that are used to do retrospective forecasts are imperfect, and different models have different model errors, leading to inaccurate, incomplete, and model-dependent estimates of signal and noise variability in ANOVA analysis, as well as false representation of the "truth" in the twin experiments used to estimate the upper predictability limit. The assessment of impact of a particular process on forecast skill is also model-dependent. Encouraging future studies to use a multi-model framework would help to reduce the uncertainty related to model configurations. Also, innovative methodologies to estimate predictability need to be explored in order to better understand the nature of S2S forecast.

It is essential to maintain and increase observational records for different components of the Earth system. These observations can be used to explore new sources of predictability and to better initialize S2S models. It is important for S2S models to capture the natural modes of variability, slow processes, and externally forced trend and variability.

Recommendation C: Identify and characterize sources of S2S predictability, including natural modes of variability (e.g., ENSO, MJO, QBO), slowly varying processes (e.g., sea ice, soil moisture, and ocean eddies), and external forcing (e.g., aerosols), and correctly represent these sources of predictability, including their interactions, in S2S forecast systems.

Specifically:

- Use long-record and process-level observations and a hierarchy of models (theory, idealized models, high-resolution models, global Earth system models, etc.) to explore and characterize the physical nature of sources of predictability and their interdependencies and dependencies on the background environment and external forcing.
- Conduct comparable predictability and skill estimation studies and assess the relative importance of different sources of predictability and their interactions, using long-term observations and multimodel approaches (such as the World Meteorological Organization-lead S2S Project's database of retrospective forecast data).

Decision makers are particularly interested in guidance on the likelihood, magnitude, and impacts of disruptive events (see also Chapter 3). Prediction of these types of events will rely on identifying multi-scale interactions of inherent, albeit intermittent sources of S2S predictability. Thus prediction of such features will require developing "forecasts of opportunity"—a foundational consideration in S2S prediction. While any given extreme event (e.g., storm) is typically not predictable more than a few days in advance, understanding interactions between sources of S2S predictability offer the means to infer changes in the likelihoods of extreme events—including their spatial distribution, occurrence frequency, magnitude, and type. More specifically, this means that an accurate S2S forecast system will provide quantitative forecast information—likelihoods and uncertainties—on extreme events with lead times from weeks to months. However, it is critical that all of the important and impactful phenomena be represented faithfully in order to yield accurate forecasts. For example, based on the discussion above, if the ENSO modulation is accurately depicted by the forecast system but there are temporal, spatial, and/or amplitude biases in the representation of the MJO, the forecast accuracy of precipitation amounts and extreme events—will be heavily compromised.

In summary, accurate prediction of extreme weather/environmental events hinges critically on the accurate representation of all of the dominant modes of variability and slowly varying processes that operate and yield predictability on S2S timescales. Forecast models must represent these processes individually as well as collectively, with specific attention to their multi-scale interactions and influences on the development of extreme events. Thus all four facets of predictability research highlighted in Figure 4.3 need to be undertaken to improve the prediction of disruptive, high impact, or extreme events.

Recommendation D: Focus predictability studies, process exploration, model development and forecast skill advancements on high impact S2S "forecasts of opportunity" that in particular target disruptive and extreme events.

Specifically:

- Determine how predictability sources (e.g., natural modes of variability, slowly varying processes, external forcing) and their multi-scale interactions can influence the occurrence, evolution, and amplitude of extreme and disruptive events using long-record and process-level observations.
- Ensure the relationships between disruptive and extreme weather/environmental events—or their proxies—and sources of S2S predictability (e.g., modes of natural variability and slowly varying processes) are represented in S2S forecast systems.
- Investigate and estimate the predictability and prediction skill of disruptive and extreme events through utilization and further development of forecast and retrospective forecast databases, such as those from the S2S Project and the NMME.

Chapter 5: S2S Forecast Systems: Capabilities, Gaps, and Potential

Chapter 4 covered the processes of discovering, characterizing, and understanding the theoretical limits of various sources of predictability in the weather-climate system. After those sources are identified and begin to be understood, they can be incorporated into Earth system models for subseasonal to seasonal (S2S) prediction. This chapter examines the features of such S2S prediction systems and makes recommendations about advancing each component in order to produce more skillful S2S forecasts. To begin, the chapter provides an overview of the functioning architecture of a typical S2S system.

The production of probabilistic forecasts on S2S timescales is similar in many ways to contemporary numerical weather prediction: observations of the atmosphere, ocean, cryosphere, and land provide initial conditions for computing the evolution of these Earth system components forward in time. But there are some important differences between S2S and shorter-term weather and ocean prediction. First, chaotic aspects of the Earth system mandate averaging S2S predictions over long enough periods, or over a large enough set of realizations, that stable forecast statistics are produced for each place and lead time. Longer and/or larger-ensemble averages are generally needed for longer lead times. A second difference is that a set of similar forecasts—made in retrospect for 20 or more years with the same forecast system—is typically compared with verification observations to calibrate the forecasts, with the aim of correcting the predicted probability distribution on the basis of how the model reproduces past conditions. This is crucial and standard practice at least at seasonal timescales (where the desired signals may be small compared to the corrections); similar methods are beginning to spread to extended range Numerical Weather Prediction (NWP). Finally, the longer-timescale predictions typically include interactive Earth system components (e.g., interactive ocean and sea ice), since the evolutions of these components have important impacts on the atmosphere or provide valuable forecasts in their own right. For weather and climate, the distinctions among prediction methods at various time ranges are beginning to diminish as even short- to medium-range weather forecast models move to encompass interactive ocean and sea ice components.

The basic architecture of S2S prediction systems is depicted in Figure 5.1, which also provides an organizational structure for the content in this chapter. Coupled Earth system models (ESMs) lie at the core of most of these systems. The ESM itself—a system of partial differential equations that describe the evolution of the components of the Earth system and the interactions between them—projects state variables forward in time. The separate components—atmosphere, ocean, land, sea ice—are discretized on a computational grid with specific spatial and temporal resolutions. The components are linked together at the interfaces via a coupler, which transfers information, such as heat and momentum fluxes. Meanwhile, the coupler also transfers model errors from one component to another, making the model error growth a coupled process as well. Due to the finite resolution in space and time, many processes in the models remain unresolved and require parameterizations of their effects on the components that are resolved. The Committee notes that for certain S2S predictions, integrating a subset of an ESM can be sufficient to achieve useful predictive skill. For example, some ocean and ice forecasts can be issued on S2S timescales with prescribed atmospheric surface conditions without two-way

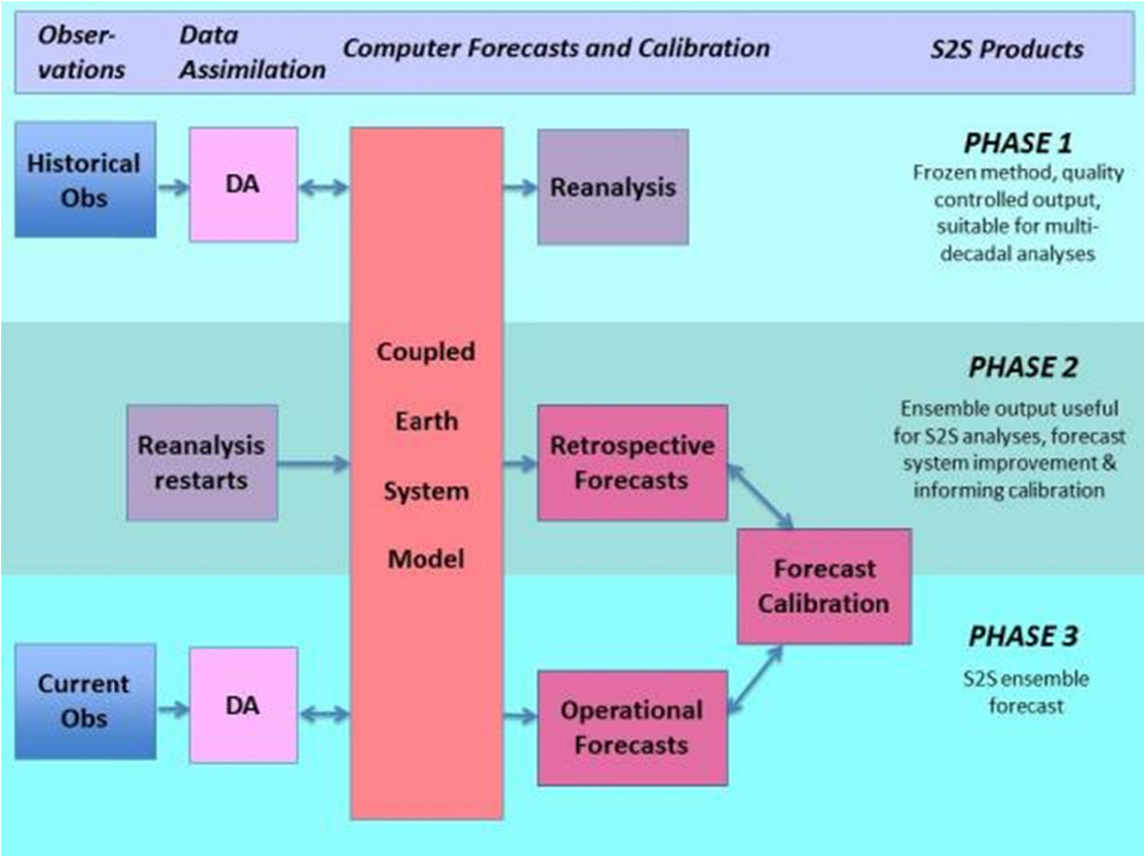


FIGURE 5.1 The production of calibrated subseasonal and seasonal forecasts involves three separate processes. In the first phase, historical observations over a period of two or more decades are combined with data assimilation (DA) and Earth system dynamics in a coupled Earth system computer model (coupled ESM) to produce a reanalysis that is a detailed history of a wide variety of atmospheric, oceanic, land, and cyrospheric variables. In the second phase, the reanalysis data is used as the initial conditions for a set of retrospective ESM S2S forecasts over the same two decades or more. The comparison of the retrospective forecasts with an appropriate set of verification data (perhaps the reanalysis) is then used to develop quantitative information for correcting biases and ensemble variance of the forecasts to be applied subsequently to operational forecasts. In the third phase, the current observations processed with data assimilation (which may be equivalent to the latest reanalysis if the forecast system is unchanged since the last reanalysis was run) serve as the initial conditions for a set of operational forecasts that are then calibrated in the S2S probability prediction system and turned into S2S forecast products. Dutton et al. (2013) describe the operation and results of this process, as implemented in a commercial S2S system.

coupling with atmospheric models. When appropriate, such scale- or process-separation can be exploited for more efficient forecasting.

ESMs are initialized by tens of millions of observations of the atmosphere, ocean, land surface, and cryosphere. In order to be integrated into the model state space, these observations must first be transformed via data assimilation, a process that attempts to optimally combine observations with a short-term (usually less than a day) model forecast using the error characteristics of each observation type. Thus the goal of data assimilation is to produce a state estimate (i.e., initial condition) that is in an appropriate and dynamically consistent format for subsequent forecast computation. Often historical observations over multiple decades are also assimilated with a frozen ESM and assimilation procedure to produce a reanalysis, suitable for investigating multi-scale variability in the Earth system with the same ESM and as consistent of observation data streams as possible. Running the ESM forward from an initial condition, with no further data assimilation, produces a forecast. The numerical output from an ESM forecast usually consists of an ensemble of ten or more members, each containing some 100 or more physical variables on spatial grids at intervals of hours (or much shorter for specific applications). The ensemble is created by running multiple realizations, perturbing the initial conditions and/or the model formulation, to produce a distribution of results that are intended to sample uncertainties in the estimate of the initial state, external forcing, and model parameterizations.

In order for these outputs to be transformed into S2S forecast products, they first must be calibrated and verified by comparing forecasts to the subsequent observations. To obtain a large enough data set to be statistically meaningful and avoid over-fitting, comprehensive retrospective forecasts or hindcasts[16] are performed in which the forecast system is exercised over a historical period of some 10 to 30 years. In this process, the reanalysis in Figure 5.1 provides initial conditions, the retrospective forecasts are computed with the ESM, and then the forecasts are compared to a reanalysis or some other verification data set.

After any part of the forecast system is changed, the retrospective forecasts must be recreated to be consistent with the modifications. Today, some forecast centers are producing them as part of the model forecast process itself. This permits the centers to take advantage of model improvements with frequent updates. Thus some retrospective forecasts are static and some are produced "on the fly" along with the forecasts themselves. Such on-the-fly retrospective forecasts have been employed in atmospheric models and ESMs (e.g. MacLachlan et al., 2015; Vitart, 2013) and also real-time ocean forecasting (e.g. Lermusiaux et al., 2011; Ramp et al., 2009; Robinson et al., 2002). Either way, calibrations derived from the retrospective forecasts are applied to improve new forecasts. For example, if August temperature in a specific geographic region of the historical forecasts tends to be biased, then the mean temperature of the new forecasts is adjusted accordingly. Similarly, if the probability distribution of the retrospective forecast is too narrow, then the probability can be made wider in subsequent operational forecasts.

The rest of this chapter examines in more detail the pieces of S2S prediction systems that were described in brief above. Aspects of S2S forecast systems—routine observations, data assimilation, models, and the calibration and production of forecast products—are covered in separate Chapter sections. For each of these sections, the Committee has identified findings and developed a set of research recommendations. The implementation of these recommendations will be critical to advancing S2S forecast skill and to better meeting the needs of users as highlighted in Chapter 3.

ROUTINE OBSERVATIONS AND THEIR USE

Observations are a fundamental building block of any prediction system. They provide a basis for understanding the Earth system, guide model development, enable the initialization of forecast systems, and provide the foundation for evaluating model fidelity and quantifying prediction skill. There is an expansive network of in situ and remotely sensed observing systems

---

[16] As noted in Chapter 1, other commonly used terms for retrospective forecasts are 'reforecast' and 'forecast history'. These terms are interchangeable.

that is used for S2S forecasting. However, maintaining this network to ensure no degradation of present-day nascent S2S forecast skill represents a significant challenge in and of itself. Improved utilization of other existing observations, along with new observations to increase geographic coverage, spatial and temporal resolution, and the breadth of routinely measured Earth system variables, are critical for further advancing S2S model development and operational S2S forecasts.

This section describes the current state of observations to support S2S forecast systems and highlights important gaps and vulnerabilities in the coverage of observational networks. The focus is on observations for operational model initialization, calibration, evaluation, and routine monitoring, though these types of observations are also generally useful for studies on sources of predictability (covered in Chapter 4). Generally the most basic quantities are needed (e.g., temperature, wind speeds, etc.), with continuous temporal and broad spatial coverage, and at spatial and temporal resolutions that are relevant for S2S processes. Because S2S forecast systems are often driven by observations of anomalies from a climatological mean, overlapping measurements between successive generations of observing systems are particularly valuable so that changing observation system biases are not aliased into estimated anomalies in the state of the real world. Observations of the atmosphere are important for S2S prediction as they are with NWP. However, observations of the ocean, land, and cryosphere represent additional critical needs for building, calibrating, initializing, and evaluating the coupled ESMs that will be used to generate S2S forecasts in the next decade. This is because while the ocean, land surface, and cryosphere contain important sources of Earth system predictability on S2S timescales, observations within these components are neither as numerous nor as distributed as observations of the atmosphere.

Recommendations and priorities for observations to support S2S forecast systems follow at the end of the section. Field observations for process studies designed to develop and improve model processes and parameterizations and reduce systematic biases are covered in more detail in the modeling section of this chapter.

Observations of the Atmosphere

The current observing system for the atmosphere is among the most comprehensive of all the components of the Earth system. Yet observations of the atmosphere need to be maintained or advanced for continued improvement to S2S prediction systems. The current atmospheric observing system includes in situ measurements of moisture, temperature, pressure, and wind from radiosondes, aircraft (e.g., Aircraft Meteorological Data Relay [AMDAR] and Tropospheric Airborne Meteorological Data Reporting [TAMDAR]), and sensors at the Earth surface (land, moorings, and ship). Satellites provide additional information on ocean surface winds (covered in more detail in the ocean observation section), clouds and precipitation, radiation, surface temperature, winds (from feature tracking), and vertical profiles of temperature and moisture. These measurements come from a range of sensors including microwave radars, radiometers and sounders, hyperspectral infrared sounders, visible and infrared imagers, scatterometers, and GPS radio occultation.

The world radiosonde network is extensive (Figure 5.2) and has been a main source of three-dimensional input to atmospheric models. These data have historically been supplemented by measurements from aircraft-based sensors. However, the radiosonde network lacks coverage

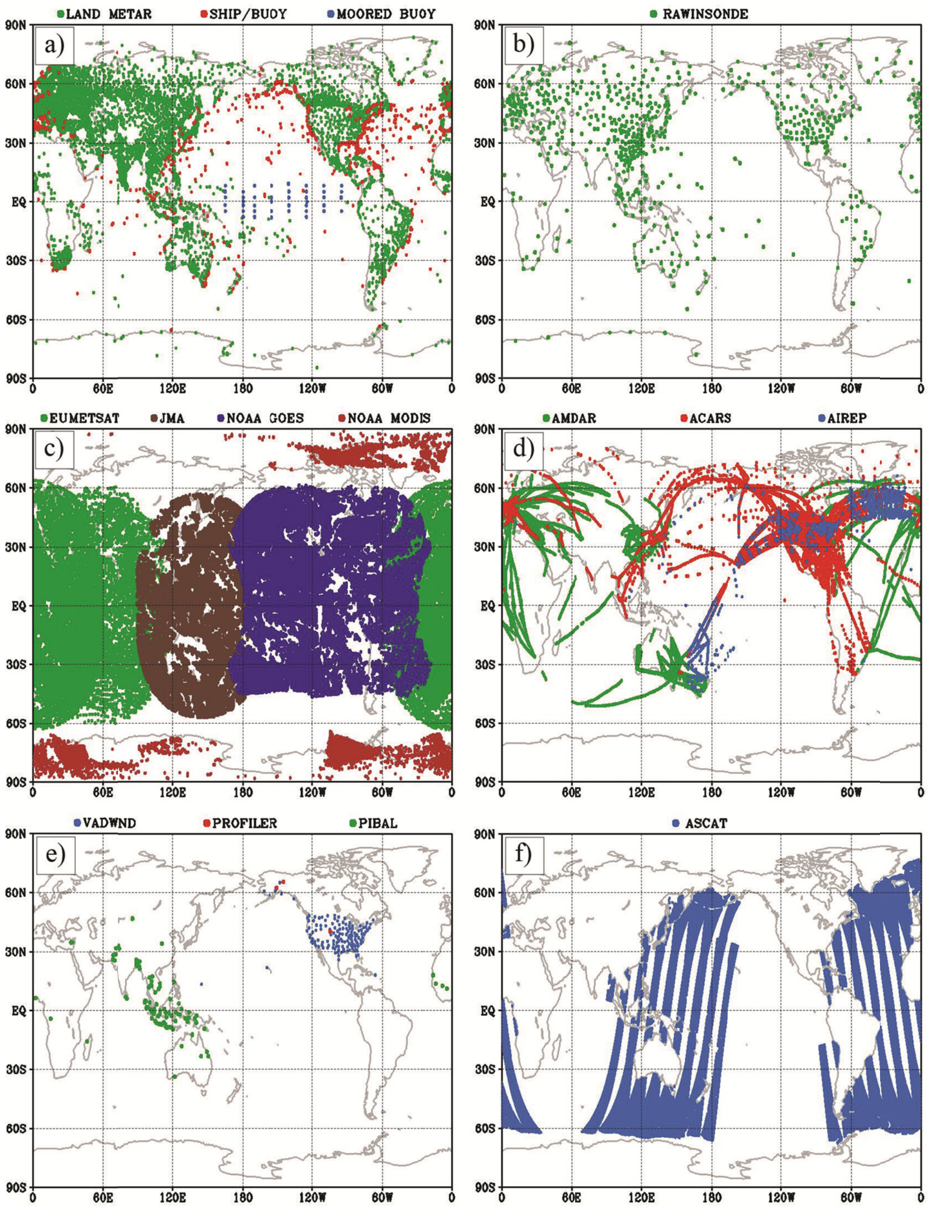


FIGURE 5.2 Spatial distribution for atmospheric observations for the six-hour window centered at 00 UTC 15 April 2015 including (a) surface, (b) rawinsonde, (c) AMVs, (d) aircraft, (e) Velocity Azimuth Display (VAD) winds , lidar wind profilers and pibal balloons, and (f), and Advanced Scatterometer (ASCAT) derived surface wind speeds.

over the ocean, in the tropics, uninhabitable areas (especially polar regions), and in less developed countries. Measurements from aircraft are mostly limited to flight level except near airports. These gaps in spatial coverage are a particular concern for S2S prediction because they span regions through which signals from phenomena over the tropical ocean (e.g., the MJO and El Niño Southern Oscillation [ENSO]) are teleconnected and hence propagate poleward and towards land.

There is some potential for the existing radiosonde network to be further exploited to support S2S applications for real time assimilation as well as in model improvement studies. Radiosondes can measure profiles at a vertical resolution of as little as five meters (Hamilton and

Vincent, 1995), but at present operational centers routinely receive only data at the mandatory pressure levels (with resolution at best of about 700 m). High altitude and finer-resolution vertical profiles could be used to help resolve troposphere-stratosphere interaction, cumulus convection, and mesoscale atmospheric organization—processes that are particularly important for S2S predictions (See Chapter 4 and Chapter 5, models section). Implementing this type of change has remained challenging because of the extensive international coordination and data management it requires.

Gaps in the coverage of radiosonde observations, along with the recent deterioration of the radiosonde network (NRC, 2000), have led to increasing reliance on satellite data for atmospheric monitoring and modeling. Today, the Advanced Microwave Sounding Unit (AMSU) is actually the most important observing system for shorter-term weather predictions in a current version of the NASA GEOS-5 global NWP model, followed closely by aircraft, radiosondes, and hyperspectral infrared sounders such as the Infrared Atmospheric Sounding Interferometer (IASI) and the Atmospheric Infrared Sounder (AIRS) (Figure 5.3). This finding is generally representative of other NWP systems such as NCEP (Ota et al., 2013) and ECMWF (Cardinali, 2009).

Given the uncertainties about the future of the radiosonde network and gaps in its coverage, continued investment into satellite-based atmospheric observations is important for moving forward. The development of platforms and algorithms for the retrieval of key variables—including vertical profiles of temperature, humidity, and wind—at resolutions that can capture the development and evolution of mesoscale systems and more detailed information in the boundary layer are particularly important. Advancing S2S predictions will also hinge on the ability to perform data assimilation in cloudy and precipitating regions (see section on data assimilation). Such capability will in turn rely on a host of routine, global high-resolution observations of radiation, clouds, and precipitation. On a slightly longer time horizon, developing such observations and the ability to assimilate them will also be important for fully implementing cloud-permitting forecast models (see section on models). Similarly, as models progress to better represent aerosol-cloud interactions—especially for regions where radiative forcing from aerosols (e.g., polluted cities) is substantial—it will become essential to expand routine in situ (e.g., Aerosol Robotic Network [AeroNet] and Micro-Pulse Lidar Network [MPLNet]) and satellite observations of aerosols and to have the capability to exploit these observations via data assimilation.

The United States is a leading contributor to the operational global satellite data coverage used in weather and climate prediction. U.S. federal agencies have been planning for replacements to aging polar orbiter and geostationary satellites, some of which are near or past their expected lifetime. However, the replacement programs have been beset with delays and cost overruns, leading to the potential for a gap in coverage. In particular, a gap in microwave sounder coverage from polar orbiting satellites could lead to significant degradations in atmospheric monitoring and prediction at weather and S2S timescales, a scenario the U.S. Government Accountability Office identified as high risk in a 2015 report.[17]

Two new satellite missions could lead to important improvements in global observations of three-dimensional winds and precipitation—two of the major gaps in the atmospheric observing network discussed above. The Atmospheric Dynamics (ADM-Aeolus) by the

[17] http://www.gao.gov/products/GAO-15-290, accessed January 27, 2016.

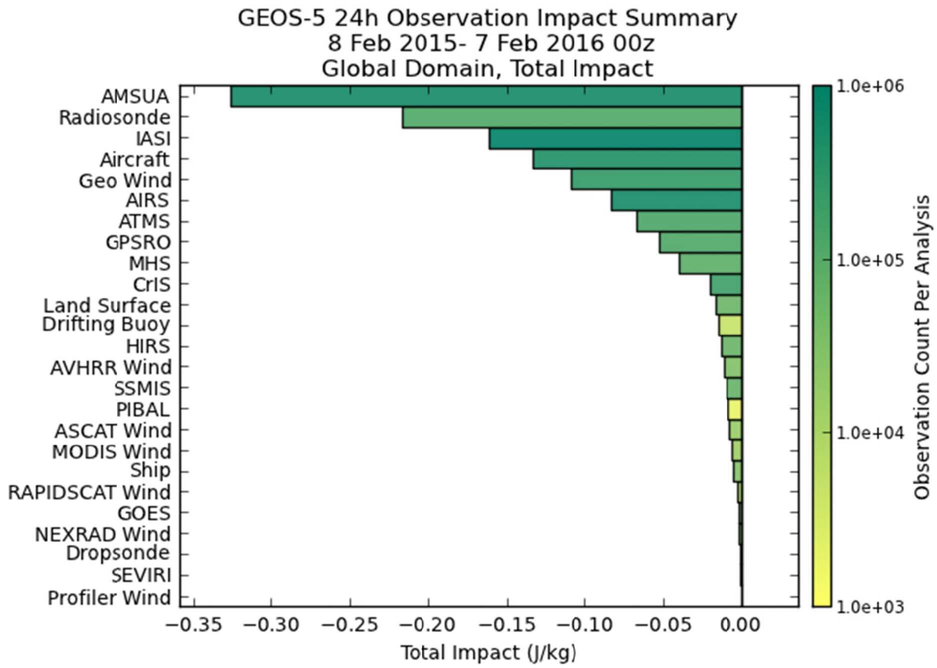


FIGURE 5.3 Adjoint-estimated daily average impacts of various observation types on the 24-h global forecast error (moist total energy, J/kg) calculated for 00 UTC each day for the period covering 08 February 2015 through 07 February 2016 for the NASA GEOS-5 modeling system. The shading corresponds to the average number of observations of each data type that are assimilated into the GEOS-5 system. SOURCE: http://gmao.gsfc.nasa.gov/forecasts/systems/fp/obs_impact, accessed February 15, 2016.

European Space Agency, set to launch in 2016, plans to provide clear-sky or above-cloud vertical profiles of wind derived from a space-based lidar.[18] A different joint satellite mission between the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA), the Global Precipitation Mission (GPM; Hou et al., 2014), was recently launched to provide high temporal resolution observations of rain and snow, expanding significantly upon the measurement portfolio and geographic coverage of its predecessor, the Tropical Rainfall Measuring Mission (TRMM). In particular, GPM could enhance capability to monitor and predict extreme events such as tropical cyclones, floods, and droughts and may provide global measurements of precipitation microphysics and storm structure, enhancing the ability to design and validate the representation of precipitation in next-generation, higher resolution Earth system models. Such measurements could also improve the representation and initialization soil moisture within the land surface component of current S2S prediction systems (see below).

Newer, non-conventional satellite technologies have the potential to improve the atmospheric observing network. Global Positioning System (GPS) radio occultation observations, for example, have the potential to provide highly accurate, unbiased retrievals of temperature and moisture, but at a much lower cost than typical satellite missions. Atmospheric motion vectors (AMVs)—winds derived by following features from geostationary satellites and from polar orbiting satellites near poles—have proven to be an important component of the observing system given the lack of wind information from other observations, particularly in the

[18]https://directory.eoportal.org/web/eoportal/satellite-missions/a/adm-aeolus, accessed January 27, 2016.

tropics, over oceans, and in polar areas. However, issues remain regarding the assignment of vertical location for these observations. On the very cusp of development are small, capable sensors that can be deployed on less expensive small satellites (e.g., "cubesats"), which in turn can be implemented into multi-satellite constellations providing rapid revisits and a low-cost approach for some operational observation needs (Ruf et al., 2013).

Finding 5.1: The current atmospheric observing system is relatively robust, but components of the network are in danger of deteriorating and/or are underutilized and spatial coverage is still poor in remote areas such as over the oceans and in polar regions.

Finding 5.2: As S2S prediction systems evolve in complexity and resolution, routine broad-coverage and higher-resolution atmospheric observations of thermodynamic profiles, clouds, precipitation, and aerosols will become essential to better characterize convection and troposphere-stratosphere interactions, as well as to enable cloud-permitting models.

Finding 5.3: Space-based satellite observations are likely to be the most efficient way to develop the new atmospheric observations that will be required for S2S predictions, although other cost-effective approaches to obtain the requisite accuracy and coverage are worthy of continued investigation.

Ocean Observations

The ocean is significantly under-observed compared with the atmosphere, despite being a major source of S2S predictability (Cummings, 2011; Robinson, 2006). Sea-surface temperature (SST) may be the most important oceanic variable for driving the atmosphere in the coupled system. This is due to the strong dependence of air-sea heat flux, evaporation, and even the stability of the atmospheric boundary layer on SSTs. Accurate initial conditions for SST as well as for ocean currents are not sufficient for predicting the time evolution of SST on S2S timescales because the effective ocean heat capacity on S2S timescales depends strongly on how deeply surface thermal anomalies are mixed by near-surface winds, ocean surface waves, and convective instabilities in the ocean mixed-layer. Thus measurements of winds, waves, air-sea fluxes, and near-surface ocean heat content anomalies and density structure (the latter determines the depths to which near-surface thermal anomalies can be easily mixed) may be just as critical for ocean prediction as SST measurements. Measurements of salinity are also important for constraining SST evolution, as both salinity and temperature determine the ocean's density structure. There are many places where a layer of relatively fresh water in the top few meters is observed to stabilize an ocean water column that would be unstable if only thermal properties were considered.

Transport of properties by ocean currents and associated eddies as well as vertical mixing driven by sheared ocean velocities also play an important role in the evolution of the coupled system at S2S and longer timescales. For example, re-stratification by finite-amplitude, submesoscale, mixed-layer eddies plays a strong role in the evolution of the coupled system (Fox-Kemper et al. 2011), as does the atmospheric response to oceanic variability in areas of high SST variability (Kirtman et al. 2012). When averaged over timescales of the inertial period and longer, extratropical ocean velocities are well approximated by a geostrophic and Ekman balance, which can be determined from knowledge of the ocean's sea-surface height or bottom pressure anomalies, surface wind stresses, and the ocean's three-dimensional density structure. Tropical currents tend not to be as well constrained by geostrophy, and tidal flows and rectified tidal effects can be important, especially in coastal areas. Thus direct measurements of ocean velocity (e.g., from moorings with current meters or drifters) or estimates of the surface geostrophic and Ekman components estimated via remote sensing (Lagerloef et al., 1999) and tides are particularly valuable for constraining the state of the ocean in tropical and coastal areas at S2S timescales. Velocity measurements that are available in real-time can be directly assimilated into S2S forecast systems, while delayed velocity data (e.g., data that is only available after instrument recovery) plays an important role in evaluating the realism of S2S forecast systems. Additional ocean-related observations that may benefit Earth system forecasts at S2S timescales include biogeochemical quantities such as nutrient distributions, oxygen levels, and initial plankton distributions. Used as tracers, these quantities may improve the initialization of the physical aspects of the system, but as the ocean model grows in sophistication to include biogeochemical processes, such quantities will be needed for initialization of these components.

Many of the ocean surface processes described above can be well sampled by remote sensing. Satellite measurements of SST, sea surface height (SSH), and scatterometer-derived surface wind stress are routinely used by ocean prediction systems. However the value of remotely sensed measurements for S2S forecasting depends critically on having enough instruments to provide continuous measurements with adequate temporal and spatial coverage. For example, the quality and reliability of forecasts of the ocean mesoscale eddy field depend upon the availability of *multiple* altimeters for coverage and resilience to instrument failures (Jacobs et al., 2014; Le Traon et al., 2003). Beyond the above physical variables, remotely sensed ocean color (visible wavelength) can be used to constrain biogeochemical ocean model components, which in their simplest use are needed to determine the vertical profile of solar heating in the near surface layer of the ocean (e.g., Murtugudde et al., 2002).

The TOPEX/Poseidon and NASA/CNES/NOAA/EUMETSAT Jason missions[19] have provided continuous SSH measurements since 1992. The Jason-3 mission, to be launched in January 2016, and the Copernicus European Program,[20] which will deliver Earth data from a dedicated constellation of satellites known as "Sentinels," will also provide operational SSH measurements into the coming decade. Additional upcoming satellite missions for oceanography and hydrology include the "Surface Water and Ocean Topography" (SWOT) mission—a collaboration between the United States and France.[21] With an estimated launch date of 2020, SWOT will continue the TOPEX/Jason record of global ocean altimetry but will also complement it by providing unprecedented global high-resolution elevations for small-scale ocean eddy features and for lakes and rivers over land. SWOT will likely allow for an important improvement in model representations of the ocean's geostrophic eddy fields and provide an altogether new resource for estimating surface-water elevations, both of significant value to S2S forecast considerations and applications. However, since SWOT is a research satellite, its three-year projected mission lifetime is shorter than is desirable for operational use as a part of a well-validated S2S forecasting system. While there is a foundation for remotely sensed SSH measurements via Jason and the European Sentinel program, there is great concern regarding the continuity of surface wind observations over the ocean. Much of the evolution of the ocean

---

[19] http://sealevel.jpl.nasa.gov/missions/ostmjason2/, accessed January 27, 2016.
[20] www.copernicus.eu, accessed January 27, 2016.
[21] http://swot.jpl.nasa.gov/mission/, accessed January 27, 2016.

circulation on S2S timescales is driven by wind stress, and scatterometer wind stress measurements are of particular importance for constraining the ocean and atmosphere in remote areas of the ocean with little other observation coverage for wind. Presently, the only U.S. scatterometry asset is RapidScat, a two-year mission on the International Space Station (ISS). While this implementation comes with some advantages (namely the orbit allows resolving the mean diurnal variability of ocean surface winds and can provide cross calibration of other agency scatterometers such as the European Organisation for the Exploitation of Meteorological Satellites [EUMETSAT] Advanced Scatterometer [ASCAT]), its inclined orbit does not provide global observations. An additional experimental resource for winds will come from NASA's upcoming Cyclone Global Navigation Satellite System (CYGNSS) mission, composed of a constellation of eight small satellites that use GPS reflections off the surface to estimate wind speed (direction not measured). While the coverage from this experimental mission will be limited to the tropics, it will provide an additional consideration for future observations of ocean surface wind speed that are likely to be complementary to the broad swath sampling of scatterometers that provide vector wind observations. Despite their potential for improving ocean wind measurements, RapidScat and CYGNSS are experimental missions with very limited lifespans. To advance S2S prediction, it is vital to determine a longer-term, sustainable plan for providing global, continuous satellite measurements of ocean surface winds.

Satellites also estimate ocean surface salinity (i.e., from the Soil Moisture and Ocean Salinity, SMOS[22], and, until recently, Aquarius missions[23]). The assimilation of such data has already improved some aspects of coupled forecasts (e.g., Hackert et al., 2011; Hackert et al., 2014; Tang et al., 2014), but salinity is a challenging measurement to make from space, and further advances are needed. Salinity anomalies of order 0.1 psu are dynamically important on S2S timescales (e.g., Guan et al., 2014), but this is near the threshold accuracy of current satellite retrieval capabilities on spatial scales relevant to S2S (cf. Tang et al., 2014).[24] However, with a combination of a robust in situ network (e.g., Argo, buoys, see below) and satellite measurements, a highly complementary set of measurements can be provided. In situ data can provide accurate absolute salinity values with the benefit of vertical profile information, and satellites can provide global coverage of (only the) surface salinity with the benefit of spatial gradient information and for measurements in marginal seas (although at a distance at least one satellite footprint away from the coast; ~50-100km) where drifters/buoys are limited.

Remote sensing has the potential to deliver routine observations of the ocean surface with coverage (space and time) that cannot be matched by current in situ observations. However, as illustrated with salinity above, in situ data will continue to be essential for calibrating remotely sensed ocean observations, and some in situ observations are critical for providing routine measurements of variables that are not well-observed via satellite platforms. Furthermore, because radiation penetrates only a short distance (millimeters to 10s of meters, depending on wavelength) into the ocean, observing the three-dimensional ocean fields mentioned above (e.g., sub-surface temperature, salinity, and ocean velocities) usually calls for in situ data.

[22] http://www.esa.int/Our_Activities/Observing_the_Earth/The_Living_Planet_Programme/Earth_Explorers/SMOS/ESA_s_water_mission_SMOS, accessed January 27, 2016.

[23] The Argentine Space Agency/CONAE's satellite, hosting NASA's Aquarius instrument, failed in June 2015, terminating the 4-year record of salinity observations. http://aquarius.nasa.gov/, accessed January 27, 2016.

[24] Recent comparisons of satellite to in situ values show RMS errors on the order of 0.28 to 0.51 psu for SMOS (Reul et al., 2014) and 0.2 to 0.3 psu for Aquarius (Tang et al., 2014), each for monthly timescales and grid averages of ~100km.

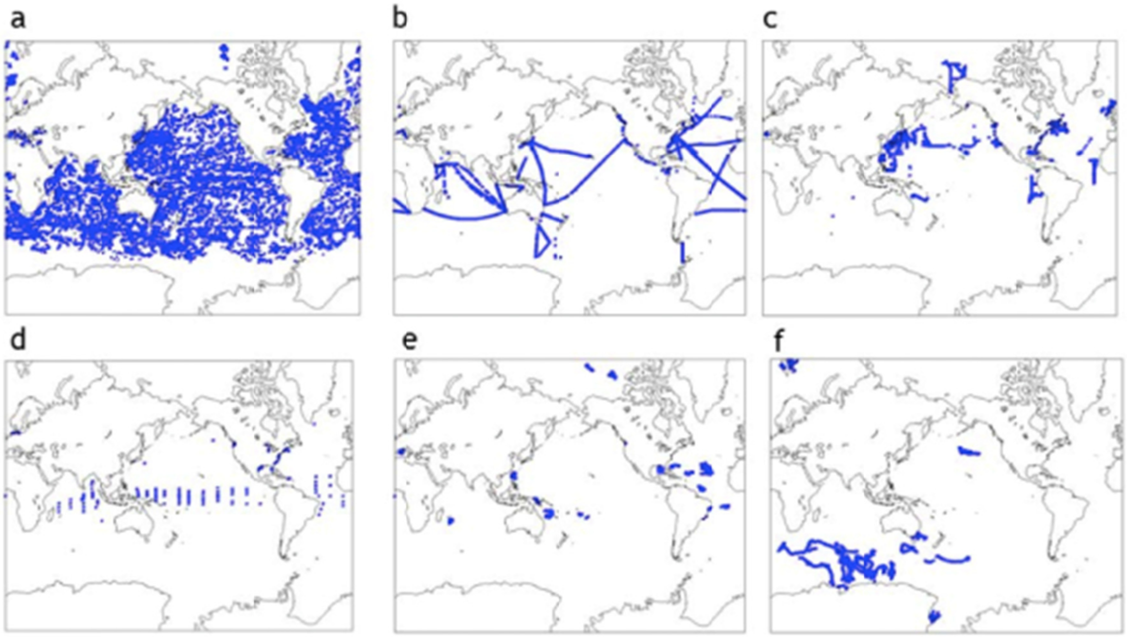


FIGURE 5.4 Ocean data coverage for September through November in 2012 from (a) Argo floats, (b) Expendable Bathythermographs (XBTs), (c) sondes (CTDs) and ocean gliders, (d) fixed buoys, (e) drifting buoys, (f) animal borne sensors. SOURCE: Fairall et al., 2013.

Argo—a global drifting sampling array that began deployments in 1999—provides the best coverage for global, in situ ocean measurements at depth (Riser et al., 2016; Figure 5.4a). Argo has close to 4,000 free-drifting profiling floats that measure temperature, salinity, and dissolved oxygen of the upper 2,000 m of the ocean and transmit the collected measurements in near real-time. The Argo network is quite coarse (roughly one float on a 3°x3° grid, but not uniformly distributed) and does not cover the deep ocean below 2,000 m. However, deep Argo float prototypes with operational ranges down to 4,000 m or 6,000 m, depending on the model, are being tested (G. Johnson; D. Roemmich, personal communication, December 2014). Other prototypes of Argo floats are adding sensors for biogeochemically important quantities such as pH, nitrate, and chlorophyll fluorescence (K. Johnson, personal communication, December 2014) and are being designed to improve their performance in seasonally sea ice covered regions.

Moored buoys also provide critical real-time observations of condition at the ocean surface (Figures 5.4d and 5.2a). Natural modes of variability highlighted in Chapter 4 as important sources of S2S predictability are predominantly tropical and are either fundamentally coupled ocean-atmosphere phenomena (e.g., ENSO), or at least influenced by ocean-atmosphere feedbacks (e.g., MJO). The TAO/TRITON moored buoy array in the Pacific, the Prediction and Research Moored Array in the Atlantic (PIRATA), and the Research Moored Array for African-Asian-Australian Monsoon Analysis and Prediction (RAMA) array the Indian Ocean provide hourly oceanic observations and surface meteorological observations, all in real-time, in locations that were selected to fill data gaps in monitoring the variability of the tropical climate system (NRC, 2010a). In particular, the observations from the Tropical Atmosphere Ocean (TAO/TRITON) moorings play an important role in the generation of skillful seasonal ENSO forecasts (NRC, 2010b), including the large ongoing 2015-2016 El Niño.

In order for tropical ocean surface moorings to continue to benefit operational ocean and S2S forecasting, they need to deliver consistent and reliable observations. However, tropical surface moorings are subject to instrument failures due to long-term exposure to a difficult environment, and they are also commonly damaged by fishing activities and vandalism. Regular and sustained maintenance of these moorings is necessary, but limited access to ship-time for missions to refresh moorings has resulted in data losses and thus time series breaks. For example, lack of maintenance during the period from June 2012 through September 2014 severely degraded the TAO array, causing the returned data volume to drop to roughly half its historical rate from the 2000s (Tollefson, 2014). Though the tropical mooring array can be expensive and logistically challenging to maintain, allowing it to decay through neglect is unacceptable for what has proven to be a vital element in delivering skillful and societally valuable ENSO forecasts (NRC, 2010c).

A global array of surface drifters (e.g., Niiler, 2001) provides synergistic information for satellite measurements of SST, salinity, and absolute sea surface height (SSH), but its spatial coverage is coarser than Argo (roughly one float on a 5°x5° grid). For example, the Global Drifter Program (GDP[25]) provides satellite-tracked surface drifting observations of currents, SST, atmospheric pressure, winds, and salinity over the world's oceans. Other routine in situ measurements are collected and reported back in real-time by volunteer observing ships and research vessels and moorings. Sensors on marine mammals also provide important subsurface ocean data, and such sensors are currently one of the only ways to observe the subsurface ocean in polar regions and beneath sea ice (Roquet et al., 2013, Charrassin et al., 2008). Autonomous Underwater Vehicles (AUVs, e.g., gliders or self-propelled vehicles) can also be used to collect routine ocean measurements (see Box 5.1). The range and usage of gliders is increasing, but the range of propelled AUVs is often still too limited. They are however, relatively cost effective and can be outfitted with many sensors and sent into areas not commonly covered by other techniques, making further development of this technology attractive.

Coastal areas represent a significant challenge for satellite observations. Specifically, satellite-based observations of winds and SSH are not yet accurate in coastal regions, where the winds can change rapidly over smaller spatial and temporal scales relative to coarse microwave footprint sizes (~25km). In addition, the side-lobe contamination from the land renders the near-costal observations unusable. Although the SWOT mission will improve the situation for SSH due to its higher resolution (~2km), coastal winds and surface current observations will need to rely on the high-frequency shore-based radar (such as Coastal ocean dynamics applications radar [CODAR] and WavE RAdar [WERA]). These radar observations are increasing in availability and are a backbone component of NOAA's Integrated Ocean Observing System (IOOS), but many more of these data sets are needed globally in order to increase predictability near the coasts. Finally, while there is a global tide network, it is important to keep maintaining it together with measurements from submarine cable instruments to ensure accurate tidal prediction. Wave predictions and the associated air-sea interactions also require that the wave buoy network is sustained to ensure availability of wave data.

In summary, while progress continues to be made in advancing in situ and remote sensing measurements of the ocean, including expanding temporal and spatial coverage and capabilities, the ocean continues to be under-observed relative to its importance in the coupled Earth system. Coverage and continuity of existing SST, SSH, and surface wind observations are important to maintain in order to produce S2S forecasts that are skillful. Further advances in observing

[25] http://www.aoml.noaa.gov/phod/goos.php, accessed January 27, 2016.

BOX 5.1—Autonomous Underwater Vehicles

Most interior properties of the ocean cannot be remotely sensed. In addition to ships and other classic in situ infrastructures (National Academies of Sciences Engineering and Medicine, 2015a), there is a need for inexpensive but efficient ocean sensing capabilities. Since the “weather of the sea” (e.g., Robinson, 1983) has timescales relevant for S2S predictions, such capabilities will likely be most useful. Fortunately for S2S, in the past 10 to 20 years, the increasing deployment of autonomous ocean observing systems has started a revolution as imagined by Stommel (1989). Autonomous underwater vehicles (AUVs) such as gliders and propelled vehicles (including surface crafts) are employed today for scientific exploration, ocean mapping, commercial applications, naval reconnaissance, and security. This is possible due to advances in manufacturing (Yuh, 2000), reliability (Bahr et al., 2009; Fiorelli et al., 2006), robotics (Bellingham and Rajan, 2007), and autonomy (Curtin and Bellingham, 2009; Curtin et al., 1993; Lermusiaux et al., 2015).

Equipped with physical sensors and even biogeochemical analyzers, AUVs collect observations useful for ocean estimation and forecasting. Their use in adaptive sampling and exploratory missions is now feasible (e.g., Fiorelli et al., 2006; Haley et al., 2009; Leonard et al., 2010; Ramp et al., 2009; Schofield et al., 2010). Such missions can involve onboard routing (Davis et al., 2009; Wang et al., 2009b) as well as coordination, cooperation, and inter-vehicle information exchanges (Bahr et al., 2009; Leonard et al., 2007; Paley et al., 2008; Zhang et al., 2007). Ocean sensing vehicles are now used in groups of heterogeneous type with varied operating speeds. They provide sparse but multivariate data, and their motions can be strongly affected by ocean currents (Lermusiaux et al., 2015). Optimal path planning towards key sampling locations is thus critical to save time and energy (Lolla et al., 2014a; Lolla et al., 2014b; Subramani et al., 2015). Since the vehicles provide observations that are ultimately assimilated into ocean models, their optimal control is thus often linked to uncertainty prediction and data assimilation (e.g., Lermusiaux, 2007; Schofield et al., 2010).

Even though the use and deployment of varied types of AUVs for S2S forecasting is not yet common, within the next 10 years they are likely to become useful for such predictions. Long-duration deployments of gliders and other AUVs with sufficient endurance or drifting capabilities is now an area of active research. Several major research projects (Northern Arabian Sea Circulation—autonomous research [NASCar], etc.) are underway. In addition, similar efforts are being completed in the air domain with autonomous sensing drones and other UAVs. Coordinating efforts among autonomous oceanic and atmospheric sensing research will improve the collection of observations for coupled S2S forecasting of the Earth system.

technology and coverage could have tremendous value for characterizing important S2S ocean processes, for model improvement, and for providing information for forecast initial conditions. Effective integration of the increasing ocean observations and platforms with S2S ocean modeling systems is also necessary, including data-model comparisons for improving ocean model formulations and advanced data-assimilation for better S2S forecasts.

Finding 5.4: Continued investment into routine space-based observations of sea-surface height, SST, surface winds—which represent key inputs to estimates of air-sea fluxes of water, heat, and momentum—are critical to support S2S prediction systems. Developing satellite-based estimates of ocean surface salinity, currents, mixed-layer, and biogeochemical properties may further advance S2S forecasts.

Finding 5.5: In situ measurements of SSH and winds in coastal areas continue to be critical for S2S forecasting, as do surface meteorological observations from tropical moored arrays. Routine, in situ measurements of temperature and salinity structure at depth, as well as of

coastal and equatorial currents, are also particularly important. Expanded use of new and improved drifters, buoys, and autonomous instruments could facilitate cost-effective expansion of the observing network below the surface.

Observations of the Cryosphere and Polar Regions

More than anywhere else on Earth, the polar regions depend on unique observing methods to confront the challenges of taking measurements in extreme and harsh environments. Much of the important phenomena for S2S polar prediction contain small spatial scales, such as the high degree of spatial variability associated with melt ponds, openings in sea ice, patchiness of snow cover, and eddies in the ocean. The high reflectivity of ice and snow surfaces on land and ocean, lack of strong horizontal and vertical temperature gradients, and the extended polar night make atmospheric observations difficult from passive radiances, e.g., visible measurements based on sunlight reflected from clouds or snow, or infrared measurements based on thermal contrasts. Further, sea ice is a barrier to most ocean-observing satellites. As a result, routine in situ observations are critical to complement satellite observations around the poles, in particular for ocean observations. Traditional field-based measurements are also hindered by the presence of sea ice (e.g., Figure 5.4) and a shortage of population centers from which to operate or launch instruments.

Sea ice concentration is one of the most essential variables for predicting weather and climate in the polar regions. Fortunately, sea ice concentration can be measured by passive microwave retrievals (the same satellites that observe terrestrial snow cover) through clouds and during both day and night. Passive microwave retrievals also can be used to distinguish first-year (ice that first grew on open water less than a year ago) and multiyear ice. These observations are available since 1979 and provide the only continuous coverage of sea ice longer than a decade. However, there is high uncertainty in sea ice concentration measurements when melt water is present at the surface and resolutions are relatively coarse (~10 km).

Sea ice thickness is less well observed than sea ice concentration, but it is at least as important for sea ice prediction (Blanchard-Wrigglesworth et al., 2011a; Day et al., 2014). Sea ice thickness is a key constraint on the timescale of variability (~ months to years) for sea ice concentration anomalies. For example, summer sea ice coverage—a variable that is often a target for prediction—is strongly influenced by sea ice thickness in spring (Chapter 4). Scattered field-based measurements of sea ice thickness are available since the late 1950s (e.g., Lindsay and Schweiger, 2015), and in the last two decades a series of satellites and aircraft have provided good spatial coverage but not continuously; in some cases instruments were turned off to extend the life of the mission (ICESat[26]) and in others melt water on the surface obscured the measurements in late spring and summer (IceBridge[27], CryoSat-2[28]). At present, the only thickness-observing satellite is CryoSat-2, operated by the European Space Agency, which has been in orbit since 2010. Because remote sensing actually measures the freeboard (height of sea ice and snow above sea level), the accuracy of estimates of sea ice thickness depends critically on the availability and quality of measurements of snow depth on top of the sea ice. The lack of simultaneous measurements of snow depths and freeboard leads to significant uncertainty in the

[26] http://icesat.gsfc.nasa.gov/, accessed January 27, 2016.
[27] http://www.nasa.gov/mission_pages/icebridge/index.html, accessed January 27, 2016.
[28] http://www.esa.int/Our_Activities/Observing_the_Earth/The_Living_Planet_Programme/Earth_Explorers/CryoSat-2, accessed January 27, 2016.

estimate of thickness, but even more problematic for S2S forecasting is the impossibility of retrieving data from the radar altimeter instrument on CryoSat-2 (and CryoSat) in the presence of surface meltwater, or roughly May-September in the Arctic. Nonetheless, CryoSat thickness measurements have been used for sea ice data assimilation to initialize forecasts in spring of the ensuing summer season (see section on data assimilation).

NASA's IceBridge aircraft mission offers one of the best opportunities to measure simultaneous freeboard and snow depth, though the measurements are limited to about a dozen flight tracks each year over a few weeks in spring since 2007. Even in these opportune conditions, the uncertainty in IceBridge sea ice thickness is estimated to still be 40 cm (Kurtz et al., 2013). Less accurate snow depths have been estimated for the purpose of computing sea ice thickness from satellite based measurements of freeboard in a variety of ways, including from climatological measurements (Kwok et al., 2004), accumulation of snowfall from reanalysis (Kwok and Cunningham, 2008), and using an empirical method based on ice type and climatological measurements (Laxon et al., 2013). However, the accuracy of resulting sea ice thickness was not reported in these studies. Recently, snow depths have also been estimated from the SMOS satellite mission to be nearly as accurate as the IceBridge measurements (Maaß et al., 2013), which is very encouraging.

NASA plans to launch a satellite known as the second generation Ice Cloud and Land Elevation Satellite (ICESat2) in 2017 that can measure sea ice thickness year round, but accurate and simultaneous snow depth measurement are still necessary to fully utilize these observations. Further, the data need to be processed within a day or so of the observation to be useful as input for prediction of the sea ice edge at shorter lead times in S2S forecasts.

Finding 5.6: Reliable and accurate year-round sea ice thickness measurements are the greatest need for sea ice prediction, and continued satellite missions will enable this key objective. However, accurate and simultaneous in situ measurements of snow depths on sea ice are needed to translate signals observable from satellite into dependable and timely sea ice thickness estimates.

Land Surface Observations

As discussed in Chapter 4, land surface characteristics are important for Earth system prediction on S2S timescales, and may be particularly important for predicting extreme events, such as heat waves and droughts, as well as for characterizing the water cycle. This may be especially true during boreal spring and summer, when coupled Earth system models often exhibit lower predictive skill due to weaker links between mid-latitude climate systems and the oceans and an increase in land-atmosphere interactions (NRC, 2010b; Roundy et al., 2014). Soil moisture, snow depth, vegetation, water table depth, and land heat content all influence the fluxes of heat and moisture between the land surface and atmosphere, sometimes with important feedbacks to large-scale weather and climate and events such as heat waves (e.g., Guo et al., 2011; Roundy et al., 2014; Roundy and Wood, 2015). As also mentioned in Chapter 4, a number of recent studies have found that more realistic initialization of precipitation and land surface variables, such as soil moisture, snow cover, and vegetation in coupled Earth system models and multi model forecast systems improves the predictability of atmosphere and hydrologic variables on S2S timescales (Koster et al., 2004; Koster et al., 2010; Koster et al., 2011; Koster and

Walker, 2015; Kumar et al., 2014; Peings et al., 2011; Prodhomme et al., 2015; Roundy and Wood, 2015; Thomas et al., 2015). The regions and time periods for which such land-atmosphere coupling is important for weather and climate prediction are also likely to expand with global warming (Dirmeyer et al., 2013; Dirmeyer et al., 2014).

The ability to measure land surface and hydrological variables, particularly on a global scale, is currently limited, hindering realistic model initialization and representation of important land processes and land-atmosphere coupling. For example, critical data input into land data assimilation systems comes from in situ measurements of precipitation (from rain gauges) and snow and snow depth (from weather stations and snow courses), but prediction skill has been shown to be limited in the many areas where such measurements are sparse (Koster et al., 2010). Networks such as CoCoRaHS29, the Community Collaborative Rain, Hail, and Snow Network, have improved the density of rain gauge data in the United States for research and monitoring purposes, and such networks might be leveraged for improving real-time modeling. However, there are still vast areas in less populated parts of the country and especially abroad where there is little to no gauge data.

While in situ networks need to be maintained and in some cases expanded in the near-term to enhance S2S forecasting (see below), measurements from satellites may hold the most promise for improving the global characterization of many land surface variables. A few recent and planned satellite missions have the potential to rapidly accelerate progress towards the goal of improved surface soil moisture estimates. The European Space Agency launched SMOS in 2009 to monitor surface soil moisture (~ < 10 cm) using an L-Band microwave radiometer (Kerr et al., 2010; Mecklenburg et al., 2012). In January of 2015, NASA launched the Soil Moisture Active Passive (SMAP) satellite[30], which is designed to monitor the freeze-thaw state as well as surface soil moisture using an L-Band microwave radiometer and radar (Entekhabi et al., 2010). Despite these recent and planned developments, a number of critical gaps remain. The current failure of SMAP's radar has (at best) delayed the full potential of SMAP data until a stand-in radar onboard another satellite can be used in tandem with SMAP's radiometer. Observations (or better estimates) of soil moisture into the root zone will be key to exploiting the longer-term predictability associated with soil moisture and are also for constraining hydrologic predictions. Root zone soil moisture provides the atmosphere a source of moisture through plant transpiration, with this deeper layer typically exhibiting longer timescales of variability than soil moisture near the surface. Remote sensing observations of root zone soil moisture are typically based on longer (i.e., P-band) microwave wavelengths. Recently, airborne radar implementations have shown skill in estimating root zone soil moisture, with an indication that satellite implementations may be possible (Konings et al., 2014; Tabatabaeenejad et al., 2015).

Observations of snow cover, multi-spectral albedo, and depth are also particularly important for improving S2S forecasts of the atmosphere and the hydrological cycle. Highly accurate global-scale observations of snow cover are currently now available from satellite platforms (e.g., the Moderate Resolution Imaging Spectroradiometer [MODIS]). Snow water equivalent (SWE) can also be estimated from space-based passive microwave radiometers, such as the special sensor microwave imager (SSM/I) and advanced microwave scanning radiometer (AMSR-E). However, these estimates contain significant caveats and uncertainties (Byun and Choi, 2014; NRC, 2010b), and the ability to retrieve snow depth and/or SWE remains a significant challenge. Continued improvement to SWE remote sensing technologies and retrieval

[29]http://www.cocorahs.org/.
[30] http://smap.jpl.nasa.gov/, accessed January 27, 2016.

algorithms are needed. However, given the importance of snow measurements, more networks like SNOTEL (Snowpack Telemetry), which provides real-time in situ measurements of snow depth from the 600-plus stations across the western United States, are likely needed, particularly in areas where accumulated snow pack is a large portion of the annual water cycle (e.g., for California—see case study in Chapter 3).

In addition to improved precipitation, soil moisture, and snow measurements for initializing S2S prediction systems, a number of other land surface measurements are important for advancing S2S model calibration, model development, and for initializing next-generation operational systems. For example, the NASA SWOT mission mentioned above will provide new constraints on surface hydrology via surface water elevations and stream flow estimates. Such data will be useful for hydrology model development and land surface model calibration; similar data may be important in the longer term for initializing hydrology and river components of future S2S forecast systems. Similarly, littoral observations are useful for monitoring and modeling the effects of coupled ocean-atmosphere processes in coastal areas. For example, characterizations and fine-scale observations of land elevation, roughness, cover, soil content, vegetation, man-made structures, and anthropogenic heating would be useful for improving models of wetting-drying, as well as for risk models for storm surges from hurricanes and typhoons making land-fall and heat wave prediction. These littoral processes are directly linked to a general need to increase and automate ocean observing systems for S2S predictions, as discussed above.

Satellite measurements that can generate better estimates of evapotranspiration are sorely needed to better constrain the terrestrial water budget and its influence on surface fluxes of heat and moisture to the atmosphere. The NASA ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) mission is an experimental multi-spectral infrared spectrometer that will provide high-resolution observations of surface temperature which will be used to explore their value for estimating evapotranspiration and plant water stress and consumptive use. The implementation of ECOSTRESS on the International Space Station (ISS) provides for characterizing the mean diurnal cycle (which the current 16-day LandSat repeat does not offer) but it does not provide global coverage. Further, the ISS arrangement only provides for a two-year hosting provision, and considerations of continuity need to be undertaken in conjunction with the determined need and value of such measurements.

The global network of flux towers are also an important source of data in this regard, as flux towers provide critical measurements of land-atmosphere fluxes of heat, moisture, and carbon dioxide (Figure 5.5). Such flux measurements are particularly useful for developing and validating the components of dynamic models that account for processes associated with surface energy balance. In order to maximize improvement in the characterization of land surfaces fluxes within S2S predictions systems, these types of observations are needed with larger spatial coverage, higher density, and in a timely enough fashion to be useful in real-time operational data assimilation.

Finding 5.7: Land observations are critical for modeling large-scale land surface-atmosphere feedbacks and for making predictions of the terrestrial water cycle. Networks of in situ measurements of precipitation, snow depth, and root-zone soil moisture are likely to remain important, but the poor spatial coverage of such networks currently limits S2S prediction. In addition to expanding in situ networks, significant research is needed to evaluate the quality

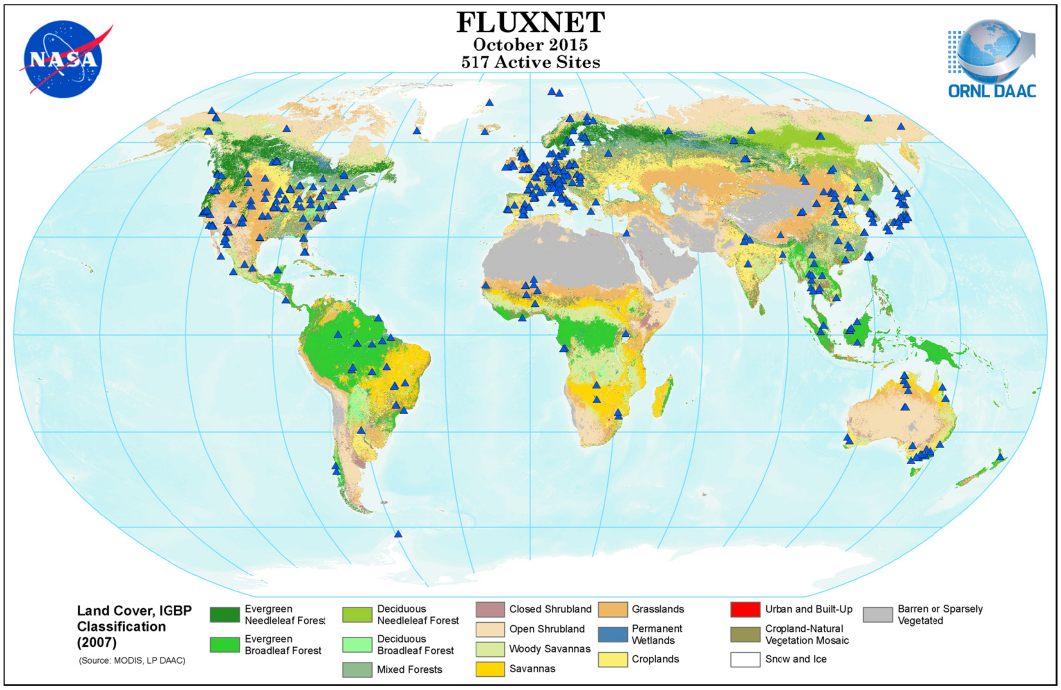


FIGURE 5.5 Distribution of 517 active flux tower sites within global Fluxnet network, as of October 2015. These towers measure exchanges of carbon dioxide, water vapor, and energy between the atmosphere and terrestrial ecosystem. SOURCE: Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC). 2013. FLUXNET Maps & Graphics Web Page. Available online [http://fluxnet.ornl.gov/maps-graphics] from ORNL DAAC, Oak Ridge, Tennessee, USA, accessed February 22, 2016

and potential use of remotely sensed measurements of precipitation, soil moisture, snow water equivalent and evapotranspiration.

Prioritizing Investment in Observations

Although a general expansion of the existing observational network will be important to improving S2S predictions, prioritizing investments is likely to be essential. One way to develop such a prioritization is through sensitivity and denial experiments using S2S forecast systems. Here, various components of the initial condition are perturbed or removed and then forecast skill impacts are assessed. As also mentioned above, a number of recent sensitivity studies have explored the importance of soil moisture initializations and associated feedbacks for S2S predictions (e.g., Fennessy and Shukla, 1999; Guo et al., 2011; Koster et al., 2004). Koster et al. (2014) further found that with certain initial perturbations, a land-atmosphere interaction resulted in a downstream phase-locking and amplification of a planetary atmospheric wave. In the weeks and months that followed, this phase-locking resulted in changes to atmospheric conditions far away from the initial perturbations. The identification of a phase-locking mechanism in a historical reanalysis dataset corroborated this finding. The ability to identify the sensitivity of remote (spatially and temporally) conditions to initial soil moisture highlights the importance of soil moisture observations for S2S predictions and also identifies regions for which accurate observations may be most important. Similarly, sensitivity studies have been carried out to explore the role of snow cover on the evolution of the winter hemisphere climate (Allen and Zender, 2010; Klingaman et al., 2008; Sobolowski et al., 2010). These types of sensitivity studies can help determine sources of predictability while also emphasizing the importance of initialization by certain variables and quantities in order to realize predictability. An alternative approach to perturbing the initial conditions explicitly is to perform data denial studies (Observing System Experiments, OSEs) using S2S prediction models. This has become common, regular practice for operational NWP and their partners in order to accurately assess the utility of various observing platforms in reducing forecast errors in real systems with real errors. Similar efforts are also done within academic and operational ocean forecasting.

Observing system simulation experiments (OSSEs) (e.g., Arnold and Dey, 1986; Dickey, 2003; Masutani et al., 2007; Masutani et al., 2010) provide another means of exploring the potential impact of future observing systems on S2S predictions. In an OSSE, a reference run, typically at the highest resolution possible, is generated from a free run of an ESM without data assimilation. This so-called "nature run" is considered to be the true state. Sampled values, considered as "observations," from this nature run are then used to initialize a forecast system. The simulated observations from the nature run are thus analogous to the traditional observations used in an actual forecast and can be used by an ESM with data assimilation to assess the impact of various observations on the analysis and forecast accuracy. Since the true state is known, analysis error can be computed explicitly. Using this methodology, a perturbation experiment is then run in which hypothetical observations are evaluated in the context of data assimilation and hypothetical forecasts. Such OSSE experiments have been used in the design and decision phases for the Aeolus Doppler wind Lidar instrument for NWP (Baker et al., 2014; Stoffelen et al., 2006). OSSEs have also been proposed as a tool designing optimal air quality observations (Timmermans et al., 2015).

OSSEs are powerful tools since they allow for the exploration of hypothetical observations. However, they need to be designed and executed carefully to ensure that the results are meaningful and applicable to the real Earth system. "Perfect model" OSSEs (such as the experiments described above) measure the impact of hypothetical observations on a forecast system in which model and forecast errors are assumed to be non-existent. To address the more realistic scenario in which models are assumed to have errors, two or more (significantly) different models are required to evaluate the impact of observations within prediction systems. The first model provides the reference/nature run and generates the "true states" from which simulated observations are extracted. The other models are then used to assimilate the simulated observations and generate forecasts that are then compared with the states generated in the first model. If the same or largely similar models are utilized, model error goes unaccounted for, resulting in a system that is too predictable.

In order to assess and prioritize new observations specific to the S2S problem, either type of OSSE would need to be designed and carried out using Earth system forecast models, with the generation of the nature run performed with a high fidelity, state-of-the-art Earth system model. This can be computationally expensive, especially when it comes to the storage and distribution of the nature run data. Coordination among the parties interested in such a nature run is critical. Once available, further coordination on the simulation of the observations that already exist in the current observing system will be required, paying special attention to the generation and calibration of realistic observation errors. Once these pieces are available, any hypothetical observation network could be explored for assessing its potential importance. This is one of the more promising avenues available for prioritizing what new observing systems will provide the largest benefit for S2S prediction systems.

Finding 5.8: Cost-benefit analyses will be necessary to prioritize what new observations (of current variables at higher spatial or temporal resolution and/or of new variables) will most benefit S2S prediction systems. OSSEs, and sensitivity studies more generally, are powerful tools for exploring the benefits of specific observations on state estimation and overall model performance, and could be better used to prioritize improvements to observing networks as well as S2S model parameterizations.

The Way Forward for Observations

Observations form the foundation of S2S prediction systems, allowing the characterization of physical processes, model initialization, and the calibration and verification of model outputs. Relatively robust observing networks exist for the atmosphere over land (outside the polar regions), but current observations networks for the ocean, cryosphere, and land surface will require more attention in order to advance S2S forecasts over the next decade. The ocean in particular does not have the necessary coverage despite its very clear importance for S2S prediction. Furthermore, even for the atmosphere, some critical networks are in danger of deteriorating or of suffering breaks in continuity within the next decade. These observing systems must be maintained or replaced to prevent an erosion of S2S forecasting skill. Beyond maintaining the current observing network, development of new observing technologies and expansion of existing observing networks will present opportunities to drive improvements in models and model initializations, especially as more components are added to ESMs and forecast system capability expands, growing the need for routine observations of new variables within the Earth system (e.g., aerosols, biogeochemistry).

As described above, special effort is needed to improve observations in many parts of the world where unique physical processes take place but few routine measurements are available. These include polar regions, where sea ice, land surface, and atmospheric processes can feed back to high and mid-latitude weather and ocean conditions; tropical areas characterized by convection centers that strongly influence global circulation (e.g., Africa, South America, Indian and western Pacific warm pool); and highly dynamic coastal areas. Developing observational networks specific to capturing the fluxes of matter and energy within the Earth system also need attention, as the improper treatment of these quantities in models can result in substantial biases in water and energy budgets that compromise S2S forecast skill.

Both remotely sensed and in situ measurements will be important to maintain and expand. Satellite-based measurements are an increasingly important component of air, ice, land, and water observing systems and are critical for initializing Earth system models. For atmospheric variables, it will be particularly important to maintain remotely sensed measurements of the vertical profiles of key atmospheric variables (e.g., temperature, moisture, wind) and to continue to develop measurements likely to become more important to S2S in the next decade (e.g., precipitation, cloud liquid/ice, aerosol concentration and composition). For the ocean, remotely sensed observations of SST, SSH, and ocean surface winds are vital globally, and preferably at resolutions fine enough to resolve mesoscale currents and eddies. Coverage in some cases is currently provided by short-term research missions, but these must be converted to long-term missions in order to remain valuable for operational S2S forecasting in the next decade. Advances in satellite observations of salinity, mixed-layer depth, and near-surface ocean currents also have potential to benefit S2S forecasting and should be pursued.

