VALUE OF IMPROVED LONG-RANGE WEATHER INFORMATION

RICHARD M. ADAMS, KELLY J. BRYANT, BRUCE A. MCCARL, DAVID M. LEGLER, JAMES O'BRIEN, ANDREW SOLOW, and RODNEY WEIHER*

An important human welfare implication of climate involves effects of interannual variation in temperature and precipitation on agriculture. Year-to-year variations in U.S. climate result from El Niño-Southern Oscillation (ENSO), a quasi-periodic redistribution of heat and momentum in the tropical Pacific Ocean. The study described here represents a preliminary assessment of the value to the entire U.S. agricultural sector of improved ENSO forecasts in the southeastern United States. This interdisciplinary assessment combines data and models from meteorology, plant sciences, and economics under a value of information framework based on Bayesian decision theory. An economic model of the U.S. agricultural sector uses changes in yields for various ENSO phases to translate physical (yield) effects of ENSO changes into economic effects on producers and on domestic and foreign consumers. The value of perfect information to agriculture is approximately $145 million. The economic value of an imperfect forecast is $96 million. These results suggest that increases in forecast accuracy have substantial economic value to agriculture.

I. INTRODUCTION

An important human welfare implication of climate involves the effects on agriculture of interannual variation in temperature and precipitation. The effects of drought and flooding provide the clearest evidence of the vulnerability of agriculture to such variations. However, less dramatic climate variations also are reflected in agricultural production, prices, and profits. In many parts of the world, including the United States, one can trace much of the year-to-year variations in climate to El Niño-Southern Oscillation.

The El Niño-Southern Oscillation (ENSO) refers to a quasi-periodic redistribution of heat and momentum in the tropical Pacific Ocean. In broad terms, one can characterize ENSO as a varying shift between a normal phase and two extreme phases: El Niño and El Viejo (sometimes called La Niña). In recent years, the ability to forecast ENSO, in particular, the occurrence of so-called El Niño events has improved (Barnett et al., 1988; Cane et al., 1986; Bengtsson et al., 1993). These forecasts have economic value because they

ABBREVIATIONS
ASM: Agricultural Sector Model
ENSO: El Niño-Southern Oscillation
EPIC: Erosion Productivity Impact Calculator
GCOS: Global Climate Observing System
MLRA: Major Land Resource Area

*Adams is Professor, Department of Agricultural and Resource Economics, Oregon State University; Bryant is Area Extension Specialist, SE Research and Extension Center, University of Arkansas; McCarl is Professor, Department of Agricultural Economics, Texas A&M University; Legler and O'Brien are Research Associate and Professor, respectively, Department of Meteorology, Florida State University; Solow is Associate Scientist, Marine Policy Center, Woods Hole Oceanographic Institute; Weiher is Senior Economist, Office of the Chief Scientist, National Oceanic and Atmospheric Administration. Funding for this research was provided by Economics Group, Office of the Chief Scientist, National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Technical paper 10670 of the Oregon Agricultural Experiment Station.

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can inform decision makers in vulnerable sectors of the economy.

A number of studies address the economic value of improved weather forecasts to agricultural producers. For example, Baquet et al. (1976) and Katz et al. (1982) assess the value of improved frost forecasts to orchardists, and Lave (1963) estimates the economic value of improved precipitation forecasts to California raisin producers. Each of these studies focuses on the value of near-term weather phenomena to producers of a specific commodity in a relatively small geographical setting. Few researchers attempt to assess the value of seasonal or longer term weather variations. Studies that do address this issue focus on individual firms (e.g., Mjelde and Cochrane, 1988). A recent workshop estimated the potential monetary value of ENSO forecasts on the U.S. agriculture, forestry, and fisheries sectors at $200 million per year, with agricultural value the most significant of the three (O'Brien, 1993). This estimate is based on a number of subjective judgements regarding avoidable losses due to ENSO. Thus, a need exists for a systematic assessment of the value of ENSO on long-range weather forecasts that reflects the economic, agronomic, and meteorological aspects of agricultural decision making and that measures sectoral level effects on both producers and consumers.

