Advancing the Seasonal Outlook of the Wet Seasons of Florida

VASUBANDHU MISRA[a,b] AND C. B. JAYASANKAR[b]

[a] Department of Earth, Ocean and Atmospheric Science, Florida State University, Tallahassee, Florida
[b] Center for Ocean-Atmospheric Prediction Studies, Florida State University, Tallahassee, Florida

(Manuscript received 24 March 2024, in final form 24 August 2024, accepted 9 September 2024)

ABSTRACT: In this study, we introduce an ensemble approach to provide a probabilistic seasonal outlook of the length and seasonal rainfall anomaly of the wet season over Florida using the observed variations of the onset date of the season at the granularity of ~10-km grid resolution (which is the spatial resolution of the observed rainfall data used for this work). The time series of daily precipitation at the grid resolution of NASA's Global Precipitation Mission is randomly perturbed 1000 times to account for the uncertainty of synoptic to mesoscale variations on the diagnosis of the onset and demise date of the wet season. The strong covariability of the onset date with the seasonal length and seasonal rainfall anomaly of the wet season is then leveraged to provide the seasonal outlooks by monitoring the onset date of the wet season. This simple seasonal outlook is effective in predicting extreme tercile and even extreme pentile anomalies across Florida. We suggest that the proposed approach to the seasonal outlook of the wet season of Florida provides a viable alternative in the absence of strong external forcing like ENSO or tropical Atlantic variability that potentially limits the predictability of numerical climate models used for seasonal prediction.

SIGNIFICANCE STATEMENT: Earlier studies have shown that the seasonal prediction from the numerical climate models even at zero lead time has very limited prediction skills over the summer in Florida, which also coincides with the wettest part of the year. Florida's wet season exhibits significant interannual variations, which exert its influence on water management decisions for subsequent drier seasons of the year. Therefore, strategies to improve this skill are highly relevant. We propose in this study that by monitoring the onset of the wet season variations, we can usefully provide a probabilistic seasonal outlook of the season over Florida. This is done by leveraging the observed linear relationships between the onset date variations with the length and the seasonal rainfall anomaly of the season. Furthermore, the outlook is provided at the spatial resolution of the observed dataset, which in this case is at 10-km grid resolution.

KEYWORDS: Climate prediction; Ensembles; Forecast verification/skill; Seasonal forecasting; Climate variability; Interannual variability

1. Introduction

Several prior studies have highlighted the robust seasonal cycle of precipitation over Florida, which roughly coincides with the boreal summer season (Misra and DiNapoli 2013; Misra and Mishra 2016; Misra et al. 2017, 2018). Some of these studies have also suggested that this seasonal cycle of precipitation over Florida is closely associated with an equally strong seasonal cycle of the Loop Current and the seasonal evolution of the SST in the Gulf of Mexico (Misra and Mishra 2016; Misra et al. 2017, 2018). In addition, Misra et al. (2018) also showed that the seasonal cycle of Florida's precipitation is also linked to the seasonal cycle of the northern tropical Atlantic trade winds. Given such robust, coupled seasonal variability of the hydroclimate of Florida, Misra et al. (2022) have introduced an objective approach to detect the onset and demise of the wet season. Furthermore, the onset date (OD) variations of Florida's wet season have a strong covariability with the length and the seasonal rainfall (SR) anomaly of the wet season. These covariations have been exploited to provide a seasonal outlook of the forthcoming wet season variations by solely monitoring the variations of the onset date.

This study is different from the previous studies in two ways. First, we now define the onset and demise dates (DDs) at the discretization of the observed precipitation dataset, unlike previous studies that aggregated precipitation over specific geographical areas. Second, we now introduce an ensemble approach for the diagnosis of the onset/demise dates, which not only provides a more robust estimate of these dates but also provides uncertainty estimates of the diagnosis. The estimation of the uncertainty becomes important given that the definition of these onset/demise dates is at a relatively higher spatial resolution than earlier studies and is to the precise calendar day of the year. Furthermore, the ensemble of the onset dates leads us to provide a probabilistic seasonal outlook of the wet season.

Florida with its unique geography and subtropical location has this unique feature of a strong seasonal cycle of precipitation in the contiguous United States. Most current climate models misrepresent this seasonal cycle (Stefanova et al. 2012; Narotsky and Misra 2022), which poses a challenge to predict the wet season variations. For instance, in Fig. 1, we show a sample of 4 years of seasonal prediction of the mean JJA

Supplemental information related to this paper is available at the Journals Online website: https://doi.org/10.1175/WAF-D-24-0063.s1.

