Application of High-Resolution Winter Seasonal Climate Forecasts for Streamflow Prediction in Central Florida

Kyra Britton
Vasubandhu Misra

Abstract

In this study, we evaluate the relationship between the streamflow of several watersheds in Central Florida and five environmental variables that were reforecasted for Florida by dynamically downscaling seasonal forecasts from a global climate model. Global models typically run at a resolution of 100 km, which is too coarse to adequately resolve the peninsular structure of Florida and the small-scale features that play a significant role in Florida's climate, such as sea breeze and tropical cyclones. The study was undertaken with the goal of developing a streamflow forecast for the winter season that will serve as an additional decision-making tool for water managers, who must make important decisions concerning the water supply during the winter in preparation for the dry spring season. The regression models presented here have undergone several methods of cross-validation to assess their robustness and to account for uncertainty. They generally show higher skill than climatology and persistence, particularly for predicting streamflow events in the upper tercile.

1. Introduction

Florida has ample freshwater resources; however, managing those resources in a sustainable way has proved to be a challenge. Although Florida is one of the wettest states in the country and receives, on average, over 50 inches of rainfall per year, approximately 70% is lost to evapotranspiration, and this percentage is expected to increase due to warming associated with climate change (since higher temperatures increase the rate of evapotranspiration). Other phenomena associated with climate change, such as sea level rise and increased intensity of tropical cyclones, are also likely to affect the hydrologic balance of Florida. Additionally, Florida is the third most populous state, and the population continues to increase. Thus, sustainable water management is expected to become more crucial for Florida during the following decades.

Seasonal climate forecasts have proven useful in making water supply decisions on a 3–12-month timescale (Misra et al., 2021). However, water managers do not often make use of these forecasts for a number of reasons, including lack of awareness of the forecasts, institutional inertia, and risk aversion to new methods (Bhardwaj et al. 2021; Misra et al. 2021). To combat these phenomena, the Florida Water and Climate Alliance (FloridaWCA) was formed in 2010. The FloridaWCA is a partnership between scientists and water utility stakeholders that aims to foster the growth of sustainable water use practices throughout the state by means of the consistent exchange of knowledge between its members. The formation of the FloridaWCA has led to numerous research projects and tangible benefits for water management groups, such as the Peace River Authority, which was able to develop a 10-variable Aquifer and Storage Recovery (ASR) initiation index (to assist in the decision of when to initiate ASR recovery) as a result of the NOAA grant that helped coalesce the FloridaWCA (Misra et al., 2021).

This project began with a focus on the Peace River, which is managed by The Peace River Manasota Regional Water Supply Authority. As of 2013, the Authority provides 26 million gallons per day of potable water to approximately 300,000 citizens across Charlotte, DeSoto, Manatee, and Sarasota counties (Morris 2013). The flow of the river varies significantly over the course of a year, with flows exceeding 40,000 cubic feet per second (cfs) during the rainy season and flows under 40 cfs during the dry season. When the river flow is high, water is extracted directly from the river and excess flow is diverted to off-stream storage sites for later use when river flow is low. Additionally, river flow is tidally influenced, and dry periods or storms can push brackish water to the extraction location, so the use of directly extracted water depends greatly on environmental conditions. Off-stream storage sites consist of 21 ASR wells, and two reservoirs. The ASR wells are located between 600 and 1,000 feet below ground surface and can store an estimated 6 billion gallons, and the reservoirs can store an estimated 6.5 billion gallons. On occasion, river flow is sufficient year-round, and water does not need to be retrieved from the ASR wells. However, most years call for ASR recovery during the dry period between February and July. The question of when to start ASR recovery is essential. Customer demand for water can exceed 30 million gallons per day (MGD), but water can be withdrawn from the wells at a maximum rate of just 18 MGD (Morris 2013). Additionally, stored water mixes with native water and minerals underground, where it can reach salinity levels of about 1100 mg/L, more than twice the drinking water standard of 500 mg/L. Thus, even though water originally enters the wells as potable water, it must be retreated upon its extraction. Water extracted from ASR wells is diverted to the reservoirs and treated at the Peace River Facility.

There are consequences to starting ASR recovery too early or too late. Reservoir water becomes more clear with the addition of the relatively colorless ASR water. Clearer water enhances light transmittance and increases the risk of algal blooms, which can add an unpleasant odor and flavor to the water that is difficult to remove. Thus, recovery should not be started too early. When recovery is started too late, high pumping rates are required to keep up with demand, resulting in less raw water available to mitigate the effects of high salinity and other dissolved solids. High pumping rates can also lead to drawdown of the water table or higher salinity water entering the well through cracks in the confining layer. Thus, starting recovery too late can lead to increased costs due to the need to maintain water quality.

As shown above, the decision of when to initiate ASR recovery is a complex one with many factors. Thus, the Authority has a strong interest in the creation of a streamflow forecast that could serve as an additional decision-making tool.

Water utility managers across Florida must make crucial decisions concerning the water supply during the winter, because the following spring season is the driest of Florida's seasons. Decisions concerning water supply in the spring are based heavily on winter water demand (Bhardwaj et al., 2021). Occasionally, an anomalously dry winter season creates an acute shortage of water in the spring, and water managers are forced to take costly remediation measures. Thus, it is desirable to have a streamflow forecast for the winter months due to the myriad of decisions that must be made during that time.

