SUWANNEE RIVER LONG RANGE STREAMFLOW FORECASTS BASED ON SEASONAL CLIMATE PREDICTORS[1]

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ABSTRACT: A study of the influence of climate variability on streamflow in the southeastern United States is presented. Using a methodology previously applied to watersheds in Australia and the United States, a long range streamflow forecast (0 to 9 months in advance) is developed. Persistence (i.e., the previous season's streamflow) and climate predictors of the previous season are used to forecast the following season's (winter and spring) streamflow of the Suwannee River located in northern Florida. The winter and spring streamflow is historically the most likely to have severe flood events due to large scale cyclonic (frontal) storms. Results of the analysis indicated that a strong El Niño-Southern Oscillation (ENSO) signal exists at various lead times to the winter and spring streamflow of the Suwannee River. These results are based on the high correlation values of two commonly used measurements of ENSO strength, the Multivariate ENSO Index (MEI) and Sea Surface Temperature Range 1. Using the relationships developed between climate and streamflow, a continuous exceedance probability forecast was developed for two Suwannee River stations. The forecast system provided an improved forecast for ENSO years. The ability to predict above normal (flood) or below normal (drought) years can provide communities the necessary lead time to protect life, property, sensitive wetlands, and endangered and threatened species.
(KEY TERMS: streamflow forecasts; El Niño-Southern Oscillation; climate; sea surface temperatures; statistical analysis.)

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INTRODUCTION

The progress in monitoring global climate conditions has led researchers to believe that hydrologic variability can sometimes be well predicted based on "teleconnections" with large scale atmospheric and oceanic patterns. The best understood atmospheric and oceanic patterns are the ENSO and the Pacific Decadal Oscillation (PDO). ENSO refers to the interaction of the periodic large scale warming or cooling of the central-eastern equatorial Pacific Ocean with the Southern Oscillation, a large scale atmospheric pressure pattern across the tropical Pacific. The warm phase of ENSO is referred to as El Niño, and the cool phase is referred to as La Niña.

ENSO teleconnections with precipitation and streamflow in the southeastern United States increase frontal precipitation in the winter of El Niño events and decrease frontal precipitation during La Niña events (Ropelewski and Halpert, 1986, 1989; Kiladis and Diaz, 1989). Florida has been identified as a region of homogeneous response to the ENSO climatic anomaly, in which mean monthly precipitation and discharge during winter are above or below normal following the onset of the warm (El Niño) or cold (La Niña) phase of ENSO, respectively (Zorn and Waylen, 1997). Hanson and Maul (1991) report that precipitation during El Niño events is anomalously high during the winter and spring in Florida. Schmidt *et al.* (2001) demonstrated that for winter months in Florida, total seasonal precipitation showed strong responses during El Niño (La Niña) events in which winter precipitation totals were higher (lower) than neutral or non-ENSO winters. Streamflow, which integrates precipitation over drainage basins, responds to precipitation by a temporally variable combination of runoff and ground water inputs. Analysis of the relationship between El Niño and regional streamflow in the southeastern United

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States demonstrates a similar but lagged response to the precipitation (Kahya and Dracup, 1993). Zorn and Waylen (1997) find wintertime responses in their analyses of mean monthly streamflow and ENSO in north central Florida, with lags of one to two months between the onset of ENSO and the subsequent streamflow. The winter/spring peak discharge tends to be higher, on average, than the summer peak discharge due to lower evapotranspiration losses (Waylen, 1991). Sun and Furbish (1997) examine annual precipitation and river discharge patterns in Florida in response to ENSO and find wet conditions and higher stream discharge in El Niño years and dry conditions and lower stream discharge in La Niña years. North Florida and the Florida Panhandle area experience winter maximums in streamflow due to the frontal systems that impinge southward from the central United States into northern Florida (Schmidt *et al.,* 2001). Zorn and Waylen (1997) showed that for the Santa Fe River, a tributary of the Suwannee River (Figure 1), mean February streamflow during warm (El Niño) events is nearly twice that of other years. Additionally, there was a tendency for the winter peak streamflow to be both greater in magnitude and longer in duration during El Niño years. This climate/streamflow relationship is important for forecasting seasonal streamflow. For instance, if an ENSO event develops in the summer/fall seasons of the previous year, the following year's winter and spring streamflow may be predicted if there is a strong relationship.