This article illustrates an approach to assessing the value of improved ENSO forecasts to agriculture in the southeastern United States. This region was selected first for its agricultural importance and second for the relatively clear ENSO signal in its climate (Ropelewski and Halpert, 1986, 1987). The region is a major United States agricultural area, containing a broader range of crops than exist in other areas, such as the Corn Belt. Changes in crop production in this region are likely to affect prices in other regions and to affect the welfare of producers and consumers nationally. The diversity of crops in the southeastern United States provides a good case study for assessing the value of improved ENSO forecasts.

The assessment is interdisciplinary in scope, combining data and models from meteorology, plant science, and economics in a value of information framework based on Bayesian decision theory. The economic model used in the analysis captures the effects of changes in this region on the entire United States. Specifically, the economic model allows for possible price and welfare changes in other regions of the United States as a result of changes in southeast crop production.

It is important to emphasize that one can undertake this assessment *prior* to the improvements in ENSO forecasting. In fact, one policy application of the approach outlined here is to determine whether investments in research and monitoring needed to achieve improvements in forecasting are cost effective. (Current discussions of such investments focus on the Global Climate Observing System (GCOS) and other monitoring systems.) Thus, the research has important policy implications in terms of investing in improved forecasting as well as reducing barriers to the use of such forecasts.

II. THE VALUE OF INFORMATION FRAMEWORK

This section briefly discusses the conceptual framework used to estimate the value of an ENSO forecast. This framework represents a straightforward application of Bayesian decision theory (Berger) and has been used to assess the value of weather forecasts in other contexts (Baquet et al., 1976; Katz et al., 1982; Lave et al., 1963; Sonka et al., 1986, 1987).

The value of an ENSO forecast to a particular enterprise is measured by the expected increase in economic benefits arising from the use of the forecast in decision making. Such benefits occur when the forecast leads to a change in economic behavior. In the case of agriculture, in the absence of an ENSO forecast, a farmer makes planting and harvesting decisions that perform well under average meteorological conditions. An ENSO forecasting scheme has economic value provided the farmer's decisions are different for different forecasts. This condition will be met if there are significant differences in meteorological conditions under the different phases of ENSO and if these meteorological differences lead to significant differences in growing conditions.

The basic behavioral assumption is that a farmer adopts a planting and harvesting strategy that maximizes expected profits under his current beliefs about the ENSO phase, S. One can summarize these beliefs in the form of a probability distribution over the three possible phases: E = El Niño, V = El Viejo, N = Normal (non-El Niño and non-El Viejo years). In the absence of an ENSO forecast, this distribution is given by:

(1) $$\pi = (\pi_E \ \pi_V \ \pi_N)$$

where π_E, π_V and π_N are the long-term relative frequencies of El Niño, El Viejo, and Normal phases, respectively.

Suppose that an ENSO forecast X takes the form of an unqualified statement predicting which ENSO phase will occur; that is, a forecast that comes without a probability. Upon receiving the forecast $X = x$ ($x = E$, V, or N), the farmer updates his beliefs according to Bayes's Theorem:

(2) $$P_s = \pi_s L(X \mid x) / p(x)$$

where P_S is the updated probability of phase S, $L(x \mid S)$ is the probability that $X = x$ given that the true phase is s, and:

(3) $$p(x) = \sum_s \pi_s \, L(x \mid s)$$

is the probability of the forecast $X = x$. The farmer then adopts the strategy that maximizes expected profits under the updated distribution:

(4) $$p = (p_E \ p_V \ p_N)$$

The likelihood $L(x \mid s)$ is a measure of the accuracy of the forecast. For a perfect forecast:

$$L(x \mid s) = 1 \text{ if } x = s$$

$$0 \text{ if } x \neq s$$

In this case, once the forecast is issued, the true ENSO phase is known with certainty and the farmer chooses the strategy that is optimal for that phase. The value of a perfect forecast to society is the average increase in the sum of producer and consumer economic well-being that results from the farmer's optimizing under certain knowledge of S rather than under the distribution of π. Calculating this value requires knowing total economic welfare for four cases: under the optimal strategy for each of the three possible ENSO phases and under the optimal strategy under average (of all years) conditions. The value of a perfect forecast is then given by the difference between a weighted sum of the first three, with weights given by the elements of π, and the last.