In coastal areas, targeted and sustained in situ measurements using moorings, ships, AUVs (including gliders), and other autonomous sensing platforms (see Box 5.1) should be better coordinated and more rapidly utilized for varied S2S research and applications. The S2S needs include critical data assimilation for land-ocean coastal predictions and also the evaluation of satellite products. Further advances in ocean observing technology and coverage could have tremendous value for characterizing important S2S processes, for model improvement, and for providing information for forecast initial conditions. Effective integration of the increasing ocean observations and platforms with S2S ocean modeling systems is also necessary, including data-model comparisons for improving ocean model formulations and advanced data-assimilation for better S2S forecasts.

For the cryosphere, continued investment into generating year-round, remotely sensed sea ice thickness measurements, including snow depth on top of the sea ice, are critical, though in situ measurements may continue to be needed in order to translate these measurements into dependable and timely routine estimates. For the land surface, new and/or planned missions for surface soil moisture, surface water, and evapotranspiration may add considerable value to S2S forecasting, especially for model development, but again many of these are research missions with limited lifespans. Quantities for which there would be a great benefit to develop new or better satellite measurements include snow water equivalent and root zone soil moisture.

For many remotely sensed variables, continued work to develop better retrieval algorithms will be necessary to realize the full potential of the observations. Looking further ahead, the development of more capable and cost-effective satellite observing systems should continue to be investigated, including constellations that provide multi-sensor observations, small satellite deployments (for example, CubeSat[31]) that reduce costs and increase sampling rates and coverage, and new, expanded, and/or more economical sensor designs that provide routine measurements for operational forecasts. Investment in in situ and high-resolution observations, especially from remote or uninhabitable regions and other regions with poor coverage remains important, in many cases even with current and planned advances in the remotely sensed observation network. These include measurements from radiosondes, precipitation gauges (particularly in mountainous areas where TRMM is compromised), snow courses, flux towers, and subsurface ocean measurements of salinity, temperature, and ocean velocity at depth from drifters. More broadly distributed coastal radar networks for surface current measurement are also a key need.

Measurements from moored tropical arrays, which are critical for S2S forecasts of ENSO, also need to be maintained. The design of the tropical moored arrays predates modern S2S forecast systems or the Argo drifter network. If the agencies that have been sustaining the tropical mooring network now find it to be fiscally unsustainable, its optimal and sustainable design should be revisited using OSSEs with modern S2S forecasts systems to assess their value for ENSO and other S2S forecasts and an analysis that deliberately takes into account the relative maintenance costs, historical instrument attrition rates, and or issues (e.g., international political considerations and cost-sharing) of the various mooring locations. However, it is the view of the Committee that until such a deliberate analysis and redesign has been carried out, every effort

[31] http://www.cubesat.org/, accessed January 27, 2016.

should be taken to maintain the current operational tropical mooring network with its current configuration.

The Committee recognizes that setting up and maintaining in situ networks poses unique challenges, especially in remote locales not suitable for staffed observations and difficult climates. Looking ahead, developing automated and semi-automated instruments that can operate to a year or longer with minimum or no maintenance would allow for large increases in spatial coverage. Technology for automated instruments (e.g., automated radiosonde launchers and ocean gliders and floats) exists but needs to mature (see Box 5.1). On the ocean side, power consumption typically limits the range or lifetime of floats and gliders, and the ongoing development of smaller and more energy efficient sensors would be beneficial for a diverse range of autonomous observing platforms. Cost-benefit analyses are necessary to justify the financial and logistical burden.

Recommendation E: Maintain continuity of critical observations, and expand the temporal and spatial coverage of in situ and remotely sensed observations for Earth system variables that are beneficial for operational S2S prediction and for discovering and modeling new sources of S2S predictability.

Specifically:

- Maintain continuous satellite measurement records of vertical profiles of atmospheric temperature and humidity without gaps in the data collection and with increasing vertical resolution and accuracy.
- Optimize and advance observations of clouds, precipitation, wind profiles, and mesoscale storm and boundary layer structure and evolution. In particular, higher-resolution observations of these quantities are needed for developing and advancing cloud-permitting components of future S2S forecast systems.
- Maintain and advance satellite and other observational capabilities (e.g., radars, drifters, and gliders) to provide continuity and better spatial coverage, resolution, and quality of key surface ocean observations (SSH, SST, and winds), particularly near the coasts, where predictions of oceanic conditions are of the greatest societal importance in their own right.
- Maintain and expand the network of in situ instruments providing routine real-time measurements of sub-surface ocean properties, such as temperature, salinity, and currents, with increasing resolutions and accuracy. Appropriate platforms for these instruments will include arrays of moored buoys (especially in the tropics), AUVs, marine mammals, and profiling floats.
- Develop accurate and timely year-round sea ice thickness measurements; if from remote sensing of sea ice freeboard, simultaneous snow depth measurements are needed to translate the observation of freeboard into sea ice thickness.
- Expand in situ measurements of precipitation, snow depth, soil moisture, and land-surface fluxes, and improve and/or better exploit remotely sensed soil moisture, snow water equivalent, and evapotranspiration measurements.
- Continue to invest in observations (both in situ and remotely sensed) that are important for informing fluxes between the component interfaces, including but not limited to land surface observations of temperature, moisture, and snow depth; marine surface

observations from tropical moored buoys; ocean observations of near-surface currents, temperature, salinity, ocean heat content, mixed-layer depth, and sea ice conditions.

- Apply autonomous and other new observing technologies to expand the spatial and temporal coverage of observation networks, and support the continued development of these observational methodologies.

Although it would be beneficial to expand the geographic coverage and resolution of many types of observations, cost and logistics demand that priorities be determined. Beyond the general need for more routine observations of the ocean, land, and cryosphere to support coupled S2S prediction systems, it is not always clear a priori what measurements will be most beneficial. Determining where to add measurements of existing variables or which new variables to add can be planned more effectively through the use of OSSEs, OSEs, and other types of sensitivity studies that specifically utilize S2S forecast systems in their design and execution. For the case of satellite observations, a recent NRC study also provides a value and decision framework that allows prioritization of new versus continuous measurements (National Academies of Sciences Engineering and Medicine, 2015b).

Recommendation F: Determine priorities for observational systems and networks by developing and implementing OSSEs, OSEs, and other sensitivity studies using S2S forecast systems.

DATA ASSIMILATION

Data assimilation (DA) is the process of quantitatively estimating dynamically evolving fields by combining information from observations with the predictive equations of models. A key purpose of DA is to create initial conditions, which are used to produce operational forecasts as well as retrospective forecasts and reanalysis (see Figure 5.1). DA is also used to control error growth within the model due to limits in predictive capability. Most assimilation schemes are derived from estimation theory (Gelb, 1974; Jazwinski, 1970), information theory (Cover and Thomas, 2012; Sobczyk, 2001), control theory (LeDimet and Talagrand, 1986; Lions, 1971), and optimization and inverse problem theory (Tarantola, 2005).

In operational weather and ocean forecasting centers today, approximations are commonly made to assimilate observations into the model state and parameter spaces. Some common assumptions include: assuming normal, Gaussian error distributions for the observations and for the model state (which are often not normally distributed); using small ensemble sizes to characterize the uncertainties in a high dimensional space (i.e., rank deficiency); assuming uncorrelated observation errors; and using linearized operators for transforming the model state to observation space or using a linearized version of the S2S model itself. These assumptions can have significant impacts on the quality of the analysis (Daley, 1991; Evensen, 2009; Kalnay, 2003), and research is needed to develop data assimilation techniques that help overcome these challenges.

While traditionally grounded in linear theory and the Gaussian approximation (Kalman, 1960), recent research progress has focused on the development of more efficient assimilation methods that account for nonlinear dynamics and to utilize non-Gaussian probabilistic features. Even though several of these schemes would be challenging to employ in large, realistic S2S systems, some of the recent progress is promising for probabilistic S2S predictions and for the reduction of inherent uncertainties. Enhancing the coupling between components of ESMs is an important challenge in S2S prediction, and recent research on coupled DA is also promising. Accounting for the accurate and possibly non-Gaussian transfer of observed information from one component of the Earth system to the other is very important for enhancing the capabilities of strongly coupled S2S forecasting systems.

In this section, the Committee provides details on the status of data assimilation efforts in major components of S2S Earth system models and then highlights opportunities for advancing S2S forecast systems through coupled data assimilation, hybrid assimilation methods, Bayesian data assimilation, reduced order stochastic modeling, and the estimation of parameter values and parameterizations. Recommendations for priority research in these topics conclude the section.

State Estimation in Earth System Model Components

State estimation of Earth system components has generally been performed using data assimilation techniques from one of two classes of estimation approaches: (1) maximum likelihood estimates or (2) minimum error variance estimates. In geophysical applications, the former can be associated with the so-called variational methods (Courtier and Talagrand, 1987) and the latter to Kalman Filters/Smoothers (Kalman, 1960) and ensemble-based schemes (Evensen, 2009).

As pointed out in the 2010 NRC report on improving ISI climate prediction, improving the assimilation of atmospheric observations has yielded significant gains in numerical weather prediction skill (Figure 5.6). For operational atmospheric NWP applications, incremental variational assimilation has become the method of choice, including 3DVAR (Kleist et al., 2009; Lorenc et al., 2000) and 4DVAR (Courtier et al., 1994; Rabier et al., 2000). More recently, hybrid assimilation algorithms that combine ensemble and variational methods have led to some further success (Bonavita et al., 2015; Clayton et al., 2013; Kuhl et al., 2013; Wang et al., 2013b). Some operational centers are pursuing hybrid four-dimensional ensemble-variational (4DEnVar) techniques either as a first implementation of a 4D scheme (NCEP, Kleist and Ide, 2015), as a replacement (Environment Canada, Buehner et al. 2013), or potential replacement (United Kingdom Met Office [UKMO], Lorenc et al., 2015) for 4DVAR. The hybrid ensemble-variational algorithms have potential computational savings and scalability. This is because tangent linear and adjoint (transpose of the tangent linear to propagate sensitivities backward in time) versions of the prediction model are not needed as direct components of the assimilation solver itself. Such scalability has implications for coupled data assimilation (see below) given that strong coupling can be achieved without the need for the adjoint of the coupled models (Bishop and Martin, 2012).

Ocean data assimilation has led to substantial improvements in ocean forecasting capabilities and scientific understanding of ocean processes (Bennett, 1992; DeMey, 1997; Evensen, 2009; Lermusiaux, 2006; Malanotte-Rizzoli, 1996; Rienecker, 2003; Robinson et al., 1998; Wunsch, 1996). Ocean data assimilation is frequently employed for reanalyses that optimally combine model simulations with observations and so allow for quantitative scientific studies of ocean phenomena from the small to the global ocean scales. Operational ocean forecasting has also been enhanced by data assimilation from estuaries and regional seas to the

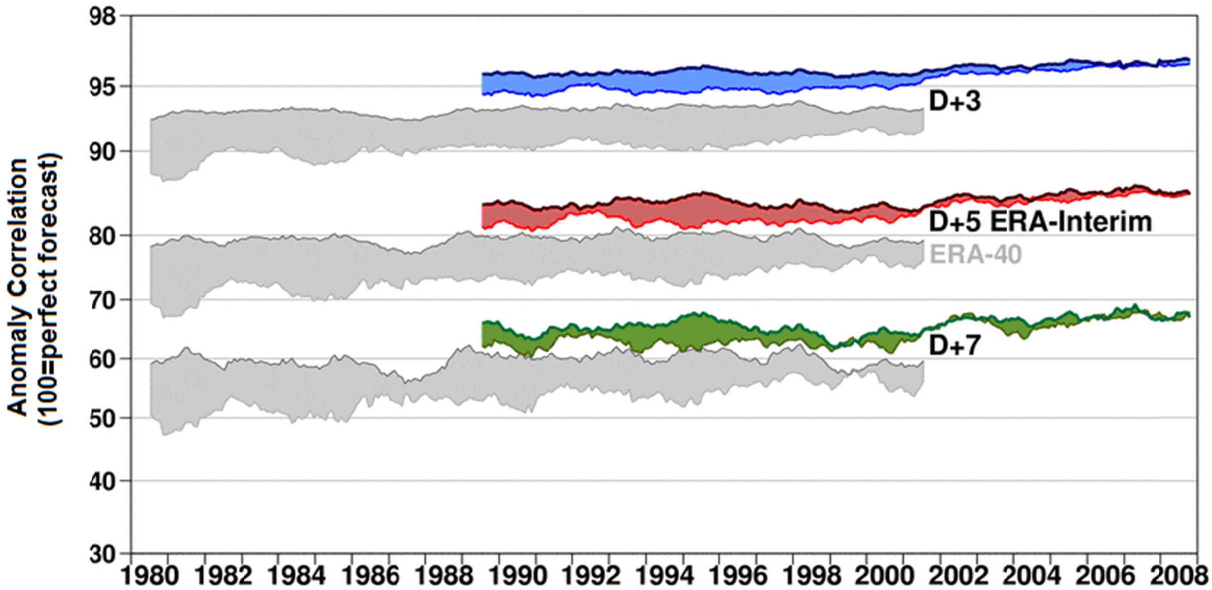


FIGURE 5.6 ECMWF 500-hPa geopotential height anomaly correlations from two different reanalysis systems. Gray: ERA-40 (Uppala et al., 2005) with 3D-Var (ca. 1998); Colors: ERA-Interim (Dee et al., 2011) which uses 4D-Var (ca. 2005). "D+3" corresponds to the 3-day forecast; "D+5" the 5-day forecast; and, "D+7" the 7-day forecast. In each case the top line is the anomaly correlation of the forecasts started from the reanalysis for the Northern Hemisphere, and the bottom line is the corresponding forecast for the Southern Hemisphere. Note the improvement brought about by the improvement of the data assimilation system, which is especially important in the Southern Hemisphere. SOURCE: NRC, 2010b and ECMWF.

global ocean (e.g., Chassignet and Verron, 2006; Fox et al., 2002; Pinardi and Woods, 2002; Schiller and Brassington, 2011). The research in data assimilation and uncertainty prediction methods has also been very active in ocean studies (Cummings et al., 2009; Evensen, 2004; Evensen, 2009; Lermusiaux et al., 2006), in part because of the lack of legacy systems (as is the case in atmospheric models) which allow for direct implementations of new methods for real-time forecasting (e.g., Lermusiaux, 1999; Oke et al., 2008) and for optimized reanalysis (Moore, 2013; Wunsch and Heimbach, 2013).

Assimilating data in sea ice models has also been done successfully (e.g., Kauker et al., 2008; Lindsay and Zhang, 2006; Stark et al., 2008; Wang et al., 2013b) but usually only for sea ice concentration using nudging or adjoint methods. Equally often, sea ice forecasts have been made in models that assimilate observations in the atmosphere and/or ocean only (e.g., Chevallier et al., 2013; Guemas et al., 2014; Merryfield et al., 2013a; Msadek et al., 2014; Wunsch and Heimbach, 2013), with mixed results in the sea ice cover. Improvements in sea ice model DA are on the horizon: The Ensemble Kalman Filter (EnKF) has been used to assimilate sea ice concentration and ice freeboard (height above sea level) by a Belgian university research group (Mathiot et al., 2012) and either sea ice concentrations alone (Lisæter et al., 2003) or with sea ice drift and a suite of upper ocean variables by a Norwegian center (Sakov et al., 2012).

Among the myriad of variables in modern land models, soil moisture and snow water equivalent (SWE) are thought to be the most important sources of predictability for the Earth system, highlighting their importance within the initialization step (e.g., Koster et al., 2011, Chapter 4, and observations section above). However, until recently, soil moisture monitoring from satellites has been too shallow (at only a few millimeters depth) to be useful for data assimilation directly, and SWE has not been available with sufficient accuracy or coverage.

Often, land surface state estimates are generated offline using Land Data Assimilation Systems (LDAS) incorporate near real-time information about meteorological forcing such as wind, temperature, and precipitation from both models and observations (NRC, 2010b). The global land data assimilation system (GLDAS; Rodell et al., 2004), developed jointly by NASA and NOAA, makes use of both ground- and space-based observational information to constrain modeled land states in addition to the meteorological forcing from a separate atmospheric data assimilation system. The GLDAS is a mixture of traditional data assimilation for parameters such as surface temperature and snow cover, with constraining offline land model-integration that produces estimates of other variables such as soil moisture, snow depth, soil temperature, surface water storage, etc. Thus for some land surface variables, LDAS systems are not necessarily data assimilation systems in the same sense as described for atmospheric and oceanic components, but instead constrain integrations of offline land surface models.

There is progress within LDAS algorithms and within the Land Information System (LIS; Kumar et al., 2006) to use more traditional assimilative techniques such as a simplified Extended Kalman Filter for other variables such as soil moisture (de Rosnay et al., 2013). This will become more viable as new instruments for measuring soil moisture from the SMOS and SMAP satellite missions come online and are directly assimilated into LDAS (e.g., LIS User's Manual). While difficulties with monitoring SWE remain, assimilation of the related variables of snow cover fraction from MODIS (Zhang et al., 2014) and terrestrial water storage from GRACE (Su et al., 2010) in an ensemble Kalman filter scheme has improved the simulation of SWE indirectly. However, progress has been slow as the application of traditional (atmospheric) data assimilation techniques for the land surface is complicated by the spatial variability and heterogeneities of surface parameters and because of the aforementioned issues with observations (Balsamo et al., 2014).

In summary, although not as advanced as data assimilation in operational atmospheric models, DA systems in other Earth system components are beginning to embrace ensemble-based or hybrid assimilation algorithms as a way forward. Results so far indicate that this is a promising direction because it allows for a combination of the advantages of the different approaches. Xu et al. (2014) show one such example for a land surface application, where a hybrid assimilation scheme is used to improve the assimilation of snow fraction information. Extending schemes such as this to generate coupled ensembles could help forecast the uncertainties and then be used to perform the data assimilation accordingly, either within a weakly or strongly coupled update step (see below). The use of an ensemble from coupled models would also significantly simplify the design and implementation of coupled background error covariances, which are needed for coupled assimilation. In other words, the data in one field can update the state in another field directly based on these coupled error covariance estimates.

As a final note, it is important to keep in mind that while advanced data techniques are generally able to extract information from observations, the process of data assimilation is fundamentally dependent on the observing system. A system that is under-observed will not yield accurate state estimates, further highlighting the need to maintain and enhance the observing system (Recommendation E) and to utilize quantitative methods (e.g., OSSEs) to do so.

Finding 5.9: In operational centers, the most advanced data assimilation techniques are usually implemented in atmospheric data assimilation. Other Earth system components are also moving towards ensemble Kalman filter-based or hybrid data assimilation algorithms, allowing for the possibility of seamless assimilation and/or synergy within a framework of coupled data assimilation.

Finding 5.10: Research activities in data assimilation schemes are occurring uniformly across fields, including for land, ocean, and ice applications, but also for engineering, applied mathematics, and other sciences. The potential of all of these multi-disciplinary advances cannot be underestimated, and several of these new schemes have potential for S2S applications.

Coupled Data Assimilation

Historically, many centers performed the assimilation of each of the Earth system components—atmosphere, ocean, land, sea ice—independently. But because the systems coevolve, such disconnected assimilations can compromise forecast skill. While this may not pose a problem for very long forecasts (annual to decadal), it can be a significant issue for S2S timescales, where initial conditions are still quite important. Advances include implementing a so-called "weakly coupled" assimilation, in which the background state (Figure 5.7) is computed from a freely evolving coupled model and then subsequently broken into parts that are needed for each component. Next, assimilation is done component-by-component (i.e., ocean, atmosphere, sea ice, and land analyses are quasi-independent). The various analyses are then stitched back together to initialize the coupled model and run the forecast. This is in contrast to the aforementioned uncoupled analyses, in which all steps in Figure 5.7 are integrated component-wise. NCEP's Climate Forecast System (v2) has already developed a weakly coupled system for both reanalysis (necessary for retrospective forecasts and calibration) and the generation of initial conditions for the real-time operational seasonal forecasts (Saha et al., 2010). Most other operational centers are moving in a similar direction, and many centers are adopting such a philosophy even for weather prediction (Hendrik Tolman, personal communication, April 22, 2015).

Weakly coupled assimilation also allows each possible Earth system component to determine its most appropriate assimilation scheme. The ECMWF OOPS (Object Oriented Programming System[32]) project and the United States JEDI (Joint Effort for Data Assimilation Integration; Tom Auligné, Personal Communication, February 5, 2016) project are examples of methods to potentially achieve such coupling in a convenient, efficient manner. Specific assimilation schemes for each component can also be employed in a strongly coupled framework, assuming connections across components are maintained within the assimilation step (this is discussed in more detail below).

A challenge for coupled assimilation is that the spatial and temporal scales of phenomena, errors, etc., are quite different among the various Earth system components. A direct practical effect of this is different assimilation update cycles employed in today's single-component assimilation systems (e.g., the time step in Figure 5.7). This is in large part a consequence of when and how often observations are available. For example, because of

[32]http://www.data-assimilation.net/Events/Year3/OOPS.pdf, accessed February 5, 2016.

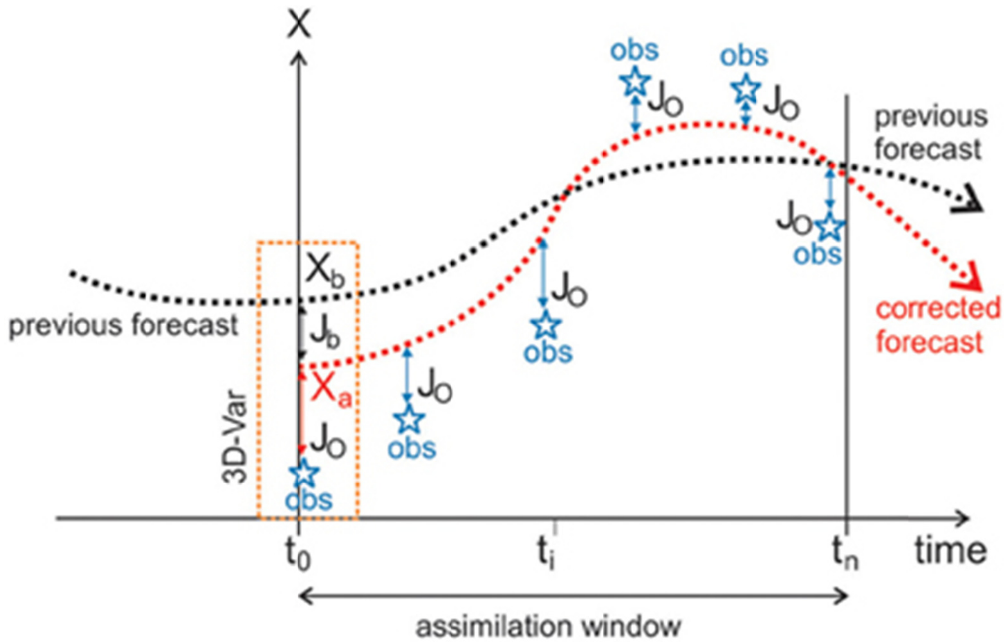


FIGURE 5.7 Schematic diagram illustrating 4D-Var data assimilation. Over the period of the assimilation window, 4D-Var is performed to assimilate the most recent observations (obs, marked as blue stars), using a segment of the previous forecast as the background (black dotted line—the background state, Xb). This updates the initial model trajectory for the subsequent forecast (red dotted line), using the analysis Xa as the initial condition. The yellow dotted box to the left identifies the special case of 3D-Var. Jo represents the misfit of the observations to the analysis trajectory and Jb represents the misfit between the analysis and original background at the initial time t0. SOURCE: Figure and caption adapted from Lahoz and Schneider (2014).

insufficient satellite coverage, most global ocean data assimilation systems utilize daily or week long assimilation windows on the order of days. This is infrequent relative to global atmospheric data assimilation systems in which more observations are available. These often use a 3hr, 6hr, or 12hr window and update cycle. Regional and coastal data assimilation, as well as submesoscale weather assimilation, can have even shorter windows (e.g., minutes to an hour) when observations are available. Considering all of these scales, some of the key questions are: What is the best way to combine the separate components into a single, streamlined algorithm? How can the error characteristics of the multiple scales and dynamics be efficiently represented for use in data assimilation? What are the most pressing needs within the context of future nonlinear, coupled data assimilation schemes?

A promising long-term solution is so-called "strongly coupled" data assimilation (e.g., Lu et al., 2015; Sluka et al., 2015; Smith et al., 2015b; Tardif et al., 2014). In strongly coupled data assimilation, observations within one component are allowed to directly and instantaneously impact the state estimate in other components (with constraints). Early attempts at performing strongly coupled data assimilation using an observing system simulation experiment (OSSE) for a relatively simple coupled-atmosphere-ocean system have shown promise (Sluka et al., 2015). The first set of experiments assimilated only atmospheric observations into the coupled model using weakly and strongly coupled assimilation configurations. Not too surprisingly for a configuration without assimilation of oceanic observations, the strongly coupled configuration

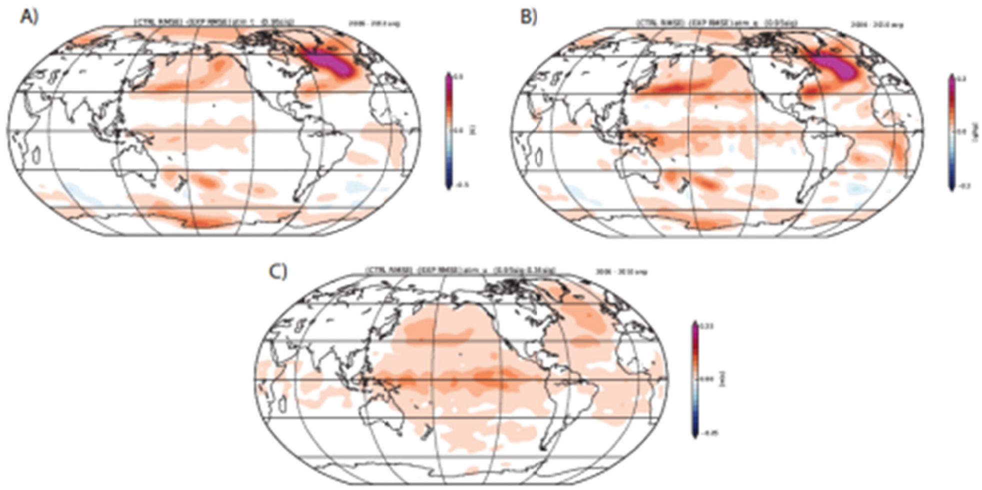


FIGURE 5.8 RMSE improvement of the atmosphere averaged over the last 5 years. Positive values (red) indicate STRONG performing better than WEAK. Fields shown are the temperature (a) and humidity (b) at the lowest model level, and zonal wind speed (c) throughout the troposphere. SOURCE: Sluka et al., 2015.

reduces the oceanic analysis root mean square error (RMSE). Perhaps more intriguing is the fact that the atmospheric analysis RMSE is also reduced within the strongly coupled configuration (Figure 5.8).

Given that weakly coupled assimilation systems have been successful thus far (Climate Forecast System Reanalysis/Climate Forecast System version 2 (CFSR/CFSv2), Saha et al., 2010; Saha et al., 2014), and that there are many computational complications to implementing strong coupling in today's operational systems, more research is needed to explore potential benefits of strongly coupled systems for operational S2S forecasting. First, techniques need to be developed to estimate and test coupled (cross-dynamics, cross-media, and cross-component) interactions (e.g., covariances) for Gaussian assimilation updates and their generalizations (e.g., mutual information) for nonlinear updates. Such estimation and verification of interactions are needed to avoid erroneous updates. Given the different spatial and temporal scales associated with observations in various components, it may not always be practical to allow some observations in one component to directly alter the fields in another component during each assimilation update: If the coupled covariances used in the direct coupled update are not accurate, observations of the ocean (perhaps observing a slow process) could, for example, erroneously update the lower atmosphere (faster processes). Theoretically, in the Gaussian assimilation update, if the covariances across components are represented with enough accuracy, such strong coupling will be successful. In nonlinear and non-Gaussian assimilation updates, covariances can be generalized to the mutual information between the field variables of the Earth system. A successful strong coupling would then require an accurate representation of such mutual information across the entire modeling system.

Multiscale data assimilation and multi-dynamics data assimilation also require more research to advance coupled data assimilation in S2S forecast systems. Ideally, observed information should be transferred across component boundaries in accord with multiple dynamics and scales, respecting dynamical causality and avoiding spurious correlations, for example due to ensemble-rank deficiencies or too approximate adjoint models. To address this issue, ensemble sizes would need to be increased or efficient reduced-order uncertainty prediction schemes employed (see below). Attention is especially needed for variational approaches, since adjoint equations derived for the coupled systems are not always the same as each component's adjoints stitched together, particularly when across-component fluxes (e.g., air-sea fluxes) are nonlinear. Similar issues apply to hybrid data assimilation schemes, as complex multiple dynamics (even within a single component of the Earth system) also need to be represented accurately in the coupled updates. Observations collected by the diverse observing system, which contain multiple dynamics and temporal and spatial scales, may also need special treatment. This might include the filtering of dynamics or scale filtering so as to remove the risk of spurious coupling before assimilation into S2S prediction systems. For example, in the ocean, short tidal scales are challenging to handle in global models, and internal tides and waves should not be assimilated as eddies. In conclusion, to be successful, strongly coupled data assimilation for S2S systems requires research in efficient methods, multiscale and coupled-dynamics assimilation updates, non-Gaussian nonlinear updates, and reduced-order stochastic schemes for efficient forecasting of coupled statistics.

Finding 5.11 While so-called weakly coupled assimilation has been successful for generating initial conditions for S2S prediction systems, there is potential for so-called strongly coupled assimilation to substantially improve state estimates for coupled systems. More research is needed to determine the benefits of strongly coupled systems.

Bayesian Data Assimilation, Reduced-order Uncertainty Quantification and Probabilistic Forecasting

As mentioned above, many data assimilation algorithms used in operational systems today are linear, based on linearizations, or based on varied heuristic hypotheses and ad hoc approximations. Most of these assumptions are related to the probability densities of the model state and its errors, and of the observations and their errors. For highly nonlinear dynamics or non-Gaussian relations, these assumptions may prove difficult to overcome. S2S dynamics are prime examples of multiscale, nonlinear dynamics, from turbulence to large-scale dynamics, across the multiple physical processes occurring in the Earth system. As a result, the field variables that describe the S2S dynamics (e.g., temperature, winds, currents, ice cover, etc.) can have complex intermittent behavior, with multiple scales and unstationary heterogeneous statistics. Furthermore, S2S prediction requires accurate forecasts of both the likelihood of specific events and of overall expected conditions over longer S2S lead times. Efficient reduced-order stochastic methods and Bayesian techniques can help address these issues of non-Gaussian relations, the former for the accurate forecast of probability densities (uncertainty quantification) and the latter for the rigorous combination of observations with these forecasts (Bayesian DA).

The importance of accounting for nonlinearities in geophysical DA has been known for some time (e.g., Miller et al., 1994). Nonlinearities affect the dynamical evolution, and as a result geophysical fields can be characterized by complex, far-from-Gaussian statistics (Dee and Da Silva, 2003; Lermusiaux et al., 2006; NRC, 1993). With the introduction of the ensemble Kalman filter (Evensen, 1994; Houtekamer and Mitchell, 1998), error subspace schemes (Lermusiaux and Robinson, 1999), square root filters (Tippett et al., 2003; Whitaker and Hamill, 2002), and Monte Carlo methods (Doucet et al., 2001) have grown rapidly within the atmospheric and oceanic DA community. In addition to utilizing the inherent nonlinearities of the governing equations, stochastic methods allow exploration and exploitation of probabilistic structures. Nonlinearities in general lead to non-Gaussian structures, which need to be used in the assimilation updates (Bocquet et al., 2010). This allows the use of mutual information in the coupled DA.

Nonlinear Non-Gaussian Data Assimilation

One class of non-Gaussian DA methods is particle filters (e.g., Ades and van Leeuwen, 2015; Pham, 2001; van Leeuwen, 2009), which evolve probability density functions (pdfs) using a discrete set of models states or particles. A related interest has been the approximation of distributions by Gaussian Mixture Models (e.g., Alspach and Sorenson, 1972; Anderson and Anderson, 1999; Bengtsson et al., 2003; Sondergaard and Lermusiaux, 2013b). An advantage of Gaussian Mixture Models (GMMs) is that they become equivalent to Gaussian schemes when a single component is found sufficient to describe the forecast pdfs but can represent more complex multi-modal pdfs by increasing and optimizing the number of components in the mixture. Such Bayesian DA methods could be further developed for the S2S system components and for strongly coupled DA. A critical need, then, is the efficient and accurate prediction of coupled pdfs, which is in the realm of uncertainty quantification.

Uncertainty Quantification and Probabilistic Forecasting

Probabilistic forecasting and the quantification of uncertainties are critical when systems are nonlinear and have uncertain terms in their governing equations or in their initial and boundary conditions (see also section below on Calibration, Verification, and Combination of S2S Forecasts). Ensemble predictions provide uncertainty estimates, but so far using only a relatively small number of forecasts. To address the resulting rank-deficiency, various localization approximations (Bengtsson et al., 2003; Lermusiaux, 2007) and useful heuristic arguments (Anderson and Anderson, 1999) have been used. However, just as the adjoint equations allow variational DA based on linearized partial differential equations (PDEs), there are now uncertainty propagation schemes that allow Bayesian DA using pdfs predicted based on nonlinear PDEs.

Stochastic model forecasts are feasible with numerical methods for stochastic PDEs (Kloeden and Platen, 1999; Xiu, 2010) including direct methods (Doucet et al., 2001) and polynomial chaos expansion and spectral methods (Ghanem and Spanos, 1991; Le Maître and Knio, 2010; Najm, 2009). These approaches can be categorized as either intrusive or non-intrusive, depending if they require modification within the numerical model itself or not. The non-intrusive Monte Carlo method (i.e., running an ensemble of simulations with or without random forcing) can provide the full statistics of the problem. However, such ensemble simulations have convergence rates usually proportional to the square root of the number of samples. The polynomial chaos expansion (Ghanem and Spanos, 1991; Li and Ghanem, 1998; Nouy, 2007; Xiu and Karniadakis, 2002) based on the theory by Wiener (e.g. Wiener, 1958) can represent and propagate large uncertainties through complex models. (For useful ocean applications, see Mattern et al. [2012] and Thacker et al. [2015; 2012]).

To account for the time-dependence of both the uncertainty and dynamics, generalized Karhunen-Loève expansion with time varying coefficients and basis functions have also been used (Lermusiaux, 2001; Lermusiaux and Robinson, 1999). Recently, dynamically orthogonal stochastic PDEs (Sapsis and Lermusiaux, 2009, 2012; Ueckermann et al., 2013) have been obtained. These reduced PDEs allow efficient probabilistic forecasts. Sondergaard and Lermusiaux (2013b, a) developed a Bayesian nonlinear filtering scheme that combines these reduced PDEs with Gaussian Mixture Models, showing advantages of respecting nonlinear ocean dynamics and preserving non-Gaussian statistics.

In summary, Bayesian DA and uncertainty quantification methods have shown significant promise to advance coupled DA and UQ, but continued research is needed to yield significant impacts within the context of realistic S2S coupled ocean, atmosphere, land, and ice applications. If new numerical modeling systems were to be developed or augmented, it would be essential to consider stochastic forcing, uncertainty quantification, observation models, and coupled DA schemes as part of their development for physical and numerical consistency. This is due to the advent of the above uncertainty forecasting and Bayesian inference methods that directly utilize the original coupled governing equations and their numerical schemes. Such integrated developments would thus be directly relevant to S2S applications, as they imply the integration and coupling of the S2S modeling components (atmosphere, land, sea, and ice) from the start.

Finding 5.12: Research on Bayesian data assimilation and uncertainty quantification has grown substantially in atmospheric and oceanic sciences and also across disciplines such as applied mathematics and engineering. These methods, which allow the optimal use of the full probabilistic information and utilize rigorous reduced-order differential equations, hold promise for integrating components of S2S prediction systems and for coupled data assimilation. This includes research in hybrid methods, multiscale and coupled-dynamics assimilation updates, Bayesian data assimilation, and rigorous reduced-order stochastic methods.

Importance of Reanalysis for Retrospective Forecasts, Validation, and Parameterization

Retrospective data assimilation with frozen variables, so-called “reanalysis,” plays a crucial role in providing initial conditions for retrospective forecasts and as validation datasets from which to perform verification and calibration (see also Combination, Calibration, Verification, and Optimization section below). Reanalyses also provide insights into model process shortcomings (see Models section below). Indeed for over 40 years, reanalysis datasets have led to improved understanding of the Earth system, prediction at longer lead times, and the diagnosis of extreme events and long-term trends. Having physically consistent datasets across Earth system components is vital for diagnosing, initializing, and validating S2S prediction systems, which are dependent on representing coupling in order to realize forecast skill. Despite their importance, global reanalyses are a huge undertaking, requiring a massive amount of staff time, computation time, and data.

There are a variety of global reanalysis efforts that have been carried out at many different prediction centers (e.g. www.reanalyses.org [accessed January 27, 2016]). These reanalyses have different motivations and goals (Dee et al., 2011; Ebita et al., 2011; Rienecker et al., 2011; Saha et al., 2010; Uppala et al., 2005). However, the advancement of modeling capabilities, coupled data assimilation techniques, and harvesting of additional historical observations continue to have potential to vastly improve reanalysis datasets, especially coupled reanalysis for S2S prediction. As an example, NCEP is planning for their next generation coupled reanalysis capability as part of the development of version 3 of their Climate Forecast System. The plan includes significant developments to aspects of the reanalysis system, including observations, modeling, assimilation (including coupled DA), and the addition of new components such as aerosols and waves. There are similar efforts elsewhere in the international community (Dee et al., 2014). While some of these efforts involve performing reanalyses through the satellite era, there are other efforts underway to recreate datasets for much longer time periods, such as the NOAA 20th century reanalysis (Compo et al., 2011), ERA CLIM (Stickler et al., 2014), and CLIM-2,[33] which will utilize the coupled data assimilation for climate reanalysis (Laloyaux et al., 2016).

While these reanalyses will provide physically consistent state estimates for the Earth system components that are part of the S2S systems, there is a disconnect between the retrospective initialization from these reanalysis datasets and the initialization of real-time forecasts. The real-time initializations generally evolve away from the frozen reanalysis systems due to the addition of new observations and/or improvements in the data assimilation itself. In other words, the real-time initialization evolves with advancements to avoid significant deterioration that could occur if the assimilation were to be kept frozen (i.e., instruments eventually disappear and are replaced with new observing platforms).

Finding 5.13: Reanalyses are critical for generating retrospective forecasts, for studying predictability, and for validating S2S forecasts. Continued investment in global reanalysis research and operational production will be important for advancing S2S predictive capabilities. Improving the temporal continuity and the frequency of reanalysis may be particularly beneficial.

Data Assimilation to Improve Cloud Representation

One difficult problem in atmospheric data assimilation involves the use of cloudy and precipitation-affected satellite radiances (Bauer et al., 2011; Errico et al., 2007). Currently, many centers ignore fields of view that are affected by clouds and precipitation (particularly for infrared radiances), only utilize the partially clear scenes, or assimilate so-called “cloud-cleared” radiances. Cloudy and precipitating radiances are particularly important as they help prescribe the state in areas of the globe undergoing disturbed conditions. Ignoring these observations leaves gaps in the most dynamic parts of the atmosphere, areas that are likely to have the largest error growth. Improving the use of observations in cloudy areas is a very active area of research amongst the operational NWP centers, with some progress being made over the past several years (European Centre for Medium-Range Weather Forecasting [ECMWF], UKMO, NCEP;

[33] http://www.ecmwf.int/en/research/projects/era-clim2, accessed February 5, 2016

Geer et al., 2014). Further advancing the use of such observations may be especially critical in the tropics, for example, in initializing the state of the MJO.

Along similar lines, only a tiny fraction of available satellite observations of the atmosphere (particularly infrared and radar observations) are actually assimilated into NWP models. While the assimilation of rain rate and precipitable water from TRMM and SSM/I has been successful for NWP (Benedetti et al., 2005; Treadon, 1996; Tsuyuki, 1997), data from space-based precipitation radars remain underutilized. Similar to cloud and precipitation-affected radiances, space-based radar is problematic for present data assimilation schemes due to nonlinearity and difficulty in forward simulation. Gaussian variable transform has the potential to improve the assimilation of precipitation data into NWP models (Lien et al, 2015), and further improvements may be possible through direct assimilation of dual-polarization reflectivities from the Global Precipitation Mission core (e.g., Hou et al., 2014, see also Observations section).

In sum, better atmospheric initializations in cloudy and precipitating areas is important for predicting the evolution of important S2S phenomena such as the MJO (e.g., Benedetti et al., 2005; Hou et al., 2014; Lien et al., 2015; Treadon, 1996; Tsuyuki, 1997; Vintzileos and Behringer, 2008), along with the potential for benefits in predicting soil moisture. Such improvements might also lead to better reanalyses, better cloud climatologies, and thus greater potential for exploration of sources of predictability.

Finding 5.14: Observations continue to be underutilized in atmospheric data assimilation, particularly satellite based microwave and infrared radiances over land and in cloudy/precipitating fields of view. Better utilization is important for filling in some of the data gaps over dynamically active regions, and also for characterizing the states and properties of cloud and precipitation-related processes, which will be essential to preparing for cloud-resolving capability.

Fully Exploiting Data Sets to Estimate Parameters and Parameterizations

In addition to being important for initializing models, data assimilation is a sophisticated means of using observational information for the estimation of uncertain model parameters (Bell et al., 2004; Evensen, 2009; Navon, 1998; Ruiz and Pulido, 2015; Smedstad and Obrien, 1991; Smith et al., 2013; Trudinger et al., 2008). Two particularly relevant recent studies have explored the use of data assimilation-based parameter estimation for coupled atmosphere-ocean models (Kondrashov et al., 2008; Zhang et al., 2015). Here, using inline parameter estimates significantly reduced model biases, even for variables such as deep ocean temperature and zonal ocean currents that had no observations assimilated to the model to constrain them directly. Parameter estimation has also been shown to be feasible for intermediate Earth system models (Annan et al., 2005). However, the challenges mentioned above for state estimation are similar or even more relevant for parameter estimation, due to intrinsic nonlinearity. More research is needed to extend the usefulness of DA for parameter estimation (e.g., Bocquet, 2012; Bocquet and Sakov, 2013). Data assimilation has also been used to estimate variables in the Earth system that are not well observed and/or may not have any a-priori information, such as surface carbon fluxes (Kang et al., 2012). Thus a bright research area is the use of data assimilation to rigorously discriminate among model formulations and parameterizations, which is critical for both scientific understanding and applications.

Finding 5.15: In addition to being useful for optimal state estimation, data assimilation can be an extremely powerful tool for performing parameter estimation and optimizing model performance, which may become critical for S2S applications. It is important that reanalysis datasets and diagnostics therein, such as analysis increment and innovation statistics, continue to be publically disseminated to assist in parameterization development and parameter estimation.

The Way Forward for Data Assimilation

Data assimilation is an essential part of S2S prediction systems and is critical for generating real-time initial conditions as well as the initial conditions for the retrospective forecasts (in the form of reanalysis). However, there are a number of issues in current DA that need to be resolved to improve S2S forecast systems. First, parts of the varied observing systems remain underutilized by current data assimilation techniques. Examples include the lack of assimilation of satellite information in cloudy and precipitation regions and the limited use of ocean observations collected by the increasing number of autonomous ocean platforms. More research is needed to comprehensively and effectively assimilate such measurements for S2S applications. Some of the challenges originate from the multiple spatial and temporal scales occurring within and across the components of the Earth system. Ideally, the multiscale and multi-dynamic information contained in the observations could be fully assimilated. Multiscale hybrid methods, coupled-covariance update algorithms, and nonlinear non-Gaussian schemes show promise for addressing these challenges, but need research to mature.

Second, given that S2S predictions will continue to rely on coupled Earth system models, coupled data assimilation will remain at the forefront of S2S research and operational innovations. However, S2S-specific challenges for coupled data assimilation originate from practical, computational, methodological, and dynamical hurdles, all of which need to be overcome. For example, most operational centers continue to face inconsistencies that result from independent or quasi-independent state estimates being pieced together in uncoupled or weakly-coupled assimilation systems. Overcoming such limitations will become ever more important as S2S prediction systems become more complex (i.e., adding new components such as aerosols and surface waves). Instead of being ignored, the complex but known dynamical inter-connections and the corresponding coupled covariances or mutual information should be exploited. If the coupling is correct, it is likely to increase accuracy of S2S forecasts. To allow such immediate impact of observations from one component to another, and across varied dynamics, efficient strongly coupled assimilation schemes are needed. The potential of the first strongly coupled algorithms has already recently been demonstrated for simple coupled models with 4DVAR (Smith et al., 2015a) and EnKF schemes (e.g., Sluka et al., 2015). However, strongly coupled assimilation schemes are in their infancy and have not yet been tested on more complex S2S coupled systems. Thus practical and computational research is needed, in part to assess the potential value added by moving to strongly coupled data assimilation schemes, and also to establish whether implementing strong coupling is worth the added cost and complexity to operational S2S systems. Methodological and dynamical research is also needed, especially to employ and improve assimilation methods that exploit the coupled dynamics to perform multiscale and coupled assimilation updates.

Third, data assimilation, uncertainty quantification, and probabilistic prediction methods are critical for S2S forecasting, but are today often characterized by heuristics and approximations that are employed for computational expedience more than accuracy. Needs in this area include efficient stochastic schemes to forecast the coupled statistics and coupled Bayesian data assimilation updates to fully utilize the coupled statistics. Novel uncertainty quantification schemes and reduced-order stochastic methods that efficiently integrate the governing stochastic partial differential equations are being developed and may in the future represent possible further avenues for improvement of S2S forecast systems. These could replace computationally expensive direct Monte-Carlo S2S ensemble predictions (i.e., the integration of a number of model simulations with different initial conditions, boundary conditions, and stochastic forcing). Research on Bayesian data assimilation has also grown recently in atmospheric and oceanic sciences, as well as across disciplines such as applied mathematics and engineering. These methods, which allow the optimal use of the full probabilistic information and utilize rigorous reduced-order differential equations, should also be considered for implementation in the components of S2S prediction systems.

Finally, as the complexity of coupled Earth system models grows, an increasing number of model and coupling parameters will need to be explored and specified. At present, this is done too often through trial and error. This could eventually become unsustainable due to the ever-growing complexity and computational cost. Hence, the most sensitive and important model parameters should be identified for the next generation of coupled prediction models. Being informed by observations from all components, data assimilation can identify and optimize these parameters and also discriminate among and learn the better parameterizations. As a whole, novel parameter estimation and model learning schemes are promising and critical for S2S applications.

Recommendation G: Invest in research that advances the development of strongly coupled data assimilation and quantifies the impact of such advances on operational S2S forecast systems.

Specifically:

- Continue to test and develop weakly coupled systems as operationally viable systems and as benchmarks for strongly coupled implementations.
- Further develop and evaluate hybrid assimilation methods, multiscale- and coupled-covariance update algorithms, non-Gaussian nonlinear assimilation, and rigorous reduced-order stochastic modeling.
- Optimize the use of observations collected for the ocean, land surface, and sea ice components, in part through coupled-covariances and mutual information algorithms, and through autonomous adaptive sampling and observation targeting schemes.
- Further develop the joint estimation of coupled states and parameters, as well as quantitative methods that discriminate among, and learn, parameterizations.
- Develop methods and systems to fully utilize relevant satellite and in situ atmospheric information, especially for cloudy and precipitating conditions.
- Foster interactions among the growing number of science and engineering communities involved in data assimilation, Bayesian inference, and uncertainty quantification.

MODELS

Central to improving S2S predictions is improving the quality of the models that are at the core of modern state-of-the-art prediction systems. In this section, the Committee provides evidence to support the conclusion that reducing errors and biases in Earth system models must be a top priority for improving coupled S2S prediction systems. We first discuss in general terms model errors and the steps that need to be taken to reduce them. For convenience, issues more specific to advancing models of the atmosphere, ocean, land surface, and sea ice are discussed in separate subsections, although of course it needs to be recognized that the full problem is inherently a coupled one. Another subsection highlights the importance of process studies for model improvement. The Committee concludes with a subsection that contains recommendations for priority research to reduce model errors in order to increase the skill of S2S predictions.

Model Errors

One of the key challenges for S2S prediction is the reduction of model errors. Model errors include two types of deviations from observations, both of which contribute to the deterioration of S2S forecast skill:

1. Deviations that are highly variable in time, which make the predicted variability unrealistic;
2. Deviations from observations that are persistent in time, which make the predicted mean state unrealistic—these are often referred to as model biases.

Improving model skill through techniques such as statistical correction using retrospective forecasts, and combining outputs of different models to create multimodel ensemble products (see section below on Combination, Calibration, Verification, and Optimization), clearly enhance forecast skill and will remain an important part of the S2S prediction process for the foreseeable future. However, model errors can be large compared to the predictable signals of variability targeted by S2S forecasts, and can also combine non-linearly, making statistical post-processing very difficult. Furthermore, without reduction of model errors, all other steps taken to improve S2S prediction systems can only shorten the distance between the current skill and the model-estimated limit of predictability (see Chapter 4), whereas reducing model errors can bring the skill of S2S forecast systems substantially closer to fundamental limits of predictability within the Earth system.

Known errors in Earth system models are numerous. For example, many global models produce an unrealistically strong Pacific equatorial cold tongue, a spurious double Inter Tropical Convergence Zone (ITCZ), erroneously high Indian Ocean and tropical South Atlantic SSTs, low SSTs in the tropical North Atlantic, and wet or dry biases in rainfall in many parts of the world (e.g., Hirota et al., 2011; Li and Xie, 2014; Richter et al., 2012; Roehrig et al., 2013; Toniazzo and Woolnough, 2014). Many climate models also have a large bias in MJO variance (Hung et al., 2013). Improving models' ability represent processes such as the MJO and ENSO—critical sources of S2S predictability (see Chapter 4)—includes not only improving the representation of means and variances of such phenomena, but also their evolution and associated global teleconnection patterns. For example, it is possible for a model to have little bias in the mean and variance of both conditions in the tropics and middle latitudes, yet the variability in these two regions may not be correctly linked. Such a connection contributes to subseasonal forecast skill in both regions (e.g., Lin et al., 2010; Vitart and Jung, 2010).

Many of the same modeling errors relevant to S2S predictions are relevant to shorter and longer range forecasts. Figure 5.9 shows an example of the growth of SST errors in coupled model simulations. It is clear that many features of climate model errors are seen in forecasts of only a few weeks or even days in length (e.g., cold equatorial Pacific, generally warm Indian Ocean, and cold Arabian Sea), and that some of the errors are quite substantial on S2S timescales. Efforts targeted at understanding and alleviating these errors are thus relevant for improving predictions on multiple timescales (NRC, 2012b). The use of observational and short-term error information has been used to identifying biases in climate models, for example through the Department of Energy Cloud-Associated Parameterizations Testbed Program.[34] Similarly, many issues are common across multiple modeling systems. For example, the strength of MJO-NAO teleconnections is deficient in subseasonal and seasonal simulations of many different operational models (Scaife et al., 2014a; Vitart et al., 2014).

Model errors often have no single cause but arise from combined deficiencies in model representations of many important processes (e.g., clouds, microphysics, radiation, boundary-layer processes, surface fluxes, and ocean mixing). Reducing these errors will require improving the representation of processes that are, for the most part, already included in models used for S2S prediction (e.g., increasing model resolution to explicitly represent critical processes and improving parameterization schemes to better represent subgrid processes—see discussions below for more details). In some cases, extra complexity needs to be added to better represent feedbacks between different components of the Earth system (e.g., coupled ocean-atmosphere, ice-atmosphere and land-atmosphere processes—discussed in more detail below). As described elsewhere in this report, an improved representation of additional variables (e.g., algal blooms, river levels, etc.) may also be crucial because these variables are important to decision makers, whether or not their evolution feeds back on other components of the Earth system.

Finding 5.16: Errors in current modeling systems are a major limiting factor in the skill of S2S predictions. Many of the issues are common across different modeling systems and a broad range of timescales (days to centuries). These errors are the result of multiple deficiencies in model representations of key processes that are currently parameterized.

Atmospheric Models

Several steps are essential to improve the atmospheric component of S2S forecast systems. These include increasing model resolution to explicitly represent important atmospheric processes, improving parameterizations of processes that remain unresolved, improving the representation of tropical convection, and enabling global cloud-permitting models. Each is discussed in detail below.

[34] http://www-pcmdi.llnl.gov/projects/capt, accessed January 27, 2016.

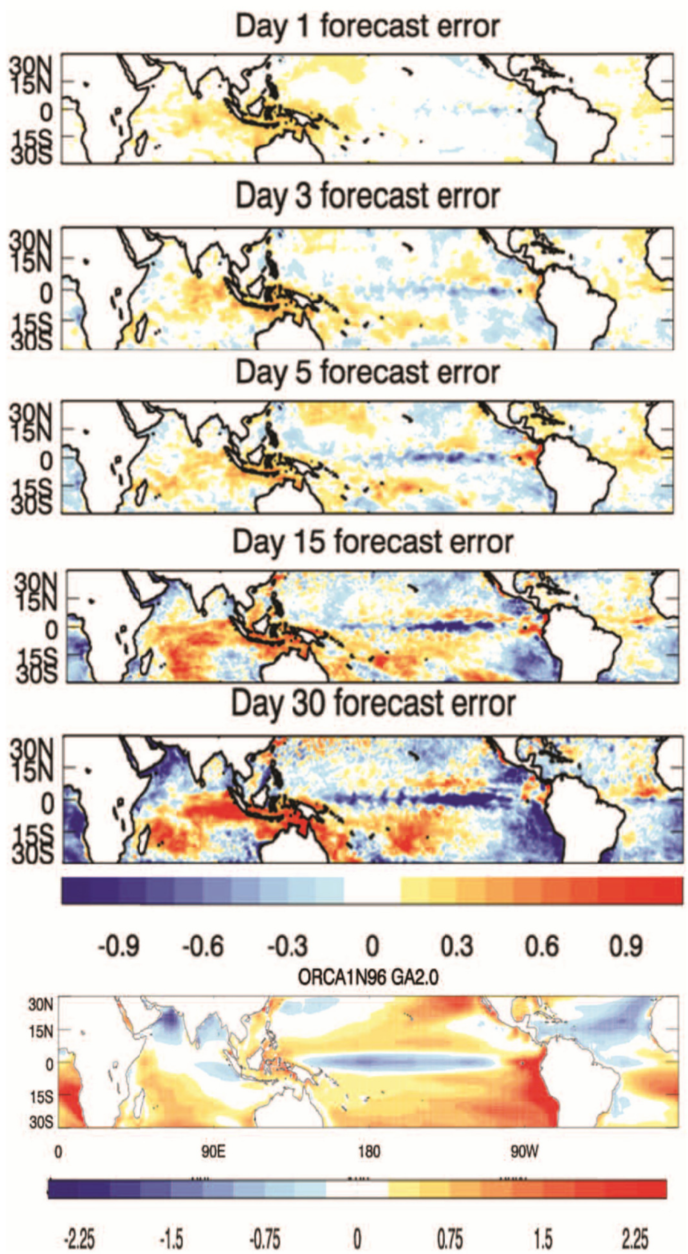


FIGURE 5.9 The drift in coupled model SST as a function of forecast lead time out to 30 days. The bias in a 20-year run from a version (GA2.0) of HadGEM3-AO climate coupled model is shown in the bottom panel. SOURCE: Brown et al. (2012).

Increasing Model Resolution

Increasing model resolution (horizontal and vertical) can reduce model errors, as more processes are explicitly resolved, and there is accordingly less reliance on uncertain physical parametrizations (Kinter et al., 2013). Later in this chapter, the Committee discusses the extreme case where the resolution is increased so significantly that deep convection becomes resolved. However, as discussed there and in Chapter 7, while an exciting research avenue, it is unknown whether this approach will be operationally viable in the coming decade due to the large computational costs involved. Recent work has shown that more modest increases in atmospheric model resolution may bring significant benefits. Examples include increasing horizontal resolutions to better resolve the land-sea distribution in the Maritime Continent (Crueger et al., 2013), where the MJO in models exhibits more difficulty propagating eastward than over the open oceans (Inness and Slingo, 2006; Weaver et al., 2011) ; increasing vertical resolution in the atmosphere to better represent the stratosphere (e.g., Roff et al., 2011; Scaife et al, 2011), which is increasingly recognized as a source of predictability on S2S timescales (see Chapter 4); increasing vertical resolution of the upper ocean to better resolve the diurnal cycle of the mixed layer that interacts with the atmosphere, leading to improved MJO simulations (Tseng et al., 2015); and increasing horizontal resolution to improve representation of blocking and the Annular Modes (Jung et al., 2012; Kinter et al., 2013; Palipane et al., 2013; Scaife et al., 2011). Further work to investigate what can be achieved by increasing resolution in the atmosphere is important, and coordinating such work with research on benefits of simultaneous increases in resolution across other components in a coupled model framework may be particularly important for S2S prediction (NOAA, 2015). However, it is already clear from existing work that increasing resolution in atmospheric models alone is not a panacea for increasing forecast skill in the current generation of models. Improvement of parameterizations will still be needed for substantial enhancement of S2S forecast skill (e.g., Jung et al., 2012; Vitart 2014).

Finding 5.17: There is evidence that increasing the resolution of atmospheric models (while still at resolutions that need deep convection parameterization) may improve the representation of processes that are key sources of S2S predictability. However increasing resolution is far from a panacea without also improving physical parameterizations.

Improving Parameterizations

There are very significant uncertainties with parameterizations of many physical processes in the atmosphere that are not currently resolved by models (e.g., boundary layer, convection, clouds and microphysics, radiation, surface fluxes, land surface and watershed scale processes, gravity wave drag). These uncertainties are in large part responsible for the model errors, which (as previously discussed) are a major limiting factor in the quality of S2S predictions. For example, leading NWP centers are taking very different approaches to the parameterization of drag on unresolved mountains (Figure 5.10). While in practice there is considerable compensation such that parameterizations with weak mountain drag tend to have higher boundary layer drag (and vice versa), these different balances cannot all be correct. Such differences matter with regard to the representation of large-scale circulation, and this situation is illustrative of the general uncertainties in the field of parameterization.

Recent experience at many operational centers has indicated that improvement in physical parameterization typically leads to improvements in features more obviously of relevance for S2S (Vitart, 2014). As an example, improved entrainment in the cumulus parameterization of the ECMWF model has led to better representation of the MJO (Hirons et al., 2013). Improving parameterization requires advanced understanding of the physical processes at play, which involves research on theory, targeted field observations, and the use of cloud-resolving or cloud-permitting models as tools. Further examples of such efforts and additional steps needed to improve parameterizations across atmosphere, ocean, land surface,

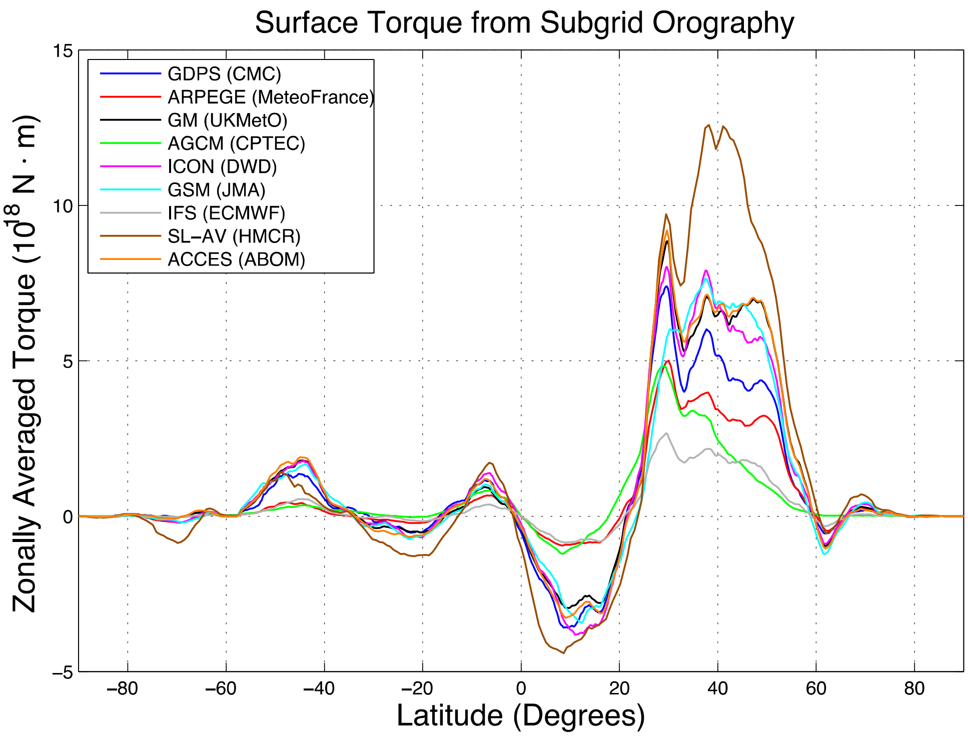


FIGURE 5.10 Zonally averaged subgrid orographic torque from a number of global NWP models for January 2012. SOURCE: Ayrton Zadra.

and sea ice models are provided below in the subsection on Process Studies for Model Advancement.

Finding 5.18: Improving physical parameterizations is essential to reducing model errors. The primary barriers are incomplete understanding of real physical processes and the challenges associated with encapsulating new knowledge of how the real atmosphere works in multiple and interacting model parameterizations.

Improving the Representation of Tropical Convection

There are important challenges associated with almost all aspects of atmospheric model physics, as described above. However, one particular issue of great importance for the quality of S2S predictions (both in the tropics and beyond) is fidelity of the representation of tropical convection in the atmosphere (e.g., Holloway et al., 2014; Sherwood et al., 2014). Tropical convection is crucial to propagating teleconnections between the tropics and mid-latitudes—associated with ENSO on the seasonal timescale and with the MJO on the subseasonal timescale (Chapter 4).

One important approach to improving the representation of tropical convection is to continue to develop and improve upon traditional parameterizations. Progress in recent years includes increasing the sensitivity of models to environmental moisture, including convective momentum transport, incorporating at least some representation of convective organization (particularly at the mesoscale), treating convection as a stochastic process, and including nonlocal effects in cumulus parameterization. Work to improve upon traditional parameterizations needs to continue; however, a more focused effort to develop completely new schemes may be especially valuable (Holloway et al., 2013). The time may be ripe for such efforts, as results from recent field campaigns continue to increase the understanding of convection and its interaction with other processes, and scientists are beginning to have access to high-resolution cloud-permitting simulations across large (e.g., Marsham et al., 2013) and even global domains (Satoh et al., 2012). Such high resolution numerical simulations were, for example, used as part of the recent international Year of Tropical Convection (YOTC—see Appendix C for more detail) program (Moncrieff et al., 2012; Waliser et al., 2012) and provide an invaluable testbed for developing understanding and approaches to be used in coarser resolution models, while also spearheading efforts to demonstrate a prototype of future, cloud-resolving S2S model systems (see also discussion below).

One intermediate step to improve cumulus parameterization within the limit of available computing capability is "super-parameterization" or multi-scale modeling (Khairoutdinov and Randall, 2001; Randall et al., 2013). In this approach, a 2-D cloud-resolving model at each grid point of the host model replaces a traditional parameterization in order to explicitly represent deep convection. This approach demands much less computational resources than a full 3-D global cloud-permitting model, although it still suffers (as do many traditional parameterizations) from the fact that it is local, e.g., without direct interaction between convection at neighboring host model grid cells. Sensitivities to other parameterizations (e.g., turbulence and microphysics) also remain. Nevertheless, there is evidence that the super-parameterization approach, by virtue of representing tropical convection more accurately than conventional parameterizations, produces superior simulations and predictions when coupled to an active ocean model (DeMott et al., 2011; Stan et al., 2010). The approach has led to important improvements, notably, in simulations of the MJO (Benedict and Randall, 2009) and diurnal cycle in rainfall (Pritchard and Somerville, 2009). Its feasibility to incorporate into operational models is worthy of further investigation.

Finding 5.19: Improving the representation of tropical convection is a particularly important challenge for S2S. Continued efforts to develop new convection parameterizations and to build on recent progress in multi-scale modeling and scale-aware parameterization are needed.

Enabling Global Cloud-Permitting Models

In a cloud-permitting model, the grid spacing is fine enough (a few kilometers or less) that deep convection is explicitly calculated without the need of parameterization. Work to move atmospheric models towards cloud-permitting capacity is motivated by the notion that behavior of deep convection can be adequately determined only when mesoscale dynamics governing convective structure and evolution are explicitly represented. Simulations by the first global cloud-permitting model have led to improved representation of important S2S processes such as the MJO (Miura et al., 2007), tropical cyclones (Fudeyasu et al., 2008), Asian summer monsoon (Oouchi et al., 2009), and the diurnal cycle of rainfall (Sato et al., 2009), among other phenomena. Although such improvements suggest that the development and use of global cloud-permitting models in operational settings should continue to be pursued, a number of important caveats to this approach need to be noted. The first is that while parameterization of deep convection would no longer be needed, parameterization of shallow convection, turbulence, radiation, cloud microphysics, and surface fluxes would all still be required. Without deep convection parameterization, deficiencies in schemes for those processes would still lead to model errors (which might be different from those in coarser resolution models). Hence research to further improve parameterization schemes will remain crucial, even with global cloud-permitting capacity. Also, the huge computational demand that would be required to make global cloud-permitting models operational for S2S is a currently a crucial limitation. For example, upgrading a model from a resolution of 60 km to 2 km would require the computational power to increase by well over a factor of ~1,000 (i.e., 30x30) for the horizontal resolution alone. A further factor of around 30 would be required to allow for desired decreases in time step and finer vertical resolution. Overall, this means increasing computation power by at least four orders of magnitude. Realistically, this will not be achieved in the next decade, based on the current trajectory of advancement in computing technology (see Chapter 7).

Caveats aside, there are many good reasons to pursue global cloud-permitting modeling in research mode. Such research will show the way for operational developments beyond the 10-year horizon and could yield significant insights and improvements to operational models with parameterized convection within 10 years. For example, predictability studies with cloud-permitting models might give different indications from coarse-resolution models of what improvements in S2S forecast skill could be possible. Furthermore, as mentioned above, detailed high-resolution synthetic datasets from these cloud-permitting research models (global, or at least large domain) will continue to provide critical insights into real atmospheric processes, as well as a testbed against which new parameterizations for operational systems can be developed and evaluated. Lastly, even if it is unlikely that global cloud-permitting models would become operational in the next decade, it could be of great benefit for the S2S research community to develop cloud-permitting research models if an unexpected revolution in computing industry allowed operational cloud-permitting models to move forward.

An alternative hybrid approach worthy of consideration is adaptive meshes, which focus high resolutions only in some areas (e.g., Chen et al., 2013 for hurricanes). Its justification comes from the fact that in many areas of the world, cloud-permitting resolution is not needed (e.g., in deserts, subtropical highs, and polar areas where deep convection is very unlikely to occur). Utilizing cloud-permitting meshes only when and where deep convection occurs would benefit computational efficiency, and this approach is becoming more feasible as scale-aware cumulus parameterization schemes are also being developed (e.g., Arakawa and Wu, 2013; Grell and Freitas, 2014).

Finding 5.20: Continued development of global cloud-permitting models is needed to provide insights for improving coarser-resolution operational models, to offer research testbeds for understanding many issues relevant to S2S prediction, and to advance prototypes for future cloud-permitting S2S model systems. Improved model equations as well as improved numerics with adaptive meshes and higher-order schemes could serve as an important alternative or an intermediate approach before global cloud-permitting models become feasible for operations.

Ocean Models

The ocean is often described as the flywheel of the Earth's climate (Visbeck et al., 2003), where the ocean's large heat capacity (2.5 m of water contains as much thermal energy as the entire atmospheric column) acts as stabilizer. Outside of the tropics, the ocean has traditionally been described as reacting to high-frequency changes of the atmospheric forcing and that its influence back to the atmosphere is weak on short timescales (Kushnir et al., 2002). However, one needs to distinguish between applications that are sensitive to slowly evolving boundary conditions (e.g., NAO, ENSO, etc.) and ones that are sensitive to rapidly evolving boundary conditions (diurnal cycle impact on MJOs, convection, severe weather, etc.). Ocean numerical models are often designed to be optimal for a specific application (global, coastal, ENSO, etc.) and do not perform equally everywhere. It is therefore important to fully understand the implications of the numerical and physical choices that were made when the model was developed in order to correctly interpret the model outputs (e.g., Griffies et al., 2000).

In this section, ocean models, their application to S2S forecast systems, and their current strengths and limitations are described. Broadly speaking, many of the issues are similar to those outlined above in the atmospheric models section, including the importance of improving parameterizations of subgrid processes, while also exploring the benefits and trade-offs of increasing ocean model resolutions.

Established Ocean Models

Most existing ocean models are community models and are used extensively for a wide range of global, basin-scale, and regional simulations, with timescales ranging from hours to millennia for both operational forecasting (see GODAE, 2015 for a review) and research (e.g., Hecht and Hasumi, 2013). Most models solve similar geophysical fluid equations and use related finite-difference or structured mesh finite-volume numerics. These have all evolved from the pioneering work of Bryan (1969) and others (e.g., Bryan and Cox, 1968; Semtner, 1995)

Substantial improvements that are typical of more modern models include the use of higher order and monotonic tracer advection schemes, the replacement of a rigid lid with a split time stepping scheme that directly models the adjustment of the free surface via external gravity waves, and more accurate representations of bathymetry. Significant effort has also gone into the selection of the vertical coordinate. This can have a large impact on the quality of a simulation, with geopotential-height-, terrain-following-, or density-coordinates, or hybrids between these options being common choices (Griffies et al., 2000). Algorithmic simplicity, interactions between the ocean flow and topography, water mass preservation, and the representation of dense gravity currents are all factors that have been used in choosing the right vertical coordinate for a particular ocean modeling application. Such mature, horizontally-structured-mesh ocean models will be the basis for global operational S2S forecasting systems for the foreseeable future, even as they continue to be incrementally improved. But it is clear that unstructured-mesh ocean models with higher order numerics have a lot of potential for S2S forecasts as discussed below.

Finding 5.21: Horizontally-structured-mesh ocean models will continue to be the basis for most operational coupled S2S forecasting systems for the foreseeable future.