The largest recorded floods of the Suwannee River occurred as the result of the cumulative effects of several consecutive broad frontal type rainfall events over the basin in March and April 1948, March 1959, and April 1973 (Giese and Franklin, 1996). Historically, precipitation is greater during the summer season. However, summer precipitation is due to multiple, almost daily, convectional storms. Although intense, these storms are for short durations, and thus the resulting streamflow (flooding) is significantly less than that of the long duration frontal storms that occur during the late winter and early spring seasons.

The ability to provide a long range (three-month to nine-month) forecast of the winter and spring season streamflow of the Suwannee River is extremely important to water resource planners, primarily the Suwannee River Water Management District. Although the Suwannee River is not a primary

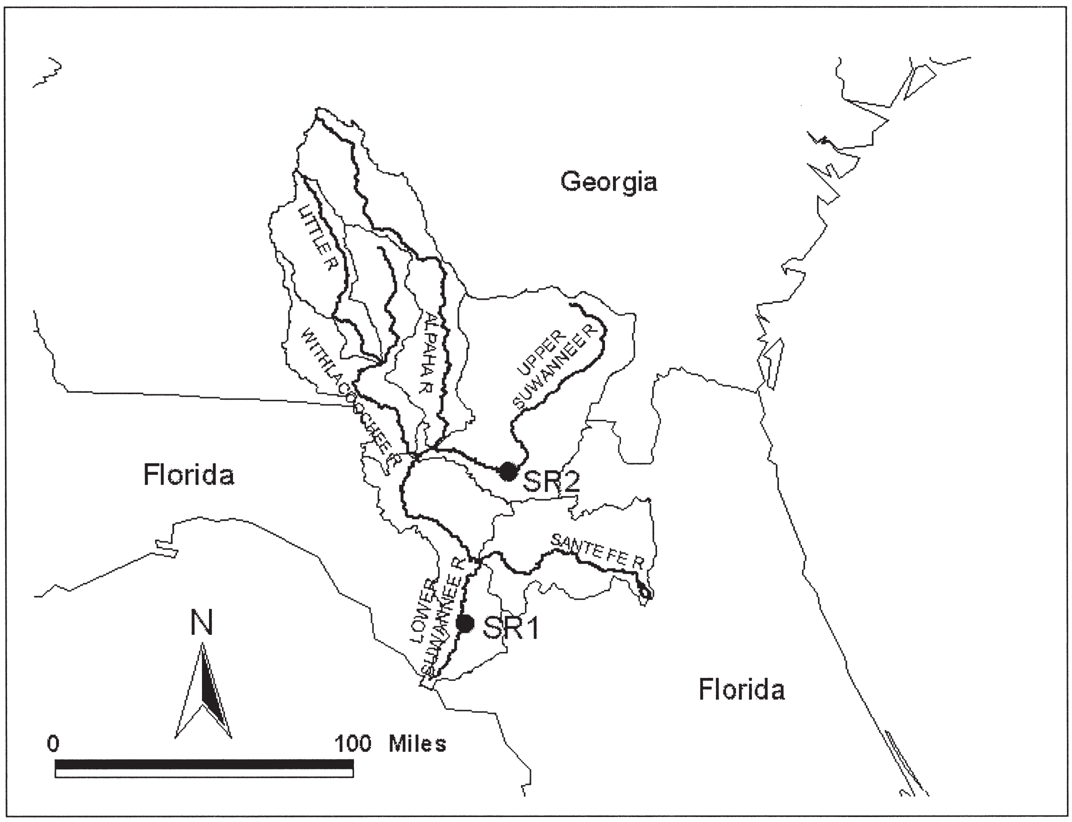

Figure 1. An Overview of the Suwannee River Watershed With Locations of USGS Streamflow Stations SR1 and SR2.

drinking water supply for the region, numerous communities and residents are adversely affected by flooding. Additionally, the Suwannee River watershed is an advanced ecosystem that relies on precipitation and streamflow to maintain hydroperiods of sensitive wetlands.

