Award # 80NSSC19K1199
Final Research Report: 6/18/2019 – 6/17/2023

Integrating NASA Earth systems data into decision-making tools of member utilities of the Florida Water and Climate Alliance

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PRA, State agency/Water wholesaler
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ARL at project initiation: 3
ARL at project termination: 6

Goals and Objectives:

Primary goal of the project was to improve water allocation and storage decisions by two member utilities of the Florida Water and Climate Alliance (FloridaWCA), TBW and PRA, using high-resolution dry season forecasts initialized using remotely sensed soil moisture. The main objectives were to **i)** develop real-time monitoring tool using NASA-based products to assess the changes in seasonal cycle of the surface climate of Florida, also adapted for developing seasonal outlooks of the oncoming wet and dry seasons **ii)** develop high-resolution seasonal dynamical forecasts for Florida during the winter dry season using NASA Earth Science data for initialization and verification; and **iii)** integrate these forecasts and monitoring tools into end-user decision support tools developed and refined via sustained scientist-stakeholder interactions with members of the FloridaWCA, enhancing potential for broader adoption.

The FloridaWCA is a stakeholder-scientist partnership that was initiated in 2010 on the basis of a shared interest in community building to create actionable science and this project leveraged this stakeholder-scientist network to examine the efficacy of its members' decision-making processes with respect to adoption of the project's forecasting and decision support products. Thus, the project aligned well with the NASA Earth Science Division Applied Science Program's interest in developing and demonstrating the integration of Earth observations and related products into water resources management and decision-making.

Objective 1: Real-time monitoring tool using NASA products

Onset and Demise of rainy season in Peninsular Florida (PF):

Florida has a distinct wet season, which serves the annual water needs of the State and beyond. Major factors contributing to the variability of the wet season over Florida are seasonal rainfall anomalies and the variations of the length of the season. Furthermore, the variations of the onset date of the rainy season relate significantly to the seasonal anomalies of length of the season and rainfall. Monitoring the onset of the rainy season could serve in providing an outlook for the season since the onset date variations of the rainy season has a bearing on the forthcoming evolution of the season. For example, an early or a delayed onset of the rainy season is likely to lead to a wetter or a drier season, respectively.

For the project, NASA'Integrated Multi-Satellite Retrievals for Global Precipitation Mission version 6 (IMERG) rainfall dataset was used to monitor the rainy season over the five Water Management Districts (see Figure 1) (WMDs) of Florida. This effort was complimented by analyzing and verifying the variations of the rainy season over the preceding 20 wet seasons from the IMERG datasets. IMERG produces rainfall datasets at various latencies, with the final product having a 3.5-month latency since the satellite measurements of radiance are made.

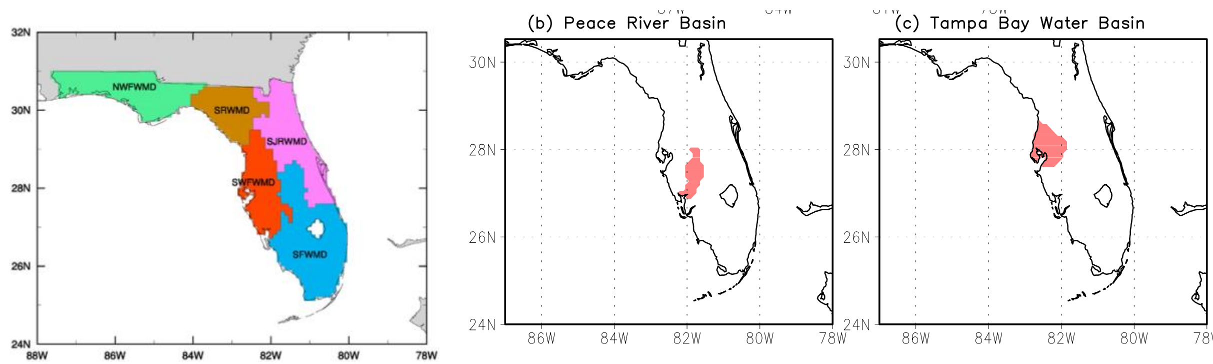

Figure 1: (a) **Water Management Districts (SFWMD, South Florida; SWFWMD, Southwest Florida; SJRWMD, St. Johns River; SRWMD, Suwannee River; NWFWMD, Northwest Florida) for which the onset and demise of the wet season is diagnosed. (b) Peace River Basin and (c) Tampa Bay Water Basin**

The onset of rainy season over Peninsular Florida (PF) is dramatic with average daily rain rates of over 7 mm/day, with significant spatial heterogeneity. The demise of the rainy season shows a significant drop to less than 5 mm/day. Figure 2 shows the robust seasonal cycle with peak rainy months in June, July, and August in the five WMDs.

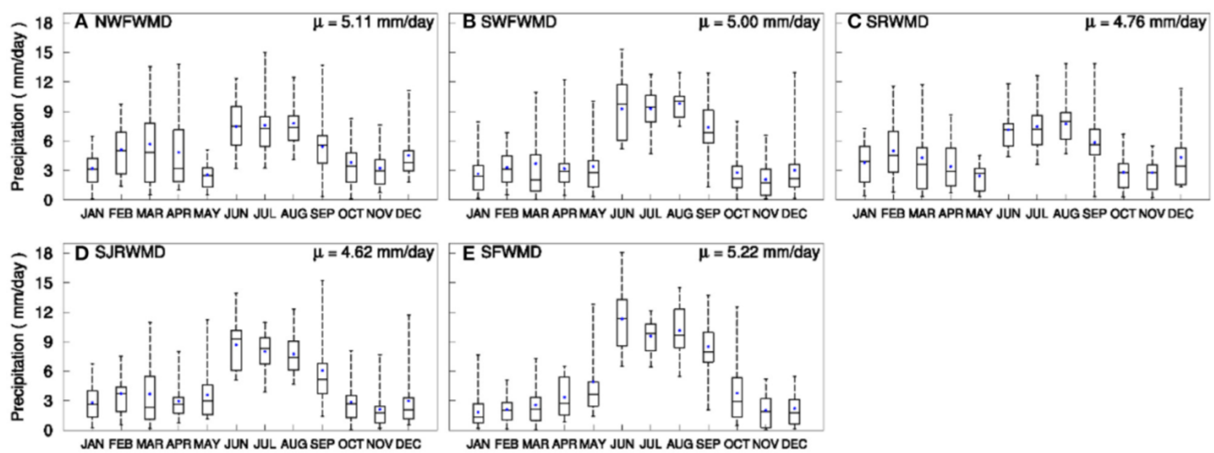

Figure 2: The box and whisker plot of the monthly mean precipitation (mm/day) over (A) NWFWMD, (B) SWFWMD, (C) SRWMD, (D) SJRWMD, and (E) SFWMD. The corresponding annual mean climatology is indicated in the top right corner.

Figure 3 shows the time series of the onset date, demise date, seasonal length, and seasonal accumulation of rainfall for the SFWMD from three rainfall datasets, and Table 1 presents the root mean squared error (RMSE) and correlation values from the Figure 3. The 3.5-month latency and 12-h latency dataset have comparable correlation values and are statistically significant at 95% confidence interval, suggesting that the 12-h latency dataset may be appropriate to diagnose the variations of the rainy season over SFWMD. In other WMDs, the 12-h latency dataset shows the highest fidelity as well.

We found that an intermediate 12-h latency product of rainfall analysis from IMERG is reasonable to use for near real-time monitoring of the wet season over Florida. The operational monitoring of the 2021 wet season using the 12-h latency dataset from IMERG was also supplemented with the extended weather 6- to 10-day and 8- to 14-day forecasts of precipitation probability issued by the NOAA's Climate Prediction Center.