Ocean Eddies, Model Resolution, and Subgrid Processes

The current resolution of horizontally-structured-mesh ocean models ranges from coarser-mesh, non-eddying (e.g., below the resolution required to resolve large scale eddies) resolutions for climate simulations (~1º), to finer-mesh, eddying models (~1/10º or 7 km at mid-latitudes). Most of the impetus for integrating high-resolution eddying models in global numerical simulations comes from the need by navies throughout the world for advanced global ocean nowcasting/forecasting systems (in the United States, the resolution will be increased in 2017 to 1/25º (~3.5 km at mid-latitudes); Chassignet et al., 2014; Metzger et al., 2014). Of course, for many ocean-related applications on S2S timescales, such as oil spill modeling (e.g., Deep Water Horizon) and fisheries/algal bloom prediction, higher resolution ocean models are necessary. While there is a demonstrated need for fine resolution ocean prediction systems for predicting oceanic variables outside the naval context (GODAE, 2009), the question arises as to whether explicitly resolving ocean eddies matters to coupling with the atmosphere and therefore to S2S atmospheric forecasts. In a recent comparison of coupled simulations with high and low resolution ocean numerical models, the correlation between SST anomalies and the surface heat flux was found to be small outside the tropics for the low resolution experiments, indicating that the atmospheric forcing of SST variability is predominant at that resolution (Kirtman et al., 2012). On the other hand, the high-resolution (1/10º horizontal resolution, i.e., eddying regime) simulation showed high correlations in regions of enhanced SST variability, such as western boundary currents and the Antarctic Circumpolar Current. This suggests that the atmosphere actually responds to the oceanic variability in areas of high SST variability and that higher model resolution is needed to improve atmospheric as well as ocean predictions.

There is also evidence that small-scale heat-content anomalies are more strongly and extensively correlated with precipitation in coupled model simulations with an eddy-resolving ocean, suggesting a mechanism whereby internally driven ocean variability may influence the deep atmosphere. For example, Bryan et al. (2010) show that characteristics of frontal scale ocean-atmosphere interaction, such as the positive correlation between SST and surface wind stress, are realistically captured only when the ocean model component explicitly resolves the ocean eddies. Griffies et al. (2015) further show the importance of transient mesoscale eddies on the ocean heat budget, providing an additional argument for either explicitly including eddies in coupled model simulations, or for employing parameterizations that faithfully reflect the role of eddies in both lateral and vertical heat transport. Submesoscale SST gradients may also be important loci for coupling to the atmosphere (Back and Bretherton, 2009; Li and Carbone, 2012; Smith, 2013).

Oceanic eddies exhibit a wide range of spatial scales, from large rings that detach from western boundary currents via mixed barotropic and baroclinic instabilities (Gulf Stream, Kuroshio, Agulhas, North Brazil, Gulf of Mexico Loop Current, etc.); to baroclinic eddies whose slumping effects need to be accounted for in order to correctly model the transports of water masses (e.g., Gent, 2011) and the dynamics and structure of major current systems like the Antarctic Circumpolar Current (e.g., Farneti et al., 2010; Hallberg and Gnanadesikan, 2006); to the sub-mesoscale eddies with horizontal scales of order of a kilometer that drive the frontal restratification of the surface mixed layer (e.g., Fox-Kemper et al., 2008). All of these oceanic eddies have effects that need to be represented in skillful ocean forecast systems, either by explicitly resolving them or through parameterization. The large meanders and rings are readily captured in ocean models with resolutions on the order of 1/4° or finer, while submesoscale eddies are characterized by spatial scales of less than a kilometer and need to be parameterized in essentially all large-scale ocean models (Fox-Kemper et al., 2011). Baroclinic eddies pose a particular challenge, as the dominant length-scale of these eddies (the first baroclinic deformation radius) varies greatly with latitude, stratification, and ocean depth. As shown in Figure 5.9, global numerical ocean models with spatial resolutions ranging from 1° down to just a few kilometers include both regions where the dominant baroclinic eddy scales are well resolved and regions where the model's resolution is too coarse for the eddies to form. Due to the relative spatial scales of these eddies and the mean state upon which they operate, commonly used baroclinic eddy parameterizations (e.g., Gent et al., 1995) are more effective at suppressing eddy variability than they are at replicating their effects on the mean state (Hallberg, 2013). Consequently, it is usually preferable to allow a model to explicitly simulate oceanic eddies rather than parameterize them, wherever the resolution permits this. Essentially all global ocean forecast models for the next 10 years and beyond will be operating within the resolution range where baroclinic eddies can be explicitly represented in most of the domain, but still have to be parameterized on the shelf and at high latitudes (Figure 5.11). Additional research is thus required to determine how best to parameterize the effects of ocean eddies where they are not resolved and how to transition between areas where eddies are resolved and where they are parameterized (see the CLIVAR Exchanges (2014) Special issue on "High Resolution Ocean Climate Modeling" for a discussion). Other subgrid processes also need to be taken into account for S2S prediction. Several National Science Foundation (NSF)/NOAA-sponsored Climate Process Teams (CPTs)[35]—e.g. groups of scientists who have worked together to improve parameterizations of particular processes—have developed parameterizations of internal tides and surface wave-induced mixing, but these need to be evaluated.

Finding 5.22: Subgrid ocean processes, including eddies, internal tides, and surface wave-induced mixing, need to be more explicitly resolved or better parameterized in ocean models used in S2S forecast systems, and their impact on S2S forecasts need to be better evaluated.

Multi-Scale Ocean Modeling

For improved S2S applications, instead of a uniform increase in resolution, one approach that may be more affordable computationally would be to increase the ocean horizontal resolution in targeted geographical areas that have a strong dynamical impact on the system, i.e., tropics, coastal regions, etc. This would improve the representation of energetic motions and exchanges that occur in regions with complex geometry and/or dynamics and that have been found significant for larger-scale regional and global ocean dynamics.

Two approaches may allow for optimized refinements in areas with larger dynamical gradients, near steep topography, or around complex coastlines. Nesting uses finer modeling grids in targeted regions, while unstructured grids increase the mesh resolution progressively where needed within the same modeling framework. New techniques that use different equations depending on the space and timescales are also very promising. This would allow for the explicit representation of, for example, small rivers, surface waves, internal waves/tides, nonhydrostatic effects, ecosystem structure, localized hypoxia, or leads in sea ice. All of these approaches are

[35] http://www.usclivar.org/climate-process-teams, accessed January 27, 2016.

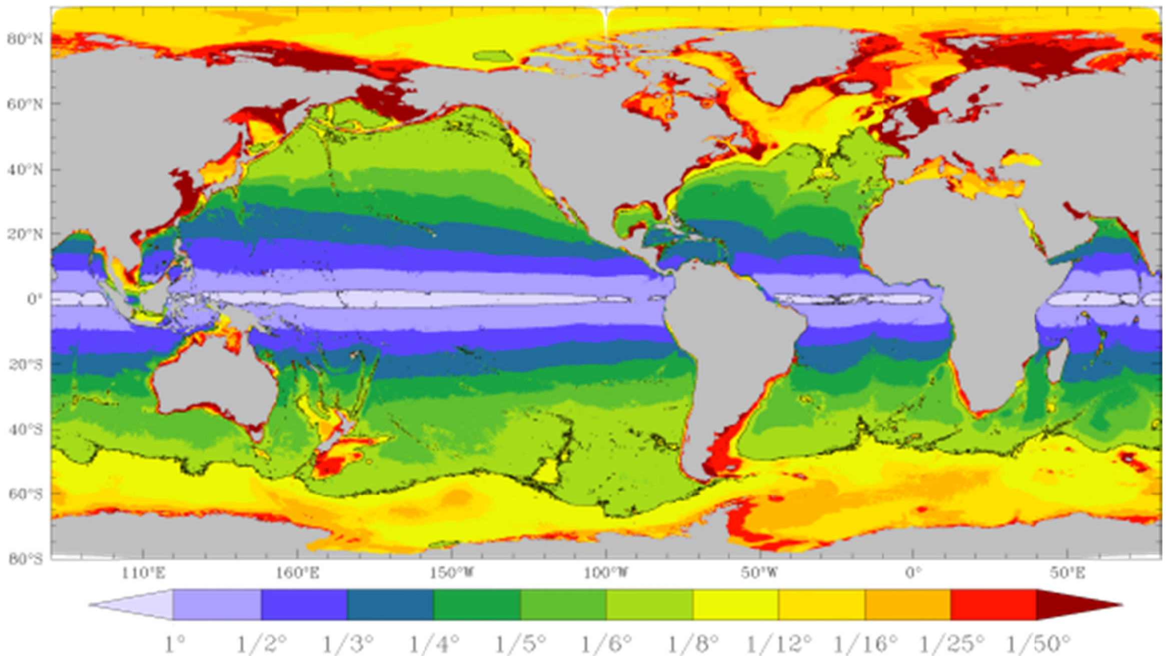


FIGURE 5.11: The horizontal resolution needed to resolve the ocean's first baroclinic deformation radius with two grid points, based on a 1/8° global ocean model on a Mercator grid with a bipolar Arctic cap north of 65°N. SOURCE: Adapted from Hallberg, 2013.

areas of active research in the multiscale ocean modeling community, but for the most part they not yet ready for immediate deployment in operational S2S forecasting systems.

However, these approaches are already starting to play an important role in targeted regional applications (e.g., Chen et al., 2011). Research into these and related approaches for improving fundamental and operational ocean modeling are a crucial part of the S2S decadal research agenda. Since development of robust numerical modeling systems takes time, strengthening research in the United States now will be required to reap potential operational benefits in the next decade and further.

Finding 5.23: There is potential benefit for including multi-resolution approaches (adaptive mesh refinement, seamless two-way nesting, multi-dynamics, adaptive super-parameterizations, etc.) in the ocean components of S2S coupled prediction models.

Parameterization of surface waves effects

There is a growing recognition that accurate modeling of the upper ocean boundary layer needs to take into account the impact of surface gravity waves. Surface waves induce Stokes drift, radiation stresses due to horizontal gradients of the momentum flux, enhanced vertical mixing due to Langmuir turbulence, and enhancement of bottom drag in shallow water. Most ocean models do not have the vertical resolution to take these effects into account and they need to be parameterized for an accurate representation of these effects. In particular, Langmuir turbulence can reach the base of the mixed layer and drive entrainment (Harcourt, 2015; Li et al., 1995). Wave-driven parameterizations have been implemented and tested for use in climate modeling (see Li et al., 2015 for an example) and have been shown to improve mixed layer representation. Furthermore, since air-sea fluxes depend not only on the conditions in the atmosphere, but also on processes in the upper boundary layer and mixed layer as well as the sea state (Chen et al., 2007), surface wave effects need to be taken into account for S2S prediction, as do tidal effects on mixing. While this air-wave-ocean coupling has been implemented in some operational models (e.g., ECMWF, COAMPS) it has not been in others (e.g., NCEP).

Finding 5.24: Including surface wave effects in S2S Earth system models could lead to a more accurate representation of the upper boundary layer and sea state.

Higher-Order Numerics

While the existing horizontally-structured-mesh ocean models described above have excellent computational efficiency per degree of freedom, most are based on conservative but relatively low-order staggered discretizations (e.g., Griffies et al., 2010; Griffies et al., 2000). There is a growing body of research on the use of unstructured-grid, adaptive-mesh, or higher-order methods (Beck, 2009; Deleersnijder et al., 2010; Mavriplis, 2011; Slingo et al., 2009) that aim to increase models' accuracy without a concomitant increase in computational cost. A specific advantage of unstructured meshes is their geometric flexibility, which allows for more accurate solutions, but a significant drawback is a reduced efficiency per degree of freedom. As a result, many unstructured-grid models have focused on shallow water regions with complex geometries (e.g., estuaries) and/or continuous schemes for finite-volume or finite-elements. In addition, unstructured finite-volume schemes are usually limited to second-order numerics in space. For higher-order spatial discretizations with significant advection, finite-elements are possibly more versatile. Discontinuous Galerkin schemes also appear promising and are being developed for open baroclinic ocean modeling (e.g., Blaise et al., 2010; Karna et al., 2013; Karna et al., 2012; Maddison et al., 2011a; Maddison et al., 2011b; Ueckermann and Lermusiaux, 2016). Similar efforts are occurring for atmospheric modeling at varied scales and resolutions, and for different purposes (e.g., Giraldo and Restelli, 2008; Marras et al., 2015; Nair et al., 2009; Palmer, 2012; Pielke, 2013). For example, the Naval Research Laboratory is developing a Discontinuous Galerkin dynamical core for its Navy Environmental Prediction sysTem Utilizing the NUMA corE (NEPTUNE) atmospheric model (NUMA is the Nonhydrostatic Unified Model of the Atmosphere DG core). It is currently being tested for accuracy, scalability, and computational cost (Gabersek et al., 2012). Other next-generation atmospheric models are under development, including community earth system models with probabilistic capabilities (e.g., Hurrell et al., 2013; Palmer, 2012).

Finding 5.25: Inspired from computational fluid dynamics and related fields, new numerical methods and higher-order schemes are being developed for ocean modeling. The resulting higher-order accuracy and enhanced refinement capabilities can reduce numerical errors in ocean models, which is a promising development for the longer-term prediction needs of S2S applications.

In summary, priorities for ocean model improvements for S2S forecasting include both fundamental numerical capabilities and improved depictions of important oceanic phenomena. An example of an important new numerical capability would be the ability to focus resolution in particular regions of phenomenological (e.g., straights that constrain flows) or forecast interest (e.g., harbors) in global ocean models. Many important oceanic phenomena are simply omitted from most S2S forecasting systems, such as tides and their interactions with storm surges. Oceanic mixing of nutrients is important for biological productivity on S2S timescales, but in models it is the result of both numerical artifacts and deliberate parameterizations, motivating improvements on both sides. The dynamics of the near surface ocean are of particular importance for the coupled ocean at S2S timescales, so the representation of ocean boundary layer turbulence and its interactions with waves and sea ice are a promising subject of study for improving S2S forecasts. But the most important limitation on oceanic S2S forecasts arises from the global influence of the ocean at these timescales, along with the need to accurately represent many important oceanic phenomena at relatively small scales to capture this influence. This need to model the global ocean with fine scale detail places a premium on computational capacity available for S2S forecasts and on utilizing numerical techniques that maximize the value of the available resources.

Sea Ice Models

As discussed in Chapter 4, sea ice is an important source of predictability to the Earth system because sea ice anomalies can persist for up to a few years, during which time the anomalies can influence ocean and atmospheric conditions. Further, predicting sea ice itself is valuable for its impact on transportation and coastal erosion vulnerability, among other things. Sea ice models need to capture the physical processes that give rise to the high degree of heterogeneity in sea ice thickness, melt-pond coverage, and other characteristics that influence shortwave radiation, clouds, atmospheric stability, and ocean freshwater exchange. Many NWP models do not include interactive sea ice components, and the local sea ice concentration and thickness in these models is prescribed and constant with only the surface temperature and (sometimes) the snow depths allowed to vary (see for example, specifications of NOAA's GFS[36]). To predict the evolution of the ice and snow thickness, and heat transfer within the ice and snow and with other components, the sea ice component in coupled Earth system models must be interactive and at a minimum include sea ice thermodynamics. Adding explicit modeling of sea ice dynamics—such as the sea ice motion and deformation that redistributes the ice thickness locally and produces openings, known as leads—can, along with modeling thermodynamics, allow for predictions of sea ice concentration.

Sea ice components in climate models and Earth system models have evolved significantly over the past two decades due to recognition that sea ice strongly influences radiative and ocean feedbacks and because observations have offered improved constraints on sea ice processes and parameterizations (e.g., Bitz et al., 2012; Notz, 2012). Many sea ice models account for an ice-thickness distribution, which treats a distribution of sea ice thicknesses in an individual model grid cell, to improve the fidelity of processes that strongly depend on sea ice thickness, such as sea ice growth and compressive strength. Models are also beginning to treat brine cycling (Hunke et al., 2011) to simulate biogeochemistry within the ice and model the process of melt pond formation and drainage. However, most of the sea ice components in models used for S2S applications are much simpler, with bare-minimum dynamics and thermodynamics (e.g., Merryfield et al., 2013b; Msadek et al., 2014; Wang et al., 2013a).

[36] http://www.emc.ncep.noaa.gov/GFS/doc.php#seaice, accessed January 27, 2016.

The small scale features at the floe scale and below suggest that model resolution may be important to improving predictions. The frequency of grid cells with very low sea ice concentration and very high net heat flux to the atmosphere has been found to increase at higher resolution (Newsom et al., 2015). New sea ice dynamical schemes that account for anisotropy of sea ice properties (e.g., preferred orientation of fractures and faults within the horizontal plane) over 10s of kilometers, and much more while treating the sea ice as a continuum, may be a promising alternative to explicitly resolving fine scales (e.g., Tsamados et al., 2013). However, such methods are not yet well tested, and little research has been done to investigate their potential for S2S applications.

Several potentially important processes are as yet missing or untested in nearly all Earth system models including (1) blowing snow and the redistribution of snow on sea ice, (2) floe size distribution influence on ice growth and deformation, (3) waves breaking floes, and (4) ice microstructure (i.e., porosity and/or defects) influence on compressive strength. Inclusion of these processes into S2S systems may offer opportunities to predict new sea ice properties with societal value.

In summary, priorities for sea ice model improvements for S2S prediction include parameterizing the sub grid-scale distribution of sea ice thickness and floe sizes and treating the evolution of albedo, heat, and liquid water of melt ponds. These aspects of sea ice strongly influence the seasonal cycle of sea ice concentration and thickness. Modeling the anisotropy of deformation offers the potential of predicting the orientation of leads, which could be an advantage for planning shipping routes. The more advanced models have these capabilities already, but they are not routinely used nor have they been investigated for the purposes of S2S prediction.

Finding 5.26: Sea ice models used for S2S often use bare-minimum thermodynamics and dynamics. However, sea ice models have been developed with sophisticated physics that account for phenomena such as the ice-thickness distribution, melt ponds, biogeochemistry, and divergence/convergence processes. New methods are being developed to account for wave-floe interactions, blowing snow, and ice microstructure.

Finding 5.27: The fidelity of sea ice simulations appears to improve with resolution. New promising sea ice dynamic parameterization schemes may preclude the need for high resolution in some situations, but little research has been done to investigate their potential for S2S applications.

Land Surface and Biogeochemical Models

The land-surface model (LSM) accounts for the land-atmosphere interactive processes, such as the exchange of heat, moisture, and momentum at the surface. As described in the Observations section of this chapter and in Chapter 4, such fluxes influence the likelihood of heat waves, droughts, storm formation, and monsoons, and may become increasingly important to climate and weather prediction as the global climate warms (e.g., Dirmeyer et al., 2013; Dirmeyer et al., 2014). Despite the ever-growing number of dynamic LSMs, a recent intercomparison has highlighted that the performance of dynamic LSMs is still in some cases inferior to much simpler statistical models for sensible heat flux (Best et al., 2015)

Another important purpose of LSMs is to model surface hydrology, where groundwater and streamflow are included to connect terrestrial water (e.g., soil moisture, surface water, and snowpack) with rivers, lakes, and oceans to complete the water cycle. LSMs are often deeply rooted in biogeochemical processes (e.g., carbon and nitrogen cycling and other ecosystem processes) due to the fundamental interactions of vegetation and soil systems with surface hydrology. Coupling between land-surface hydrology and the ocean can be important for determining near shore currents and salinity and for ocean biogeochemical cycles. Indeed, coastal ocean salinity can be strongly determined by river discharges, particularly during flood events and seasonal flooding (Milliman and Farnsworth, 2013).

The LSMs in NWP systems typically focus on dynamically representing snow cover and soil moisture, while prescribing vegetation cover to vary seasonally based on satellite observations.[37] LSMs in Earth system models today usually also predict vegetation at some level (Bonan, 2008 and see below), which permits a greater degree of interaction with the hydrologic cycle and biogeochemical cycling—both of which have significant societal impacts on S2S timescales (Chapter 3).

Representation of surface hydrology is still often relatively simplistic in Earth system models used for S2S forecasting, with water runoff not collected and moved through rivers to coastal areas. Many more complex hydrologic modeling systems exist with river routing and drainage basin models layered atop land surface models, but they are typically run “off-line” and are driven by climate and weather forecasts from coupled models. These models incorporate the influence of human water management and use on surface and groundwater storage and river streamflow. Systems are being actively developed and used for operational hydrologic forecasting (for example within NOAA’s NWS and Office of Hydrologic Development, see also Yuan et al., 2015). While further research is needed to understand the extent to which inclusion of such hydrological models within coupled S2S forecast systems would benefit S2S forecasts across the system (for example, by explicitly informing coastal salinity and currents), such coupling would enable more direct, dynamical S2S predictions of stream and river flow as well as coastal flooding and hypoxia. Furthermore, the potential user base for such S2S hydrologic predictions is large (Chapter 3). Enabling and supporting the coupling of hydrologic and river routing models to climate and weather models is a strategic science goal of NOAA’s Office of Hydrologic Development (NOAA, 2010).

Whether they include hydrologic processes such as river routing or not, LSMs in coupled S2S forecast systems need to continue to be improved through higher fidelity and increased complexity in order to represent important coupled processes in S2S forecast systems and also to meet increasing user needs for hydrologic, ecological, littoral, and coastal ocean S2S predictions. This includes (but is not limited to) improving the parameterization of surface energy partitioning into sensible, latent, soil, and outgoing longwave radiation through improved plant and soil processes, snow/soil-ice physics, and by including biogeochemical cycles. Land-atmosphere interactions (see Figure 5.12) also need to be carefully evaluated and considered, in particular feedbacks with surface and boundary-layer physics, convection, and water and energy budgets (Chapter 4). This needed progress in land and hydrological model development is slowed by lack of reliable observations and climatology estimates. Process-level studies and

[37] See for example, specifications associated with the LSM used in NOAA’s Global Forecast system: http://www.emc.ncep.noaa.gov/GFS/doc.php#lansurproc (accessed January 27, 2016).

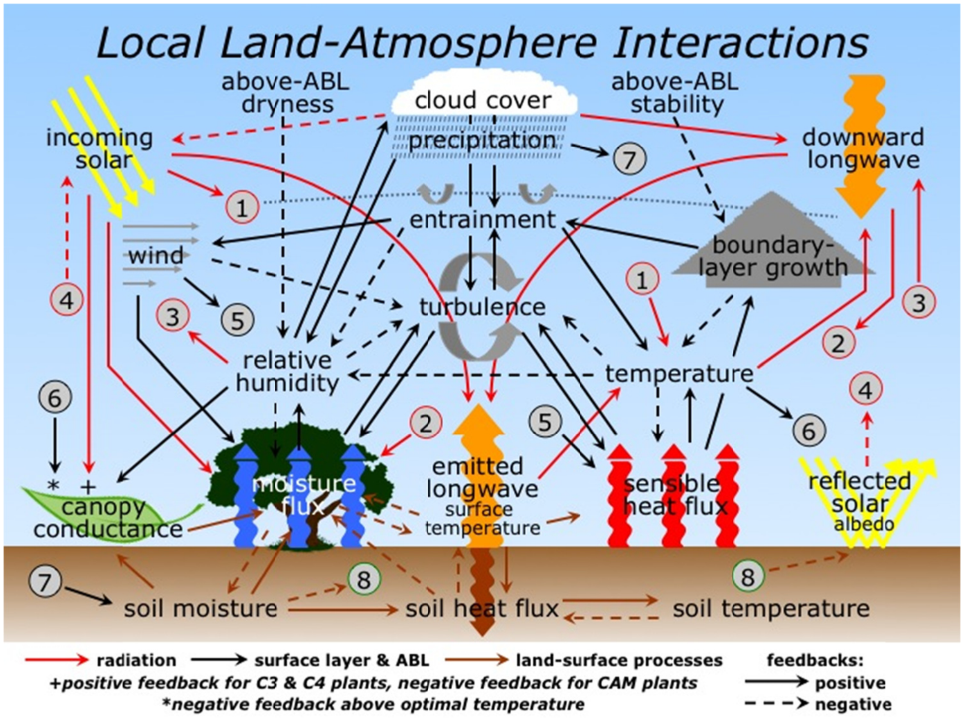


FIGURE 5.12, Schematic showing the many interactive processes in the land surface and atmospheric boundary layer (ABL). SOURCE: Mike Ek, adapted from Ek and Holtslag (2004).

significant efforts in model optimization (including parameter estimation) will be necessary to continue to improve the LSM component of coupled S2S prediction systems.

Land-surface models used for S2S prediction also need to improve treatment of the hydrological cycle and aspects of the land surface that are coupled to hydrology. Effort is needed to incorporate surface and underground water storage and river routing in models, including the role of human water management and use. These important aspects of the land system have been implemented in "off-line" hydrologic forecast systems, but they are usually over-simplified or neglected altogether in fully coupled S2S forecast systems.

Finding 5.28: Advancements in modeling and parameterization of land processes and feedbacks is important for improving S2S prediction model skill, especially for events such as droughts, heat waves, floods, monsoons, and storm formation, as well as for improved hydrological predictions.

Biogeochemical processes in ESMs extend beyond the land surface to include ecosystems in the ocean and sea ice, and geophysically important reactive chemistry, aerosols, and aerosol-cloud interactions in the larger Earth system. As highlighted in Chapter 3, biogeochemical-related events that are modeled in LSMs and ESMs that are desirable to predict on S2S timescales include ocean and large-lake hypoxia, fish stocks, marine productivity, harmful algae blooms, crop yields, disease epidemics, and fire occurrence. For S2S prediction, it can be desirable to predict, as opposed to prescribe, certain parts of biogeochemical cycles that influence predictability and/or involve societally relevant impacts. A volcanic eruption is an example of a biogeochemically relevant event that influences both chemical and physical systems, via the formation of volcanically derived aerosols, which in turn force an atmospheric and/or ecosystem response. A volcanic eruption is an unanticipated event with consequences on regional to global scales whose evolution and outcomes on S2S timescales are addressed as a key prediction need elsewhere in this report (Chapter 6).

Coupling biogeochemical dynamics to other ESM components may also be important for S2S predictions of the atmosphere because biogeochemical dynamics can influence albedo, moisture availability, and temperature profiles on S2S timescales. For example, it is increasingly recognized that initializing and representing vegetation can also impact S2S predictability of the atmosphere (e.g., Koster and Walker, 2015). Whether physical and biogeochemical models should be coupled or uncoupled—with the biogeochemical model run "off line" and on demand due to the vast input data requirements of accurate biogeochemical modeling in a turbulent fluid—depends on the timescale on which land and ocean biota feedback to the physical models.

Global climate models began to include a wide array of biogeochemical cycles in the last two decades, and model terminology has evolved to reflect this new capability. Today, a global climate model that includes biogeochemical cycles is often called an Earth system model. Carbon vegetation modeling usually involves predicting the leaf area and treating leaf processes that influence photosynthesis at a minimum, and may also allow vegetation growth and decay, competition, and soil carbon pools. The current capability in atmospheric components includes the formation of aerosols, aerosol-cloud interactions, and the evolution of atmospheric composition (greenhouse gases, ozone, and other pollutants). Biogeochemical modeling in the ocean involves both uptake and release of gases, chemical reactions, and biology from the single celled (algae and bacteria) to multicellular phytoplankton, zooplankton, and sometimes even seaweed and fish. ESMs have generally not yet incorporated biogeochemical cycling in sea ice. However, there is active development in a few models now to include sea ice algae, gas exchange, chemical cycling, and soot deposition on sea ice (e.g., Holland et al., 2012; Vancoppenolle et al., 2013).

Finding 5.29: Incorporating biogeochemical cycles into S2S prediction systems has the potential to improve S2S forecasts because biogeochemical cycles often feedback to other components of the physical system, and because they influence societally important concerns such as ocean and large-lake hypoxia, fish stocks, marine productivity, harmful algae blooms, crop yields, disease epidemics, and fire occurrence.

Coupling Between Model Components

As highlighted above, S2S prediction is inherently a coupled problem. Information transfer between the atmosphere, ocean, ice, wave, and land provides fundamental sources of predictability on the S2S timescales. Meanwhile, model errors are also passed between different components and this error growth represents a consequential limitation to S2S prediction skill. The importance of air-sea coupling, land-air coupling, and sea ice coupling has been fully recognized, but representations of such coupling in models still need substantial improvement.

Several types of coupling are priorities for implementation or improvement in S2S operational systems. Ocean surface waves are needed as a buffer between atmospheric momentum and ocean currents. Precipitation arriving at a catchment basin and delivered to the coastal ocean via an estuary through river routing requires hydrological and land surface models that are coupled to atmospheric and ocean models. Other examples include biogeochemistry models coupled with ocean, and land and atmospheric models that include biogeochemical feedback on S2S timescales. Reliable couplers need to be designed based on advanced knowledge of coupled processes with an aim to matching observed fluxes where measurements are available. These processes are often not resolved explicitly in S2S models and need to be parameterized.

Because changes in parameterization in one component can lead to increased model errors in another part of the coupled system, coordination and collaboration among different communities of researchers focused on different parts of the Earth system is important in this context.

Finding5.30: Because of the coupled nature of S2S variability and prediction, parameterization for either interactive processes within individual components of the Earth system or coupled processes between them must be improved in a cohesive manner instead of in isolation.

Process Studies for Model Advancement

As discussed earlier, reducing model errors is among the highest priorities for advancing S2S forecast systems. Major sources of model errors are parameterization schemes for unresolved, poorly understood, or computationally burdensome processes across all model components (atmosphere, ocean, sea ice, and land surface). Developing and refining parameterization schemes can be achieved through three closely connected steps: observing physical processes in the real world, improving understanding of these physical processes, and translating that new knowledge into improved models.

Field observations

As model resolution continues to increase towards cloud and eddy permitting or resolving scales (similarly for resolving sea ice floes and fracture heterogeneity, watersheds, mesoscale and stand scales in hydrology and land ecosystem modeling), more detailed information of physical processes is needed to develop a new breed of parameterization. It is important to recognize that field observations for process studies are different from sustained observations for climate and applications monitoring (e.g., Observations section of this Chapter), though some data sets may meet both purposes. Observations for improving parameterizations are most often taken from special field experiments that include ground-based, seaborne, and airborne in situ, along with space-based remote measurements.

In situ measurements are the most reliable sources of information for many physical processes central to model parameterization (e.g., cloud, precipitation, radiation, turbulence, aerosol, soil moisture, vegetation, surface waves, and surface fluxes of land, ocean, and ice) and the only sources of information for subsurface oceanic processes (e.g., mixing and currents). Modern observing technology affords observations of these processes with ever-increasing details and accuracy to meet the need of developing parameterization schemes. Moreover, in situ observations provide the most accurate descriptions of coupling or interaction among the multiple processes that must be adequately represented in models to advance S2S prediction.

Processes-level observations need to take the full advantage of the most advanced technology, including seaborne, airborne, and land-based autonomous devices.

Space-based data provide global and routine coverage, augmenting the limits of temporal and spatial coverage inherent in field observations. Products with reliable vertical profiling of the atmosphere, information of ocean and land surfaces, and higher sampling rates by multiple sensors are the best complements to in situ observations for process studies. More specifically, there are key physical processes where experimental satellite observations are sorely needed to characterize processes critical to modeling S2S phenomena (e.g., deep convection, soil moisture, ocean mixed-layer depth). Key among these are information on vertical motion within storm systems, increased thermodynamic and wind information within the boundary layer, and simultaneous measurements of aerosol, clouds, and precipitation to better describe cloud/precipitation growth. In this regard, and with the expected increases in resolution of models in mind, it is essential that these types of space-based measurements are able to resolve mesoscale features of the atmosphere.

Field experiments targeting a single process (e.g., cloud ice, ocean mixing) with single observing platform (e.g., an airplane, a ship) have effectively improved many individual parameterizations and need to continue. S2S prediction systems include coupled components of Earth, and their skill can be dramatically improved only when all model components and their coupling are advanced. Indeed global models have evolved to a stage that errors are unlikely due to deficiencies in representing a single process. Such coupled processes can be adequately observed through field experiments with sufficient breadth to cover multiple processes across more than one component of the Earth system. Past success stories of coupled experiments with lasting and broad impact all involved multiple observing platforms and international participations. Examples are the GARP (Global Atmosphere Research Program) Atlantic Tropical Experiment (GATE; Houze and Betts, 1981), the Tropical Ocean Global Atmosphere Coupled Ocean-Atmosphere Response Experiment (TOGA COARE; Webster and Lukas, 1992), Surface Heat Budget of the Arctic Ocean (SHEBA; Uttal et al., 2002), the African Monsoon Multidisciplinary Analysis (AMMA; Lebel et al., 2010), and the VAMOS (Variability of the American Monsoon Systems) Ocean-Cloud-Atmosphere-Land Study Regional Experiment (VOCALS-REX; Wood et al., 2011) (see Appendix C for more details on past and current major coupled field campaigns). Common to these and other successful process studies is that they all address coupling or interaction between various processes within the same components of the Earth system and interactive processes between different components of the Earth system (land, ice, atmosphere, and ocean). Field experiments of that scale are expensive and logistically challenging but their data are singularly beneficial to model development (e.g., Fairall et al., 2003; Park and Bretherton, 2009).

Finding 5.31: Specialized and comprehensive field observations are necessary to inform and improve representations of unresolved processes, including coupled processes in and between various components of S2S prediction models. New observing technology, both remote sensing and in situ, and international collaboration/coordination could enhance the ability to meet the demand for more detailed information on interactive and coupled processes within S2S models.

Transforming understanding of physical processes to model improvement

Field observations provide the foundation for new knowledge of interactive processes key to S2S prediction. However, the tremendous knowledge gained from many field observations has helped more to diagnose sources of model errors than to actually reduce these errors. One reason for this is the distance between what model developers need and what can be observed. For example, many cumulus parameterization schemes depend on vertical mass fluxes in clouds, and as mentioned above, these are very difficult to observe. In this case and in many others, advancing observing technology is critical to shorten the distance between what is needed and what is currently observable. Meanwhile, fully tapping the rich information from existing field observations for model development requires knowledge of observing technology by modelers and knowledge of modeling by observation experts. Thus transforming new knowledge from observations into model improvement requires collaborative and persistent efforts by teams that include observationalists, data analysts, and modelers. For the longer (climate) timescales, the NSF/NOAA Climate Process Teams have been highly successful in developing improved parameterizations. Further support for this and similar efforts, including staff and computing time, is critical for transferring knowledge gained through process studies into actual improvements in parameterizations (see also Chapters 6 and 7).

Given the nature of field observations—namely limited coverage in space and time—it is naïve to expect a single field experiment would lead to a breakthrough in model development and S2S prediction. Each field experiment fills a gap in our in situ observational database, but it is the totality of all field experiments together that provides the needed information for overall improvement for S2S systems. Because it is impossible to have detailed process observations at all desired locations and time, an approach of integrating field observations and high-resolution modeling is essential to bridge the gap between field data and improvement of model parameterization. As discussed earlier, global and large-domain cloud-permitting and non-hydrostatic ocean models that are well calibrated and validated by field observations serve as vital tools for transforming knowledge gained from field observations to model improvement. Large-eddy simulation (LES) models provide additional details, such as shallow clouds and ocean internal waves.

Finding 5.32: Transforming field observations to model improvement requires persistent collaborations among experts with knowledge of observations, data analysis, and modeling who can effectively integrate field observations and modeling for model improvement.

The Way Forward for Advancing S2S Models

In current forecast systems, model errors are one of the most limiting factors in achieving the skill that might be afforded by S2S Earth system predictability. Many of the issues that lead to model errors are common across different modeling systems and a broad range of timescales covering days to centuries, i.e., across weather forecasts, S2S forecasts, and long-term climate simulations. These model errors are likely the result of multiple deficiencies in model representations of key processes that are currently parameterized. Investment in research aimed at understanding and reducing model errors is absolutely essential in improving S2S predictions. Because of the commonality across timescales of many Earth system model errors, a seamless

BOX 5.2—Seamless Prediction

The goal of "seamless prediction" is to use the same prediction system software at all timescales (weather, subseasonal, seasonal, and climate) and also at all needed resolutions[38]. The motivations for this concept are that weather and climate prediction models are built upon the same physical principles, and cross-scale interactions in the Earth system provide predictive power and predictability limits across these scales and thus need to be adequately represented in all models (Hoskins, 2013). Indeed, although numerical weather prediction (NWP) and climate prediction sometimes have different requirements (e.g., model resolution and complexity, integration length), they share many commonalities. They are both based on the same set of equations of motion. They both need parameterization to represent unresolved processes, and many of their biases can be traced to the same deficiencies in parameterization of phenomena such as tropical convection. They both rely on observed states of the Earth system to initialize their integrations and to verify and calibrate their predictions.

A seamless framework for weather and climate models has been advocated by many (Hurrell et al., 2009; Palmer et al., 2008; Shapiro et al., 2010; WMO, 2015a). Seamless prediction systems may offer numerous advantages for S2S forecasting and for related decision-making frameworks such as "ready-set-go" (Brunet et al., 2010; Robertson et al., 2015; Chapter 3). As discussed elsewhere in this report, an adequate S2S prediction system needs to embrace aspects that are common in conventional NWP—including high resolutions and adequate representation of complex, mesoscale storm systems—and those that are essential to climate prediction—complexity and coupling of Earth system components. For example, important sources of S2S predictability such as the MJO depend on (and feed back onto) climate modes like ENSO and also interact with higher-frequency weather perturbations. Other cross-timescale interactions may be important for developing so-called "forecasts of opportunity" (Chapter 4), and exploiting the conditional skill in such forecasts is especially important to S2S prediction. Seamless prediction systems also require common central elements including dynamic cores and parameterization systems, expanded computational infrastructure, dedicated manpower, and coordination between research communities to test developments such as new parameterization schemes on different timescales. These are many of the same issues that are advocated elsewhere in this report as ways to advance S2S forecasting. Thus S2S forecasting serves as both a motivation and an ideal testbed for seamless prediction systems.

In operational settings, seamless prediction has the potential to reduce manpower costs of maintaining several models to produce operational forecasts with various lead times, and the practice and benefit of seamless prediction systems have been demonstrated by several successful efforts (Brown et al., 2012; Hazeleger et al., 2010; Vitart et al., 2008). The UK Met Office uses its main atmospheric model at all timescales, the Navy is developing NEPTUNE, a possible next generation unified global-regional prediction system, and NCEP has proposed a similar path with the selection of its next operational atmospheric model. Recent advancement in modeling has helped to meet some challenges to building seamless prediction systems (Brown et al., 2012). For example, the issue of scale dependence of parameterization is being tackled using new schemes that are scale aware or independent (see above). Across multiple U.S. agencies, the Earth System Prediction Suite (Theurich et al., 2015) is working to develop a common modeling infrastructure and component interface standards for a suite of national weather and climate models, which, while not providing seamless prediction, will facilitate greater use of common components and more rapid transition of new technology.

framework for reducing such errors and developing new parameterizations may be useful (see Box 5.2 for a description of seamless prediction).

[38] Note that "seamless forecasts" discussed in Chapter 3 refers to creating products that are consistent across short range, subseasonal, seasonal, and climate timescales.

More efficient computational schemes would benefit S2S forecasts as well as weather, ocean, and climate forecasts. Advances in S2S systems can benefit tremendously from the experience of weather, ocean, and climate model developers, and vice versa. New high-order computational schemes and implementations that minimize numerical diffusion on S2S timescales are needed for multi-resolution ocean and atmospheric modeling. Developing these computational schemes jointly with new uncertainty quantification and data assimilation capabilities would be an efficient path forward: It would directly integrate three critical components of S2S forecasting systems from the start.

There are several crucial steps that need to be taken in parallel to reduce model errors. First, research to systematically quantify and understand the improvements that can be made through modest increases in resolution (horizontal, vertical, and multi-resolution, and across coupled components) is needed to help determine the optimal design of operational systems (e.g., trade-offs between costs and benefits of increased resolution, ensembles, parameterizations, and multimodels—see Recommendation J described in the next section). For ocean models in particular, there may be benefit for including robust, advanced, and highly conservative multi-resolution approaches (adaptive mesh refinement, seamless two-way nesting, multi-dynamics, adaptive super-parameterizations, etc.) for operational global S2S forecasting over the next decade. Some emerging research further suggests that there may be important gains from concurrent increases in resolution up to the point of resolving mesoscale processes across the atmosphere, ocean, sea ice, and land surface. However, research into how increased resolution can reduce model biases, especially in coupled ESM models, is just beginning and needs further support (e.g., NOAA, 2015). Ideally, continued research on the topic of model resolution needs to be carried out with more than one S2S forecast system in order to be sure that the lessons learned are generic.

Second and perhaps most importantly, it is clear that uncertainties in parameterizations of unresolved processes—both processes internal to a given Earth system component and in the representation of coupled processes between them—are and will continue to be major sources of model errors. Thus efforts to improve parameterization of many processes must be one of the highest priorities for improving S2S prediction systems. The difficulties in improving parameterization arise from both incomplete process understanding and failure to properly encapsulate process knowledge into parameterization schemes of operational S2S systems. Acceleration of both process understanding and the transfer of knowledge into model development are thus essential.

New field observations are critical to improving process understanding and the development of subgrid scale parameterizations. Given the complexity of S2S models, which involve multiple, interacting components of the Earth system, it is critical to understand coupling processes between different components as well as interactive processes within components. Particular foci for new field campaigns and process studies should include tropical convection, ocean turbulence, sea ice, stratospheric and land surface processes, and coupling among different Earth system components (land, ice, ocean, and atmosphere). Observations of coupled processes between components are particularly useful for monitoring and initializing S2S prediction systems. They are also essential for model validation and the identification of bias/error sources in coupled Earth system models. Spatial coverage of this type of observation (e.g., tropical mooring arrays, land surface flux towers) remains inadequate and faces deterioration. To maximize impact, research and operation communities need as far as possible to collaborate in the design of future field observations and to take full advantage of new observing technology and opportunities for international collaborations and coordination.

Transforming new knowledge gained from field observations and process studies to model improvement requires close collaboration among experts on observations, data analysis, and modeling. Persistent and painstaking efforts among two generations of scientists has been necessary to advance ESMs and operational forecast systems to the point at which they are today, and it will take no less to reach our goals for S2S forecasting. Teams that allow scientists with diverse expertise to collaborate effectively are necessary to accelerate this transformation (such as NSF/NOAA Climate Process Teams), and it is crucial to further develop an enhanced, sustainable community of scientists spanning academic, research, and operational centers to develop, test, and optimize new parameterization schemes (see also Chapter 6).

Finally, improving subgrid scale parameterization needs to be supported by research that explores the benefits of extremely fine resolutions (meters to a few kilometers), even though these are unlikely to be affordable or computationally feasible operationally in the next ten years. For atmosphere models, this would involve global or large-domain cloud-permitting grid spacing without the need of deep cumulus parameterization and regional large-eddy simulation (LES) models without the need of shallow cumulus parameterization. For ocean models, this would include explicitly representing submesocale features and possibly non-hydrostatic processes such as wave-induced circulation and mixing. The development and exploitation of such extremely high-resolution model systems should be encouraged, and they should be used to advance the study of S2S predictability (Chapter 4), generate high-resolution datasets for process studies, and provide testbeds to improve, develop, and evaluate parameterization schemes, as well as demonstrate possible future S2S prediction systems (see also Recommendation I).

Recommendation H: Accelerate research to improve parameterization of unresolved (e.g., subgrid scale) processes, both within S2S system submodels and holistically across models, to better represent coupling in the Earth system.

Specifically:

- Foster long-term collaborations among scientists across academia and research and operational modeling centers, and across ocean, sea ice, land and atmospheric observation and modeling communities, to identify root causes of error in parameterization schemes, to correct these errors, and to develop, test, and optimize new (especially scale-aware or independent) parameterization schemes in a holistic manner.
- Continue to investigate the potential for reducing model errors through increases in horizontal and vertical resolutions in the atmosphere and other model components, ideally in a coupled model framework (see also Recommendation L).
- Encourage field observations targeted at increasing knowledge of poorly understood or poorly represented processes in S2S models, including tropical convection, ocean mixing, polar, sea ice and stratospheric processes, and coupling among different Earth system components (e.g., air-sea-ice-wave-land, troposphere-stratosphere, dynamics-biogeochemistry).
- Develop extremely high-resolution (or multi-resolution) modeling systems (e.g., that permit atmospheric deep convection and non-hydrostatic ocean processes) to advance

process understanding and to promote the development of high-resolution operational prototypes (see also Recommendation I).

Representing oceans, sea ice, land surface and hydrology, and biogeochemical cycles (including aerosol and air quality) in coupled Earth system models is more important for S2S predictions than for traditional weather prediction because much of the predictability of the Earth system on these timescales arises from conditions outside the troposphere or from interactions between Earth system components. However, the representation of processes outside the troposphere has generally been less well developed in Earth system models used for making S2S forecasts. Thus improving model representation of land surface and terrestrial hydrology, ocean, sea ice, and upper atmosphere—including fluxes and feedbacks between these components and the troposphere—should be central to the S2S research agenda. For example, improving the representation of land surface processes such as soil moisture storage and snow may be important for predicting events such as heat waves, cold surges, storm formation, and predicting run-off may help to enable S2S forecasts of flooding and lake and coastal hypoxia. Similarly, connecting advances in cutting-edge sea ice models (including sophisticated physics representations of ice-thickness distribution, melt ponds, biogeochemistry, and divergence/convergence, as well as new methods to account for wave-floe interactions, blowing snow, and ice microstructure) with sea ice models used in S2S forecast system could advance S2S predictions of the atmosphere through improved representation of radiative and ocean feedbacks, as well as advancing S2S prediction of sea ice and polar ocean conditions. As demand grows for forecasts of phenomena that are predictable on S2S timescales but that do not feedback strongly to the atmosphere, improving the dynamical representation of many of these Earth system processes in S2S prediction systems may also become important in its own right.

As coupled systems become increasingly complex and the linkages between variables expand, the uncertainty in coupled model output increases, particularly for downstream products. Understanding the nonlinear ways in which these uncertainties can interact should be a key area of focus. Utilizing recently developed reduced-order methods described above, which predict and quantify uncertainty across models directly using model equations themselves, would thus be useful (Smith et al., 2014).

Beyond advancing the representation of the land surface, hydrology, stratosphere, sea ice, ocean, and biogeochemical models and translating these advancements to the Earth system models used for S2S forecasting, efforts are needed to pave the way towards global cloud/eddy-resolving atmosphere-ocean-land-sea ice coupled models, which will one day become operational for S2S prediction. While this goal is unlikely to be reached in the next decade, revolutions in the computing industry may shorten the distance between now and the otherwise long way to go, and the S2S research community needs to be proactive and poised if/when that happens. Substantial research is needed in several specific areas to ready global cloud/eddy-resolving models for operation. First, models' dynamic cores need to be made more efficient to take the advantage of new computer technology (Chapter 7). Second, new parameterization schemes needed at cloud/eddy-resolving resolutions must be advanced. Third, probabilistic predictability on cloud/eddy-resolving scales would be different from that based on models of coarse resolutions, especially for some extreme events, which require additional studies. Finally, cloud/eddy-resolving (or permitting) models will not replace the need for multimodel ensembles (MME). Considering the huge demand on computing capability, cloud/eddy-resolving MME needs to be approached through international collaboration and coordination.

Recommendation I: Pursue next-generation ocean, sea ice, wave, biogeochemistry, and land surface/hydrologic as well as atmospheric model capability in fully coupled Earth system models used in S2S forecast systems.

Specifically:

- Build a robust research program to explore potential benefits to S2S predictive skill and to forecast users from adding more advanced Earth system components in forecast systems.
- Initiate new efficient partnerships between academics and operational centers to create the next generation model components that can be easily integrated into coupled S2S Earth system models.
- Support and expand model coupling frameworks to link ocean/atmosphere/land/wave/ice models inter-operably for rapidly and easily exchanging flux and variable information.
- Develop a strategy to transition high resolution (cloud/eddy-resolving) atmosphere-ocean-land-sea ice coupled models to operations, including strategies for new parameterization schemes, data assimilation procedures, and multi-model ensembles (MME).

COMBINATION, CALIBRATION, VERIFICATION AND OPTIMIZATION OF S2S FORECAST SYSTEMS

As discussed in previous sections, there will always be uncertainties in observations that are used to initialize S2S systems and in the parameters and equations used to represent processes. The net result is biases and errors in the forecast. Significant effort has gone into reducing systematic model errors and biases in Earth system prediction systems, and these efforts must continue in order for S2S forecasts to advance. However, uncertainties in initial conditions and model formulations are certain to remain for the foreseeable future. This necessitates the careful assessment of uncertainties and efforts to account for them (e.g., ensemble prediction and other methods of uncertainty quantification), and statistical post-processing to adjust forecasts so that systematic biases are reduced (calibration). Both are essential for improving the reliability and skill of S2S forecasts, and along with efforts to improve forecast verification, are critical to advance.

This section highlights some recent advances and challenges in improving forecast skill through ensemble forecasting and calibration. It also covers technical aspects of forecast verification—the process of comparing forecasts with observations in order to test forecasts' reliability, measure their skill, assess their value, and develop bias corrections. Given the range of possible methods and options for improving forecast skill through such techniques, this section also discusses the optimization of forecast systems through an exploration of costs and benefits of various forecast system configurations.

Accounting for Uncertainty to Improve Probabilistic S2S Forecast Reliability and Skill

As briefly discussed in Chapter 2, a notable strategy for advancing the skill and utility of S2S forecasts in the past few decades, apart from efforts to reduce model errors, has been the inclusion of quantitative information regarding uncertainty (i.e., probabilistic prediction) (e.g., Dewitt, 2005; Doblas-Reyes et al., 2005; Goddard et al., 2001; Hagedorn et al., 2005; Kirtman, 2003; Palmer et al., 2004; Palmer et al., 2000; Saha et al., 2006, among many others). This change in prediction strategy naturally follows from the fact that climate variability includes a chaotic or irregular component, and because of this, forecasts must include a quantitative assessment of this uncertainty. More importantly, the prediction community now understands that the potential utility of forecasts is based on end-user decision uptake and utilization (Challinor et al., 2005; Morse et al., 2005; Palmer et al., 2000), which requires probabilistic forecasts that include quantitative information regarding forecast uncertainty or reliability.

Ensembles of perturbed initial observational values are now commonly used to represent uncertainty associated with model initial conditions; however, the number of ensembles and the method of ensemble creation vary widely across operational systems (Appendix B, Tables B.1 and B.2). Little systematic work has been done to evaluate the costs and benefits of different ensemble sizes and methods in relation to other investments.

In addition to uncertainty in initialization, uncertainty quantification is also necessary to account for uncertainty associated with model formulation. A number of methods exist or are under development to try and account for this type of uncertainty. Perturbed physics ensembles (currently in use at the Met Office for their operational system) or stochastic physics (e.g., Berner et al., 2008; Berner et al., 2011) appear to be quite promising for representing some aspects of model uncertainty (e.g., Weisheimer et al., 2011, and see section above on Data Assimilation).

The multi-model ensemble (MME) approach, in which forecasts are made from an ensemble of separate models, has been the most widely tested and implemented of such methods. As also discussed in Chapter 2, a number of routine MME S2S forecasts are currently issued: The Canadian Meteorological Centre has been producing operational MME seasonal forecasts using two coupled models since 2011.[39] Seasonal MME forecasts are also being produced at the APCC every month based on data collected from 17 operational centers and research institutions (see Box 2.1). The North American Multi-Model Ensemble (NMME) is approaching quasi-operational status on the seasonal scale, and planning for subseasonal capabilities is at the beginning stages (see Box 2.2). Forecasts from these and other MMEs, which include multiple operational and/or research models, generally achieve a better skill and reliability than individual models (Kirtman, 2014; Kirtman et al., 2014; Min et al., 2014; Weigel et al., 2008; Doblas-Reyes et al., 2009; Kharin and Zwiers, 2002; Kirtman, 2014; Krishnamurti et al., 2000; Palmer et al., 2004; Wang et al., 2009c; Weisheimer et al., 2009), although in some cases, only marginal skill improvement has been achieved when verifying the ensemble mean (e.g., Doblas-Reyes et al., 2000; Doblas-Reyes et al., 2009; Weisheimer et al., 2009).

The precise reasons for these improvements in skill are not totally clear, but when separate prediction systems are combined into a single prediction system of systems, model-and data-induced errors or uncertainty tend to cancel out, which improves the overall probabilistic distribution of likely outcomes (Doblas-Reyes et al., 2005; Hagedorn et al., 2005; Palmer et al., 2004; Palmer et al., 2008). Different model configurations, along with different

[39] http://weather.gc.ca/saisons/index_e.html, accessed January 27, 2016.

parameterizations and physics likely both play a role in this reduction of error: forecast models in different operational centers and institutions have different configurations (e.g., resolutions, physics parameterization schemes, strategies for initialization, ensemble, coupling, and retrospective forecasts). Multi-model ensemble (MME) forecasts likely cover a more complete probability distribution than a single model because of these different configurations and also because different models tend to have their own strengths in capturing different sources of predictability. Thus forecast skill improvement may also come from combination of different signals.

Despite their current value and future promise for further improving S2S forecasts, there are a number of important gaps in our understanding of MMEs and how to assemble them strategically. Currently, MMEs are largely systems of opportunity, not systems made through careful design (Sandgathe et al., 2013). Furthermore, there are tradeoffs between developing independent multiple models and focusing resources on one system, including focusing on other methods of capturing uncertainty associated with model formulation. A further challenge for MMEs is how to combine models with unequal skill (Sandgathe et al., 2013). Different methods have been used to combine multi-model ensembles for deterministic and probabilistic forecasts, including simple averaged MMEs where the contribution of each model is equally weighted and empirically weighted MMEs using multiple linear regressions. The relative skill of forecast models can also be used to weight the contributions of each model to the multi-ensemble, either point-by-point or over larger regions. The choice of method may depend on parameters, locations, and applications. For example, Kharin and Ziwers (2003) found that for 500-hPa geopotential height forecasts, the simple ensemble mean produces the most skillful forecasts in the tropics, whereas the regression-improved ensemble mean performs best in the extratropics, and the MME forecast that is obtained by optimally weighting the individual ensemble members does not perform as well as either the simple ensemble mean or the regression-improved ensemble mean. In the case of the APCC MME (Box 2.1), products are generated using a number of methods, including simple equal weight for all members, empirically weighted coefficients, and probabilistic forecast. In this case, simple averaged MMEs generally outperform MMEs of other weighting methods over most latitudinal zones for all variables and seasons (Min et al., 2014).

Finding 5.33: Although perturbed physics and other methods continue to be studied and implemented, given current modeling capabilities, a multi-model strategy is a practical and relatively simple approach for quantifying forecast uncertainty due to errors in model formulation, although optimal methods for combining models are not always clear, and MMEs will not fully account for forecast uncertainty.

Calibration of S2S Probability Forecasts

Calibration is a post-process that uses statistical methods based on discrepancies between past forecasts and observations to adjust ensemble forecasts and improve forecast skill. Today, all operational S2S models include a number of ensemble members whose individual forecasts can be arranged to estimate probability distributions for the predicted variables, point-by-point across the forecast grid. However, in their original form, the statistical characteristics of S2S forecasts often differ from those of the environmental features they attempt to predict. The aim of calibration or post-processing of model output is to remove these systematic errors and to reshape the predicted probability distribution so that it resembles as closely as possible the distributions that will be found when the forecasts are verified.

Calibration processes are developed by comparing forecasts made with the current prediction model to actual observations for as many cases as possible over a historical period (retrospective forecasts or "reforecasts"), usually ten to thirty years for S2S forecasts. The comparison produces statistical information that is used in calibration algorithms to ensure that the long-term statistical moments (mean, variance, spread, etc.) of the forecast at any given lead time match the long-term observed statistical variability. Some calibration methods are based on the Bayesian model averaging approach proposed by Raftery et al. (2005), including those described by Dutton et al. (2013). Other methods focus on more direct adjustment of variances, including those of Doblas-Reyes et al. (2005) and Johnson and Bowler (2009). S2S ensembles are often under-dispersive and the calibration methods usually amplify the variance to correspond more closely to the observed variance.

Statistical-dynamical (S-D) techniques, e.g., model output statistics (MOS), can be very beneficial for improving model calibrations where the models cannot capture all the processes that are occurring. For example, the tropical cyclone forecast community has used S-D techniques for a number of years, where the dynamics involved in hurricane track and intensity are not completely understood. Analog techniques have shown fewer uses but may have value in helping to capture uncertainty, potentially reducing model retrospective forecast requirements and reducing or eliminating the need for additional models (Hamill et al., 2006).

In practice, the calibration of S2S forecasts is not a well-organized process, and there is no single approach that works best for all applications. The forecast centers provide the forecasts and corresponding retrospective or historical forecast sets and frequently provide some calibration. Commercial providers or other users also often compute and apply their own calibrations in order to enhance skill or target specific applications.

Looking forward, as more of the components of the Earth system are included in the models, the challenges of model calibration will intensify—not least due to the need for more comprehensive and long-record observations across components of the Earth system. The atmospheric, ocean, land, and ice models evolve towards their own model climate and do not necessarily combine and converge on the actual Earth system climate. For example, as mentioned in earlier in this chapter (Figure 5.7), SST errors in coupled model simulations with the UK Met Office model grow rapidly. Identifying model error and compensating for model tendencies will continue to be a key activity in S2S model development and operation.

Finding 5.34: Calibration of S2S probability forecasts is a critical process in preparing the forecasts to serve users. Forecast centers, private sector users, and value-added providers use various calibration methods, but there has been no comprehensive effort to compare methods or to find optimum approaches for the variables of most interest. Ascertaining whether some methods offer clear advantage over others would be useful.

Verification of Forecasts and Metrics of Model Skill

Proper verification of forecasts is critical to all aspects of model improvement, system design, ensemble configuration, and the determination use and value by decision makers. A variety of options exist for verifying and estimating the skill of S2S probability forecasts. Some are related to atmospheric or oceanic phenomena and some to quantities of interest to users such as the financial consequences of hedging when adverse conditions are predicted. A standard approach is to estimate model skill through anomaly correlations or root-mean-square errors of common meteorological variables such as temperature and precipitation (see Figure 2.4). Although such metrics have been used for decades, they provide only a limited view of forecast skill. They are traditionally carried out on a grid-point-by-grid-point, variable-by-variable basis, and often do not provide a comprehensive picture of model or forecast skill (Brown et al., 2004; Brown et al., 2002).

Significant recent research has been devoted to improved verification techniques, targeted mainly at very high resolution mesoscale predictions and also at ensemble predictions (Gilleland et al., 2010), yet significant research opportunities exist for improving verification beneficial to S2S prediction. For S2S prediction, as in mesoscale prediction where predictability limits are an issue (e.g., thunderstorms or tornadoes), the opportunity exists for feature-based prediction in which skill is measured not on a grid-point by grid-point basis, but on the basis of predicting larger features (ENSO, MJO, NAO, warm SST pools, sea ice extent, etc.) within the Earth system (Cornuelle et al., 2014). Put another way, while model skill in predicting surface wind at a point one to three months in advance may be lacking, as discussed in Chapter 2, certain structures and indices are predictable at these timescales and have verifiable attributes using newer object-oriented, feature verification techniques (Gilleland et al., 2010). These techniques are just recently being extended to ensemble prediction (Gallus, 2010; Johnson et al., 2013) and potentially provide a means for credible verification of feature skill for S2S predictions.

Successful prediction and verification of S2S “features” also leads to a two-step process of prediction and verification where successful prediction of a “feature” can be correlated to a likely environmental event for a user, e.g., strong ENSO leads to increased rainfall in California by shifting the location of the subtropical jet and tropical flow of moisture further east (WMO, 2015a). However, location, areal extent and intensity of the SST anomaly determine the location and intensity of rainfall. Potentially, using feature-based verification as an example (Box 5.3), this could be refined to correlate intensity and location of ENSO anomalous SST to more refined watershed regions of rainfall. Clearly, predictability limits are a factor here; however, there is significant user value if, through proper verification, accurate probabilities can be assigned to user-critical events or thresholds.

More challenging is the verification of forecasts of rare events at S2S timescales (Hitchens et al., 2013). Credible reanalysis or retrospective forecast history is limited to approximately forty years, providing a small sample for verification of long-range predictions of extreme or rare events. Techniques for verifying ensemble predictions of rare events are being explored (Gneiting and Ranjan, 2011); however, longer data records are required to provide credible validation and verification.

Finding 5.35: Aggregating observations into features or indices provides added S2S predictability. Feature-based or object-oriented verification, especially ensemble feature-based verification, needs to be pursued for S2S to support Earth system model development and forecast calibration and validation.

Finding 5.36: Two-step verification correlating a feature, index, or object to a user-valued event shows promise for extracting useful signal at the limits of predictability.

BOX 5.3—Feature-Based Verification

Feature-based verification as proposed by Brown, et. al., 2002 has been heavily researched for mesoscale prediction over the past decade with several developed methodologies, including wavelet techniques, empirical orthogonal functions, and clustering (Gilleland et al 2010). A "feature" for mesoscale prediction can represent both temporal and spatial features that are recognizable and that have societally relevant consequences, such as a mesoscale cloud cluster, an area of heavy precipitation, or duration of extreme winds, or it may be a combination of these attributes. Conceptually, we understand a "hurricane" as a feature, but it can be defined as an area of cloud cover, rainfall, a radius of winds exceeding a threshold, or a moving point of maximum wind. For S2S, a "feature" might be an area of SST anomalies that exists in both time and space (e.g. ENSO), an area of severe drought defined by rainfall, temperature, area, and temporal extent, or an area of sea ice coverage. Many indices discussed in the preceding chapters such as ENSO, PDO, MJO, etc., are roughly based on features. Feature-based verification has the advantage that it can "recognize" and verify a feature that may occur slightly earlier or late, may cover a smaller or larger area, may be more or less intense, may be of shorter or longer duration, etc., than predicted. This enables more accurate quantitative evaluation of model performance in "near miss" situations and better refinement of model skill and reliability. Feature-based verification also has the advantage that is an aggregation of model variables in space and time and consequently has greater predictability that a single variable at a single grid-point (see also Chapter 2).

Research to develop feature-based verification techniques will be important, but it is important not to lose track of the fact that verification metrics are a critical part of building trust in the use of forecasts, and the design of metrics that are effective for users can also help drive model development in directions that lead to enhancements in skill that are most beneficial to decision makers (Hartmann et al., 2002; Morss et al., 2008; Pagano et al., 2002). The need to develop verification metrics that are more closely associated with user needs and desired forecast products, such as quantities that may be more directly used by the energy, transportation, hazard, water, and agriculture sectors, among others, in combination with the need to develop common S2S-specific forecast skill metrics to target core physical characteristics of the forecast that are particularly relevant to S2S processes and timescales (e.g. SST, sea ice thickness, upper level atmospheric flow, soil moisture, upper ocean heat content, etc., in addition to indices of S2S relevant modes of variability), highlights the need for a community-wide effort to develop skill and verification metrics that will build user trust while also driving the development of S2S forecast systems in directions that most beneficial to society. An understanding of the different ways in which users interpret forecasts and what they consider to be skillful is clearly necessary to inform the types of evaluation metrics that will influence use of forecasts (see Chapter 3). In developing such common skill and verification metrics, attention is also needed to ensure that such metrics reflect appropriate and optimal combinations of spatial and temporal averaging as the lead time increases from weeks to seasons. Thus developing this range of verification metrics/diagnostics targeting S2S forecast skill improvements, dissemination, and monitoring will require input from, and dialogue among, the operational, research and stakeholder communities (see also Chapters 3 and 6). In some cases, there already exist forums where such a dialogue can begin. For subseasonal prediction, for example, the S2S Project has begun a process to develop common and community-accepted verification and process-oriented skill metrics for forecast systems.

Finding 5.37: Meeting the objectives to increase the skill of S2S forecasts by improving and expanding the representation of the physical system and expanding their utility will require a

community-wide process with operational, research and stakeholder involvement, to develop common S2S forecast skill and verification metrics, as well as process-oriented diagnostics that target S2S processes and phenomena.

Often decision makers simply want to know whether to have confidence in a particular forecast. Should I act on the basis of this forecast? What are the expected consequences if I do? In these cases, effective use of the forecast in decision making requires quantitative knowledge of historical performance of the forecast system in order to link predictions with expected outcomes, i.e., "If I act on this forecast, then I can expect…" In these cases, a quantitative business model or decision process model based on predicted probabilities will then dictate the appropriate measure of model skill. For example, a simple business model for characterizing the effect of warm or cold seasons on electric utilities demonstrates that the critical model performance statistics for analyzing the impact of forecasts (in order to mitigate such predicted adverse events) are the climatological and predicted frequencies of such events, along with the fraction of adverse forecasts that are correct (Dutton et al., 2015).

Verification metrics are most useful when decision makers are involved in their design (see also Chapter 3 and Recommendation B), and for many users, the success of the S2S forecasts is directly proportional to the favorable results achieved by acting on the forecast at various predicted probabilities. Knowing whether to act on a forecast requires detailed and reliable statistics about forecast performance that must be obtained from retrospective forecasts. These retrospective forecasts, then, can be as important to effective user decisions as the forecasts themselves.

In most current operational S2S systems, however, there is inconsistency between real-time forecasts and retrospective forecasts in initialization as well as ensemble size (Appendix B, Tables B.1 and B.2). Furthermore, retrospective forecasts are usually initialized from reanalysis, which can be inconsistent with the state-of-art operational analysis used to initialize the real-time forecasts. This is particularly true for the land surface (e.g., soil moisture and snow). Such inconsistency, particularly the inconsistency in initialization and model configuration for real-time forecasts and retrospective forecasts, can generate anomalies with amplitude as large as the signal we want to predict.

Finally, the full probabilistic information contained in the ensemble forecast is essential to decision making, as emphasized by Dutton et al (2013; 2015). Anomaly correlations or root-mean-square errors use only one or two statistical moments and may or may not be relevant to decisions to act. The critical question is the extent to which predicted probabilities model the frequencies of occurrence in the verification data.

Thus in S2S forecasts, it is important to convey the associated forecast skill to users along with the forecast itself. In addition to providing data for calibration, retrospective forecasts are used to evaluate forecast skill of the S2S system. When retrospective forecasts are made with the same fixed version of model and same ensemble number as the forecast, forecast skill of the system can be more easily assessed with the retrospective forecast data. For those systems doing retrospective forecasts on the fly, the assessment of forecast skill can be more challenging. In these cases, conducting retrospective forecasts with a full set of ensemble members and evaluating the skill once a month could be beneficial. This is true for most of the current operational subseasonal forecast systems.

Finding 5.38: Retrospective forecasts using the current version of the forecast system and up to date reanalyses are important for advancing calibration and validation efforts of ensemble prediction.

The Way Forward for Model Calibration, Combination, Verification, and Optimization of User-Focused Skill

A key conclusion of this section is that the value of S2S forecasts is proportional to the success of the users in acting on the forecasts to take advantage of opportunity or to mitigate risk. Thus the two key components are the forecasts that look to the future and the retrospective forecasts, which inform users what to expect if they act on the forecast. The success of the forecasts also depends on the calibration processes that shape predicted probability distributions to improve the likelihood they will match the verification data. Underpinning this is a the need for a credible verification methodology that reflects the aggregating of observations to extend predictability, the spatial and temporal variability of predictability at S2S timescales, and the unique characteristics of multi-model ensembles.

The opportunity exists for feature-based predictions with S2S lead times. The community is gaining the ability to predict certain features, structures, or indices (MJO, ENSO, sea ice extent, etc.) at S2S timescales and have verifiable attributes using newer object-oriented verification techniques, with extensions to ensemble prediction. There is the potential to provide credible verification of feature skill for S2S predictions, and the Committee believes that this is an important direction to be pursued.

Recommendation J: Pursue feature-based verification techniques in order to more readily capture limited predictability at S2S timescales, as part of a larger effort to improve S2S forecast verification.

Specifically:

- Investigate methodologies for ensemble feature verification including two-step processes linking features to critical user criterion.
- Pursue verification methodologies for rare and extreme events at S2S timescales, especially those related to multi-model ensemble predictions.
- Consider the benefits of producing more frequent reanalyses using coupled S2S forecast systems in order for the initial conditions of retrospective forecasts to be more consistent with the real time forecasts, as well as for the purposes of predictability studies.

Optimization of the Configurations of S2S Forecast Systems

As is clear from the supporting paragraphs above, S2S forecast systems, including the coupled Earth system model, the reanalysis, and retrospective forecasts, can be configured in a wide variety of ways. Designing and implementing a S2S forecast system to operate within finite computing resources always requires trade-offs between spatial resolution, length of forecast lead times, coupled system complexity, the number of model forecast systems for MME approaches, and the number of ensemble members in each forecast system. Thus, the specifications can vary widely over a configuration space of these parameters.

Today the S2S community has little sense of how forecast performance depends on that configuration (Cornuelle et al., 2014; Sandgathe et al., 2013). In addition to research on reducing model errors through parameterizations, increases in model resolution, and adding complexity in coupled submodels, it would be enormously beneficial to ascertain which configurations can produce optimum forecast systems, as defined by reliable probability forecasts across a wide spectrum of climate variability and Earth system variables and by optimum levels of user-focused skill. Although the focus of this report to this point has been on developing dynamical predictions, such an assessment should also consider the value of lower-order models and analog methods for reducing computational costs while maintaining prediction skill.

This determination of how performance depends on configuration is a central key task in any S2S research agenda. Exploring the configuration space (or "trade space") of S2S forecast systems will be a large, complicated, and expensive endeavor, expanding as computer and Earth system modeling capabilities expand over the next decade or more. Such an experiment would benefit tremendously from a central, coordinating authority, and preferably central funding as well (see discussion in Chapter 6).

This work to optimize system configuration is essential to progress today, but it will also never be complete. New methods for representing physical processes (Recommendation H), new computer capabilities (Chapter 7), and new calibration strategies all will mandate a continued search for trajectories through the model and forecast system configuration space that are most advantageous to improving S2S forecast skill and use.

Exploring the "trade-space" thus represents a major and long-term research effort, undoubtedly distributed through the modeling community, which will provide a foundation for the continuing development and improvement of the operational forecast systems to be considered in the next chapter. In summary, the Committee has defined users acting on forecasts as a key metric for measuring S2S success, and we recommend a continuing search for configurations of S2S forecast systems that will optimize the probabilistic information required by users.