Currently, no streamflow forecast is made for the Suwannee River. The National Weather Service Office of Hydrology Advance Hydrologic Prediction Services does, however, provide a five-day forecast for the Suwannee and an Ensemble Streamflow Prediction (ESP) for two adjacent rivers, the Savannah River to the east and the Apalachicola River to the west. This forecast is based on data from radar, reservoir releases, river gages, and historical climate data. These data are input into a physical hydrologic model that generates the streamflow prediction. ESP forecasts provide an exceedance probability curve of the predicted streamflow. An exceedance probability is the probability that the specified value (i.e., streamflow) will be equaled or exceeded during a time period. An exceedance probability forecast can be used depending on an assumed level of risk. For example, a water agency may choose to take a 10 percent risk, which would correspond to a streamflow value that has a 90 percent probability of exceedance. A continuous exceedance probability forecast can be made by several methods, including principal component analysis, regression, and linear discriminant analysis (Piechota *et al.,* 2001).

The research presented here focuses on identifying the best climate predictors for Suwannee River streamflow. The best climate predictors are used to develop a statistically based exceedance probability forecast for the winter and spring season streamflow of the Suwannee River. The research demonstrates the strength of the ENSO signal for the watershed.

WATERSHED DESCRIPTION

The Suwannee River watershed (Figure 1) has a total area of approximately 9,950 square miles. The watershed is heavily forested, and development is primarily low density agriculture. The annual precipitation is approximately 55 inches per year. The Suwannee River flows through two states, 13 counties in Florida, and 21 counties in Georgia. Approximately 60 percent of the watershed is within Georgia where it originates in the Okefenokee Swamp. The river has three major tributaries – the Alapaha, Little, and Withlacoochee Rivers. The Suwannee River has been designated an Outstanding Florida Waters (OFW) under State of Florida Administrative Code 62-302.700 (State of Florida, 2003). An OFW is a water system designated worthy of special protection because of its natural attributes. This special designation is intended to protect existing good water quality.

DATA

The major datasets used to develop the relationships between climate variability and streamflow are historical streamflow data for the Suwannee River and historical climate and oceanic data for the Pacific Ocean.

Streamflow Data

Streamflow data were obtained from the U.S. Geological Survey (USGS) National Water Information System (USGS, 2003) for two unimpaired USGS streamflow stations on the Suwannee River (Figure 1). The average monthly streamflow rate, in cubic feet per second (cfs) for the winter season (January, February, and March, or JFM) and the spring season (April, May, and June, or AMJ) are averaged for each season and converted into streamflow volumes, in acre feet, by multiplying the seasonal average rate values times the total number of days in the season, with proper conversions. USGS Station 02323500 (referred to in this paper as SR1) is located in the lower region of the watershed and measures a drainage area of 9,640 square miles. USGS Station 02315500 (referred to in this paper as SR2) is located in the upper region of the watershed and measures a drainage area of 2,430 square miles. Both stations are unimpaired, and 46 years of monthly streamflow data covering a period from 1952 to 1997 are used. Persistence (the previous season's streamflow) is used as a predictor of future season's streamflow (the predictand).

Climatic and Oceanic Data

Climate predictors include the MEI, the PDO, and a series of 12 sea surface temperatures (SSTs) located in the Pacific Ocean. The climate predictors cover a period from 1951 to 1996. Like the predictand, average monthly values of the climate predictors are averaged for each season: JFM, the winter season, AMJ, the spring season, July-August-September (JAS), the summer season, and October-November-December (OND) the fall season. The (-1) notation represents the year before the streamflow year, while the (0) notation represents the streamflow year.

The MEI is a broad measure of ENSO conditions and is based on the six observed variables over the tropical Pacific (Wolter and Timlin, 1998): sea level pressure, zonal and meridianal components of the surface wind, sea surface temperature, surface air temperature, and total cloudiness fraction of the sky. These observations have been collected and are published in the Comprehensive Ocean-Atmosphere Data Set (NOAA, 2003). Negative values of the MEI represent the cold ENSO phase (La Niña), while positive MEI values represent the warm ENSO phase (El Niño).

The PDO (Mantua *et al.,* 1997) is a climate phenomenon associated with persistent, bimodal climate patterns in the northern Pacific Ocean that oscillate with a characteristic period on the order of 50 years (a single phase of the PDO will typically persist for about 25 years). The strength of the PDO is measured by a climate index comprising sea surface temperatures in the northern Pacific Ocean and acts at longer time scales than ENSO (Mantua *et al.,* 1997). The warm phase of the PDO has a positive numerical index value, while the cold phase has a negative numerical value.