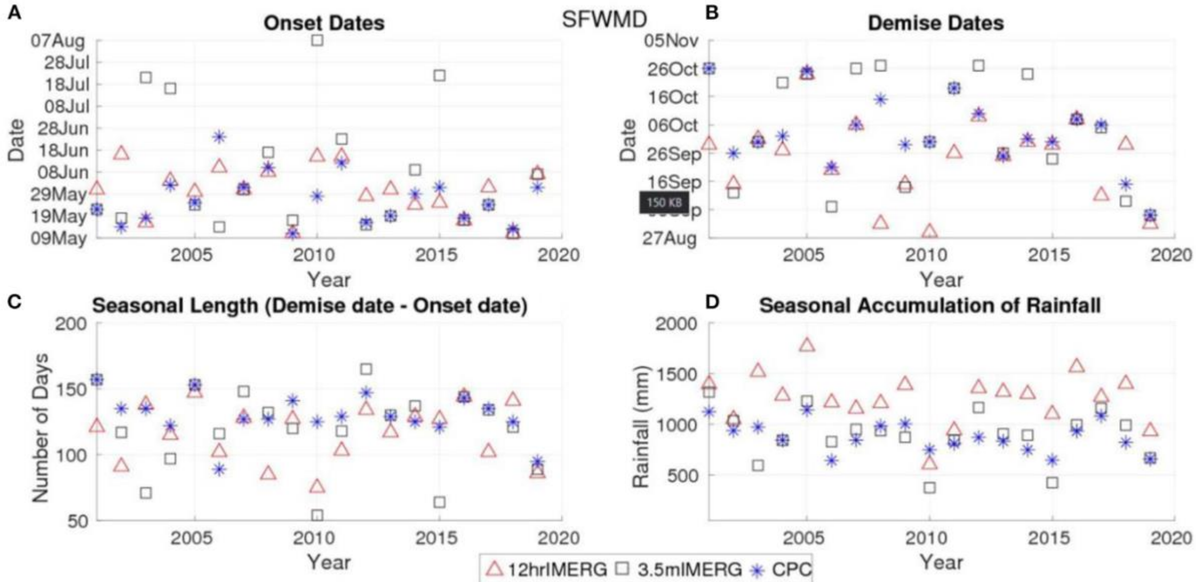

Figure 3: Time series of (A) onset date, (B) demise date, (C) seasonal length (number of days), and (D) seasonal accumulation of rainfall of the wet season for South Florida Water Management District (SFWMD). Blue dots are for CPC, black dots are for 3.5-month latency IMERG (3.5m IMERG), and red dots are for the 12-h latency IMERG (12 h IMERG) rainfall datasets, respectively.

TABLE 1 | The correlation coefficient (CC) and root mean squared error (RMSE) of the onset date, demise date, season length, and total seasonal rainfall anomalies for the five WMDs of Florida from the 12-h latency and 3.5 month latency datasets of IMERG, computed relative to the rain gauge based analysis of CPC data.

	SFWMD		SWFWMD		SJRWMD		SRWMD		NWFWMD	
	CC	RMSE	CC	RMSE	CC	RMSE	CC	RMSE	CC	RMSE
12-h vs. CPC										
Onset	**0.58**	10.77	**0.95**	3.48	**0.78**	7.81	**0.72**	9.39	**0.41**	49.11
Demise	**0.43**	16.85	**0.88**	7.23	**0.59**	18.02	**0.71**	14.08	**0.71**	16.38
Seasonal length	**0.48**	23.42	**0.93**	7.99	**0.59**	21.72	**0.79**	15.12	0.33	49.83
Seasonal rainfall	**0.59**	426.13	**0.79**	343.46	**0.85**	212.33	**0.69**	223.23	**0.72**	388.99
3.5-month vs. CPC										
Onset	0.27	28.78	**0.59**	24.62	0.38	64.47	**0.65**	31.55	**0.7**	46.73
Demise	**0.82**	11.27	0.31	18.51	**0.53**	41.99	**0.78**	26.19	**0.61**	16.83
Seasonal length	**0.49**	28.67	**0.52**	28.19	0.11	78.65	**0.46**	33.09	**0.57**	42.70
Seasonal rainfall	**0.69**	178.4	**0.70**	189.14	**0.46**	419.45	**0.83**	158.98	**0.82**	211.91

The bold values of the correlation coefficient indicate that they are significant at 95% confidence interval according to t-test.

Table 2 shows that the onset and demise dates of the rainy season in each WMD is significantly correlated to season length and rain anomalies. This suggests that early or later onset of the rainy season is more likely to be associated with longer or shorter and wetter or drier season, respectively. The demise date variations can be used to analyze the season posteriorly. For example, later or early demise of the season is likely to be associated with shorter or longer and drier or wetter season, respectively.

Our study suggests that the current methodology of monitoring the onset date variations of the rainy season provides a viable alternative to assess and anticipate the seasonal variations amidst the moderate to insignificant weather and climate prediction skill of the numerical forecast models of the wet season of Florida. Figure 4 shows the monitoring discussion and graphic generated from the monitoring tool for SFWMD for the 2021 season. This discussion was issued on May 28, which was the 7th update since the first one was issued on May 1. This type of

TABLE 2 | The correlations of onset and demise dates of the rainy season with the seasonal length and seasonal rainfall anomalies over the five WMDs of Florida.

Region		Demise	Seasonal length	Seasonal rainfall
SFWMD	Onset	0.17	**−0.46**	**−0.41**
	Demise	1	**0.80**	**0.53**
SWFWMD	Onset	**−0.39**	**−0.79**	**−0.57**
	Demise	1	**0.87**	**0.64**
SJRWMD	Onset	0.11	**−0.45**	**−0.40**
	Demise	1	**0.84**	**0.47**
SRWMD	Onset	0.11	**−0.48**	−0.24
	Demise	1	**0.82**	**0.66**
NWFWMD	Onset	**0.38**	**−0.40**	**−0.50**
	Demise	1	**−0.69**	0.34

The bold values of the correlation coefficient indicate that they are significant at 95% confidence interval according to t-test.

discussion was updated at intervals of approximately 4 days to closely monitor the date of the onset of the 2021 wet season. The interval of these discussions was changed to monthly once the onset was reached in all WMDs.

Figure 5 shows the final discussion generated on September 29, 2021. In these figures, the daily cumulative anomaly curve of rainfall shows that a peak was reached before it started to decline. The peak is diagnosed as the demise of the wet season. In all WMDs except for SRWMD and SFWMD, the demise date in 2021 was reached within a couple of days of the corresponding climatological demise date. In SRWMD and SFWMD, the demise date was 4 days after and 5 days earlier than climatology, respectively.

We note that the IMERG rainfall dataset with a spatial resolution that is nearly five times higher than the CPC rainfall dataset provides additional impetus to pursue such real-time monitoring of the wet season over relatively small areas like theWMDs in Florida.

Monitoring onset/demise of the rainy season over South Florida (SFWMD): May 28, 2021

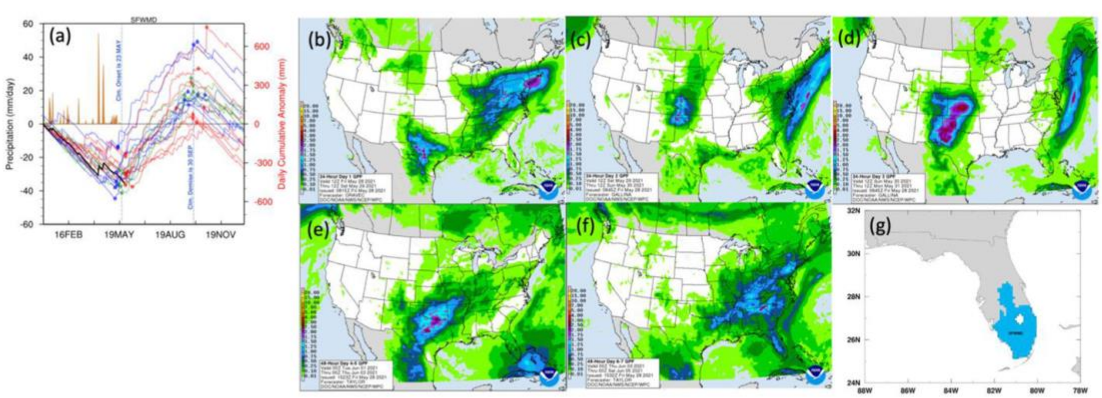

Figure 4: An illustration of the monitoring discussion for SFWMD issued on May 28, 2021. Similar monitoring discussion was issued for the remaining four WMDs of Florida. (a) The daily rainfall from

IMERG-12 h latency dataset for 2021 is in brown. The daily cumulative rainfall anomaly curve is in blue, red and green for early, late and neutral onset seasons based on IMERG-12 h latency dataset over the time period of 2000–2020, respectively. The anomalous onset seasons are based on terciles. The corresponding dots and diamonds in the curve mark the onset and the demise of the rainy season, respectively. The daily cumulative anomaly curve for the current rainy season in 2021 is in bold red. (a–f) The quantitative short-term precipitation forecast from NOAA's Weather Prediction Center (https://www.wpc.ncep.noaa.gov/qpf/qpf2.shtml). (g) Mask of South Florida Water Management District (SFWMD). Discussion: (1) The range of onset dates from the historical 20 years shows that the earliest was on 11 May 2018 and the latest was on 11 June 2011. (2) The onset has not reached for this region as of 27 May 2021. (3) The onset of the rainy season is delayed relative to the climatology onset date (23 May). (4) Given the precipitation forecasts for the next few days, it is anticipated that the onset of the rainy season could occur in the next few days.