Due to its peninsular structure, Florida has a unique climate that is influenced heavily by both local and global climate variations. Peninsular Florida displays a distinct rainy season spanning from June to August. Much of the summer precipitation can be attributed to the sea breeze phenomenon, in which the differing heat capacities of land and sea create pressure gradients that allow convection to form. Additionally, tropical cyclones (which occur primarily in the summer months) contribute 10-15% of Florida's annual rainfall (Misra et al., 2017). The winter season is consequently much drier due to the absence of these effects. Most winter precipitation in Florida comes from passing frontal systems. Due to the small scale and high variability of summer precipitation, climate models display low skill over Florida in the summer. The models perform better for the winter months due to the predictability of large-scale phenomena that influence Florida's climate indirectly, such as the El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO). ENSO is characterized by 2- to 10-year oscillations between cool, warm, and neutral sea surface temperature (SST) anomalies in the Tropical Pacific. The shift in SSTs causes a shift in the location of tropical convection, which leads to changes in the atmospheric circulation that have global effects on variables like temperature, humidity, and more (Kirtman et al. 2017). These links between the Tropical Pacific and other parts of the globe are known as "teleconnections". An El Niño event (the warm phase of ENSO) generally leads to an increase in winter precipitation and colder winter temperatures over Florida, while a La Niña event (cool phase) decreases winter precipitation and warmer winter temperatures. The PDO is similar to ENSO in that it is a cycling of SSTs, but different in that it is stronger in the Northern Pacific and weaker in the Tropical Pacific, and it acts on time scales of 10-20 years as opposed to the much shorter interannual scales of ENSO. The PDO can interact with ENSO, constructively interfering when they are in phase (both warm or both cold) and destructively interfering when they are out of phase (Kirtman et al., 2017). The link between the PDO and Florida precipitation is weaker than that between ENSO and Florida precipitation; however, the PDO still explains roughly 25% of interannual dry season rainfall variability (Kirtman et al., 2017). PDO and ENSO events reach their mature stage during the winter and thus the teleconnections with Florida's climate are strongest at that time, leading to increased predictability of precipitation and temperature over Florida.

2. Methodology

The regression models presented here were developed step-by-step using streamflow data from the Peace River. After finding the optimal set of predictors in the regression equation to predict streamflow of Peace River, we then used the same set of predictors to develop the final regression model for the neighboring Hillsborough and Alafia Rivers. The flow of the project generally followed these steps:

1. Perform simple linear regressions of streamflow (as the predictand) and each of the environmental variables (as predictors) separately.
2. Perform a multiple linear regression with all of the environmental variables. Then remove one variable and perform a regression with the 4 remaining variables. Repeat for all combinations of 4.
3. Add in streamflow from the previous month as an additional predictor from step 2.
4. Add in environmental predictors from the previous month one at a time.
5. Determine which regression model is best, based primarily on r-squared and standard error values in holdout cross-validation test and rolling cross validation tests.
6. Evaluate the skill of the selected model(s) by testing for deterministic and probabilistic skill, and account for uncertainty by developing an ensemble of streamflow forecasts.

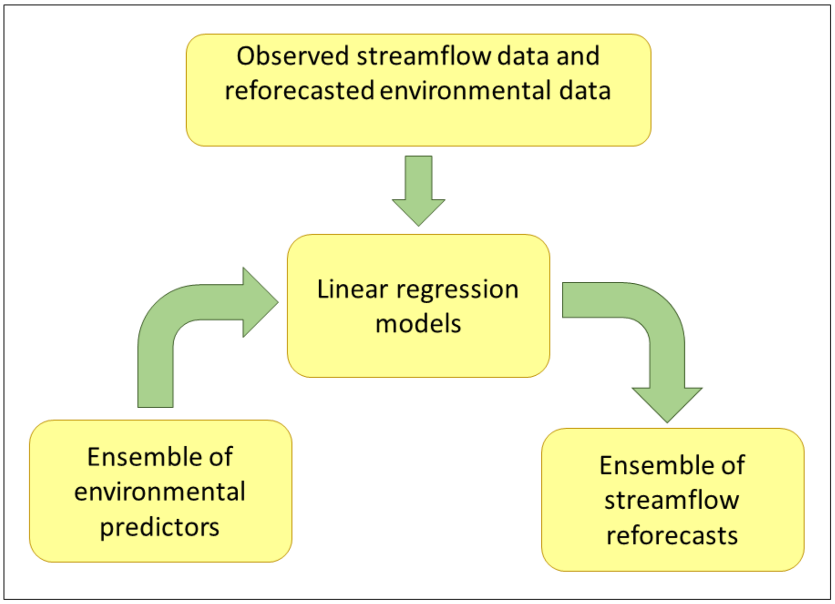


Fig. 1. Visual representation of project flow.

As mentioned previously, seasonal climate models have proven useful in making water management decisions. However, while current weather prediction models are running at a resolution of 10 km or finer, seasonal climate models are running at a much coarser resolution of 100 km or more. This resolution is too coarse to adequately resolve the coastlines and watersheds of Florida (Figure 2). Thus, these climate models are not useful for streamflow prediction. For this project, we used customized seasonal forecasts for Florida that were produced by dynamically downscaling a global climate model to a resolution of 10 km (Bhardwaj et al. 2021). These forecasts were developed specifically for the use of water managers in Florida and contain 30 ensemble members to account for uncertainty in initial and boundary conditions. They cover the winter season due to the fact that models display more skill in winter, as well as the operational need for forecasts in the winter. These forecasts will be discussed further in the next chapter.