Recommendation K: Explore systematically the impact of various S2S forecast system design elements on S2S forecast skill. This includes examining the value of model diversity, as well as the impact of various selections and combinations of model resolution, number of ensemble perturbations, length of lead, averaging period, length of retrospective forecasts, and options for coupled sub-models.

Specifically:

- Design a coordinated program to assess the costs and benefits of including additional processes in S2S systems, and relate those to benefits from other investments, for example in higher resolution. In doing so, take advantage of the opportunity to leverage experience and codes from the climate modeling community.
- Encourage systematic studies of the costs and benefits of increasing the vertical and horizontal resolution of S2S models.

- Evaluate calibration methods and ascertain whether some methods offer clear advantage for certain applications over others, as part of studies of the optimum configurations of S2S models.
- Explore systematically how many unique models in a multi-model ensemble are required to predict useful S2S parameters, and whether those models require unique data assimilation, physical parameterizations, or atmosphere, ocean, land, and ice components (see also Recommendation L).

Chapter 6: Interface Between Research and Operations

The aim of research efforts to make subseasonal to seasonal (S2S) predictions is to operationalize forecasts on these timescales to provide consistent and timely forecast information that various sectors can rely upon for decision making. As described in Chapter 3, there is an increasing demand for easily accessible and comprehensible S2S forecasting information that is updated on a regular basis, which provides an increasing demand for operational S2S products. As described in Chapter 4, there is ongoing progress to identify and characterize sources of predictability for S2S forecasts. As described in Chapter 5, the models that have been developed as research tools to study scientific questions regarding the processes responsible for weather and ocean variability, climate change, and predictability are being improved at a rapid pace (e.g., Delworth et al., 2006; Gent et al., 2011; Kiehl et al., 1998). Any strategy to improve the provision of operational S2S products needs to incorporate the efficient migration of advances from the research community into operational forecasts (NRC, 2012b).

A key part of the interface between research and operations will need to take into account the interaction between the research and operational communities. There is a natural tension between the academic research community and the operational forecasting community. Researchers within the academic community are generally rewarded for exploring new concepts, as scientific journals often favor publications that are viewed as making major advancements as opposed to incremental changes. Forecasters in the operational community are often under pressure to maintain a natural conservatism. Because numerous users depend on operational forecasts and invest in using specific outputs, there is pressure on the forecasters to maintain consistency in their forecast products. This tension can be healthy, but some of these cultural differences between the two communities can impede dialogue and collaboration. Facilitating work across this interface between research and operations needs to start by acknowledging these cultural differences.

This chapter describes several ongoing efforts to promote collaboration across the research and operational communities both in the United States and elsewhere. The topic of forging better links between research and operations in climate modeling was covered comprehensively in a recent NRC report (NRC, 2012b), and the Committee builds upon rather than repeats the highly relevant but more general findings of that report here. Thus in this Chapter, the Committee makes the case for several recommendations that are more specific to the S2S context. In particular, because of their importance in reducing uncertainty and increasing the skill and reliability of S2S forecasts (Chapter 5), the Committee's emphasis is on research to operations related to the development of Multi-model Ensemble forecast systems (MMEs).

CURRENT ACTIVITIES AT THE INTERFACE OF S2S RESEARCH AND OPERATIONS

There are a number of efforts, both nationally and internationally, that work at the interface of research and operations in S2S forecasting. Many of these efforts were introduced previously in in Chapter 2. This section describes in greater detail several prominent efforts, highlighting their importance for bridging research and operations, particularly in the area of developing MME prediction systems; it is not intended as a comprehensive list.

Demonstration MME S2S Forecast Systems

As introduced and described in Chapter 2 there are a number of international efforts aimed at improving MMEs and issuing MME forecasts in demonstration mode. The North American Multi-Model Ensemble (NMME-40) (Box 2.2) is a demonstration project for S2S prediction involving universities and laboratories in the United States, NCEP, and the Canadian Meteorological Center. It is supported largely through research dollars from NOAA, NSF, NASA, and DOE. Participating modeling groups include both operational and research centers[41], with forecasts from each provided to the NOAA Climate Prediction Center for evaluation and consolidation as an experimental multi-model ensemble S2S prediction system.

Phase 2 of the project focuses on bridging research and operations, and requirements for operational S2S prediction are used to define the specifications of a rigorous retrospective forecast experiment and evaluation regime. Other more specific goals of the NMME-2 experiment include (Kirtman, 2014):

i. Build on existing state-of-the-art U.S. climate prediction models and data assimilation systems that are already in use in NMME-1 (as well as upgraded versions of these forecast systems), introduce a new forecast system, and ensure interoperability so as to easily incorporate future model developments.
ii. Take into account operational forecast requirements (forecast frequency, lead time, duration, number of ensemble members, etc.) and regional/user-specific needs. A focus of this aspect of the experiment will be the hydrology of various regions in the United States and elsewhere in order to address drought and extreme event prediction. An additional focus of NMME-2 will be to develop and evaluate a protocol for intraseasonal or subseasonal multi-model prediction.
iii. Utilize the NMME system experimentally in a near-operational mode to demonstrate the feasibility and advantages of running such a system as part of NOAA's operations.
iv. Enable rapid sharing of quality-controlled retrospective forecast data among the NMME team members and develop procedures for timely and open access to the data, including documentation of models and forecast procedures, by the broader climate research and applications community.

The Asia-Pacific Climate Center (APCC [Box 2.1]) is a joint activity of Asia-Pacific Economic Cooperation involving 17 operational and research centers from nine APEC member countries. It collects dynamic ensemble seasonal prediction data from these centers, and

---

[40] More information on the National Multi-Model Ensemble is available at http://www.cpc.ncep.noaa.gov/products/NMME/NMME_description.html and https://www.earthsystemcog.org/projects/nmme/ (both accessed January 27, 2016).
[41] Details of each of the participating models can be found at http://www.cpc.ncep.noaa.gov/products/NMME/Phase1models.png (accessed February 10, 2016).

produces seasonal forecasts and outlook that are disseminated to APEC members every month (see Box 2.1). Together with its aligned research institute —CliPAS—the APCC project has established protocols and databases for contributing model centers' forecast data, which in turn supports research on predictability. As part of the project, APCC also conducts research on multi-model ensemble methods, which in turn feeds work to issue MME forecasts using the most beneficial methodology (Min et al. 2014).

Through these and other MME research and demonstration efforts (e.g., ENSEMBLES, DEMETER —see Chapter 2), much has been learned about MME forecast systems. As also described in Chapter 5, a primary finding has been that MME forecasts in general show improved forecast skill and reliability when compared with the individual model forecasts. Thus first and foremost, these demonstration and aligned research-operational efforts have shown the potential for operational MMEs.

Finding 6.1: Previous MME efforts have demonstrated MMEs as a viable mechanism for advancing S2S forecasts.

Although it is not yet a forecast demonstration project as both NMME and APCC are, the WWRP/WCRP joint research project—the S2S Project—started in January 2013 with a primary goal to advance subseasonal forecasting by coordinating prediction and predictability research enabled by the establishment of a multi-model data base. The data base consists of ensembles of subseasonal (up to 60 days) forecasts and supplemented with an extensive set of reforecasts following TIGGE-the THORPEX Interactive Grand Global Ensemble-protocols (Box 2.3). Note that while this project leverages operational systems, the forecasts are currently disseminated with a three-week delay, thus emphasizing the use of operational forecast system data for use by both the research and operational communities.

One advantage of the S2S Project database is the diversity of operational models. However, there is inconsistency among the models in forecast start date, frequency, lead time, and reforecast strategy, which makes it difficult for data exchange, performance inter-comparison, and research. This also reflects the fact that the subseasonal forecast is still in its infancy stage.

There are significant opportunities for leveraging the S2S Project, not only the database but also the associated subproject research and activities. Most of the subprojects already strongly link to entities and activities outside the S2S Project (e.g., the MJO Subproject links to the WCRP-WWRP's Working Group on Numerical Experimentation (WGNE) MJO Task Force). During a recent workshop on Subseasonal Prediction hosted by ECMWF[42], in concert with an S2S Project Steering Group meeting, for example, a working group discussed and recommended avenues for broader international collaboration that would more fully take advantage of the S2S Project and NMME. These included: 1) the establishment of a Task Team on S2S process-oriented diagnostics as well as forecast skill verification metrics—keeping in mind both model development and stakeholder interests, 2) more routine interaction between the leads of the subseasonal NMME Core Team, S2S project co-chairs, S2S Verification subproject leads, and WMO Commission for Basic Systems (CBS) leads, 3) joint workshops between NMME, S2S, CBS, etc., 4) coordinated research experimentation, with leadership in part provided by WGNE, etc. Additional recommendations and full details on the above will be given in the final report of the ECWMF workshop expected to be posted in early 2016. There is an

[42]http://www.ecmwf.int/en/learning/workshops-and-seminars/past-workshops/workshop-subseasonal-predictability.

opportunity for enhanced collaboration between the operational centers contributing to the S2S Project and the WMO Joint CBS/CCl Expert Team on Operational Predictions from Subseasonal to Longer-time Scales (ET-OPSLS), which operates through the WMO Lead Centre in Korea. Building on the existing mechanism whereby the LC has access the same S2S database, but without the three-week embargo, could enable a closer synergy between the research community and operational centers' research efforts.

Finding 6.2: The S2S Project has begun a process for archiving data from operational forecast systems and coordinating research using these databases to accelerate improvements in subseasonal prediction, as well as play key role in guiding the development of decision support projects.

Example R2O Strategies and Arrangements

ESPC

The National Earth System Prediction Capability (ESPC) Inter-Agency program was established in 2010 "to improve coordination and collaboration across the federally sponsored environmental research and operational prediction communities for the scientific development and operational implementation of improved global prediction at the weather to climate interface."[43] ESPC advocates for a number of things at the interface of research and operations, including common coupled modeling architectures and standardization of data, archives, and forecast skill metrics.

As part of ESPC, NOAA and the U.S. Navy use a number of mechanisms to improve the flow of technology into operational weather and ocean systems. These include focused workshops, visiting scientist programs, special sessions at professional conferences, testbeds and focused transition teams such as the Navy's development- and operations-transition teams and NSF/NOAA's Climate Process Teams.

European Efforts

The UK Met Office operates a single science program, covering both weather and climate and both research and transition to operations. This approach, with the same management responsible for all parts, means that R2O challenges are significantly lessened, in part as the whole program can be designed with R2O in mind. In addition, there is an active science partnerships program, which seeks to entrain developments and expertise from international partners and the academic community. The latter is facilitated by relationships with a number of key universities (including jointly funded positions and PhD studentships). There is also a crucial strategic relationship with the Natural Environment Research Council (who fund much of the academic research in the UK), which enables co-design and co-funding of major research programs such as those developing the next generation dynamical core and working on improvement of the representation of convection in weather and climate models. This integrated

[43] http://espc.oar.noaa.gov/.

approach—both in the design of the programs and in having a mixture of academic and Met Office scientists carrying them out—is of great benefit for R2O.

The European Centre for Medium-Range Weather Forecasting (ECMWF) also has a strongly focused research program, targeted at generating operational improvements. They also host a significant number of visiting scientists, and host numerous workshops (involving international experts), seminars, and training programs.

Finding 6.3: The United States can learn from international efforts to connect research and operations more closely and can build upon current national efforts to coordinate research and operational activities.

CHALLENGES IN RESEARCH TO OPERATIONS (R2O) AND OPERATIONS TO RESEARCH (O2R)

Motivated by the growing expectation for governments to provide S2S services (e.g., Dr. Jane Lubchenco's testimony before Congress during the hearings to confirm her as Undersecretary of Commerce for Oceans and Atmosphere and Administrator of NOAA [Lubchenco, 2009]), there is a desire within the research community to migrate experimental prediction models into operational use, e.g., the NOAA Climate Test Bed effort to build the NMME (described previously). There is also a desire to improve on operational models by transitioning model components and/or parameterization schemes from experimental models developed in the broader community. In theory, this migration of experimental model components and parameterizations into operational use has the potential to efficiently leverage the U.S. S2S research community and to provide more skillful and comprehensive operational predictions.

However, there are gaps between research goals and operational imperatives, e.g., that changing an operational model requires a more careful and elaborate process than for a research model. There are also mismatches between resource requirements needed to maintain an operational model and the current distribution of resources between research, development, and operations.

There is also a mismatch between the expectations of the operational NWP and seasonal prediction community and the model research and development community. The principal measure of success of work that is supported by a typical short-term (e.g., three-year) research grant is the number, quality, and impact of the research publications that result from any project. Researchers receive no reward for developments that become "operational," so there is little incentive to do what is viewed as very substantial extra work to transform research results into operational methods or procedures. There is a view that the scholarly publications speak for themselves, which has been described as a "loading dock" approach—the research results are made available to the operational prediction community via peer reviewed publications (left on the loading dock), and it is up to users to figure out how to use the results (see Chapter 7 for more discussion of workforce issues).

From the operational community point of view, there are a great many constraints imposed by operations that need to be taken into account by the researchers who seek to improve operational predictions. In order to effect a transition from research to operations, they argue, the research community needs to modify its developments to conform to the constraints of the operational models and resources. However, in order for the research community to use operational models for research, operational centers need to provide infrastructure support for developments to be fully tested in the operational environment. The mismatch between the two communities' expectations has been called the "valley of death," that is, a communication and interaction gap (NRC, 2012b). There is a need to better align the two communities and provide adequate resources so that good ideas can be more rapidly and effectively transformed into operational practice.

Operations-to-research is a similar issue. In order to make research relevant and focused on scientific issues exposed by operations, operational centers must provide access to their data and analysis, access to operational models, and access to multiyear reanalysis and retrospective forecasting runs. In addition, operational and agency development laboratories must provide access to key model developers and software engineers to facilitate use of code and data by the outside community. These activities are demanding for personnel, computational and storage resources, something operational centers have traditionally lacked (see also Chapter 7).

At the core of the challenges within R2O for S2S is the question of how to expand participation in the development and improvement of the operational prediction systems in the operational centers. Currently, the major route for research results and successes to move into operations is by diffusion through the professional literature and meetings and some focused symposia, like those of ECMWF, for example, Seasonal Prediction in 2012 and Subseasonal Predictability in 2015. Continuation of these efforts is important to continue the transfer of information along the R2O pipeline. However, common access to operational systems and data is a requirement for improving the flow of technology and information.

Finding 6.4: There is a clear need to provide the research community with greater access to operational systems or mirror systems to aid in transitioning component, and parameterizations from the research community into operational centers.

WAY FORWARD FOR RESEARCH TO OPERATIONS

Over the past two decades, substantial progress has been made understanding some of the phenomenological drivers for S2S prediction, and operational centers have made progress in improving S2S forecast skill (see Chapters 2 and 5). However, there is significant opportunity for increased operational skill from current levels in both seasonal and subseasonal forecasts (Chapter 4). Connecting the research and operational communities together more effectively is an important part of improving that operational skill, and advancing research and quasi-operational prediction systems into operational mode. Operational centers need to carefully choose which updates to make because there are often trade-offs in which improving one type of forecast may come at the expense of another, and users who invest heavily in developing products based on the output from operational centers and rely on that output being in a specific form. Ensuring that the best research results get into operational use and allowing researchers to contribute and learn from the experiences of the operational centers is an ongoing challenge for the weather/climate community at large (NRC, 2012b). For S2S in particular, there are a few areas that need enhanced attention, including planning and work to develop operationalized multi-model S2S forecast systems, providing the S2S research community greater access to the data and models from operational systems, and organizing the operational community to be ready to provide S2S forecasts on the consequences of large, unanticipated events.

Operationalizing MMEs

As described in Chapter 5, MMEs have demonstrated a potential for improving the skill and uncertainty quantification of S2S forecasts. Although there are many design considerations that must be addressed to develop the best operational S2S forecast systems (see Recommendation K), it has been established that a multi-model ensemble outperforms a single model ensemble at extended timescales (Kirtman, 2014; Chapter 5). The Committee believes that all evidence points to the necessity of multi-model ensembles for enabling more skillful S2S forecasts in the next decade. Thus a long term goal of the U.S. operational centers should be to develop an operational MME.

An immediate question to ask is whether the existing North American Multi-Model Ensemble (NMME; see above) could be built upon to develop a fully operational MME. While the NMME-2 is being used in a quasi-operational mode and providing data that is incorporated into NCEP operational products, external users, and the research community on a near real-time basis, its existence is almost entirely dependent on research funding. The CFSv2 is the current NCEP operational seasonal prediction system and is supported as such. The Canadian Meteorological Center systems are being provided in a demonstration mode, complementary to the U.S. systems. However, all other systems in the NMME are supported through federal research funding activities including NOAA Office of Oceanic & Atmospheric Research (OAR), NASA, NSF, and DOE. There have been calls to operationalize the NMME; however, in the Committee's view these are misguided. Participants such as universities or research laboratories have little motivation or funding to sustain the provision of 99.9% reliable, on-time data delivery of forecasts with adherence to rigorous software validation and verification or to scheduled software update cycles. Even the more applied laboratories such as NASA and NOAA's Geophysical Fluid Dynamics Laboratory (GFDL) do not have the mission, funding, or infrastructure to meet the rigorous requirements imposed upon operational data providers. NMME is funded and intended to provide a—highly valuable—research vehicle for advancing seasonal prediction and especially for investigations into optimal multi-model ensemble configurations.

It will be difficult to create a multi-model ensemble in a true operational environment. The value of the multi-model ensemble appears to be in the differing data assimilation, dynamics, and physical parameterizations of the contributing models, which leads to cancelation of model biases and a better assessment of predicted probability distributions. This implies that an operational system of systems should include distinctly different systems. However, each individual system requires an expensive host of scientists and software engineers, especially as computer systems become more complex (Chapter 5). Seasonal forecast systems are also very computationally expensive and would significantly impact a single operational center's computing resources.

A critical challenge for the next decade therefore will be the design and implementation of an operational multi-model S2S forecast system that operates within finite operational resources. Meeting this challenge will require exploring the entire trade space for S2S prediction systems including using common model components (ocean, wave, land, aerosol, ice), using statistical-dynamical prediction such as analogs, or using stochastic parameterizations to achieve suitable skill with fewer or even a single system. Thus, the Committee's related recommendation above (Recommendation K) is an important step in the process of deliberately designing an operational MME system (and not basing the MME design solely on expediency). Exploring the various options in this space with the goal of optimizing skill while ultimately reducing the number and uniqueness of system members should lead to a tremendous reduction in the cost of human resources to maintain a multi-model operational system.

This exploration of strategies needs to take place within the context of the current NMME, WWRP/WWCRP S2S Project, and/or APCC S2S forecast efforts, but further demonstration of benefits in increased skill and reliability as part of this exploration will be a key component of the national research agenda for S2S prediction. However, it is critical that the broader research community be engaged in this effort. As described for climate models generally (NRC, 2012b), operational centers would best promote these advances by providing operational models, supporting data sets, and a user-friendly model testing environment that allows external researchers to test experimental parameterizations and/or model components in an operational setting. This requires a "collaborative framework where datasets and metrics/targets are standardized for careful intercomparison" (Sandgathe et al., 2013). The NOAA Climate Test Bed activity[44] provides the potential for such a connection. In addition, the Next Generation Global Prediction System (NGGPS[45]) is an effort by the National Weather Service to accelerate R2O for weather forecasting. The current efforts would need significant enhancement to fully address the challenges of designing an operational MME.

As described above and in Chapter 5, systematic design of a robust multi-model S2S system will be a large, complicated, and expensive experiment, which would benefit tremendously from a central, coordinating authority and preferably central funding as well. The various interagency efforts within the U.S. government, for example ESPC described above would be positioned to do this coordination and determine a plan forward with the long-term goal of establishing an operational MME. The plan for an operational MME could start with models from North American operational centers, but could be expanded to include models from other countries.

Recommendation L: Accelerate efforts to carefully design and create robust operational multi-model ensemble S2S forecast systems.

Specifically:

- Use test beds and interagency and international collaborations where feasible to systematically explore the impact of various S2S forecast system design elements on S2S forecast skill, in particular the question how many and what formulations of unique models are optimum in an operational multi-model ensemble (see also Recommendation K).
- Assess realistically the available operational resources and centers that are able to contribute to an operational MME.

---

[44] http://www.nws.noaa.gov/ost/CTB/, accessed January 27, 2016.
[45] http://www.nws.noaa.gov/ost/nggps/, accessed January 27, 2016.

Provide Research Community with Greater Access to Operational Systems

There are a number of ongoing activities working at the interface of research and operations (described above). As such, rather than recommend a wholesale restructuring of the relationship between these communities, the Committee chooses to make several targeted recommendations to help continue progress in this area. That said, the Committee emphasizes that these recommendations will take significant time and effort to accomplish and that they should be viewed as part of a longer term challenge to address over the course of the next decade.

As the S2S community looks to bridge S2S research into S2S operational predictions a new paradigm is needed for the U.S. research to operations (R2O) pipeline. At the center of the challenges within R2O for S2S is the participation by researchers with new ideas and tools in development and improvement of the prediction systems in the operational centers. Closing the gap between research and development and operational prediction will require the capability to establish workflow provenance and automate analysis where feasible and reasonable, for which research and development are needed. The major route for research results and successes to move into operations are by diffusion through the professional literature and meetings and some focused symposia, like those of ECMWF, for example, Seasonal Prediction in 2012 and on Subseasonal Prediction in 2015. Continuation of these efforts is important to further the transfer of information along the R2O pipeline.

The section on current activities above describes efforts by the U.S. Government, ECMWF, and the UK Met Office to improve the flow of research to operations. Promoting and expanding these mechanisms would help to include more scientists in plowing the new ground of S2S.

Beyond current activities, the Committee recommends two additional approaches. One is the use of a data archive of operational deterministic and ensemble forecasts and retrospective forecasts and their initialization data by the research community outside the operational centers. This would facilitate further analyses of sources of predictability; identify new sources of predictability, skill diagnostics, and more. Data storage will be a challenge for these types of request, but not an insurmountable one. These activities could focus on specific periods of time, for example, targeting a field campaign relevant to S2S or a special year of interest such as a given phase of the QBO, to help minimize the archiving effort required by operational modeling centers. Or, national data depositories could be established for this and other "big data" projects.

The WWRP / WCRP S2S project and NMME described above have already begun working on making operational center data available to the research community, including both the reforecast and forecast data. Overall, there is a pragmatic and near-term opportunity for operational centers to help make such archived data more available—through the S2S Project or otherwise—for the research community to use. This could potentially be achieved via test centers. In addition, there is an opportunity for the research community to take more advantage of the operational center data that is now becoming available from the S2S project.

A second approach of substantial benefit would be to provide researchers with the capability to request re-runs of operational models or conduct numerical experiments using operational models themselves. Some of the visiting scientists programs have enabled researcher the ability to insert their diagnostics into operational models, but the ability for researchers to request re-runs of operational models for specific time periods or even test their new parameterization will be difficult given the resource constraints of operational centers. The ability for users to run operational models themselves will be a more difficult challenge, one that involves making the modeling code itself accessible to the research community as well as access to sufficient computing power to run the code. Some modeling centers have already released the codes of their previous versions of operational models. But making codes of current operational models available and accessible is a difficult endeavor that requires a significant effort on the part of the operational centers. To improve the flow of advances between research and operations, operational centers should work towards addressing these substantial challenges of meeting requests for re-runs and making model codes available for researchers over the course of the next couple of decades.

Lastly, most decision makers are likely to acquire information via an intermediary. As described in Chapter 3, the Committee recommends an ongoing process that involves those that use forecast products to make decisions and those who produce forecasts to work iteratively to develop improved forecast products. The private sector will be a key part of that process. Transferring enhancements in private sector products or performance to improvements at the operational centers presents a significant challenge, but part of the iterative process of product development could include feedback from private industry for identifying and improving system performance.

Recommendation M: Provide mechanisms for research and operational communities to collaborate, and aid in transitioning components and parameterizations from the research community into operational centers, by increasing researcher access to operational or operational mirror systems.

Specifically:

- Increase opportunities for S2S researchers to participate in operational centers.
- Enhance interactions with the international community (e.g., the S2S Project and APCC) and with the WMO Lead Centers.
- Provide better access in the near-term to archived data from operational systems, potentially via test centers.
- Develop, in the longer term, the ability for researchers to request re-runs or do runs themselves of operational model forecasts.
- Encourage effective partnerships with the private sector through ongoing engagement (see also Recommendation B).

Establish Capability to Respond to Unanticipated Events

Large, unanticipated events that may influence the weather/climate system may be natural, accidental, or deliberately caused by humans. Natural events of this scale within the last couple centuries have included major volcanic eruptions (such as Pinotubo, El Chichon, and Agung in the 20th century or Krakatoa and Tambora in the 19th century), but could also include meteoroid or comet impacts. Prominent recent accidental events that raised this level of public concern about their wide-spread impact on timescales of weeks and longer have included the Deepwater Horizon Oil spill (NRC, 2013) and the Fukushima Diachi nuclear accident—for its potential to spread radioactivity (NRC, 2014; also see Chapter 3). Deliberate events have included the 1991 Kuwait oilfield fires, or more benignly the decision to substantially curtail Chinese industrial emissions to improve air quality during the 2008 Olympics. On geological timescales there is strong evidence of much larger volcanic eruptions and impacts by extra-planetary bodies. Similarly, future human-induced climate forcing events could greatly exceed the magnitude of historical events. Of particular note, the 2015 NRC report on "Climate Intervention: Reflecting Sunlight to Cool Earth" finds that large-scale albedo modification to cool the climate system is technically feasible with a scope that could be done unilaterally by a single nation or even a wealthy non-state actor, but that the consequences of such actions would not be evenly distributed and could alter atmospheric circulation and precipitation patterns. These types of large unanticipated events have the potential to affect the weather/climate system (and potentially much of the Earth system depending on the event) over S2S timescales.

The Committee recommends that the nation should develop and maintain a system for projecting the consequences of any unusual forcing events—in particular over S2S timescales—in order to aid emergency response and disaster planning. This system should be able to be mobilized within one week (giving time to ascertain the details of the forcing and select the appropriate set of predicted quantities), and return preliminary results for timescales from the near-term to seasonal and out to a one year forecast horizon by the end of a second week. Components of this system should have their quality established before any such event via documentation of hypothetical test cases in the peer-reviewed literature. For longer timescales than one year, there is time to mobilize the broader scientific community to expand the recommended on-demand prediction system and develop new capabilities tailored to the specifics of the major event in question. This system should be initialized using the same datasets and systems as the operational S2S prediction, and have configurations that include a full range of physical and chemical atmospheric, oceanic, cryosphere, and ecosystem processes, drawing upon capabilities from the nation's operational and research weather and climate forecasting systems. Other scientific disciplines should be engaged to prepare components for this system that may be appropriate for such events as volcanic eruptions, meteor impacts, a limited nuclear war, oil or other chemical spills in large water bodies, atmospheric or oceanic releases of radioactivity, or releases of biologically or radiatively active gases and aerosols. Although this system will draw upon the expertise of the nation's research community, it will need to be considered an operational system, with the same robustness and reliability as is expected from other operational forecast systems. The development of this new capability for projecting the consequences of unusual forcing events will leverage off many existing research activities or efforts to develop longer-term Earth system projection capabilities, but it will still constitute a substantial new effort by the nation. As such, the fiscal and computational resources to support this new capability should not be drawn from the limited resources currently dedicated to improving existing S2S forecasts.

By their very nature, it is not possible to statistically validate predictions of the consequences of unusual events by examining skill in simulating large numbers of observed events, or to do bias corrections in the same way as is done for operational predictions. Instead, bias control could be done analogously to how it is handled for centennial scale climate projections: predictions of consequences should be taken from the difference between an ensemble of simulations in which a forcing event occurs and an ensemble of identically initialized "control runs" in which the event does not occur. The credibility of the prediction system can be evaluated by examining its ability to simulate well-observed smaller analogous events (e.g., reasonable simulations of the 1991 Mt. Pinotubo eruptions are a necessary condition for credibly simulating the consequences of a hypothetical Yellowstone Caldera mega-eruption of the magnitude that occurred 640,000 years ago; this is analogous to the use of 20th century simulations to establish the credibility of coupled climate models for 21st century projections of climate change). In addition, since there can be significant nonlinearities in the Earth System, the prediction systems should be used for a diverse series of hypothetical forcing event scenarios of sufficiently large magnitude to ascertain that they will work sensibly when called upon.

Quality assurance and a critical evaluation of skill are essential for any official forecast product. For routinely generated products, this is usually done via making a large number of retrospective forecasts of well-observed previous situations. For unprecedented forcing events, this may not be possible. Publication of simulations of hypothetical or poorly observed historical events in the peer-reviewed scientific literature may provide one adequate path towards providing quality assurance. However, it is important that protocols for quality assurance be agreed upon and these steps towards quality assurance be taken for a wide range of potentially useful projection capabilities. This quality assurance must occur before an unanticipated forcing event, so that these capabilities are available to provide timely and useful guidance to decision makers and the public once such an event occurs.

Recommendation N: Develop a national capability to forecast the consequences of unanticipated forcing events.

Specifically:

- Improve the coordination of government agencies and academics to be able to quickly respond to unanticipated events to provide S2S forecasts and associated responses using the unanticipated events as sources of predictability.
- Utilize emerging applications of Earth system models for long-range transport and dispersion processes (e.g., of aerosols).
- Increase research on the generation, validation, and verification of forecasts for the aftermath of unanticipated forcing events.

Chapter 7: Cyberinfrastructure and Workforce Capacity Building

Previous reports from the National Academies of Sciences, Engineering, and Medicine (NRC, 2010b, 2012a, b) have highlighted the central role that infrastructural, institutional, and workforce capabilities will play in advancing weather and climate modeling and forecasting capacity in the coming decades. Specifically, the reports recognized: 1) the importance of aligning modeling research and development with trends in computing; and 2) creating professional incentive structures and workforce pipelines to ensure investment in pivotal yet currently under-represented activities such as model development, moving research to operational systems, and meeting decision maker needs.

Many of the barriers identified in these previous reports for weather forecasting and climate modeling are common to subseasonal to seasonal (S2S) prediction. Thus realizing the full potential of Earth system forecasts on S2S timescales will require overcoming many similar challenges to weather and climate modeling. This chapter describes two core capacity-building elements required for the success of an advanced S2S forecasting capability, building on, and sometimes reiterating, findings and recommendations issued in the previously mentioned reports (NRC, 2010b, 2012a, b):

- Building S2S cyberinfrastructure capacity, and
- Building the S2S workforce.

BUILDING CAPACITY FOR S2S CYBERINFRASTRUCTURE

This section reviews the risks and opportunities posed to the current S2S computational and data infrastructure by changes in technology as well as the growing cyberinfrastructure requirements to support S2S forecasting. Although the challenges posed by S2S prediction systems are similar to those faced by weather or climate modeling systems, the data and processing requirements for S2S prediction systems will likely test the current cyberinfrastructure capacity to at least as great an extent as those other systems, and an expansion of the cyberinfrastructure and human capital will be necessary to realize the potential of S2S forecasting.

There are several factors driving the growing demand for cyberinfrastructure. Data assimilation, which integrates observational data with models, will be a major driver in growing computational and storage infrastructure needed to enable significant improvements in S2S forecasting. As detailed for climate models generally (NRC, 2012b), future S2S models will require increased computational capacity due to the scientific need for higher spatial and temporal resolutions (e.g., for resolving clouds, ocean eddies, and orographic processes—see Chapter 5).

Typical data volumes from the output of S2S prediction models are discussed in Box 7.1. On the observing side, over one billion scalars will be typical input volumes into the data assimilation component (see Chapter 5, sections on routine observations and data assimilation).

BOX 7.1—Typical Data Volumes from Today's S2S Prediction Forecasts

Data characteristics for eleven operational forecast systems participating in the WCRP-WWRP Subseasonal Prediction Project (see Chapter 6) are shown in Table B.2. Forecast lead times range from 32 to 60 days, spatial resolutions range from about 20 to 250 km, frequency ranges from monthly to daily, and ensemble sizes range from 4 to 51 members. A conservative estimate for what these variables would be expected to be in 10 years for a U.S.-based S2S forecast system would be 90-day lead times, 20km spatial resolution, a doubling of the number of vertical levels, 51 member ensemble size, and daily frequency for the forecasts. This would represent about a 300-fold increase in computational resources. This amounts to forecast data volumes on the order of more than 1 Terabyte per day including just the more typical and basic atmosphere, land, and near-surface ocean quantities. Similar considerations can be made for the retrospective forecast requirements, which essentially represent a multi-decade, ensemble retrospective forecast calculated daily for calibration and validation purposes, and can amount to hundreds of Terabytes per day.

This will drive a greater than 1,000-times increase in data volume and transport from what is seen today by the S2S community. Finally, the analysis phase is multi-purpose and computationally significant; it needs to produce the first-guess fields for the next prediction run, and prepare numerous products for forecasting, decision making, and research. All these developments are seen as essential for more accurate, reliable, and useful S2S forecasts. Taking all these factors together in an example, improving model resolution from 100 km to 25 km and doubling the number of vertical levels as well as model complexity, while running on the order of 100 ensemble members, could easily result in a 1,000-fold increase in computational costs compared to today. Thus, the S2S modeling enterprise fundamentally relies on sustained, dramatic improvements in supercomputing capabilities and needs to strategically position itself to fully exploit them.

Finding 7.1: Needed advances in S2S forecast models (higher resolutions, increased complexity, etc.), require dramatically increased computing capacities (perhaps 1,000x) and similar advances in related storage and data transport capacities.

Computing Infrastructure

The backdrop for this increase in computational requirements is a disruptive time in the broader landscape of computing systems and programming models. All indications are that increases in computing performance through the next decade will arrive not in the form of faster chips, but slightly slower chips with many more computational elements on them (ASCAC, 2015; NRC, 2012b). Exploiting these new many-core chips will not only require refactoring existing parallelism to effectively take advantage of their architectures, but will also require finding additional parallelism throughout S2S applications. As highlighted previously in NRC 2012a for climate modeling, there are three primary ways to do this: 1) add parallelism by scaling the problem out—increasing the horizontal resolution does this, but at the expense of shortening the model time-step; 2) exploit parallelism that is already there but has not been used before, for example by introducing task parallelism by overlapping certain physics calculations or by finding shared-memory parallelism (e.g., Open Multi-Processing [OpenMP]), or finally, 3) develop new algorithms with more inherent parallelism-an example of this is the effort to create so-called parallel in time (PinT) algorithms (e.g. Cotter and Shipton, 2012). All three efforts will require much higher levels of collaboration between computer scientists, software engineers, applied mathematicians, and S2S scientists.

Finding 7.2: The transition to new computing hardware and software through the next decade will not involve faster processing elements, but rather more of them with considerably more complex embodiments of concurrency; this transition will be highly disruptive.

Storage Infrastructure

As with computing infrastructure, the hierarchy of storage devices, including cache, memory, disk, and tape, as well as the virtual memory and file-system abstractions that overlay them, will also undergo a dramatic, transformative change in the coming years (NRC, 2012b). As with climate modeling, these changes will require an assessment of most data storage elements (both memory and disk) of S2S applications in order to fully leverage the storage and memory hierarchy of emerging computer architectures. The work of identifying the elements of the code that can or should be addressed is in itself a daunting task. Technologies like Solid State Devices (SSD), 3-D "stacked" memory, and non-volatile memory (NVM) have been, or will soon be introduced into planned compute and storage systems. These and other innovations will augment and blur the price points, sizes, and performance characteristics of the traditional storage hierarchy. Further out, hybrid devices like memristors and other processor in memory (PIM) technologies will begin to blur even the distinction between memory and computing itself. Adapting the modeling systems and managing and optimizing the utilization of this increasingly complex storage hierarchy will be fundamental to realizing the full potential of supercomputing investments.

As with computing, a new breed of software engineers and modelers, and actual data scientists, will be needed to fully realize the potential of these new technologies. More training and workforce development will be required of new and existing software engineers, and universities will need to play a larger role in building the next generation of computational and data scientists (see section below on Building Capacity in the S2S Modeling and Prediction Workforce).

Finding 7.3: Future storage technologies will be more complex and varied than today; leveraging these technological innovations will require numerous software changes and will likely be highly disruptive.

S2S Application Challenges

For climate models generally, increasing numbers of processing elements combined with deep and abstruse memory hierarchies will continue to push the limits of application code design and parallel programming standards and will make for a challenging environment for high-performance-computing (HPC) application programmers (NRC, 2012b). S2S applications today are already challenged in taking advantage of modern supercomputing systems (with efficiencies typically below 5%) [Roe and Wilkie, 2015; Wilkie, 2015]. S2S applications possess several special characteristics that make them particularly challenging relative to current and even more so future HPC architectural trends:

- S2S applications require long simulations compared with traditional numerical weather prediction simulations. This in turn limits the resolution, the inherent number of parallel degrees of freedom, and therefore their scalability. Similar concerns accompany certain data assimilation algorithms, such as 4D variational methods, which have limited scalability relative to ensemble approaches (NRC, 2008).
- S2S applications are large and complex with many component models. Both the Community Earth System Model (CESM) and the Climate Forecast System (CFS) for example, have over 1.5 million lines of source code. Characteristics typical of many algorithms in S2S applications—large numbers of variables (e.g., from increased model complexity) and/or irregular memory access patterns (e.g., unstructured grids and some advection schemes)—do not work well on memory systems with deep cache hierarchies, wide cache lines, and decreasing amounts of memory per processing element. The introduction of vector capabilities into many core processors creates challenges for the "branchy" physics codes[46] typical of S2S applications.
- S2S phenomena are representative of chaotic systems that are sensitive to initial conditions (see Chapters 4 and 5). For this reason, developers currently require bit-for-bit reproducibility (i.e., providing the same output when provided with the same input across different runs [Arteaga et al., 2014]) for testing and verification of model results. This restriction is a limiting factor in fully leveraging the optimization capabilities of compilers and elemental math libraries. In the future, this bit-for-bit requirement may become untenable when issues of fault resilience, and architectures with extreme levels of concurrency and complexity further erode reproducibility (NRC, 2012b; Palmer, 2015). The possibility of irreproducible computation presents a fundamental challenge to the present methodology for the testing, verification, and validation of S2S model results. If architectural or software infrastructure changes, or compiler optimization nudges the answers, even by a minute amount, there is no other way to prove whether the change has or has not pushed the system into a different climate state other than computing the climatology of long control runs (usually 100-years-long to take into account slow climate processes). This requirement is restrictive and represents a considerable barrier to the development, testing, and optimization cycle. However, given the computation power that will be utilized for daily, multi-member, long-lead S2S forecasts, that in some cases may involve daily reforecasts as well, the computation of a 100-year climatological simulation does not seem formidable even in the development cycle. There is evolving research into the use of imprecise computing (in which irreproducibility is not elevated to the level of a requirement) to address some of these issues (Palmer, 2015). One alternative being explored to reduce this cost is to run statistical tests on single ensemble members for consistency with the parent distribution over much shorter periods (Baker et al., 2015). On the other hand, having a mode where S2S models are able to give bit-by-bit reproducibility on computers that are able to support this is essential for the efficient development and debugging of such models. The S2S modeling community may very well need to adapt to a world where reruns of experiments are only the same in a

[46] "Branchy" refers to physics codes that include a lot of if-then statements, thus involving significantly more computing time.

statistical sense. Similar to climate models, such adaptation would entail profound changes in methodology and be an important research challenge for this decade (NRC, 2012b). A possible resolution of this issue is a compromise in which exact reproducibility is available for model development and testing but abandoned for large-scale operational computations that involve many ensemble members and stochastic parameterization and forcing.

Finding 7.4: S2S models are not taking full advantage of current computing architectures, and improving their performance will likely require new algorithms with better data locality, and significant refactoring of existing ones for more parallelism.

Shared Software Infrastructure Components

Similar to the climate modeling community (NRC, 2012a), a renewed and aggressive commitment to shared software infrastructure components across the S2S community could be an efficient way to navigate likely transitions in computing and storage infrastructure, and to overcome poor efficiencies from current applications. The transition will likely be more disruptive than the transition from shared memory vector to distributed memory parallel that started in the late 1990s. Indeed, conventional wisdom in the HPC community (see Zwieflhofer [2008] and Takahara and Parks [2008]) is that the next generation conversion will be significantly more complex and unpredictable than previous changes, given the absence of a clear technology path, programming model, performance analysis tools, etc.

The S2S modeling community is seeing the natural evolution of software component adoption (regridding from Earth System Modeling Framework [ESMF] used by CESM, the National Centers for Atmospheric Research's [NCAR's] Parallel I/O [PIO] library used by others). The Committee believes that the community is now at the point where developing an integrative modeling environment (across models and organizations) outweighs the costs of developing the tools to enable an integrative environment (e.g., Common Infrastructure for Modeling the Environment [CIME] at NCAR, Earth System Modeling Framework [ESMF] at NOAA and Navy) and the cost of moving to them. With the experience, successes, and lessons learned in the past decade, the forecasting community is positioned to accelerate the development and adoption of an integrative modeling strategy.

So far, not many software components have been broadly adopted as a standard, because modeling centers that initially invested in one solution have had insufficient funding and incentives to switch to another. The vector to parallel disruption led to widespread adoption of coupler technologies at the scale of individual institutions. The forecast modeling community can conceive of a common integrative modeling environment that includes a set of component elements that could be subscribed to by all major U.S. forecast modeling groups, supports a hierarchy of models with component-wise interchangeability, and also supports development of high-performance implementations that enable forecast models of unprecedented resolution and complexity to be efficiently adapted to new architectural platforms. The U.S. Global Change Research Program's Interagency Group on Integrative Modeling (IGIM[47]) has begun work to better coordinate the country's climate modeling efforts (USGCRP IGIM, 2015); such coordination would likely benefit S2S forecasting efforts as well. Concurrently, the National

[47] http://www.globalchange.gov/about/iwgs/igim-resources, accessed January 27, 2016.

Earth System Prediction Capability (ESPC)—an agreement between NOAA, DOD, NASA, DOE, and NSF to work on weather to subseasonal timescales—has adopted a standardized version of ESMF and has proposed common standards for implementing physics parameterizations into atmospheric models[48]. ESPC and IGIM are exploring the potential for more commonality as their efforts go forward. Adopting joint standards between IGIM and ESPC will be especially important as the community moves towards seamless prediction as discussed in Box 5.2.

Finding 7.5: An integrative modeling environment presents an appealing option for how to face some of the large uncertainty about the evolution of hardware and programming models over the next two decades.

Data Storage, Transfer, and Workflow for S2S Prediction

In addition to the supercomputer/storage infrastructure and the forecasting models, a key element of the forecasting workflow includes data cyberinfrastructure, including the storage, transfer, analysis, and visualization workflows associated with big data sets. The data cyberinfrastructure for the end-to-end forecasting workflows may ultimately be an even larger challenge than the compute challenges confronting S2S prediction. The data elements include several elements assimilating the large quantities of operational data with model simulation data and facilitating the data analysis, visualization, and overall workflow for all these elements.

Observational Data

Remote sensing systems (satellites, radars, instrumented aircraft, and drones) along with conventional and automated in situ measurements in both the atmosphere and ocean will produce over one billion scalars per forecast cycle (see Chapter 5). Transport and preparation of these data for model assimilation is a challenge. Networks need to have the necessary carrying capacity with minimal latency, and computing and storage need to be available for data processing into model ready quantities (e.g., sea surface temperature in degrees Kelvin).

Model Simulation Data

Fundamentally this effort needs to be operationalized and extended to provide these vital functions. The data sharing and management infrastructure benefits from a "network effect" (where value grows exponentially as more nodes are added; see, e.g., Church and Gandal, 1992; Katz and Shapiro, 1985). It involves developing operational infrastructure for petabyte-scale (and soon exabyte-scale; see Overpeck et al., 2011) distributed data stores. The S2S project (described in Chapter 6) has begun efforts to archive and share data from multiple operational S2S forecasting systems, but this effort is still growing and is underutilized by the research community (see Finding 6.2).

[48] ftp://ftp.oar.noaa.gov/ESPC%5CNUOPC%20Douments%5CNUOPC%20%20CMA%20One%20Pager.pdf

Finding 7.6: Researchers do not currently have a good solution for processing and analyzing S2S data that is federated across many institutions. A dedicated and enhanced data-intensive cyberinfrastructure will be required to enable the distributed S2S community to access the enormous data sets generated from both simulation and observations.

Data Analysis Workflow

S2S data-intensive applications and workflows are likely to face data analysis challenges of similar scale and scope to those faced by the Coupled Model Intercomparison Projects (CMIP). The CMIPs have observed that because storage systems—as part of an integrated data-intensive computing environment—have not kept up with advances in computing, they have become a bottleneck and as a result a ripe target for enhancements. These lessons from CMIP efforts are a bell-weather to what the S2S prediction community could expect. In addition, the demand for data storage, analysis, and distribution resources will grow as models move to finer resolutions, incorporate more complexity, and serve needs of an increasingly diverse and sophisticated set of users. In response, data-centric workflows, like the applications themselves, need to become more parallel, and use storage infrastructure more efficiently. In addition, the community needs to consider reductions of data volumes that can be achieved through both lossless and lossy compression of datasets, as well as a shift away from the paradigm of store-now-analyze-later to mechanisms that allow model output to be analyzed on the fly and re-ran as needed.

There is an increasing need to use, access, and manipulate large volumes of remotely stored data, and this places new demands on infrastructure and requires systematic planning and investment at the national level.

Finding 7.7: New approaches to data-centric workflow software that incorporate parallelism, remote analysis, and data compression will be required to keep up with the demands of the S2S forecasting community.

Moving Forward with Building Capacity for S2S Cyberinfrastructure

As has been discussed in this section, advances in S2S forecast models will require dramatically increased computing capacities, but the transition to new computing hardware and software through the next decade will be highly disruptive with the increasing concurrency of new HPC systems. In addition, future storage technologies will be more complex and varied than today. S2S models are not taking full advantage of current computing architectures, and improving their performance to leverage the coming technology innovations will require numerous software changes and will likely be highly disruptive.

At this time, the many emerging architectures do not adhere to a common programming model. While new ways to express parallelism may well hold the key to progress, from the point of view of the software developers of large and complex scientific applications, the transition path is not clear (NRC, 2012b). Assessments undertaken by the Defense Advanced Research Projects Agency (DARPA) and the Department of Energy (DOE) (e.g., DOE, 2008; Kogge et al., 2008) indicate profound uncertainty about how one might program a future system that may encompass many-core chips, coprocessors and accelerators, and unprecedented core counts requiring the management of tens of millions of concurrent threads on such hardware. The President's Council of Advisors on Science and Technology (PCAST) has called for the nation to "undertake a substantial and sustained program of fundamental research on hardware, architectures, algorithms and software with the potential for enabling game-changing advances in high-performance computing" (PCAST, 2010). This challenge will grow to a billion threads by the end of this decade. The prevalent programming model for parallel systems today is based on MPI (Lusk and Yelick, 2007), shared-memory directives (e.g., OpenMP [Chandra et al., 2001]), or a hybrid of both. The adaptation of the *Message Passing Interface* (MPI)/OpenMP paradigm to exascale architectures is an area of active research investigation.

The weather and climate forecasting community has never retreated from experimenting with leading-edge systems and programming approaches to achieve required levels of performance. The current high-performance computing (HPC) architectural landscape, however, is particularly challenging because it is not clear what direction future hardware and software paradigms may follow. The collaborative nature of system co-design involves end-user/developer community and private sector involvement (e.g., the Coral system[49]).

It is clear that more resources are needed to make the progress necessary to prepare S2S applications for next generation supercomputers. In light of these challenges, the Committee recommends a national plan and investment strategy be developed to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all components of the prediction process.

Recommendation O: Develop a national plan and investment strategy for S2S prediction to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all stages of the prediction process, including data assimilation, operation of high-resolution coupled Earth system models, and storage and management of results.

Specifically:

- Redesign and recode S2S models and data assimilation systems so they will be capable of exploiting current and future massively parallel computational capabilities; this will require a significant and long-term investment in computer scientists, software engineers, applied mathematicians, and statistics researchers in partnership with the S2S researchers.
- Increase efforts to achieve an integrated modeling environment using the opportunity of S2S and seamless prediction to bring operational agency (ESPC) efforts and IGIM efforts together to create common software infrastructure and standards for component interfaces.
- Provide larger and dedicated supercomputing and storage resources.
- Resolve the emerging challenges around S2S big data, including development and deployment of integrated data-intensive cyberinfrastructure, utilization of efficient data-centric workflows, reduction of stored data volumes, and deployment of data serving and analysis capabilities for users outside the research/operational community.

[49] http://energy.gov/articles/department-energy-awards-425-million-next-generation-supercomputing-technologies, accessed January 27, 2016.

- Further develop techniques for high volume data processing and in-line data volume reduction.
- Continue to develop dynamic model cores that take the advantage of new computer technology.

BUILDING CAPACITY IN THE S2S MODELING AND PREDICTION WORKFORCE

The current workforce of S2S model developers is insufficient to meet the growing need for S2S model development work (Jakob, 2010). Most modeling centers have only a small number of people directly involved in model development. It is difficult to quantify the number of S2S model developers in the United States, because a systematic study on the modeling workforce has never been done. Many of the challenges faced in maintaining a robust S2S model development workforce are similar to those faced in climate model development. As such, much of the work in this section draws heavily on previous work on climate modeling (NRC, 2012b).

Current Challenges in the S2S Model Development Workforce

The development and use of comprehensive S2S models in the United States requires a large number of talented individuals in a diverse set of disciplines. The critical point is that development of atmospheric and environmental prediction models, for S2S and other ranges, needs to become an interdisciplinary effort involving scientists, software engineers, and applied mathematicians (NRC, 2008). As described for climate models, these areas of expertise include (NRC, 2012b):

- scientists engaged in understanding the S2S prediction system, leading to the development of new parameterizations and other model improvements (distinct cadres of scientists are often needed for various model components, such as the ocean or terrestrial ecosystem models);
- scientists engaged in using the models for well-designed numerical experiments and conducting extensive diagnostics of the models to better understand their behavior, ultimately leading both to model products and to scientific insights that provide the impetus and context for model improvements;
- scientists studying the regional details provided by the archived results from global model simulations and related downscaling efforts, and how these vary across various models;
- support scientists and programmers to conduct extensive sets of numerical simulations in support of various scientific programs and to ensure their scientific integrity;
- software engineers, applied mathematicians and scientists that straddle these areas to explore fundamental new algorithms and approaches that can fully utilize new generations of computing and storage architectures;
- software engineers to create efficient, parallelizable and portable underlying codes, including the development and use of common software components;
- data scientists to understand and manage complex workflows and to facilitate easy and open access to model output through modern technologies;

- hardware and software engineers to maintain the high-end computing facilities that underpin the modeling enterprise; and
- interpreters to translate model output for decision makers.

From the limited data available (NRC, 2012b), it appears that the level of human resources available for S2S modeling has not kept pace with the demands for increasing realism and comprehensiveness of the models. Data on the numbers of students involved in S2S model development do not exist, and any proxy data and anecdotal evidence (NRC, 2012b) suggest that the pipeline for S2S model developers is not growing in a robust fashion.

These considerations suggest that the development of S2S and other predictive models needs to increasingly be a community endeavor involving the operational centers and the academic community. And to be effective, there must be mechanisms to encourage interchange of personnel and talent, either as long-term collaborators or as shorter-term visitors. For example, students might well perform their dissertation research in an operational center under the collaborative supervision of center scientists and faculty members in their academic institution.

In addition to not having sufficient human resources, many of the skills needed by the S2S workforce are yet to be developed (e.g., new algorithms, tight coupling between the understanding of the science and the software requirements), which places an even greater imperative on maintaining a robust pipeline of early-career scientists who are involved in model development. This will become more critical with the next generation of supercomputers (see section above on Building Capacity for S2S Cyberinfrastructure), and serious efforts will be needed to bridge the gap between scientists and the software engineering and numerical algorithms skills needed to utilize this new hardware. These gaps in the necessary workforce skills need significant attention and could be significant impediments to progress in S2S forecasting.

Finding 7.8: From the limited data available, it seems that the cadre of S2S modelers being trained is not growing robustly in the United States and is not keeping pace with the needs of this rapidly evolving field.

Current Challenges in the S2S Applications Workforce

There are some programs that train students to work at the interface of climate science and society (e.g., Columbia University's Master's program in Climate and Society[50]), which could be a valuable resource to the S2S enterprise. However, as demands for S2S products continue to grow, there is also likely to be a shortage of interdisciplinary researchers needed to improve connectivity between S2S forecasts and use. This includes interdisciplinary researchers in boundary organizations and other interdisciplinary research centers, product development specialists in the private sector, and agency operations personnel with training or expertise in S2S predictability. This also includes social and behavioral researchers capable of examining decision processes to identify barriers to use and improve the flow of information between physical scientists and users.

The challenges of connecting information production to use are discussed in Chapter 3. Here, the focus is on the skills needed to enable those connections. The potential scale of use

[50] http://climatesociety.ei.columbia.edu/, accessed January 27, 2016.

dwarfs the current production of people trained in interdisciplinary research or research in the social and behavioral sciences focused on using weather or climate information in decision making. Weather and climate information is not well integrated into traditional academic disciplines that produce many of the agency personnel who may use S2S information, such as staff at water management agencies or large agricultural businesses. In addition, relatively few academic institutions offer interdisciplinary degrees that include physical, social, and behavioral sciences focused on issues related to weather or climate.

Finding 7.9: Interdisciplinary academic programs and centers lack the capacity to meet growing needs for research and applications necessary to maximize the use of S2S information. Few academic programs include weather or climate as a component of training the future workforce.

Building a More Robust S2S Workforce

S2S model development is a challenging job. It involves synthesizing deep and broad knowledge, working across the interface between science and computing, and working well in a team. Thus it is important to attempt to hire, train, and retain the most talented, available people in this field. There are often insufficient incentives to compel promising young people to work on S2S model development; this applies to both early-career computer programmers who may have other more lucrative career opportunities, and to early-career scientists who may choose to work with S2S model output to examine scientific questions or other strategies that allow them to publish more journal articles, rather than work on model development. A suggested method for combatting this bias would be an enhanced recognition and reward system for S2S model computer code writing and for the production of modeling data sets, including the recognition of such effort through stronger requirements for citation and co-authorship, both within modeling institutions and by academic users and collaborators; this is a non-trivial challenge as discussed in a previous report (NRC, 2012b). S2S modeling groups could also compete by marketing relatively stable career tracks and the opportunity for stimulating cross-disciplinary interactions with a variety of scientists.

Modeling centers outside of the United States, such as the European Centre for Medium-Range Weather Forecasts (ECMWF), have attempted to attract and retain more people in S2S model development work by appointing model developers to 5-year terms, which is longer than typical research grant cycles in the United States (3 years). ECMWF offers strong incentives to bring top scientists to model development, such as access to excellent facilities, excellent tools (e.g., what some regard as the most advanced numerical weather prediction model in the world), and high, tax-free salaries. Further, the inclusion of highly reputed scientists within the limited staff (150 staff members and 80 consultants) encourages a stimulating environment where delivering end-use forecasting products and doing cutting-edge scientific research are valued and are directly coupled.

Beyond the specific model developer needs of the S2S enterprise, there is an additional need for people who work at the component interfaces. As examined in this report, many of the challenges in the S2S realm arise from the linkages of the model components. Therefore the overall S2S forecasting endeavor would benefit from paying particular attention to recruiting and rewarding scientists who can work across specific disciplines of earth science to improve our ability to forecast the behavior of the Earth system as a whole.

Attention to workforce development is also needed to help ensure that forecasts are as useful as possible to decision makers. Chapter 3 discussed that, as with weather forecasts and climate projections, most decision makers are likely to acquire S2S information via an intermediary. There are a number of existing avenues for decision makers to interact with experts working on S2S forecasting, through so-called "boundary organizations" and other interdisciplinary entities. Boundary organizations exist within the public sector (for example NOAA's Regional Integrated Sciences and Assessments program actively engages decision makers through tailored products, educational programs, and efforts to co-produce climate products and services), within academia (for example, Colombia University's International Research Institute for Climate and Society), and within the private sector. Looking forward, continued growth of both the private sector and the array of products and services in the public sector are required to meet the growing demand for services on S2S timescales. In light of similar trends related to information on climate timescales, a recent NRC report (NRC, 2012b) recommended the formation of training programs for climate model interpreters—people who are trained in both physical and social sciences related to climate, weather and decision making, and who can facilitate two-way co-production of knowledge. There is a similar need at S2S timescales for such training programs.

A possible concrete step forward would be a series of workshops to explore how to feature S2S in more undergraduate and graduate curriculums, how to identify and connect with organizations that can help this (e.g., the National Science Teachers Association), and how to interact with the private sector to help understand what skills are needed. Other entities such as the American Meteorological Society (AMS) or NSF may play a role with some of this coordination.

Forecasting work at all of these timescales—weather, S2S, and climate—involves the prediction of outcomes which people use to make important decisions, and is therefore judged in very public ways. Predicted outcomes are validated (or not) on a continuous basis. The fact that S2S connects very strongly to managing environmental risks could be drawn upon more heavily to entrain talented and mission-driven young people into the field.

In looking across the numerous challenges facing the S2S workforce, the Committee recommends that the Nation pursue a collection of actions to examine the S2S workforce, remove barriers that exist across the entire workforce pipeline, and develop mechanisms to improve and sustain the workforce.

Recommendation P: Pursue a collection of actions to address workforce development that removes barriers that exist across the entire workforce pipeline and in the diversity of scientists and engineers involved in advancing S2S forecasting and the component and coupled systems.

Specifically:

- Gather quantitative information about workforce requirements and expertise base to support S2S modeling in order to more fully develop such a training program and workforce pipeline.

- Improve incentives and funding to support existing professionals and to attract new professionals to the S2S research community, especially in model development and improvement, and for those who bridge scientific disciplines and/or work at component interfaces.
- Expand interdisciplinary programs to train a more robust workforce to be employed in boundary organizations that work in between S2S model developers and those who use forecasts.
- Integrate basic meteorology and climatology into academic disciplines, such as business and engineering, to improve the capacity within operational agencies and businesses to create new opportunities for use of S2S information.
- Provide more graduate and postgraduate training opportunities, enhanced professional recognition and career advancement, and adequate incentives to encourage top students in relevant scientific and computer programming disciplines to choose S2S model development and research as a career.

Chapter 8: Vision and Way Forward for S2S Earth System Prediction

Previous chapters in this report identified the societal value of predictions of the Earth system in the subseasonal to seasonal time range; pointed out emerging science and technical capabilities that make advances in forecasts at these timescales possible; and identified areas that need substantial improvement. This chapter draws from the text, findings, and recommendations presented in previous chapters to develop a vision to serve as an inspirational yet possible target for a desired future state of subseasonal to seasonal (S2S) prediction in the next 10 years, and a set of research strategies to guide actions that are necessary to move towards that vision. All of the recommendations from previous chapters are organized within these strategies and together serve as the Committee's comprehensive research agenda for S2S forecasting over the next decade. Implementing the research agenda for improving S2S predictions will require collaboration between researchers and users to develop more useful forecast products, basic research to advance understanding of the processes governing predictability in the Earth system, exploiting these new discoveries in models, and melding existing with new modeling and computing capabilities. Thus the S2S research agenda should simultaneously foster work in areas that are nearing maturity with more ambitious objectives that may take a decade or more to fully realize.

VISION FOR THE NEXT DECADE

For the past several decades, weather forecasts on the scale of a few days have yielded invaluable information to improve decision making across all sectors of society. Determining the total economic value of this forecasting information is an area of active research (Letson et al., 2007; Morss et al., 2008), but previous research indicates that a significant portion of annual U.S. gross domestic product (tens of billions or even trillions of dollars) is sensitive to fluctuations in weather (Dutton, 2002; Lazo et al., 2011; U.S. Department of Commerce, 2014). Certainly short-term forecasts play a vital role in helping society manage this economic exposure and the associated social risk. However, many critical decisions must be made several weeks to months in advance of potentially favorable or disruptive environmental conditions. As demonstrated by case studies and other information presented in Chapter 3, S2S forecasts have great potential to inform such decisions across a wide variety of sectors. For example, it can take weeks or months to move emergency and disaster-relief supplies. Pre-staging resources to areas that are likely to experience extreme weather or an infectious disease outbreak could save lives and stretch the efficacy of limited resources. Similarly, emergency managers responding to unanticipated events such as nuclear power plant accidents or large oil spills are faced with the task of communicating the ramifications of such events on timescales that stretch well beyond a few days. There are many more such examples: naval and commercial shipping planners designate shipping routes weeks in advance, seeking to stage assets strategically, avoid hazards, and/or take advantage of favorable conditions; with improved knowledge of the likelihood of precipitation or drought, farmers can purchase seed varieties that are most likely to increase yields and reduce costs; and depending on the year, water resource managers can face a multitude of decisions about reservoir levels in the weeks, months, and seasons ahead of eventual water consumption (Table 3.1 lists additional examples).

S2S forecasts are already proving to be of value in making such decisions in sectors such as agriculture, energy, water resources management, and public health. However, there are many sectors that have yet to exploit even the S2S information that is currently available. The Committee believes that the benefits of S2S forecasts to society will only increase as the quality of S2S forecasts improves, as more variables are represented in forecast products, and as social and computer science research and boundary institutions accelerate awareness of, access to, and use of S2S information. This potential of S2S forecasts to benefit society is only likely to grow due to the increased exposure to risk and increased severity and frequency of hazards expected with climate change and continued globalization.

Working iteratively with water resources professionals, emergency managers, military planners, and a myriad of other potential users to co-design new S2S forecast products and related decision-making tools has the potential to further expand use and enable stakeholders to derive much more value from S2S forecasts. Along with an enhanced focus on developing predictions of extreme and other disruptive events, such iterative engagement with forecast users has the potential to foster a stronger culture of planning across S2S and longer timescales, including adaptation and resilience to climate change. This could provide social and economic benefits that amplify and transcend the direct benefits of S2S forecasts themselves.

This evidence influenced the Committee's finding that more skillful and useful S2S forecasts—developed through sustained engagement with users and advances in basic knowledge and technological capabilities—could radically improve the basis for decision making on S2S timescales. There are also emerging science and technical capabilities that make rapid advances in S2S forecasts more likely than envisioned even 5 years ago. Advances both in technology—satellites, computing, etc.—and in science—model parameterizations, data assimilation techniques, etc.—are now on the horizon that make advances in S2S forecasting more feasible. Further, the Committee's recommendations are targeted at areas where efforts are most needed and therefore investments are most likely to lead to advances.

Such advances now have the potential to increase the flow of benefits from S2S forecasts so that, in the Committee's view, they have high potential to outweigh the costs and effort associated with improving S2S forecasts. Thus the Committee developed a vision to serve as a target for S2S predictions over the next decade: **S2S forecasts will be as widely used a decade from now as weather forecasts are today**. This is admittedly a bold vision because overcoming the challenges to developing S2S forecasting will take sustained effort and investment. However, the Committee believes that realizing this vision is now possible within the next decade.

Achieving the Committee's vision in this report is not incompatible with other visions for Earth system prediction systems (such as for the creation of a Virtual Earth System (VES)—see Box 8.1), but it has the potential to become reality within a much shorter timeframe. The Committee's strategies and research agenda, which are presented next in this chapter, provide describe priority actions for moving towards this desired future state.

Box 8.1—Long-Term Visions

In 2008, the NRC Committee on The Potential Impact of High-End Capability Computing on Illustrative Fields of Science and Engineering foresaw a Virtual Earth System (VES) that would maintain "a continuous and dynamically consistent portrait of the atmosphere, oceans, and land…a digital mirror reflecting events all over the planet." The VES would operate in the cloud on linked petascale machines, assimilating data from tens of satellites and myriad other observations. (NRC, 2008). The VES would serve as the foundation for a companion Future Earth System that would offer a probabilistic portrait of events and Earth states expected over ranges of leads much wider than those available today (e.g., Dutton, 2010). Indeed in the conclusion to the 2008 report, the NRC stated:

> "The new dynamic record of Earth and the predictions of the VES model would bring forth an era of enlightened management of weather and climate risk, contributing to national economic vitality and stimulating a strong commitment to environmental stewardship. The creation and operation of an accurate and reliable VES would be a stunning and commanding national achievement—a dramatic demonstration of the benefits that can be realized for society by linking Earth and atmospheric science with the most advanced computers."

The VES described in the 2008 NRC report thus presented a visionary consideration of the future of environmental forecasting and its impacts on decision making. However, it also identified the incredible demands and resources that would be required to develop and maintain such a system. Along with the 2010 NRC Report on Intraseasonal to Interannaual climate and weather prediction (NRC, 2010b), this report presents a vision and research agenda that takes society a step towards grand visions for environmental prediction systems such as a VES—specifically by targeting the development of Earth system predictions on S2S lead times, where there is good potential for gains to be made in the coming years (NRC, 2010a, the present report). These advances include improved accuracies, extended lead times, and prediction of other components of the environment beyond the traditional weather variables.

S2S RESEARCH STRATEGIES AND RECOMMENDATIONS

Maximizing benefits of S2S forecasts while minimizing the associated costs will be important for rapidly improving S2S forecasting. The Committee drew on findings in Chapters 3 through 7 to develop four overarching research strategies to help prioritize activities in S2S forecasting and to organize activities so that they most directly support the vision to substantially expand the use of S2S forecast information in the next decade:

1. Engage Users in the Process of Developing S2S Forecast Products
2. Increase S2S Forecast Skill
3. Improve Prediction of Extreme and Disruptive Events and Consequences of Unanticipated Forcing Events
4. Include More Components of the Earth System in S2S Forecast Models

Fourteen associated recommendations derived from Chapters 3 through 6 describe research and aligned activities in the physical and social sciences that the Committee has determined to have the greatest potential for advancing in each of the four strategic directions. In addition, the Committee proposes a set of supporting recommendations, derived from findings in Chapter 7, related to cyberinfrastructure and workforce. These are necessary for advancing the research strategies and achieving the Committee's vision for S2S forecasting. Additional activities that the Committee envisioned would fall under each of the 16 main recommendations add further specificity and breadth to the research agenda. While the main recommendations are placed under the research strategy or supporting activity that they primarily support, implementing each recommendation will often help to advance multiple strategies. Collectively these strategies and recommendations constitute an S2S research agenda for the nation.

Figure 8.1 presents a schematic of the relationship between the strategies and supporting activities and the Committee's vision.

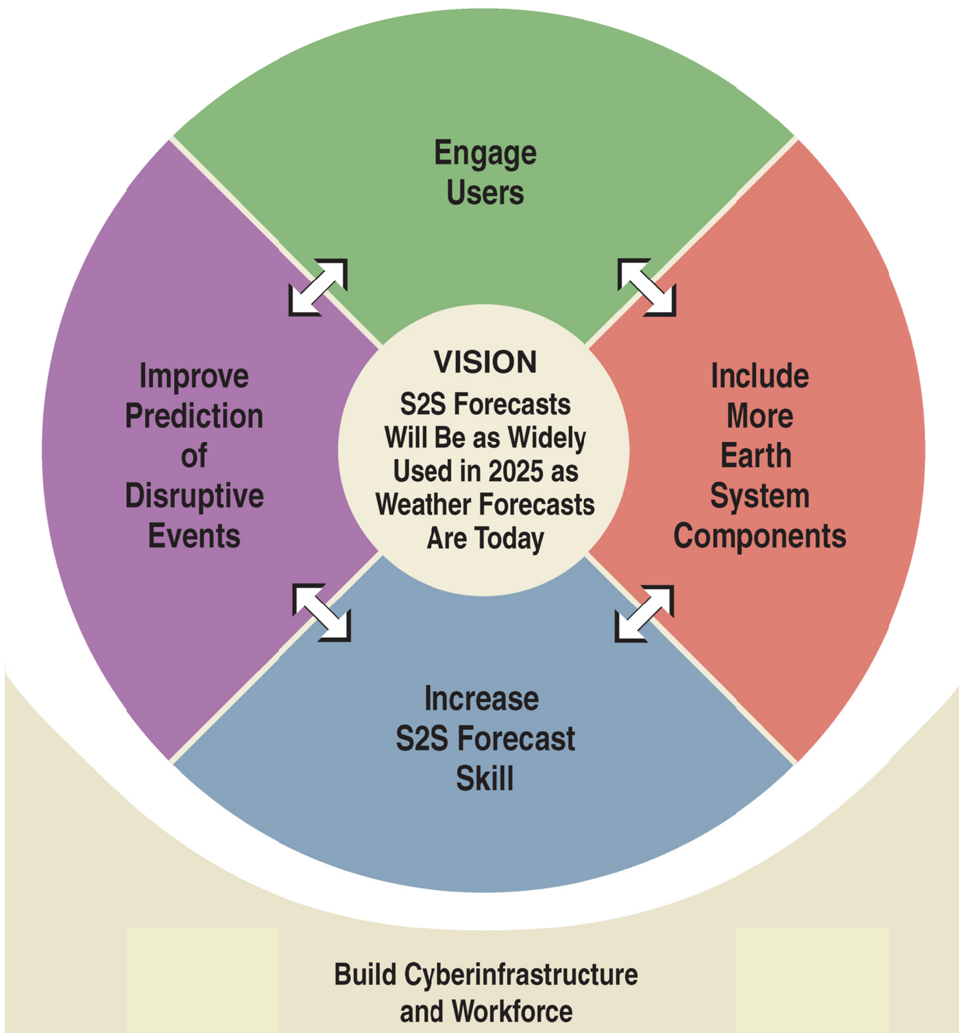


FIGURE 8.1 This schematic illustrates the relationship between the four research strategies and supporting activities outlined in this report for advancing subseasonal to seasonal forecasting over the next decade, which all contribute to the overarching vision. The white arrows indicate that the four research strategies interact and are not mutually exclusive.