One must modify this approach in two ways in order to find the value of an imperfect forecast. (i) The optimal strategy for the updated distribution p in general will not correspond to the optimal strategy for any one of the three possible ENSO phases. In the case where the forecast takes the form of an unqualified statement about which phase will occur, the farmer will face one of three possible updated distributions—one for each of the three possible values of X. Calculating the value of an imperfect forecast requires determining the optimal strategy and total economic welfare under each of these three possible distributions. (ii) The expected economic welfare under an imperfect forecast still is given by a weighted sum of the economic welfare under the three possible distributions. However, the weights correspond to the relative frequencies of the three possible forecasts, rather than the relative frequencies of the three possible ENSO phases. These weights are given by (2).

Implementing this framework requires knowing information about differences in the meteorological conditions under the three ENSO phases, the consequences of these meteorological differences for crop yields, and the consequences of these differences in yields for decision making and economic welfare. The following section discusses each of these components.

III. DATA AND MODELS

Assessing the value of improved ENSO forecasts involves using a three stage process. The first stage estimates seasonal temperature and precipitation conditions under the three ENSO phases using historical data for 13 sites in the southeastern United States. This analysis uncovers a number of significant meteorological differences between ENSO phases. The second stage estimates the consequences of these meteorological differences on crop yields using crop biophysical simulation models. Again, a number of significant differences in yields appear. The third stage incorporates these yield differences into a decision making model in order to assess the aggregate economic value of ENSO forecasting. The value of both perfect and imperfect forecasts are estimated in this way.

A. *Meteorological Information*

Three key meteorological variables used by the biophysical model to estimate crop yields are minimum and maximum daily temperature and monthly precipitation. In the first stage of the analysis, climate data covering the period 1948-1987 were used to estimate monthly means of these variables under the three ENSO phases. The data are from the Historical Climatology Network for 13 southeastern stations. These stations were chosen primarily for regional balance.[1] Each year was categorized as El Niño, El Viejo, or Normal based on an ENSO index produced by the Japan Meteorological Agency. This index is constructed from spatially averaged sea surface temperatures in the tropical Pacific Ocean (see Legler, 1993, for details on procedures). For the 1948–1987 period, eight years were categorized as El Niño, 14 as El Viejo and 19 as Normal. (This categorization is based on the tropical Pacific (SSTA) index for northern hemisphere wintertime values.)

The analysis reveals significant meteorological differences between ENSO phases. The analysis uses meteorological data for *all* three month periods between October and September of the ENSO year. Table 1 gives some examples for a three month period (May to July). Although there is some geographic coherence in these differences, significant variations occur over the region. El Niño years generally have cooler and wetter springs and falls and dryer summers, while El Viejo years have warmer winters and springs. Much of the data in the analysis here has been examined to determine probabilities of above or below normal conditions (Sittel, 1994). The results vary widely with season and location. Significant probabilities occur primarily in the winter-spring periods.

B. *Description of the EPIC Model*

Estimating the yield implications of the weather events discussed above involves using a mathematical model called Ero-

1. The thirteen stations are Thomasville, Ala.; Pocohontas, Ark.; Federal Point, Fla.; Newnan, Ga.; Lafayette, La.; Water Valley, Miss.; Reidsville, N.C.; Hobart, Okla.; Newberry, S.C.; Beeville, Tex.; Crosbyton, Tex.; Fort Stockton, Tex.; and Weatherford, Tex. sites selected are the median counties of each of the Major Land Resource Areas (MLRA) as specified by the USDA.

TABLE 1

Differences between EL Niño, El Viejo and Average (all years) Conditions for Maximum and Minimum Temperatures and Total Monthly Precipitation Totals

	Maximum Temperature (C)		Minimum Temperature (C)		Precipitation (mm)	
Site	EN-A	EV-A	EN-A	EV-A	EN-A	EV-A
Thomasville, AL	–0.01	–0.14	0.14	–0.12	+0.36	+9.5
Water Valley, MS	0.28	–0.19	0.18	–0.28	–13.3	+5.8
Reidsville, NC	0.60	–0.21	0.31	–0.09	–10.2	+10.9
Beeville, TX	–1.04	–0.40	–0.31	–0.22	–15.3	–1.5

Notes: These examples are the differences between three-month and seasonal means averaged for the period of May-July of the ENSOP year. The temperature differences represent small (less than 2 percent) changes in the mean temperatures for this period. The mean precipitation for these periods is approximately 100 mm per month, so the precipitation differences represent equivalent percentage changes.