Corresponding author: Vasubandhu Misra, vmisra@fsu.edu

DOI: 10.1175/WAF-D-24-0063.1

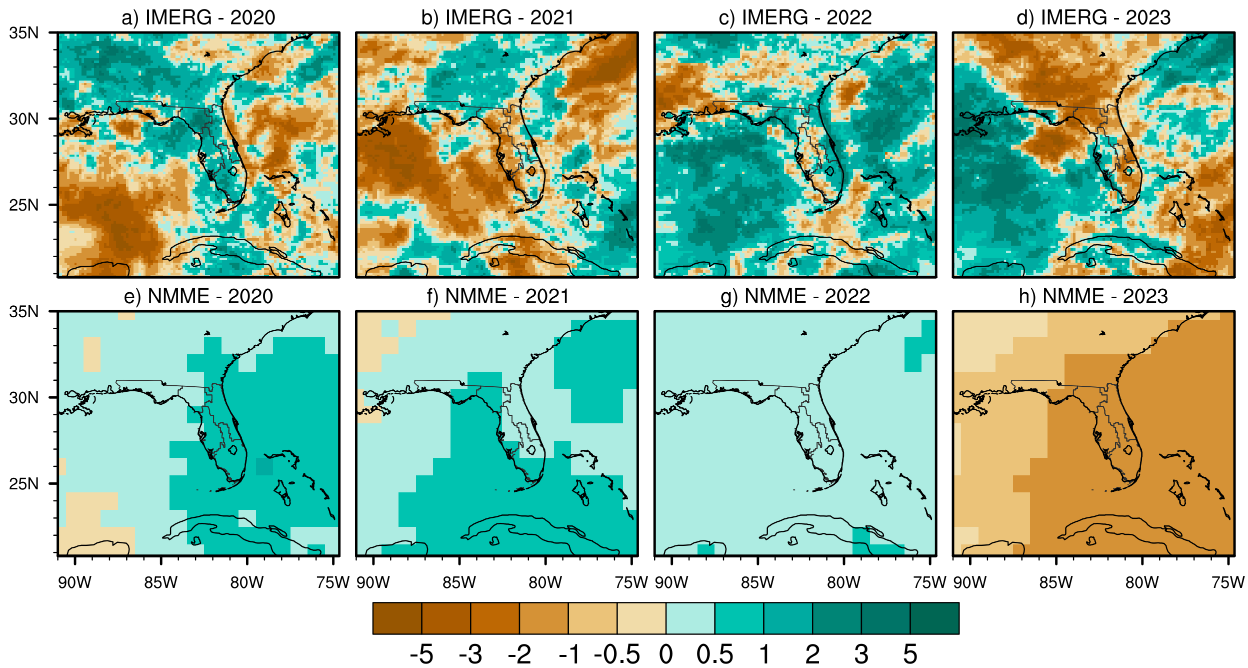

FIG. 1. The seasonal mean precipitation anomalies for JJA from (a)–(d) IMERG and (e)–(h) NMME at zero lead time for (a),(e) 2020, (b),(f) 2021, (c),(g) 2022, and (d),(h) 2023.

seasonal precipitation from the multimodel ensemble mean of five North American Multi-Model Ensemble (NMME; Kirtman et al. 2014), which include CCSM4, CanCM4, CFSv2, GEMNEMO, and GOES5. In comparison to the observations, the rainfall from NMME predictions lacks considerable details over Florida (Fig. 1), which becomes important especially when these predictions are being adopted for applications in various sectors including regional/local water management decisions (Misra et al. 2021). Moreover, the fidelity of the multimodel seasonal summer mean of the precipitation from NMME in Figs. 1e–h is inconsistent from 1 year to the next. For example, the verifiable wet seasonal anomaly of 2020 season (Figs. 1a,e) is followed by an inaccurate wet seasonal anomaly across Florida in 2021 (Fig. 1f) when a large swath of peninsular Florida shows a dry anomaly (Fig. 1b). A detailed probabilistic and deterministic forecast skill analysis of one of the NMME models in Narotsky and Misra (2022) further highlights these poor skills in the summer even at zero lead time. Similarly, Stefanova et al. (2012) indicate that the seasonal prediction skills of the summer hydroclimate in the southeastern United States including Florida are the least and insignificant among all seasons. They allude to the lack of significant external forcing like the ENSO variability for the poor summer seasonal prediction skills over the southeastern United States. It should also be noted that the resolution of the model and its fidelity in simulating the seasonal cycle are intertwined. For example, Misra et al. (2019) indicate that owing to the coarse resolution of the global models, the ocean bathymetry around Florida is poorly resolved, which implies that the West Florida Shelf is nearly nonexistent in the model. These resolution issues in the global models could lead to errors in the simulation of the Loop Current in the Gulf of Mexico (Misra et al. 2016), which is critical in regulating the seasonal cycle of Florida's hydroclimate (Misra and Mishra 2016; Misra et al. 2017).

In this study, we offer a tangible alternative solution to the seasonal predictability of precipitation over Florida in the summer. In the following section, we describe the methodology and data followed by results in section 3 and concluding remarks in section 4.

2. Methodology and data

The methodology to detect the onset and demise date of the wet season follows from earlier studies (Misra and DiNapoli 2013; Misra et al. 2018). The onset date and demise date are detected by the minimum and maximum inflection points in the daily cumulative anomaly curve of the precipitation at a given grid point. Unlike previous applications of this methodology, which was done by area averaging the rainfall over a relatively large area (e.g., Misra et al. 2022), the detection of the onset and demise dates of the wet season is diagnosed at individual grid points of the observed rainfall data. Therefore, the likelihood of diagnosing false onset and demise dates of the season as a result of random convective activity unconnected to the seasonal cycle is greater. To ameliorate this limitation of the methodology, we perturb the original time series of the rainfall 1000 times. The technique following Misra et al. (2023) involves randomly perturbing the time series on the time scale of 7 days to represent the uncertainty on the meso to synoptic scales of these precipitation events. Although Misra et al. (2023) used just 100 perturbations to generate