Twelve Pacific Ocean SST series are used – these also are used by the Australian Bureau of Meteorology (BOM). The SST values are from an experimental set developed by the BOM and are the first 12 components of an empirical orthogonal function (EOF) analysis of the Pacific and Indian Ocean SSTs (Drosdowsky and Chambers, 1998). The SST1 series represents the ENSO cycle with large anomalies (or high EOF loadings) in the central and eastern tropical Pacific. The SST8 series represents an area near the eastern coast of Japan; the SST11 series represents an area in the southern Pacific Ocean near Antarctica. The other nine SST series represent regions of the Pacific and Indian Oceans that tend to behave similarly.

Pacific Ocean climate predictors were selected for several reasons. Although the Suwannee River watershed is adjacent to the Gulf of Mexico, the previously discussed large scale cyclonic (frontal) storms originate in the Pacific Ocean. During the winter and spring seasons, these storms move from west to east across the United States and ultimately release precipitation on the Suwannee River watershed. ENSO and PDO are Pacific Ocean climate phenomena and thus could have a direct impact on precipitation and resulting streamflow in the Suwannee River watershed.

CLIMATE/STREAMFLOW RELATIONSHIPS

Linear correlations between seasonal climate indicators and seasonal streamflow were performed to determine if there was a significant relationship between the various predictors (persistence, seasonal averages of climate) and the predictand (seasonal averages of streamflow) at various lead times (zero, three, six, and nine months). The linear correlation analysis is meant to identify the predictor. The artificial skill associated with the predictors is addressed in the Cross Validation Results section through the use of cross validation. The most significant relationships were selected to be included in the forecast model. A 0-month lead time predicts streamflow based on the previous (months zero through three) season's climate indicator. A three-month lead time predicts streamflow based the climate indicator for months three through six prior to the streamflow season. The (-1) notation [i.e., JAS(-1)] represents data from the previous year, and the (0) notation [i.e., JFM(0)] represents data from the current year.

Tables 1 through 4 display the seasonal predictors for the various lead times. For instance, the AMJ(0) streamflow for SR1 would be based on the best three predictors noted in Table 2 at various lead times. Note that only the "best" three predictors are shown in Tables 1 through 4.

TABLE 1. Summary of the Correlation Results Between the Winter (JFM) Streamflow at the Suwannee River, Station 02323500 (SR1) and Climate Indicators.

	JFM(-1)	**AMJ(-1)**	**JAS(-1)**	**OND(-1)**
MEI		0.30 (100%)	0.42 (100%)	0.41 (5%)
PDO			0.38 (0%)	
SST1		0.26 (0%)	0.36 (0%)	0.41 (95%)
SST8	0.32 (100%)			
SST11	0.16 (0%)	0.29 (0%)		
Persistence	0.24 (0%)			0.47 (0%)
Calibration	9.4%	11.5%	18.7%	17.8%
Cross Val	-1.9%	-0.5%	11.0%	8.1%

Note: Correlation values (greater than 0.33 are significant at the 99 percent level) and weights (percent in parentheses) used by the model for the best three predictors are noted. Calibration and cross validation LEPS scores are shown at the bottom of the table.

TABLE 2. Summary of the Correlation Results Between the Spring (AMJ) Streamflow at the Suwannee River, Station #02323500 (SR1) and Climate Indicators.

	AMJ(-1)	JAS(-1)	OND(-1)	JFM(-1)
MEI	0.36 (0%)	0.49 (0%)	0.45 (0%)	0.49 (0%)
SST1	0.50 (100%)	0.56 (100%)	0.50 (100%)	0.44 (0%)
SST8		0.38 (0%)	0.23 (0%)	
SST11	0.35 (0%)			
Persistence				0.58 (100%)
Calibration	10.9%	14.4%	13.4%	31.8%
Cross Val	-0.3%	-1.6%	-3.2%	19.4%

Note: Correlation values (greater than 0.33 are significant at the 99 percent level) and weights (percent in parentheses) used by the model for the best three predictors are noted. Calibration and cross validation LEPS scores are shown at the bottom of the table.

TABLE 3. Summary of the Correlation Results Between the Winter (JFM) Streamflow at the Suwannee River, Station 02315500 (SR2) and Climate Indicators.