Research Strategy 1: Engage Users in the Process of Developing S2S Forecast Products

As highlighted in Chapter 3, providing useable, valuable forecast information involves developing S2S forecast products that are more readily integrated into user decision making. Ten years hence, the Committee envisions an S2S prediction system that is much more interactive with decision makers from a wide array of sectors. In order to achieve this level of interaction, the user community must be brought into the research and development process sooner rather than later. In fact, a key finding of the Committee is that the S2S research and operational prediction community would benefit from engaging in an iterative dialogue with the user community, beginning as soon as possible. Such a process can help further prioritize the development of specific forecast variables and metrics, and ensure that data and resource-intensive retrospective forecasts, as well as the operational forecasts themselves, retain and exploit parameters that are most critical to user decision making.

In order to maximize benefits of investments into improving S2S forecasts over time, there should be an ongoing effort to co-design forecast products on S2S timescales that match what is scientifically feasible with what users can make actionable. In many cases, this might involve a relatively straightforward extension of existing applications that have skill at shorter timescales and for which sophisticated users already exist. In other cases, there may be novel, actionable prediction products that can be identified through more extensive discussions between potential users and the developers of prediction systems and forecast products. Such discussions will be required to identify what operational S2S forecasts will look like, including how the skill of such forecasts will be verified. Public and academic-sector boundary institutions, such as the National Oceanic and Atmospheric Administration (NOAA) Regional Integrated Sciences and Assessments Program (RISA) programs, the International Research Institute for Climate and Society (IRI) at Columbia University, and several private sector companies, have already started these discussions. Leveraging the entire weather and climate enterprise will be necessary for further developing effective S2S products and services that maximize benefit to society.

Recommendations

Research into the use of S2S forecasts thus far indicates that users desire finer temporal and spatial resolutions, more actionable forecast variables (e.g., extreme, disruptive and other important events as well as mean conditions), as well as a better understanding of how probabilistic S2S forecast information at varying levels of skill can be integrated directly into decision making. However, user needs, how these match with current forecast capabilities, and barriers to use of forecasts, have not been thoroughly investigated across sectors. An important first step in providing more actionable S2S forecast information is to develop a body of social and behavioral science research that leads to a more comprehensive understanding of the current use and barriers to use of S2S predictions. This includes a better understanding of specific aspects of products—forecast variables, spatial and temporal resolutions, necessary levels of skill, formats, etc.—that would make S2S predictions more useful to different communities. This research is necessary in order to develop a high-level view of how S2S forecast systems and outputs might be designed to meet the basic needs of the broadest number of potential users.

While all weather and climate forecasts are inherently probabilistic, this probabilistic nature gets more difficult to disregard for forecasts at S2S and longer timescales than at shorter lead times. Probabilistic predictions in particular represent a significant hurdle for some forecast users, as there often are substantial differences between the large-scale probabilistic forecasts that are possible at S2S timescales and the specific information that decision makers might currently find actionable. Research on the use of probabilistic forecast information is thus also necessary.

Recommendation A: Develop a body of social science research that leads to more comprehensive understanding of the use and barriers to use of seasonal and subseasonal Earth system predictions.

Specifically:

- Characterize current and potential users of S2S forecasts and their decision making contexts, and identify key commonalities and differences in needs (e.g., variables, temporal and spatial scale, lead times, and forecast skill) across multiple sectors.
- Promote social and behavioral science research on the use of probabilistic forecast information.
- Create opportunities to share knowledge and practices among researchers working to improve the use of predictions across weather, subseasonal, and seasonal timescales.

Beyond the research recommended above, engaging the S2S research and operational prediction communities in an iterative dialogue with users is necessary to help ensure that forecasts systems, forecast products, other model output, and other decision making tools maximize their benefit to society. This includes effective probabilistic forecasts products, verification metrics, and communication strategies. Ongoing efforts will be needed to match what is scientifically predictable and technologically feasible at S2S timescales with what users can make actionable, as scientific skill, user needs, and user perspectives continually evolve. Such iterative efforts can also help stakeholders develop and implement decision making strategies, such as 'ready-set-go' scenarios, that utilize S2S forecasts together with shorter and longer-lead information. These scenarios help organizations utilize a suite of forecasts with different lead times, promoting advance preparation for potential hazards even while forecast uncertainty is relatively high, and then adjusting actions as forecast lead times shorten and forecast uncertainty decreases. As mentioned above, private industry and 'boundary organizations' within academia and the public sector (NOAA's RISA program, the IRI at Columbia University, and many others) have already started such discussions. Efforts to further engage users in the iterative process of making S2S forecasts more actionable and used more in decision making should build on the experience of this boundary workforce (see also section on Supporting the S2S Forecasting Enterprise below).

Recommendation B: Establish an ongoing and iterative process in which stakeholders, social and behavioral scientists, and physical scientists co-design S2S forecast products, verification metrics, and decision making tools.

Specifically:

- Engage users with physical, social, and behavioral scientists to develop requirements for new products as advances are made in modeling technology and forecast skill, including forecasts for additional environmental variables.
- In direct collaboration with users, develop ready-set-go scenarios that incorporate S2S predictions and weather forecasts to enable advance preparation for potential hazards as timelines shorten and uncertainty decreases.
- Support boundary organizations and private sector enterprises that act as interfaces between forecast producers and users.

Research Strategy 2: Increase S2S Forecast Skill

Operational weather and ocean forecasts have steadily increased in accuracy and lead time over the past few decades. However, there is still significant room for improving the skill of many S2S forecasts. An important prerequisite for achieving the vision of widely used S2S forecasts is to significantly improve the skill of forecasts so that users' confidence in such predictions increases, and so that S2S forecasts can be applied to a range of decisions that requires higher forecast skill in order to act. Analogous to routine weather forecasting, there should be an emphasis on skillful, routine forecasts of Earth system components 2 weeks to 12 months in advance. Prediction at these timescales will necessarily be more probabilistic and less precise as to timing and spatial location than shorter-term weather forecasts, but there is strong evidence for predictability for many Earth system variables on S2S timescales. As discussed in Chapter 4, important sources of predictability on S2S timescales originate from: 1) modes of variability (e.g., the El Niño Southern Oscillation [ENSO], the Madden-Julian Oscillation [MJO], the Quasi-Biennial Oscillation [QBO]), 2) from slowly varying processes in the ocean on the land surface (e.g., soil moisture, surface water, snow-pack, ocean heat content, ocean currents, eddy positions, and sea ice conditions), and 3) elements of external forcing (e.g., aerosols, greenhouse gasses).

Exploiting these sources of predictability to increase forecast skill will require developing better physical understanding of sources of S2S predictability, as well as improving all aspects of S2S forecast systems. This includes sustaining and improving the network of observations used to study predictability and to initialize models, developing improved techniques for data assimilation and uncertainty quantification in coupled Earth system models, and importantly, the reduction of Earth system model errors through a combination of increases in model resolution and the development of better model parameterizations to represent subgrid processes. Research to spur the development of new methods for probabilistic forecasting and probabilistic skill verification and calibration are also necessary.

With many possible avenues available for improving the skill of S2S forecasts, efforts to optimize the design of S2S forecast systems are also essential. S2S forecast systems can be configured in a wide variety of ways, and there are numerous possible selections and combinations of the design elements ("trade space") in any forecast system. For example, what is the cost-benefit to the skill of S2S forecasts of adding more dynamical representation of different Earth system components and increasing the complexity of their coupling, versus increasing model resolution, extending retrospective forecast length or averaging period, increasing ensemble runs, and/or increasing the number of models in a multi model ensemble system? While all may improve forecast skill, finite computing and human resources implies trade-offs in the design and implementation of any system. Thus a key part of improving and maximizing the cost-benefit relationship for producing probabilistic information 2 weeks to 12 months into the future will be to undertake a systematic exploration of the optimal use of available resources to support the development of more skillful forecast systems. The development of a cost effective and skillful operational multi-model ensemble forecast system is important, will require particular care and attention, and will involve the use of current operational models along with support for the research community to actively engage in the development and validation of new or updated members of these ensemble systems (see discussion below). Similar methods for probabilistic skill verification and calibration also need to be employed and developed for the evaluation of the forecasts of probabilities. Such probabilistic skill metrics would characterize, and ultimately improve, the capability of forecasting common but also rare S2S events (Research Strategy 3).

Recommendations

Making S2S predictions relies on the identification and understanding of sources of Earth system predictability in the S2S time range. The 2010 NRC report (NRC, 2010b) identified a number of sources of predictability, including inertia in various slow-varying components of the Earth system, modes of variability in the coupled ocean-atmospheric system (e.g., ENSO, MJO), and external forcing (from either human or natural sources). Chapter 4 further explores current understanding of these sources of S2S predictability, and emphasizes that much remains to be learned about these sources, especially their interactions and teleconnections. Research to advance understanding of sources and limits of predictability for specific Earth system phenomena will be critical to improving the fidelity of S2S Earth system models, as well as to improving the ability to forecast extreme or other disruptive events with longer lead times (Research Strategy 3).

Recommendation C: Identify and characterize sources of S2S predictability, including natural modes of variability (e.g., ENSO, MJO, QBO), slowly varying processes (e.g., sea ice, soil moisture, and ocean eddies), and external forcing (e.g., aerosol emissions), and correctly represent these sources of predictability, including their interactions, in S2S forecast systems.

Specifically:

- Use long-record and process-level observations and a hierarchy of models (theory, idealized models, high-resolution models, global earth system models, etc.) to explore and characterize the physical nature of sources of predictability and their interdependencies and dependencies on the background environment and external forcing.
- Conduct comparable predictability and skill estimation studies and assess the relative importance of different sources of predictability and their interactions, using long-term observations and multi-model approaches (such as the World Meteorological Organization-lead S2S Project's database of retrospective forecast data).

Chapter 5 emphasizes the importance of improving routine observations, developing more sophisticated data assimilation and uncertainty quantification techniques, reducing individual model errors through increased resolution and better parameterizations, and developing advanced calibration techniques and model combinations in order to develop more skillful S2S forecast systems. Routine observations are essential for initializing models to more accurately reflect the state of the Earth system and for validating model output; they can also contribute to improved understanding of the physical system and its predictability on S2S timescales (Chapter 4). Current observing networks for the atmosphere are more capable and robust than those for the other components of the Earth system. However, sustaining atmospheric observations is critical for S2S as well as weather forecasting; research to increase the use of currently available atmospheric observations, such as assimilation of satellite radiances in cloudy and precipitating areas, could unlock a wealth of new information related to representing convection and precipitation in models.

Relative to the atmosphere, the ocean, land surface, and cryosphere remain significantly under-observed, despite being major sources of S2S predictability. For the oceans, more routine and targeted observations are essential for S2S applications. In particular, sustaining and enhancing the capability to provide remotely sensed sea surface height (SSH), sea surface temperature (SST), and near-surface winds is critical, as is expanding the use of measurement arrays such as Argo floats and moored buoys to better measure key ocean properties below the surface (temperature, salinity and current velocity). In addition to improving classic observing capabilities for the ocean, smart utilization of novel autonomous platforms could have an important impact.

Reliable and accurate year-round sea ice thickness measurements are the greatest need for improving the understanding and modeling of sea ice and its influence on the coupled system. Current (CryoSat2) and planned (ICESat2) satellite missions will help to meet this key objective. Because these satellites measure freeboard (the height of sea ice and snow above the sea level), accurate and simultaneous measurements of snow depths are also needed to solve for sea ice thickness. The procedure for solving for sea ice thickness needs to be efficient enough to be ready in about a day, so such measurements can contribute to initialization of S2S forecasts.

Land observations are critical for modeling large-scale land surface-atmosphere feedbacks and for predictions of the terrestrial water cycle. Several new satellite missions (Soil Moisture Active Passive [SMAP] and Surface Water and Ocean Topography [SWOT]) are focused on observing near-surface soil moisture and other aspects of surface hydrology that will be useful for improving S2S predictions. However, a number of critical gaps remain. Lack of adequate precipitation measurements currently hinder S2S prediction, and measurements of soil moisture in the root zone, as well as measurements of evapotranspiration, are needed globally to better constrain hydrology and surface fluxes. Measurements of snow depth or snow water equivalent (SWE) are also critical. SWE can be estimated from existing satellite platforms, however retrieval algorithms must be improved in order to take full advantage of these observations. Because of gaps in the satellite observing network, in situ measurements of variables such as precipitation, snow depth and land-surface atmosphere fluxes are likely to remain important and should be expanded to improve their spatial coverage.

In summary, observations of the atmosphere, ocean, land surface, and cryosphere play a critical role in building, calibrating, initializing, and evaluating the coupled Earth system models that are used to generate S2S forecasts. Better representing slow-varying processes in the Earth system—such as the ocean, cryosphere, and land surface hydrology—and their coupling to the atmosphere, as well as developing observations to inform deep convection and storm formation, are important to capturing S2S predictability, but they represent the largest gaps in the current observing network. Improved observations are also critical for improving the ability to forecast important and/or extreme events (Research Strategy 3). Including observations of phenomena that remain insufficiently observed, such as the properties of oceans or sea ice, can also facilitate the inclusion of more and more complex components of the Earth system in S2S prediction systems (Research Strategy 4).

Recommendation E: Maintain continuity of critical observations, and expand the temporal and spatial coverage of in situ and remotely sensed observations for Earth system variables that are beneficial for operational S2S prediction and for discovering and modeling new sources of S2S predictability.

Specifically:

- Maintain continuous satellite measurement records of vertical profiles of atmospheric temperature and humidity without gaps in the data collection and with increasing vertical resolution and accuracy.
- Optimize and advance observations of clouds, precipitation, wind profiles, and mesoscale storm and boundary layer structure and evolution. In particular, higher-resolution observations of these quantities are needed for developing and advancing cloud-permitting components of future S2S forecast systems.
- Maintain and advance satellite and other observational capabilities (e.g., radars, drifters, and gliders) to provide continuity and better spatial coverage, resolution, and quality of key surface ocean observations (SSH, SST, and winds), particularly near the coasts, where predictions of oceanic conditions are of the greatest societal importance in their own right.
- Maintain and expand the network of in situ instruments providing routine real-time measurements of sub-surface ocean properties, such as temperature, salinity, and currents, with increasing resolutions and accuracy. Appropriate platforms for these instruments will include arrays of moored buoys (especially in the tropics), AUVs, marine mammals, and profiling floats.
- Develop accurate and timely year-round sea ice thickness measurements; if from remote sensing of sea ice freeboard, simultaneous snow depth measurements are needed to translate the observation of freeboard into sea ice thickness.
- Expand in situ measurements of precipitation, snow depth, soil moisture, and land-surface fluxes, and improve and/or better exploit remotely sensed soil moisture, snow water equivalent, and evapotranspiration measurements.
- Continue to invest in observations (both in situ and remotely sensed) that are important for informing fluxes between the component interfaces, including but not limited to land surface observations of temperature, moisture, and snow depth; marine surface observations from tropical moored buoys; and ocean observations of near-surface currents, temperature, salinity, ocean heat content, mixed-layer depth, and sea ice conditions.

- Apply autonomous and other new observing technologies to expand the spatial and temporal coverage of observation networks, and support the continued development of these observational methodologies.

As the scope of S2S models evolves to include and resolve more physical processes and components of the Earth system, there will be an increasing need for observations of new variables (Research Strategy 4). Furthermore, and as detailed above, current routine observations may not have sufficient resolution or coverage for S2S applications. Although it would be beneficial to expand the geographic coverage and resolution of many types of observations, cost and logistics will continue to demand that priorities are determined, and it is not always clear a-priori what measurements will be most beneficial to support S2S prediction systems. Thus careful study of the improvements anticipated in S2S forecasting systems will be needed to quantify the cost-benefit ratio for various types of additional observations. Such study requires integrating ocean, land, atmosphere and sea ice modeling in the planning of observing networks. Observing system simulation experiments (OSSEs) and other sensitivity studies are powerful tools for exploring the importance of specific observations on state estimation and overall model performance, and could be better used to prioritize improvements to observation networks (as well as model parameterizations) for S2S prediction systems.

Recommendation F: Determine priorities for observational systems and networks by developing and implementing OSSEs, OSEs, and other sensitivity studies using S2S forecast systems.

There are many challenges associated with integrating tens of millions of observations into the different components of an Earth system model, including ensuring that initializations are dynamically consistent and minimize the growth of errors. Given that coupling between the multiple, dynamic components of the Earth system (e.g., atmosphere, ocean, ice, land) is central to the S2S prediction problem, developing and implementing coupled data assimilation methods is at the forefront of S2S model development.

The implementation of "weakly coupled" assimilation, in which an independently coupled Earth system model is integrated forward in time as part of the assimilation process, represents an important and ongoing step in improving both weather and S2S forecast systems. "Strongly coupled" data assimilation, in which observations within one media are allowed to impact the state estimate in other components (with constraints), may allow for another important leap forward, especially for S2S systems in which the representation of the interaction between Earth system components is essential for capturing inherent predictability. However, research into the use of strongly coupled data assimilation algorithms is in its infancy, has not yet been tested on complex S2S coupled prediction models, and presently faces several barriers to implementation. Fundamental research is needed to explore and realize the potential benefits to more advanced but expensive strongly coupled data assimilation, while continuing to pursue and implement weakly coupled methods in current systems.

Efforts to improve the skill of S2S predictions will also benefit from more realistic representation of the uncertainty and statistical properties of observations and model output. Research on Bayesian data assimilation and uncertainty quantification has grown substantially in atmospheric and oceanic sciences and also in disciplines such as applied mathematics and engineering. These methods, which allow the optimal prediction and utilization of the full probabilistic information and utilize rigorous reduced-order differential equations, are strong candidates for implementation in the components of S2S prediction systems, but require more development to be implemented into operational settings.

Recommendation G: Invest in research that advances the development of strongly coupled data assimilation and quantifies the impact of such advances on operational S2S forecast systems.

Specifically:

- Continue to test and develop weakly coupled systems as operationally viable systems and as benchmarks for strongly coupled implementations.
- Further develop and evaluate hybrid assimilation methods, multiscale- and coupled-covariance update algorithms, non-Gaussian nonlinear assimilation, and rigorous reduced-order stochastic modeling.
- Optimize the use of observations collected for the ocean, land surface, and sea ice components, in part through coupled-covariances and mutual information algorithms, and through autonomous adaptive sampling and observation targeting schemes.
- Further develop the joint estimation of coupled states and parameters, as well as quantitative methods that discriminate among, and learn, parameterizations.
- Develop methods and systems to fully utilize relevant satellite and in situ atmospheric information, especially for cloudy and precipitating conditions.
- Foster interactions among the growing number of science and engineering communities involved in data assimilation, Bayesian inference, and uncertainty quantification.

Systematic errors are numerous within the Earth system models used for S2S forecasting. For example, many global models produce an unrealistically strong Pacific equatorial cold tongue, a spurious double Inter Tropical Convergence Zone (ITCZ), erroneously high Indian Ocean and tropical South Atlantic SSTs, low SSTs in the tropical North Atlantic, wet or dry biases in rainfall in many parts of the world, and a bias in MJO variance. These model errors can be large compared to the predictable signals targeted by S2S forecasts.

Reducing such model errors represents one of the most important ways to improve the skill of S2S predictions (Chapter 5, models subsection). There is evidence that increasing the resolution of modeling systems (while still at resolutions that need deep convection parameterization) can reduce model errors. However, resolution is far from a panacea. Improving physical parameterizations of unresolved processes remains essential to reducing errors, even as the capability to resolve more and more processes expands. One important barrier to improving parameterizations is incomplete understanding of actual physical processes and the challenges associated with encapsulating new knowledge of these processes in (multiple, interacting) parameterizations. Coordinated, coupled field campaigns, as well as process-targeted satellite missions and other observations, are essential for developing the understanding required to improve parameterizations. To maximize impact, field campaigns should, as far as possible, be co-designed by academics and operational centers and take full advantage of opportunities for national and international coordination.

Continuing to develop high-resolution research models will also be important for developing better parameterizations that reduce model errors. We note that model resolution encompasses time and space resolution, but also a balance between the order of the numerical computation and the refinement of the discretization. Further development of high resolution models will also be extremely beneficial for examining predictability on S2S timescales, and will help pave the way for future operational use of global cloud and eddy-permitting models or cloud and eddy-permitting meshes in critical areas. This approach is becoming more feasible as scale-aware cumulus parameterization schemes are being developed. Finally, in parallel to spatiotemporal model resolution and parameterizations, incorporating new stochastic statistical methods is also important to advance S2S forecasting. In particular, as described in Chapter 5, there are now several promising stochastic methods and reduced-order partial differential equations that could provide improved probabilistic forecasts for the same cost as running the present number of ensemble members. Furthermore, including efficient stochastic components in S2S modeling systems has the potential to increase the skill of S2S probabilistic forecasts and benefit decision making. For example, stochastic computing and stochastic parameterizations of unresolved processes (Palmer, 2014) can be used to better represent rare but significant S2S events.

To summarize, investment in research aimed at physical understanding and reducing model errors is seen by this Committee as a top priority in improving the skill of S2S predictions. In addition to contributing to Research Strategy 2, reducing model errors also contributes to Strategies 3 and 4.

Recommendation H: Accelerate research to improve parameterization of unresolved (e.g., subgrid scale) processes, both within S2S system submodels and holistically across models, to better represent coupling in the Earth system.

Specifically:

- Foster long-term collaborations among scientists across academia and research and operational modeling centers, and across ocean, sea ice, land and atmospheric observation and modeling communities, to identify root causes of error in parameterization schemes, to correct these errors, and to develop, test, and optimize new (especially scale-aware or independent) parameterization schemes in a holistic manner.
- Continue to investigate the potential for reducing model errors through increases in horizontal and vertical resolutions in the atmosphere and other model components, ideally in a coupled model framework (see also Recommendation L).
- Encourage field campaigns targeted at increasing knowledge of processes that are poorly understood or poorly represented in S2S models, including tropical convection, ocean mixing, polar, sea ice and stratospheric processes, and coupling among different Earth system components (e.g., air-sea-ice-wave-land; troposphere-stratosphere; dynamics-biogeochemistry).
- Develop high-resolution (or multi-resolution) modeling systems (e.g., that permit atmospheric deep convection and non-hydrostatic ocean processes) to advance process understanding and promote the development of high-resolution operational prototypes (see also Recommendation I).

Verification metrics are important for tracking and comparing model improvements, and are also a critical part of enabling use and building trust in S2S forecasts. Understanding the different ways users interpret forecasts and what they consider to be skillful is necessary to inform the development of better verification metrics (Recommendation B). Improving verification should also involve continued research on feature-based and two-step verification methods, along with consideration of how the design of retrospective forecasts and reanalyses can influence the ability of some users to directly evaluate the consequences of acting on forecasts at various predicted probabilities.

Recommendation J: Pursue feature-based verification techniques in order to more readily capture limited predictability at S2S timescales, as part of a larger effort to improve S2S forecast verification.

Specifically:

- Investigate methodologies for ensemble feature verification including two-step processes linking features to critical user criterion.
- Pursue verification methodologies for rare and extreme events at S2S timescales, especially those related to multi-model ensemble predictions.
- Consider the benefits of producing more frequent reanalyses using coupled S2S forecast systems in order for the initial conditions of retrospective forecasts to be more consistent with the real time forecasts, as well as for the purposes of predictability studies.

Multi-model ensembles (MMEs) are one of the most promising ways to account for errors associated with Earth system model formulation, and the use of MMEs is likely to remain critical for S2S prediction. However, current MMEs are largely systems of opportunity, and research is required to develop more intentional MME forecast systems. S2S forecast systems, including the coupled Earth system model, the reanalysis, and retrospective forecasts, can be configured in a wide variety of ways. Careful optimizing of the configurations of a multi-model prediction system will include systematic exploration of the benefits and costs of adding unique models to an MME.

Today, little information is available about optimum configurations for individual or multi-model S2S ensemble forecast systems. It is likely that much can be gained in both skill and resource utilization by ascertaining which configurations produce optimum forecast systems, as defined by reliable probability forecasts and optimum levels of user-focused skill.

Forecast centers, private sector users, and value-added providers use various calibration methods, but there has not been a comprehensive effort to compare methods or to find optimum approaches for the variables of most interest. Studies of the optimum configurations of S2S probability models (mentioned below) should include an attempt to evaluate calibration methods and ascertain whether some methods offer clear advantage over others, recognizing that some of these methods will likely be application-specific.

Exploring the “trade space,” i.e., the configuration of S2S forecast systems, will be a large, complicated, and expensive endeavor, expanding as computer and Earth system modeling capabilities expand over the next decade or more, but determining how performance depends on configuration is a key task in any S2S research agenda. As such, this exploration would benefit tremendously from a central, coordinating authority and central funding, as well. Exploring the “trade space” will be important for increasing forecast skill, advancing the prediction of events

(Research Strategy 3) and helping decide how to expand and design new S2S systems to include more complexity in S2S Earth system models (Research Strategy 4).

Recommendation K: Explore systematically the impact of various S2S forecast system design elements on S2S forecast skill. This includes examining the value of model diversity, as well as the impact of various selections and combinations of model resolution, number of ensemble perturbations, length of lead, averaging period, length of retrospective forecasts, and options for coupled sub-models.

Specifically:

- Design a coordinated program to assess the costs and benefits of including additional processes in S2S systems, and relate those to benefits from other investments, for example in higher resolution. In doing so, take advantage of the opportunity to leverage experience and codes from the climate modeling community.
- Encourage systematic studies of the costs and benefits of increasing the vertical and horizontal resolution of S2S models.
- Evaluate calibration methods and ascertain whether some methods offer clear advantage for certain applications over others, as part of studies of the optimum configurations of S2S models.
- Explore systematically how many unique models in a multi-model ensemble are required to predict useful S2S parameters, and whether those models require unique data assimilation, physical parameterizations, or atmosphere, ocean, land, and ice components (see also Recommendation L).

Transitioning new ideas, tools, and other technology between the S2S research community and operational centers is challenging but essential to translating research discoveries into informed decision making. In the S2S context, one key element of this transfer will be to bring the best research to bear on developing an operational MME S2S forecast system. The use of multi-model ensembles (MMEs) in non-operational, research settings has demonstrated the potential for advancing S2S forecasts, for example the North American Multimodel Ensemble program (NMME) (see Chapter 6). An operational NMME relying on research institutions for funding and operations is not a viable long-term option, but there would be great value in the development of an operational MME forecast system that includes the operational centers of the United States.

Developing an operational MME forecasting system will require careful optimizing of the configurations of a multi-model prediction system (Recommendation K). Test beds, such as the National Oceanic and Atmospheric Administration (NOAA) Climate Test Bed activity, provide the potential for such coordinating activities; however, the Test Bed would need significant enhancement if it were to be relied on as the primary mechanism for the development of a MME forecasting system. Where feasible, interagency and international collaborations could accelerate efforts to create an operational MME. Realistic assessment of available operational resources and centers that are able to contribute operationally rigorous prediction systems would be a useful starting point for determining the best path forward.

Recommendation L: Accelerate efforts to carefully design and create robust operational multi-model ensemble S2S forecast systems.

Specifically:

- Use test beds and interagency and international collaborations where feasible to systematically explore the impact of various S2S forecast system design elements on S2S forecast skill, in particular the question how many unique models in a multi-model ensemble are required to predict operationally useful S2S parameters (see also Recommendation K).
- Assess realistically the available operational resources and centers that are able to contribute operationally rigorous prediction systems.

To make the kind of rapid improvements to operational S2S prediction systems that are envisioned by the Committee, it will be more generally important to speed the flow of information between scientists with research and operational foci. There are a number of mechanisms to improve the flow of technology into operational weather and ocean systems, including focused workshops, visiting scientist programs, special sessions at professional conferences, testbeds and focused transition teams such as the Navy's development-and-operations transition teams and NSF/NOAA's Climate Process Teams. These mechanisms should be promoted and expanded to include more scientist involvement for plowing the new ground of S2S.

New mechanisms should also be developed especially to enhance researcher access to operational forecast data, including access to archives of ensemble forecasts themselves, retrospective forecasts, and initialization data. There are data storage challenges with such an endeavor, but it would facilitate further analyses of sources of S2S predictability and efforts to diagnose skill, among other benefits. The WWRP/WCRP S2S Project described in Chapters 4 and 6 is already making some operational center data available to the research community to study subseasonal processes, but S2S Project data is just beginning to be explored by the research community.

In the longer term, allowing researchers to conduct or request specific experiments on operational systems would provide an additional boost to the flow of discoveries and technical advances between research and operational communities. Allowing researchers to run operational models will be a difficult challenge, one that involves making the modeling code itself accessible to the research community as well as ensuring access to sufficient computing power to run the code. All of these actions will require a significant effort on the part of the operational centers. To improve the flow of advances between research and operations, operational centers should work towards addressing these challenges over the next couple of decades.

Recommendation M: Provide mechanisms for research and operational communities to collaborate, and aid in transitioning components and parameterizations from the research community into operational centers, by increasing researcher access to operational or operational mirror systems.

Specifically:

- Increase opportunities for S2S researchers to participate in operational centers.
- Enhance interactions with the international community (e.g., the S2S Project and APCC) and with the WMO Lead Centers.
- Provide better access in the near-term to archived data from operational systems, potentially via test centers.
- Develop, in the longer term, the ability for researchers to request re-runs or do runs themselves of operational model forecasts.
- Encourage effective partnerships with the private sector through ongoing engagement (see also Recommendation B).

Research Strategy 3: Improve Prediction of Extreme and Disruptive Events and Consequences of Unanticipated Forcing Events

Within the efforts to improve the overall skill of S2S forecasts and to provide more actionable information to users, there are two areas that the Committee believes deserve special attention (Research Strategies 3 and 4). Research Strategy 3 involves an increased focus on discrete events, and the Committee made two recommendations to address this focus. The first is to emphasize the prediction of weather, climate and other Earth system events that disrupt society's normal functioning. Weather extremes and other relatively infrequent events can greatly disrupt society's normal functioning and are therefore of significant concern to many users: drought and flood, strong storms with excessive precipitation, heat waves, and major wind events are all examples. A coordinated effort to improve the forecasting of these events could provide the huge benefits achieved by allowing communities more time to plan for, and mitigate the damages from these events. Thus it is important to explore the possibilities of using model output to suggest the likelihood of such disruptive events. For some of these events, a quantitative estimate of probability would provide the opportunity to consider whether specific mitigation actions are cost effective. But whether action is justified would depend on the skill of the forecasts for extreme events as determined by a history of such forecasts.

Improved forecasting of extreme or disruptive events may entail an emphasis on forecasts of opportunity—windows in time when expected skill for predicting specific events is high because of the presence of certain features in the Earth system—rather than simply predicting average conditions for given time periods, as is done today. Skillful extended-range prediction of such events may only be possible for certain phases of large-scale climate patterns, such as the seasonal cycle, ENSO, or MJO, or NAO, or may be contingent on interactions between these modes and other slowly varying processes. Moreover, skillful prediction of the probabilities of some types of disruptive events will be possible at these timescales, whereas others may not. Examples of events for which there is good evidence for predictive skill at S2S timescales include: regional drought; watershed-scale melt-driven flooding; and significant shifts in hurricane tracks or land-falling events in various ocean basins (Vecchi et al., 2011). More research is needed to investigate the potential skill for forecasts of different types of disruptive events, with a focus on discovering the potential for so-called forecasts of opportunity.

In addition to the improved prediction of events within the Earth system, there are events driven by outside forces that have major—and potentially predictable—consequences on the

Earth system. Such outside forces include volcanoes, meteor impacts, and human actions (e.g., aerosol emissions, widespread fires, large oil spills, certain acts of war, or climate intervention). Over the past 25 years, there have been a number of these unusual natural or human-caused events that have had, or were initially feared to have, the possibility of large-scale consequences to the Earth system (Chapters 3 and 6) and accompanying adverse impacts to a wide range of human activities.

Some consequences of high-impact events are predictable on timescales of weeks to a year. These events are unusual because they are of a nature or magnitude not represented within the recent past (for instance since the start of observational satellite climate records in about 1979), and hence do not have well-observed analogs that can be used to validate prediction systems. Moreover, depending on the nature of the event, the operational forecast systems may not be suited for predicting the event's consequences. While some of these events, such as the 1991 eruption of Mt. Pinatubo, had clear consequences for the global system for a year and beyond (0.3 °C global-mean cooling averaged over the 3 years following the Pinatubo eruption), many other events had much smaller impacts than originally projected. However, these were notable in raising significant public concern that might have required action by decision makers.

Recommendations

The improved prediction of extreme or disruptive events on S2S timescales is an extension of improvements in S2S forecasting skill (Research Strategy 2). But given the importance of having actionable information about these events for users and decision makers (Research Strategy 1), the Committee believes it is important to highlight the prediction of events as a separate strategy. Improving the prediction of such events will involve improved understanding of sources of predictability of extreme and disruptive events in the S2S time range. It will also involve ensuring that all relevant sources of predictability and their interactions are represented in Earth system models (Chapter 4).

Recommendation D: Focus predictability studies, process exploration, model development and forecast skill advancements on high impact S2S "forecasts of opportunity" that in particular target disruptive and extreme events (e.g. tropical cyclones, mesoscale convection, topographic forcing, coastal surge).

Specifically:

- Determine how predictability sources (e.g. natural modes of variability, slowly varying processes, external forcing) and their multi-scale interactions can influence the occurrence, evolution and amplitude of extreme and disruptive events using long-record and process-level observations.
- Ensure the relationships between disruptive and extreme weather/environmental events—or their proxies—and sources of S2S predictability (e.g. modes of natural variability and slowly varying processes) are represented in S2S forecast systems.
- Investigate and estimate the predictability and prediction skill of disruptive and extreme events through utilization and further development of forecast and retrospective forecast databases, such as those from the S2S Project and the NMME.

The second part of this research strategy involves using S2S forecast systems to predict the consequences of disruptive events caused by an unusual Earth system event, like a volcanic eruption or a major oil spill. Such an outside event generates an immediate demand for scientific guidance for the public and policy-makers about potential consequences. A flexible system for estimating Earth system consequences of such unusual forcing events would address a national need that has become evident several times over the past few decades.

The nation should develop a capability for estimating the range of possible impacts and consequences of unexpected but critical events such as volcanic eruptions, nuclear detonations, widespread fires, or large spills of toxic materials (Chapters 3 and 6). Such a capability would need to be mobilized within one week and return preliminary results for S2S timescales and beyond as appropriate.

Performing regular full-scale exercises in collaboration with the response community in the spirit of war games would help improve this capability and maintain it for any new event. This could serve as a focal point and help to improve the connections of advances in the academic sector in modeling unexpected events with operational model development.

Recommendation N: Develop a national capability to forecast the consequences of unanticipated forcing events.

Specifically:

- Improve the coordination of government agencies and academics to be able to quickly respond to unanticipated events to provide S2S forecasts and associated responses using the unanticipated events as sources of predictability.
- Utilize emerging applications of Earth system models for long-range transport and dispersion processes (e.g., of aerosols).
- Increase research on the generation, validation, and verification of forecasts for the aftermath of unanticipated forcing events.

Research Strategy 4: Include More Components of the Earth System in S2S Forecast Models

The other area that the Committee feels needs more focused attention is accelerating the development of Earth system model components outside the troposphere—Research Strategy 4. As mentioned above, representing oceans, sea ice, land surface and hydrology, and biogeochemical cycles (including aerosol and air quality) in coupled Earth system models is more important for S2S predictions than for traditional weather prediction, because much of the predictability of the Earth system on these timescales arises from conditions outside the troposphere or from interactions between Earth system components. Operational S2S forecast systems increasingly utilize coupled Earth system models that include major Earth system components (e.g., ocean, atmosphere, ice, land) (Brassington et al., 2015; Brunet et al., 2010). However, the representation of processes outside the troposphere has generally been less well developed. Improving model representation of land surface and terrestrial hydrology, ocean, sea ice, and upper atmosphere—including fluxes and feedbacks between these components—will be important for increasing the skill of S2S forecasts. This includes advancing the observations, modeling, data assimilation, and integrated prediction capabilities in those components. Those components that have significant interactions with the weather and climate system as a whole will need to be dynamically integrated into the operational forecasting systems. Other fields that do not contribute substantially to the evolution of the rest of the system could be predicted by post-processing operations or by independent activities after the primary forecasts have been carried out. However, as demand grows for forecasts of phenomena that are predictable on S2S timescales but that do not feedback strongly to the atmosphere, improving the dynamical representation of many of these Earth system processes in S2S prediction systems may also become important in its own right.

Representing interactions between the various Earth system components has become increasingly important for climate projections. Comprehensive Earth system models (ESMs), which include composition, aerosols, vegetation, snow and glaciers, etc., are increasingly being used to provide projections on decadal to centennial timescales (e.g., Coupled Model Intercomparison Project Phase 5 [CMIP5]; IPCC, 2013; Taylor et al., 2012). The extension of operational S2S forecasts towards dynamic predictions of more of the Earth system will be carried out most effectively by leveraging these existing efforts.

Recommendations

Improving the representation of more components and variables of the Earth system in S2S forecasts, including the ocean, sea ice, biogeochemistry, and land surface, will produce information applicable to a new and wider range of decisions. Iterative interaction with forecast users (Research Strategy 1) can help determine what processes and variables are most important to include in coupled S2S systems as these systems evolve. Expanding the comprehensiveness of such component models and advancing their coupling in Earth system models will also help improve the overall skill of forecasts (Research Strategy 2).

Priorities for improving ocean models include both fundamental numerical capabilities and improved depictions of important oceanic phenomena that are currently omitted from most S2S forecasting systems, for example tides and their interactions with storm surges, and oceanic mixing of nutrients. The dynamics of the near surface ocean are of particular importance for the coupled ocean at S2S timescales, so the representation of ocean boundary layer turbulence and its interactions with waves and sea ice are a promising subject of study for improving S2S forecasts. But the most important limitation on oceanic S2S forecasts arises from the global influence of the ocean at these timescales, along with the need to accurately represent many important oceanic phenomena at relatively small scales to capture this influence. Implementing a regionally eddy-resolving ocean component along with additional research on parameterizing the effects of unresolved baroclinic and sub-mesoscale oceanic eddies would thus help improve S2S coupled prediction models.

Sea ice models used for S2S often contain only rudimentary thermodynamics and dynamics. Connecting advances in cutting-edge sea ice models (including more sophisticated physics representations of ice-thickness distribution, melt ponds, biogeochemistry, and divergence/convergence, as well as new methods to account for wave-floe interactions, blowing snow, and ice microstructure) with sea ice models used in S2S forecast system could advance

S2S predictions of the atmosphere through improved representation of radiative and ocean feedbacks, as well as advancing S2S prediction of sea ice and polar ocean conditions.

Similarly, land-surface models used for S2S prediction need to improve treatment of the hydrological cycle and aspects of the land surface that are coupled to hydrology, such as vegetation. Effort is needed to incorporate surface and underground water storage and river routing in models, including the role of human water management and use. These important aspects of the land system have been implemented in "off-line" hydrologic forecast systems, but they are usually over-simplified or neglected altogether in fully coupled S2S forecast systems. Improving the representation of land surface processes such as soil moisture storage and snow may in such fully coupled systems will be important for predicting events such as heat waves, cold surges, storm formation, and predicting run-off may also help to enable S2S forecasts of flooding and lake and coastal hypoxia.

Additional strong candidates for improvements to existing practice for operational S2S forecasting systems include advancing the observations, modeling, data assimilation, and integrated prediction capabilities of aerosols and air quality, and aquatic and marine ecosystems.

Beyond advancing the representation of the land surface, hydrology, stratosphere, sea ice, ocean, and biogeochemical models and translating these advancements to the coupled Earth system models used for S2S forecasting, efforts are needed to pave the way towards global cloud/eddy-resolving atmosphere-ocean-land-sea ice coupled models, which will one day become operational for S2S prediction. While this goal is unlikely to be reached in the next decade, revolutions in the computing industry may shorten the distance between now and the otherwise long way to go, and the S2S research community needs to be proactive and poised if/when that happens.

Recommendation I: Pursue next-generation ocean, sea ice, wave, biogeochemistry, and land surface/hydrologic, as well as atmospheric model capability in fully coupled Earth system models used in S2S forecast systems.

Specifically:

- Build a robust research program to explore potential benefits to S2S predictive skill and to forecast users from adding more advanced Earth system components in forecast systems.
- Initiate new efficient partnerships between academics and operational centers to create the next generation model components that can be easily integrated into coupled S2S Earth system models.
- Support and expand model coupling frameworks to link ocean/atmosphere/land/wave/ice models inter-operably for rapidly and easily exchanging flux and variable information.
- Develop a strategy to transition high resolution (cloud/eddy-resolving) atmosphere-ocean-land-sea ice coupled models to operations, including strategies for new parameterization schemes, data assimilation procedures, and multi-model ensembles (MME).

Supporting the S2S Forecasting Enterprise

It is essential to highlight two specific cross-cutting challenges that must be met in order to support the four research strategies for reaching the Committee's vision for S2S prediction. These are ensuring that the computational infrastructure is sufficient to support the S2S forecasting enterprise; and developing and maintaining the workforce that will be needed realize potential advances in S2S forecasting. These challenges are not necessarily unique to the S2S enterprise—they are also faced by the numerical weather prediction and climate modeling communities, and indeed, across many other technical enterprises.

Recommendations

The volume of observational data, data assimilation steps, model outputs, and reanalysis and retrospective forecasts involved in S2S forecasting means that the S2S modeling process is extremely data intensive. S2S prediction systems test the limits of current cyber-infrastructure, as do weather forecasting and climate modeling. Advances in S2S forecast models (higher resolutions, increased complexity, the generation and retention of long retrospective forecasts, etc.), will require dramatically increased computing capacities (perhaps 1,000 times), and similar expansion of related storage and data transport capacities.

That said, today's Earth system models are not taking full advantage of current computing architectures and improving their performance will likely require new algorithms that do more to work on data locally before transporting it to those analyzing it, as well as significant refactoring of existing algorithms to exploit more parallelism. To compound these challenges, the transition to new computing hardware and software through the next decade will be highly disruptive. This transition will not involve faster processing elements, but rather more processors with considerably more complex embodiments of concurrency. In addition, future storage technology will be more complex and varied than it is today, and leveraging these innovations will require fundamental software changes.

An integrative modeling environment presents an appealing future option for facing some of the large uncertainty about the evolution of hardware and programming models over the next two decades. New approaches to data-centric workflow software that incorporates parallelism, remote analysis, and data compression will be required to keep up with the demands of the S2S forecasting community.

Recommendation O: Develop a national plan and investment strategy for S2S prediction to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all stages of the prediction process, including data assimilation, operation of high-resolution coupled Earth system models, and storage and management of results.

Specifically:

- Redesign and recode S2S models and data assimilation systems so they will be capable of exploiting current and future massively parallel computational capabilities; this will require a significant and long-term investment in computer scientists, software engineers, applied mathematicians, and statistics researchers in partnership with the S2S researchers.

- Increase efforts to achieve an integrated modeling environment using the opportunity of S2S and seamless prediction to bring operational agency (ESPC) efforts and IGIM efforts together to create common software infrastructure and standards for component interfaces.
- Provide larger and dedicated supercomputing and storage resources.
- Resolve the emerging challenges around S2S big data, including development and deployment of integrated data-intensive cyberinfrastructure, utilization of efficient data-centric workflows, reduction of stored data volumes, and deployment of data serving and analysis capabilities for users outside the research/operational community.
- Further develop techniques for high volume data processing and in-line data volume reduction.
- Continue to develop dynamic model cores that take the advantage of new computer technology.

As highlighted in Chapters 3 and 6, the Committee believes there are significant challenges in maintaining a pipeline of talented workers in the S2S enterprise. S2S is complex and involves working across computing-Earth science boundaries to develop and improve S2S models and working across science-user decision boundaries to better design and communicate forecast products and decision tools.

From the limited data available, it appears that the pipeline of S2S modelers being trained is not growing robustly in the United States, and is not keeping pace with this rapidly evolving field (Chapter 7). Given the importance of S2S predictions to the nation, a concerted effort is needed to entrain, develop, and retain a robust S2S workforce.

Similar to weather forecasting, S2S forecasts are used or have the potential to be used by many people to make important decisions. Because S2S connects in a very public way to risk management, there will be many opportunities within the S2S enterprise to help society better manage risks. These factors can be exploited to entrain more talented and mission-driven people into the field.

One possible concrete step forward would be a series of workshops to explore how to feature S2S in more undergraduate and graduate curriculums, how to identify and connect with organizations that can help with this (e.g., the National Science Teachers Association), and how to interact with the private sector to help understand what skills are needed. Other entities such as American Meteorological Society (AMS) or the National Science Foundation (NSF) could also play an important role in coordinating the entrainment of talented young people.

Recommendation P: Pursue a collection of actions to address workforce development that removes barriers that exist across the entire workforce pipeline and in the diversity of scientists and engineers involved in advancing S2S forecasting and the component and coupled systems.

Specifically:

- Gather quantitative information about workforce requirements and expertise base to support S2S modeling in order to more fully develop such a training program and workforce pipeline.

- Improve incentives and funding to support existing professionals and to attract new professionals to the S2S research community, especially in model development and improvement, and for those who bridge scientific disciplines and/or work at component interfaces.
- Expand interdisciplinary programs to train a more robust workforce to be employed in boundary organizations that work in between S2S model developers and those who use forecasts.
- Integrate basic meteorology and climatology into academic disciplines, such as business and engineering, to improve the capacity within operational agencies and businesses to create new opportunities for use of S2S information.
- Provide more graduate and postgraduate training opportunities, enhanced professional recognition and career advancement, and adequate incentives to encourage top students in relevant scientific and computer programming disciplines to choose S2S model development and research as a career.

CONCLUSION

This report envisions a substantial improvement in S2S prediction capability and expects valuable benefits to flow from these improvements to a wide range of public and private activities. It sets forth a research agenda that describes what must be done—with observations, data management, computer modeling, and interactions with users—to advance prediction capability and improve societal benefits.

Despite the specificity of the report in recommending what should be done, it does not address the challenging issues of how the agenda should actually be pursued—who will do what and how the work will be supported financially. Given that this research agenda significantly expands the scope of the current S2S efforts, the Committee believes that some progress can be made with current levels of support and within current organizational structures, but fully achieving the S2S vision will likely require additional resources for basic and applied research, observations, and forecast operations. The scope of the research agenda will also require closer collaboration between federal agencies and international partners, better flow of ideas and data between the research and operational forecasting communities, and engagement of the entire weather and climate enterprise.

The four research strategies provide broad guidance for how to focus effort, and the recommendations under each strategy in and of themselves represent the Committee's view of the most important actions to advance S2S forecasting, presented without any prioritization or sequencing. The technological, political, and financial environment in which the research agenda will be implemented is constantly changing and will continue to be fluid, and multiple pathways to success exist. As such, the Committee believes it was more important to provide a list of the most important areas where progress can be made towards improving S2S forecasts without overly prescribing the sequence or priority in which they should be addressed. All of these actions can improve S2S forecasting and the more that is done to implement these recommendations, the more advances can be made.

To help agencies and other actors within the weather/climate enterprise select specific parts of the research agenda to pursue, Table 8.1 provides additional details about both the main recommendations and more specific or related activities the Committee envisions to be part of implementing each main recommendation: whether they involve basic or applied research; which are expected to have short-term benefits; which might require a new initiative; and which have a scope that calls for international collaboration that can help leverage U.S. effort. While recognizing that it might not be possible to pursue all of these actions simultaneously, the Committee hopes that these strategies, recommendations, and designations can help guide progress across the span of recommended S2S research and forecasting activities.

The vision for the future of S2S forecasting can be achieved with a national will to pursue this research agenda and to convert the results into daily operations. The more that can be pursued within this research agenda, the closer the nation can be towards realizing the full potential of S2S forecasting and the more benefits that can be produced for a wide range of users and the nation as a whole.

TABLE 8.1 The Committee's 16 main recommendations—lettered in the order they appear in the report—are shown in bold typeface along with information to help guide their implementation. The Committee sometimes recommends more specific or related activities that they envision to be part of implementing each main recommendation. These are listed in plain text under each main recommendation. The second column indicates the research strategy that each recommendation and associated activity primarily supports (colors are the same as in Figure 8.1). Additional research strategies (1-4) supported by each recommendation are indicated by numbers. The final columns contain the Committee's opinion on whether each recommendation will involve mainly basic or applied research/operational activities, or both; whether a short-term return-on-investment is likely (≤ 5 years); and whether a new initiative or program, or a significant expansion of a program, may be necessary to implement each recommendation. The last column indicates recommendations for which the Committee believes that international collaboration and coordination is particularly important.

Recommendation	Research Strategies	Basic Research	Applied Research/ Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Criticlal
Chapter 3						
A: ***Develop a body of social science research that leads to more comprehensive and systematic understanding of the use and barriers to use of seasonal and subseasonal Earth system predictions.***	1, 4	■	■	■		
Characterize current and potential users of S2S forecasts and their decision-making contexts, and identify key commonalities and differences in needs (e.g., variables, temporal and spatial scale, lead times, and forecast skill) across multiple sectors.	1, 4		■	■		
Promote social and behavioral science research on the use of probabilistic forecast information.	1	■		■		
Create opportunities to share knowledge and practices among researchers working to improve the use of predictions across weather, subseasonal, and seasonal timescales.	1	■	■	■		
B: ***Establish an ongoing and iterative process in which stakeholders, social and behavioral scientists, and physical scientists co-design S2S forecast products, verification metrics, and decision-making tools.***	1, 4	■	■	■		
Engage users with physical, social, and behavioral scientists to develop requirements for new products as advances are made in modeling technology and forecast skill, including forecasts for additional environmental variables.	1, 4	■	■	■		
In direct collaboration with users, develop ready-set-go scenarios that incorporate S2S predictions and weather forecasts to enable advance preparation for potential hazards as timelines shorten and uncertainty decreases.	1		■	■		
Support boundary organizations and private sector enterprises that act as interfaces between forecast producers and users.	1		■	■		
Chapter 4						
C: ***Identify and characterize sources of S2S predictability, including natural modes of variability (e.g., ENSO, MJO, QBO), slowly varying processes (e.g., sea ice, soil moisture, and ocean eddies), and external forcing (e.g., aerosols), and correctly represent these sources of predictability, including their interactions, in S2S forecast systems.***	2, 3	■		■		■
Use long-record and process-level observations and a hierarchy of models (theory, idealized models, high-resolution models, global earth system models, etc.) to explore and characterize the physical nature of sources of predictability and their interdependencies and dependencies on the background environment and external forcing.	2, 3	■		■		

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Criticlal
Conduct comparable predictability and skill estimation studies and assess the relative importance of different sources of predictability and their interactions, using long-term observations and multi-model approaches (such as the World Meteorological Organization (WMO)-lead S2S Project's database of retrospective forecast data).	2, 3	■		■		■
D: ***Focus predictability studies, process exploration, model development and forecast skill advancements on high impact S2S "forecasts of opportunity" that in particular target disruptive and extreme events.***	3, 2	■		■		■
Determine how predictability sources (e.g. natural modes of variability, slowly varying processes, external forcing) and their multi-scale interactions can influence the occurrence, evolution and amplitude of extreme and disruptive events using long-record and process-level observations.	3, 2	■		■		
Ensure the relationships between disruptive and extreme weather/environmental events – or their proxies - and sources of S2S predictability (e.g. modes of natural variability and slowly-varying processes) are represented in S2S forecast systems.	3, 2	■		■		■
Investigate and estimate the predictability and prediction skill of disruptive and extreme events through utilization and further development of forecast and retrospective forecast databases, such as those from the S2S Project and the NMME.	3, 2	■		■		■
Chapter 5						
E: ***Maintain continuity of critical observations, and expand the temporal and spatial coverage of in situ and remotely-sensed observations for Earth system variables that are beneficial for operational S2S prediction and for discovering and modeling new sources of S2S predictability.***	2, 3, 4	■	■	■	■	■
Maintain continuous satellite measurement records of vertical profiles of atmospheric temperature and humidity without gaps in the data collection, and with increasing vertical resolution and accuracy.	2, 3, 4		■	■		■
Optimize and advance observations of clouds, precipitation, wind profiles and mesoscale storm and boundary layer structure and evolution. In particular, higher resolution observations of these quantities are needed for developing and advancing cloud-permitting components of future S2S forecast systems.	2, 3, 4	■	■			■
Maintain and advance satellite and other observational capabilities (e.g., radars, drifters, and gliders) to provide continuity and better spatial coverage, resolution, and quality of key surface ocean observations (SSH, SST, and winds), particularly near the coasts, where predictions of oceanic conditions are of the greatest societal importance in their own right	2, 3, 4	■	■	■	■	■

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Critical
Maintain and expand the network of in situ instruments providing routine real-time measurements of sub-surface ocean properties, such as temperature, salinity, and currents, with increasing resolutions and accuracy. Appropriate platforms for these instruments will include arrays of moored buoys (especially in the tropics), AUVs, marine mammals, and profiling floats.	2, 3, 4		■	■	■	■
Develop accurate and timely year-round sea ice thickness measurements; if from remote sensing of sea ice freeboard, simultaneous snow depth measurements are needed to translate the observation of freeboard into sea ice thickness.	2, 3, 4	■	■	■		■
Expand in situ measurements of precipitation, snow depth, soil moisture, and land-surface fluxes, and improve and/or better exploit remotely-sensed soil moisture,, snow water equivalent, and evapotranspiration measurements.	2, 3, 4	■	■	■	■	■
Continue to invest in observations (both in situ and remotely sensed) that are important for informing fluxes between the component interfaces, including but not limited to land surface observations of temperature, moisture, and snow depth; marine surface observations from tropical moored buoys; ocean observations of near-surface currents, temperature, salinity, ocean heat content, mixed-layer depth, and sea ice conditions.	2, 3, 4	■	■	■		■
Apply autonomous and other new observing technologies to expand the spatial and temporal coverage of observation networks, and support the continued development of these observational methodologies.	2, 3, 4	■	■			
F: ***Determine priorities for observational systems and networks by developing and implementing OSSEs, OSEs, and other sensitivity studies using S2S forecast systems***	2, 3, 4	■	■	■	■	
G: ***Invest in research that advances the development of strongly-coupled data assimilation and quantifies the impact of such advances on operational S2S forecast systems***	2, 3, 4	■	■	■	■	■
Continue to test and develop weakly coupled systems as operationally viable systems and as benchmarks for strongly coupled implementations.	2, 3, 4	■	■	■		
Further develop and evaluate hybrid assimilation methods, multiscale- and coupled-covariance update algorithms, non-Gaussian nonlinear assimilation, and rigorous reduced-order stochastic modeling.	2, 3, 4	■	■	■	■	
Optimize the use of observations collected for the ocean, land surface, and sea ice components, in part through coupled-covariances and mutual information algorithms, and through autonomous adaptive sampling and observation targeting schemes.	4, 2, 3	■	■	■		

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Critical
Further develop the joint estimation of coupled states and parameters, as well as quantitative methods that discriminate among, and learn, parameterizations.	2, 3, 4	■	■	■		
Develop methods and systems to fully utilize all relevant satellite and in situ atmospheric information, especially for cloudy and precipitating conditions	2, 3, 4	■	■			
Foster interactions among the growing number of science and engineering communities involved in data assimilation, Bayesian inference, and uncertainty quantification.	2, 3, 4	■	■			■
H: ***Accelerate research to improve parameterization of unresolved (e.g., subgrid scale) processes, both within S2S system submodels, and holistically across models to better represent coupling in the Earth system.***	2, 3, 4	■		■	■	■
Foster long-term collaborations among scientists across academia, and research and operational modeling centers, and across ocean, sea ice, land and atmospheric observation and modeling communities, to identify root causes of error in parameterization schemes, to correct these errors, and to develop, test and optimize new (especially scale-aware or independent) parameterization schemes in a holistic manner	2, 3, 4	■		■		
Continue to investigate the potential for reducing model errors through increases in horizontal and vertical resolutions in the atmosphere and other model components, ideally in a coupled model framework (see also Recommendation L).	2, 3, 4	■		■		
Encourage field campaigns targeted at increasing knowledge of processes that are poorly understood or poorly represented in S2S models, including tropical convection, ocean mixing, polar sea-ice and stratospheric processes, and coupling among different Earth system components (e.g., air-sea-ice-wave-land; troposphere-stratosphere; dynamics-biogeochemistry).	2, 3, 4	■		■	■	■
Develop high-resolution (or multi-resolution) modeling systems (e.g., that permit atmospheric deep convection and non-hydrostatic ocean processes) to advance process understanding and promote the development of high-resolution operational prototypes (see also Recommendation I).	2, 3, 4	■			■	
I: ***Pursue next-generation ocean, sea ice, wave, biogeochemistry, and land surface/hydrologic as well as atmospheric model capability in fully-coupled Earth system models used in S2S forecast systems.***	4, 2, 3	■	■	■	■	
Build a robust research program to explore potential benefits to S2S predictive skill and to forecast users from adding more advanced Earth system components in forecast systems.	4, 2, 3	■		■		

Recommendation	Research Strategies	Basic Research	Applied Research / Operational	Benefits Likely in the Short Term	May Need New Initiative	International Collab. Critical
Initiate new efficient partnerships between academics and operational centers to create the next generation model components that can be easily integrated in coupled S2S Earth system models.	4, 2, 3	■	■		■	
Support and expand model coupling frameworks to link ocean/atmosphere/land/wave/ice models inter-operably for rapidly and easily exchanging flux and variable information.	4, 2, 3	■	■	■		
Develop a strategy to transition very high resolution (eddy/cloud-resolving) atmosphere-ocean-land-sea ice coupled models to operations, including strategies for new parameterization schemes, data assimilation procedures, and multi-model ensembles (MME).	2, 3, 4	■	■		■	■
J: ***Pursue feature-based verification techniques in order to more readily capture limited predictability at S2S timescales, as part of a larger effort to improve S2S forecast verification.***	2, 1, 3	■	■	■	■	■
Investigate methodologies for ensemble feature verification including two-step processes linking features to critical user criterion.	2, 1	■		■	■	
Pursue verification methodologies for rare and extreme events at S2S timescales, especially those related to multi-model ensemble predictions.	3, 1, 2	■		■		
Consider the benefits of producing more frequent reanalyses using coupled S2S forecast systems in order for the initial conditions of retrospective forecasts to be more consistent with the real time forecasts, as well as for the purposes of predictability studies.	2, 1		■	■		■
K: ***Explore systematically the impact of various S2S forecast system design elements on S2S forecast skill. This includes examining the value of model diversity, as well as the impact of various selections and combinations of model resolution, number of ensemble perturbations, length of lead, averaging period, length of retrospective forecasts, and options for coupled sub-models.***	2, 3, 4	■	■	■	■	■
Design a coordinated program to assess the costs and benefits of including additional processes in S2S systems, and relate those to benefits from other investments, for example in higher resolution. In doing so, take advantage of the opportunity to leverage experience and codes from the climate modeling community.	2, 3, 4	■	■		■	
Encourage systematic studies of the costs and benefits of increasing the vertical and horizontal resolution of S2S models.	2, 3, 4	■	■			
Evaluate calibration methods and ascertain whether some methods offer clear advantage over others for certain applications, as part of studies of the optimum configurations of S2S models.	2, 3, 4	■	■	■		

Recommendation	Research Strategies	Basic Research	Applied Research / Operational	Benefits Likely in the Short Term	May Need New Initiative	International Collab. Criticial
Explore systematically how many unique models in a multi-model ensemble are required to predict useful S2S parameters, and whether those models require unique data assimilation, physical parameterizations, or atmosphere, ocean, land, and ice components (see also Recommendation L).	2, 3, 4	■	■	■		■
Chapter 6						
L: ***Accelerate efforts to carefully design and create robust operational multi-model ensemble S2S forecast systems.***	2, 3		■		■	■
Use test beds and interagency and international collaborations where feasible to systematically explore the impact of various S2S forecast system design elements on S2S forecast skill, in particular the question how many unique models in a multi-model ensemble are required to predict operationally useful S2S parameters (see also Recommendation K).	2, 3		■			■
Assess realistically the available operational resources and centers that are able to contribute operationally rigorous prediction systems.	2, 3		■		■	
M: ***Provide mechanisms for research and operational communities to collaborate, and aid in transitioning components and parameterizations from the research community into operational centers, by increasing researcher access to operational or operational mirror systems.***	2, 1, 3, 4		■	■		■
Increase opportunities for S2S researchers to participate in operational centers.	2, 3, 4		■	■		
Enhance interactions with the international community, e.g., the S2S Project and APCC, and with the WMO Lead Centers.	2, 3, 4		■	■		■
Provide better access in the near-term to archived data from operational systems, potentially via test centers.	2, 3, 4		■	■		
Develop, in the longer term, the ability for researchers to request re-runs or do runs themselves of operational model forecasts.	2, 3, 4		■			
Encourage effective partnerships with the private sector through ongoing engagement (see also Recommendation 3B)	2, 1		■	■		
N: ***Develop a national capability to forecast the consequences of unanticipated forcing events.***	3, 1		■		■	
Improve the coordination of government agencies and academics to be able to quickly respond to unanticipated events to provide S2S forecasts and associated responses using the unanticipated events as sources of predictability.	3, 1		■		■	
Utilize emerging applications of Earth system models for long-range transport and dispersion processes (e.g., of aerosols).	3, 1		■			

Recommendation	Research Strategies	Basic Research	Applied Research / Opera-tional	Benefits Likely in the Short Term	May Need New Initiative	Inter-national Collab. Criticlal
Increase research on the generation, validation, and verification of forecasts for the aftermath of unanticipated forcing events.	3, 1	■	■			
Chapter 7						
O: ***Develop a national plan and investment strategy for S2S prediction to take better advantage of current hardware and software and to meet the challenges in the evolution of new hardware and software for all stages of the prediction process, including data assimilation, operation of high-resolution coupled Earth system models, and storage and management of results.***	Supporting	■	■	■	■	
Redesign and recode S2S models and data assimilation systems so they will be capable of exploiting current and future massively parallel computational capabilities; this will require a significant and long-term investment in computer scientists, software engineers, applied mathematicians, and statistics researchers in partnership with the S2S researchers.	Supporting	■	■		■	
Increase efforts to achieve an integrated modeling environment using the opportunity of S2S and seamless prediction to bring operational agency (ESPC) efforts and IGIM efforts together to create common software infrastructure and standards for component interfaces.	Supporting	■	■	■		
Provide larger and dedicated supercomputing and storage resources.	Supporting		■	■	■	
Resolve the emerging challenges around S2S big data, including development and deployment of integrated data-intensive cyberinfrastructure, utilization of efficient data-centric workflows, reduction of stored data volumes, and deployment of data serving and analysis capabilities for users outside the research/operational community.	Supporting	■	■			
Further develop techniques for high volume data processing and in-line data volume reduction.	Supporting	■	■	■		
Continue to develop dynamic model cores that take the advantage of new computer technology.	Supporting	■	■	■		
P: ***Pursue a collection of actions to address workforce development that removes barriers that exist across the entire workforce pipeline and in the diversity of scientists and engineers involved in advancing S2S forecasting and the component and coupled systems.***	Supporting		■	■	■	
Gather quantitative information about workforce requirements and expertise base to support S2S modeling in order to more fully develop such a training program and workforce pipeline.	Supporting		■	■		

Recommendation	Research Strategies	Basic Research	Applied Research / Operational	Benefits Likely in the Short Term	May Need New Initiative	International Collab. Criticlal
Improve incentives and funding to support existing professionals and to attract new professionals to the S2S research community, especially in model development and improvement, and for those who bridge scientific disciplines and/or work at component interfaces.	Supporting		■		■	
Expand interdisciplinary programs to train a more robust workforce to be employed in boundary organizations that work in between S2S model developers and those who use forecasts.	Supporting		■		■	
Provide more graduate and postgraduate training opportunities, enhanced professional recognition and career advancement, and adequate incentives to encourage top students in relevant scientific and computer programming disciplines to choose S2S model development and research as a career.	Supporting		■		■	

Acronym List

4DEnVar	four-dimensional ensemble-variational
ABL	atmospheric boundary layer
ABOM	Australian Bureau of Meteorology
AFWA	Air Force Weather Agency
AIRS	Atmospheric Infrared Sounder
AMDAR	Aircraft Meteorological Data Relay
AMS	American Meteorological Society
AMSR-E	advanced microwave scanning radiometer
AMSU	Advanced Microwave Sounding Unit
AMV	atmospheric motion vector
AMY	Asian Monsoon Year
ANOVA	analysis of variance
AO	Atlantic Oscillation
APCC	APEC (Asia-Pacific Economic Cooperation) Climate Center
ASCAT	Advanced Scatterometer
AUV	autonomous underwater vehicle
CESM	Community Earth System Model
CFS	Climate Forecast System
CFSR	Climate Forecast System Reanalysis
CFSv2	Climate Forecast System version 2
CIME	Common Infrastructure for Modeling the Environment
CliPAS	Climate Prediction and its Application to Society
CMC	Canadian Meteorological Centre
CMIP	Coupled Model Intercomparison Project
COAMPS	Coupled Ocean/Atmosphere Mesoscale Prediction System
CODAR	Coastal ocean dynamics applications radar
CPC	Climate Prediction Center
CPT	Climate Process Team
CPTEC	Brazil Center for Weather Forecasting and Climate Studies
CrIS	Crosstrack Infrared Sounder
CYGNSS	Cyclone Global Navigation Satellite System
DA	data assimilation
DARPA	Defense Advanced Research Projects Agency
DEMETER	Development of a European Multi-model Ensemble system for seasonal to inTERannual predictions
DHS	U.S. Department of Homeland Security
DO	Dynamically Orthogonal
DOD	U.S. Department of Defense
DOE	U.S. Department of Energy
DTRA	Defense Threat Reduction Agency
DWH	Deepwater Horizon
DYNAMO	Dynamics of the Madden-Julian Oscillation

ECMWF	European Centre for Medium-Range Weather Forecasting
ECOSTRESS	ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station
EnKF	Ensemble Kalman Filter
ENSEMBLES	European Commission FP7 project
ENSO	El Niño-Southern Oscillation
ERA Interim	ECMWF Interim Reanalysis
ESM	Earth system model
ESMF	Earth System Modeling Framework
ESPC	Earth System Modeling Capability
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FNMOC	Fleet Numerical Meteorology and Oceanography Center
GATE	GARP (Global Atmosphere Research Program) Atlantic Tropical Experiment
GDP	Global Drifter Program
GEFS	global ensemble forecast system
GFDL	Geophysical Fluid Dynamics Laboratory
GHG	Greenhouse Gas
GMM	Gaussian Mixture Model
GOES	Geostationary Operational Environmental Satellite
GPM	Global Precipitation Mission
GPS	Global Positioning System
GPS-RO	Global Positioning System Radio Occulation
GTH	Global Tropics Hazards and Benefits Assessment
HadGEM3	Hadley Centre Global Environment Model version 3
HPC	high-performance computing
IASI	Infrared Atmospheric Sounding Interferometer
ICESat2	Second generation Ice Cloud and Land Elevation Satellite
IGIM	Interagency Group on Integrative Modeling
IMAAC	Interagency Modeling and Atmospheric Assessment Center
IMD	India Meteorology Department
IOD	Indian Ocean Dipole
IOOS	Integrated Ocean Observing System
IOP	intensive observing period
IRI	International Research Institute for Climate and Society
ISI	Intraseasonal to Interannual
ISS	International Space Station
ITCZ	Inter Tropical Convergence Zone
JAXA	Japan Aerospace Exploration Agency
JMA	Japan Meteorological Agency
KL	Karhunen-Loève
LANL	Los Alamos National Laboratory
LDAS	Land Data Assimilation System
LES	Large-eddy simulation
LSM	land-surface model
MCMC	Markov chain Monte Carlo
MERIT	Meningitis Environmental Research Information Technologies
MIZ	Marginal Ice Zone

MJO	Madden-Julian Oscillation
MME	multi-model ensemble
MODIS	Moderate Resolution Imaging Spectroradiometer
MOS	model output statistics
MOSAiC	Multidisciplinary drifting Observatory for the Study of Arctic Climate
MPI	Message Passing Interface
NAM	Northern Annular Mode
NAO	North Atlantic Oscillation
NARAC	National Atmospheric Release Advisory Center
NASA	National Aeronautics and Space Administration
NASCar	Northern Arabian Sea Circulation—autonomous research
NAVGEM	NAVy Global Environmental Model
NAVO	Naval Oceanographic Office
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NEMO	Nucleus for European Modelling of the Ocean
NISAC	National Infrastructure Simulation and Analysis Center
NMME	North American Multi-Model Ensemble
NOAA	National Oceanic and Atmospheric Administration
NRL	Naval Research Laboratory
NSF	National Science Foundation
NVM	non-volatile memory
NWP	Numerical Weather Prediction
NWS	U.S. National Weather Service
OAR	Office of Oceanic & Atmospheric Research
OLR	outgoing longwave radiation
ONR	Office of Naval Research
OpenMP	Open Multi-Processing
OSSE	observing system simulation experiment
PCAST	President’s Council of Advisors on Science and Technology
PDE	partial differential equation
PIM	processor in memory
PinT	parallel in time
PIO	Parallel I/O
PNA	Pacific/North American teleconnection pattern
QBO	Quasi-Biennial Oscillation
R2O	research to operations
RISA	Regional Integrated Sciences and Assessments Program
RMM	Real-time Multivariate MJO index
RMSE	root mean square error
S2S	subseasonal to seasonal
SAON	Sustaining Arctic Observing Network
SBIR	Small Business Innovation Research
SHEBA	Surface Heat Budget of the Arctic Ocean
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity

SNOTEL	Snowpack Telemetry
SOCRATES	Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study
SPERR	Scientific Partnerships Enabling Rapid Response
SSD	Solid State Devices
SSH	sea surface height
SSM/I	special sensor microwave imager
SST	Sea Surface Temperature
SSW	sudden stratospheric warning
SWE	snow water equivalent
SWOT	Surface Water and Ocean Topography
TAMDAR	Tropospheric Airborne Meteorological Data Reporting
TCWB	Taiwan Central Weather Bureau
TIROS	Television Infrared Observation Satellite
TOGA COARE	Tropical Ocean Global Atmosphere Coupled Ocean-Atmosphere Response Experiment
TRMM	Tropical Rainfall Measuring Mission
UKMO	United Kingdom Met Office
USGCRP	U.S. Global Change Research Program
VAD	Velocity Azimuth Display
VES	Virtual Earth System
VOCALS-Rex	VAMOS (Variability of the American Monsoon Systems) Ocean-Cloud-Atmosphere-Land Study Regional Experiment
WCRP	World Climate Research Programme
WCS	World Climate Service
WERA	WavE RAdar
WHO	World Health Organization
WMO	World Meteorological Organization
WWRP	World Weather Research Programme
XBT	Expendable Bathythermograph
YMC	Years of the Maritime Continent
YOPP	The Year of Polar Prediction
YOTC	Year of Tropical Convection

References

Adcroft, A., R. Hallberg, J. P. Dunne, B. L. Samuels, J. A. Galt, C. H. Barker and D. Payton. 2010. Simulations of underwater plumes of dissolved oil in the Gulf of Mexico. Geophysical Research Letters 37. DOI: 10.1029/2010gl044689.