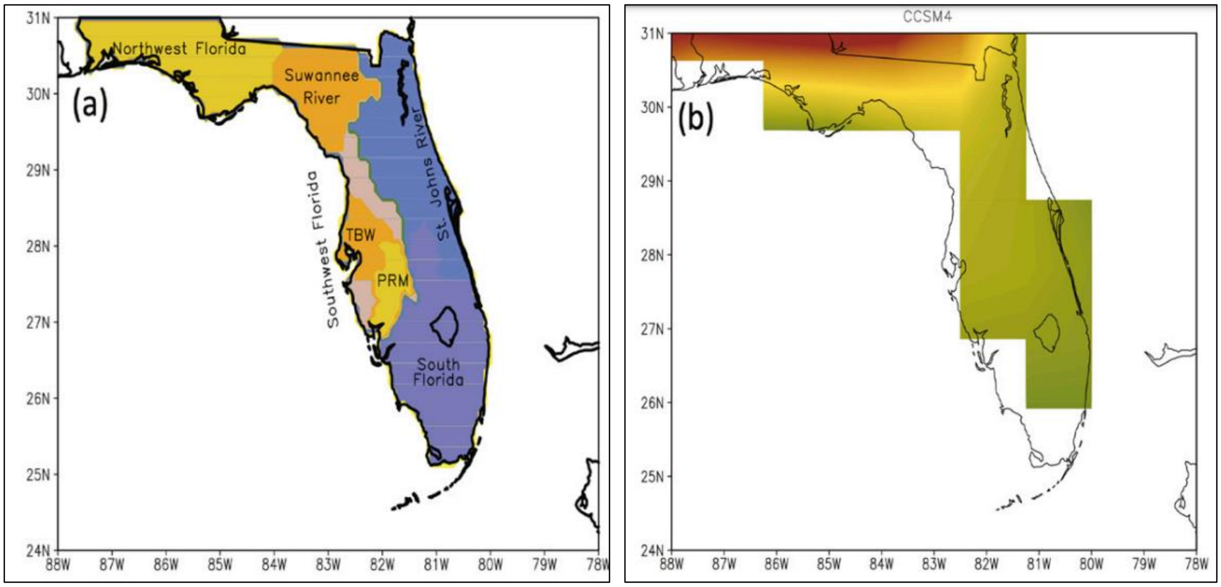


Fig. 2. (a) The five water management districts and two water utilities of Florida, overlaid on a 10-km grid. (b). Land-sea mask of the Community Climate System Model, version 4 (CCSM4), at 100-km resolution.

Regressions were developed separately for each month of the winter season: November, December, January, and February; as well as two 3-month seasons: NDJ (November-December-January) and DJF (December-January-February). Monthly streamflow averages for the Peace River were computed, using daily streamflow data measured by the United States Geological Survey. Then, values for the five environmental predictors (precipitation, evaporation, surface-level soil moisture, root-level soil moisture, and surface temperature) were averaged over all 30 ensemble members and area averaged over these watersheds to give an ensemble monthly mean for each predictor. For the holdout cross-validation tests, the first 16 years of data were used to develop the linear regression model in each case (training data), and the following 5-6 years were used as a testing period (testing data) to examine the skill of each model. The development of each regression equation is outlined in the table below (Table 1).

Table 1: The performance of the regression equations.

Equation name	Predictors	Month/Season	r^2	SE
5C	Precipitation, evaporation, soil moistures, and temperature, from the current month being analyzed	Nov	0.400	398.854
		Dec	0.225	891.213
		Jan	0.403	707.299
		Feb	0.776	273.728
		NDJ	0.461	565.614
		DJF	0.554	469.885
5C-T	Current month's precipitation, evaporation, and soil moistures	Nov	0.342	398.363
		Dec	0.219	852.910
		Jan	0.358	699.676
		Feb	0.601	347.796
		NDJ	0.461	536.626
		DJF	0.553	446.683
5C-E	Current month's precipitation, soil moistures, and temperature	Nov	0.179	444.960
		Dec	0.216	854.320
		Jan	0.392	680.695
		Feb	0.776	260.990
		NDJ	0.285	617.775
		DJF	0.401	516.845
5C-P	Current month's evaporation, soil moistures, and temperature	Nov	0.381	386.234
		Dec	0.222	851.149
		Jan	0.325	717.401
		Feb	0.776	260.998
		NDJ	0.446	543.615
		DJF	0.497	473.758
5C-Sm1	Current month's precipitation, evaporation, root level soil moisture, and temperature	Nov	0.229	431.213
		Dec	0.161	884.160
		Jan	0.398	677.426
		Feb	0.774	262.116
		NDJ	0.407	562.700
		DJF	0.549	448.617
5C-Sm2	Current month's precipitation, evaporation, surface level soil moisture, and temperature	Nov	0.192	441.358
		Dec	0.142	893.623
		Jan	0.403	674.826
		Feb	0.767	265.997
		NDJ	0.370	580.009
		DJF	0.339	543.155
5C+PSF (Note that since PSF showed to be such a strong predictor, it is included in every regression hereafter and dropped from the acronym.)	Current month's precipitation, evaporation, soil moistures, temperature, and previous month's streamflow	Nov	0.481	391.154
		Dec	0.544	720.685
		Jan	0.923	267.697
		Feb	0.813	263.512
		NDJ	0.571	516.318
		DJF	0.736	383.356

5Pre	Previous month’s precipitation, evaporation, soil moistures, temperature, and streamflow	Dec	0.777	503.465
5Pre	Previous month’s precipitation, evaporation, soil moistures, temperature, and streamflow	Jan	0.888	322.873
5Pre	Previous month’s precipitation, evaporation, soil moistures, temperature, and streamflow	Feb	0.702	332.382
5Pre	Previous month’s precipitation, evaporation, soil moistures, temperature, and streamflow	DJF	0.846	293.201
CPET+PreSm	Current month’s precipitation, evaporation, and temperature; previous month’s soil moistures and streamflow	Dec	0.799	478.463
CPET+PreSm	Current month’s precipitation, evaporation, and temperature; previous month’s soil moistures and streamflow	Jan	0.925	264.394
CPET+PreSm	Current month’s precipitation, evaporation, and temperature; previous month’s soil moistures and streamflow	Feb	0.799	273.276
CPET+PreSm	Current month’s precipitation, evaporation, and temperature; previous month’s soil moistures and streamflow	DJF	0.855	284.585
5C+PreSm2	Current month’s precip, evap, soil moistures, temp, and previous month’s root level soil moisture	Dec	0.616	701.156
5C+PreSm2	Current month’s precip, evap, soil moistures, temp, and previous month’s root level soil moisture	Jan	0.924	282.869
5C+PreSm2	Current month’s precip, evap, soil moistures, temp, and previous month’s root level soil moisture	Feb	0.813	279.492
5C+PreSm2	Current month’s precip, evap, soil moistures, temp, and previous month’s root level soil moisture	DJF	0.891	263.295
5C+PreSm	Current month’s precip, evap, soil moistures, temp, and previous month’s soil moistures (1 and 2)	Dec	0.822	510.152
5C+PreSm	Current month’s precip, evap, soil moistures, temp, and previous month’s soil moistures (1 and 2)	Jan	0.927	296.156
5C+PreSm	Current month’s precip, evap, soil moistures, temp, and previous month’s soil moistures (1 and 2)	Feb	0.816	296.192
5C+PreSm	Current month’s precip, evap, soil moistures, temp, and previous month’s soil moistures (1 and 2)	DJF	0.915	251.726
5C+PreESm	Current month’s precip, evap, soil moistures, temp, and previous month’s evaporation and soil moistures	Dec	0.825	546.097
5C+PreESm	Current month’s precip, evap, soil moistures, temp, and previous month’s evaporation and soil moistures	Jan	0.938	294.033
5C+PreESm	Current month’s precip, evap, soil moistures, temp, and previous month’s evaporation and soil moistures	Feb	0.821	315.650
5C+PreESm	Current month’s precip, evap, soil moistures, temp, and previous month’s evaporation and soil moistures	DJF	0.918	271.022
5C+PrePESm	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, and soil moistures	Dec	0.828	593.109
5C+PrePESm	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, and soil moistures	Jan	0.939	319.328
5C+PrePESm	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, and soil moistures	Feb	0.878	285.923
5C+PrePESm	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, and soil moistures	DJF	0.953	228.887
5C+5P	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, temp, and soil moistures	Dec	0.835	650.035
5C+5P	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, temp, and soil moistures	Jan	0.939	356.433
5C+5P	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, temp, and soil moistures	Feb	0.878	319.582
5C+5P	Current month’s precip, evap, soil moistures, temp, and previous month’s precip, evap, temp, and soil moistures	DJF	0.995	90.093