	JFM(-1)	AMJ(-1)	JAS(-1)	OND(-1)
MEI		0.31 (100%)	0.45 (100%)	0.43 (0%)
PDO			0.41 (0%)	
SST1		0.31 (0%)	0.43 (0%)	0.46 (0%)
SST8	0.28 (0%)			
SST11	0.20 (0%)	0.34 (0%)		
Persistence	0.18 (100%)			0.24 (100%)
Calibration	7.1%	10.2%	19.0%	25.1%
Cross Val	-5.2%	-2.7%	2.8%	11.5%

Note: Correlation values (greater than 0.33 are significant at the 99 percent level) and weights (percent in parentheses) used by the model for the best three predictors are noted. Calibration and cross validation LEPS scores are shown at the bottom of the table.

The correlation analysis reveals that climate, specifically ENSO, as measured by the MEI, is a good predictor of winter and spring season streamflow (Tables 1 through 4). The SR1 streamflow station is near the terminus of the Suwannee River and receives drainage from almost the entire watershed area (see Figure 1). The JFM(0) streamflow for SR1 was highly correlated with OND(-1) values of Persistence (0.47), MEI (0.41), and SST1 (0.41) (Table 1). JFM(0) streamflow correlates well with JAS(-1) values of MEI (0.42), PDO (0.38), and SST1 (0.36). The trend of MEI and SST1 having the best correlations for SR1 streamflow continues in Table 2 when predicting AMJ(0) streamflow. For every seasonal prediction, that is, JFM(0), OND(-1), JAS(-1), and AMJ(-1), MEI and SST1 are two of the best three predictors. The ability to provide a winter and spring forecast is significant. As previously noted, the winter/spring seasons are traditionally the seasons of significant flood events. Based on previous research, ENSO events, specifically El Niño, produce significantly higher amounts of rainfall and resulting streamflow. The ability to predict streamflow for these seasons can prove valuable for water resource planners and affected communities.

TABLE 4. Summary of the Correlation Results Between the Spring (AMJ) Streamflow at the Suwannee River, Station 02315500 (SR2) and Climate Indicators.

	AMJ(-1)	JAS(-1)	OND(-1)	JFM(-1)
MEI		0.31 (100%)	0.45 (100%)	0.43 (0%)
MEI	0.26 (0%)	0.40 (0%)	0.35 (0%)	0.39 (0%)
SST1	0.43 (0%)	0.51 (10%)	0.43 (100%)	0.37 (0%)
SST8		0.30 (90%)	0.19 (0%)	
SST11	0.41 (100%)			
Persistence				0.39 (100%)
Calibration	16.1%	10.8%	8.9%	15.0%
Cross Val	8.0%	-9.6%	-9.4%	-1.0%

Note: Correlation values (greater than 0.33 are significant at the 99 percent level) and weights (percent in parentheses) used by the model for the best three predictors are noted. Calibration and cross validation LEPS scores are shown at the bottom of the table.

It is noteworthy that Persistence has the highest correlation values when predicting both JFM and AMJ streamflow at SR1 for a zero-month lead time. However, Tables 1 and 2 show that MEI and SST1 have consistently high correlation values for longer lead times, while Persistence and other climate predictors do not. This is not too surprising since it is typical to have seasonal "memory" in streamflow. Also, it is noteworthy that for two cases with the longest lead times – JFM(-1) to predict JFM(0) for SR1 and AMJ(-1) to predict AMJ(0) for SR2 – SST8 and SST11 are used as predictors. As previously described, these regions are outside the established ENSO SST region. These regions may influence jet stream movement or influence the warming and cooling of the equatorial SSTs.

The streamflow ENSO signal is also strong for SR2 (Tables 3 and 4) in the Upper Suwannee River Basin (Figure 1). For instance, the OND(-1), MEI (0.43), and SST1 (0.46) have higher correlation values than Persistence (0.24) for the zero-month lead time of JFM(0) streamflow (Table 3). Furthermore, the MEI and SST1 have high correlation values and are used as two of the best three predictors for every lead time for AMJ(0) streamflow.