Gap-free 16 year meteorological data record across Florida:

The rather unique sub-tropical, flat, peninsular region of Florida produces a unique climate with extreme weather events across the year that impacts agriculture, public health, and management of natural resources. Meteorological data at high temporal resolutions are essential for estimating climate variations and issuing the predictions in such regions that exhibit strong sub-daily variations like the diurnal and semi-diurnal cycles. However, many meteorological datasets contain gaps that limit diurnal trend analysis. We developed a gap-free dataset with 15-minute observations for the sub-tropical region of Florida for 2005-2020.

Yearly observations at 15-minute intervals were obtained from Florida Automated Weather Network (FAWN) for all active stations. This study used data available over the longest period of time across the highest number of stations, resulting in 30 stations over 2005-2020, as shown in Figure 6. In the northern part of the State, 16 stations were located in forested and woody environments, and in the South, nine stations were in areas classified as savanna. Four of the stations were positioned in urban areas, and one station was located in cropland.

Using air temperature at 60 cm, 2m, and 10 m; dew temperature, soil temperature, relative humidity, precipitation, wind speed and direction, and solar radiation from FAWN, methods of linear interpolation, trend continuation, reference to external sources, and nearest station substitution were applied to fill in the data gaps depending on the extent of the gap. The outcome of this study provides continuous surface meteorological observations for 30 FAWN stations at 15-minute intervals for the years 2005-2020. The gap-free data record is available at https://fawn.ifas.ufl.edu/data/ . It establishes a foundation for understanding climate variability and developing prediction models, as it can be used to improve the representation of the diurnal cycle of numerical weather prediction (NWP) models. The NWP models use current observations to predict future weather conditions.

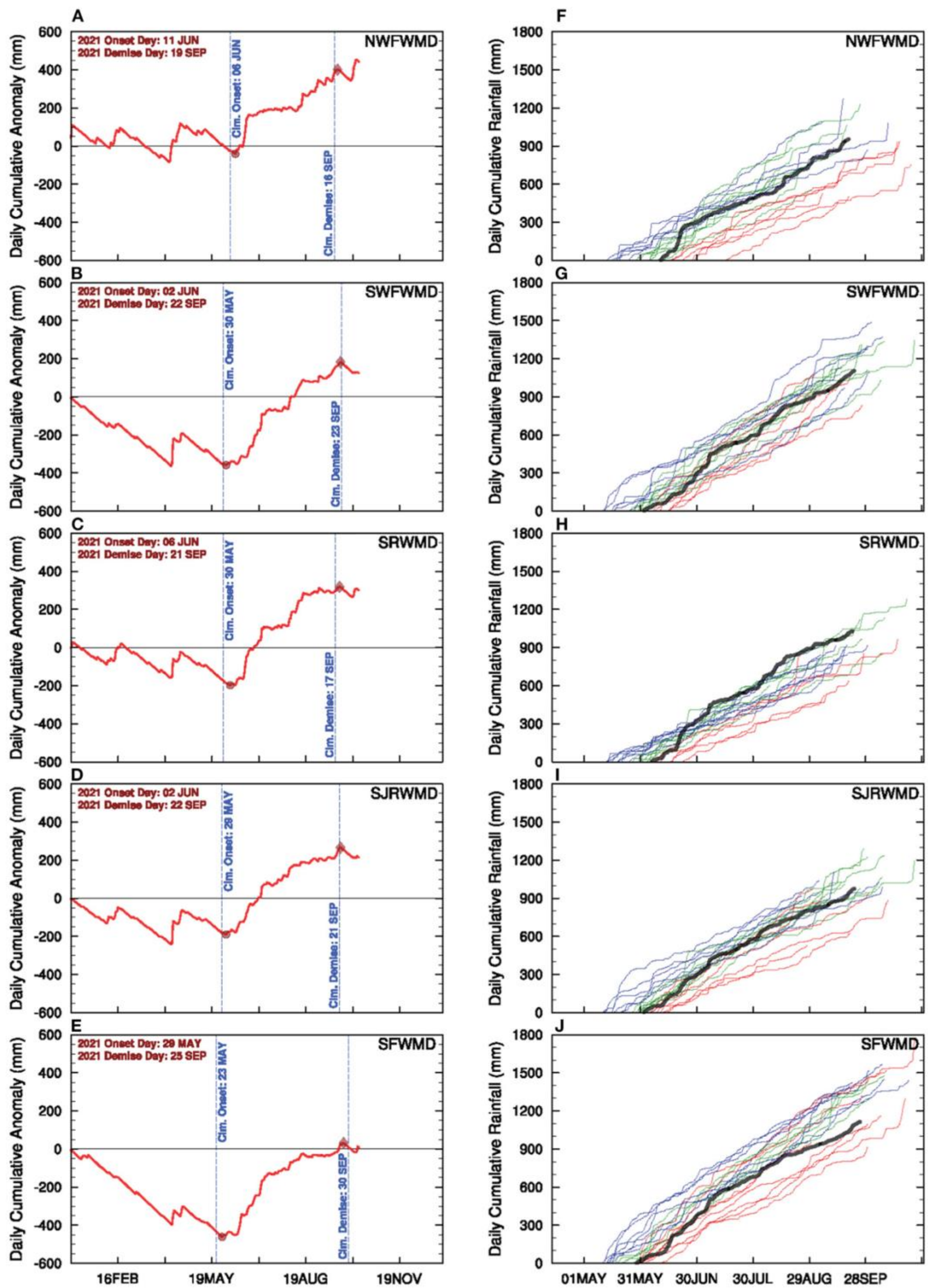

Figure 5: Graphics for the culminating discussion on the monitoring of the rainy season over Florida issued on September 29, 2021. The daily cumulative precipitation anomaly curve for the five WMDs ending on (A–E) September 29 and the cumulative daily rainfall from day of onset for early (blue), late (red), and normal (green) onset date seasons released with the monitoring discussion of (F–J) September 29.

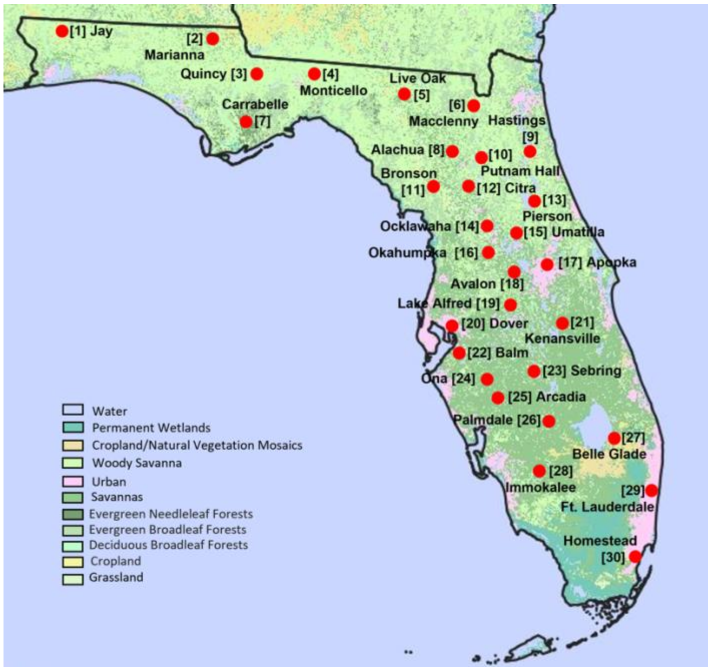

Figure 6: Thirty FAWN stations selected for the project to produce 16-year gap-free meteorological dataset.