Ades, M. and P. J. van Leeuwen. 2015. The equivalent-weights particle filter in a high-dimensional system. Quarterly Journal of the Royal Meteorological Society 141(687):484-503. DOI: 10.1002/Qj.2370.

Ajayamohan, R. S., S. A. Rao, J. J. Luo and T. Yamagata. 2009. Influence of Indian Ocean Dipole on boreal summer intraseasonal oscillations in a coupled general circulation model. Journal of Geophysical Research-Atmospheres 114. DOI: 10.1029/2008jd011096.

Alexander, M. A., C. Deser and M. S. Timlin. 1999. The reemergence of SST anomalies in the North Pacific Ocean. Journal of Climate 12(8):2419-2433. DOI: 10.1175/1520-0442(1999)012<2419:Trosai>2.0.Co;2.

Allen, R. J. and C. S. Zender. 2010. Effects of continental-scale snow albedo anomalies on the wintertime Arctic oscillation. Journal of Geophysical Research-Atmospheres 115. DOI: 10.1029/2010jd014490.

Alspach, D. L. and H. W. Sorenson. 1972. Nonlinear Bayesian Estimation Using Gaussian Sum Approximations. IEEE Transactions on Automatic Control Ac17(4):439-448. DOI: 10.1109/Tac.1972.1100034.

Anderson, J. L. and S. L. Anderson. 1999. A Monte Carlo implementation of the nonlinear filtering problem to produce ensemble assimilations and forecasts. Monthly Weather Review 127(12):2741-2758. DOI: 10.1175/1520-0493(1999)127<2741:Amciot>2.0.Co;2.

Annan, J. D., J. C. Hargreaves, N. R. Edwards and R. Marsh. 2005. Parameter estimation in an intermediate complexity earth system model using an ensemble Kalman filter. Ocean Modelling 8(1-2):135-154. DOI: 10.1016/j.ocemod.2003.12.004.

Arakawa, A. and C. M. Wu. 2013. A Unified Representation of Deep Moist Convection in Numerical Modeling of the Atmosphere. Part I. Journal of the Atmospheric Sciences 70(7):1977-1992. DOI: 10.1175/Jas-D-12-0330.1.

Arnold, C. P. and C. H. Dey. 1986. Observing-Systems Simulation Experiments - Past, Present, and Future. Bulletin of the American Meteorological Society 67(6):687-695. DOI: 10.1175/1520-0477(1986)067<0687:Ossepp>2.0.Co;2.

Arteaga, A., O. Fuhrer and T. Hoefler. 2014. Designing Bit-Reproducible Portable High-Performance Applications. Presented at IEEE 28th International Parallel and Distributed Processing Symposium, Washington, DC.

ASCAC. 2015. Exascale Computing Initiative. Washington, DC: US DOE.

Athanasiadis, P. J., A. Bellucci, L. Hermanson, A. A. Scaife, C. MacLachlan, A. Arribas, S. Materia, A. Borrelli and S. Gualdi. 2014. The Representation of Atmospheric Blocking and the Associated Low-Frequency Variability in Two Seasonal Prediction Systems. Journal of Climate 27(24):9082-9100. DOI: 10.1175/Jcli-D-14-00291.1.

Back, L. E. and C. S. Bretherton. 2009. On the Relationship between SST Gradients, Boundary Layer Winds, and Convergence over the Tropical Oceans. Journal of Climate 22(15):4182-4196. DOI: 10.1175/2009JCLI2392.1.

Bahr, A., J. J. Leonard and M. F. Fallon. 2009. Cooperative Localization for Autonomous Underwater Vehicles. International Journal of Robotics Research 28(6):714-728. DOI: 10.1177/0278364908100561.

Baker, A. H., D. M. Hammerling, M. N. L. H. Xu, J. M. Dennis, B. E. Eaton, J. Edwards, C. Hannay, S. A. Mickelson, R. B. Neale, D. Nychka, J. Shollenberger, J. Tribbia, M. Vertenstein and D.

Williamson. 2015. A new ensemble-based consistency test for the Community Earth System Model (pyCECT v1.0). Geoscientific Model Development 8:2829-2840. DOI: 10.5194/gmd-8-2829-2015.
Baker, W. E., R. Atlas, C. Cardinali, A. Clement, G. D. Emmitt, B. M. Gentry, R. M. Hardesty, E. Kallen, M. J. Kavaya, R. Langland, Z. Z. Ma, M. Masutani, W. McCarty, R. B. Pierce, Z. X. Pu, L. P. Riishojgaard, J. Ryan, S. Tucker, M. Weissmann and J. G. Yoe. 2014. Lidar-Measured Wind Profiles: The Missing Link in the Global Observing System. Bulletin of the American Meteorological Society 95(4):543-564. DOI: 10.1175/Bams-D-12-00164.1.
Baldwin, M. P. and T. J. Dunkerton. 2001. Stratospheric harbingers of anomalous weather regimes. Science 294(5542):581-584. DOI: 10.1126/science.1063315.
Baldwin, M. P., D. B. Stephenson, D. W. J. Thompson, T. J. Dunkerton, A. J. Charlton and A. O'Neill. 2003. Stratospheric memory and skill of extended-range weather forecasts. Science 301(5633):636-640. DOI: 10.1126/science.1087143.
Balmaseda, M. A., L. Ferranti, F. Molteni and T. N. Palmer. 2010. Impact of 2007 and 2008 Arctic ice anomalies on the atmospheric circulation: Implications for long-range predictions. Quarterly Journal of the Royal Meteorological Society 136(652):1655-1664. DOI: 10.1002/Qj.661.
Balsamo, G., A. Agustì-Panareda, C. Albergel, A. Beljaars, S. Boussetta, E. Dutra, T. Komori, S. Lang, J. Muñoz-Sabater, F. Pappenberger, P. d. Rosnay, I. Sandu, N. Wedi, A. Weisheimer, F. Wetterhall and E. Zsoter. 2014. Representing the Earth surfaces in the Integrated Forecasting System: Recent advances and future challenges. Special topic paper on surface processes presented at the 43rd ECMWF Scientific Advisory Committee. Reading, UK: European Centre for Medium Range Weather Forecasts.
Barnhart, K. R., I. Overeem and R. S. Anderson. 2014. The effect of changing sea ice on the physical vulnerability of Arctic coasts. Cryosphere 8(5):1777-1799. DOI: 10.5194/tc-8-1777-2014.
Barnston, A. G., S. H. Li, S. J. Mason, D. G. DeWitt, L. Goddard and X. F. Gong. 2010. Verification of the First 11 Years of IRI's Seasonal Climate Forecasts. Journal of Applied Meteorology and Climatology 49(3):493-520. DOI: 10.1175/2009JAMC2325.1.
Bauer, P., G. Ohring, C. Kummerow and T. Auligne. 2011. Assimilating Satellite Observations of Clouds and Precipitation into Nwp Models. Bulletin of the American Meteorological Society 92(6):Es25-Es28. DOI: 10.1175/2011bams3182.1.
Beck, M. 2009. Grand Challenges for the Future for Environmental Modeling. White Paper NFS Award# 0630367, NSF's Environmental Observatories Initiatives, Warnell School of Forestry and Natural Resources, University of Georgia, Athens, Georgia 30602-2152, Aug. 2009.
Bell, M. J., M. J. Martin and N. K. Nichols. 2004. Assimilation of data into an ocean model with systematic errors near the equator. Quarterly Journal of the Royal Meteorological Society 130(598):873-893. DOI: 10.1256/Qj.02.109.
Benedetti, A., P. Lopez, P. Bauer and E. Moreau. 2005. Experimental use of TRMM precipitation radar observations in 1D+4D-Var assimilation. Quarterly Journal of the Royal Meteorological Society 131(610):2473-2495. DOI: 10.1256/qj.04.89.
Benedict, J. J. and D. A. Randall. 2009. Structure of the Madden-Julian Oscillation in the Superparameterized CAM. Journal of the Atmospheric Sciences 66(11):3277-3296. DOI: 10.1175/2009jas3030.1.
Bengtsson, T., C. Snyder and D. Nychka. 2003. Toward a nonlinear ensemble filter for high-dimensional systems. Journal of Geophysical Research-Atmospheres 108(D24). DOI: 10.1029/2002jd002900.
Bennett, A. F. 1992. Inverse Methods in Physical Oceanography. Cambridge, UK: Cambridge University Press.
Berner, J., F. J. Doblas-Reyes, T. N. Palmer, G. Shutts and A. Weisheimer. 2008. Impact of a quasi-stochastic cellular automaton backscatter scheme on the systematic error and seasonal prediction skill of a global climate model. Philosophical Transactions of the Royal Society a-Mathematical Physical and Engineering Sciences 366(1875):2561-2579. DOI: 10.1098/rsta.2008.0033.

Berner, J., S. Y. Ha, J. P. Hacker, A. Fournier and C. Snyder. 2011. Model Uncertainty in a Mesoscale Ensemble Prediction System: Stochastic versus Multiphysics Representations. Monthly Weather Review 139(6):1972-1995. DOI: 10.1175/2010MWR3595.1.

Best, M. J., G. Abramowitz, H. R. Johnson, A. J. Pitman, G. Balsamo, A. Boone, M. Cuntz, B. Decharme, P. A. Dirmeyer, J. Dong, M. Ek, Z. Guo, V. Haverd, B. J. J. Van den Hurk, G. S. Nearing, B. Pak, C. Peters-Lidard, J. A. Santanello, L. Stevens and N. Vuichard. 2015. The Plumbing of Land Surface Models: Benchmarking Model Performance. Journal of Hydrometeorology 16(3):1425-1442. DOI: 10.1175/Jhm-D-14-0158.1.

Bishop, C. and M. Martin. 2012. Joint GODAE OceanView - WGNE workshop on Short- to Medium-range coupled prediction for the atmosphere-wave-sea-ice-ocean: Status, needs and challenges. Data Assimilation – Whitepaper. Retrieved August 21, 2015, from https://www.godae-oceanview.org/files/download.php?m=documents&f=130130121715-CoupledDAWhitePaperv01November232012.doc.

Bitz, C. M., D. S. Battisti, R. E. Moritz and J. A. Beesley. 1996. Low-frequency variability in the arctic atmosphere, sea ice, and upper-ocean climate system. Journal of Climate 9(2):394-408. DOI: 10.1175/1520-0442(1996)009<0394:Lfvita>2.0.Co;2.

Bitz, C. M., P. R. Gent, R. A. Woodgate, M. M. Holland and R. Lindsay. 2006. The influence of sea ice on ocean heat uptake in response to increasing CO2. Journal of Climate 19(11):2437-2450. DOI: 10.1175/Jcli3756.1.

Bitz, C. M., J. K. Ridley, M. M. Holland and H. Cattle. 2012. 20th and 21st century Arctic Climate in Global Climate Models. In Arctic Climate Change: The ACSYS Decade and Beyond. P. Lemke and H.-W. Jacobi, eds. Dordrecht: Springer.

Blaise, S., R. Comblen, V. Legat, J. F. Remacle, E. Deleersnijder and J. Lambrechts. 2010. A discontinuous finite element baroclinic marine model on unstructured prismatic meshes Part I: space discretization. Ocean Dynamics 60(6):1371-1393. DOI: 10.1007/s10236-010-0358-3.

Blanchard-Wrigglesworth, E., K. C. Armour, C. M. Bitz and E. DeWeaver. 2011a. Persistence and Inherent Predictability of Arctic Sea Ice in a GCM Ensemble and Observations. Journal of Climate 24(1):231-250. DOI: 10.1175/2010jcli3775.1.

Blanchard-Wrigglesworth, E., C. M. Bitz and M. M. Holland. 2011b. Influence of initial conditions and boundary forcing on predictability in the Arctic. Geophysical Research Letters 38:L18503. DOI: 10.1029/2011GL048807.

Blanchard-Wrigglesworth, E. and C. M. Bitz. 2014. Characteristics of Arctic Sea-Ice Thickness Variability in GCMs. Journal of Climate 27(21):8244-8258. DOI: 10.1175/Jcli-D-14-00345.1.

Blanchard-Wrigglesworth, E., R. Cullather, W. Wanqiu, J. Zhang and C. M. Bitz. 2015. Model skill and sensitivity to initial conditions in a sea-ice prediction system. Geophysical Research Letters(in review). DOI.

Boas, A. B. V., O. T. Sato, A. Chaigneau and G. P. Castelao. 2015. The signature of mesoscale eddies on the air-sea turbulent heat fluxes in the South Atlantic Ocean. Geophysical Research Letters 42(6):1856-1862. DOI: 10.1002/2015GL063105.

Bocquet, M., C. A. Pires and L. Wu. 2010. Beyond Gaussian Statistical Modeling in Geophysical Data Assimilation. Monthly Weather Review 138(8):2997-3023. DOI: 10.1175/2010MWR3164.1.

Bocquet, M. 2012. An introduction to inverse modelling and parameter estimation for atmosphere and ocean sciences. Oxford Scholarship Online. DOI: 10.1093/acprof:oso/9780198723844.003.0020.

Bocquet, M. and P. Sakov. 2013. Joint state and parameter estimation with an iterative ensemble Kalman smoother. Nonlinear Processes in Geophysics 20(5):803-818. DOI: 10.5194/npg-20-803-2013.

Bonan, G. B. 2008. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. Science 320(5882):1444-1449. DOI: 10.1126/science.1155121.

Bonavita, M., M. Hamrud and L. Isaksen. 2015. EnKF and Hybrid Gain Ensemble Data Assimilation. Part II: EnKF and Hybrid Gain Results. Monthly Weather Review 143(12):4865-4882. DOI: 10.1175/Mwr-D-15-0071.1.

Braman, L. M., M. K. van Aalst, S. J. Mason, P. Suarez, Y. Ait-Chellouche and A. Tall. 2013. Climate forecasts in disaster management: Red Cross flood operations in West Africa, 2008. Disasters 37(1):144-164. DOI: 10.1111/j.1467-7717.2012.01297.x.

Brands, S., R. Manzanas, J. M. Gutierrez and J. Cohen. 2012. Seasonal Predictability of Wintertime Precipitation in Europe Using the Snow Advance Index. Journal of Climate 25(12):4023-4028. DOI: 10.1175/Jcli-D-12-00083.1.

Brassington, G. B., M. J. Martin, H. L. Tolman, S. Akella, M. Balmeseda, C. R. S. Chambers, E. P. Chassignet, J. A. Cummings, Y. Drillet, P. A. E. M. Janssen, P. Laloyaux, D. Lea, A. Mehra, I. Mirouze, H. Ritchie, G. Samson, P. A. Sandery, G. C. Smith, M. Suarez and R. Todling. 2015. Progress and challenges in short- to medium-range coupled prediction. Journal of Operational Oceanography(in press). DOI.

Breuer, N. E., C. W. Fraisse and V. E. Cabrera. 2010. The Cooperative Extension Service as a boundary organization for diffusion of climate forecasts: a 5-year study. Journal of Extension 48(4). DOI.

Broman, D., B. Rajagopalan and T. Hopson. 2014. Spatiotemporal Variability and Predictability of Relative Humidity over West African Monsoon Region. Journal of Climate 27(14):5346-5363. DOI: 10.1175/Jcli-D-13-00414.1.

Brown, A., S. Milton, M. Cullen, B. Golding, J. Mitchell and A. Shelly. 2012. Unified Modeling and Prediction of Weather and Climate: A 25-Year Journey. Bulletin of the American Meteorological Society 93(12):1865-1877. DOI: 10.1175/Bams-D-12-00018.1.

Brown, B. G., J. L. Mahoney, C. A. Davis, R. Bullock and C. K. Mueller. 2002. Improved approaches for measuring the quality of convective weather forecasts. Presented at 16th Conference on Probability and Statistics in the Atmospheric Sciences, Orlando, FL.

Brown, B. G., R. Bullock, C. A. Davis, J. H. Gotway, M. Chapman, A. Takacs, E. Gilleland, J. L. Mahoney and K. Manning. 2004. New verification approaches for convective weather forecasts. Presented at 11th Conference on Aviation, Range, and Aerospace, Hyannis, MA.

Brunet, G., M. Shapiro, B. Hoskins, M. Moncrieff, R. Dole, G. N. Kiladis, B. Kirtman, A. Lorenc, B. Mills, R. Morss, S. Polavarapu, D. Rogers, J. Schaake and J. Shukla. 2010. Collaboration of the Weather and Climate Communities to Advance Subseasonal-to-Seasonal Prediction. Bulletin of the American Meteorological Society 91(10):1397-1406. DOI: 10.1175/2010bams3013.1.

Bryan, F. O., R. Tomas, J. M. Dennis, D. B. Chelton, N. G. Loeb and J. L. McClean. 2010. Frontal Scale Air-Sea Interaction in High-Resolution Coupled Climate Models. Journal of Climate 23(23):6277-6291. DOI: 10.1175/2010jcli3665.1.

Bryan, K. and M. D. Cox. 1968. A Nonlinear Model of an Ocean Driven by Wind and Differential Heating .I. Description of 3-Dimensional Velocity and Density Fields. Journal of the Atmospheric Sciences 25(6):945-978. DOI: Doi 10.1175/1520-0469(1968)025<0945:Anmoao>2.0.Co;2.

Bryan, K. 1969. A numerical method for the study of the circulation of the world ocean. Journal of Computational Physics 4(3):347-376. DOI: 10.1006/jcph.1997.5699.

Buontempo, C., C. D. Hewitt, F. J. Doblas-Reyes and S. Dessai. 2014. Climate service development, delivery and use in Europe at monthly to inter-annual timescales. Climate Risk Management 6:1-5. DOI: 10.1016/j.crm.2014.10.002.

Bushuk, M. and D. Giannakis. 2015. Sea-ice reemergence in a model hierarchy. Geophysical Research Letters 42(13):5337-5345. DOI: 10.1002/2015GL063972.

Byun, K. and M. Choi. 2014. Uncertainty of snow water equivalent retrieved from AMSR-E brightness temperature in northeast Asia. Hydrological Processes 28(7):3173-3184. DOI: 10.1002/Hyp.9846.

Cai, W. J., A. Santoso, G. J. Wang, S. W. Yeh, S. I. An, K. M. Cobb, M. Collins, E. Guilyardi, F. F. Jin, J. S. Kug, M. Lengaigne, M. J. McPhaden, K. Takahashi, A. Timmermann, G. Vecchi, M. Watanabe and L. X. Wu. 2015. ENSO and greenhouse warming. Nature Climate Change 5(9):849-859. DOI: 10.1038/Nclimate2743.

Cane, M. A., S. E. Zebiak and S. C. Dolan. 1986. Experimental Forecasts of El-Niño. Nature 321(6073):827-832. DOI: 10.1038/321827a0.
Capotondi, A., A. T. Wittenberg, M. Newman, E. D. Lorenzo, J.-Y. Yu, P. Braconnot, J. Cole, B. Dewitte, B. Giese, E. Guilyardi, F.-F. Jin, K. Karnauskas, B. Kirtman, T. Lee, N. Schneider, Y. Xue and S.-W. Yeh. 2014. Understanding ENSO diversity. Bulletin of the American Meteorological Society(e-view). DOI: http://dx.doi.org/10.1175/BAMS-D-13-00117.1.
Cardinali, C. 2009. Monitoring the observation impact on the short-range forecast. Quarterly Journal of the Royal Meteorological Society 135(638):239-250. DOI: 10.1002/qj.366.
Cassou, C. 2008. Intraseasonal interaction between the Madden-Julian Oscillation and the North Atlantic Oscillation. Nature 455(7212):523-527. DOI: 10.1038/Nature07286.
Challinor, A. J., J. M. Slingo, T. R. Wheeler and F. J. Doblas-Reyes. 2005. Probabilistic simulations of crop yield over western India using the DEMETER seasonal hindcast ensembles. Tellus Series a-Dynamic Meteorology and Oceanography 57(3):498-512. DOI: 10.1111/j.1600-0870.2005.00126.x.
Chandra, R., L. Dagum, D. Kohr, D. Maydan, J. McDonald and R. Menon. 2001. Parallel Programming in OpenMP. San Diego: Academic Press.
Chassignet, E. P. and J. Verron. 2006. Ocean Weather Forecasting: An Integrated View of Oceanography. Dordrecht: Springer.
Chassignet, E. P., J. G. Richman, E. J. Metzger, X. Xu, P. G. Hogan, B. K. Arbic and A. J. Wallcraft. 2014. HYCOM high resolution eddying simulations. CLIVAR Exchanges 19(2):22-25. DOI.
Chelton, D. B., M. G. Schlax, M. H. Freilich and R. F. Milliff. 2004. Satellite measurements reveal persistent small-scale features in ocean winds. Science 303(5660):978-983. DOI: 10.1126/science.1091901.
Chelton, D. B. and S. P. Xie. 2010. Coupled Ocean-Atmosphere Interaction at Oceanic Mesoscales. Oceanography 23(4):52-69. DOI: http://dx.doi.org/10.5670/oceanog.2010.05.
Chen, C. S., H. S. Huang, R. C. Beardsley, Q. C. Xu, R. Limeburner, G. W. Cowles, Y. F. Sun, J. H. Qi and H. C. Lin. 2011. Tidal dynamics in the Gulf of Maine and New England Shelf: An application of FVCOM. Journal of Geophysical Research-Oceans 116. DOI: 10.1029/2011jc007054.
Chen, S. Y. S., J. F. Price, W. Zhao, M. A. Donelan and E. J. Walsh. 2007. The CBLAST-hurricane program and the next-generation fully coupled atmosphere-wave-ocean. Models for hurricane research and prediction. Bulletin of the American Meteorological Society 88(3):311-317. DOI: 10.1175/Bams-88-3-311.
Chen, S. Y. S., W. Zhao, M. A. Donelan and H. L. Tolman. 2013. Directional Wind-Wave Coupling in Fully Coupled Atmosphere-Wave-Ocean Models: Results from CBLAST-Hurricane. Journal of the Atmospheric Sciences 70(10):3198-3215. DOI: 10.1175/Jas-D-12-0157.1.
Chevallier, M. and D. Salas-Melia. 2012. The Role of Sea Ice Thickness Distribution in the Arctic Sea Ice Potential Predictability: A Diagnostic Approach with a Coupled GCM. Journal of Climate 25(8):3025-3038. DOI: 10.1175/Jcli-D-11-00209.1.
Chevallier, M., D. S. Y. Melia, A. Voldoire, M. Deque and G. Garric. 2013. Seasonal Forecasts of the Pan-Arctic Sea Ice Extent Using a GCM-Based Seasonal Prediction System. Journal of Climate 26(16):6092-6104. DOI: 10.1175/Jcli-D-12-00612.1.
Chowdary, J. S., S. P. Xie, J. J. Luo, J. Hafner, S. Behera, Y. Masumoto and T. Yamagata. 2011. Predictability of Northwest Pacific climate during summer and the role of the tropical Indian Ocean. Climate Dynamics 36(3-4):607-621. DOI: 10.1007/s00382-009-0686-5.
Church, J. and N. Gandal. 1992. Network effects, software provision, and standardization. Journal of Industrial Economics 40(1):85-103. DOI: 10.2307/2950628.
Clayton, A. M., A. C. Lorenc and D. M. Barker. 2013. Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. Quarterly Journal of the Royal Meteorological Society 139(675):1445-1461. DOI: 10.1002/qj.2054.
CLIVAR Exchanges. 2014. Special Issue on High Resolution Ocean Climate Modeling. 19(2). DOI.

Cohen, J., J. A. Screen, J. C. Furtado, M. Barlow, D. Whittleston, D. Coumou, J. Francis, K. Dethloff, D. Entekhabi, J. Overland and J. Jones. 2014. Recent Arctic amplification and extreme mid-latitude weather. Nature Geoscience 7(9):627-637. DOI: 10.1038/NGEO2234.

Compo, G. P., J. S. Whitaker, P. D. Sardeshmukh, N. Matsui, R. J. Allan, X. Yin, B. E. Gleason, R. S. Vose, G. Rutledge, P. Bessemoulin, S. Bronnimann, M. Brunet, R. I. Crouthamel, A. N. Grant, P. Y. Groisman, P. D. Jones, M. C. Kruk, A. C. Kruger, G. J. Marshall, M. Maugeri, H. Y. Mok, O. Nordli, T. F. Ross, R. M. Trigo, X. L. Wang, S. D. Woodruff and S. J. Worley. 2011. The Twentieth Century Reanalysis Project. Quarterly Journal of the Royal Meteorological Society 137(654):1-28. DOI: 10.1002/qj.776.

Cornuelle, B., J. Hansen, B. Kirtman, S. Sandgathe and S. Warren. 2014. Issues and Challenges with Using Ensemble-Based Prediction to Probe the Weather-Climate Interface. Bulletin of the American Meteorological Society 95(11):213-215. DOI: 10.1175/Bams-D-13-00235.1.

Cotter, C. J. and J. Shipton. 2012. Mixed finite elements for numerical weather prediction. Journal of Computational Physics 231(21):7076-7091. DOI: 10.1016/j.jcp.2012.05.020.

Coughlan de Perez, E. and S. J. Mason. 2014. Climate information for humanitarian agencies: Some basic principles. Earth Perspectives 1(11). DOI: 10.1186/2194-6434-1-11.

Courtier, P. and O. Talagrand. 1987. Variational Assimilation of Meteorological Observations with the Adjoint Vorticity Equation. 2. Numerical Results. Quarterly Journal of the Royal Meteorological Society 113(478):1329-1347. DOI: 10.1256/Smsqj.47812.

Courtier, P., J. N. Thepaut and A. Hollingsworth. 1994. A Strategy for Operational Implementation of 4D-Var, Using an Incremental Approach. Quarterly Journal of the Royal Meteorological Society 120(519):1367-1387. DOI: 10.1002/qj.49712051912.

Cover, T. M. and J. A. Thomas. 2012. Elements of information theory. Hoboken, NJ: John Wiley & Sons.

Crueger, T., B. Stevens and R. Brokopf. 2013. The Madden-Julian Oscillation in ECHAM6 and the Introduction of an Objective MJO Metric. Journal of Climate 26(10):3241-3257. DOI: 10.1175/Jcli-D-12-00413.1.

Cummings, J., L. Bertino, P. Brasseur, I. Fukumori, M. Kamachi, M. J. Martin, K. Mogensen, P. Oke, C. E. Testut, J. Verron and A. Weaver. 2009. Ocean Data Assimilation Systems for Godae. Oceanography 22(3):96-109. DOI.

Cummings, J. A. 2011. Ocean Data Quality Control. In Operational Oceanography in the 21st Century. A. Schiller and G. B. Brassington, eds. Dordrecht: Springer.

Curtin, T. B., J. G. Bellingham, J. Catipovic and D. Webb. 1993. Autonomous oceanographic sampling networks. Oceanography 6(3):86-94. DOI: http://dx.doi.org/10.5670/oceanog.1993.03.

Curtin, T. B. and J. G. Bellingham. 2009. Progress toward autonomous ocean sampling networks. Deep-Sea Research Part Ii-Topical Studies in Oceanography 56(3-5):62-67. DOI: 10.1016/j.dsr2.2008.09.005.

Daley, R. 1991. Atmospheric data analysis. New York: Cambridge University Press.

Davis, R. E., N. E. Leonard and D. M. Fratantoni. 2009. Routing strategies for underwater gliders. Deep-Sea Research Part Ii-Topical Studies in Oceanography 56(3-5):173-187. DOI: 10.1016/j.dsr2.2008.08.005.

Day, J. J., S. Tietsche and E. Hawkins. 2014. Pan-Arctic and Regional Sea Ice Predictability: Initialization Month Dependence. Journal of Climate 27(12):4371-4390. DOI: 10.1175/Jcli-D-13-00614.1.

de Rosnay, P., M. Drusch, D. Vasiljevic, G. Balsamo, C. Albergel and L. Isaksen. 2013. A simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF. Quarterly Journal of the Royal Meteorological Society 139(674):1199-1213. DOI: 10.1002/qj.2023.

Dee, D. P. and A. M. Da Silva. 2003. The choice of variable for atmospheric moisture analysis. Monthly Weather Review 131(1):155-171. DOI: 10.1175/1520-0493(2003)131<0155:Tcovfa>2.0.Co;2.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A. J. Geer, L. Haimberger, S. B. Healy, H.

Hersbach, E. V. Holm, L. Isaksen, P. Kallberg, M. Kohler, M. Matricardi, A. P. McNally, B. M. Monge-Sanz, J. J. Morcrette, B. K. Park, C. Peubey, P. de Rosnay, C. Tavolato, J. N. Thepaut and F. Vitart. 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137(656):553-597. DOI: 10.1002/qj.828.

Dee, D. P., M. Balmaseda, G. Balsam, R. Engelen, A. J. Simmons and J. N. Thepaut. 2014. Toward a Consistent Reanalysis of the Climate System. Bulletin of the American Meteorological Society 95(8):1235-1248. DOI: 10.1175/Bams-D-13-00043.1.

Deleersnijder, E., V. Legat and P. F. J. Lermusiaux. 2010. Multi-scale modelling of coastal, shelf and global ocean dynamics. Ocean Dynamics 60(6):1357-1359. DOI: 10.1007/s10236-010-0363-6.

Delworth, T. L., A. J. Broccoli, A. Rosati, R. J. Stouffer, V. Balaji, J. A. Beesley, W. F. Cooke, K. W. Dixon, J. Dunne, K. A. Dunne, J. W. Durachta, K. L. Findell, P. Ginoux, A. Gnanadesikan, C. T. Gordon, S. M. Griffies, R. Gudgel, M. J. Harrison, I. M. Held, R. S. Hemler, L. W. Horowitz, S. A. Klein, T. R. Knutson, P. J. Kushner, A. R. Langenhorst, H. C. Lee, S. J. Lin, J. Lu, S. L. Malyshev, P. C. D. Milly, V. Ramaswamy, J. Russell, M. D. Schwarzkopf, E. Shevliakova, J. J. Sirutis, M. J. Spelman, W. F. Stern, M. Winton, A. T. Wittenberg, B. Wyman, F. Zeng and R. Zhang. 2006. GFDL's CM2 global coupled climate models. Part I: Formulation and simulation characteristics. Journal of Climate 19(5):643-674. DOI: 10.1175/Jcli3629.1.

DeMey, P. 1997. Data assimilation at the oceanic mesoscale: A review. Journal of the Meteorological Society of Japan 75(1B):415-427. DOI.

DeMott, C. A., C. Stan, D. A. Randall, J. L. Kinter and M. Khairoutdinov. 2011. The Asian Monsoon in the Superparameterized CCSM and Its Relationship to Tropical Wave Activity. Journal of Climate 24(19):5134-5156. DOI: 10.1175/2011JCLI4202.1.

Dettinger, M. D., F. M. Ralph, T. Das, P. J. Neiman and D. R. Cayan. 2011. Atmospheric Rivers, Floods and the Water Resources of California. Water 3(2):445-478. DOI: 10.3390/W3020445.

Dettinger, M. D. 2013. Atmospheric Rivers as Drought Busters on the US West Coast. Journal of Hydrometeorology 14(6):1721-1732. DOI: 10.1175/Jhm-D-13-02.1.

Dewitt, D. G. 2005. Retrospective forecasts of interannual sea surface temperature anomalies from 1982 to present using a directly coupled atmosphere-ocean general circulation model. Monthly Weather Review 133(10):2972-2995. DOI: 10.1175/Mwr3016.1.

Dickey, T. D. 2003. Emerging ocean observations for interdisciplinary data assimilation systems. Journal of Marine Systems 40:5-48. DOI: 10.1016/S0924-7963(03)00011-3.

Dirmeyer, P. A., Y. Jin, B. Singh and X. Q. Yan. 2013. Trends in Land-Atmosphere Interactions from CMIP5 Simulations. Journal of Hydrometeorology 14(3):829-849. DOI: 10.1175/Jhm-D-12-0107.1.

Dirmeyer, P. A., Z. Y. Wang, M. J. Mbuh and H. E. Norton. 2014. Intensified land surface control on boundary layer growth in a changing climate. Geophysical Research Letters 41(4):1290-1294. DOI: 10.1002/2013gl058826.

Doblas-Reyes, F. J., M. Deque and J. P. Piedelievre. 2000. Multi-model spread and probabilistic seasonal forecasts in PROVOST. Quarterly Journal of the Royal Meteorological Society 126(567):2069-2087. DOI: 10.1256/Smsqj.56704.

Doblas-Reyes, F. J., R. Hagedorn and T. N. Palmer. 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting - II. Calibration and combination. Tellus Series a-Dynamic Meteorology and Oceanography 57(3):234-252. DOI: DOI 10.1111/j.1600-0870.2005.00104.x.

Doblas-Reyes, F. J., R. Hagedorn, T. N. Palmer and J. J. Morcrette. 2006. Impact of increasing greenhouse gas concentrations in seasonal ensemble forecasts. Geophysical Research Letters 33(7). DOI: 10.1029/2005gl025061.

Doblas-Reyes, F. J., A. Weisheimer, M. Deque, N. Keenlyside, M. McVean, J. M. Murphy, P. Rogel, D. Smith and T. N. Palmer. 2009. Addressing model uncertainty in seasonal and annual dynamical

ensemble forecasts. Quarterly Journal of the Royal Meteorological Society 135(643):1538-1559. DOI: 10.1002/qj.464.
Doblas-Reyes, F. J., J. Garcia-Serrano, F. Lienert, A. P. Biescas and L. R. L. Rodrigues. 2013. Seasonal climate predictability and forecasting: status and prospects. Wiley Interdisciplinary Reviews-Climate Change 4(4):245-268. DOI: 10.1002/wcc.217.
DOE. 2008. Report on the DOE/BERAC Workshop. Identifying Outstanding Grand Challenges in Climate Change Research: Guiding DOE's Strategic Planning. Washington, DC: US Department of Energy.
Doucet, A., N. De Freitas and N. Gordon. 2001. Sequential Monte-Carlo Methods in Practice. Berlin: Springer.
Dutton, J. A. 2002. Opportunities and priorities in a new era for weather and climate services. Bulletin of the American Meteorological Society 83(9):1303-1311. DOI.
Dutton, J. A. 2010. Weather, Climate, and the Energy Industry: A Story of Sunlight—Some Old, Some New. In Management of Weather and Climate Risk in the Energy Industry. NATO Science for Peace and Security Series. Alberto Troccoli, eds. Dordrecht: Springer.
Dutton, J. A., R. P. James and J. D. Ross. 2013. Calibration and combination of dynamical seasonal forecasts to enhance the value of predicted probabilities for managing risk. Climate Dynamics 40(11-12):3089-3105. DOI: 10.1007/s00382-013-1764-2.
Dutton, J. A., R. P. James and J. D. Ross. 2015. Bridging the Gap Between Seasonal Forecasts and Decisions to Act. Presented at American Meteorological Society, Phoenix, AZ.
Ebita, A., S. Kobayashi, Y. Ota, M. Moriya, R. Kumabe, K. Onogi, Y. Harada, S. Yasui, K. Miyaoka, K. Takahashi, H. Kamahori, C. Kobayashi, H. Endo, M. Soma, Y. Oikawa and T. Ishimizu. 2011. The Japanese 55-year Reanalysis "JRA-55": An Interim Report. Sola 7:149-152. DOI: 10.2151/sola.2011-038.
Ek, M. B. and A. A. M. Holtslag. 2004. Influence of soil moisture on boundary layer cloud development. Journal of Hydrometeorology 5(1):86-99. DOI: 10.1175/1525-7541(2004)005<0086:Iosmob>2.0.Co;2.
Entekhabi, D., E. G. Njoku, P. E. O'Neill, K. H. Kellogg, W. T. Crow, W. N. Edelstein, J. K. Entin, S. D. Goodman, T. J. Jackson, J. Johnson, J. Kimball, J. R. Piepmeier, R. D. Koster, N. Martin, K. C. McDonald, M. Moghaddam, S. Moran, R. Reichle, J. C. Shi, M. W. Spencer, S. W. Thurman, L. Tsang and J. Van Zyl. 2010. The Soil Moisture Active Passive (SMAP) Mission. Proceedings of the Ieee 98(5):704-716. DOI: Doi 10.1109/Jproc.2010.2043918.
Errico, R. M., P. Bauer and J. F. Mahfouf. 2007. Issues regarding the assimilation of cloud and precipitation data. Journal of the Atmospheric Sciences 64(11):3785-3798. DOI: 10.1175/2006jas2044.1.
Evensen, G. 1994. Sequential Data Assimilation with a Nonlinear Quasi-Geostrophic Model Using Monte-Carlo Methods to Forecast Error Statistics. Journal of Geophysical Research-Oceans 99(C5):10143-10162. DOI: 10.1029/94jc00572.
Evensen, G. 2004. Sampling strategies and square root analysis schemes for the EnKF. Ocean Dynamics 54(6):539-560. DOI: 10.1007/s10236-004-0099-2.
Evensen, G. 2009. Data assimilation: the ensemble Kalman filter. Dordrecht: Springer Science & Business Media.
Fairall, C., J. Cummings, T. Jung, N. Gordon, P. Bauer, D. Bromwich, G. Smith, F. Doblas-Reyes, K. Hines, M. Holland, T. Iversen, S. Klebe, P. Lemke, B. Mills, P. Nurmi, I. Renfrew, G. Svensson and M. Tolstykh. 2013. Observational Aspects of the WWRP Polar Prediction Project. Presented at Arctic Observing Summit, 30 April-2 May, Vancouver, BC, Canada.
Fairall, C. W., E. F. Bradley, J. E. Hare, A. A. Grachev and J. B. Edson. 2003. Bulk parameterization of air-sea fluxes: Updates and verification for the COARE algorithm. Journal of Climate 16(4):571-591. DOI: 10.1175/1520-0442(2003)016<0571:Bpoasf>2.0.Co;2.

Farneti, R., T. L. Delworth, A. J. Rosati, S. M. Griffies and F. R. Zeng. 2010. The Role of Mesoscale Eddies in the Rectification of the Southern Ocean Response to Climate Change. Journal of Physical Oceanography 40(7):1539-1557. DOI: 10.1175/2010jpo4353.1.

Fennessy, M. J. and J. Shukla. 1999. Impact of initial soil wetness on seasonal atmospheric prediction. Journal of Climate 12(11):3167-3180. DOI: 10.1175/1520-0442(1999)012<3167:Ioiswo>2.0.Co;2.

Ferranti, L., T. N. Palmer, F. Molteni and E. Klinker. 1990. Tropical Extratropical Interaction Associated with the 30-60 Day Oscillation and Its Impact on Medium and Extended Range Prediction. Journal of the Atmospheric Sciences 47(18):2177-2199. DOI: 10.1175/1520-0469(1990)047<2177:Teiawt>2.0.Co;2.

Fiorelli, E., N. E. Leonard, P. Bhatta, D. A. Paley, R. Bachmayer and D. M. Fratantoni. 2006. Multi-AUV control and adaptive sampling in Monterey Bay. IEEE Journal of Oceanic Engineering 31(4):935-948. DOI: 10.1109/Joe.2006.880429.

Fletcher, C. G., P. J. Kushner and J. Cohen. 2007. Stratospheric control of the extratropical circulation response to surface forcing. Geophysical Research Letters 34(21). DOI: 10.1029/2007gl031626.

Fox-Kemper, B., R. Ferrari and R. Hallberg. 2008. Parameterization of mixed layer eddies. Part I: Theory and diagnosis. Journal of Physical Oceanography 38(6):1145-1165. DOI: 10.1175/2007jpo3792.1.

Fox-Kemper, B., G. Danabasoglu, R. Ferrari, S. M. Griffies, R. W. Hallberg, M. M. Holland, M. E. Maltrud, S. Peacock and B. L. Samuels. 2011. Parameterization of mixed layer eddies. Part III: Implementation and impact in global ocean climate simulations. Ocean Modelling 39(1-2):61-78. DOI: 10.1016/j.ocemod.2010.09.002.

Fox, D. N., W. J. Teague, C. N. Barron, M. R. Carnes and C. M. Lee. 2002. The Modular Ocean Data Assimilation System (MODAS). Journal of Atmospheric and Oceanic Technology 19(2):240-252. DOI: 10.1175/1520-0426(2002)019<0240:Tmodas>2.0.Co;2.

Francis, J. A. and S. J. Vavrus. 2012. Evidence linking Arctic amplification to extreme weather events in the mid-latitudes. Geophysical Research Letters 39(6). DOI: 10.1029/2012GL051000.

Fudeyasu, H., Y. Q. Wang, M. Satoh, T. Nasuno, H. Miura and W. Yanase. 2008. Global cloud-system-resolving model NICAM successfully simulated the lifecycles of two real tropical cyclones. Geophysical Research Letters 35(22). DOI: 10.1029/2008gl036003.

Gabersek, S., F. X. Giraldo and J. D. Doyle. 2012. Dry and Moist Idealized Experiments with a Two-Dimensional Spectral Element Model. Monthly Weather Review 140(10):3163-3182. DOI: 10.1175/Mwr-D-11-00144.1.

Gallus, W. A. 2010. Application of Object-Based Verification Techniques to Ensemble Precipitation Forecasts. Weather and Forecasting 25(1):144-158. DOI: 10.1175/2009WAF2222274.1.

GAO. 2014. Climate Change Adaptation: DOD Can Improve Infrastructure Planning and Processes to Better Account for Potential Impacts. Washington, DC: GAO.

Gaube, P., D. J. McGillicuddy, D. B. Chelton, M. J. Behrenfeld and P. G. Strutton. 2014. Regional variations in the influence of mesoscale ocean eddies on near-surface chlorophyll. Journal of Geophysical Research-Oceans 119(12):8195-8220. DOI: 10.1002/2014JC010111.

Geer, A. J., F. Baordo, N. Bormann and S. English. 2014. All-sky assimilation of microwave humidity sounders. Technical Report 741. Shinfield Park, UK: ECMWF.

Gelb, A. 1974. Applied Optimal Estimation. Cambridge, MA: MIT Press.

Gent, P. R., J. Willebrand, T. J. Mcdougall and J. C. Mcwilliams. 1995. Parameterizing Eddy-Induced Tracer Transports in Ocean Circulation Models. Journal of Physical Oceanography 25(4):463-474. DOI: 10.1175/1520-0485(1995)025<0463:Peitti>2.0.Co;2.

Gent, P. R. 2011. The Gent-McWilliams parameterization: 20/20 hindsight. Ocean Modelling 39(1-2):2-9. DOI: 10.1016/j.ocemod.2010.08.002.

Gent, P. R., G. Danabasoglu, L. J. Donner, M. M. Holland, E. C. Hunke, S. R. Jayne, D. M. Lawrence, R. B. Neale, P. J. Rasch, M. Vertenstein, P. H. Worley, Z. L. Yang and M. H. Zhang. 2011. The

Community Climate System Model Version 4. Journal of Climate 24(19):4973-4991. DOI: 10.1175/2011JCLI4083.1.

Gerber, E. P., C. Orbe and L. M. Polvani. 2009. Stratospheric influence on the tropospheric circulation revealed by idealized ensemble forecasts. Geophysical Research Letters 36. DOI: 10.1029/2009gl040913.

Gerber, E. P., A. Butler, N. Calvo, A. Charlton-Perez, M. Giorgetta, E. Manzini, J. Perlwitz, L. M. Polvani, F. Sassi, A. A. Scaife, T. A. Shaw, S. W. Son and S. Watanabe. 2012. Assessing and Understanding the Impact of Stratospheric Dynamics and Variability on the Earth System. Bulletin of the American Meteorological Society 93(6):845-859. DOI: 10.1175/Bams-D-11-00145.1.

Ghanem, R. G. and P. D. Spanos. 1991. Stochastic Finite Elements: A Spectral Approach. Berlin: Springer-Verlag.

Gilleland, E., D. D. A. Ahijevych, B. G. Brown and E. E. Ebert. 2010. Verifying Forecasts Spatially. Bulletin of the American Meteorological Society 91(10):1365-1373. DOI: 10.1175/2010BAMS2819.1.

Giraldo, F. X. and M. Restelli. 2008. A study of spectral element and discontinuous Galerkin methods for the Navier-Stokes equations in nonhydrostatic mesoscale atmospheric modeling: Equation sets and test cases. Journal of Computational Physics 227(8):3849-3877. DOI: 10.1016/j.jcp.2007.12.009.

Gneiting, T. and R. Ranjan. 2011. Comparing Density Forecasts Using Threshold- and Quantile-Weighted Scoring Rules. Journal of Business & Economic Statistics 29(3):411-422. DOI: 10.1198/jbes.2010.08110.

GODAE. 2009. Special Issue on the Revolution in Global Ocean Forecasting—The Global Ocean Data Assimilation Experiment: 10 Years of Achievement. Oceanography 22(3). DOI.

GODAE. 2015. Special Issue: GODAE OceanView Part 1. Journal of Operational Oceanography 8(Supplement 1). DOI.

Goddard, L., S. J. Mason, S. E. Zebiak, C. F. Ropelewski, R. Basher and M. A. Cane. 2001. Current approaches to seasonal-to-interannual climate predictions. International Journal of Climatology 21(9):1111-1152. DOI: 10.1002/Joc.636.

Goddard, L., W. E. Baethgen, H. Bhojwani and A. W. Robertson. 2014. The International Research Institute for Climate & Society: why, what and how. Earth Perspectives 1(10). DOI: 10.1186/2194-6434-1-10.

Gottschalck, J., M. Wheeler, K. Weickmann, F. Vitart, N. Savage, H. Lin, H. Hendon, D. Waliser, K. Sperber, M. Nakagawa, C. Prestrelo, M. Flatau and W. Higgins. 2010. A Framework for Assessing Operational Madden-Julian Oscillation Forecasts: A CLIVAR MJO Working Group Project. Bulletin of the American Meteorological Society 91(9):1247-1258. DOI: 10.1175/2010bams2816.1.

Graham, B., W. K. Reilly, F. Beinecke, D. F. Boesch, T. D. Garcia, C. A. Murray and F. Ulmer. 2011. Deep Water: The Gulf Oil Disaster and the Future of Offshore Drilling. Report to the President. National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling. Washington, DC: US Government Printing Office.

Graham, N. E., J. Michaelsen and T. P. Barnett. 1987. An Investigation of the El Niño-Southern Oscillation Cycle with Statistical Models. 2: Model Results. Journal of Geophysical Research-Oceans 92(C13):14271-14289. DOI: 10.1029/Jc092ic13p14271.

Grell, G. A. and S. R. Freitas. 2014. A scale and aerosol aware stochastic convective parameterization for weather and air quality modeling. Atmospheric Chemistry and Physics 14(10):5233-5250. DOI: 10.5194/acp-14-5233-2014.

Griffies, S. M., C. Boning, F. O. Bryan, E. P. Chassignet, R. Gerdes, H. Hasumi, A. Hirst, A. M. Treguier and D. Webb. 2000. Developments in ocean climate modelling. Ocean Modelling 2(3-4):123-192. DOI: 10.1016/S1463-5003(00)00014-7.

Griffies, S. M., A. J. Adcroft, H. Banks, C. W. Böning, E. P. Chassignet, G. Danabasoglu, S. Danilov, E. Deleersnijder, H. Drange, M. England, B. Fox-Kemper, R. Gerdes, A. Gnanadesikan, R. J. Greatbatch, R. W. Hallberg, E. Hanert, M. J. Harrison, S. Legg, C. M. Little, G. Madec, S. J. Marsland, M. Nikurashin, A. Pirani, H. L. Simmons, J. Schröter, B. L. Samuels, A.-M. Treguier, J. R. Toggweiler, H. Tsujino, G. K. Vallis and L. White. 2010. Problems and prospects in large-scale ocean circulation models. In OceanObs' 09 Conference: Sustained Ocean Observations and Information for Society, Vol. 2. Hall, J., D. E. Harrison and D. Stammer.

Griffies, S. M., M. Winton, W. G. Anderson, R. Benson, T. L. Delworth, C. O. Dufour, J. P. Dunne, P. Goddard, A. K. Morrison, A. Rosati, A. T. Wittenberg, J. Yin and R. Zhang. 2015. Impacts on Ocean Heat from Transient Mesoscale Eddies in a Hierarchy of Climate Models. Journal of Climate 28:952-977. DOI: http://dx.doi.org/10.1175/JCLI-D-14-00353.1.

Griffin, D. and K. J. Anchukaitis. 2014. How unusual is the 2012-2014 California drought? Geophysical Research Letters 41(24):9017-9023. DOI: 10.1002/2014GL062433.

Guan, B., N. P. Molotch, D. E. Waliser, E. J. Fetzer and P. J. Neiman. 2010. Extreme snowfall events linked to atmospheric rivers and surface air temperature via satellite measurements. Geophysical Research Letters 37. DOI: 10.1029/2010gl044696.

Guan, B., D. E. Waliser, N. P. Molotch, E. J. Fetzer and P. J. Neiman. 2012. Does the Madden-Julian Oscillation Influence Wintertime Atmospheric Rivers and Snowpack in the Sierra Nevada? Monthly Weather Review 140(2):325-342. DOI: 10.1175/Mwr-D-11-00087.1.

Guan, B., N. P. Molotch, D. E. Waliser, E. J. Fetzer and P. J. Neiman. 2013. The 2010/2011 snow season in California's Sierra Nevada: Role of atmospheric rivers and modes of large-scale variability. Water Resources Research 49(10):6731–6743. DOI: 10.1002/wrcr.20537.

Guan, B., T. Lee, D. J. Halkides and D. E. Waliser. 2014. Aquarius surface salinity and the Madden-Julian Oscillation: The role of salinity in surface layer density and potential energy. Geophysical Research Letters 41(8):2858-2869. DOI: 10.1002/2014GL059704.

Guemas, V., E. Blanchard-Wrigglesworth, M. Chevallier, J. J. Day, M. Déqué, F. J. Doblas-Reyes, N. S. Fučkar, A. Germe, E. Hawkins, S. Keeley, T. Koenigk, D. S. y. Mélia and S. Tietsche. 2014. A review on Arctic sea-ice predictability and prediction on seasonal to decadal time-scales. Quarterly Journal of the Royal Meteorological Society 141(691). DOI: 10.1002/qj.2401.

Guo, Y., D. E. Waliser and X. Jiang. 2015. A Systematic Relationship between the Representations of Convectively Coupled Equatorial Wave Activity and the Madden-Julian Oscillation in Climate Model Simulations. Journal of Climate 28(1881-1904). DOI: http://dx.doi.org/10.1175/JCLI-D-14-00485.1.

Guo, Z. C., P. A. Dirmeyer and T. DelSole. 2011. Land surface impacts on subseasonal and seasonal predictability. Geophysical Research Letters 38. DOI: 10.1029/2011gl049945.

Guo, Z. C., P. A. Dirmeyer, T. DelSole and R. D. Koster. 2012. Rebound in Atmospheric Predictability and the Role of the Land Surface. Journal of Climate 25(13):4744-4749. DOI: 10.1175/Jcli-D-11-00651.1.

Hackert, E., J. Ballabrera-Poy, A. J. Busalacchi, R. H. Zhang and R. Murtugudde. 2011. Impact of sea surface salinity assimilation on coupled forecasts in the tropical Pacific. Journal of Geophysical Research-Oceans 116. DOI: 10.1029/2010jc006708.

Hackert, E., A. J. Busalacchi and J. Ballabrera-Poy. 2014. Impact of Aquarius sea surface salinity observations on coupled forecasts for the tropical Indo-Pacific Ocean. Journal of Geophysical Research-Oceans 119(7):4045-4067. DOI: 10.1002/2013JC009697.

Hagedorn, R., F. J. Doblas-Reyes and T. N. Palmer. 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting - I. Basic concept. Tellus Series a-Dynamic Meteorology and Oceanography 57(3):219-233. DOI: 10.1111/j.1600-0870.2005.00103.x.

Haley, P. J., P. F. J. Lermusiaux, A. R. Robinson, W. G. Leslie, O. Logoutov, G. Cossarini, X. S. Liang, P. Moreno, S. R. Ramp, J. D. Doyle, J. Bellingham, F. Chavez and S. Johnston. 2009. Forecasting and reanalysis in the Monterey Bay/California Current region for the Autonomous Ocean

Sampling Network-II experiment. Deep-Sea Research Part Ii-Topical Studies in Oceanography 56(3-5):127-148. DOI: 10.1016/j.dsr2.2008.08.010.

Hallberg, R. and A. Gnanadesikan. 2006. The role of eddies in determining the structure and response of the wind-driven southern hemisphere overturning: Results from the Modeling Eddies in the Southern Ocean (MESO) project. Journal of Physical Oceanography 36(12):2232-2252. DOI: 10.1175/Jpo2980.1.

Hallberg, R. 2013. Using a resolution function to regulate parameterizations of oceanic mesoscale eddy effects. Ocean Modelling 72:92-103. DOI: 10.1016/j.ocemod.2013.08.007.

Hamilton, K. and R. A. Vincent. 1995. High-resolution radiosonde data offer new prospects for research. Eos Transactions AGU 76(49). DOI: 10.1029/ 95EO00308.

Hansen, J. W., A. Challinor, A. Ines, T. Wheeler and V. Moron. 2006. Translating climate forecasts into agricultural terms: advances and challenges. Climate Research 33(1):27-41. DOI: 10.3354/Cr033027.

Hansen, J. W., S. J. Mason, L. Q. Sun and A. Tall. 2011. Review of Seasonal Climate Forecasting for Agriculture in Sub-Saharan Africa. Experimental Agriculture 47(2):205-240. DOI: 10.1017/S0014479710000876.

Harcourt, R. R. 2015. An Improved Second-Moment Closure Model of Langmuir Turbulence. Journal of Physical Oceanography 45(1):84-103. DOI: 10.1175/Jpo-D-14-0046.1.

Hartmann, H. C., T. C. Pagano, S. Sorooshian and R. Bales. 2002. Confidence builders - Evaluating seasonal climate forecasts from user perspectives. Bulletin of the American Meteorological Society 83(5):683-+. DOI: 10.1175/1520-0477(2002)083<0683:Cbescf>2.3.Co;2.

Hartmann, H. C. 2005. Use of climate information in water resources management. In Encyclopedia of Hydrological Sciences. M.G. Anderson, eds. West Sussex, UK: John Wiley and Sons, Ltd.

Hazeleger, W., C. Severijns, T. Semmler, S. Stefanescu, S. T. Yang, X. L. Wang, K. Wyser, E. Dutra, J. M. Baldasano, R. Bintanja, P. Bougeault, R. Caballero, A. M. L. Ekman, J. H. Christensen, B. van den Hurk, P. Jimenez, C. Jones, P. Kallberg, T. Koenigk, R. McGrath, P. Miranda, T. Van Noije, T. Palmer, J. A. Parodi, T. Schmith, F. Selten, T. Storelvmo, A. Sterl, H. Tapamo, M. Vancoppenolle, P. Viterbo and U. Willen. 2010. EC-Earth A Seamless Earth-System Prediction Approach in Action. Bulletin of the American Meteorological Society 91(10):1357-1363. DOI: 10.1175/2010BAMS2877.1.

Hecht, M. W. and H. Hasumi, Eds. 2013. Ocean Modeling in an Eddying Regime. Geophysical Monograph Series, Vol. 177. Washington, DC: American Geophysical Union.

Hendon, H. H., B. Liebmann, M. Newman, J. D. Glick and J. E. Schemm. 2000. Medium-range forecast errors associated with active episodes of the Madden-Julian oscillation. Monthly Weather Review 128(1):69-86. DOI: 10.1175/1520-0493(2000)128<0069:Mrfeaw>2.0.Co;2.

Hirons, L. C., P. Inness, F. Vitart and P. Bechtold. 2013. Understanding advances in the simulation of intraseasonal variability in the ECMWF model. Part I: The representation of the MJO. Quarterly Journal of the Royal Meteorological Society 139(675):1417-1426. DOI: 10.1002/qj.2060.

Hirota, N., Y. N. Takayabu, M. Watanabe and M. Kimoto. 2011. Precipitation Reproducibility over Tropical Oceans and Its Relationship to the Double ITCZ Problem in CMIP3 and MIROC5 Climate Models. Journal of Climate 24(18):4859-4873. DOI: 10.1175/2011jcli4156.1.

Hitchens, N. M., H. E. Brooks and M. P. Kay. 2013. Objective Limits on Forecasting Skill of Rare Events. Weather and Forecasting 28(2):525-534. DOI: 10.1175/Waf-D-12-00113.1.

Hoerling, M. P. and A. Kumar. 2000. Understanding and predicting extratropical teleconnections related to ENSO. In El Niño and the Southern Oscillation: Multi-scale Variationsnd Global and Regional Impacts. H.F. Diaz and V. Markgraf, eds. Cambridge, UK: Cambridge University Press.

Holland, M. M., D. A. Bailey, B. P. Briegleb, B. Light and E. Hunke. 2012. Improved Sea Ice Shortwave Radiation Physics in CCSM4: The Impact of Melt Ponds and Aerosols on Arctic Sea Ice. Journal of Climate 25(5):1413-1430. DOI: 10.1175/Jcli-D-11-00078.1.

Holland, M. M., E. Blanchard-Wrigglesworth, J. Kay and S. Vavrus. 2013. Initial-value predictability of Antarctic sea ice in the Community Climate System Model 3. Geophysical Research Letters 40(10):2121-2124. DOI: 10.1002/grl.50410.

Holloway, C. E., S. J. Woolnough and G. M. S. Lister. 2013. The Effects of Explicit versus Parameterized Convection on the MJO in a Large-Domain High-Resolution Tropical Case Study. Part I: Characterization of Large-Scale Organization and Propagation. Journal of the Atmospheric Sciences 70(5):1342-1369. DOI: 10.1175/Jas-D-12-0227.1.

Holloway, C. E., J. C. Petch, R. J. Beare, P. Bechtold, G. C. Craig, S. H. Derbyshire, L. J. Donner, P. R. Field, S. L. Gray, J. H. Marsham, D. J. Parker, R. S. Plant, N. M. Roberts, D. M. Schultz, A. J. Stirling and S. J. Woolnough. 2014. Understanding and representing atmospheric convection across scales: recommendations from the meeting held at Dartington Hall, Devon, UK, 28-30 January 2013. Atmospheric Science Letters 15(4):348-353. DOI: 10.1002/Asl2.508.

Horel, J. D. and J. M. Wallace. 1981. Planetary-Scale Atmospheric Phenomena Associated with the Southern Oscillation. Monthly Weather Review 109(4):813-829. DOI: 10.1175/1520-0493(1981)109<0813:Psapaw>2.0.Co;2.

Hoskins, B. 2013. The potential for skill across the range of the seamless weather-climate prediction problem: a stimulus for our science. Quarterly Journal of the Royal Meteorological Society 139(672):573-584. DOI: 10.1002/qj.1991.

Hoskins, B. and T. Woollings. 2015. Persistent Extratropical Regimes and Climate Extremes. Current Climate Change Reports 1(3):115-124. DOI: 10.1007/s40641-015-0020-8.

Hoskins, B. J. and D. J. Karoly. 1981. The Steady Linear Response of a Spherical Atmosphere to Thermal and Orographic Forcing. Journal of the Atmospheric Sciences 38(6):1179-1196. DOI: 10.1175/1520-0469(1981)038<1179:Tslroa>2.0.Co;2.

Hou, A. Y., R. K. Kakar, S. Neeck, A. A. Azarbarzin, C. D. Kummerow, M. Kojima, R. Oki, K. Nakamura and T. Iguchi. 2014. The Global Precipitation Measurement Mission. Bulletin of the American Meteorological Society 95(5):701-+. DOI: 10.1175/Bams-D-13-00164.1.

Houtekamer, P. L. and H. L. Mitchell. 1998. Data assimilation using an ensemble Kalman filter technique. Monthly Weather Review 126(3):796-811. DOI: Doi 10.1175/1520-0493(1998)126<0796:Dauaek>2.0.Co;2.

Houze, R. A. and A. K. Betts. 1981. Convection in GATE. Reviews of Geophysics 19(4):541-576. DOI: 10.1029/Rg019i004p00541.

Hung, M. P., J. L. Lin, W. Q. Wang, D. Kim, T. Shinoda and S. J. Weaver. 2013. MJO and Convectively Coupled Equatorial Waves Simulated by CMIP5 Climate Models. Journal of Climate 26(17):6185-6214. DOI: 10.1175/Jcli-D-12-00541.1.

Hunke, E. C., D. Notz, A. K. Turner and M. Vancoppenolle. 2011. The multiphase physics of sea ice: a review for model developers. Cryosphere 5(4):989-1009. DOI: 10.5194/tc-5-989-2011.

Hurrell, J., G. A. Meehl, D. Bader, T. L. Delworth, B. Kirtman and B. Wielicki. 2009. A Unified Modeling Approach to Climate System Prediction. Bulletin of the American Meteorological Society 90(12):1819-1832. DOI: 10.1175/2009BAMS2752.1.

Hurrell, J. W., M. M. Holland, P. R. Gent, S. Ghan, J. E. Kay, P. J. Kushner, J. F. Lamarque, W. G. Large, D. Lawrence, K. Lindsay, W. H. Lipscomb, M. C. Long, N. Mahowald, D. R. Marsh, R. B. Neale, P. Rasch, S. Vavrus, M. Vertenstein, D. Bader, W. D. Collins, J. J. Hack, J. Kiehl and S. Marshall. 2013. The Community Earth System Model A Framework for Collaborative Research. Bulletin of the American Meteorological Society 94(9):1339-1360. DOI: 10.1175/Bams-D-12-00121.1.

Inness, P. M. and J. M. Slingo. 2006. The interaction of the Madden-Julian Oscillation with the Maritime Continent in a GCM. Quarterly Journal of the Royal Meteorological Society 132(618):1645-1667. DOI: 10.1256/qj.05.102.

IPCC. 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Jacobs, G. A., R. Woodham, D. Jourdan and J. Braithwaite. 2009. GODAE Applications Useful to Navies Throughout the World. Oceanography 22(3):182-189. DOI: http://dx.doi.org/10.5670/oceanog.2009.77.

Jacobs, G. A., J. G. Richman, J. D. Doyle, P. L. Spence, B. P. Bartels, C. N. Barron, R. W. Helber and F. L. Bub. 2014. Simulating conditional deterministic predictability within ocean frontogenesis. Ocean Modelling 78:1-16. DOI: 10.1016/j.ocemod.2014.02.004.

Jakob, C. 2010. Accelerating Progress in Global Atmospheric Model Development through Improved Parameterizations Challenges, Opportunities, and Strategies. Bulletin of the American Meteorological Society 91(7):869-+. DOI: 10.1175/2009bams2898.1.

Jancloes, M., M. Thomson, M. M. Costa, C. Hewitt, C. Corvalan, T. Dinku, R. Lowe and M. Hayden. 2014. Climate Services to Improve Public Health. International Journal of Environmental Research and Public Health 11(5):4555-4559. DOI: 10.3390/ijerph110504555.

Jazwinski, A. H. 1970. Stochastic processes and filtering theory. New York: Academic Press.

Jeong, J. H., H. W. Linderholm, S. H. Woo, C. Folland, B. M. Kim, S. J. Kim and D. L. Chen. 2013. Impacts of Snow Initialization on Subseasonal Forecasts of Surface Air Temperature for the Cold Season. Journal of Climate 26(6):1956-1972. DOI: 10.1175/Jcli-D-12-00159.1.

Jiang, X. A., M. Zhao and D. E. Waliser. 2012a. Modulation of Tropical Cyclones over the Eastern Pacific by the Intraseasonal Variability Simulated in an AGCM. Journal of Climate 25(19):6524-6538. DOI: 10.1175/Jcli-D-11-00531.1.

Jiang, X. N., D. E. Waliser, D. Kim, M. Zhao, K. R. Sperber, W. F. Stern, S. D. Schubert, G. J. Zhang, W. Q. Wang, M. Khairoutdinov, R. B. Neale and M. I. Lee. 2012b. Simulation of the intraseasonal variability over the Eastern Pacific ITCZ in climate models. Climate Dynamics 39(3-4):617-636. DOI: 10.1007/s00382-011-1098-x.

Jin, E. K., J. L. Kinter, B. Wang, C. K. Park, I. S. Kang, B. P. Kirtman, J. S. Kug, A. Kumar, J. J. Luo, J. Schemm, J. Shukla and T. Yamagata. 2008. Current status of ENSO prediction skill in coupled ocean-atmosphere models. Climate Dynamics 31(6):647-664. DOI: 10.1007/s00382-008-0397-3.

Johnson, A., X. G. Wang, F. Y. Kong and M. Xue. 2013. Object-Based Evaluation of the Impact of Horizontal Grid Spacing on Convection-Allowing Forecasts. Monthly Weather Review 141(10):3413-3425. DOI: 10.1175/Mwr-D-13-00027.1.

Johnson, C. and N. Bowler. 2009. On the Reliability and Calibration of Ensemble Forecasts. Monthly Weather Review 137(5):1717-1720. DOI: 10.1175/2009mwr2715.1.

Johnson, N. C., D. C. Collins, S. B. Feldstein, M. L. L'Heureux and E. E. Riddle. 2014. Skillful Wintertime North American Temperature Forecasts out to 4 Weeks Based on the State of ENSO and the MJO. Weather and Forecasting 29(1):23-38. DOI: 10.1175/Waf-D-13-00102.1.

Jones, A. E. and A. P. Morse. 2010. Application and Validation of a Seasonal Ensemble Prediction System Using a Dynamic Malaria Model. Journal of Climate 23(15):4202-4215. DOI: 10.1175/2010jcli3208.1.

Jones, A. E. and A. P. Morse. 2012. Skill of ENSEMBLES seasonal re-forecasts for malaria prediction in West Africa. Geophysical Research Letters 39. DOI: 10.1029/2012gl054040.

Jones, C., D. E. Waliser, J. K. E. Schemm and W. K. M. Lau. 2000. Prediction skill of the Madden and Julian Oscillation in dynamical extended range forecasts. Climate Dynamics 16(4):273-289. DOI: 10.1007/s003820050327.

Joslyn, S. and S. Savelli. 2010. Communicating forecast uncertainty: public perception of weather forecast uncertainty. Meteorological Applications 17(2):180-195. DOI: 10.1002/met.190.

Jung, T., M. J. Miller, T. N. Palmer, P. Towers, N. Wedi, D. Achuthavarier, J. M. Adams, E. L. Altshuler, B. A. Cash, J. L. Kinter, L. Marx, C. Stan and K. I. Hodges. 2012. High-Resolution Global Climate Simulations with the ECMWF Model in Project Athena: Experimental Design, Model Climate, and Seasonal Forecast Skill. Journal of Climate 25(9):3155-3172. DOI: 10.1175/Jcli-D-11-00265.1.

Jung, T., M. A. Kasper, T. Semmler and S. Serrar. 2014. Arctic influence on subseasonal midlatitude prediction. Geophysical Research Letters 41(10):3676-3680. DOI: 10.1002/2014gl059961.

Jutla, A. S., A. S. Akanda, J. K. Griffiths, R. Colwell and S. Islam. 2011. Warming Oceans, Phytoplankton, and River Discharge: Implications for Cholera Outbreaks. American Journal of Tropical Medicine and Hygiene 85(2):303-308. DOI: 10.4269/ajtmh.2011.11-0181.

Kalman, R. E. 1960. A New Approach to Linear Filtering and Prediction Problems. Transactions of the ASME--Journal of Basic Engineering 82(Series D):35-45. DOI.

Kalnay, E. 2003. Atmospheric modeling, data assimilation, and predictability. New York: Cambridge University Press.

Kang, J. S., E. Kalnay, T. Miyoshi, J. J. Liu and I. Fung. 2012. Estimation of surface carbon fluxes with an advanced data assimilation methodology. Journal of Geophysical Research-Atmospheres 117. DOI: 10.1029/2012jd018259.

Karna, T., V. Legat, E. Deleersnijder and H. Burchard. 2012. Coupling of a discontinuous Galerkin finite element marine model with a finite difference turbulence closure model. Ocean Modelling 47:55-64. DOI: 10.1016/j.ocemod.2012.01.001.

Karna, T., V. Legat and E. Deleersnijder. 2013. A baroclinic discontinuous Galerkin finite element model for coastal flows. Ocean Modelling 61:1-20. DOI: 10.1016/j.ocemod.2012.09.009.

Katz, M. L. and C. Shapiro. 1985. Network Externalities, Competition, and Compatibility. American Economic Review 75(3):424-440. DOI.

Kauker, F., C. Koberle, R. Gerdes and M. Karcher. 2008. Modeling the 20th century Arctic Ocean/Sea ice system: Reconstruction of surface forcing. Journal of Geophysical Research-Oceans 113(C9). DOI: 10.1029/2006jc004023.

Kelly-Hope, L. and M. C. Thomson. 2008. Climate and infectious diseases. In Seasonal Forecasts, Climatic Change and Human Health. Thomson, M. C., R. Garcia-Herrera and M. Beniston, eds. Dordrecht: Springer Netherlands.

Kerr, Y. H., P. Waldteufel, J. P. Wigneron, S. Delwart, F. Cabot, J. Boutin, M. J. Escorihuela, J. Font, N. Reul, C. Gruhier, S. E. Juglea, M. R. Drinkwater, A. Hahne, M. Martin-Neira and S. Mecklenburg. 2010. The SMOS Mission: New Tool for Monitoring Key Elements of the Global Water Cycle. Proceedings of the Ieee 98(5):666-687. DOI: 10.1109/Jproc.2010.2043032.