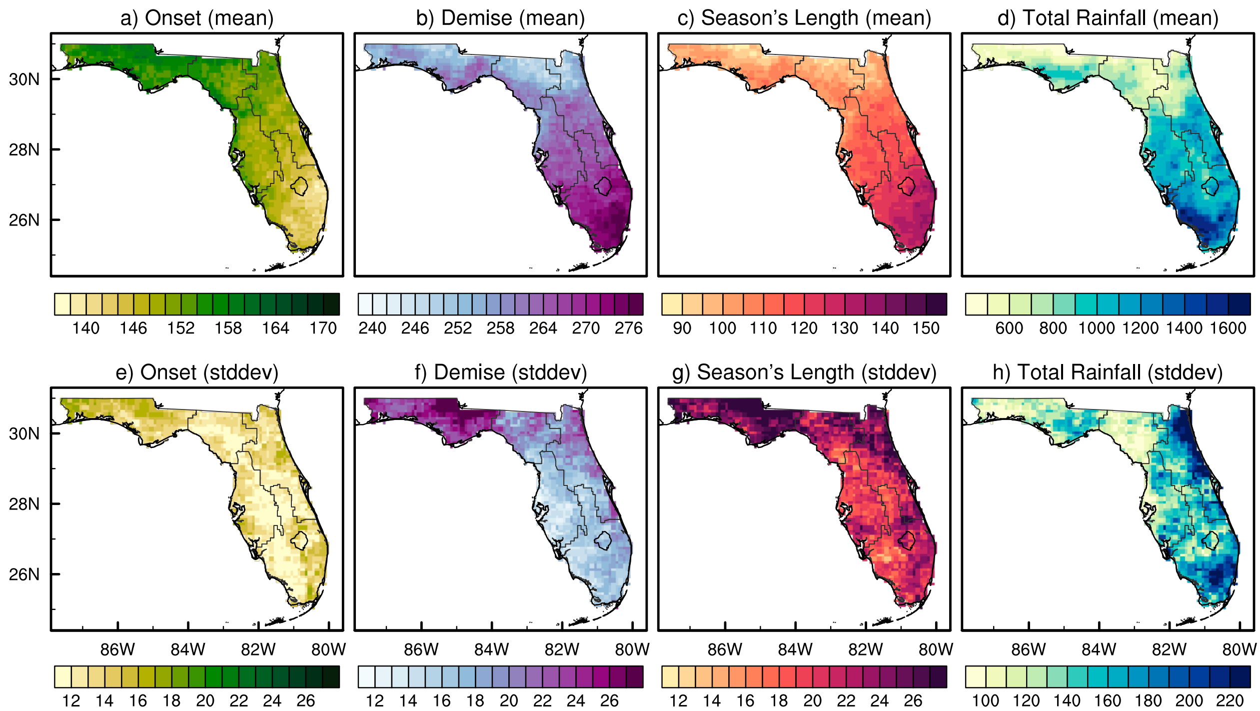

FIG. 2. The climatological (a) OD (Julian day), (b) DD (Julian day), (c) SL (days), and (d) seasonal rainfall (mm) of the wet season from IMERG. The corresponding standard deviation of (e) OD (days), (f) DD (days), (g) SL (days), and (h) seasonal rainfall (mm). The outlines of the five water management districts of Florida are overlaid.

their ensemble, we have expanded it to 1000 perturbations in this study to develop a more robust estimate the seasonal outlook. The perturbation technique involves replacing the rain rate of each day with rain rates occurring within the sequence of ±3 days. An illustration of this technique is shown in Fig. S1a in the online supplemental material, which shows the original rainfall time series over a grid point over south Florida for the year 2007 overlaid with a perturbed time series. The differences between the time series are subtle, given that in the perturbed time series, the rain of each day could be borrowed from the range of −3 to 3 days around it from the original time series. The logic of this perturbation is to assess the uncertainty of the diagnosis of the onset date of the wet season at any given grid point to the uncertainty of the day of occurrence of the rain at any given day of the grid point over a margin of ±3 days. It is therefore conceivable that a very large set of such perturbed time series could be generated that are unique from one another but subtly different from one another. Figure S1b shows the ensemble mean of the 1001 (=1000 perturbations + original time series) with the corresponding range of the ensemble spread for south Florida region. By adopting this perturbation technique, a random rain event that surpasses the annual mean climatology and is not linked to the annual cycle will either average out in the ensemble mean or will yield an unusual start or demise date with a very low likelihood.

The daily rainfall data used in this study were sourced from the Integrated Multi-satellitE Retrievals for GPM (IMERG; Huffman et al. 2019) as the main dataset. The IMERG rainfall is at a grid spacing of 0.1° (~10 km) with hourly temporal resolution spanning from June 2000 to the current date. It may be noted that we use the 12-h latency product in order that the proposed methodology can be easily adopted for real-time application. This precipitation product has been extensively validated with 3.5-month latency product of IMERG which uses multiple sources of data to produce the final product of rainfall analysis. Misra et al. (2022) have shown that the 12-h latency product of IMERG yields similar results as the 3.5-month latency product for this application over Florida.

3. Results

a. Climatology

The climatological onset and demise date, seasonal length (SL), and seasonal rainfall anomaly from IMERG are shown in Figs. 2a–d, respectively. The early onset in south Florida relative to the Panhandle region suggests the south-to-north progression of the wet season (Fig. 2a). Likewise, the early demise of the rainy season in the Panhandle region and progressively later in south Florida in Fig. 2b suggests the north-to-south retreat of the wet season. Consequently, the length of the wet season (Fig. 2c) and the seasonal accumulation of rainfall (Fig. 2d) are longer and higher in south Florida relative to northern Florida, respectively. In addition, the southeast peninsular Florida has the earliest onset date, latest demise date, longest seasonal length, and highest seasonal rainfall followed by southwest peninsular Florida, which gives