The strong ENSO signal is most likely due to the abundance of large frontal storms during the winter and spring seasons, while the summer and fall seasons are dominated by convectional storms. Florida's winter and spring season precipitation is dominated by large and sometimes slow moving frontal storms that originate in the Pacific Ocean and move from west to east across the United States. The "track" or traditional path that these storms travel across the United States is altered by ENSO activity. This leads to greater activity (i.e., enhanced subtropical jet) and more precipitation during El Niño years. Based on the historical flooding of the Suwannee River during the winter and spring seasons, the strong ENSO signal, and the need to provide a forecast for these seasons, this research focuses on using climate as a predictor of winter and spring seasonal streamflow volumes. Additional analysis of correlations of climate (and Persistence) with summer and fall streamflow at various lead times (zero, three, six, and nine months) did not result in strong correlations and are not presented here.

The streamflow forecast described in the following sections requires three variables as a predictor of streamflow. From the correlation analysis and the values of the predictors shown in Tables 1 through 4, MEI and SST1 are two of the three predictors used for every forecast with the exception of the nine-month lead time for the JFM forecast for both SR1 and SR2. The third predictor is PDO, SST8, SST11, or Persistence.

FORECAST METHODOLOGY

The streamflow forecast developed is a continuous exceedance probability curve that can be used for any assumed risk level and was developed by Piechota *et al.* (2001). The "no skill/climatology" forecast curve is generated by dividing the rank of each historical value by the total number of years in the record. In developing the streamflow forecast for this study, three streamflow forecast models, each using a different predictor, are combined to form a final combination forecast. With the exception of the nine-month lead time forecast of the JFM streamflow, the first model uses the MEI, and the next model uses SST1 as predictor variables. The third and final forecast model uses the best predictors (PDO, SST8, SST11, or Persistence) of streamflow at each station.

Two advantages are found with this method: it considers the continuous relationship between the predictand and the predictor, and it does not assume a particular model structure. It suffers, however, from its semi-empiricism – fitting the model to the data points assumes that the historical data represents the entire population. A detailed description of the methodology and model can be found in Piechota *et al.,* (1998, 2001). A brief description of the model (for one predictor) is provided below.

1. The climate predictor values (P_i) for each year and the corresponding streamflow predictand values (Q_i) for each year are compiled.
2. The streamflow values (Q_i) are ranked in ascending order, and the corresponding climate predictor (P_i) for the corresponding year of the streamflow are noted.
3. The first data point for analysis occurs immediately after the five lowest streamflow values (Q_i), and the last point for analysis occurs immediately prior to the five highest streamflow values (Q_i). This is required since a minimum of five values are needed to generate a probability density function.
4. The first data point for analysis is the sixth-ranked streamflow value (lowest to highest) based on Step 3 above. Using the kernel density estimator (Silverman, 1986; Piechota *et al.,* 1998), a probability density function is developed for all climate predictor values below the first data point, and a probability function is developed for all climate predictor values above the first data point.
5. A unique probability value is determined for each predictor value, given the sixth-ranked streamflow value. These values are single points on the exceedance probability curve (Probability versus Streamflow). The procedure is then repeated for the seventh-ranked streamflow value and so on.
6. An exceedance probability is then determined for each predictor value. The forecast curve will represent the probability of exceeding a value of streamflow, based on the value of the predictor.
7. The final exceedance probability forecast is found by combining the three individual forecasts into one combination forecast that has better overall skill. The combination forecast is found by applying weights a, b, and c to the three models so that the weights add up to 1. The optimal forecast is found by applying more weight to individual forecasts that better predicts streamflow and less weight to poor individual forecasts. These optimal weights are determined by an optimization procedure that evaluates the Linear Error in Probability Space (LEPS) score for all possible combinations, using weighting increments of 0.02 in which the weights vary between

0 and 1 for each model. The final combination forecast is the model with the highest LEPS score.

The skill of the forecast was measured using the LEPS score. This score is a measure of skill that was developed originally to assess the position of the forecast and the position of the observed values in the cumulative probability distribution (nonexceedance probability). The LEPS score can be used for continuous and categorical variables (Ward and Folland, 1991; Potts *et al.,* 1996). The skill associated with each individual forecast and the final combination forecast are calculated for calibration and cross validation analyses. The LEPS score for the calibration analysis does not provide an independent skill score because it is based on the same data on which the model was calibrated.