Objective 2: High-resolution dynamical forecasts for Florida during winter dry seasons

Seasonal climate forecasts were downscaled for boreal winter at 10 km to allow for decision making in the following spring season, that is based upon the prior water demand in the winter. These winter seasonal reforecasts were dynamically downscaled by the regional spectral model (RSM) from a global model run at T62 spectral resolution (210-km grid spacing at the equator) forced with sea surface temperatures (SST) obtained from one of the global models in the North American Multimodel Ensemble (NMME). We found that RSM runs at 5 km grid did not yield significant benefit, while it consumed 6 times more computing resources. Ensemble of seasonal forecasts based upon uncertainties in sampling and boundary conditions, were made for each winter season from 2000-2022, called seasonal recasts for Florida (CLIFF). These hindcasts were used to assess the fidelity of the forecast system. CLIFF was designed in consultation with water managers at TBW and PRA, targeting the five water management districts, including two smaller watersheds of two specific stakeholders in central Florida that manage the public water supply.

We found that both deterministic and probabilistic skill measures of the seasonal precipitation at the zero-month lead for November–December–January (NDJ) and one-month lead for December–January–February (DJF) show that CLIFF has higher seasonal prediction skill than persistence. The results of the seasonal prediction skill of land surface temperature are more sobering than precipitation, although, in many instances, it is still better than the persistence skill.

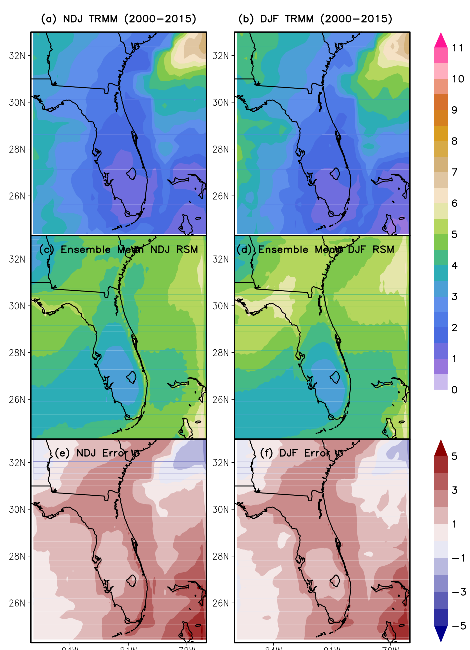

Figure 7: Climatological seasonal mean precipitation (mm/day) for (a, b) November-December-January (NDJ) and (d, e) December-January-February (DJF) from (a, d) TRMM and (b, e) ensemble mean RSM reforecast. Note that NDJ is at 0-month forecast lead in (b) and DJF is at 1-month forecast lead in (e). The corresponding climatological errors (RSM reforecast-TRMM; in mm/day) are shown for (c) NDJ and (f) DJF seasons.

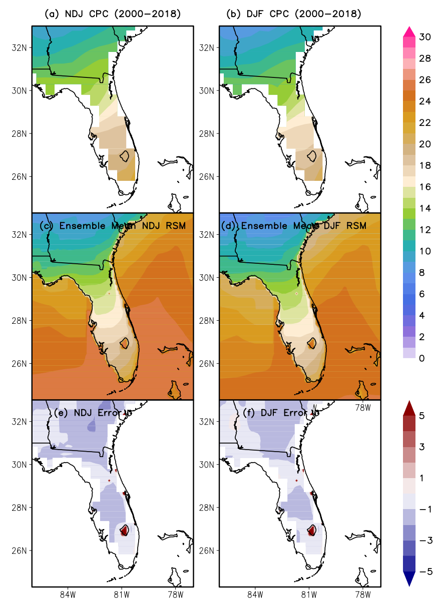

Figure 8: Climatological seasonal mean surface temperature (°C) for (a, b) November-December-January (NDJ) and (d, e) December-January-February (DJF) from (a, d) CPC and (b, e) ensemble mean RSM reforecast. Note that NDJ is at 0-month forecast lead in (b) and DJF is at 1-month forecast lead in (e). The corresponding climatological errors (RSM reforecast-CPC; in degrees C) are shown for (c) NDJ and (f) DJF seasons.

Figures 7 and 8 show the climatological seasonal mean precipitation and surface temperature, respectively from CLIFF.

Figure 9 shows the forecast skill in terms of anomaly correlation of winter seasonal precipitation between CLIFF and the corresponding observations. The 32 daily and monthly variables are archived at https://data.coaps.fsu.edu/pub/abhardwaj/PR/G_RSM/

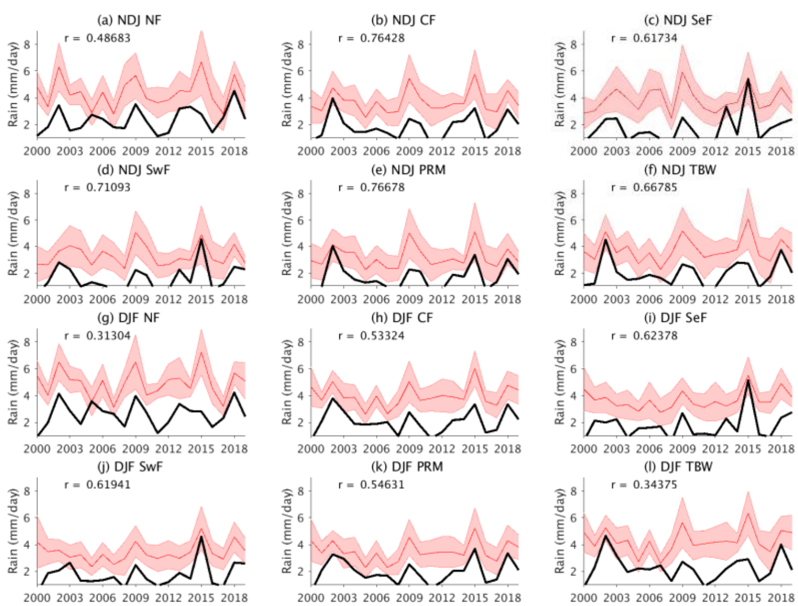

Figure 9: Anomaly correlation of seasonal mean rainfall by region (regions shown top left)

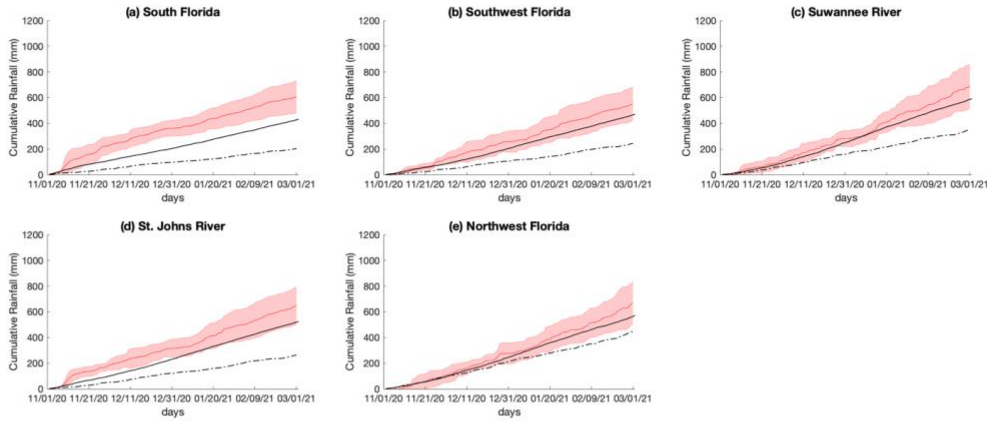

Figure 10: The cumulative rainfall (in mm) over a) South Florida, b) Southwest Florida, c) Suwannee River, d) St. Johns River, and e) Northwest Florida Water Management Districts from 1 November, 2020 to 1 March, 2021 of the following year for the ensemble mean (thin red line) and the individual ensemble members (shaded) of CLIFF. The solid black line is the corresponding model climatological cumulative rainfall for the season, and the dashed black line is the observed climatology.

CLIFF forecasts were presented by cumulative precipitation and by freshwater flux. It was evaluated for all 5 water management districts in Florida (see Figure 1) as well as for the TBW and PWA service areas (see Figure 10) and found to have systematic wet bias (see Figure 11).