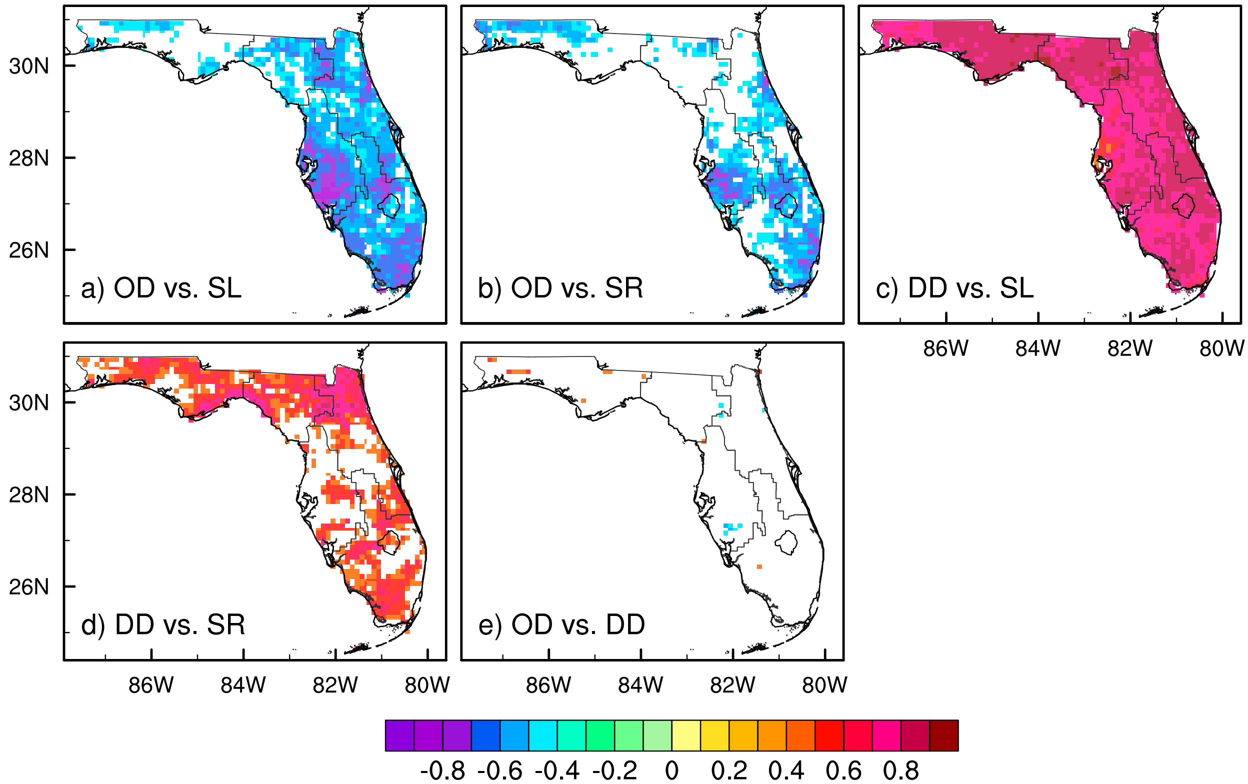

FIG. 3. The correlations of the OD with (a) SL, (b) SR, and (e) DD. Similarly, the correlations of DD with (c) SL and (d) SR. Correlations that are significant at 5% significance level are shaded.

a slight east–west gradient to these variables. The corresponding standard deviation of the onset date (Fig. 2e), demise date (Fig. 2f), seasonal length (Fig. 2g), and seasonal rainfall (Fig. 2h) suggests a significant range of variability, which motivates the reason for their predictions.

b. *Interannual variability*

The correlations of the onset date with seasonal length (Fig. 3a) and seasonal rainfall (Fig. 3b) confirm the results from earlier studies (Misra et al. 2018, 2022), which suggest that early or later onset date of the wet season is associated with longer or shorter and wetter or drier season, respectively. Similarly, the correlations of the demise date with seasonal length (Fig. 3c) and seasonal rainfall anomalies (Fig. 3d) suggest that later or early demise of the wet season is associated with longer or shorter and wetter or drier seasons, respectively. Figure 3e indicates that onset and demise date variations are largely uncorrelated, suggesting that their variations are independent of each other. These correlations in Fig. 3 suggest that the onset date could be used as a useful predictor for the outlook of the forthcoming seasonal length and seasonal rainfall anomalies.

We also computed the correlations of the onset date variations with the variability of the frequency of occurrence of precipitation events that are above the 95th percentile (R95p) in the season in Fig. 4a. The negative correlations in Fig. 4a suggest that early or later onset seasons are associated with more or less frequent R95p events in the season, respectively. The correlations in Fig. 4b suggest that wetter or drier seasons are associated with more or less R95p events in the season, respectively. These relationships in Fig. 4 are again showing the important relevance of monitoring the variations of the onset of the wet season.

c. *Signal-to-noise ratio*

We computed the signal-to-noise ratio of these quantities given that we have an ensemble of time series. This ratio would give a sense of the seasonal predictability of the wet season of Florida from the proposed methodology of generating the ensembles. This ratio is computed as

$$\sigma^2_{\text{noise}} = \frac{1}{M(m-1)}\sum_{r=1}^{M}\sum_{q=1}^{m}(x_{rq} - \overline{x}_q)^2, \tag{1}$$

$$\sigma^2_{\text{signal}} = \sigma^2_{\text{em}} - \frac{1}{m}\sigma^2_{\text{noise}}, \tag{2}$$

where x could be anyone of onset date, demise date, seasonal length, and seasonal rainfall anomalies; r and q are indices for M years and m ensemble members, respectively; and

$$\sigma^2_{\text{em}} = \frac{1}{(M-1)}\sum_{r=1}^{M}(\overline{x}_r - \overline{\overline{x}})^2,$$

where $\overline{x}_r = [1/(m-1)]\sum_{q=1}^{m} x_{rq}$ and $\overline{\overline{x}} = [1/(M-1)]\sum_{r=1}^{M}\overline{x}_r$.