EN = El Niño, *EV* = El Viejo and *A* = Average of all years (EN, EVE and Normal)

sion Productivity Impact Calculator (EPIC). The model originally was developed to determine the relationship between soil erosion and soil productivity (Williams et al., 1984; Williams et al., 1989). EPIC is appropriate for this study because it relates meteorological and other inputs to estimated yields for the crops of interest. EPIC has been used in numerous scientific studies for a variety of purposes and has gained popularity across disciplines in agriculture. Additionally, EPIC has been shown to provide reasonable simulations of crop yields in a variety of geographical settings (Bryant et al., 1992; Steiner et al., 1982; Williams et al., 1989).

EPIC has the ability to simulate many different crops. The analysis here uses a single crop growth model to simulate crops by specifying unique values for the model parameters to represent each crop. In addition to soil and other environmental factors, the model includes the effect of various measures of temperature and precipitation on yield.

C. *EPIC Runs for This Study*

An EPIC data set consists of weather data, wind data, soil data, and crop management data for a specific location. The analysis here constructs one EPIC data set for each of the 13 stations. Weather data includes average monthly maximum air temperature, average monthly minimum air temperature, and average monthly precipitation for the three ENSO phases (El Niño, El Viejo, and Normal) and for an "average" or all-years situation for the entire growing season. Changes in the three weather variables are calculated between the average or all years scenario and each of the three ENSO phases. The growing season monthly weather data in the EPIC base data sets are adjusted by these changes to create data sets for each ENSO phase.

Yields for cotton, corn, sorghum, and soybeans are simulated for the four weather scenarios. These four crops are major income producing row crops in the southeast and occupy over 50 percent of

TABLE 2
Percent Change in Yields (from Average) for Each State of Nature for Selected Crops in Each State

Station	Crop	El Viejo	El Niño	Normal[a]
Thomasville, Ala.	Soybeans	+7%	–3%	–5%
Pocohontas, Ark.	Cotton	+6%	–7%	–2%
Federal Point, Fla.	Corn	+10%	–5%	–6%
Newnan, Ga.	Corn	+5%	–5%	–1%
Lafayette, La.	Soybeans	+5%	–5%	–1%
Water Valley, Miss.	Soybeans	+8%	–10%	–2%
Reidsville, N.C.	Soybeans	+8%	–12%	–2%
Hobart, Okla.	Grain Sorghum	+10%	–10%	–2%
Newberry, S.C.	Corn	+15%	–10%	–7%
Weatherford, Tex.	Cotton	+8%	–2%	–8%
Beeville, Tex.	Grain Sorghum (irrigated)	0%	+14%	–4%
Crosbyton, Tex.	Cotton (irrigated)	+7%	+3%	–2%
Fort Stockton, Tex.	Cotton (irrigated)	+13%	+5%	+2%

[a]Normal refers to non-El Niño and non-El Viejo years.

the cropland acreage in the region. Crop growth is simulated for 10 years, for each crop, for each weather scenario, for each location. The averages of these 10 observations on yields generate a percent change in crop yield by crop, climate condition, and location. Yields are not simulated for wheat and barley because the results of ocean temperature monitoring are not known until February. Wheat, barley, and other winter crops are planted by February, so ocean temperature information would have no value in planning for winter crop production.

D. *Yield Results*

Yields are obtained from the EPIC model for four crops, in 13 locations, under dryland and irrigated conditions. The yields are then converted to percent differences from the average or all years scenario. Table 2 presents percent changes for selected crops in each region. In almost every case, the El Viejo weather pattern produces the highest crop yields. El Niño produces the lowest crop yields, and crop yields under the normal scenario fall somewhere between these two extremes. Some crops in some regions are affected substantially while other crops in other regions are not. In most regions, corn is most affected by changes in these weather variables. States experiencing the greatest percentage changes include the Carolinas, Mississippi, and Oklahoma with El Viejo years exceeding El Niño yields by 16 to 27 percent. States least affected are Alabama and Louisiana with El Viejo yields exceeding El Niño yields by 10 percent or less. Dryland yields experience greater changes than do the irrigated yields because water is not limited under irrigated conditions.

E. *Economic Modeling*

The yield changes (table 2) for each state of nature are inputs for the third stage of the assessment, the economic component. Specifically, the changes in yields for the three ENSO phases and for the average for all years case are used in an economic model of the U.S. agricultural sector, identified as the Agricultural Sector Model or ASM (see Chang and McCarl, 1992, for details). This permits translating the physical (yield) effects of ENSO changes into economic effects on producers and on domestic and foreign consumers.