As shown, the regressions with individual predictors are not skillful. Using all 5 predictors in combination resulted in an improvement. But removing individual predictors with relatively higher p-values (surface temperature and evaporation) did not improve it further. Adding the previous month's streamflow led to significant improvement and thus previous streamflow became a parameter in all final regressions. Adding the previous month's environmental variables into the regression one at a time led to slight improvement each time. At the end of this process, we settled on two final regression models. For December, January, February, and DJF, 5C+5P showed to perform the best (Table 1). For November and NDJ, 5C+PSF preformed the best out of the available options—we could not run regressions involving the previous month's values since CLIFF is only produced for November through February. Both of the final models were selected based on their high r^2 values and low standard error values when compared to previous models. These two regression models also underwent rolling cross validation (RCV) tests. As mentioned previously for holdout cross validation, each equation was developed using the first 16 years of data and tested on the remaining 5-6 years. In RCV, an equation is developed using the first 21 years, tested on the remaining year, and repeated for each combination of 21 years to produce a total of 22 regressions. Then r^2 and standard error values, as well as the coefficients of the predictors, were compared across all 22 regressions to check for consistency and to ensure that no single year was introducing significant bias to the regressions.

To account for uncertainty in the input to the models, we developed an ensemble of streamflow forecasts using input from each of CLIFF's 30 ensemble members. We were thus able to produce 30 reforecasted streamflow values for each month in the validation period. These ensemble reforecasts will be discussed further in a subsequent section. The process of RCV generated 22 different models, which in theory could each be used to generate 30 streamflow predictions for a total of 660 predicted streamflow values for a given month. This endeavor was not undertaken in this study, but could be used in the future if a fuller assessment of environmental uncertainty is desired.

An issue that we ran into several times throughout the regression building process was high p-values associated with the individual predictors. Generally, a p-value of 0.05 or less indicates that the relationship between the predictor and predictand is statistically significant. A few p-values that we observed met these criteria, but most did not, and many were 0.5 or greater. This was a bit unexpected given that many of the models had r^2 values of 0.8 and above. A possible cause is the noise that is commonly seen in environmental data such as temperature and precipitation. To test this theory, we recalibrated the model using CLIFF data with the noise filtered out. This had the expected result of lowering the p-values, confirming that the noise, and not an issue inherent to the model, was causing the high p-values.

After adding previous month's streamflow and observing significant improvement in the skill of the models, a further examination of streamflow as a predictor was desired. Autocorrelation is a measure of how correlated a dataset is with a time-lagged version of itself. We plotted the autocorrelation of monthly streamflow over the full data set (shown in Figure 3). At a lag of 0 months, the autocorrelation is always 1 because it is the relation of the dataset with itself. Lines that extend beyond the shaded blue area represent statistical significance. From the graphs we can conclude that for each river, the previous month's streamflow is strongly related to the current month's streamflow. Streamflow from two months prior is significant as well, but less so. Building regression models with previous month's streamflow as the only predictor for current streamflow confirmed these observations. Adding the second previous and third previous month's streamflow into the regression improved the models, but only slightly. Ultimately, we decided not to add second and third previous month's streamflow into our final models because such a slight improvement is insignificant, and the model is likely to become redundant as more variables are added.

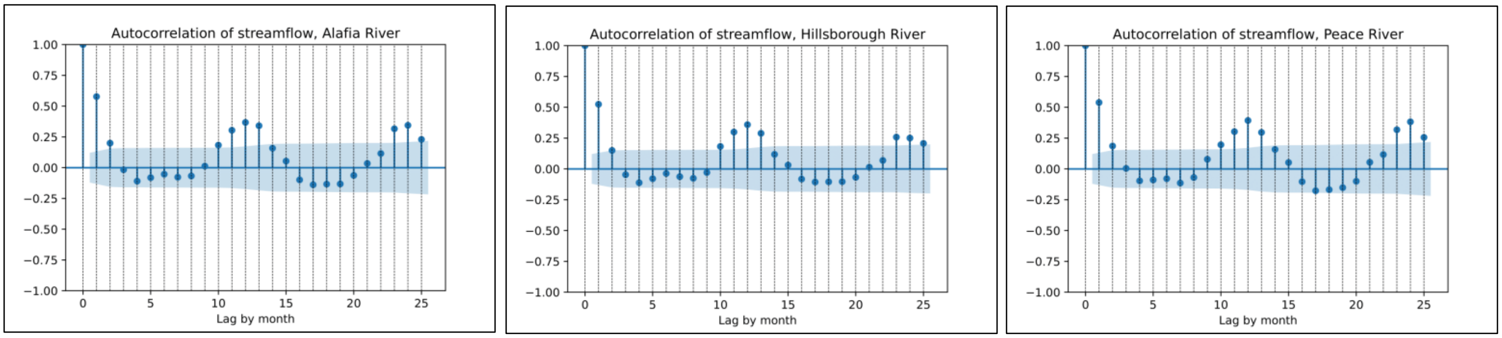


Fig. 3. Autocorrelation of monthly streamflow for Alafia, Hillsborough, and Peace Rivers.