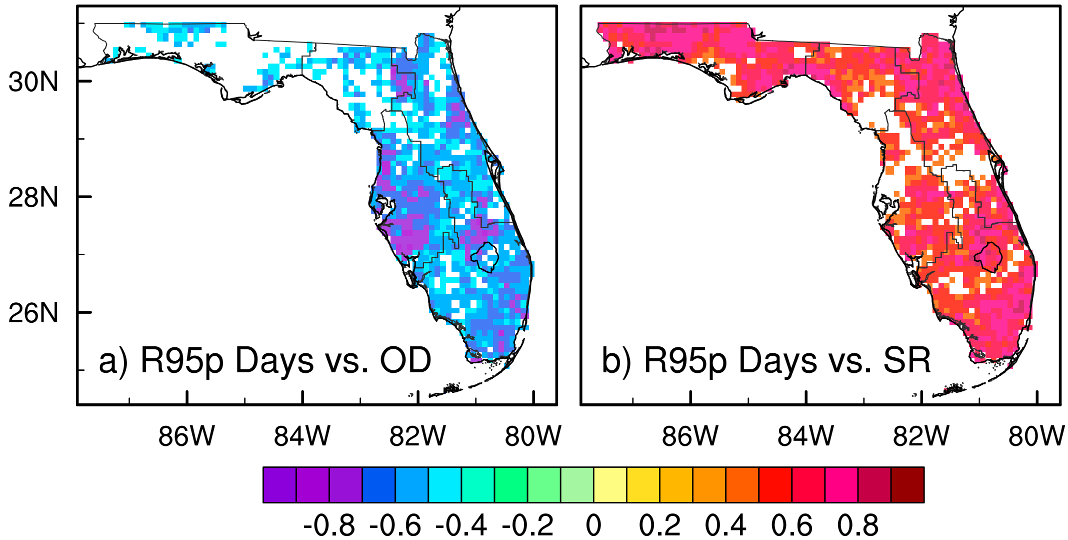

FIG. 4. (a) The correlations of the OD of wet season with the number of days of daily precipitation exceeding the 95th percentile in the season. (b) The correlations of the seasonal rainfall anomaly and the number of days of daily precipitation exceeding the 95th percentile in the season. Correlations that are significant at 5% significance level are shaded.

The signal-to-noise ratio λ is then given by

$$\lambda = \frac{\sigma^2_{\text{signal}}}{\sigma^2_{\text{noise}}}.$$

A higher noise component when $\lambda < 1$ will signify that chaotic variations are dominating, which would imply a low predictability. On the contrary, when $\lambda \gg 1$, then the prospects of predicting the seasonal evolution of the wet season are relatively high. A dominating signal suggests that the perturbations of the time series (conducted in the proposed manner of this study) will not significantly modulate the x diagnostic of the time series. In Fig. 5a, λ in the diagnosis of the onset date suggests that noise dominates in the Panhandle region, while in south Florida, signal is dominating. However, for the demise date, there is a large swath of Florida extending from Panhandle to central Florida, where the noise dominates, with the signal dominating in the tip of south Florida (Fig. 5b). In comparing Figs. 5a and 5b, it is suggested that the variability of the onset date of the wet season is more strongly dictated than the demise date by low-frequency variations (e.g., seasonal cycle and Atlantic Warm Pool), while the demise date is more influenced by chaotic variations. Consequently, λ in the seasonal length (which is influenced by variations of both onset and demise dates) is larger than 1 in south Florida, that progressively reduces to less than 1 northward (where λ of the onset date variations is small compared to south Florida while the demise date variations are <1). The λ in the seasonal rain, however, shows an east–west contrast with the Atlantic Coast of peninsular Florida exhibiting a strong signal while the Gulf Coast has a weaker signal (and even dominated by noise near the Tampa Bay region; Fig. 5d). The Panhandle region also exhibits some weak signal in the seasonal rainfall of the wet season (Fig. 5d). To put the signal-to-noise ratio in Fig. 5d in perspective, we have plotted these ratios for fixed length season of winter (January–March) in Fig. S2a and compared it with the fixed length season of summer (June–September). In the winter, the signal-to-noise ratio is largest in central and south Florida while it is weak in Panhandle region (Fig. S2a). In the summer, the high signal-to-noise ratio is comparatively far more heterogeneous and is confined to the coasts (Fig. S2b). In comparison to Fig. S2b, the signal-to-noise ratio of seasonal rainfall with a varying length (Fig. 5d) is reduced overall, reflecting the impact of including the variations of the seasonal length of the wet season.

d. *Probabilistic skill assessment*

The correlations in Figs. 3a and 3b suggest that monitoring the onset date variations of the wet season can yield a reasonable seasonal outlook of the seasonal length and seasonal rainfall anomaly of the forthcoming wet season, respectively. Furthermore, with the availability of the 1001 ensemble members, it is now possible to provide a probabilistic outlook. Therefore, in this subsection, we provide an assessment of the probabilistic skill of the seasonal outlook from the monitoring of the onset date variations using the area under the relative operating characteristic (AUROC) curve, a metric used in many previous studies (e.g., Mason and Graham 2002; Narotsky and Misra 2022). The anomalies of the onset date, seasonal length, and seasonal rainfall are classified into terciles. Then, a contingency table is prepared to assess the probability of the categorical forecasts of early or later onset date seasons leading to longer or shorter and wetter or drier wet seasons, respectively. In this contingency table, we also include an assessment for the middle