Khairoutdinov, M. F. and D. A. Randall. 2001. A cloud resolving model as a cloud parameterization in the NCAR Community Climate System Model: Preliminary results. Geophysical Research Letters 28(18):3617-3620. DOI: 10.1029/2001gl013552.

Kharin, V. V. and F. W. Zwiers. 2002. Climate predictions with multimodel ensembles. Journal of Climate 15(7):793-799. DOI: 10.1175/1520-0442(2002)015<0793:Cpwme>2.0.Co;2.

Kharin, V. V. and F. W. Zwiers. 2003. On the ROC score of probability forecasts. Journal of Climate 16(24):4145-4150. DOI: 10.1175/1520-0442(2003)016<4145:Otrsop>2.0.Co;2.

Khon, V. C., I. I. Mokhov, M. Latif, V. A. Semenov and W. Park. 2010. Perspectives of Northern Sea Route and Northwest Passage in the twenty-first century. Climatic Change 100(3-4):757-768. DOI: 10.1007/s10584-009-9683-2.

Kiehl, J. T., J. J. Hack, G. B. Bonan, B. A. Boville, D. L. Williamson and P. J. Rasch. 1998. The National Center for Atmospheric Research Community Climate Model: CCM3. Journal of Climate 11(6):1131-1149. DOI: 10.1175/1520-0442(1998)011<1131:Tncfar>2.0.Co;2.

Kim, H. M., P. J. Webster and J. A. Curry. 2012. Seasonal prediction skill of ECMWF System 4 and NCEP CFSv2 retrospective forecast for the Northern Hemisphere Winter. Climate Dynamics 39(12):2957-2973. DOI: 10.1007/s00382-012-1364-6.

Kinter, J. L., B. Cash, D. Achuthavarier, J. Adams, E. Altshuler, P. Dirmeyer, B. Doty, B. Huang, E. K. Jin, L. Marx, J. Manganello, C. Stan, T. Wakefield, T. Palmer, M. Hamrud, T. Jung, M. Miller, P. Towers, N. Wedi, M. Satoh, H. Tomita, C. Kodama, T. Nasuno, K. Oouchi, Y. Yamada, H. Taniguchi, P. Andrews, T. Baer, M. Ezell, C. Halloy, D. John, B. Loftis, R. Mohr and K. Wong. 2013. Revolutionizing Climate Modeling with Project Athena a Multi-Institutional, International Collaboration. Bulletin of the American Meteorological Society 94(2):231-245. DOI: 10.1175/Bams-D-11-00043.1.

Kirtman, B. 2014. Assessment of Intraseasonal to Interannual Climate Prediction and Predictability. Presented to the Committee on Developing a U.S. Research Agenda to Advance Subseasonal to Seasonal Forecasting, National Research Council, October 7, 2014, Washington, DC.

Kirtman, B. P. 2003. The COLA anomaly coupled model: Ensemble ENSO prediction. Monthly Weather Review 131(10):2324-2341. DOI: 10.1175/1520-0493(2003)131<2324:Tcacme>2.0.Co;2.

Kirtman, B. P., C. Bitz, F. Bryan, W. Collins, J. Dennis, N. Hearn, J. L. Kinter, R. Loft, C. Rousset, L. Siqueira, C. Stan, R. Tomas and M. Vertenstein. 2012. Impact of ocean model resolution on CCSM climate simulations. Climate Dynamics 39(6):1303-1328. DOI: 10.1007/s00382-012-1500-3.

Kirtman, B. P., D. Min, J. M. Infanti, J. L. Kinter, D. A. Paolino, Q. Zhang, H. van den Dool, S. Saha, M. P. Mendez, E. Becker, P. T. Peng, P. Tripp, J. Huang, D. G. DeWitt, M. K. Tippett, A. G. Barnston, S. H. Li, A. Rosati, S. D. Schubert, M. Rienecker, M. Suarez, Z. E. Li, J. Marshak, Y. K. Lim, J. Tribbia, K. Pegion, W. J. Merryfield, B. Denis and E. F. Wood. 2014. The North American Multimodel Ensemble: Phase-1 Seasonal-to-Interannual Prediction; Phase-2 toward Developing Intraseasonal Prediction. Bulletin of the American Meteorological Society 95(4):585-601. DOI: 10.1175/Bams-D-12-00050.1.

Kleist, D. T., D. F. Parrish, J. C. Derber, R. Treadon, W. S. Wu and S. Lord. 2009. Introduction of the GSI into the NCEP Global Data Assimilation System. Weather and Forecasting 24(6):1691-1705. DOI: 10.1175/2009WAF2222201.1.

Kleist, D. T. and K. Ide. 2015. An OSSE-Based Evaluation of Hybrid Variational-Ensemble Data Assimilation for the NCEP GFS. Part II: 4DEnVar and Hybrid Variants. Monthly Weather Review 143(2):452-470. DOI: 10.1175/Mwr-D-13-00350.1.

Klingaman, N. P., B. Hanson and D. J. Leathers. 2008. A teleconnection between forced Great Plains snow cover and European winter climate. Journal of Climate 21(11):2466-2483. DOI: 10.1175/2007JCLI1672.1.

Kloeden, P. E. and E. Platen. 1999. Numerical solution of stochastic differential equations. Berlin; New York: Springer.

Klopper, E., C. H. Vogel and W. A. Landman. 2006. Seasonal climate forecasts - Potential agricultural-risk management tools? Climatic Change 76(1-2):73-90. DOI: 10.1007/s10584-005-9019-9.

Kogge, P., K. Bergman, S. Borkar, D. Campbell, W. Carlson, W. Dally, M. Denneau, P. Franzon, W. Harrod, K. Hill, J. Hiller, S. Karp, S. Keckler, D. Klein, R. Lucas, M. Richards, A. Scarpelli, S. Scott, A. Snavely, T. Sterling, R. S. Williams and K. Yelick. 2008. ExaScale Computing Study: Technology Challenges in Achieving Exascale Systems. Exascale Study Group, University of Notre Dame.

Kondrashov, D., C. J. Sun and M. Ghil. 2008. Data Assimilation for a Coupled Ocean-Atmosphere Model. Part II: Parameter Estimation. Monthly Weather Review 136(12):5062-5076. DOI: 10.1175/2008mwr2544.1.

Konings, A. G., D. Entekhabi, M. Moghaddam and S. S. Saatchi. 2014. The Effect of Variable Soil Moisture Profiles on P-Band Backscatter. Ieee Transactions on Geoscience and Remote Sensing 52(10):6315-6325. DOI: 10.1109/Tgrs.2013.2296035.

Kosaka, Y., S. P. Xie, N. C. Lau and G. A. Vecchi. 2013. Origin of seasonal predictability for summer climate over the Northwestern Pacific. Proceedings of the National Academy of Sciences of the United States of America 110(19):7574-7579. DOI: 10.1073/pnas.1215582110.

Koster, R. D., P. A. Dirmeyer, Z. C. Guo, G. Bonan, E. Chan, P. Cox, C. T. Gordon, S. Kanae, E. Kowalczyk, D. Lawrence, P. Liu, C. H. Lu, S. Malyshev, B. McAvaney, K. Mitchell, D. Mocko, T. Oki, K. Oleson, A. Pitman, Y. C. Sud, C. M. Taylor, D. Verseghy, R. Vasic, Y. K. Xue, T. Yamada and G. Team. 2004. Regions of strong coupling between soil moisture and precipitation. Science 305(5687):1138-1140. DOI: 10.1126/science.1100217.

Koster, R. D., S. P. P. Mahanama, T. J. Yamada, G. Balsamo, A. A. Berg, M. Boisserie, P. A. Dirmeyer, F. J. Doblas-Reyes, G. Drewitt, C. T. Gordon, Z. Guo, J. H. Jeong, D. M. Lawrence, W. S. Lee, Z. Li, L. Luo, S. Malyshev, W. J. Merryfield, S. I. Seneviratne, T. Stanelle, B. J. J. M. van den

Hurk, F. Vitart and E. F. Wood. 2010. Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment. Geophysical Research Letters 37. DOI: 10.1029/2009gl041677.

Koster, R. D., S. P. P. Mahanama, T. J. Yamada, G. Balsamo, A. A. Berg, M. Boisserie, P. A. Dirmeyer, F. J. Doblas-Reyes, G. Drewitt, C. T. Gordon, Z. Guo, J. H. Jeong, W. S. Lee, Z. Li, L. Luo, S. Malyshev, W. J. Merryfield, S. I. Seneviratne, T. Stanelle, B. J. J. M. van den Hurk, F. Vitart and E. F. Wood. 2011. The Second Phase of the Global Land-Atmosphere Coupling Experiment: Soil Moisture Contributions to Subseasonal Forecast Skill. Journal of Hydrometeorology 12(5):805-822. DOI: 10.1175/2011JHM1365.1.

Koster, R. D., Y. H. Chang and S. D. Schubert. 2014. A Mechanism for Land-Atmosphere Feedback Involving Planetary Wave Structures. Journal of Climate 27(24):9290-9301. DOI: 10.1175/Jcli-D-14-00315.1.

Koster, R. D. and G. K. Walker. 2015. Interactive Vegetation Phenology, Soil Moisture, and Monthly Temperature Forecasts. Journal of Hydrometeorology 16(4):1456-1465. DOI: 10.1175/Jhm-D-14-0205.1.

Krishnamurti, T. N., C. M. Kishtawal, Z. Zhang, T. LaRow, D. Bachiochi, E. Williford, S. Gadgil and S. Surendran. 2000. Multimodel ensemble forecasts for weather and seasonal climate. Journal of Climate 13(23):4196-4216. DOI: 10.1175/1520-0442(2000)013<4196:Meffwa>2.0.Co;2.

Kug, J. S., J. Y. Lee, I. S. Kang, B. Wang and C. K. Park. 2008. Optimal Multi-model Ensemble Method in Seasonal Climate Prediction. Asia-Pacific Journal of Atmospheric Sciences 44(3):259-267. DOI.

Kuhl, D. D., T. E. Rosmond, C. H. Bishop, J. McLay and N. L. Baker. 2013. Comparison of Hybrid Ensemble/4DVar and 4DVar within the NAVDAS-AR Data Assimilation Framework. Monthly Weather Review 141(8):2740-2758. DOI: 10.1175/Mwr-D-12-00182.1.

Kuhn, K., D. Campbell-Lendrum, A. Haines and J. Cox. 2005. Using climate to predict infectious disease epidemics. Geneva: World Health Organization.

Kumar, S., P. A. Dirmeyer, D. M. Lawrence, T. DelSole, E. L. Altshuler, B. A. Cash, M. J. Fennessy, Z. C. Guo, J. L. Kinter and D. M. Straus. 2014. Effects of realistic land surface initializations on subseasonal to seasonal soil moisture and temperature predictability in North America and in changing climate simulated by CCSM4. Journal of Geophysical Research-Atmospheres 119(23):13250-13270. DOI: 10.1002/2014JD022110.

Kumar, S. V., C. D. Peters-Lidard, Y. Tian, P. R. Houser, J. Geiger, S. Olden, L. Lighty, J. L. Eastman, B. Doty, P. Dirmeyer, J. Adams, K. Mitchell, E. F. Wood and J. Sheffield. 2006. Land information system: An interoperable framework for high resolution land surface modeling. Environmental Modelling & Software 21(10):1402-1415. DOI: 10.1016/j.envsoft.2005.07.004.

Kurtz, N., J. Richter-Menge, S. Farrell, M. Studinger, J. Paden, J. Sonntag and J. Yungel. 2013. IceBridge Airborne Survey Data Support Arctic Sea Ice Predictions. Eos, Transactions American Geophysical Union 94(4):41. DOI: 10.1002/2013eo040001.

Kushnir, Y., W. A. Robinson, I. Blade, N. M. J. Hall, S. Peng and R. Sutton. 2002. Atmospheric GCM response to extratropical SST anomalies: Synthesis and evaluation. Journal of Climate 15(16):2233-2256. DOI: 10.1175/1520-0442(2002)015<2233:Agrtes>2.0.Co;2.

Kwok, R., H. J. Zwally and D. H. Yi. 2004. ICESat observations of Arctic sea ice: A first look. Geophysical Research Letters 31(16). DOI: 10.1029/2004gl020309.

Kwok, R. and G. F. Cunningham. 2008. ICESat over Arctic sea ice: Estimation of snow depth and ice thickness. Journal of Geophysical Research-Oceans 113(C8). DOI: 10.1029/2008jc004753.

Lagerloef, G. S. E., G. T. Mitchum, R. B. Lukas and P. P. Niiler. 1999. Tropical Pacific near-surface currents estimated from altimeter, wind, and drifter data. Journal of Geophysical Research-Oceans 104(C10):23313-23326. DOI: 10.1029/1999jc900197.

Lahoz, W. A. and P. Schneider. 2014. Data assimilation: making sense of Earth Observation. Frontiers in Environmental Science 2(16). DOI: http://dx.doi.org/10.3389/fenvs.2014.00016.

Laloyaux, P., M. Balmaseda, D. Dee, K. Mogensen and P. Janssen. 2016. A coupled data assimilation system for climate reanalysis. Quarterly Journal of the Royal Meteorological Society 142(694):65-78. DOI: 10.1002/qj.2629.

Lambrechts, L., K. P. Paaijmans, T. Fansiri, L. B. Carrington, L. D. Kramer, M. B. Thomas and T. W. Scott. 2011. Impact of daily temperature fluctuations on dengue virus transmission by Aedes aegypti. Proceedings of the National Academy of Sciences of the United States of America 108(18):7460-7465. DOI: 10.1073/pnas.1101377108.

Langmann, B., K. Zaksek, M. Hort and S. Duggen. 2010. Volcanic ash as fertiliser for the surface ocean. Atmospheric Chemistry and Physics 10(8):3891-3899. DOI.

Lasswell, H. D. 1971. A Pre-View of Policy Sciences. New York: American Elsevier

Latif, M., D. Anderson, T. Barnett, M. Cane, R. Kleeman, A. Leetmaa, J. O'Brien, A. Rosati and E. Schneider. 1998. A review of the predictability and prediction of ENSO. Journal of Geophysical Research-Oceans 103(C7):14375-14393. DOI: 10.1029/97jc03413.

Lau, W. K.-M. and D. E. Waliser. 2011. Intraseasonal variability in the atmosphere-ocean climate system. Berlin: Springer Verlag.

Lauderdale, J. M., C. Caminade, A. E. Heath, A. E. Jones, D. A. MacLeod, K. C. Gouda, U. S. Murty, P. Goswami, S. R. Mutheneni and A. P. Morse. 2014. Towards seasonal forecasting of malaria in India. Malaria Journal 13. DOI: 10.1186/1475-2875-13-310.

Laxon, S. W., K. A. Giles, A. L. Ridout, D. J. Wingham, R. Willatt, R. Cullen, R. Kwok, A. Schweiger, J. L. Zhang, C. Haas, S. Hendricks, R. Krishfield, N. Kurtz, S. Farrell and M. Davidson. 2013. CryoSat-2 estimates of Arctic sea ice thickness and volume. Geophysical Research Letters 40(4):732-737. DOI: 10.1002/grl.50193.

Lazo, J. K., M. Lawson, P. H. Larsen and D. M. Waldman. 2011. US Economic Sensitivity to Weather Variability. Bulletin of the American Meteorological Society 92(6):709-720. DOI: 10.1175/2011BAMS2928.1.

Le Maître, O. P. and O. M. Knio. 2010. Spectral Methods for Uncertainty Quantification with Applications to Computational Fluid Dynamics. Dordrecht, Netherlands; New York: Springer.

Le Traon, P. Y., Y. Faugere, F. Hernandez, J. Dorandeu, F. Mertz and M. Ablain. 2003. Can we merge GEOSAT Follow-On with TOPEX/Poseidon and ERS-2 for an improved description of the ocean circulation? Journal of Atmospheric and Oceanic Technology 20(6):889-895. DOI: 10.1175/1520-0426(2003)020<0889:Cwmgfw>2.0.Co;2.

Lebel, T., D. J. Parker, C. Flamant, B. Bourles, B. Marticorena, E. Mougin, C. Peugeot, A. Diedhiou, J. M. Haywood, J. B. Ngamini, J. Polcher, J. L. Redelsperger and C. D. Thorncroft. 2010. The AMMA field campaigns: Multiscale and multidisciplinary observations in the West African region. Quarterly Journal of the Royal Meteorological Society 136:8-33. DOI: 10.1002/qj.486.

LeDimet, F. X. and O. Talagrand. 1986. Variational Algorithms for Analysis and Assimilation of Meteorological Observations - Theoretical Aspects. Tellus Series A--Dynamic Meteorology and Oceanography 38(2):97-110. DOI: 10.1111/j.1600-0870.1986.tb00459.x.

Lee, C. M., S. Cole, M. Doble, L. Freitag, P. Hwang, S. Jayne, M. Jeffries, R. Krishfield, T. Maksym, W. Maslowski, B. Owens, P. Posey, L. Rainville, A. Roberts, B. Shaw, T. Stanton, J. Thomson, M.-L. Timmermans, J. Toole, P. Wadhams, J. Wilkinson and Z. Zhang. 2012. Marginal Ice Zone (MIZ) Program: Science and Experiment Plan, Technical Report APL-UW 1201. Seattle, WA: Applied Physics Laboratory, University of Washington.

Lee, S. K., P. N. DiNezio, E. S. Chung, S. W. Yeh, A. T. Wittenberg and C. Z. Wang. 2014. Spring persistence, transition, and resurgence of El Niño. Geophysical Research Letters 41(23):8578-8585. DOI: 10.1002/2014gl062484.

Lemke, P., E. W. Trinkl and K. Hasselmann. 1980. Stochastic Dynamic Analysis of Polar Sea Ice Variability. Journal of Physical Oceanography 10(12):2100-2120. DOI: 10.1175/1520-0485(1980)010<2100:Sdaops>2.0.Co;2.

Lemos, M. C. and B. J. Morehouse. 2005. The co-production of science and policy in integrated climate assessments. Global Environmental Change-Human and Policy Dimensions 15(1):57-68. DOI: 10.1016/j.gloenvcha.2004.09.004.

Lemos, M. C. 2008. What Influences Innovation Adoption by Water Managers? Climate Information Use in Brazil and the United States. Journal of the American Water Resources Association 44(6):1388-1396. DOI: 10.1111/j.1752-1688.2008.00231.x.

Lemos, M. C. and R. B. Rood. 2010. Climate projections and their impact on policy and practice. Wiley Interdisciplinary Reviews-Climate Change 1(5):670-682. DOI: 10.1002/Wcc.71.

Lemos, M. C., C. J. Kirchhoff and V. Ramprasad. 2012. Narrowing the climate information usability gap. Nature Climate Change 2(11):789-794. DOI: 10.1038/Nclimate1614.

Leonard, N. E., D. A. Paley, F. Lekien, R. Sepulchre, D. M. Fratantoni and R. E. Davis. 2007. Collective motion, sensor networks, and ocean sampling. Proceedings of the IEEE 95(1):48-74. DOI: 10.1109/Jproc.2006.887295.

Leonard, N. E., D. A. Paley, R. E. Davis, D. M. Fratantoni, F. Lekien and F. M. Zhang. 2010. Coordinated Control of an Underwater Glider Fleet in an Adaptive Ocean Sampling Field Experiment in Monterey Bay. Journal of Field Robotics 27(6):718-740. DOI: 10.1002/Rob.20366.

Lermusiaux, P. F. J. 1999. Data assimilation via error subspace statistical estimation. Part II: Middle Atlantic Bight shelfbreak front simulations and ESSE validation. Monthly Weather Review 127(7):1408-1432. DOI: 10.1175/1520-0493(1999)127<1408:Davess>2.0.Co;2.

Lermusiaux, P. F. J. and A. R. Robinson. 1999. Data assimilation via error subspace statistical estimation. Part I: Theory and schemes. Monthly Weather Review 127(7):1385-1407. DOI: 10.1175/1520-0493(1999)127<1385:Davess>2.0.Co;2.

Lermusiaux, P. F. J. 2001. Evolving the subspace of the three-dimensional multiscale ocean variability: Massachusetts Bay. Journal of Marine Systems 29(1-4):385-422. DOI: 10.1016/S0924-7963(01)00025-2.

Lermusiaux, P. F. J. 2006. Uncertainty estimation and prediction for interdisciplinary ocean dynamics. Journal of Computational Physics 217(1):176-199. DOI: 10.1016/j.jcp.2006.02.010.

Lermusiaux, P. F. J., C.-S. Chiu, G. G. Gawarkiewicz, P. Abbot, A. R. Robinson, R. N. Miller, P. J. Haley, W. G. Leslie, S. J. Majumdar, A. Pang and F. Lekien. 2006. Quantifying Uncertainties in Ocean Predictions. Oceanography 19(1):92-105. DOI: 10.5670/oceanog.2006.93.

Lermusiaux, P. F. J. 2007. Adaptive modeling, adaptive data assimilation and adaptive sampling. Physica D-Nonlinear Phenomena 230(1-2):172-196. DOI: 10.1016/j.physd.2007.02.014.

Lermusiaux, P. F. J., P. J. Haley, W. G. Leslie, A. Agarwal, O. G. Logutov and L. J. Burton. 2011. Multiscale Physical and Biological Dynamics in the Philippine Archipelago: Predictions and Processes. Oceanography 24(1):70-89. DOI: http://dx.doi.org/10.5670/oceanog.2011.05.

Lermusiaux, P. F. J., T. Lolla, P. J. Haley Jr., K. Yigit, M. P. Ueckermann, T. Sondergaard and W. G. Leslie. 2015. Science of Autonomy: Time-Optimal Path Planning and Adaptive Sampling for Swarms of Ocean Vehicles. In Springer Handbook of Ocean Engineering: Autonomous Ocean Vehicles, Subsystems and Control. T. Curtin, eds. New York: Springer (in press).

Letson, D., D. Sutter and J. Lazo. 2007. Economic Value of Hurricane Forecasts: An Overview and Research Needs. Natural Hazards Review 8(3):78-86. DOI: 10.1061/(ASCE)1527-6988(2007)8:3(78).

Li, G. and S. P. Xie. 2014. Tropical Biases in CMIP5 Multimodel Ensemble: The Excessive Equatorial Pacific Cold Tongue and Double ITCZ Problems. Journal of Climate 27(4):1765-1780. DOI: 10.1175/Jcli-D-13-00337.1.

Li, M., K. Zahariev and C. Garrett. 1995. Role of Langmuir Circulation in the Deepening of the Ocean Surface Mixed-Layer. Science 270(5244):1955-1957. DOI: 10.1126/science.270.5244.1955.

Li, Q., A. Webb, B. Fox-Kemper, A. Craig, G. Danabasoglu, W. G. Large and M. Vertenstein. 2015. Langmuir mixing effects on global climate: WAVEWATCH III in CESM. Ocean Modelling. DOI: 10.1016/j.ocemod.2015.07.020.

Li, R. and R. Ghanem. 1998. Adaptive polynomial chaos expansions applied to statistics of extremes in nonlinear random vibration. Probabilistic Engineering Mechanics 13(2):125-136. DOI: 10.1016/S0266-8920(97)00020-9.

Li, Y. P. and R. E. Carbone. 2012. Excitation of Rainfall over the Tropical Western Pacific. Journal of the Atmospheric Sciences 69(10):2983-2994. DOI: 10.1175/Jas-D-11-0245.1.

Lien, G.-Y., T. Miyoshi and E. Kalnay. 2015. Assimilation of TRMM multi satellite precipitation analysis with a low-resolution NCPE global forecast system. Monthly Weather Review. DOI: 10.1175/MWR-D-15-0149.1.

Lin, H., G. Brunet and J. Derome. 2008. Forecast Skill of the Madden-Julian Oscillation in Two Canadian Atmospheric Models. Monthly Weather Review 136(11):4130-4149. DOI: 10.1175/2008mwr2459.1.

Lin, H. and G. Brunet. 2009. The Influence of the Madden-Julian Oscillation on Canadian Wintertime Surface Air Temperature. Monthly Weather Review 137(7):2250-2262. DOI: 10.1175/2009mwr2831.1.

Lin, H., G. Brunet and J. Derome. 2009. An Observed Connection between the North Atlantic Oscillation and the Madden-Julian Oscillation. Journal of Climate 22(2):364-380. DOI: 10.1175/2008jcli2515.1.

Lin, H., G. Brunet and J. S. Fontecilla. 2010. Impact of the Madden-Julian Oscillation on the intraseasonal forecast skill of the North Atlantic Oscillation. Geophysical Research Letters 37. DOI: 10.1029/2010gl044315.

Lindsay, R. and A. Schweiger. 2015. Arctic sea ice thickness loss determined using subsurface, aircraft, and satellite observations. Cryosphere 9(1):269-283. DOI: 10.5194/tc-9-269-2015.

Lindsay, R. W. and J. Zhang. 2006. Assimilation of ice concentration in an ice-ocean model. Journal of Atmospheric and Oceanic Technology 23(5):742-749. DOI: 10.1175/Jtech1871.1.

Lindsay, R. W., J. Zhang, A. J. Schweiger and M. A. Steele. 2008. Seasonal predictions of ice extent in the Arctic Ocean. Journal of Geophysical Research-Oceans 113(C2). DOI: 10.1029/2007jc004259.

Lions, J. L. 1971. Optimal control of systems governed by partial differential equations. Dordrecht: Springer Verlag.

Lisæter, K. A., J. Rosanova and G. Evensen. 2003. Assimilation of ice concentration in a coupled ice–ocean model, using the Ensemble Kalman filter. Ocean Dynamics 53(4):368-388. DOI.

Liu, C. X., B. J. Tian, K. F. Li, G. L. Manney, N. J. Livesey, Y. L. Yung and D. E. Waliser. 2014. Northern Hemisphere mid-winter vortex-displacement and vortex-split stratospheric sudden warmings: Influence of the Madden-Julian Oscillation and Quasi-Biennial Oscillation. Journal of Geophysical Research-Atmospheres 119(22):12599-12620. DOI: 10.1002/2014jd021876.

Lolla, T., P. J. Haley and P. F. J. Lermusiaux. 2014a. Time-optimal path planning in dynamic flows using level set equations: realistic applications. Ocean Dynamics 64(10):1399-1417. DOI: 10.1007/s10236-014-0760-3.

Lolla, T., P. F. J. Lermusiaux, M. P. Ueckermann and P. J. Haley. 2014b. Time-optimal path planning in dynamic flows using level set equations: theory and schemes. Ocean Dynamics 64(10):1373-1397. DOI: 10.1007/s10236-014-0757-y.

Lorenc, A. C., S. P. Ballard, R. S. Bell, N. B. Ingleby, P. L. F. Andrews, D. M. Barker, J. R. Bray, A. M. Clayton, T. Dalby, D. Li, T. J. Payne and F. W. Saunders. 2000. The Met. Office global three-dimensional variational data assimilation scheme. Quarterly Journal of the Royal Meteorological Society 126(570):2991-3012. DOI: 10.1256/Smsqj.57001.

Lorenc, A. C., N. E. Bowler, A. M. Clayton, S. R. Pring and D. Fairbairn. 2015. Comparison of Hybrid-4DEnVar and Hybrid-4DVar Data Assimilation Methods for Global NWP. Monthly Weather Review 143(1):212-229. DOI: 10.1175/Mwr-D-14-00195.1.

Lorenz, E. N. 1963. Deterministic Nonperiodic Flow. Journal of the Atmospheric Sciences 20(2):130-141. DOI: 10.1175/1520-0469(1963)020<0130:Dnf>2.0.Co;2.

Lu, F., Z. Liu, S. Zhang and Y. Liu. 2015. Strongly coupled data assimilation using leading averaged coupled covariance (LACC). Part I: Simple Model Study. Monthly Weather Review(in press). DOI: http://dx.doi.org/10.1175/MWR-D-14-0322.1.

Lubchenco, J. 2009. Testimony of Dr. Jane Lubchenco before the Senate Commerce Committee, February 12, 2009.

Lubchenco, J., M. K. McNutt, G. Dreyfus, S. A. Murawski, D. M. Kennedy, P. T. Anastas, S. Chu and T. Hunter. 2012. Science in support of the Deepwater Horizon response. Proceedings of the National Academy of Sciences of the United States of America 109(50):20212-20221. DOI: 10.1073/pnas.1204729109.

Lusk, E. and K. Yelick. 2007. Languages for High-Productivity Computing: The DARPA HPCS Language Project. Parallel Processing Letters 17:89-102. DOI.

Maaß, N., L. Kaleschke, X. Tian-Kunze and M. Drusch. 2013. Snow thickness retrieval over thick Arctic sea ice using SMOS satellite data. Cryosphere 7(6):1971-1989. DOI: 10.5194/tc-7-1971-2013.

MacLachlan, C., A. Arribas, K. A. Peterson, A. Maidens, D. Fereday, A. A. Scaife, M. Gordon, M. Vellinga, A. Williams, R. E. Comer, J. Camp, P. Xavier and G. Madec. 2015. Global Seasonal forecast system version 5 (GloSea5): a high-resolution seasonal forecast system. Quarterly Journal of the Royal Meteorological Society 141(689):1072-1084. DOI: 10.1002/qj.2396.

MacLeod, D. A., A. Jones, F. Di Giuseppe, C. Caminade and A. P. Morse. 2015. Demonstration of successful malaria forecasts for Botswana using an operational seasonal climate model. Environmental Research Letters 10(4). DOI: 10.1088/1748-9326/10/4/044005.

Maddison, J. R., C. J. Cotter and P. E. Farrell. 2011a. Geostrophic balance preserving interpolation in mesh adaptive linearised shallow-water ocean modelling. Ocean Modelling 37(1-2):35-48. DOI: 10.1016/j.ocemod.2010.12.007.

Maddison, J. R., D. P. Marshall, C. C. Pain and M. D. Piggott. 2011b. Accurate representation of geostrophic and hydrostatic balance in unstructured mesh finite element ocean modelling. Ocean Modelling 39(3-4):248-261. DOI: 10.1016/j.ocemod.2011.04.009.

Malanotte-Rizzoli, P., Ed. 1996. Modern Approaches to Data Assimilation in Ocean Modeling. Amsterdam: Elsevier.

Maltrud, M., S. Peacock and M. Visbeck. 2010. On the possible long-term fate of oil released in the Deepwater Horizon incident, estimated using ensembles of dye release simulations. Environmental Research Letters 5(3). DOI: 10.1088/1748-9326/5/3/035301.

Marras, S., J. F. Kelly, M. Moragues, A. Müller, M. A. Kopera, M. Vázquez, F. X. Giraldo, G. Houzeaux and O. Jorba. 2015. A review of element-based Galerkin methods for numerical weather prediction: Finite elements, spectral elements, and discontinuous Galerkin. Archives of Computational Methods in Engineering:1-50. DOI: 10.1007/s11831-015-9152-1.

Marshall, A. G. and A. A. Scaife. 2010. Improved predictability of stratospheric sudden warming events in an atmospheric general circulation model with enhanced stratospheric resolution. Journal of Geophysical Research-Atmospheres 115. DOI: 10.1029/2009jd012643.

Marsham, J. H., N. S. Dixon, L. Garcia-Carreras, G. M. S. Lister, D. J. Parker, P. Knippertz and C. E. Birch. 2013. The role of moist convection in the West African monsoon system: Insights from continental-scale convection-permitting simulations. Geophysical Research Letters 40(9):1843-1849. DOI: 10.1002/Grl.50347.

Mase, A. S. and L. S. Prokopy. 2014. Unrealized Potential: A Review of Perceptions and Use of Weather and Climate Information in Agricultural Decision Making. Weather Climate and Society 6(1):47-61. DOI: 10.1175/Wcas-D-12-00062.1.

Masutani, M., E. Andersson, J. Terry, O. Reale, J. C. Jusem, L. P. Riishojgaard, T. Schlatter, A. Stoffelen, J. Woollen, S. Lord, Z. Toth, Y. Song, D. Kleist, Y. Xie, N. Prive, E. Liu, H. Sun, D. Emmitt, S. Greco, S. A. Wood, G.-J. Marseille, R. Errico, R. Yang&, G. McConaughy, D. Devenyi, S. Weygandt, A. Tompkins, T. Jung, V. Anantharaj, C. Hill, P. Fitzpatrick, F. Weng, T. Zhu and S. Boukabara. 2007. Progress in Joint OSSEs: A new nature run and international collaboration.

AMS preprint for 18th conference on NWP, Park City, UT, 25-29 June 2007. Available at http://ams.confex.com/ams/pdfpapers/124080.pdf; accessed July 2, 2015.

Masutani, M., J. S. Woollen, S. J. Lord, G. D. Emmitt, T. J. Kleespies, S. A. Wood, S. Greco, H. B. Sun, J. Terry, V. Kapoor, R. Treadon and K. A. Campana. 2010. Observing system simulation experiments at the National Centers for Environmental Prediction. Journal of Geophysical Research-Atmospheres 115. DOI: 10.1029/2009jd012528.

Mathiot, P., C. K. Beatty, T. Fichefet, H. Goosse, F. Massonnet and M. Vancoppenolle. 2012. Better constraints on the sea-ice state using global sea-ice data assimilation. Geoscientific Model Development 5(6):1501-1515. DOI: 10.5194/gmd-5-1501-2012.

Mattern, J. P., K. Fennel and M. Dowd. 2012. Estimating time-dependent parameters for a biological ocean model using an emulator approach. Journal of Marine Systems 96-97:32-47. DOI: 10.1016/j.jmarsys.2012.01.015.

Mavriplis, C. 2011. The challenges of high order methods in numerical weather prediction. In Spectral and High Order Methods for Partial Differential Equations. Selected papers from the ICOSAHOM '09 conference, June 22-26, Trondheim, Norway. Hesthaven, J. S. and E. M. Ronquist, eds. Berlin: Springer.

McNutt, M., R. Cammilli, G. Guthrie, P. Hsieh, V. Labson, B. Lehr, D. Maclay, A. Latzel and M. Sogge. 2011. Assessment of Flow Rate Estimates for the Deepwater Horizon / Macondo Well Oil Spill. Flow Rate Technical Group report to the National Incident Command, Interagency Solutions Group. . Washington, DC: US Department of the Interior.

McNutt, M. 2015. A community for disaster science. Science 348(6230):11-11. DOI: 10.1126/science.aab2091.

McPhaden, M. J. 2015. Commentary: Playing hide and seek with El Nino. Nature Climate Change 5(9):791-795. DOI: 10.1038/nclimate2775.

Meadow, A. M., D. B. Ferguson, Z. Guido, A. Horangic, G. Owen and T. Wall. 2015. Moving toward the Deliberate Coproduction of Climate Science Knowledge. Weather Climate and Society 7(2):179-191. DOI: 10.1175/Wcas-D-14-00050.1.

Mecklenburg, S., M. Drusch, Y. H. Kerr, J. Font, M. Martin-Neira, S. Delwart, G. Buenadicha, N. Reul, E. Daganzo-Eusebio, R. Oliva and R. Crapolicchio. 2012. ESA's Soil Moisture and Ocean Salinity Mission: Mission Performance and Operations. Ieee Transactions on Geoscience and Remote Sensing 50(5):1354-1366. DOI: 10.1109/Tgrs.2012.2187666.

Meinke, H., R. Nelson, P. Kokic, R. Stone, R. Selvaraju and W. Baethgen. 2006. Actionable climate knowledge: from analysis to synthesis. Climate Research 33(1):101-110. DOI: 10.3354/Cr033101.

Mera, R., A. G. Laing and F. Semazzi. 2014. Moisture Variability and Multiscale Interactions during Spring in West Africa. Monthly Weather Review 142(9):3178-3198. DOI: 10.1175/Mwr-D-13-00175.1.

Merryfield, W. J., W. S. Lee, G. J. Boer, V. V. Kharin, J. F. Scinocca, G. M. Flato, R. S. Ajayamohan, J. C. Fyfe, Y. M. Tang and S. Polavarapu. 2013a. The Canadian Seasonal to Interannual Prediction System. Part I: Models and Initialization. Monthly Weather Review 141(8):2910-2945. DOI: 10.1175/Mwr-D-12-00216.1.

Merryfield, W. J., W. S. Lee, W. Wang, M. Chen and A. Kumar. 2013b. Multi-system seasonal predictions of Arctic sea ice. Geophysical Research Letters 40(8):1551-1556. DOI: 10.1002/grl.50317.

Metzger, E. J., O. M. Smedstad, P. G. Thoppil, H. E. Hurlburt, J. A. Cummings, A. J. Wallcraft, L. Zamudio, D. S. Franklin, P. G. Posey, M. W. Phelps, P. J. Hogan, F. L. Bub and C. J. DeHaan. 2014. US Navy Operational Global Ocean and Arctic Ice Prediction Systems. Oceanography 27(3):32-43. DOI: http://dx.doi.org/10.5670/oceanog.2014.66.

Miller, R. N., M. Ghil and F. Gauthiez. 1994. Advanced Data Assimilation in Strongly Nonlinear Dynamical-Systems. Journal of the Atmospheric Sciences 51(8):1037-1056. DOI: 10.1175/1520-0469(1994)051<1037:Adaisn>2.0.Co;2.

Milliman, J. D. and K. L. Farnsworth. 2013. River Discharge to the Coastal Ocean: A Global Synthesis. Cambridge, UK: Cambridge University Press.

Mills, M. J., O. B. Toon, J. Lee-Taylor and A. Robock. 2014. Multidecadal global cooling and unprecedented ozone loss following a regional nuclear conflict. Earth's Future 2(161-176). DOI: 10.1002/2013EF000205.

Min, Y. M., V. N. Kryjov and S. M. Oh. 2014. Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: Retrospective (1983-2003) and real-time forecasts (2008-2013). Journal of Geophysical Research-Atmospheres 119(21):12132-12150. DOI: 10.1002/2014jd022230.

Miura, H., M. Satoh, T. Nasuno, A. T. Noda and K. Oouchi. 2007. A Madden-Julian Oscillation event realistically simulated by a global cloud-resolving model. Science 318(5857):1763-1765. DOI: 10.1126/science.1148443.

Molesworth, A. M., L. E. Cuevas, S. J. Connor, A. P. Morse and M. C. Thomson. 2003. Environmental risk and meningitis epidemics in Africa. Emerging Infectious Diseases 9(10):1287-1293. DOI: 10.3201/eid0910.030182.

Moncrieff, M. W., D. E. Waliser, M. J. Miller, M. A. Shapiro, G. R. Asrar and J. Caughey. 2012. Multiscale Convective Organization and the Yotc Virtual Global Field Campaign. Bulletin of the American Meteorological Society 93(8):1171-1187. DOI: 10.1175/Bams-D-11-00233.1.

Moore, G. W. K. 2013. The Novaya Zemlya Bora and its impact on Barents Sea air-sea interaction. Geophysical Research Letters 40(13):3462-3467. DOI: 10.1002/grl.50641.

Mori, M. and M. Watanabe. 2008. Growth and triggering mechanisms of the PNA: A MJO-PNA coherence. Journal of the Meteorological Society of Japan 86(1):213-236. DOI: 10.2151/Jmsj.86.213.

Morse, A. P., F. J. Doblas-Reyes, M. B. Hoshen, R. Hagedorn and T. N. Palmer. 2005. A forecast quality assessment of an end-to-end probabilistic multi-model seasonal forecast system using a malaria model. Tellus Series a-Dynamic Meteorology and Oceanography 57(3):464-475. DOI: 10.1111/j.1600-0870.2005.00124.x.

Morss, R. E., J. K. Lazo, B. G. Brown, H. E. Brooks, P. T. Ganderton and B. N. Mills. 2008. Societal and economic research and applications for weather forecasts - Priorities for the North American THORPEX program. Bulletin of the American Meteorological Society 89(3):335-346. DOI: 10.1175/Bams-89-3-335.

Msadek, R., G. A. Vecchi, M. Winton and R. G. Gudgel. 2014. Importance of initial conditions in seasonal predictions of Arctic sea ice extent. Geophysical Research Letters 41(14):5208-5215. DOI: 10.1002/2014GL060799.

Mueller, B. and S. I. Seneviratne. 2012. Hot days induced by precipitation deficits at the global scale. Proceedings of the National Academy of Sciences of the United States of America 109(31):12398-12403. DOI: 10.1073/pnas.1204330109.

Murphy, A. H. 1977. The Value of Climatological, Categorical and Probabilistic Forecasts in the Cost-Loss Ratio Situation. Monthly Weather Review 105:803-816. DOI: http://dx.doi.org/10.1175/1520-0493(1977)105<0803:TVOCCA>2.0.CO;2.

Murtugudde, R., J. Beauchamp, C. R. McClain, M. Lewis and A. J. Busalacchi. 2002. Effects of penetrative radiation on the upper tropical ocean circulation. Journal of Climate 15(5):470-486. DOI: 10.1175/1520-0442(2002)015<0470:Eoprot>2.0.Co;2.

Myers, M. F., D. J. Rogers, J. Cox, A. Flahault and S. I. Hay. 2000. Forecasting disease risk for increased epidemic preparedness in public health. Advances in Parasitology, Vol 47 47:309-330. DOI: 10.1016/S0065-308X(00)47013-2.

Nair, R. D., H. W. Choi and H. M. Tufo. 2009. Computational aspects of a scalable high-order discontinuous Galerkin atmospheric dynamical core. Computers & Fluids 38(2):309-319. DOI: 10.1016/j.compfluid.2008.04.006.

Najm, H. N. 2009. Uncertainty Quantification and Polynomial Chaos Techniques in Computational Fluid Dynamics. Annual Review of Fluid Mechanics 41:35-52. DOI: 10.1146/annurev.fluid.010908.165248.
Namias, J. 1953. Thirty-day forecasting: A review of a ten-year experiment. Meteorological Monograph No. 2. American Meteorological Society, Washington, DC.
National Academies of Sciences Engineering and Medicine. 2015a. Sea Change: 2015-2025 Decadal Survey of Ocean Sciences Washington, DC: National Academies Press.
National Academies of Sciences Engineering and Medicine. 2015b. Continuity of NASA Earth Observations from Space: A Value Framework. Washington, DC: National Academies Press.
Navon, I. M. 1998. Practical and theoretical aspects of adjoint parameter estimation and identifiability in meteorology and oceanography. Dynamics of Atmospheres and Oceans 27(1-4):55-79. DOI: 10.1016/S0377-0265(97)00032-8.
Neena, J. M., J. Y. Lee, D. Waliser, B. Wang and X. N. Jiang. 2014. Predictability of the Madden-Julian Oscillation in the Intraseasonal Variability Hindcast Experiment (ISVHE). Journal of Climate 27(12):4531-4543. DOI: 10.1175/Jcli-D-13-00624.1.
Newsom, E., C. M. Bitz, F. Bryan, R. Abernathey and P. Gent. 2015. Sea ice processes control abyssal Southern Ocean heat uptake in a fine resolution ocean climate model. Journal of Climate(in press). DOI.
NIDIS Program Implementation Team. 2007. The National Integrated Drought Information System Implementation Plan: A Pathway for National Resilience. Silver Spring, MD: NOAA.
Niiler, P. P. 2001. The world ocean surface circulation. In Ocean Circulation and Climate. G. Siedler, J. Church and J. Gould, eds. Kidlington, UK: Academic Press.
NOAA. 2010. Office of Hydrologic Development Hydrology Laboratory Strategic Science Plan Silver Spring, MD: National Oceanic and Atmospheric Administration.
NOAA. 2015. Workshop on High-Resolution Coupling and Initialization to Improve Predictability and Predictions in Climate Models. Retrieved December 8, 2015, from http://cpo.noaa.gov/ClimatePrograms/ModelingAnalysisPredictionsandProjections/OutreachPublications/MeetingsWorkshops/HighResolutionWorkshop.
Notz, D. 2012. Challenges in simulating sea ice in Earth System Models. Wiley Interdisciplinary Reviews--Climate Change 3(6):509-526. DOI: 10.1002/Wcc.189.
Nouy, A. 2007. A generalized spectral decomposition technique to solve a class of linear stochastic partial differential equations. Computer Methods in Applied Mechanics and Engineering 196(45-48):4521-4537. DOI: 10.1016/j.cma.2007.05.016.
NRC. 1985. The Effects on the Atmosphere of a Major Nuclear Exchange. Washington, DC: National Academy Press.
NRC. 1986. U.S. Participation in the TOGA Program: A Research Strategy. Washington, DC: National Academy Press.
NRC. 1991a. TOGA: A Review of Progress and Future Opportunities. Washington, DC: National Academy Press.
NRC. 1991b. Toward a New National Weather Service: A First Report. Washington, DC: National Academy Press.
NRC. 1993. Statistics and Physical Oceanography Washington, DC: 1993.
NRC. 1994. GOALS (Global Ocean-Atmosphere-Land System)—for Predicting Seasonal-to-Interannual Climate. Washington, DC: National Academy Press.
NRC. 1999. Making Climate Forecasts Matter. Washington, DC: National Academy Press.
NRC. 2000. Improving Atmospheric Temperature Monitoring Capabilities: Letter Report. Washington, DC: National Academies Press.
NRC. 2003. Fair Weather: Effective Partnership in Weather and Climate Services. Washington, DC: National Academies Press.
NRC. 2008. The Potential Impact of High-End Capability Computing on Four Illustrative Fields of Science and Engineering. Washington, DC: National Academies Press.

NRC. 2010a. Facilitating Climate Change Responses: A Report of Two Workshops on Insights from the Social and Behavioral Sciences. Washington, DC: National Academies Press.
NRC. 2010b. Assessment of Intraseasonal to Interannual Climate Prediction and Predictability. Washington, DC: National Academies Press.
NRC. 2010c. When Weather Matters: Science and Service to Meet Critical Societal Needs. Washington, DC: National Academies Press.
NRC. 2012a. Disaster Resilience: A National Imperative. Washington, DC: National Academies Press.
NRC. 2012b. A National Strategy for Advancing Climate Modeling. Washington, DC: National Academies Press.
NRC. 2013. An Ecosystem Services Approach to Assessing the Impacts of the Deepwater Horizon Oil Spill in the Gulf of Mexico. Washington, DC: National Academies Press.
NRC. 2014. Lessons Learned from the Fukushima Nuclear Accident for Improving Safety of U.S. Nuclear Plants. Washington, DC: National Academies Press.
O'Donnell, M. and B. Colby. 2009. Dry-Year Water Supply Reliability Contracts: A Tool for Water Managers. Tucson, AZ: University of Arizona, Department of Agricultural and Resource Economics.
Oke, P. R., G. B. Brassington, D. A. Griffin and A. Schiller. 2008. The Bluelink ocean data assimilation system (BODAS). Ocean Modelling 21(1-2):46-70. DOI: 10.1016/j.ocemod.2007.11.002.
Oouchi, K., A. T. Noda, M. Satoh, B. Wang, S. P. Xie, H. G. Takahashi and T. Yasunari. 2009. Asian summer monsoon simulated by a global cloud-system-resolving model: Diurnal to intra-seasonal variability. Geophysical Research Letters 36. DOI: 10.1029/2009gl038271.
Orsolini, Y. J., R. Senan, G. Balsamo, F. J. Doblas-Reyes, F. Vitart, A. Weisheimer, A. Carrasco and R. E. Benestad. 2013. Impact of snow initialization on sub-seasonal forecasts. Climate Dynamics 41(7-8):1969-1982. DOI: 10.1007/s00382-013-1782-0.
Orsolini, Y. J., L. Zhang, D. H. W. Peters, K. Fraedrich, X. H. Zhu, A. Schneidereit and B. van den Hurk. 2015. Extreme precipitation events over north China in August 2010 and their link to eastward-propagating wave-trains across Eurasia: observations and monthly forecasting. Quarterly Journal of the Royal Meteorological Society 141(693):3097-3105. DOI: 10.1002/qj.2594.
Ota, Y., J. C. Derber, E. Kalnay and T. Miyoshi. 2013. Ensemble-based observation impact estimates using the NCEP GFS. Tellus Series a-Dynamic Meteorology and Oceanography 65. DOI: 10.3402/Tellusa.V65i0.20038.
Overpeck, J. T., G. A. Meehl, S. Bony and D. R. Easterling. 2011. Climate Data Challenges in the 21st Century. Science 331(6018):700-702. DOI: 10.1126/science.1197869.
Paaijmans, K. P., S. Blanford, A. S. Bell, J. I. Blanford, A. F. Read and M. B. Thomas. 2010. Influence of climate on malaria transmission depends on daily temperature variation. Proceedings of the National Academy of Sciences of the United States of America 107(34):15135-15139. DOI: 10.1073/pnas.1006422107.
Pagano, T. C., H. C. Hartmann and S. Sorooshian. 2002. Factors affecting seasonal forecast use in Arizona water management: a case study of the 1997-98 El Nino. Climate Research 21(3):259-269. DOI: 10.3354/Cr021259.
Paley, D. A., F. M. Zhang and N. E. Leonard. 2008. Cooperative control for ocean sampling: The Glider Coordinated Control System. IEEE Transactions on Control Systems Technology 16(4):735-744. DOI: 10.1109/Tcst.2007.912238.
Palipane, E., J. Lu, G. Chen and J. L. Kinter. 2013. Improved annular mode variability in a global atmospheric general circulation model with 16 km horizontal resolution. Geophysical Research Letters 40(18):4893-4899. DOI: 10.1002/grl.50649.
Palmer, T. 2015. Modelling: Build imprecise supercomputers. Nature 526(7571). DOI: 10.1038/526029a.
Palmer, T. N., C. Brankovic and D. S. Richardson. 2000. A probability and decision-model analysis of PROVOST seasonal multi-model ensemble integrations. Quarterly Journal of the Royal Meteorological Society 126(567):2013-2033. DOI: 10.1256/Smsqj.56702.

Palmer, T. N., A. Alessandri, U. Andersen, P. Cantelaube, M. Davey, P. Delecluse, M. Deque, E. Diez, F. J. Doblas-Reyes, H. Feddersen, R. Graham, S. Gualdi, J. F. Gueremy, R. Hagedorn, M. Hoshen, N. Keenlyside, M. Latif, A. Lazar, E. Maisonnave, V. Marletto, A. P. Morse, B. Orfila, P. Rogel, J. M. Terres and M. C. Thomson. 2004. Development of a European multimodel ensemble system for seasonal-to-interannual prediction (DEMETER). Bulletin of the American Meteorological Society 85(6):853-872. DOI: 10.1175/Bams-85-6-853.

Palmer, T. N., F. J. Doblas-Reyes, A. Weisheimer and M. J. Rodwell. 2008. Toward seamless prediction: Calibration of climate change projections using seasonal forecasts. Bulletin of the American Meteorological Society 89(4):459-470. DOI: 10.1175/Bams-89-4-459.

Palmer, T. N. 2012. Towards the probabilistic Earth-system simulator: a vision for the future of climate and weather prediction. Quarterly Journal of the Royal Meteorological Society 138(665):841-861. DOI: 10.1002/qj.1923.

Palmer, T. N. 2014. More reliable forecasts with less precise computations: a fast-track route to cloud-resolved weather and climate simulators? Philosophical Transactions of the Royal Society a-Mathematical Physical and Engineering Sciences 372(2018). DOI: 10.1098/Rsta.2013.0391.

Pandya, R., A. Hodgson, M. H. Hayden, P. Akweongo, T. Hopson, A. A. Forgor, T. Yoksas, M. A. Dalaba, V. Dukic, R. Mera, A. Dumont, K. McCormack, D. Anaseba, T. Awine, J. Boehnert, G. Nyaaba, A. Laing and F. Semazzi. 2015. Using Weather Forecasts to Help Manage Meningitis in the West African Sahel. Bulletin of the American Meteorological Society 96(1):103-+. DOI: 10.1175/Bams-D-13-00121.1.

Park, S. and C. S. Bretherton. 2009. The University of Washington Shallow Convection and Moist Turbulence Schemes and Their Impact on Climate Simulations with the Community Atmosphere Model. Journal of Climate 22(12):3449-3469. DOI: 10.1175/2008jcli2557.1.

Patt, A. G., L. Ogallo and M. Hellmuth. 2007. Sustainability - Learning from 10 years of climate outlook forums in Africa. Science 318(5847):49-50. DOI: 10.1126/science.1147909.

PCAST. 2010. Report to the president and congress. Designing a digital future: Federally funded research and development in networking and information technology. Executive Office of the President, President's Council of Advisors on Science and Technology, Washington, DC.

Peings, Y., H. Douville, R. Alkama and B. Decharme. 2011. Snow contribution to springtime atmospheric predictability over the second half of the twentieth century. Climate Dynamics 37(5-6):985-1004. DOI: 10.1007/s00382-010-0884-1.

Pepler, A. S., L. B. Díaz, C. Prodhomme, F. J. Doblas-Reyes and A. Kumar. 2015. The ability of a multi-model seasonal forecasting ensemble to forecast the frequency of warm, cold and wet extremes. Weather and Climate Extremes 9:68-77. DOI: 10.1016/j.wace.2015.06.005.

Pham, D. T. 2001. Stochastic methods for sequential data assimilation in strongly nonlinear systems. Monthly Weather Review 129(5):1194-1207. DOI: 10.1175/1520-0493(2001)129<1194:Smfsda>2.0.Co;2.

Pielke, R. and R. E. Carbone. 2002. Weather impacts, forecasts, and policy - An integrated perspective. Bulletin of the American Meteorological Society 83(3):393-+. DOI: 10.1175/1520-0477(2002)083<0393:Wifap>2.3.Co;2.

Pielke, R. A. 2013. Mesoscale meteorological modeling. 3rd edition. San Diego: Academic Press.

Pinardi, N. and J. Woods, Eds. 2002. Ocean Forecasting: Conceptual Basis and Applications. Dordrecht: Springer.

Post, E., U. Bhatt, C. M. Bitz, J. Brodie, T. L. Fulton, M. Hebblewhite, J. Kerby, S. Kutz, I. Stirling and D. A. Walker. 2013. Sea ice as driver of ecological responses to climate change in the Polar Regions. Science 341. DOI: 10.1126/science.1235225.

Pritchard, M. S. and R. C. J. Somerville. 2009. Assessing the Diurnal Cycle of Precipitation in a Multi-Scale Climate Model. Journal of Advances in Modeling Earth Systems 1(4). DOI: 10.3894/JAMES.2009.1.12.

Prodhomme, C., F. Doblas-Reyes, O. Bellprat and E. Dutra. 2015. Impact of land-surface initialization on sub-seasonal to seasonal forecasts over Europe. Climate Dynamics. DOI: 10.1007/s00382-015-2879-4.

Pullen, J., J. Chang and S. Hanna. 2013. Air-Sea Transport, Dispersion, and Fate Modeling in the Vicinity of the Fukushima Nuclear Power Plant: A Special Conference Session Summary. Bulletin of the American Meteorological Society 94:31-39. DOI: http://dx.doi.org/10.1175/BAMS-D-11-00158.1.

Pulwarty, R. S. and K. T. Redmond. 1997. Climate and salmon restoration in the Columbia River basin: The role and usability of seasonal forecasts. Bulletin of the American Meteorological Society 78(3):381-397. DOI: 10.1175/1520-0477(1997)078<0381:Casrit>2.0.Co;2.

Pulwarty, R. S., C. Simpson and C. R. Nierenberg. 2009. The Regional Integrated Sciences and Assessments (RISA) Program: crafting effective assessments for the long haul. In Integrated Regional Assessments of Global Climate Changes. C.G. Wright and J. Jaeger, eds. Cambridge, UK: Cambridge University Press.

Qian, Y., W. I. Gustafson, L. R. Leung and S. J. Ghan. 2009. Effects of soot-induced snow albedo change on snowpack and hydrological cycle in western United States based on Weather Research and Forecasting chemistry and regional climate simulations. Journal of Geophysical Research-Atmospheres 114. DOI: 10.1029/2008jd011039.

Quan, X. W., P. J. Webster, A. M. Moore and H. R. Chang. 2004. Seasonality in SST-forced atmospheric short-term climate predictability. Journal of Climate 17(16):3090-3108. DOI: Doi 10.1175/1520-0442(2004)017<3090:Sisasc>2.0.Co;2.

Rabier, F., H. Jarvinen, E. Klinker, J. F. Mahfouf and A. Simmons. 2000. The ECMWF operational implementation of four-dimensional variational assimilation. I: Experimental results with simplified physics. Quarterly Journal of the Royal Meteorological Society 126(564):1143-1170. DOI: Doi 10.1256/Smsqj.56414.

Raftery, A. E., T. Gneiting, F. Balabdaoui and M. Polakowski. 2005. Using Bayesian model averaging to calibrate forecast ensembles. Monthly Weather Review 133(5):1155-1174. DOI: 10.1175/Mwr2906.1.

Ramp, S. R., R. E. Davis, N. E. Leonard, I. Shulman, Y. Chao, A. R. Robinson, J. Marsden, P. F. J. Lermusiaux, D. M. Fratantoni, J. D. Paduan, F. P. Chavez, F. L. Bahr, S. Liang, W. Leslie and Z. Li. 2009. Preparing to predict: The Second Autonomous Ocean Sampling Network (AOSN-II) experiment in the Monterey Bay. Deep-Sea Research Part Ii-Topical Studies in Oceanography 56(3-5):68-86. DOI: 10.1016/j.dsr2.2008.08.013.

Randall, D., M. Branson, M. Wang, S. Ghan, C. Craig, A. Gettelman and J. Edwards. 2013. A Community Atmosphere Model With Superparameterized Clouds. Eos Transactions AGU 94(25):221. DOI.

Rasmusson, E. M. and K. T. Mo. 1993. Linkages between 200-Mb Tropical and Extratropical Circulation Anomalies during the 1986-1989 Enso Cycle. Journal of Climate 6(4):595-616. DOI: Doi 10.1175/1520-0442(1993)006<0595:Lbmtae>2.0.Co;2.

Reeves, R. W. and D. D. Gemmill. 2004. Climate Prediction Center: Reflections on 25 Years of Analysis, Diagnosis, and Prediction. Washington, DC: US Government Printing Office.

Reul, N., S. Fournier, J. Boutin, O. Hernandez, C. Maes, B. Chapron, G. Alory, Y. Quilfen, J. Tenerelli, S. Morisset, Y. Kerr, S. Mecklenburg and S. Delwart. 2014. Sea Surface Salinity Observations from Space with the SMOS Satellite: A New Means to Monitor the Marine Branch of the Water Cycle. Surveys in Geophysics 35(3):681-722. DOI: 10.1007/s10712-013-9244-0.

Richter, I., S.-P. Xie, S. K. Behera, T. Doi and Y. Masumoto. 2012. Equatorial Atlantic variability and its relation to mean state biases in CMIP5. Climate Dynamics 42(1-2):171-188. DOI: 10.1007/s00382-012-1624-5.

Riddle, E. E., A. H. Butler, J. C. Furtado, J. L. Cohen and A. Kumar. 2013. CFSv2 ensemble prediction of the wintertime Arctic Oscillation. Climate Dynamics 41(3-4):1099-1116. DOI: 10.1007/s00382-013-1850-5.

Rienecker, M. M. 2003. Report of the Coupled Data Assimilation Workshop (NOAA/OGP), Portland, OR, 21-23 April.
Rienecker, M. M., M. J. Suarez, R. Gelaro, R. Todling, J. Bacmeister, E. Liu, M. G. Bosilovich, S. D. Schubert, L. Takacs, G. K. Kim, S. Bloom, J. Y. Chen, D. Collins, A. Conaty, A. Da Silva, W. Gu, J. Joiner, R. D. Koster, R. Lucchesi, A. Molod, T. Owens, S. Pawson, P. Pegion, C. R. Redder, R. Reichle, F. R. Robertson, A. G. Ruddick, M. Sienkiewicz and J. Woollen. 2011. MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications. Journal of Climate 24(14):3624-3648. DOI: 10.1175/Jcli-D-11-00015.1.
Rigor, I. G., J. M. Wallace and R. L. Colony. 2002. Response of sea ice to the Arctic oscillation. Journal of Climate 15(18):2648-2663. DOI: Doi 10.1175/1520-0442(2002)015<2648:Rositt>2.0.Co;2.
Riser, S. C., H. J. Freeland, D. Roemmich, S. Wijffels, Ariel Troisi, M. Belbéoch, D. Gilbert, J. Xu, S. Pouliquen, A. Thresher, P.-Y. L. Traon, G. Maze, B. Klein, M. Ravichandran, F. Grant, P.-M. Poulain, T. Suga, B. Lim, A. Sterl, P. Sutton, Kjell-Arne Mork, P. J. Vélez-Belchí, I. Ansorge, B. King, J. Turton, M. Baringer and S. R. Jayne. 2016. Fifteen years of ocean observations with the global Argo array. Nature Climate Change 6:145-153. DOI: 10.1038/nclimate2872.
Roads, J. O. 1999. Jerome Namias, 1910-1996: A Biographical Memoir. Washington, DC: National Academies Press.
Robertson, A. W., W. Baethgen, P. Block, U. Lall, A. Sankarasubramanian, F. d. A. d. S. Filho and K. M. J. Verbist. 2014. Climate risk management for water in semi-arid regions. Earth Perspectives 1(12). DOI: 10.1186/2194-6434-1-12.
Robertson, A. W., A. Kumar, M. Pena and F. Vitart. 2015. Improving and Promoting Subseasonal to Seasonal Prediction. Bulletin of the American Meteorological Society 96(3):Es49-Es53. DOI: 10.1175/Bams-D-14-00139.1.
Robinson, A. R., Ed. 1983 Eddies in marine science. Berlin: Springer-Verlag.
Robinson, A. R., P. F. J. Lermusiaux and N. Q. Sloan. 1998. Data Assimilation. In The Sea: The Global Coastal Ocean, Vol. 10: Processes and Methods. K. H. Brink and A. R. Robinson, eds. New York: John Wiley and Sons.
Robinson, A. R., P. J. Haley, P. F. J. Lermusiaux and W. G. Leslie. 2002. Predictive Skill, Predictive Capability and Predictability in Ocean Forecasting. In Proceedings of the OCEANS 2002 MTS/IEEE conference, eds. Biloxi, MS: Holland Publications.
Robinson, I. 2006. Satellite Measurements for Operational Ocean Models. In Ocean Weather Forecasting: An Integrated View of Oceanography. E. P. Chassignet and J. Verron, eds. Dordrecht: Springer.
Rodell, M., P. R. Houser, U. Jambor, J. Gottschalck, K. Mitchell, C. J. Meng, K. Arsenault, B. Cosgrove, J. Radakovich, M. Bosilovich, J. K. Entin, J. P. Walker, D. Lohmann and D. Toll. 2004. The global land data assimilation system. Bulletin of the American Meteorological Society 85(3):381-394. DOI: 10.1175/Bams-85-3-381.
Rodney, M., H. Lin and J. Derome. 2013. Subseasonal Prediction of Wintertime North American Surface Air Temperature during Strong MJO Events. Monthly Weather Review 141(8):2897-2909. DOI: 10.1175/Mwr-D-12-00221.1.
Roe, R. and T. Wilkie. 2015. The new realism: software runs slowly on supercomputers. Scientific Computing World(143). DOI.
Roehrig, R., D. Bouniol, F. Guichard, F. Hourdin and J.-L. Redelsperger. 2013. The Present and Future of the West African Monsoon: A Process-Oriented Assessment of CMIP5 Simulations along the AMMA Transect. Journal of Climate 26:6471-6505. DOI: http://dx.doi.org/10.1175/JCLI-D-12-00505.1.
Roff, G., D. W. J. Thompson and H. Hendon. 2011. Does increasing model stratospheric resolution improve extended-range forecast skill? Geophysical Research Letters 38. DOI: 10.1029/2010gl046515.
Roulston, M. S. and L. A. Smith. 2004. The Boy who Cried Wolf revisited: The impact of false alarm intolerance on cost-loss scenarios. Weather and Forecasting 19(2):391-397. DOI: 10.1175/1520-0434(2004)019<0391:Tbwcwr>2.0.Co;2.

Roundy, J. K., C. R. Ferguson and E. F. Wood. 2014. Impact of land-atmospheric coupling in CFSv2 on drought prediction. Climate Dynamics 43(1-2):421-434. DOI: 10.1007/s00382-013-1982-7.

Roundy, J. K. and E. F. Wood. 2015. The Attribution of Land-Atmosphere Interactions on the Seasonal Predictability of Drought. Journal of Hydrometeorology 16(2):793-810. DOI: 10.1175/Jhm-D-14-0121.1.

Ruf, C., A. Lyons, M. Unwin, J. Dickinson, R. Rose, D. Rose and M. Vincent. 2013. CYGNSS: Enabling the Future of Hurricane Prediction. IEEE Geoscience and Remote Sensing Magazine 1(2):52-67. DOI: 10.1109/MGRS.2013.2260911.

Ruiz, J. and M. Pulido. 2015. Parameter Estimation Using Ensemble-Based Data Assimilation in the Presence of Model Error. Monthly Weather Review 143(5):1568-1582. DOI: 10.1175/Mwr-D-14-00017.1.

Saha, S., S. Nadiga, C. Thiaw, J. Wang, W. Wang, Q. Zhang, H. M. Van den Dool, H. L. Pan, S. Moorthi, D. Behringer, D. Stokes, M. Pena, S. Lord, G. White, W. Ebisuzaki, P. Peng and P. Xie. 2006. The NCEP Climate Forecast System. Journal of Climate 19(15):3483-3517. DOI: 10.1175/Jcli3812.1.

Saha, S., S. Moorthi, H. L. Pan, X. R. Wu, J. D. Wang, S. Nadiga, P. Tripp, R. Kistler, J. Woollen, D. Behringer, H. X. Liu, D. Stokes, R. Grumbine, G. Gayno, J. Wang, Y. T. Hou, H. Y. Chuang, H. M. H. Juang, J. Sela, M. Iredell, R. Treadon, D. Kleist, P. Van Delst, D. Keyser, J. Derber, M. Ek, J. Meng, H. L. Wei, R. Q. Yang, S. Lord, H. Van den Dool, A. Kumar, W. Q. Wang, C. Long, M. Chelliah, Y. Xue, B. Y. Huang, J. K. Schemm, W. Ebisuzaki, R. Lin, P. P. Xie, M. Y. Chen, S. T. Zhou, W. Higgins, C. Z. Zou, Q. H. Liu, Y. Chen, Y. Han, L. Cucurull, R. W. Reynolds, G. Rutledge and M. Goldberg. 2010. The NCEP Climate Forecast System Reanalysis. Bulletin of the American Meteorological Society 91(8):1015-1057. DOI: 10.1175/2010bams3001.1.

Saha, S., S. Moorthi, X. R. Wu, J. Wang, S. Nadiga, P. Tripp, D. Behringer, Y. T. Hou, H. Y. Chuang, M. Iredell, M. Ek, J. Meng, R. Q. Yang, M. P. Mendez, H. Van Den Dool, Q. Zhang, W. Q. Wang, M. Y. Chen and E. Becker. 2014. The NCEP Climate Forecast System Version 2. Journal of Climate 27(6):2185-2208. DOI: 10.1175/Jcli-D-12-00823.1.

Sakov, P., F. Counillon, L. Bertino, K. A. Lisaeter, P. R. Oke and A. Korablev. 2012. TOPAZ4: an ocean-sea ice data assimilation system for the North Atlantic and Arctic. Ocean Science 8(4):633-656. DOI: 10.5194/os-8-633-2012.

Sandgathe, S., B. Brown, B. Etherton and E. Tollerud. 2013. Designing Multimodel Ensembles Requires Meaningful Methodologies. Bulletin of the American Meteorological Society 94(12):Es183-Es185. DOI: 10.1175/Bams-D-12-00234.1.

Sapsis, T. P. and P. F. J. Lermusiaux. 2009. Dynamically orthogonal field equations for continuous stochastic dynamical systems. Physica D-Nonlinear Phenomena 238(23-24):2347-2360. DOI: 10.1016/j.physd.2009.09.017.

Sapsis, T. P. and P. F. J. Lermusiaux. 2012. Dynamical criteria for the evolution of the stochastic dimensionality in flows with uncertainty. Physica D-Nonlinear Phenomena 241(1):60-76. DOI: 10.1016/j.physd.2011.10.001.

Sato, T., H. Miura, M. Satoh, Y. N. Takayabu and Y. Q. Wang. 2009. Diurnal Cycle of Precipitation in the Tropics Simulated in a Global Cloud-Resolving Model. Journal of Climate 22(18):4809-4826. DOI: 10.1175/2009jcli2890.1.

Satoh, M., S. Iga, H. Tomita, Y. Tsushima and A. T. Noda. 2012. Response of Upper Clouds in Global Warming Experiments Obtained Using a Global Nonhydrostatic Model with Explicit Cloud Processes. Journal of Climate 25(6):2178-2191. DOI: 10.1175/Jcli-D-11-00152.1.

Savelli, S. and S. Joslyn. 2012. Boater Safety: Communicating Weather Forecast Information to High-Stakes End Users. Weather Climate and Society 4(1):7-19. DOI: 10.1175/Wcas-D-11-00025.1.

Scaife, A. A., D. Copsey, C. Gordon, C. Harris, T. Hinton, S. Keeley, A. O'Neill, M. Roberts and K. Williams. 2011. Improved Atlantic winter blocking in a climate model. Geophysical Research Letters 38. DOI: 10.1029/2011gl049573.

Scaife, A. A., A. Arribas, E. Blockley, A. Brookshaw, R. T. Clark, N. Dunstone, R. Eade, D. Fereday, C. K. Folland, M. Gordon, L. Hermanson, J. R. Knight, D. J. Lea, C. MacLachlan, A. Maidens, M. Martin, A. K. Peterson, D. Smith, M. Vellinga, E. Wallace, J. Waters and A. Williams. 2014a. Skillful long-range prediction of European and North American winters. Geophysical Research Letters 41(7):2514-2519. DOI: 10.1002/2014GL059637.

Scaife, A. A., M. Athanassiadou, M. Andrews, A. Arribas, M. Baldwin, N. Dunstone, J. Knight, C. MacLachlan, E. Manzini, W. A. Muller, H. Pohlmann, D. Smith, T. Stockdale and A. Williams. 2014b. Predictability of the quasi-biennial oscillation and its northern winter teleconnection on seasonal to decadal timescales. Geophysical Research Letters 41(5):1752-1758. DOI: 10.1002/2013gl059160.

Schiller, A. and G. B. Brassington, Eds. 2011. Operational Oceanography in the 21st Century. Dordrecht: Springer.