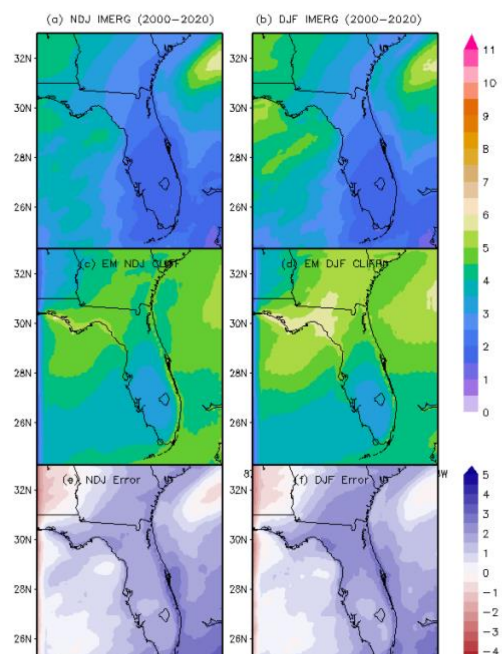

Figure 11: Systematic wet bias found in CLIFF. Top row IMERG rainfall. Middle row ensemble mean (EM) of CLIFF. Bottom row difference (CLIFF-IMERGE).

Objective 3: Integration of forecasts into operational decision making and capacity building

The output from monitoring tools and the CLIFF were integrated into the seasonal rainfall-runoff model for TBW for use in their source allocation model that specifies supply source mix to meet seasonal demands and in the adaptive seasonal risk management tool.

For.

The framework consists of a statistical streamflow generation model, four different sets of rainfall inputs, and distinct metrics for evaluating the resulting streamflow forecasts. The four sets of rainfall inputs include rainfall climatology, observed rainfall, NOAA-based seasonal rainfall forecasts, and CLIFF-based rainfall forecasts. Because NOAA ensemble precipitation forecasts were not available in this study, NOAA-based categorical precipitation outlooks were postprocessed via a hidden Markov chain model to obtain the corresponding NOAA-based seasonal rainfall forecasts. Streamflow forecasts based on rainfall climatology served as a reference. Different evaluation metrics, including Spearman correlation, mean absolute percent error (MAPE), and rank probability skill score (RPSS), were employed to evaluate model performance. The framework was demonstrated for streamflow forecasts for two rivers in the southwest of Florida, serving as a major source of a regional water supply agency. Figure 12 shows the TBW water demands for the month of November. A retrospective streamflow forecasting model was designed for the dry season [November, December, January, and February (NDJF) months] for each of the 20 years from 2000 to 2019. Results revealed that CLIFF-based streamflow forecasts (shown in Figure 13) are a promising alternative to NOAA-based forecasts. Deterministic streamflow forecasts based on CLIFF rainfall have a smaller mean absolute percent error (MAPE) compared with the NOAA-based streamflow forecasts. Although NOAA-based probabilistic streamflow forecasts outperformed CLIFF-based probabilistic streamflow forecasts for the winter forecasting periods of November, December, and January, the latter forecasts performed better for the forecasting period of February. Thus, the two probabilistic forecasts are complementary. Although the results are limited to the study area, it has general application for evaluating the utility of different rainfall forecasts in providing deterministic/probabilistic streamflow forecasts.

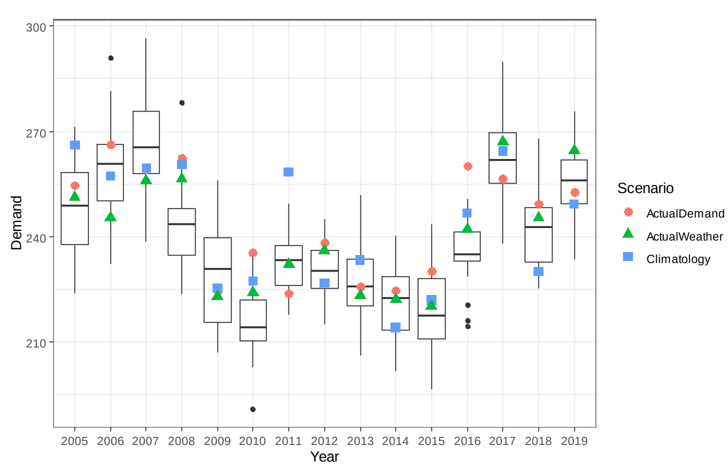

Figure 12: Forecasts of Municipal water Demand for Tampa Bay Water for the month of November. Forecasts using Actual Weather are a "Perfect" forecast and shows the error in the model itself.

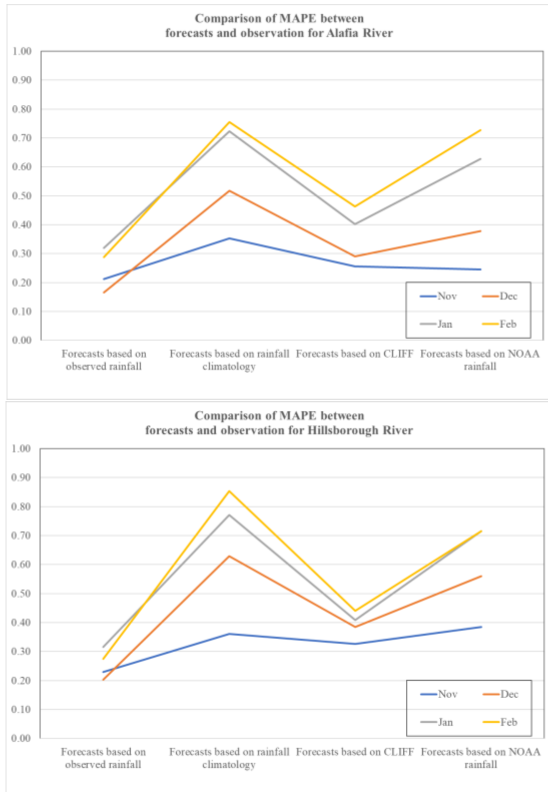

Figure 13: Mean Absolute Percent Error (MAPE) for the Tampa Bay Water Rainfall-Streamflow Model using observations (perfect forecast), climatology, CLIFF, and NOAA CPC Outlooks for the Alafia (top) and Hillsborough (lower) Rivers. Lower MAPE indicates a better forecasts. Forecasts using CLIFF outperform NOAA CPC Outlooks and Climatology (with the exception of November for the Alafia River).

Figure 14 shows the comparisons of streamflow for the PRA watershed.

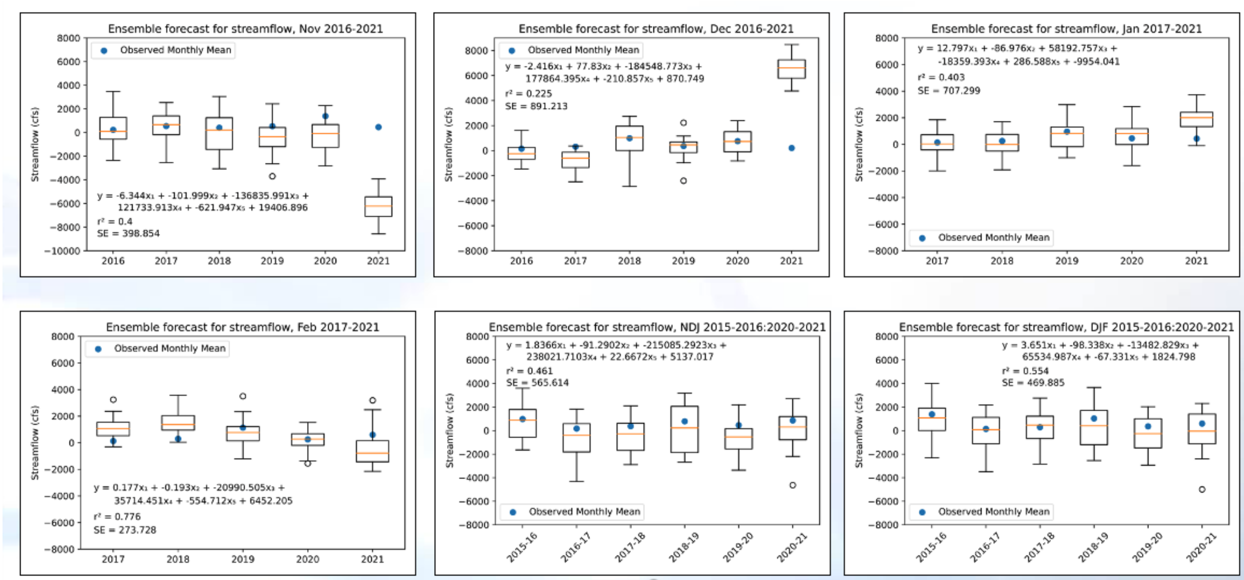

Figure 14: Boxplots for the ensemble forecasts compared to observations for Peace River streamflow.