RESULTS

The model described in the previous section was applied to two unimpaired streamflow stations (SR1 and SR2) of the Suwannee River. A seasonal streamflow forecast was made using the "best" three predictors (MEI, PDO, SST1, SST8, SST11, or Persistence) to forecast streamflow for zero-, three-, six-, and nine-month lead times (Tables 1 through 4). For example, the winter JFM(0) streamflow at SR1 and SR2 is forecasted using the previous year's summer JAS(-1) values of MEI, PDO, and SST1 (see Table 1). A summary of the results is presented in Tables 1 through 4, which include: (a) the correlation values for the "best" three predictors at the various lead times (zero, three, six, and nine months); (b) the optimized weights (0 to 100 percent) used for the "best" three predictors when all the data are used to calibrate the model at the various lead times; and (c) the LEPS score for the calibration and cross validation at the various lead times.

Calibration Results

The calibration results using the "best" three predictors (climate and/or persistence) of winter and spring streamflow (based on correlation values) for Stations SR1 and SR2 of the Suwannee River are shown in Tables 1 through 4. Calibration uses all the data to calibrate the weights and then computes the skill based on all the data. The weights in Tables 1 through 4 suggest a strong ENSO signal at Station SR1. For three of the four cases with a zero-month lead time, Persistence was used as the main predictor. For the eight lead times (four each to predict JFM and AMJ), MEI and/or SST1 were used as the predictor six times.

The LEPS scores for the calibration analyses were greater than 10 percent in 13 of the 16 simulations (Tables 1 through 4). A 10 percent or greater value is generally considered a LEPS score with good skill. As expected, the zero-month lead time generally provided the highest calibrated LEPS scores, ranging from a low value of 15.0 percent to a high value of 31.8 percent. The summer JAS(-1) season provided consistently higher LEPS scores when predicting both JFM(0) and AMJ(0) streamflow. The summer season is the traditional time frame in which Pacific Ocean climate phenomena, most notably ENSO, develop. The previously established strong signal between ENSO and streamflow in the Suwannee River could possibly validate the higher summer LEPS scores. The development of an El Niño during the summer time frame would result in higher streamflow during the following year's winter and spring seasons, and the development of a La Niña would result in a lower streamflow.

Cross Validation Results

Cross validation provides a more independent assessment of the forecast skill and of the weights applied to each model (Michaelsen, 1987; Elsner and Schmertmann, 1994). Cross validation allows the model to remove a year, calibrate the model, and then test the model on the year that was removed. This procedure is repeated for all years. The use of cross validation eliminates spurious predictors and artificial skill. The LEPS score for the cross validation analyses drops considerably when compared to the LEPS score for the calibration analysis. Tables 1 through 4 indicate that the LEPS scores for the cross validation analyses were greater than 10 percent in three of the 16 simulations. However, it should be noted that for the lead times of three, six, and nine months, the highest cross validation LEPS score (11.0 percent) determined was JAS(-1), with a three-month lead time, to predict JFM(0) for SR1. For this prediction, 100 percent of the weight was placed on the MEI.

For all lead times (zero, three, six, and nine months), the highest reported cross validation LEPS score (19.4 percent) was JFM(0), a zero-month lead time, to predict AMJ(0) for SR1. For this prediction, 100 percent of the weight was placed on persistence. Based on these results, it may be possible to predict JFM and AMJ streamflow for SR1 by first using summer JAS(-1) MEI to forecast JFM(0) streamflow and then using JFM(0) persistence to forecast AMJ(0) streamflow.

El Niño and La Niña Years

To further examine the strength of the ENSO signal, exceedance probability streamflow forecasts were developed for El Niño and La Niña events between 1951 and 1996. Based on information obtained from the National Oceanic and Atmospheric Administration (NOAA) Climate Diagnostics Center, for this study, El Niño years are 1957, 1965, 1972, 1982, 1986, and 1991, and La Niña years are 1954, 1964, 1970, 1973, 1975, and 1988. Due to El Niño and La Niña events transgressing multiple calendar years, the selection of the years could vary. SST data for 1997 were unavailable, and thus no 1997 El Niño forecast is provided. Additionally, hurricane related precipitation during the period of study was reviewed. For the period of 1950 to 1997, Florida experienced 23 hurricanes. However, none of these hurricanes contributed precipitation during OND for the El Niño years selected. The streamflow forecasts shown here use summer JAS(-1) MEI (three-month lead time) of the El Niño (or La Niña) years to predict JFM(0) streamflow for SR1 streamflow station.