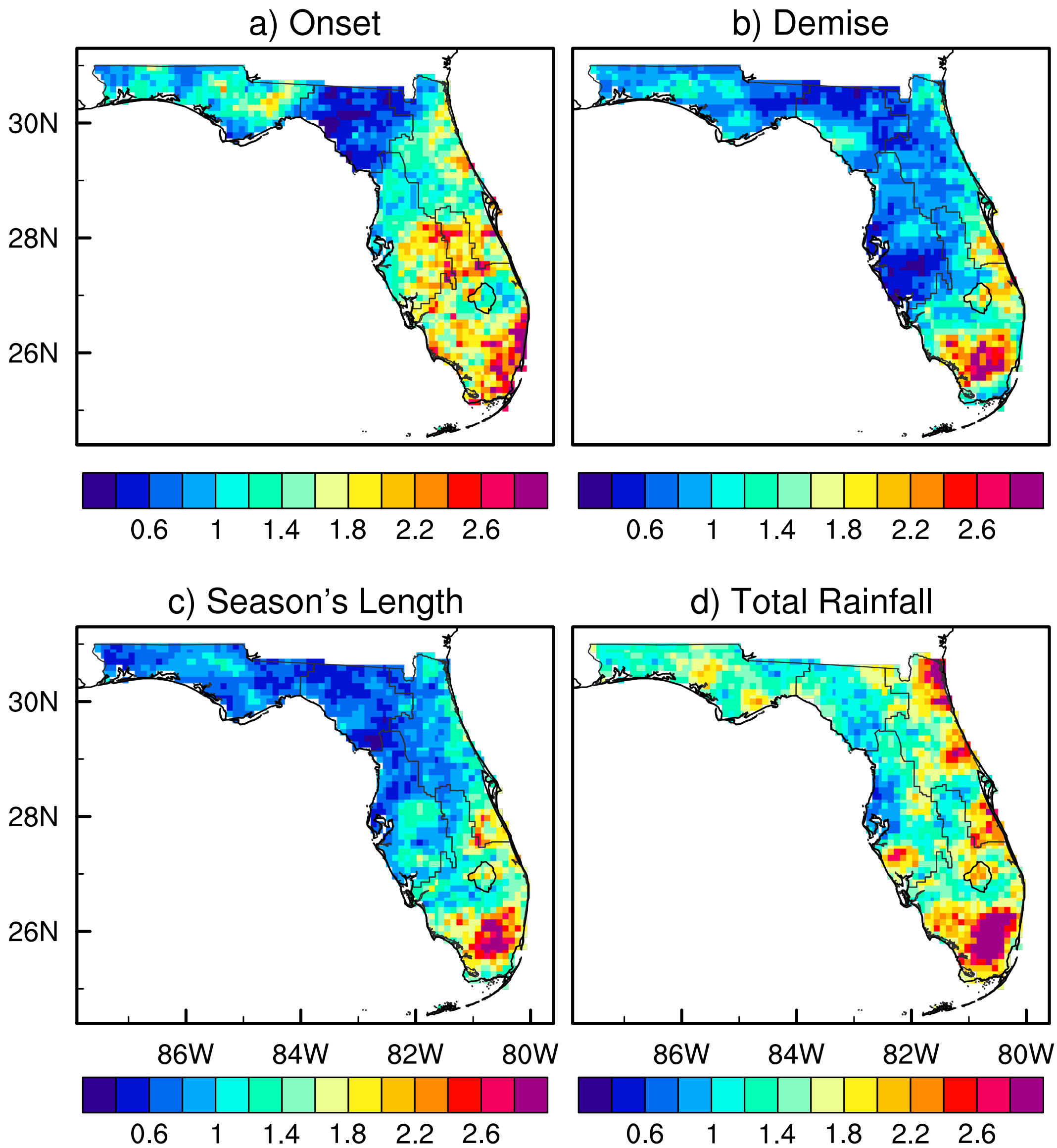

FIG. 5. The signal-to-noise ratio of (a) OD, (b) DD, (c) SL, and (d) seasonal rainfall.

tercile (normal start) of the wet season leading to normal (climatological) length and seasonal rain. The seasonal outlook is skillful when AUROC is ≥0.5, which suggests that the outlook is better than a random forecast (Mason and Graham 2002).

In Figs. 6a–d, we see that for anomalous seasons (with earlier or later onset date compared to climatology), the skills (AUROC is ≥0.5) are widespread across Florida, relative to normal seasons (Figs. 6e,f). In Fig. 6a, the association of early start with the longer season has the most skill in central Florida and generally across peninsular Florida compared to the Panhandle region. In Fig. 6b, the association of early start season with wetter season also shows a similar pattern as in Fig. 6a, but the skill scores are slightly diminished in peninsular Florida while it comparatively enhanced in the Panhandle region. The skill scores of the late-start season leading to shorter length season are much higher (Fig. 6c) across Florida relative to the corresponding skill of early start season with longer length season (Fig. 6a). Similarly, the drier season from late-start wet seasons also shows higher skill in Fig. 6d than in Fig. 6b. In contrast, the normal-start seasons show highly diminished skills with AUROC values slightly over 0.5 across Florida with some regions like southwest Florida and Panhandle region showing some slight enhancement. These relatively low skill scores for normal-start seasons are because these outlooks are based on the linear correlations shown in Fig. 3, which are strongest when the anomalies are largest and least when the anomalies are small. Furthermore, from Fig. 5a, we note that in the Big Bend region of Florida (Suwanee Water Management