3. Datasets

As previously mentioned, the precipitation, evaporation, soil moisture, and temperature datasets used in this project are high-resolution experimental winter seasonal climate reforecasts for Florida (CLIFF). CLIFF was developed by using a regional atmospheric model to dynamically downscale a global model to 10 km grid spacing, a resolution that has been shown to work well for the operational needs of water managers in Florida (Bhardwaj et al., 2021). The Atmospheric General Circulation Model (AGCM) was run with 5 ensemble members at 210 km grid spacing. For three of the ensemble members, the initial conditions of the atmosphere were perturbed. In the remaining two, the atmospheric convection parameterization was changed. For each run of the AGCM, 6 ensemble members from a regional atmosphere model were run (at 10 km grid spacing) to give a total of 30 ensemble members, each predicting daily values for precipitation, evaporation, soil moisture, and surface temperature, from November 1st through February 28th of the following year, over a 20-year period. The purpose of the ensembles is to thoroughly sample the uncertainties arising from the initial and boundary conditions, as well as the uncertainties present in the model itself (Bhardwaj et al., 2021).

The verification of CLIFF's skill is limited to surface temperature and precipitation—soil moisture and evaporation are calculated values, meaning there are not real-world measurements available against which to verify. However, precipitation is generally a good metric for evaluating model performance, and precipitation and temperature have the most practical value for stakeholders (Bhardwaj et al., 2021). CLIFF overestimates precipitation amounts, but reasonably estimates the meridional gradient of precipitation, and to a lesser extent, the zonal gradient as well. For surface temperature, CLIFF preserves the meridional and zonal gradients, and displays a significant cold bias. CLIFF has slightly less skill in predicting temperature than in predicting precipitation. However, for both precipitation and temperature, CLIFF generally shows higher prediction skill (both deterministic and probabilistic) than persistence.

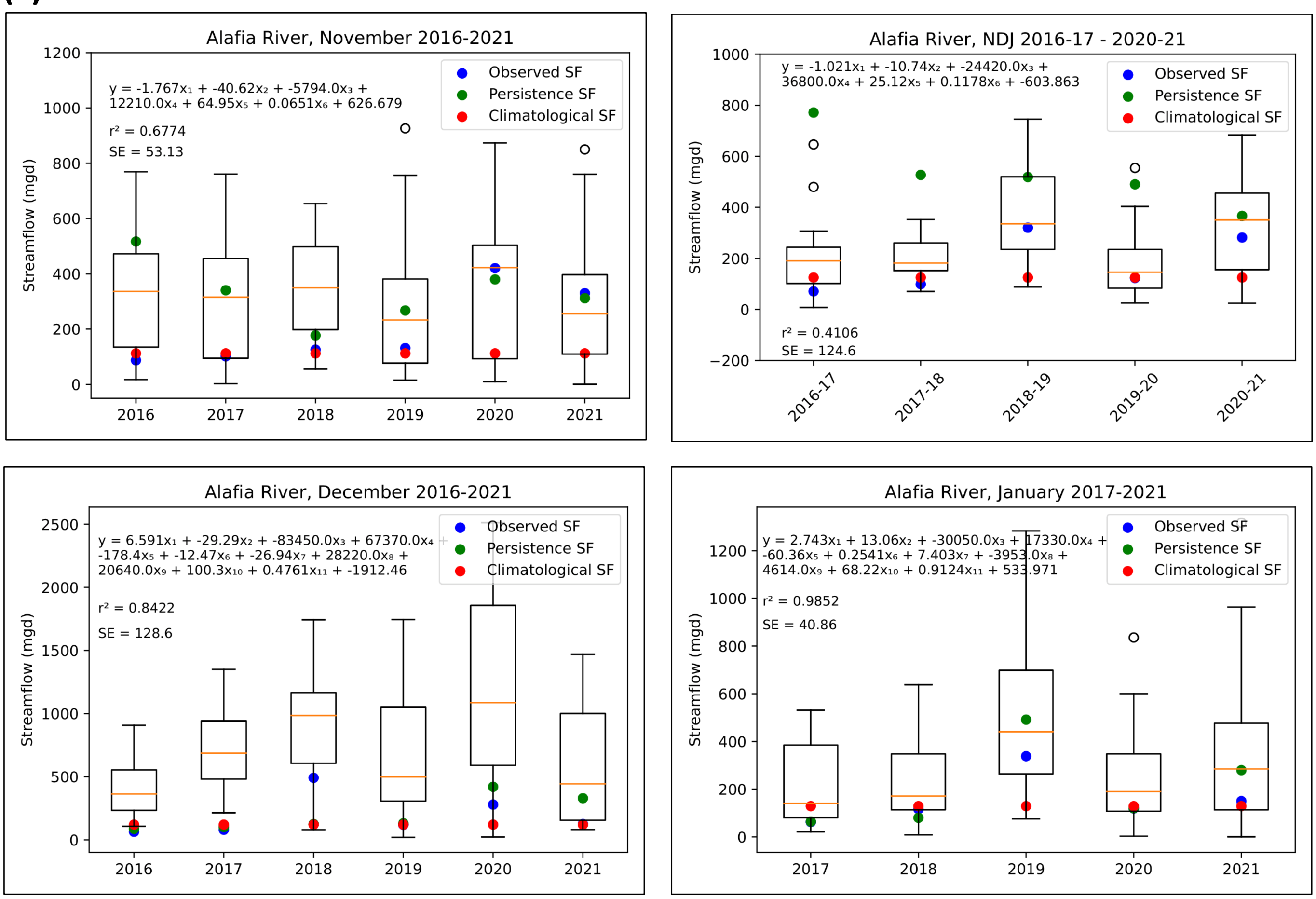
4. Results

Deterministic skill

Deterministic skill of the models is generally not too impressive. Using the ensemble mean of CLIFF to reforecast streamflow sometimes resulted in a reasonable prediction but in many instances resulted in a poor prediction that was an order of magnitude larger or smaller than the observed value. These errors suggest model bias of CLIFF as well as the regression model.