The model is a spatial equilibrium model formulated as a mathematical programming problem. The model represents production and consumption of 30 primary agricultural products including both crop and livestock products. Processing of agricultural products into 12 secondary commodities also is included. Prices for these commodities are determined endogenously for both national and international (export) markets. The model maximizes the sum of the area under the demand curves but above the price (consumer surplus) plus the area above the supply curves but below the price (producer surplus) for these commodities. One can interpret changes in this area as a measure of the economic welfare equivalent of the annual net income lost or gained by agricultural producers and consumers as a consequence of yield or other changes, expressed in 1990 dollars. Both domestic and foreign consumption (exports) are included. ASM can be solved both with and without provisions of the U.S. farm program (e.g., deficiency payments, set-asides, Conservation Reserve Program diversions).

The model takes regional level responses and aggregates these to national level responses. Specifically, producer-level behavior is captured in a series of technical coefficients that portray the physical and economic environment of agricultural producers in each of the 63 homogeneous production regions in the model, encompassing the 48 contiguous states. The analysis also considers irrigated and non-irrigated crop production and water supply relationships. Availability of land, labor, and irrigation water is determined by supply curves for each input. Farm-level supply responses generated from the 63 individual regions are linked to national demand through the objective function of the sector model, which features demand relationships for various market outlets for the included commodities.

Using ASM to place an economic value on improved ENSO forecasts requires certain assumptions and procedures: (i) The base economic model is keyed to 1990 economic, agriculture, and environmental conditions. (ii) EPIC yield forecasts are assumed to reflect biophysical consequences of the three ENSO phases, as well as the average (all years) expectation. (iii) The assessment of value of improved or perfect forecasts focuses on changes in cropping patterns and irrigation technology in the ASM. These changes reflect actions taken in expectation of the various weather events. For example, if farmers expect an El Viejo growing season, then they plant crops that perform better under those conditions. In the perfect information case, these expectations are realized; in the imperfect use, the forecast improves the farmers' ability to plan for these weather events. Note that in addition to these adjustments within the ASM, the EPIC yield results reflect changes in planting dates and other cultural practices under the states of nature evaluated here. (iv) The analysis examines the value of forecasts under both a continuation of federal farm programs (keyed to 1990 provisions) and the elimination of federal farm program provisions.

The value of information is captured in the economic model through effects on cropping patterns (and associated livestock production). Two distinct analyses are performed based on assumptions concerning cropping plans. The first involves a perfect information plan. Here no cropping patterns are imposed on the model; the model is solved to obtain maximum total social welfare in the face of each of the weather scenarios. This involves running the model with perfect foresight of the El Niño, El Viejo, Normal, and average (all years) scenarios. In turn, the model is then run under the ENSO phases with the cropping pattern restricted to the historical cropping pattern reflecting average weather conditions across the three phases. Comparisons between the model solution with the knowledge that a specific weather event is forthcoming without a cropping pattern imposed and the average or historical cropping pattern under that same weather scenario provide an estimate of the value of perfect information. Specifically, the value of perfect information is calculated as the weighted average of the benefits of having selected (*a priori*) the optimal crop mix for each event. The weights are the historical frequency of each event.

The second type of analysis pertains to the value of imperfect information. Currently, the probability of a correct ENSO forecast six months prior to planting decisions is assumed to be 0.6, as reflected in the likelihood function across the possible ENSO forecasts. Here, imperfect information is valued in terms of improving this ENSO forecast accuracy to 0.8 probability of a correct forecast across the three possible forecasts. The benefits of this increased accuracy are less than that from a perfect forecast because the optimal strategies must reflect the costs of "wrong" planting decisions or crop mixes. "Wrong" is defined as a planting decision motivated by a forecast which is not realized—e.g., planting an El Niño crop mix in response to an El Niño forecast and then having a normal event occur. Estimating the value of improved (from 0.6 to 0.8 probability) but imperfect forecasts involves evaluating alternative model solutions and by representing pairs of ENSO phases and planning actions and their associated probabilities and consequences. The net gain from improving the forecast is the weighted average across the alternative distribution of outcomes, weighted by the relative frequency of the forecasts.