Machine Learning-Based streamflow model

In addition to the streamflow model used by TBW, we explored ML-based approach for seasonal streamflow forecast. However, much ML literature focuses on point forecasts rather than the complete predictive distribution. Here, we developed a methodology for probabilistic forecasting of seasonal streamflow using a suite of ML models. These predictive distributions can be integrated into probability-of-exceedance (POE) analyses and decision-making tools such as those being used by TBW.

We evaluated multiple ML models that use lagged observations to generate probabilistic forecasts and POE curves for the JFM (January-February-March) seasonal streamflow. Given the significant influence of the El Niño-Southern Oscillation (ENSO) in this season, our evaluation focused on climate-driven streamflow forecasts. Forecasts derived from the predictive distributions were evaluated with multiple predictive performance metrics, including the RMSE for point-level prediction, the NOIS for interval prediction, and CRPS/LEPS for the whole predictive distribution and the POE forecast.

We focused on ML methods that provide conditional distribution estimates of unobserved streamflow based on training data and tuned model parameters, enabling the derivation of POE forecasts from predictive distributions. The models based on multiple predictors used the streamflow and Niño indices of the preceding seasons (Oct.—Dec., Jul.—Sep., and Apr.--Jun in the previous year). We listed the models applied in this study and their key descriptions in Table 3.

Table 3 The abbreviation and the key description for the 10 models in the study

Abbreviation	Description
Climatology	ECDF based on historical records of JFM streamflow
SF_1	Simple linear regression with lag 1 streamflow
Nino_1	Simple linear regression with lag 1 Nino 3.4 index
MLR	Multiple linear regression with all the 15 predictors
VIF	pre-screen covariates using variance inflation factor (VIF) threshold of 10 to suppress multicollinearity
Forward	Forward stepwise selection with tuning number of covariates
ElasticNet	Penalized regression with a mixture of Lasso (L1) and Ridge (L2) penalties on coefficients
GAM	Generalized additive model (GAM) consist of a linear combination of nonlinear smooth functions with smooth terms selection
QRF	Quantile regression forest (QRF) estimate quantiles using random forest, which is composed of de-correlated decision trees
GBM	Quantile regression forest with Gradient boosting machine (GBM), whose decision trees consider the error from subsequent trees

After evaluating the streamflow forecasts over 46 years, we categorized the models into three groups based on their performance. The first category, consisting of Forward, GAM, ElasticNet, MLR, and VIF, outperformed the second category (GBM, QRF, and SF_1), while both surpassed the third category (Nino_1 and Climatology) across various evaluation metrics, including RMSE, NOIS, CRPS, and LEPS. Notably, the models in the first category share a common feature of additive function comprising multiple predictors. Among them, Forward, ElasticNet, and GAM consistently achieved superior scores in mean CRPS and mean LEPS in pairwise t-tests. Particularly, Forward consistently achieved the highest scores across various performance metrics, making it the preferred choice for seasonal streamflow volume forecasting in the area.

Furthermore, the model that incorporated lagged streamflow and all four Niño indices demonstrated superior performance compared to SF_1 and Nino_1, which either do not utilize any Niño index or rely on a single Niño index. This finding underscores the importance of incorporating lagged streamflow and multiple Niño indices in streamflow forecasting. Suggested by feature selection methods (employed in Forward, ElasticNet, and GAM), streamflow and the Niño1.2 from October-December were the most important predictors, and QRF identified streamflow and the four Niño indices from October-December as the most important predictors. Additionally, QRF revealed that among the variables spanning April to September, all the lagged Niño indices exhibited greater importance than lagged streamflow, highlighting the lagged influence of ENSO.

In conclusion, this study demonstrates the potential of machine learning algorithms for seasonal streamflow volume forecasting in West-Central Florida rivers. The comparison of different ML methods revealed that incorporating multiple Niño indices along with lagged streamflow significantly improves probabilistic forecasts. This work demonstrated the usefulness of machine learning-based streamflow forecasts for water management by providing the forecasted Probability of Exceedance (POE) curves that facilitate decision-making in water management.

Analyzing the decision-making process and implementation of forecasts by TBW & PRA:

To understand the scientist-stakeholder interactions and its impact on adoption and decision making, we developed a contextual model (Figure 15) of a decision-making process and utilized the FloridaWCA, TBW, and PRA as a collaboratory for the development, implementation, and refinement of seasonal forecasts that can be used to help utilities make decisions about water resource allocations. We explored how interacting with scientists and modelers as project develops affect adoption and sustainability, the process do utility decision makers use in deciding how they will use climate data in their operations (benefits/risks), and whether the process was affected by utility characteristics, and the prospect of other utility members of FloridaWCA l to adopt/adapt?

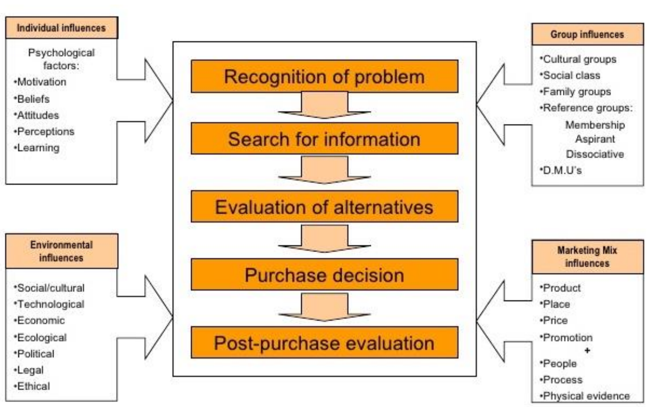

Figure 15: Decision as problem solving – Consumer problem solving

Several FloridaWCA capacity building and stakeholder engagement workshops were conducted, as shown in Table 4. All the presentation recordings are available at [www.FloridaWCA.org.](www.FloridaWCA.org) In-person meetings canceled due to COVID-19 and moved to online webinars

Table 4: FloridaWCA webinars for capacity building and stakeholder engagement

	Theme	# participants
February 2020	In-person quarterly meeting	37
July 2020	Water, climate and COVID-19	115
September 2020	Water utility risk and resilience to climate change impacts	105
November 2020	Water quality and climate change issues	108
April 2021	Hurricane season impacts on water management in Florida	123
September 2021	Climate change impacts on wastewater and stormwater management	173
January 2022	Perspectives on saltwater intrusion	191
April 2022	Integrating seasonal forecasts into utility operations	95
October 2022	Impacts of extreme weather and climate on florida water agencies	142
March 2023	Future rainfall projections for florida water resources planning and management: Stakeholder needs assessment	195

In addition, interviews interviews were conducted with the stakeholders at TBW and PRA were conducted. The stakeholders included board members of FloridaWCA and other members of the FloridaWCA. The results of these stakeholder interviews (see Figure 16) were shared with all the members of the FloridaWCA.

Figure 16: Stakeholder responses to integrating new information into existing operations

The interviews showed that stakeholders appreciate and utilize a wide range of climate information/data from a multiplicity of sources with varying levels of integration into existing analytical tools and decision processes. However, certain barriers were identified to utilizing climate projections for decision-making. They ranged from the complexity and trustworthiness of the data; lack of standardized procedures; educational gaps among constituents to insufficient funding. Also, the panelists reported a noted mismatch between “data that is needed and what is available.” Given the unique state topography, the need for varied levels of downscaling of gridded data is an ongoing issue. Since decision data come from multiple sources, there is an additional need for guidance on integrating these sources to understand a given local situation best. All this underscores a unique characteristic of the water resource field – the need for highly specialized and often location-specific data, further complicating the decision-making process.