As previously mentioned, we developed an ensemble of streamflow forecasts using input from each of CLIFF's 30 ensemble members. We were thus able to produce 30 reforecasted streamflow values for each month in the validation period. After removing ensemble members that produce negative values for streamflow, we can plot the spread of the reforecasts and compare the mean forecasted streamflow with observed, climatological, and persistence streamflow (Figure 4). This process generally gave more promising results than using ensemble mean alone. The average predictions of the ensemble members often vary somewhat from the observed streamflow, but in many cases it is still a better prediction than either persistence or climatology. The models are overestimating in many cases, so that is an issue that could be further investigated in the future.

(a)



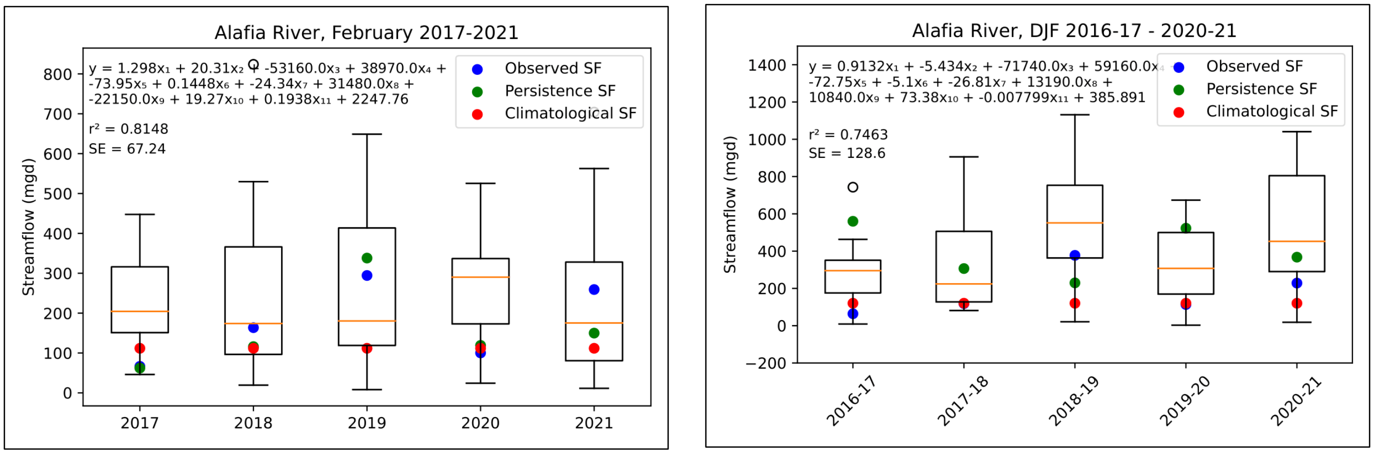
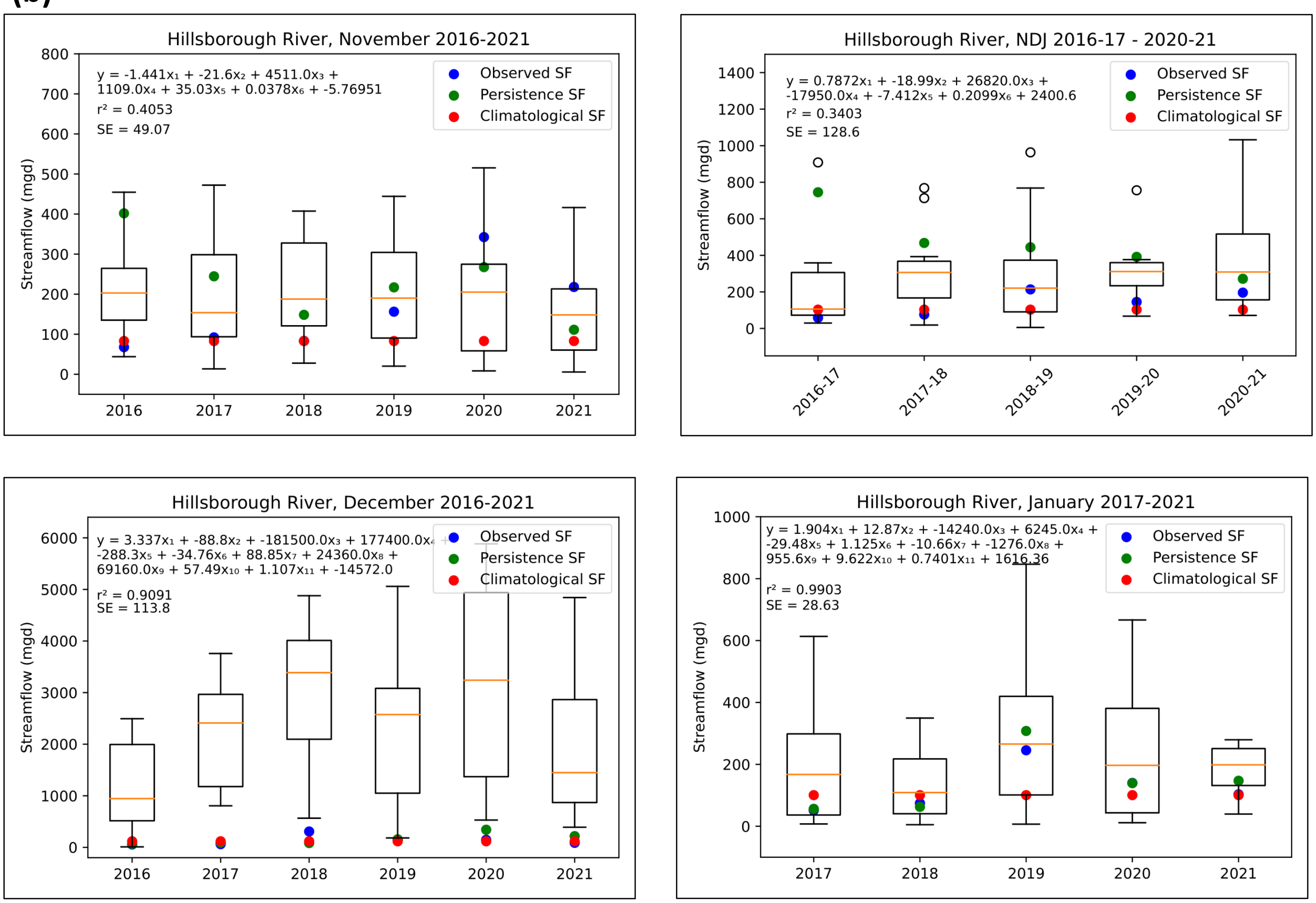


Fig 4. (a) Spread of ensemble reforecasts for streamflow for Alafia River. The middle 50% of predictions are contained within the box, meaning that if observed streamflow falls within the box, the model is capturing the observed flow at least 50% of the time.