Cost-benefit analysis of such projects and programs should occur under undistorted market conditions (commonly called shadow pricing). However, the U.S. agricultural sector experiences significant price distortions caused by government interaction (through the provisions of federal farm program legislation). For comparative purposes, the analysis here first includes and then excludes the presence of the farm program provisions. The scenarios deal with two polar cases: the full 1990 farm program and the elimination of all federal farm program provisions (a "free market" situation). Encompassing the farm program effects requires more model solutions (the same weather-planning combinations and strategies, but now with farm programs). In addition, two other farm program analyses were performed. These allowed for partial elimination of farm programs. Since the resultant economic estimates are bounded by the polar cases, only the polar cases appear here.

IV. RESULTS

Table 3 summarizes the results of the two information cases. Table 3 reports results of the "perfect information" case under two situations: one with U.S. farm program provisions and one with these provisions removed from the economic model. As the tables show, the value of perfect information (a perfect forecast) to agriculture in the southeast under undistorted market conditions (w/o farm programs) is approximately \$145 million. With farm programs, the value of the forecast is \$265 million. Both values reflect the sum of gains to producers and consumers or gains in social welfare and are on a per annum basis, measured in 1990 dollars. For perspective, these estimates represent about 2 to 3 percent of farm-gate value of total crop production for the southeast region in 1990 (USDA).

TABLE 3
Value of Perfect and Improved ENSO Forecast

Scenario	Economic Value ($ millions, 1990)
Perfect Information	
1990 Farm Program Provision	265.0
No Farm Programs (free market)	144.5
Imperfect but Improved	
1990 Farm Program Provisions	130.0
No Farm Programs (free market)	96.0

Table 3 also reports the value of improved but less than perfect forecasts of ENSO events. Specifically, the results represent the economic value of increasing the accuracy of ENSO forecasts from an assumed 0.6 probability of a correct forecast to an 0.8 probability, or by 33 percent.

As expected, the economic values of such forecasts are less than for the case of perfect information of $130 million and $96 million for the "with and without" farm programs cases, respectively. However, these increases in accuracy capture about one-half of the perfect information case value. Thus, under the conditions of these experiments, increases in forecast accuracy do have economic value to this sector.

These gains in net social welfare arise from only one production area in the United States. Other areas experience ENSO-related weather patterns. The results of the current study indicate that the value of improved forecasts to these other agricultural areas also is likely to be positive.

V. CONCLUSIONS

This study represents the first systematic attempt to value improved forecasts of long-range or ENSO-type weather phenomena to the agricultural sector in an important production region of the United States. The interdisciplinary assessment framework integrates concepts, data, and models from meteorology, statistics, plant science, and economics. While estimates are conditional on the experiments performed here, the economic benefits of improved ENSO forecasts are approximately $100 million per year or greater.

The positive value of improved forecasts supports to previous firm-level assessments of the value of weather forecasts to agriculture. However, one should compare the benefits of improved forecasts with current expenditures on ENSO monitoring and research. Benefits to other agricultural regions and other sectors also are needed in order to calculate the overall benefit-cost ratio of such expenditures on monitoring and forecasting. Finally, the results also have implications with respect to potential global warming effects on agriculture since global change will influence interannual variability. Specifically, these findings indicate that the agricultural sector can, under the conditions of study, "adapt" to climate variation.

A number of assumptions affect the magnitude of these estimates. Some assumptions, such as emphasis only on planting decisions (crop mixes), likely result in estimates that are lower than would actually occur. For example, farmers also could adopt other strategies, including input substitutions, which would increase the value of weather information. A related assumption is that this is a long-run adjustment process; farmers as modeled here thus make instantaneous adjustments. The economic model also does not include fruit and vegetable production. These are important crops in the southeast; benefits of improved forecasts to citrus, vegetables, and other excluded crops likely are an important component of the total value from such information. Finally, the analyses abstract from changes in credit and crop insurance markets that may occur due to improved weather information.

Despite the uncertainties and abstractions, the estimates suggest that the economic value of planned improvements in ENSO forecasts may be substantial for U.S. agriculture. Economic information from this and similar studies, when combined with cost estimates to achieve this increase forecast accuracy, can help inform the policy debate on investments in more accurate global monitoring and forecasts systems by national and international agencies.

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