Participants and panelists agreed on the importance of developing comprehensive regulatory standards, accessible tools, better education, and more secure funding to better incorporate climate projections in decision-making. This includes advocating for a holistic approach that combines data from various sources and fosters collaboration across different organizations.

Figure 17 shows the conceptual model rainfall pattern impacts on resilience planning across various sectors. This model illustrates the intricate relationships and interdependencies between the sectors, based upon the data provided by the experts. It also sheds light on decision-making processes concerning resilience planning.

Figure 17: Conceptual model representing the impact of changing rainfall patterns on resilience planning across various sectors.

Figure 18 shows some key examples of stakeholder responses.

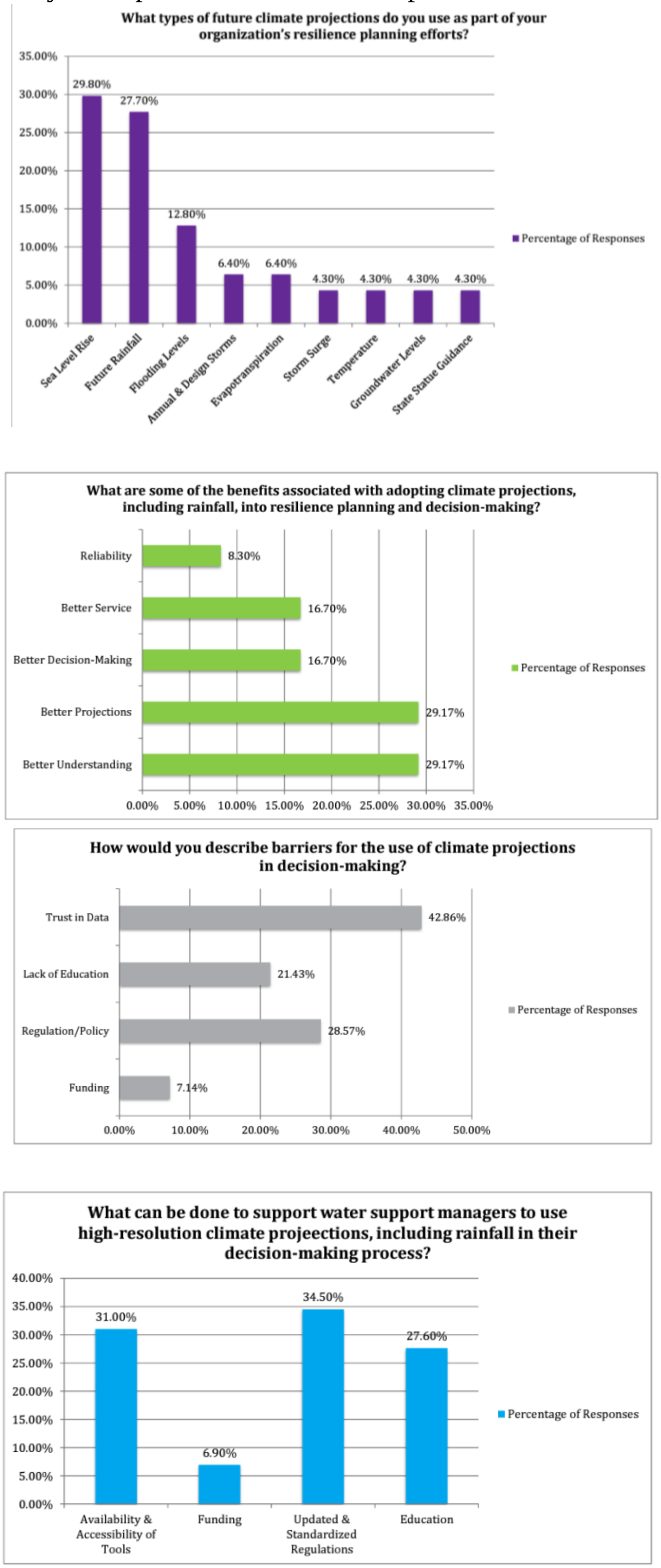

Figure 18: Examples of responses from stakeholders

Key findings include the risk-averse nature of water resource decision-making, the complexity of data used, and the necessity for a holistic approach. These findings reveal how difficult it may be for the water management sector to embrace new methods due to the potential consequences of inaccurate projections, i.e., risk aversion on the part of constituents and board members, the struggle to effectively employ extensive datasets, and the need for interorganizational collaboration to overcome these difficulties.

Recommendations emphasize the need for a better understanding of the risk analysis calculations of water resource managers, a deeper exploration into how practitioners use, combine, and tailor data, and the establishment of partnerships between practitioners and scientists to foster greater collaboration. Implementing these recommendations will enhance decision-making processes and enable better adaptation and mitigation strategies in the face of climate change.

- Future research must assess water resource managers' knowledge level and awareness. The existing literature lacks a comprehensive understanding of the data and support tools managers perceive to be available for making climate projections. Identifying these gaps in access will help determine how to effectively disseminate data and tools that managers are unaware of. Despite its highly risk-averse nature, the literature has not adequately explored risk aversion in water resource management. Conducting further research to examine different types of risks and how managers calculate risk costs when making decisions is essential.

- To further enhance water-resource decision-making, it is crucial to gain a deeper understanding of how practitioners and scientists currently utilize, combine, and tailor the available data. This examination will offer valuable insights into presenting data in a manner most useful to practitioners and identifying decision-support tools that would enhance the integration of high-resolution climate forecasts within their organizations. Climate Projections & Water Resources: Addressing Barriers & Advancing Solutions for Effective Decision-Making

- Additionally, further research should aim to understand how to advance effective decision-making under uncertainty. Navigating ranges of projections that incorporate uncertainty and account for future evolving conditions is vital in considering multiple scenarios. Even sensitive analysis of possible futures can lead to better decision-making compared to not adopting any projections at all. Therefore, it is essential for academics to understand and promote these complex decision-making skills.

- Moreover, academics should delve into knowledge management and knowledge translation within this field. While the necessary knowledge and data exist, the challenge lies in effectively integrating and utilizing them. Exploring the most effective ways to share and co-produce knowledge in this sector will be instrumental in bridging this gap and fostering better-informed water-resource decisions in the face of climate change.

- Finally, stakeholders in the water-resource sector should strongly consider establishing partnerships between practitioners and scientists. Such collaborations would foster greater collaboration and enhance the overall field. By breaking down knowledge silos and addressing the issue of service replication, these partnerships would lead to more efficient and effective decision-making processes.

Overall, implementing these recommendations will contribute to advancing our understanding of water-resource decision-making and enable better adaptation and mitigation strategies in the face of climate change.

Project Results and Outcomes

A high-resolution retrospective seasonal forecast dataset from 2000-2022 has been created for the state of Florida for this project. Evaluations of the forecasts have shown improvement in skill comparable to the CPC. Forecasts have been integrated into stakeholder models and were found to provide improved forecasts compared to climate prediction center outlooks. These forecasts using stakeholder models have been published in peer-reviewed journals. Machine learning models have been evaluated and found to provide better forecasts than simpler models.

As the forecasts, integrated into stakeholder models, have been shown to provide improved skill compared to previously available forecasts, our stakeholders will be better able to rotate between water sources (e.g. one utility uses groundwater, surface water, and desalinated water and another uses surface water and aquifer storage and recovery) in anticipation of forecasted drought conditions as well as forecasted wetter than normal conditions.

This proposed work is innovative in that:

1) It has been designed and proposed by an established stakeholder-scientist partnership,
2) For the first time, a regional climate model at 10km spatial resolution has been deployed for Florida to conduct real-time seasonal forecasts for the winter season. The results of this exercise clearly show the benefits of high resolution in terms of the fidelity of the seasonal forecasts of precipitation that does not necessarily always follow the canonical El Niño and the Southern Oscillation teleconnections. This is largely from the fact that chaotic variations (or noise) is much higher as the granularity of the forecast is reduced, which our modeling system at 10km was able to simulate.
3) It provides forecasts at a desired frequency, lead time, and resolution of derived variables that are relevant to hydrologic applications but are not currently available from operational centers,
4) The real-time monitoring of the evolution of the wet season was notable for its reliability of the seasonal outlook. When most numerical climate models display poor seasonal prediction skill in the wet season owing to the overwhelming contribution of small-scale thunderstorms to the seasonal rainfall, the approach of real-time monitoring of the onset of the wet season to provide outlook of the forthcoming season is a good alternative.
5) The real-time monitoring of the evolution of the wet season used the IMERG -12h latency product of NASA and demonstrated its efficacy in providing credible seasonal outlook of the rainy season at the granularity of the water management districts of Florida.