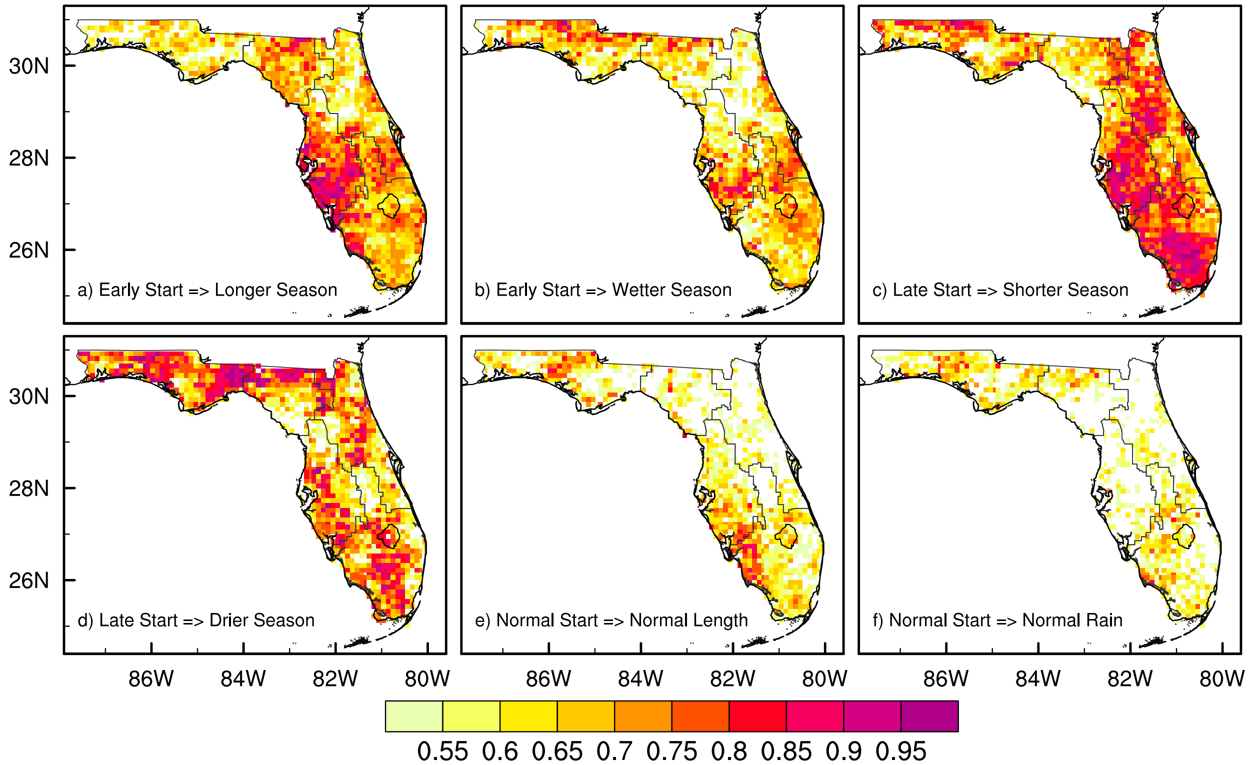

FIG. 6. The probabilistic skill score as measured by the AUROC curve for the early start (lowest tercile) wet season associated with (a) longer (highest tercile) and (b) wetter (highest tercile) season, late-start (highest tercile) wet season associated with (c) shorter (lowest tercile) and (d) drier (lowest tercile) season, and normal (middle tercile) start of wet season associated with (e) normal (middle tercile) SL and (f) normal (middle tercile) seasonal rain. AUROC ≥ 0.5 is shaded.

District), the signal-to-noise ratio of the onset date is <1, which suggests that its chaotic variations dominate over its low-frequency variations. Therefore, logically it follows that the onset date is going to be a relatively less reliable predictor for the seasonal rainfall of the wet season in the Big Bend region. We note this feature by the comparatively low skill scores in this Big Bend region compared to the rest of Florida in Figs. 6b–f. The relatively high skill for early start season yielding an anomalous wet season in Fig. 6a over the Big Bend region is an interesting result, which requires further investigation.

We further extended this analysis to assess the outlook for extreme pentiles in Fig. 7. In fact, in comparison to the outlook of tercile anomalies in Fig. 6, Fig. 7 displays slightly higher skill. This is encouraging as it suggests that the outlook can more reliably predict the outcome of the more extreme shorter and drier or longer and wetter seasons. One of the reasons for this enhanced skill for pentile extremes is that the linear correlations shown in Fig. 3 are going to be stronger for the most anomalous seasons, which is being leveraged for these seasonal outlooks. It may be noted, however, that the Big Bend (or the Suwanee Water Management District) continues to show comparatively lower skill than the rest of Florida in Fig. 7.

4. Conclusions

In this study, we have introduced an ensemble approach to providing a seasonal outlook of the wet season over Florida from just monitoring the onset date of the wet season. The proposed methodology leverages the local covariability of the onset date variations with the length and seasonal rainfall anomaly of the wet season. In the absence of strong external forcing like ENSO during the wet season, the numerical climate models display poor seasonal prediction skill over the summer season that coincides with the wet season over Florida. Under such circumstances, the proposed methodology for obtaining the seasonal outlook of the wet season over Florida by monitoring the onset date is very useful. Our results show that for anomalous start date seasons, the probabilistic skill scores of the seasonal outlook are high and widespread across Florida. Furthermore, these skill scores are highest for late-start seasons that are linked to shorter and drier seasons. Since these seasonal outlooks leverage on the strong linear correlations of the onset date with seasonal length and seasonal rainfall anomaly of the wet season, they become more reliable as the anomalies get stronger. Therefore, the outlook for extreme pentile anomalies is slightly more skillful than extreme tercile anomalies. The proposed method for seasonal outlook serves as a good