Schofield, O., S. Glenn, J. Orcutt, M. Arrott, M. Meisinger, A. Gangopadhyay, W. Brown, R. Signell, M. Moline, Y. Chao, S. Chien, D. Thompson, A. Balasuriya, P. F. J. Lermusiaux and M. Oliver. 2010. Automated sensor network to advance ocean science. Eos, Transactions American Geophysical Union 91(39):345-346. DOI.

Screen, J. A., I. Simmonds and K. Keay. 2011. Dramatic interannual changes of perennial Arctic sea ice linked to abnormal summer storm activity. Journal of Geophysical Research-Atmospheres 116. DOI: 10.1029/2011jd015847.

Semtner, A. J. 1995. Modeling Ocean Circulation. Science 269(5229):1379-1385. DOI: 10.1126/science.269.5229.1379.

Shapiro, M., J. Shukla, G. Brunet, C. Nobre, M. Beland, R. Dole, K. Trenberth, R. Anthes, G. Asrar, L. Barrie, P. Bougeault, G. Brasseur, D. Burridge, A. Busalacchi, J. Caughey, D. L. Chen, J. Church, T. Enomoto, B. Hoskins, O. Hov, A. Laing, H. Le Treut, J. Marotzke, G. McBean, G. Meehl, M. Miller, B. Mills, J. Mitchell, M. Moncrieff, T. Nakazawa, H. Olafsson, T. Palmer, D. Parsons, D. Rogers, A. Simmons, A. Troccoli, Z. Toth, L. Uccellini, C. Velden and J. M. Wallace. 2010. An Earth-System Prediction Initiative for the Twenty-First Century. Bulletin of the American Meteorological Society 91(10):1377-1388. DOI: 10.1175/2010BAMS2944.1.

Sherwood, S. C., S. Bony and J. L. Dufresne. 2014. Spread in model climate sensitivity traced to atmospheric convective mixing. Nature 505(7481):37-42. DOI: 10.1038/nature12829.

Shukla, J. 1998. Predictability in the midst of chaos: A scientific basis for climate forecasting. Science 282(5389):728-731. DOI: 10.1126/science.282.5389.728.

Shukla, J., J. Anderson, D. Baumhefner, C. Brankovic, Y. Chang, E. Kalnay, L. Marx, T. Palmer, D. Paolino, J. Ploshay, S. Schubert, D. Straus, M. Suarez and J. Tribbia. 2000. Dynamical seasonal prediction. Bulletin of the American Meteorological Society 81(11):2593-2606. DOI: 10.1175/1520-0477(2000)081<2593:Dsp>2.3.Co;2.

Siegel, D. A., J. C. Ohlmann, L. Washburn, R. R. Bidigare, C. T. Nosse, E. Fields and Y. M. Zhou. 1995. Solar-Radiation, Phytoplankton Pigments and the Radiant Heating of the Equatorial Pacific Warm Pool. Journal of Geophysical Research-Oceans 100(C3):4885-4891. DOI: 10.1029/94jc03128.

Sigmond, M., J. F. Scinocca, V. V. Kharin and T. G. Shepherd. 2013. Enhanced seasonal forecast skill following stratospheric sudden warmings. Nature Geoscience 6(2):98-102. DOI: 10.1038/Ngeo1698.

Slingo, J., K. Bates, N. Nikiforakis, M. Piggott, M. Roberts, L. Shaffrey, I. Stevens, P. L. Vidale and H. Weller. 2009. Developing the next-generation climate system models: challenges and achievements. Philosophical Transactions of the Royal Society a-Mathematical Physical and Engineering Sciences 367(1890):815-831. DOI: 10.1098/rsta.2008.0207.

Sluka, T., S. Penny, E. Kalnay and T. Miyoshi. 2015. Using Strongly Coupled Ensemble Data Assimilation to Assimilate Atmospheric Observations into the Ocean. Geophysical Research Letters(submitted). DOI.

Smedstad, O. M. and J. J. Obrien. 1991. Variational Data Assimilation and Parameter-Estimation in an Equatorial Pacific-Ocean Model. Progress in Oceanography 26(2):179-241. DOI: 10.1016/0079-6611(91)90002-4.

Smith, M. J., P. I. Palmer, D. W. Purves, M. C. Vanderwel, V. Lyutsarev, B. Calderhead, L. N. Joppa, C. M. Bishop and S. Emmott. 2014. Changing How Earth System Modeling Is Done to Provide More Useful Information for Decision Making, Science, and Society. Bulletin of the American Meteorological Society 95(9):1453-1464. DOI: 10.1175/Bams-D-13-00080.1.

Smith, P. J., G. D. Thornhill, S. L. Dance, A. S. Lawless, D. C. Mason and N. K. Nichols. 2013. Data assimilation for state and parameter estimation: application to morphodynamic modelling. Quarterly Journal of the Royal Meteorological Society 139(671):314-327. DOI: Doi 10.1002/Qj.1944.

Smith, P. J., A. M. Fowler and A. S. Lawless. 2015a. Exploring strategies for coupled 4D-Var data assimilation using an idealised atmosphere-ocean model. Tellus Series a-Dynamic Meteorology and Oceanography 67. DOI: 10.3402/Tellusa.V67.27025.

Smith, P. J., A. M. Fowler and A. S. Lawless. 2015b. Exploring strategies for coupled 4DVAR data assimilation using an idealised atmosphere-ocean model. Tellus A 67. DOI: http://dx.doi.org/10.3402/tellusa.v67.27025.

Smith, R. B. 2013. The Lower Atmospheric Observing Facilities Workshop: Meeting the Challenges of Climate System Science. June 18-19, 2012, Boulder, Colorado. Boulder, CO: University Corporation for Atmospheric Research.

Sobczyk, K. 2001. Information dynamics: Premises, challenges and results. Mechanical Systems and Signal Processing 15(3):475-498. DOI: 10.1006/mssp.2000.1378.

Sobolowski, S., G. Gong and M. F. Ting. 2010. Modeled Climate State and Dynamic Responses to Anomalous North American Snow Cover. Journal of Climate 23(3):785-799. DOI: 10.1175/2009JCLI3219.1.

Sondergaard, T. and P. F. J. Lermusiaux. 2013a. Data Assimilation with Gaussian Mixture Models Using the Dynamically Orthogonal Field Equations. Part II: Applications. Monthly Weather Review 141(6):1761-1785. DOI: 10.1175/Mwr-D-11-00296.1.

Sondergaard, T. and P. F. J. Lermusiaux. 2013b. Data Assimilation with Gaussian Mixture Models Using the Dynamically Orthogonal Field Equations. Part I: Theory and Scheme. Monthly Weather Review 141(6):1737-1760. DOI: 10.1175/Mwr-D-11-00295.1.

Srinivasan, G., K. M. Rafisura and A. R. Subbiah. 2011. Climate information requirements for community-level risk management and adaptation. Climate Research 47(1-2):5-12. DOI: 10.3354/Cr00962.

Stan, C., M. Khairoutdinov, C. A. DeMott, V. Krishnamurthy, D. M. Straus, D. A. Randall, J. L. Kinter and J. Shukla. 2010. An ocean-atmosphere climate simulation with an embedded cloud resolving model. Geophysical Research Letters 37. DOI: 10.1029/2009gl040822.

Stark, J. D., J. Ridley, M. Martin and A. Hines. 2008. Sea ice concentration and motion assimilation in a sea ice-ocean model. Journal of Geophysical Research-Oceans 113(C5). DOI: 10.1029/2007jc004224.

Stickler, A., S. Bronnimann, M. A. Valente, J. Bethke, A. Sterin, S. Jourdain, E. Roucaute, M. V. Vasquez, D. A. Reyes, R. Allan and D. Dee. 2014. ERA-CLIM Historical Surface and Upper-Air Data for Future Reanalyses. Bulletin of the American Meteorological Society 95(9):1419-1430. DOI: 10.1175/Bams-D-13-00147.1.

Stockdale, T. N., D. L. T. Anderson, M. A. Balmaseda, F. Doblas-Reyes, L. Ferranti, K. Mogensen, T. N. Palmer, F. Molteni and F. Vitart. 2011. ECMWF seasonal forecast system 3 and its prediction of sea surface temperature. Climate Dynamics 37(3-4):455-471. DOI: 10.1007/s00382-010-0947-3.

Stoffelen, A., G. J. Marseille, F. Bouttier, D. Vasiljevic, S. d. Haan and C. Cardinali. 2006. Doppler Wind Lidar Observation System Simulation Experiment. Quarterly Journal of the Royal Meteorological Society 132:1927-1947. DOI.

Stommel, H. M. 1989. The Slocum Mission. Oceanography 2(1):22-25. DOI: http://dx.doi.org/10.5670/oceanog.1989.26.
Straus, D., J. Shukla, D. Paolino, S. Schubert, M. Suarez, P. Pegion and A. Kumar. 2003. Predictability of the seasonal mean atmospheric circulation during autumn, winter, and spring. Journal of Climate 16(22):3629-3649. DOI: Doi 10.1175/1520-0442(2003)016<3629:Potsma>2.0.Co;2.
Strong, C. and I. G. Rigor. 2013. Arctic marginal ice zone trending wider in summer and narrower in winter. Geophysical Research Letters 40(18):4864-4868. DOI: 10.1002/grl.50928.
Su, H., Z. L. Yang, R. E. Dickinson, C. R. Wilson and G. Y. Niu. 2010. Multisensor snow data assimilation at the continental scale: The value of Gravity Recovery and Climate Experiment terrestrial water storage information. Journal of Geophysical Research-Atmospheres 115. DOI: 10.1029/2009jd013035.
Suarez, P. and A. Tall. 2010. Towards forecast-based humanitarian decisions: Climate science to get from early warning to early action. London: Humanitarian Futures Programme, Kings College.
Subramani, D. N., T. Lolla, P. J. Haley Jr. and P. F. J. Lermusiaux. 2015. A stochastic optimization method for energy-based path planning. In Dynamic Data-driven Environmental Systems Science Conference: Lecture Notes in Computer Science. S. Ravela and A. Sandu, eds. Berlin: Springer International Publishing, in Press.
Sultan, B., K. Labadi, J. F. Guegan and S. Janicot. 2005. Climate drives the meningitis epidemics onset in West Africa. Plos Medicine 2(1):43-49. DOI: 10.1371/journal.pmed.0020006.
Tabatabaeenejad, A., M. Burgin, X. Y. Duan and M. Moghaddam. 2015. P-Band Radar Retrieval of Subsurface Soil Moisture Profile as a Second-Order Polynomial: First AirMOSS Results. IEEE Transactions on Geoscience and Remote Sensing 53(2):645-658. DOI: 10.1109/Tgrs.2014.2326839.
Takahara, H. and D. Parks. 2008. NEC High Performance Computing. Presented at World Modelling Summit for Climate Prediction, May 6-9, 2008, Reading, UK.
Tang, W. Q., S. H. Yueh, A. G. Fore and A. Hayashi. 2014. Validation of Aquarius sea surface salinity with in situ measurements from Argo floats and moored buoys. Journal of Geophysical Research-Oceans 119(9):6171-6189. DOI: 10.1002/2014JC010101.
Tarantola, A. 2005. Inverse problem theory and methods for model parameter estimation. Philadelphia, PA: Society for Industrial and Applied Mathmatics.
Tardif, R., G. J. Hakim and C. Snyder. 2014. Coupled atmosphere-ocean data assimilation experiments with a low-order climate model. Climate Dynamics 43(5-6):1631-1643. DOI: 10.1007/s00382-013-1989-0.
Taylor, K. E., R. J. Stouffer and G. A. Meehl. 2012. An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society 93(4):485-498. DOI: 10.1175/Bams-D-11-00094.1.
Thacker, W. C., A. Srinivasan, M. Iskandarani, O. M. Knio and M. Le Henaff. 2012. Propagating boundary uncertainties using polynomial expansions. Ocean Modelling 43-44:52-63. DOI: 10.1016/j.ocemod.2011.11.011.
Thacker, W. C., M. Iskandarani, R. C. Goncalves, A. Srinivasan and O. M. Knio. 2015. Pragmatic aspects of uncertainty propagation: A conceptual review. Ocean Modelling 95:25-36. DOI: 10.1016/j.ocemod.2015.09.001.
Theurich, G., C. DeLuca, T. Campbell, F. Liu, K. Saint, M. Vertenstein, J. Chen, R. Oehmke, J. Doyle, T. Whitcomb, A. Wallcraft, M. Iredell, T. Black, A. M. da Silva, T. Clune, R. Ferraro, P. Li, M. Kelley, I. Aleinov, V. Balaji, N. Zadeh, R. Jacob, B. Kirtman, F. Giraldo, D. McCarren, S. Sandgathe, S. Peckham and R. Dunlap IV. 2015 The Earth System Prediction Suite: Toward a Coordinated U.S. Modeling Capability. Bulletin of the American Meteorological Society. DOI: http://dx.doi.org/10.1175/BAMS-D-14-00164.1.
Thiaw, W. M. and V. B. Kumar. 2015. NOAA'S African Desk: Twenty Years of Developing Capacity in Weather and Climate Forecasting in Africa. Bulletin of the American Meteorological Society 96(5). DOI: 10.1175/Bams-D-13-00274.1.

Thomas, J. A., A. A. Berg and W. J. Merryfield. 2015. Influence of snow and soil moisture initialization on sub-seasonal predictability and forecast skill in boreal spring. Climate Dynamics. DOI: 10.1007/s00382-015-2821-9.

Thompson, D. W. J. and J. M. Wallace. 2000. Annular modes in the extratropical circulation. Part I: Month-to-month variability. Journal of Climate 13(5):1000-1016. DOI: 10.1175/1520-0442(2000)013<1000:Amitec>2.0.Co;2.

Thompson, D. W. J., M. P. Baldwin and J. M. Wallace. 2002. Stratospheric connection to Northern Hemisphere wintertime weather: Implications for prediction. Journal of Climate 15(12):1421-1428. DOI: 10.1175/1520-0442(2002)015<1421:Sctnhw>2.0.Co;2.

Thomson, M. C., F. J. Doblas-Reyes, S. J. Mason, R. Hagedorn, S. J. Connor, T. Phindela, A. P. Morse and T. N. Palmer. 2006a. Malaria early warnings based on seasonal climate forecasts from multi-model ensembles. Nature 439(7076):576-579. DOI: 10.1038/Nature04503.

Thomson, M. C., A. M. Molesworth, M. H. Djingarey, K. R. Yameogo, F. Belanger and L. E. Cuevas. 2006b. Potential of environmental models to predict meningitis epidemics in Africa. Tropical Medicine & International Health 11(6):781-788. DOI: 10.1111/j.1365-3156.2006.01630.x.

Thomson, M. C., S. Mason, B. Platzer, A. Mihretie, J. Omumbo, G. Mantilla, P. Ceccato, M. Jancloes and S. Connor. 2014. Climate and health in Africa. Earth Perspectives 1(17). DOI: 10.1186/2194-6434-1-17.

Timmermans, R. M. A., W. A. Lahoz, J.-L. Attié, V.-H. Peuch, R. L. Curier, D. P. Edwards, H. J. Eskes and P. J. H. Builtjes. 2015. Observing System Simulation Experiments for air quality. Atmospheric Environment 115:199-213. DOI.

Tippett, M. K., J. L. Anderson, C. H. Bishop, T. M. Hamill and J. S. Whitaker. 2003. Ensemble square root filters. Monthly Weather Review 131(7):1485-1490. DOI: 10.1175/1520-0493(2003)131<1485:Esrf>2.0.Co;2.

Tollefson, J. 2014. El Niño monitoring system in failure mode. Nature. DOI: 10.1038/nature.2014.14582.

Tompkins, A. M. and F. Di Giuseppe. 2015. Potential Predictability of Malaria in Africa Using ECMWF Monthly and Seasonal Climate Forecasts. Journal of Applied Meteorology and Climatology 54(3):521-540. DOI: 10.1175/Jamc-D-14-0156.1.

Toniazzo, T. and S. Woolnough. 2014. Development of warm SST errors in the southern tropical Atlantic in CMIP5 decadal hindcasts. Climate Dynamics 43(11):2889-2913. DOI: 10.1007/s00382-013-1691-2.

Treadon, R. E. 1996. Physical initialization in the NMC global data assimilation system. Meteorology and Atmospheric Physics 60(1-3):57-86. DOI: 10.1007/Bf01029786.

Trenberth, K. E., G. W. Branstator, D. Karoly, A. Kumar, N. C. Lau and C. Ropelewski. 1998. Progress during TOGA in understanding and modeling global teleconnections associated with tropical sea surface temperatures. Journal of Geophysical Research-Oceans 103(C7):14291-14324. DOI: 10.1029/97jc01444.

Trudinger, C., M. Raupach, P. Rayner and I. Enting. 2008. Using the Kalman filter for parameter estimation in biogeochemic models. Environmetrics 19(849-870). DOI: 10.1002/env.910.

Tsamados, M., D. L. Feltham and A. V. Wilchinsky. 2013. Impact of a new anisotropic rheology on simulations of Arctic sea ice. Journal of Geophysical Research-Oceans 118(1):91-107. DOI: 10.1029/2012jc007990.

Tseng, W. L., B. J. Tsuang, N. S. Keenlyside, H. H. Hsu and C. Y. Tu. 2015. Resolving the upper-ocean warm layer improves the simulation of the Madden-Julian oscillation. Climate Dynamics 44(5-6):1487-1503. DOI: 10.1007/s00382-014-2315-1.

Tsuyuki, T. 1997. Variational data assimilation in the tropics using precipitation data .3. Assimilation of SSM/I precipitation rates. Monthly Weather Review 125(7):1447-1464. DOI: Doi 10.1175/1520-0493(1997)125<1447:Vdaitt>2.0.Co;2.

U.S. Department of Commerce. 2014. Fostering Innovation, Creating Jobs, Driving Better Decisions: The Value of Government Data. Washington, DC: U.S. Department of Commerce, Economics and Statistics Administration.

Ueckermann, M. P., P. F. J. Lermusiaux and T. P. Sapsis. 2013. Numerical schemes for dynamically orthogonal equations of stochastic fluid and ocean flows. Journal of Computational Physics 233:272-294. DOI: 10.1016/j.jcp.2012.08.041.

Ueckermann, M. P. and P. F. J. Lermusiaux. 2016. Hybridizable discontinuous Galerkin projection methods for Navier-Stokes and Boussinesq equations. Journal of Computational Physics 306:390-421. DOI: 10.1016/j.jcp.2015.11.028.

Uppala, S. M., P. W. Kallberg, A. J. Simmons, U. Andrae, V. D. Bechtold, M. Fiorino, J. K. Gibson, J. Haseler, A. Hernandez, G. A. Kelly, X. Li, K. Onogi, S. Saarinen, N. Sokka, R. P. Allan, E. Andersson, K. Arpe, M. A. Balmaseda, A. C. M. Beljaars, L. Van De Berg, J. Bidlot, N. Bormann, S. Caires, F. Chevallier, A. Dethof, M. Dragosavac, M. Fisher, M. Fuentes, S. Hagemann, E. Holm, B. J. Hoskins, L. Isaksen, P. A. E. M. Janssen, R. Jenne, A. P. McNally, J. F. Mahfouf, J. J. Morcrette, N. A. Rayner, R. W. Saunders, P. Simon, A. Sterl, K. E. Trenberth, A. Untch, D. Vasiljevic, P. Viterbo and J. Woollen. 2005. The ERA-40 re-analysis. Quarterly Journal of the Royal Meteorological Society 131(612):2961-3012. DOI: 10.1256/qj.04.176.

US Navy Task Force Climate Change. 2014. The United States Navy Arctic Roadmap for 2014 to 2030. Washington, DC: US Navy.

USCG. 2013. U.S. Coast Guard Arctic Strategy. Washington, DC: USCG Headquarters.

USGCRP IGIM. 2015. Report of the First U.S. Climate Modeling Summit (USCMS), NOAA Center for Weather and Climate Prediction, College Park MD, April 26, 2015. Washington, DC: USGCRP.

Uttal, T., J. A. Curry, M. G. McPhee, D. K. Perovich, R. E. Moritz, J. A. Maslanik, P. S. Guest, H. L. Stern, J. A. Moore, R. Turenne, A. Heiberg, M. C. Serreze, D. P. Wylie, O. G. Persson, C. A. Paulson, C. Halle, J. H. Morison, P. A. Wheeler, A. Makshtas, H. Welch, M. D. Shupe, J. M. Intrieri, K. Stamnes, R. W. Lindsey, R. Pinkel, W. S. Pegau, T. P. Stanton and T. C. Grenfeld. 2002. Surface heat budget of the Arctic Ocean. Bulletin of the American Meteorological Society 83(2):255-275. DOI: 10.1175/1520-0477(2002)083<0255:Shbota>2.3.Co;2.

van Leeuwen, P. J. 2009. Particle Filtering in Geophysical Systems. Monthly Weather Review 137(12):4089-4114. DOI: 10.1175/2009mwr2835.1.

Vancoppenolle, M., K. M. Meiners, C. Michel, L. Bopp, F. Brabant, G. Carnat, B. Delille, D. Lannuzel, G. Madec, S. Moreau, J. L. Tison and P. van der Merwe. 2013. Role of sea ice in global biogeochemical cycles: emerging views and challenges. Quaternary Science Reviews 79:207-230. DOI: 10.1016/j.quascirev.2013.04.011.

Vecchi, G. A., M. Zhao, H. Wang, G. Villarini, A. Rosati, A. Kumar, I. M. Held and R. Gudgel. 2011. Statistical-Dynamical Predictions of Seasonal North Atlantic Hurricane Activity. Monthly Weather Review 139(4):1070-1082. DOI: 10.1175/2010MWR3499.1.

Vedda, J. A. 2011. Climate Change and National Security: Implications for Space Systems. Crosslink 12(2). DOI.

Vintzileos, A. and D. Behringer. 2008. On the importance of atmospheric and oceanic initial conditions for forecasting the MJO. Abstract #A52B-05. Presented at American Geophysical Union Fall Meeting, San Fransisco, CA.

Visbeck, M., E. P. Chassignet, R. G. Curry, T. L. Delworth, R. R. Dickson and G. Krahmann. 2003. The Ocean's Response to North Atlantic Oscillation Variability. In The North Atlantic Oscillation: Climatic Significance and Environmental Impact. Hurrell, J. W., Y. Kushnir, G. Ottersen and M. Visbeck, eds. Washington, D. C.: American Geophysical Union.

Vitart, F., M. R. Huddleston, M. Deque, D. Peake, T. N. Palmer, T. N. Stockdale, M. K. Davey, S. Ineson and A. Weisheimer. 2007a. Dynamically-based seasonal forecasts of Atlantic tropical storm activity issued in June by EUROSIP. Geophysical Research Letters 34(16). DOI: 10.1029/2007gl030740.

Vitart, F., S. Woolnough, M. A. Balmaseda and A. M. Tompkins. 2007b. Monthly forecast of the Madden-Julian oscillation using a coupled GCM. Monthly Weather Review 135(7):2700-2715. DOI: 10.1175/Mwr3415.1.

Vitart, F., R. Buizza, M. A. Balmaseda, G. Balsamo, J. R. Bidlot, A. Bonet, M. Fuentes, A. Hofstadler, F. Molteni and T. N. Palmer. 2008. The new VarEPS-monthly forecasting system: A first step towards seamless prediction. Quarterly Journal of the Royal Meteorological Society 134(636):1789-1799. DOI: 10.1002/qj.322.

Vitart, F. and T. Jung. 2010. Impact of the Northern Hemisphere extratropics on the skill in predicting the Madden Julian Oscillation. Geophysical Research Letters 37. DOI: 10.1029/2010gl045465.

Vitart, F. and F. Molteni. 2010. Simulation of the Madden-Julian Oscillation and its teleconnections in the ECMWF forecast system. Quarterly Journal of the Royal Meteorological Society 136(649):842-855. DOI: 10.1002/qj.623.

Vitart, F., A. W. Robertson and D. L. T. Anderson. 2012. Subseasonal to seasonal prediction project: Bridging the gap between weather and climate. WMO Bulletin 61(2):23-28. DOI.

Vitart, F. 2013. Evolution of ECMWF sub-seasonal forecast skill scores over the past 10 years. ECMWF Research Dept. Tech. Memo. 220. Available at http://old.ecmwf.int/publications/library/ecpublications/_pdf/tm/601-700/tm694.pdf, accessed September 2, 2015.

Vitart, F. 2014. Evolution of ECMWF sub-seasonal forecast skill scores. Quarterly Journal of the Royal Meteorological Society 140(683):1889-1899. DOI: 10.1002/Qj.2256.

Vitart, F., G. Balsamo, R. Buizza, L. Ferranti, S. Keeley, L. Magnusson, F. Molteni and A. Weisheimer. 2014. Sub-seasonal predictions. ECMWF technical memorandum no. 738. Reading, Berkshire, UK: European Centre for Medium-Range Weather Forecasts.

Waliser, D., K. Weickmann, R. Dole, S. Schubert, O. Alves, C. Jones, M. Newman, H. L. Pan, A. Roubicek, S. Saha, C. Smith, H. van den Dool, F. Vitart, M. Wheeler and J. Whitaker. 2006. The experimental MJO prediction project. Bulletin of the American Meteorological Society 87(4):425-431. DOI: 10.1175/Bams-87-4-425.

Waliser, D. E., R. Murtugudde, P. Strutton and J. L. Li. 2005. Subseasonal organization of ocean chlorophyll: Prospects for prediction based on the Madden-Julian Oscillation. Geophysical Research Letters 32(23). DOI: 10.1029/2005gl024300.

Waliser, D. E. 2011. Predictability and Forecasting. In Intraseasonal Variability of the Atmosphere-Ocean Climate System, 2nd Edition. Lau, W. K. M. and D. E. Waliser, eds. Heidelberg, Germany: Springer.

Waliser, D. E., M. W. Moncrieff, D. Burridge, A. H. Fink, D. Gochis, B. N. Goswami, B. Guan, P. Harr, J. Heming, H. H. Hsu, C. Jakob, M. Janiga, R. Johnson, S. Jones, P. Knippertz, J. Marengo, H. Nguyen, M. Pope, Y. Serra, C. Thorncroft, M. Wheeler, R. Wood and S. Yuter. 2012. The "Year" of Tropical Convection (May 2008-April 2010) Climate Variability and Weather Highlights. Bulletin of the American Meteorological Society 93(8):1189-1218. DOI: 10.1175/2011bams3095.1.

Walker, G. T. 1924. Correlation in seasonal variations of weather, IX. A further study of world weather. Memoirs of the India Meteorological Department 24(9):275-333. DOI.

Wallace, J. M. and D. S. Gutzler. 1981. Teleconnections in the Geopotential Height Field during the Northern Hemisphere Winter. Monthly Weather Review 109(4):784-812. DOI: 10.1175/1520-0493(1981)109<0784:Titghf>2.0.Co;2.

Wang, B., J. Y. Lee, I. S. Kang, J. Shukla, J. S. Kug, A. Kumar, J. Schemm, J. J. Luo, T. Yamagata and C. K. Park. 2008. How accurately do coupled climate models predict the leading modes of Asian-Australian monsoon interannual variability? Climate Dynamics 30(6):605-619. DOI: 10.1007/s00382-007-0310-5.

Wang, B., J. Y. Lee, I. S. Kang, J. Shukla, C. K. Park, A. Kumar, J. Schemm, S. Cocke, J. S. Kug, J. J. Luo, T. Zhou, B. Wang, X. Fu, W. T. Yun, O. Alves, E. K. Jin, J. Kinter, B. Kirtman, T. Krishnamurti, N. C. Lau, W. Lau, P. Liu, P. Pegion, T. Rosati, S. Schubert, W. Stern, M. Suarez and T. Yamagata. 2009a. Advance and prospectus of seasonal prediction: assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980-2004). Climate Dynamics 33(1):93-117. DOI: 10.1007/s00382-008-0460-0.

Wang, D., P. F. J. Lermusiaux, P. J. Haley, D. Eickstedt, W. G. Leslie and H. Schmidt. 2009b. Acoustically focused adaptive sampling and on-board routing for marine rapid environmental assessment. Journal of Marine Systems 78:S393-S407. DOI: 10.1016/j.jmarsys.2009.01.037.

Wang, Q., S. Danilov and J. Schroter. 2009c. Bottom water formation in the southern Weddell Sea and the influence of submarine ridges: Idealized numerical simulations. Ocean Modelling 28(1-3):50-59. DOI: 10.1016/j.ocemod.2008.08.003.

Wang, W., M. Chen and A. Kumar. 2013a. Seasonal Prediction of Arctic Sea Ice Extent from a Coupled Dynamical Forecast System. Monthly Weather Review 141(4):1375-1394. DOI: http://dx.doi.org/10.1175/MWR-D-12-00057.1.

Wang, X. G., D. Parrish, D. Kleist and J. Whitaker. 2013b. GSI 3DVar-Based Ensemble-Variational Hybrid Data Assimilation for NCEP Global Forecast System: Single-Resolution Experiments. Monthly Weather Review 141(11):4098-4117. DOI: 10.1175/Mwr-D-12-00141.1.

Weaver, S. J., W. Q. Wang, M. Y. Chen and A. Kumar. 2011. Representation of MJO Variability in the NCEP Climate Forecast System. Journal of Climate 24(17):4676-4694. DOI: 10.1175/2011JCLI4188.1.

Webster, P. J. and R. Lukas. 1992. TOGA COARE: The Coupled Ocean Atmosphere Response Experiment. Bulletin of the American Meteorological Society 73(9):1377-1416. DOI: 10.1175/1520-0477(1992)073<1377:Tctcor>2.0.Co;2.

Weigel, A. P., M. A. Liniger and C. Appenzeller. 2008. Can multi-model combination really enhance the prediction skill of probabilistic ensemble forecasts? Quarterly Journal of the Royal Meteorological Society 134(630):241-260. DOI: 10.1002/qj.210.

Weisheimer, A., F. J. Doblas-Reyes, T. N. Palmer, A. Alessandri, A. Arribas, M. Deque, N. Keenlyside, M. MacVean, A. Navarra and P. Rogel. 2009. ENSEMBLES: A new multi-model ensemble for seasonal-to-annual predictions-Skill and progress beyond DEMETER in forecasting tropical Pacific SSTs. Geophysical Research Letters 36. DOI: 10.1029/2009gl040896.

Weisheimer, A., T. N. Palmer and F. J. Doblas-Reyes. 2011. Assessment of representations of model uncertainty in monthly and seasonal forecast ensembles. Geophysical Research Letters 38. DOI: 10.1029/2011gl048123.

WGA. 2008. Water Needs and Strategies for a Sustainable Future: Next Steps Denver, CO: Western Governors' Association.

Wheeler, M. C. and H. H. Hendon. 2004. An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. Monthly Weather Review 132(8):1917-1932. DOI: 10.1175/1520-0493(2004)132<1917:Aarmmi>2.0.Co;2.

Whitaker, J. S. and T. M. Hamill. 2002. Ensemble data assimilation without perturbed observations. Monthly Weather Review 130(7):1913-1924. DOI: 10.1175/MWR3156.1.

WHO. 2001. Malaria early warning systems. Concepts, indicators and partners. A framework for field research in Africa. WHO/CDS/RBM 2001.32. Geneva: World Health Organization.

WHO. 2015. World Malaria Report 2015. Geneva: WHO/ UNICEF.

Wiener, N. 1958. Nonlinear problems in random theory. New York: MIT Technology Press and John Wiley and Sons.

Wilkie, T. 2015. Exascale: expect poor performance. Scientific Computing World. DOI.

WMO. 2013. Sub-Seasonal to Seasonal Prediction Research Implementation Plan. Geneva: World Meteorological Organization.

WMO. 2015a. Seamless prediction of the earth system: From minutes to months. World Weather Open Science Conference, August 16-21, 2014, Montréal, Canada. Geneva: World Meteorological Organization.

WMO. 2015b. Seventeenth World Meteorological Congress: Abridged final report with resolutions. Geneva: WMO. Available at http://library.wmo.int/opac/index.php?lvl=notice_display&id=18648#.VrNwC7IrKWh, accessed February 4, 2016.

Wood, R., C. R. Mechoso, C. S. Bretherton, R. A. Weller, B. Huebert, F. Straneo, B. A. Albrecht, H. Coe, G. Allen, G. Vaughan, P. Daum, C. Fairall, D. Chand, L. G. Klenner, R. Garreaud, C. Grados, D. S. Covert, T. S. Bates, R. Krejci, L. M. Russell, S. de Szoeke, A. Brewer, S. E. Yuter, S. R. Springston, A. Chaigneau, T. Toniazzo, P. Minnis, R. Palikonda, S. J. Abel, W. O. J. Brown, S. Williams, J. Fochesatto, J. Brioude and K. N. Bower. 2011. The VAMOS Ocean-Cloud-Atmosphere-Land Study Regional Experiment (VOCALS-REx): goals, platforms, and field operations. Atmospheric Chemistry and Physics 11(2):627-654. DOI: 10.5194/acp-11-627-2011.

Woollings, T., B. Hoskins, M. Blackburn and P. Berrisford. 2008. A new Rossby wave-breaking interpretation of the North Atlantic Oscillation. Journal of the Atmospheric Sciences 65(2):609-626. DOI: 10.1175/2007JAS2347.1.

World Bank. 2013. Building Resilience: Integrating climate and disaster risk into development. Lessons from World Bank Group experience. Washington, DC: The World Bank.

Wunsch, C. 1996. The Ocean Circulation Inverse Problem. Cambridge, UK: Cambridge University Press.

Wunsch, C. and P. Heimbach. 2013. Dynamically and kinematically consistent global ocean circulation and ice state estimates. In Ocean Circulation and Climate: A 21st century perspective. 2nd Edition. Siedler, G., S. Griffies, J. Gould and J. Church, eds. Dordrecht: Springer.

Xiu, D. 2010. Numerical Methods for Stochastic Computations: A Spectral Method Approach. Princeton, NJ: Princeton University Press.

Xiu, D. B. and G. E. Karniadakis. 2002. The Wiener-Askey polynomial chaos for stochastic differential equations. Siam Journal on Scientific Computing 24(2):619-644. DOI: 10.1137/S1064827501387826.

Xu, J. H., H. Shu and L. Dong. 2014. DEnKF-Variational Hybrid Snow Cover Fraction Data Assimilation for Improving Snow Simulations with the Common Land Model. Remote Sensing 6(11):10612-10635. DOI: 10.3390/rs61110612.

Yao, W. Q., H. Lin and J. Derome. 2011. Submonthly Forecasting of Winter Surface Air Temperature in North America Based on Organized Tropical Convection. Atmosphere-Ocean 49(1):51-60. DOI: 10.1080/07055900.2011.556882.

Yuan, X., E. F. Wood and Z. Ma. 2015. A review on climate-model-based seasonal hydrologic forecasting: physical understanding and system development. Wiley Interdisciplinary Reviews: Water 2(5):523–536. DOI: 10.1002/wat2.1088.

Yuh, J. 2000. Design and control of autonomous underwater robots: A survey. Autonomous Robots 8(1):7-24. DOI: 10.1023/A:1008984701078.

Zhang, C. D. 2005. Madden-Julian oscillation. Reviews of Geophysics 43(2). DOI: 10.1029/2004rg000158.

Zhang, C. D. 2013. Madden-Julian Oscillation Bridging Weather and Climate. Bulletin of the American Meteorological Society 94(12):1849-1870. DOI: 10.1175/Bams-D-12-00026.1.

Zhang, F., D. M. Fratantoni, D. A. Paley, J. M. Lund and N. E. Leonard. 2007. Control of coordinated patterns for ocean sampling. International Journal of Control 80(7):1186-1199. DOI: 10.1080/00207170701222947.

Zhang, X. F., S. Q. Zhang, Z. Y. Liu, X. R. Wu and G. J. Han. 2015. Parameter Optimization in an Intermediate Coupled Climate Model with Biased Physics. Journal of Climate 28(3):1227-1247. DOI: 10.1175/Jcli-D-14-00348.1.

Zhang, Y., J. M. Wallace and D. S. Battisti. 1997. ENSO-like interdecadal variability: 1900-93. Journal of Climate 10(5):1004-1020. DOI: 10.1175/1520-0442(1997)010<1004:Eliv>2.0.Co;2.

Zhang, Y. F., T. J. Hoar, Z. L. Yang, J. L. Anderson, A. M. Toure and M. Rodell. 2014. Assimilation of MODIS snow cover through the Data Assimilation Research Testbed and the Community Land Model version 4. Journal of Geophysical Research-Atmospheres 119(12):7091-7103. DOI: 10.1002/2013JD021329.

Zwiefelhofer, W. 2008. Trends in High-Performance Computing. Presented at World Modelling Summit for Climate Prediction, May 6-9, 2008, Reading, UK.

Zwiers, F. W. 1996. Interannual variability and predictability in an ensemble of AMIP climate simulations conducted with the CCC GCM2. Climate Dynamics 12(12):825-847. DOI: 10.1007/s003820050146.

Appendix A: Committee's Statement of Task

An ad hoc committee will conduct a study that will identify opportunities to increase forecasting skill on subseasonal to seasonal (S2S) timescales based on the 2010 NRC report Assessment of Intraseasonal to Interannual Climate Prediction and Predictability and progress since. The report will describe a strategy to increase the nation's scientific capability for research on S2S forecasting. The committee will develop a 10 year scientific research agenda to accelerate progress on extending prediction skill for weather and ocean forecasts from currently operational meso/synoptic scales to higher spatial and longer temporal resolutions to aid in decision making at medium and extended lead times. The committee's report will cover:

- Identification of potential sources of predictability and assessment of their relative value for advancing predictive skill;
- Identification of process studies for incorporating new sources of predictability into models;
- Application and advancement of ocean-atmosphere-ice-land coupled models;
- Key observations needed for model initialization and verification of S2S forecasts;
- Uncertainty quantification and verification of probabilistic products;
- Approaches to communicating this type of prediction in a way that is useful to and understandable by decision makers; and
- Computational and data storage and visualization infrastructure requirements.

Appendix B: Details of Seasonal and Subseasonal Forecast Systems

EXAMPLES OF MODELS USED BY OPERATIONAL CENTERS FOR SUBSEASONAL AND SEASONAL FORECASTING

At the National Centers for Environmental Prediction (NCEP), the Climate Forecasting System version 2 (CFSv2) is currently used for both the subseasonal and seasonal predictions. CFSv2 is a fully coupled model representing the interaction between the Earth's atmosphere, oceans, land, and sea ice (Saha et al., 2014). It became operational at NCEP in March 2011. The atmospheric model has a horizontal resolution of T126 (about 100 km) and 64 vertical levels. The ocean component is the Modular Ocean Model developed by the Geophysical Fluid Dynamics Laboratory (GFDL) with 0.5 to 0.25 degree resolution and 40 vertical levels, with interactive sea ice model. For the subseasonal forecast (defined by NCEP as days 0-45), 16 members are run every day (4 members run four times a day at 00Z, 06Z, 12Z and 18Z). The retrospective forecasts are done from 1999 to 2010, four members a day. For the seasonal forecast (defined by NCEP as months 0-9), four runs per day are performed. The retrospective forecasts are constructed with four members run every fifth day for the past 29 years (1982-2010).

The European Centre for Medium-Range Weather Forecasting (ECMWF) utilizes two different systems for the subseasonal and seasonal predictions. The operational seasonal forecasting system, known as System 4, was implemented in 2011. The atmospheric model is the ECMWF Integrated Forecast System (IFS) model frozen version 36r4. It has a horizontal resolution of TL255 (~60km) and 91 vertical levels. The ocean component is from the Nucleus for European Modeling of the Ocean (NEMO), with the ORCA1 configuration, which has a 1x1 degree resolution in mid-latitudes and enhanced meridional resolution near the equator. The retrospective forecast is done from 1981 to 2010 for 15 members for 7 months initialized with ECMWF Interim Reanalysis (ERA Interim) on the 1st day of each month. The seasonal forecasts consist of a 51-member ensemble. The ensemble is constructed by combining the 5-member ensemble ocean analysis with SST perturbations and the activation of stochastic physics. The forecasts have an initial date of the 1st of each month, and run for 7 months. For the subseasonal prediction, ECMWF's monthly forecasting system is used. The atmospheric model is the same version as ECMWF's deterministic forecast. The atmospheric model is run at TL639 resolution from day 0 to day 10 and at T319 from day 10 to 32 with 62 vertical levels. The ocean component is also NEMO with the ORCA1 configuration. 51 members run to 46 days twice a week (Monday and Thursday at 00Z). The ocean and atmosphere models are fully coupled, and the retrospective forecasts are constructed with 11 members run at the same day and month as the Thursday real time forecast over the past 20 years.

Additional details about these and other operational seasonal forecast systems are shown in Table B.1, and Table B.2 provides similar information for subseasonal systems.

TABLE B.1 Forecast and retrospective forecast system characteristics of the 12 Global Prediction Centers (GPC) of the WMO. SOURCE: Adapted from the S2S Research Implementation Plan and http://www.wmo.int/pages/prog/wcp/wcasp/gpc/gpc.php (accessed January 27, 2016).

	Time range	Model	Resolution	Coupled	Ensemble Size	Frequency	Reforecast length	Reforecast frequency	Reforecast size
BoM	m 0-9	POAMA	T47L17	yes	33	2/week	1981-2010	6/month	33
CMA	m 0-3	BCC-CM1	T63L16	yes	48	1/month	1982-now	1/month	6
EC	m 0-12	CanSIPS	T63L35	yes	20	1/month	1981-2010	1/month	20
ECMWF	m 0-7/12	System4	T255L91	yes	51	1/month	1981-2010	1/month	15
HMCR	m 0-4	SL-AV	1.1x1.4L28	no	20	1/month	1981-2010	1/month	10
JMA	m 0-3/6	JMA/MRI-CPS2	TL150L60	yes	51	1/month	1979-2010	2/month	5
KMA	m 0-3/6	GDAPS	T106L21	no	20	1/month	1979-2010	1/month	20
Météo-France	m 0-7	ARPEGE	T63L31	yes	41	1/month	1993-2003	1/month	5
NCEP	m 0-9	CFSv2	T126L64	yes	40	1/month	1982-2010	1/month	24
UKMO	m 0-6	GloSea5	N216L85	yes	42	1/week	1996-2009	4/month	12
CPTEC	m 0-7	CPTEC AGCM	T62L28	no	15	1/month	1979-2001	1/month	10
SAWS	m 0-5	ECHAM4.5	T42L19	no	6	1/month	1981-2001	1/month	6

TABLE B.**2** Forecast and retrospective forecast system characteristics for subseasonal forecasting systems from operational centers participating in the WCRP-WWRP Subseasonal to Seasonal Prediction Project. SOURCE: Adapted from s2sprediction.net and https://software.ecmwf.int/wiki/display/S2S/Models, both accessed January 27, 2016.

	Time range	**Resolution**	**Ensemble Size**	**Frequency**	**Reforecasts**	**Reforecast length**	**Reforecast frequency**	**Reforecast size**
BoM (ammc)	d 0-60	T47L17	33	2/week	fix	1981-2013	6/month	33
CMA (babj)	d 0-60	T106L40	4	daily	fix	1994-2014	daily	4
EC (cwao)	d 0-32	0.6x0.6 L40	21	weekly	on the fly	1995-2012	weekly	4
ECMWF (ecmf)	d 0-46	T639/319 L62	51	2/week	on the fly	past 20 years	2/week	11
HMCR (rums)	d 0-63	1.1x1.4 L28	20	weekly	fix	1985-2010	weekly	10
ISAC-CNR (isac)	d 0-32	0.75x0.56 L54	40	weekly	fix	1981-2010	6/month	1
JMA (rjtd)	d 0-34	T319L60	25	2/week	fix	1981-2010	3/month	5
KMA (rksl)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3
Météo-France (lfpw)	d 0-61	T255L91	51	monthly	fix	1993-2014	2/monthly	15
NCEP (kwbc)	d 0-44	T126L64	16	daily	fix	1999-2010	day	4
UKMO (egrr)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3

Appendix C: Past, Current and Planned Major International Process Studies

PAST PROCESS STUDIES

GATE (GARP51 Atlantic Tropical Experiment)—GATE was the first major international field experiment in the tropics with the purpose to understand the tropical atmosphere and its role in the global circulation of the atmosphere and the predictability of the atmosphere in the time range of daily weather forecasts to over two weeks. It took place in the summer of 1974 over the tropical Atlantic Ocean from Africa to South America. Twenty countries participated in GATE with 40 research ships, 12 research aircraft, and numerous buoys. These data are still being used today in research. Over a thousand papers have been published based on the GATE data. A major breakthrough of GATE is the recognition of organized mesoscale convective systems as the main sources of precipitation and convective energy in the tropics. Among others, the GATE soundings have been used as a golden standard in the development of cumulus parameterization in weather and climate models.

TOGA COARE (Tropical Ocean Global Atmosphere Coupled Ocean-Atmosphere Response Experiment) — TOGA COARE was the second major international field campaign in the tropics. Its goal was to describe and understand the principal processes responsible for the coupling and multi-scale variability of the ocean and atmosphere in the western Pacific and their interaction with other regions. The field experiment took place over the western Pacific during November 1992 through February 1993. Eighteen countries participated in TOGA CAORE with 12 ships 7 airplanes, and more than 40 moorings. Close to a thousand papers have been published that are related to TOGA COARE. Among many of its outcomes, the one that contribute most significantly to model improvement is the COARE flux algorithm that is recognized as the best flux scheme that can be used in models and observational diagnostics.

VOCAL-REx (The VAMOS[52] Ocean-Cloud-Atmosphere-Land Study Regional Experiment) — VOCAL-REx is another example of multi-nation collaboration to address interactive processes of different components of the Earth system. It objectives are to understand links between aerosols, clouds and precipitation and their impacts on marine stratocumulus radiative properties, and physical and chemical couplings between the upper ocean and the lower atmosphere, including the role of mesoscale ocean eddies. It took place during October and November 2008 on and off shore of Chile. Eight countries participated in the field experiment with 5 research aircraft, 2 ships and 2 surface sites in northern Chile. A major breakthrough of VOCAL-REx is the understanding of the strong role aerosol-cloud-precipitation coupling plays in marine low clouds, which had previously been thought as controlled mainly by dynamics. Data collected by VOCAL-REx have played crucial roles in developing and refining new parameterization schemes that are used in regional and global models.

SHEBA (The Surface Heat Budget of the Arctic Ocean)-SHEBA is an international research program designed to document, understand, and predict the physical processes that

[51] Global Atmosphere Research Program
[52] Variability of the American Monsoon Systems

determine the surface energy budget and the sea-ice mass balance in the Arctic. Its overall goal is to acquire the measurements needed to improve the parameterizations of key processes and to integrate new and improved parameterizations into general circulation and climate models. Scientists from 7 countries participated in SHEBA. The SHEBA field experiment was a yearlong (2 October 1997-12 October 1998) measurement on a drifting station in the pack ice of the Arctic Ocean. The drift station made measurement of the vertical column of the ocean, sea ice, and the atmosphere. It was augmented by a buoy array, research aircraft, helicopter surveys, and submarine transects on a larger scale. SHEBA data provide up to date the first and only annual cycle of the surface energy budget for multi-year Artic ice. They helped improve understanding of many processes critical to the surface energy balance and variability, including supercooled liquid water and advective events from lower latitudes. Knowledge gained from SHEBA data have led to new and improved parameterization of melt ponds, cloud microphysics, and turbulence.

AMMA (The African Monsoon Multidisciplinary Analysis) — AMMA is an international project with an objective of improving our knowledge and understanding of the West African monsoon, as well as the environmental and socio-economic impacts of its variability. It is the biggest program of research on environment and climate issues in Africa. AMMA involved a comprehensive field experiment including ocean, land and atmospheric measurements in many West African nations and their adjacent seas, on hourly, daily and up to seasonal timescales over a number of years. The field campaign consisted of a long-term monitoring program (2001-2009) based on the existing infrastructure, an Enhanced Observing Period (2005-2007) with specific land-based and sea-based instruments, and four Special Observing Periods in 2006 with intensive measurements from the surface (continent-based and ocean-based) and from the air (research aircraft and balloons) that monitored the pre-monsoon dry season, as well as the onset, peak, and decay of the monsoon. Data collected by the AMMA field campaign have greatly advanced our knowledge on coupling between the atmosphere, land and ocean, and between dynamics, physics, chemistry, biology, and hydrology. These data have also been used in validation and development of global and regional climate and weather models and specific process models (Lebel et al., 2010).

AMY (Asian Monsoon Year)-AMY was a cross-cutting coordinated observation and modeling initiative participated by more than twenty countries. The objectives of AMY are to enhance understanding of ocean-land-atmosphere-biosphere interactions, multiple timescale (from diurnal to intra-seasonal) interaction, and the aerosol-water cycle interaction in the Asian monsoon system, in order to improve their physical representations in coupled climate models, and to develop data assimilation for the ocean-atmosphere-land system in the Asian monsoon region. Its majority of field observations took place during 2008-2010, with 23 field campaigns throughout the Asian monsoon region in four targeted periods: the pre-monsoon period in March-May, the monsoon onset phase in May-June; the monsoon mature phase in July-August; and the winter monsoon from December to February. Among many results, AMY data have revealed how the diurnal cycle, intraseasonal oscillation, and monsoon flow interact to general extreme rainfall that led to flood events with tremendous socioeconomic impacts.

DYNAMO (Dynamics of the Madden-Julian Oscillation) — DYNAMO was the most recent international field campaign aiming at the tropical atmosphere-ocean system. Its overall goal was to improve understanding the processes key to MJO initiation. Based on its three main hypotheses on the roles of convection-environment interaction, evolution of cloud population, and air-sea interaction, DYNAMO's intensive sounding and radar arrays over the central equatorial Indian Ocean collected data from October 2011 to February 2012 and its broad sounding network continued data collection until March 2012. Sixteen countries participated in DYNAMO with four research vessels, 2 airplanes, 5 special ground stations, and several sites of enhanced radiosondes. While DYNAMO data are still being analyzed, initial results have revealed new findings in regime change of aerosol and evolution of cloud microphysics through the MJO life cycle, interaction between the MJO and ITCZ, and ocean memory of MJO forcing through mixing related to prolonged vertical current shear, among others. DYNAMO data have been used in testing parameterization of cloud microphysics and convective cold pools and in helping validate numerical models of the atmosphere and ocean of different configurations and complexities.

CURRENT AND FUTURE PROCESS STUDIES

YOPP (The Year of Polar Prediction) — YOPP (mid-2017 to mid-2019) is an international program that coordinates a period of intensive observing, modeling, verification, user-engagement and education activities for the purpose of enabling a significant improvement in environmental prediction capabilities for the polar regions and beyond on a wide range of timescales. The observational component of YOPP is built upon several elements. A major one is MOSAiC (Multidisciplinary drifting Observatory for the Study of Arctic Climate), which will deploy a polar research vessel starting in newly formed Arctic sea ice around September 2018, and drifting with the ice over the course of a year, to study a full annual cycle of coupled atmosphere-ice-ocean-biogeochemical system processes. Other observational activities will include intensive observing periods (IOPs) during which aircraft flights and other research vessels will be deployed. In addition, land-based stations as part of the Sustaining Arctic Observing Network (SAON) provide numerous observations of Arctic system through staffed observatories and autonomous instruments. Many model experiments on a hierarchy of scales will be conducted, aimed at understanding and improving model predictability. Many countries will participate in the YOPP field observations.

SOCRATES (Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study)-SOCRATES is another on-going international field experiment, which will take place in 2016 -2019 in a region where numerical models perform particularly poorly. Its primary objective is to collect a data set suitable to study interactions between microphysics dynamics and radiation in mixed-phase and supercooled clouds. It includes four themes: Synoptically varying vertical structure of boundary layers and clouds, Seasonal and synoptic variability in cloud condensation and ice nucleus concentration and the role of local biogenic sources, Supercooled liquid and mixed-phase clouds, and Satellite retrievals related to clouds, precipitation, and aerosols. Five countries participate will in its field observations aboard ships (July -September 2017 and January -March 2018), airplanes and pilotless aircraft (January -March 2018), ground stations (several IOPs during 2016 -2019), and moorings (January 2016 -December 2019). SOCRATES observations will be used to advance our understanding of the variability of Southern Ocean cloud systems on a broad scale and their underpinning processes, such as aerosol physicochemical properties, aerosol-cloud-precipitation interactions, and to reduce model biases in this region.

YMC (Years of the Maritime Continent) — YMC is a two-year (planned for mid-2017 -mid-2019) international project with its goal of "observing the weather-climate system of the

Earth's largest archipelago to improve understanding and prediction of its local variability and global impact". There are five YMC science themes: Atmospheric Convection, Upper-Ocean Processes and Air-Sea Interaction, Stratosphere-Troposphere Interaction, Aerosol, and Prediction Improvement. YMC will engage in five main activities: Data Sharing, Field Campaigns, Modeling, Prediction and Applications, and Outreach and Capacity Building. Scientists from 13 countries are participating in the planning of YMC. The platform for the YMC field experiment will include numerous research vessels, airplanes, suites of ground facilities, mobile radars, and oceanic autonomous devices and moorings. These special instruments will be augmented by the regional observing networks of radars, radiosondes, surface meteorological and climatological observations, and marine stations. Cloud-permitting data assimilation products will be made to synthesize data to be collected by the field experiment and the observing networks. YMC data will be used to test and evaluate parameterization schemes in climate models, which have suffered from several severe biases in the Maritime Continent region.

Process Study for the Marginal Ice Zone (MIZ)-The MIZ refers to the region near the sea ice edge where sea ice concentrations are low and floes are small enough to permit the influx of ocean waves. The MIZ is widest in late summer, and the summertime width in the Arctic has broadened significantly in recent decades (Strong and Rigor, 2013). The Office of Naval Research (ONR) is already conducting a five-year study of the Arctic MIZ that began in 2012, with project web site[53] and science and experimental plan (Lee et al., 2012). The project has an extensive observational component that extensively utilizes autonomous sampling with sea gliders and acoustically tracked floats, both of which can measure under sea ice. An array of buoys measures wave heights and ice mass balance. A goal of the project is to improve estimates of wave-floe interactions and develop methods of modeling the sea ice floe size distributions. Three models are taking part in the project. All three are Arctic regional models, and only one has an atmosphere component (the other two are ocean-sea ice only). One of the ocean-sea ice only modeling groups is undertaking the development of floe size distribution capability (Zhang et al., 2015). The other two are specializing in fine resolution (up to 1/12 degree).

[53] http://www.apl.washington.edu/project/project.php?id=miz, accessed January 27, 2016.

Appendix D: Committee Bios

Mr. Raymond J. Ban (Chair) is retired Executive Vice President of Programming, Operations and Meteorology at The Weather Channel, Inc. (TWC). Currently, he serves as Consultant for Weather Industry and Government Partnerships, responsible for growing TWC relationships with the atmospheric science community across the entire weather and climate enterprise. He is currently President of Ban and Associates, LLC, providing consultative services to the weather media industry and also a guest lecturer in the Meteorology Department at Penn State University where he teaches one month each semester in the Weather Communications Program. He has served on the Board on Atmospheric Sciences and Climate of the National Academy of Sciences, and was Chair of the Academy Committee on Effective Communication of Uncertainty in Weather and Climate Forecasts and most recently as Chair of the NOAA Science Advisory Board. Currently, he is active on several Boards and Committees including Co-Chair of the Weather Coalition, a member of the Board of Directors of the National Environmental Education Foundation and a member of the Advisory Council to The National Center for Atmospheric Research. He earned his B.S. in Meteorology from The Pennsylvania State University in 1973.

Dr. Cecilia Bitz is a Professor in the Atmospheric Sciences Department at the University of Washington. Her research interests include climate dynamics, polar climate predictability, climate change, paleoclimate, the role of sea ice in the climate system, and sea ice model development. The primary tools for her research are a variety of models, from simple reduced models to sophisticated climate system models. Dr. Bitz is co-lead of the new Polar Climate Predictability Initiative of the World Climate Research Program and co-PI on the Sea Ice Prediction Network. Dr Bitz is an active participant in the Community Earth System Model project,, which is sponsored by the National Science Foundation and Department of Energy. She received her Ph.D. in Atmospheric Sciences from the University of Washington in 1997.

Dr. Andy Brown is the Director of Science at the UK Met Office. He works with the Chief Scientist on the development and implementation of the Science Strategy. He has particular responsibilities for the Foundation Science area, which provides the underpinning science and modelling capabilities that support Met Office weather and climate services. Dr. Brown joined the Met Office in 1990 and has worked in a number of roles in science aimed at improving our understanding of the atmosphere and improving its representation in the Unified Model used for weather and climate prediction. Additionally he has undertaken a secondment to the European Centre for Medium-Range Weather Forecasts (ECMWF). He has been active in international science coordination through involvement with the World Meteorological Organization and for 5 years was co-chair of the World Climate Research Programme / Commission for Atmospheric Sciences Working Group on Numerical Experimentation (WGNE).

Dr. Eric Chassignet is a Professor and Director of the Center for Ocean-Atmospheric Prediction Studies at Florida State University. His current area of research interest is on the role of the ocean in climate variability from the complementary perspectives of coupled ocean-atmosphere modeling and observations. Dr. Chassignet's emphasis is on the study of the thermohaline circulation, western boundary currents, associated eddies and their impact on the world ocean circulation. Dr. Chassignet earned his Ph.D. in Physical Oceanography from the University of Miami.

Dr. John A. Dutton is President of Prescient Weather, Ltd., a firm providing information and strategies for managing weather and climate risk, and is chief executive of the World Climate Service, a commercial seasonal forecasting enterprise. He is professor emeritus of meteorology and dean emeritus of the College of Earth and Mineral Sciences at The Pennsylvania State University. Dr. Dutton holds B.S., M.S. and Ph.D. degrees from the University of Wisconsin—Madison and served for three years as an officer in the Air Weather Service of the U.S. Air Force. He is a fellow of the American Meteorological Society (AMS) and the American Association for the Advancement of Science and is the author of a variety of articles on the dynamics of atmospheric motion as well as two text books: Dynamics of Atmospheric Motion (Dover, originally The Ceaseless Wind) and Atmospheric Turbulence (with Hans Panofsky). Dr. Dutton has been active in the AMS, the University Corporation for Atmospheric Research, and in National Academy of Science studies related to atmospheric science, space science, and aviation. He chaired the National Research Council (NRC) Board on Atmospheric Sciences and Climate while it produced The Atmospheric Sciences Entering the Twenty-First Century and most recently chaired an NRC committee that produced a report For Greener Skies—Reducing the Environmental Impacts of Aviation. Dr. Dutton also served on an NRC committee that examined the potential of high-end computing for the atmospheric and other sciences. Earlier, he was the principal author of an award-winning NRC report Weather for Those Who Fly. He is a recent member of the Climate Working Group of the Science Advisory Board of the U.S. National Oceanographic and Atmospheric Administration (NOAA) and co-chaired a task force that produced a recent report, A Vision and a Model for NOAA and Private Sector Collaboration in a National Climate Services Enterprise. In recent years, he has been a member of the community-based committee reviewing and advising on the operations of the National Centers for Environmental Prediction (NCEP) of the U.S. National Weather Service. Dr. Dutton and his wife Elizabeth reside in Boalsburg, PA. Dr. Dutton is a licensed commercial pilot with multi-engine and instrument ratings.

Dr. Robert Hallberg is an Oceanographer and the Head of the Oceans and Ice-sheet Processes and Climate Group at NOAA's Geophysical Fluid Dynamics Laboratory, and a Lecturer on the faculty of Princeton University. He has a 1995 Ph.D. in Oceanography from the University of Washington and a 1990 B.A. in Physics from the University of Chicago. He has spent many years developing isopycnal (density) coordinate ocean models to the point where they now are valuable tools for coupled climate studies, including extensive work on the robustness of the models' numerical techniques, and on the development or incorporation of parameterizations of a wide range of physical processes. The isopycnal coordinate ocean model that Dr. Hallberg developed provides the physical ocean component of GFDL's ESM2G comprehensive Earth System Model, which was used in the IPCC 5th Assessment Report, and its dynamic core is the basis for version 6 of the Modular Ocean Model (MOM6). Dr. Hallberg has used global-scale numerical ocean simulations to study topics as varied as the dynamics of Southern Ocean eddies and their role in the ocean's response to climate, sources of steric sea level rise, and the fate of the deep plumes of methane and oil from the Deepwater Horizon oil spill. Dr. Hallberg has been actively involved in three ocean Climate Process Teams, studying Gravity Current Entrainment, Eddy-Mixed Layer Interactions, and Internal Wave Driven Mixing. These teams aim to improve the representation of these processes in climate-scale models, based on the best understanding that can be obtained from observations, process studies, and theory. He is currently working on coupling a dynamic ice-sheet and ice-shelf model with high resolution versions of GFDL's coupled climate models for improved prediction of sea-level rise, and is leading the effort to modernize GFDL's sea ice model.

Ms. Anke Kamrath is director of Computing Operations and Services in NCAR's Computational and Information Systems Laboratory. She came to NCAR in 2009 after 22 years at the San Diego Supercomputer Center at the University of California, San Diego. Ms. Kamrath has over 27 years of experience in supporting, operating, deploying and managing world-class supercomputing resources in support of scientific research. She has oversight responsibilities for the NCAR-Wyoming Supercomputing Center, all supercomputing operations and for all computing systems, operational and services staff. Prior to her experience in supercomputing, she worked as a rocket scientist at the Aerospace Corporation in El Segundo, California and has a M.S. in Mechanical Engineering from U.C. Berkeley.

Dr. Daryl T. Kleist is an Assistant Professor at the University of Maryland. His research interests include data assimilation, numerical weather prediction, atmospheric predictability, targeted observing, data thinning and forecast sensitivity. His data assimilation research has primarily focused on improving initial conditions through algorithm development for operational numerical weather prediction for short- and medium-range timescales. Most recently, he has worked on developing and testing a hybrid ensemble-variational (EnVar) algorithm with an extension to four dimensions that does not require the use of an adjoint model. Before joining the faculty at Maryland, Dr. Kleist spent more than ten years working at the National Centers for Environmental Prediction (NCEP) Environmental Modeling Center as a member of the data assimilation team and within the global climate and weather modeling branch. There, he worked on various aspects of the operational data assimilation system for the global forecast system. Prior to leaving NCEP, he was leading the effort on the testing and development of the 4D EnVar algorithm for operational implementation in the global data assimilation system. Dr. Kleist earned his Ph.D. in Atmospheric and Oceanic Science from the University of Maryland.

Dr. Pierre F.J. Lermusiaux is an Associate Professor of Mechanical Engineering and Ocean Science and Engineering at Massachusetts Institute of Technology (MIT). He has made outstanding contributions in the fields of data assimilation, ocean modeling, and uncertainty predictions. His research thrusts include understanding and modeling complex physical and interdisciplinary oceanic dynamics and processes. With his group, he creates, develops, and utilizes new mathematical models and computational methods for ocean predictions and dynamical diagnostics, for optimization and control of autonomous ocean systems, for uncertainty quantification and prediction, and for data assimilation and data-model comparisons. He has participated in many national and international sea exercises. He received a Fulbright Foundation Fellowship, the Wallace Prize at Harvard (1993), and the Ogilvie Young Investigator Lecture in Ocean Engineering at MIT (1998). He was awarded the MIT Doherty Chair in Ocean Utilization (2009-2011) and the 2010 Ruth and Joel Spira Award for Distinguished Teaching by the School of Eng. at MIT.

Dr. Hai Lin is a Senior Research Scientist at Environment and Climate Change Canada. He is also an adjunct professor at McGill University, and Editor-in-Chief of Atmosphere-Ocean. His research interests include climate dynamics and numerical weather prediction. He was the recipient of the 2010 President's Prize of the Canadian Meteorological and Oceanographic Society. He is a member of the Steering Group for Subseasonal to Seasonal Prediction of the World Weather Research Programme (WWRP) and World Climate Research Programme (WCRP) of the World Meteorological Organization (WMO). He earned his Ph.D. in Atmospheric and Oceanic Sciences at McGill University.

Dr. Laura Myers is a Senior Research Social Scientist and Deputy Director, Center for Advanced Public Safety, at The University of Alabama. Her research, publication and training areas include disaster management and planning, weather enterprise application research, criminal justice education, criminal courts, criminal justice ethics, and criminal justice administration. Dr. Myers has received over $600,000 in Department of Homeland Security grants to develop and create a model for regional emergency planning, with emphasis on the social science aspects of partnership planning between the National Weather Service and their weather enterprise partners including emergency management, broadcast meteorology, and end users of their products. Through these grants, Dr. Myers works with the National Weather Service providing social science research for severe weather warning improvement and risk communication projects. Dr. Myers earned her Ph.D. in Criminology from Florida State University.

Dr. Julie Pullen is an Associate Professor in Ocean Engineering at Stevens Institute of Technology. She uses high-resolution coupled ocean-atmosphere modeling in order to understand and forecast the dynamics of coastal urban regions throughout the world. Her research interests encompass the ocean response to atmospheric flows around island topography, as well as sea breeze interactions with city morphology during heat waves. Applications include predicting chemical, biological, radiological and nuclear (CBRN) dispersion in coastal cities in the event of a terrorist or accidental release. She has served on the steering team for field studies in urban air dispersion (DHS/DTRA NYC Urban Dispersion Program) and archipelago oceanography (ONR Philippines Straits Dynamics Experiment). She is a member of the international GODAE Coastal Ocean and Shelf Seas Task Team and is the physical oceanography councilor for The Oceanography Society. Dr. Pullen earned her Ph.D. in Physical Oceanography at Oregon State University and did postdoctoral work at the Naval Research Laboratory's Marine Meteorology Division. She is an Adjunct Research Scientist at Columbia's Lamont Doherty Earth Observatory.

Dr. Scott Sandgathe is a Senior Principal Meteorologist in the Applied Physics Laboratory at the University of Washington and an Adjunct Research Scientist at Oregon State University. He has extensive experience in operational oceanography and meteorology including tropical meteorology, synoptic analysis and forecasting, and numerical weather prediction. He is a retired Navy Commander and has served as the Deputy Director of the Joint Typhoon Warning Center and onboard the USS Carl Vinson supporting battle group operations including meteorological and oceanographic support. In addition, he has held a number of positions in research policy and planning in the Navy. Prior to joining the Applied Physics Laboratory at the University of Washington, he was the Team Leader for the Office of Naval Research Marine Meteorology and

Atmospheric Effects Program where he supported research and technology development. He served as the DoD working group member on the Federal Coordinating Committee on Science, Engineering and Technology Subcommittee on U.S. Global Climate Change Research Program and the Climate Modeling working group and chaired the working group to develop the joint DoD-DoE-EPA Strategic Environmental Research and Development Program research agenda. He is currently a technical advisor to National Earth System Prediction Capability and the National Unified Operational Prediction Capability, two multi-agency programs focused on improving operational numerical weather and climate prediction through multi-agency collaboration. His current research is in developing automated forecast verification techniques for mesoscale numerical weather prediction and developing parameter optimization techniques for numerical modeling. Dr. Sandgathe is a Fellow of the American Meteorological Society and currently holds a top-secret security clearance. Dr. Sandgathe received a BS in Physics from Oregon State University and a PhD in Meteorology from the Naval Postgraduate School.

Dr. Mark Shafer is Associate State Climatologist at the Oklahoma Climatological Survey and established and leads the Southern Climate Impacts Planning Program (SCIPP), a NOAA Regional Integrated Sciences and Assessments (RISA) Program based at The University of Oklahoma and Louisiana State University. SCIPP focuses on place-based applications of climate and weather information to improve community preparedness to a range of natural hazards. His research interests focus upon communication between the scientific community and policy makers, particularly in managing societal response to extreme events and climate change. Primary areas of research include the influence of scientific and technical information on policy outcomes and institutional factors that can affect the flow of information. Dr. Shafer earned a M.S. in Meteorology and a Ph.D. in Political Science from the University of Oklahoma and was a coordinating lead author on the Great Plains chapter in the 2014 National Climate Assessment.

Dr. Duane Waliser is Chief Scientist of the Earth Science and Technology Directorate at the Jet Propulsion Laboratory in Pasadena, CA, which formulates, develops and operates of a wide range of Earth Science remote sensing instruments for NASA's airborne and satellite program. His principle research interests lie in climate dynamics and in global atmosphere-ocean modeling, prediction and predictability, with emphasis on the Tropics and the Earth's water cycle. His recent research foci at JPL involves utilizing new and emerging satellite data sets to study weather and climate as well as advance our model simulation and forecast capabilities, particularly for long-range weather and short-term climate applications. He received a B.S. in Physics and a B.S. in Computer Science from Oregon State University in 1985, a M.S. in Physics from U.C. San Diego in 1987, and his Ph.D. in Physical Oceanography from the Scripps Institution of Oceanography at U.C. San Diego in 1992. He is presently a member of the WCRP-WWRP Subseasonal to Seasonal (S2S) Project Steering Committee and Co-Chair of the WCRP Data Advisory Council's obs4MIPs Task Team. Dr. Waliser is also a Visiting Associate in the Geological and Planetary Sciences Division at Caltech and an Adjunct Professor in the Atmospheric and Oceanic Sciences Department at UCLA.

Dr. Chidong Zhang is a Professor of at the University of Miami. His research interests include large-scale air-sea interaction and atmospheric dynamics in the tropics. He was the Chief Scientist of the 2011-12 Indian Ocean field campaign of DYNAMO (Dynamics of the Madden-Julian Oscillation). He served as a member of the American Meteorological Society Council, WWRP/WCRP YOTC MJO Task Force, International CLIVAR's Atlantic Implementation Panel, and International Science Working Group of North American Monsoon Experiment., He is currently an Editor of Journal of Geophysical Research — Atmosphere, Co-Chair of the Science Steering Committee of Years of the Maritime Continent (YMC), member of the US Steering Committee of International Indian Ocean Expedition 2 (IIOP-2), the Steering Committee of Salinity Processes in the Upper Ocean Regional Study 2 (SPURS-2), and Tropical Pacific Observing System (TPOS) Planetary Boundary Layer Task Team. Dr. Zhang earned his Ph.D. in Meteorology from The Pennsylvania State University in 1989.