Publications

Book:

- Misra, V., 2020: Regionalizing Global Climate Variations: A Study of the Southeastern US Regional Climate.Elsevier, 324 pp, ISBN:978-0-12-821826-6.

Refereed and Non-refereed Publications:

- Peeling, J., J. Judge, V. misra, C. Jayasankar, and W. Lusher (2023) Gap-free 16-year (2005-2020) sub-diurnal surface meteorological observations across Florida, *In review*, Tracking number SDATA-23-00867, Scientific Data.
- Irani, T., Anderson, R., Pierre, B., & Michael, A. (2023). Climate projections & water resources: Addressing barriers & advancing solutions for effective decision-making. Gainesville, FL: University of Florida
- Misra, V., S. Dixit,and C. B. Jayasankar, 2023: The Regional Diagnosis of Onset and Demise of the Rainy Season over Tropical and Subtropical Australia Earth Interactions, https://doi.org/10.1175/EI-D-22-0026.1.
- Jayasankar, C. B., V. Misra, and N. Karmakar 2023: A comparative Study Between Regional Atmospheric Model Simulations Coupled and Uncoupled to a Regional Ocean Model of the Indian Summer Monsoon Earth and Space Science, 10, e2022EA002733. https://doi.org/10.1029/2022EA002733.
- Anandhi, A., R. Deepa, A. Bhardwaj, and V. Misra, 2023: Temperature, Precipitation, and Agro-Hydro-Meteorological Indicator Based Scenarios for Decision Making in Ogallala Aquifer Region. Water, 15, 600. https://doi.org/10.3390/w15030600.
- Misra, V., C. B. Jayasankar, A. K. Mishra, A. Mitra, and P. Murgavel, 2022: Dynamic downscaling the South Asian summer monsoon from a global reanalysis using a regional coupled ocean-atmosphere model J. Geophys. Res., 127, e2022JD037490. https://doi.org/10.1029/2022JD037490.
- Liu, H., Z. Song, X. Wang and V. Misra, 2022: An ocean perspective on CMIP6 climate model evaluations Deep-Sea Research Part II, https://doi.org/10.1016/j.dsr2.2022.105120.
- Misra, V. and A. Bhardwaj, 2022: The impact of air-sea coupling on the simulation of the hydroclimatic change over Peninsular Florida Clim. Dyn., https://doi.org/10.1007/s00382-022-06294-1.
- Wang, H., A. Asefa, V. Misra, and A. Bhardwaj, 2022: Assessing the value of a regional climate model's rainfall forecasts in improving dry season streamflow predictions. J. Water Resources Planning and Management, 148(6), doi:10.1061/(ASCE)WR.1943-5452.0001571.
- Misra, V., C. B. Jayasankar, P. Beasley, and A. Bhardwaj, 2022: Operational Monitoring of the Evolution of the Rainy Season over Florida Front. Clim., 4, 793959, doi:10.3389/fclim.2022.793959.

- Misra, V. and C. B. Jayasankar, 2022: A high resolution coupled ocean-atmosphere simulation of the regional climate over Central America Clim. Dyn., https://doi.org/10.1007/s00382-021-06083-2.
- Narotsky, C. D. and V. Misra 2022: The Seasonal Predictability of the Wet Season over Peninsular Florida Int. J. Climatol., https://doi.org/10.1002/joc.7423.
- Uehling, J., V. Misra, A. Bhardwaj, and N. Karmakar 2021: Characterizing the local variations of the Northern Australian Rainy Season Mon. Wea. Rev., https://doi.org/10.1175/MWR-D-21-0093.1.
- Bhardwaj, A., V. Misra, B. Kirtman, T. Asefa, C. Maran, K. Morris, E. Carter, C. Martinez, and D. Roberts 2021: Experimental high-resolution winter seasonal climate reforecasts for Florida Wea. and Forecasting, https://doi.org/10.1175/WAF-D-21-0004.1.
- Misra, V. and A. Bhardwaj 2021: Estimating the thermodynamic and dynamic contributions to hydroclimatic change over Peninsular Florida J. Hydromet., https://doi.org/10.1175/JHM-D-20-0159.1.
- Bhardwaj, A., Misra, V., Kirman, B., Asefa, T., Maran, C., Morris, K., Carter, E., Martinez, C. and D. Roberts. 2021. Experimental high-resolution winter seasonal climate reforecasts for Florida. Weather and Forecasting. https://doi.org/10.1175/WAF-D-21-0004.1
- Misra, V., Irani, T., Staal, L., Morris, K., Asefa, T., Martinez, C., Graham, W. 2021. The Florida Water and Climate Alliance (FloridaWCA): Developing a stakeholder-scientist partnership to create actionable science in climate adaption and water resource management. Bulletin of the American Meteorological Society. https://doi.org/10.1175/BAMS-D-19-0302.1

PhD. Dissertation

- Uehling, J., "Characterizing the northern australian rainy season from the large-scale to the local scale in the current and future climate", PhD. Dissertation, 2021.

Masters Thesis

- Beasley, P., "Heatwaves in Florida and their future", 2023.
- Sherrod, T., "Flash droughts in the wake of landfalling Atlantic tropical cyclones, 2022
- Nartosky, C., "Predictability of the peninsular florida wet season, 2021
- Uehling, J., "Describing the onset and demise of Australian monsoon", 2019

Undergraduate Honors Thesis

- Beasley, P., "Validation of IMERG rainfall to monitor onset and demise of the rainy season over Peninsular Florida", 2021.

Presentations

- Li, J-Y., Martinez, C.J., Bliznyuk, N. 2022. Machine Learning Forecasting for Streamflow in West-Central Florida using Climate Drivers. Presented at the 2022 Fall Meeting of the American Geophysical Union, Chicago, IL, December 12-16.

- Martinez, C.J. 2020. Improving Dry Season Hydrological Forecasts by Utilities of the Florida Water and Climate Alliance using Remotely Sensed Data and Regional Climate Models. Presented at the Water, Wetlands, and Watersheds Seminar, Center for Wetlands, University of Florida, January 29.
- Asefa, T*. 2020. Best Practices in Climate Adaptation: The Water Utilities Climate Alliance Example. Presented at the University of Florida Water Institute Symposium, February 25-26.
- Maran, C*. 2020. Future Extreme Rainfall Projections in Broward County. Presented at the University of Florida Water Institute Symposium, February 25-26.
- Martinez, C*. 2020. Using Seasonal Climate Forecasts to Improve Source-Allocation Decisions by Member Utilities of the Florida Water and Climate Alliance. Presented at the University of Florida Water Institute Symposium, February 25-26.
- Misra, V*. 2020. A Coupled Ocean-Atmosphere Downscaled Climate Projection for the Peninsular Florida Region. Presented at the University of Florida Water Institute Symposium, February 25-26.
- Morris, K*. 2020. Aquifer Storage and Recovery (ASR) System Recovery Initiation Index. Presented at the University of Florida Water Institute Symposium, February 25-26.
- Martinez, C.J. 2020, Integrating NASA Earth system data into decision making tools of member utilities of the florida water and climate alliance, Applied Science Week.
- Martinez, C.J., Asefa, T., Irani, T., Judge, J., Misra, V., Morris, K., Staal, L. 2019. Using High-Resolution Forecasting of the Dry Season of Peninsular Florida to Improve Source-Water Allocation Decision Making. Presented at the 2019 Fall Meeting of the American Geophysical Union, San Francisco, CA, December 9 – 13.
- Martinez, C.J., Asefa, T., Irani, T., Judge, J., Misra, V., Morris, K., Staal, L. 2019. Using High-Resolution Forecasting of the Dry Season of Peninsular Florida to Improve Source-Water Allocation Decision Making Presented at the 2019 Fall Meeting of the American Geophysical Union, San Francisco, CA, December 9 – 13.
- Martinez C. J., T. Asefa, T. Irani, J. Judge, V. Misra, K. Morris, L. Staal, "Using high-resolution forecasting of the dry season of peninsular florida to improve source-water allocation decision making, Poster presentation at the AGU Fall Meeting, 2019.