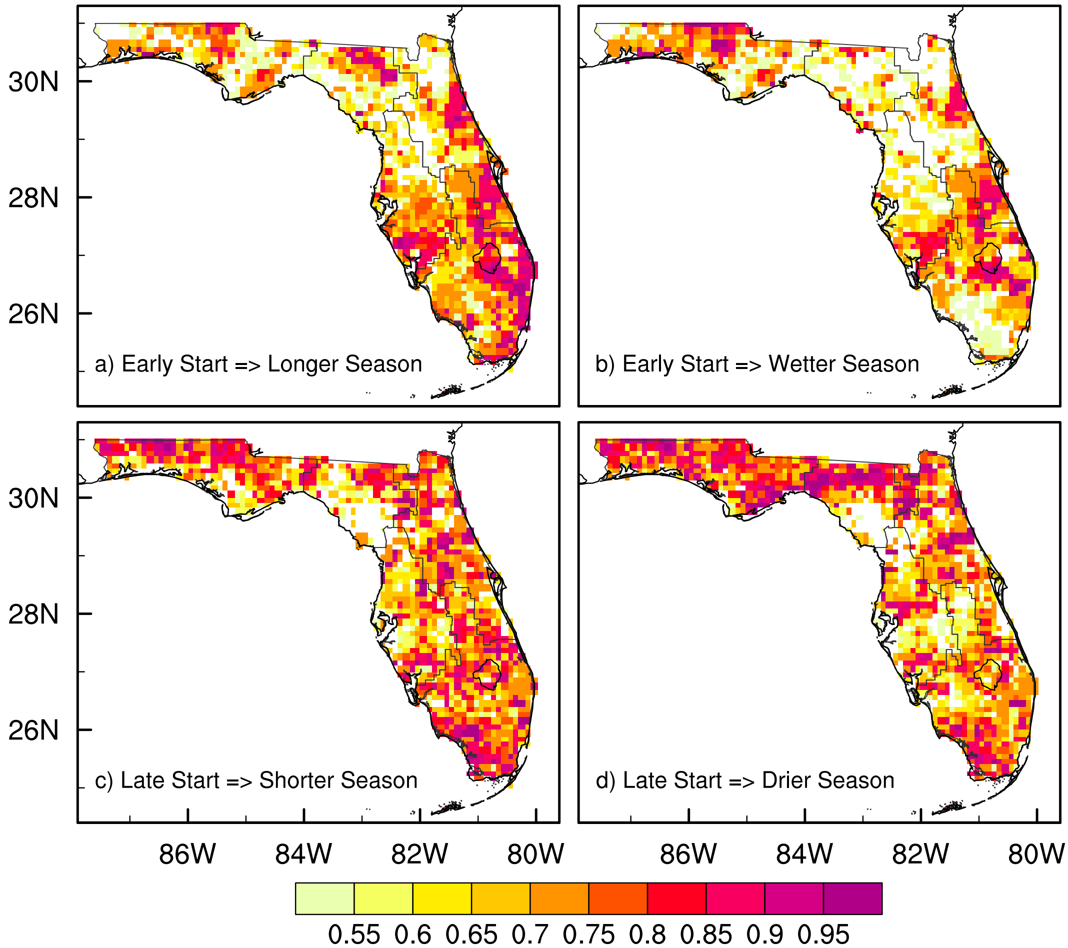

FIG. 7. The probabilistic skill score as measured by the AUROC curve for the early start (lowest pentile) wet season associated with (a) longer (highest pentile) and (b) wetter (highest pentile) season and late-start (highest pentile) wet season associated with (c) shorter (lowest pentile) and (d) drier (lowest pentile) season. AUROC ≥ 0.5 is shaded.

complement to other existing efforts for seasonal prediction over Florida's wet season.

Acknowledgments. We acknowledge the support from NASA Grant 80NSSC22K0595. The IMERG dataset was provided by the NASA/Goddard Space Flight Center and PPS which developed and computed the IMERG as a contribution to GPM and archived at the NASA GES DISC.

Data availability statement. The IMERG rainfall from NASA was obtained from https://gpm1.gesdisc.eosdis.nasa.gov/data/GPM_L3/GPM_3IMERGDL.06/. The monthly North American Multi-Model Ensemble (NMME) datasets were obtained from https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/.

REFERENCES

Huffman, G. J., R. F. Adler, D. T. Bolvin, K. Hsu, C. Kidd, E. J. Nelkin, J. Tan, and P. Xie, 2019: Algorithm Theoretical Basis Document (ATBD) for global precipitation climatology project version 3.0 precipitation data. MEaSUREs project, 52 pp., https://arthurhou.pps.eosdis.nasa.gov/Documents/IMERG_V07_ATBD_final.pdf.

Kirtman, B. P., and Coauthors, 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, **95**, 585–601, https://doi.org/10.1175/BAMS-D-12-00050.1.

Mason, S. J., and N. E. Graham, 2002: Areas beneath the relative operating characteristics (ROC) and relative operating levels (ROL) curves: Statistical significance and interpretation. *Quart. J. Roy. Meteor. Soc.*, **128**, 2145–2166, https://doi.org/10.1256/003590002320603584.

Misra, V., and S. M. DiNapoli, 2013: Understanding the wet season variations over Florida. *Climate Dyn.*, **40**, 1361–1372, https://doi.org/10.1007/s00382-012-1382-4.

——, and A. Mishra, 2016: The oceanic influence on the rainy season of Peninsular Florida. *J. Geophys. Res. Atmos.*, **121**, 7691–7709, https://doi.org/10.1002/2016JD024824.

——, ——, and H. Li, 2016: The sensitivity of the regional coupled ocean-atmosphere simulations over the intra-Americas

Seas to the prescribed bathymetry. *Dyn. Atmos. Ocean*, **76**, 29–51, https://doi.org/10.1016/j.dynatmoce.2016.08.007.

——, ——, and A. Bhardwaj, 2019: A coupled ocean-atmosphere downscaled climate projection for the peninsular Florida region. *J. Mar. Syst.*, **194**, 25–40, https://doi.org/10.1016/j.jmarsys.2019.02.010.

——, C. Selman, A. J. Waite, S. Bastola, and A. Mishra, 2017: Terrestrial and ocean climate of the 20th century. *Florida's Climate: Changes, Variations, and Impacts*, E. P. Chassignet et al., Eds., Florida Climate Institute, 485–509, https://doi.org/10.17125/fci2017.ch16.

——, A. Bhardwaj, and A. Mishra, 2018: Characterizing the rainy season of Peninsular Florida. *Climate Dyn.*, **51**, 2157–2167, https://doi.org/10.1007/s00382-017-4005-2.

——, T. Irani, K. Morris, T. Asefa, C. Martinez, and G. Wendy, 2021: The Florida Water and Climate Alliance (FloridaWCA): Developing a stakeholder–scientist partnership to create actionable science in climate adaptation and water resource management. *Bull. Amer. Meteor. Soc.*, **102**, E367–E382, https://doi.org/10.1175/BAMS-D-19-0302.1.

——, C. B. Jayasankar, P. Beasley, and A. Bhardwaj, 2022: Operational monitoring of the evolution of rainy season over Florida. *Front. Climate*, **4**, 793959, https://doi.org/10.3389/fclim.2022.793959.

——, S. Dixit, and C. B. Jayasankar, 2023: The regional diagnosis of onset and demise of the rainy season over tropical and subtropical Australia. *Earth Interact.*, **27**, https://doi.org/10.1175/EI-D-22-0026.1.

Narotsky, C. D., and V. Misra, 2022: The seasonal predictability of the wet season over Peninsular Florida. *Int. J. Climatol*, **42**, 3408–3417, https://doi.org/10.1002/joc.7423.

Stefanova, L., V. Misra, J. J. O'Brien, E. P. Chassignet, and S. Hameed, 2012: Hindcast skill and predictability for precipitation and two-meter air temperature anomalies in global circulation models over the Southeast United States. *Climate Dyn.*, **38**, 161–173, https://doi.org/10.1007/s00382-010-0988-7.