(b)



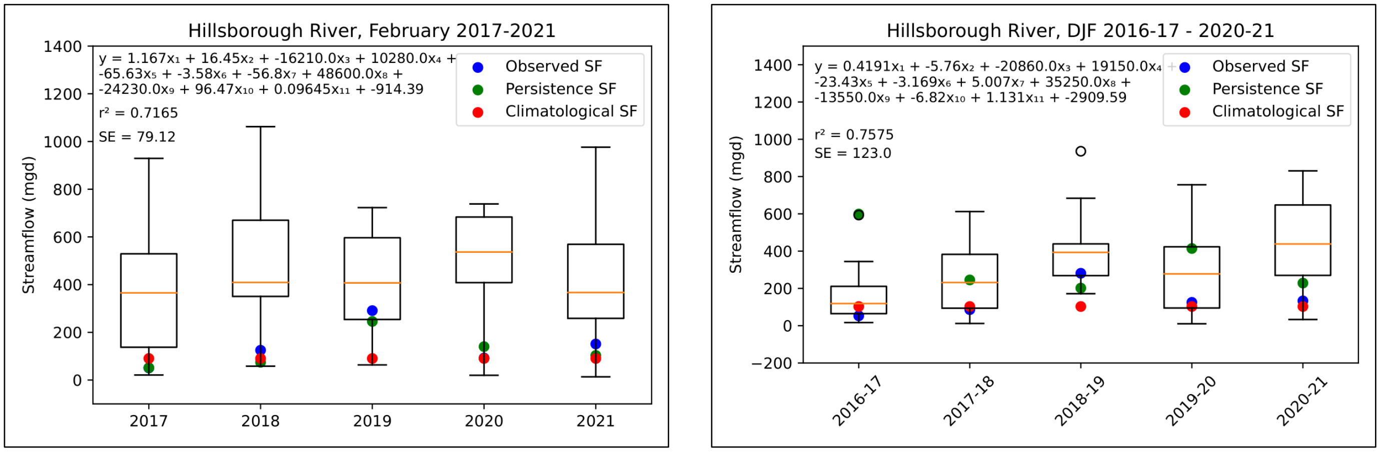
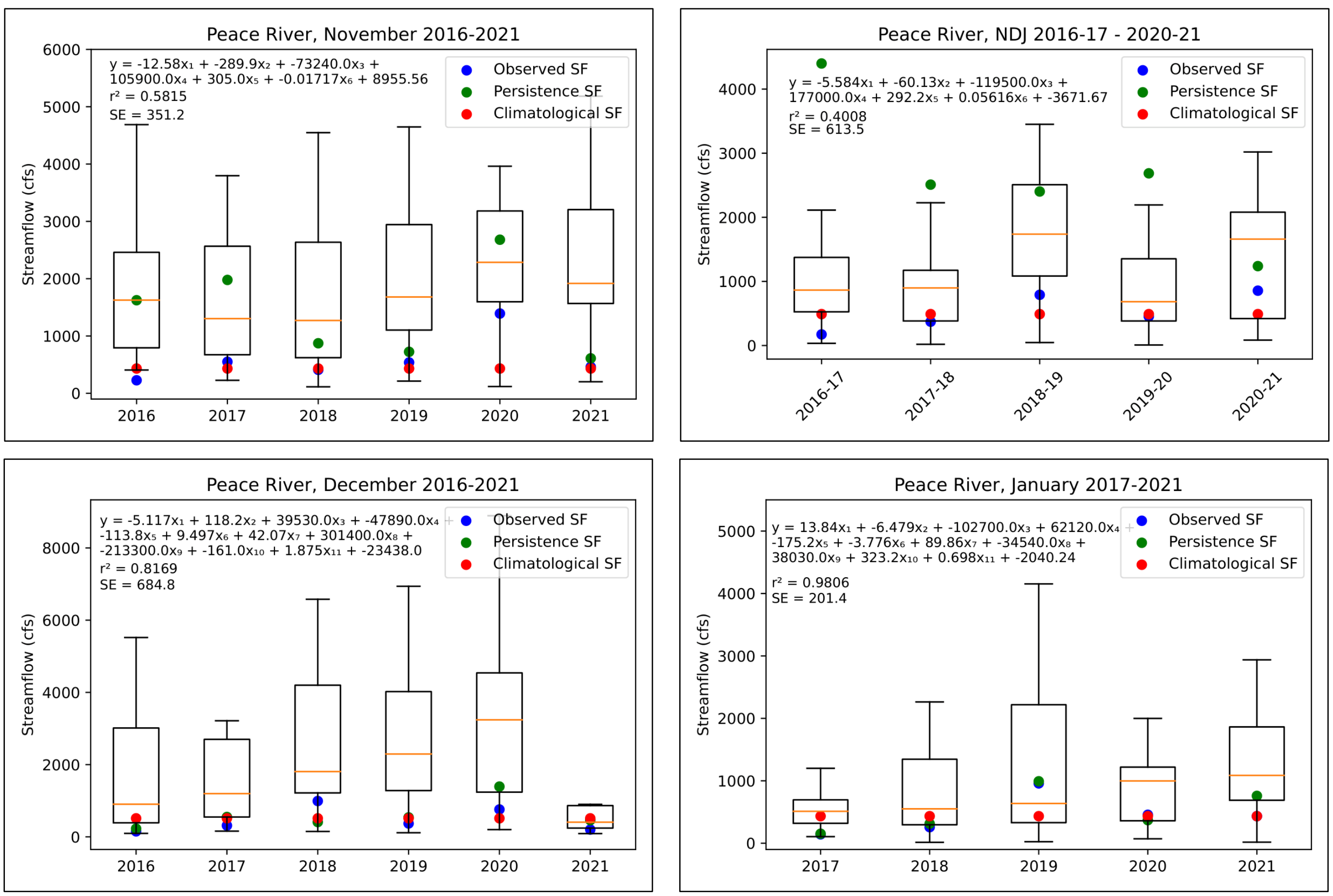


Fig 4. (b) Spread of ensemble reforecasts for streamflow for Hillsborough River.

(c)



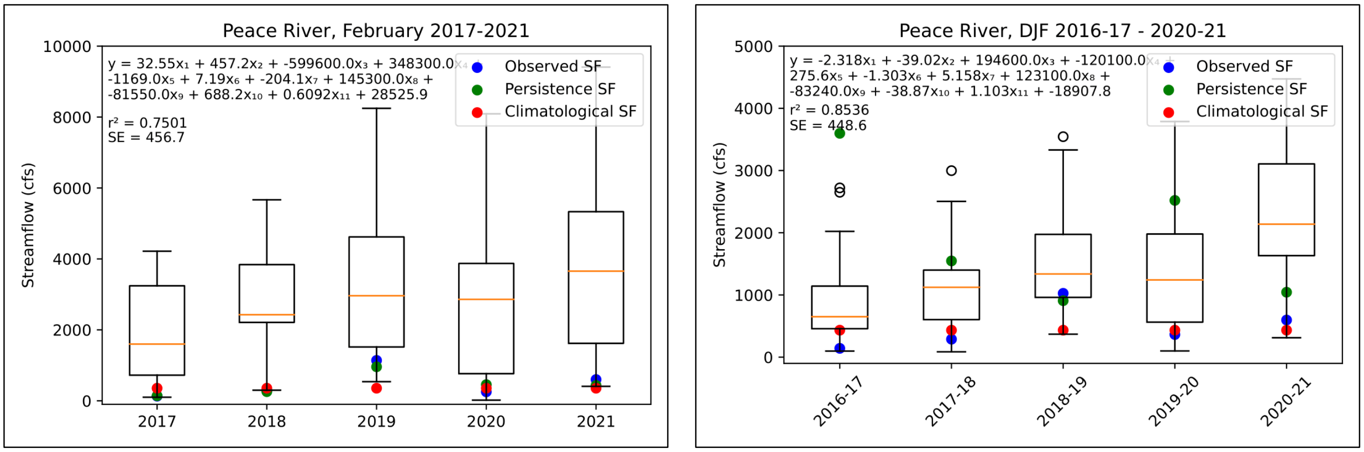


Fig 4. (c) Spread of ensemble reforecasts for streamflow for Peace River.

Probabilistic skill

Deterministic skill is one way to quantitatively assess a model. Here it is based on using the ensemble mean values of CLIFF to reforecast streamflow. However, it is not a complete picture of a model's skill since it does not account for the forecast uncertainty. A probabilistic forecast quantifies this uncertainty and is often more valuable to the end users of the forecasts. In this study, we are using the area under the relative operating characteristic (ROC) curve (AUC) following Narotsky & Misra (2021) to assess the probabilistic skill of the streamflow reforecasts. ROC curves are created for each month and season by first splitting observed and reforecasted streamflow into terciles, then using these thresholds to evaluate the models' skill at predicting low, moderate, or high streamflow. Then the AUC is computed for all ROC curves. An AUC greater than 0.5 represents a skillful reforecast. (Figure 5).

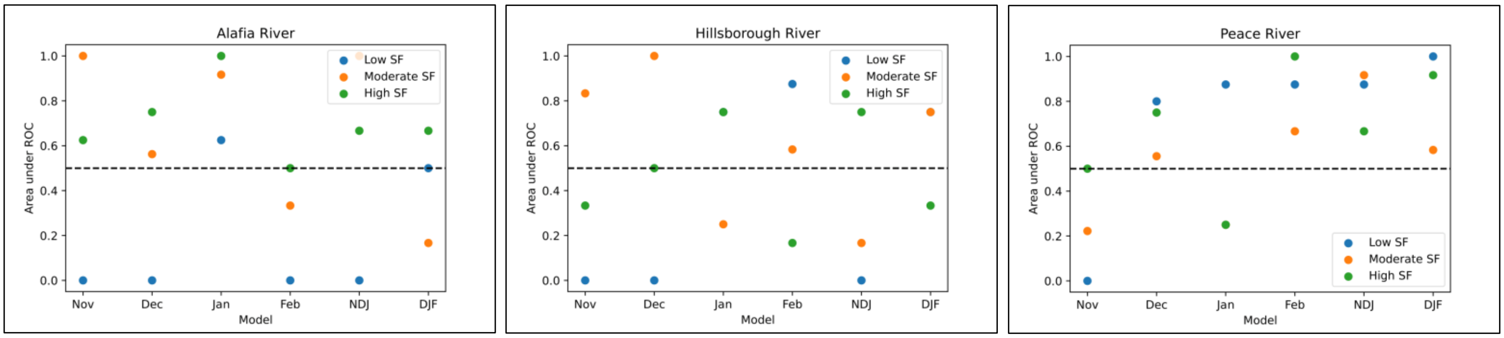


Fig. 5. AUCs for Alafia, Hillsborough, and Peace Rivers.

The models are generally unskillful at forecasting low streamflow events, but occasionally show some skill for the later winter months such as January and February. One factor that may be contributing to the poor skill of the models at predicting low streamflow is the small dataset used—many testing periods were as short as five years and in several instances no low streamflow events were observed during the testing period, making it difficult to evaluate the model's skill at predicting those events. The models are somewhat more skillful at predicting moderate streamflow events, and generally skillful for high streamflow events.

5. Conclusions

The results of this study indicate that there is significant merit in using CLIFF to predict streamflow in Central Florida. While it is unlikely that the models will be able to produce an accurate deterministic forecast for streamflow, it shows promising results when predicting whether or not streamflow will fall within a certain range. The hope is that this information will prove useful to the planning processes of water utility managers.

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