Figures 2 and 3 show the exceedance probability forecasts for the six El Niño and six La Niña events along with the previously discussed climatology forecast. The observed JFM(0) streamflow values (dark circles) are displayed and the cross validation LEPS scores for each event are shown in parentheses. In Figure 2, each El Niño forecast is greater than the climatology forecast. In the La Niña events (see Figure 3), each forecast is lower than the climatology forecast. This is consistent with the previously stated effect of ENSO, that is, greater streamflow during El Niño, lesser streamflow during La Niña. Observed streamflow values show that four out of six El Niño events resulted in above normal streamflow, while five out of six La Niña events resulted in below normal streamflow.

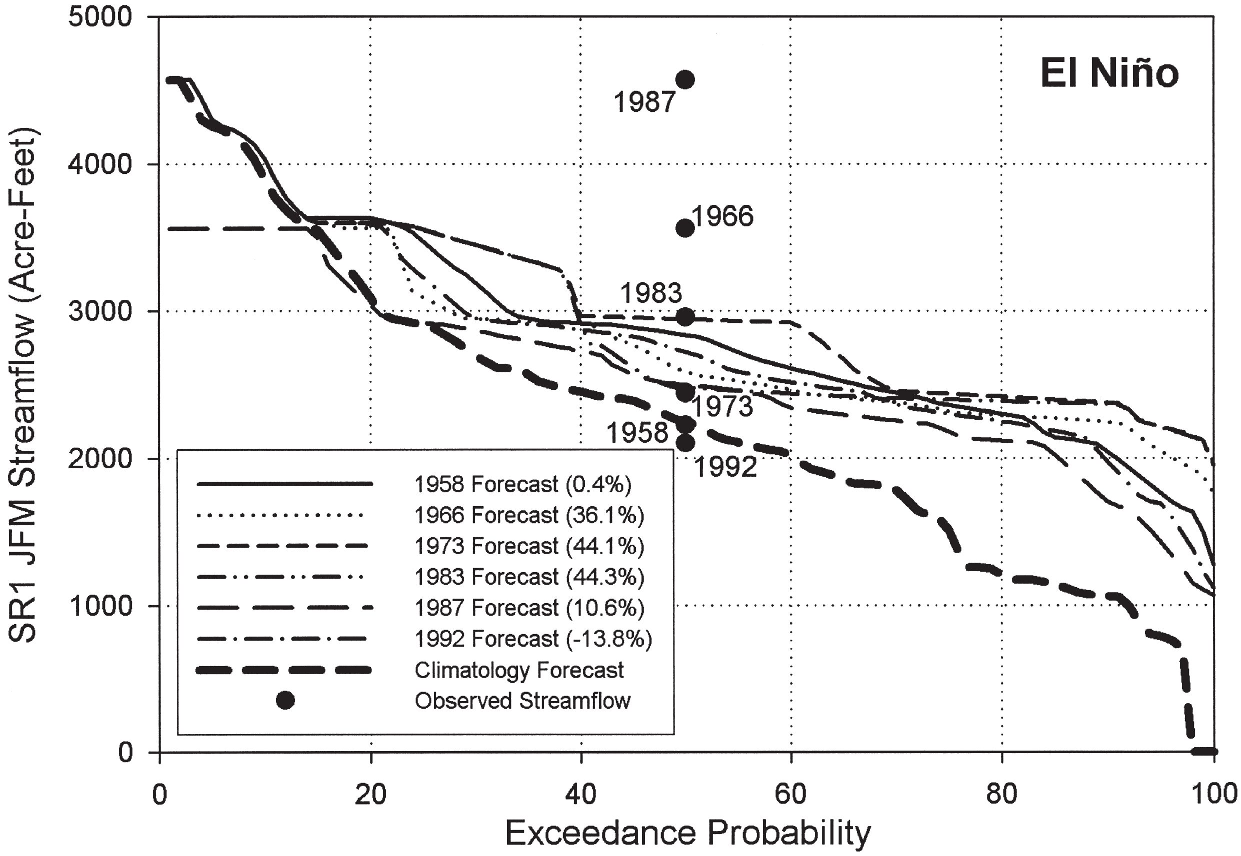

Figure 2. Exceedance Probability Forecasts for El Niño Years Between 1951 and 1996 for the Suwannee River, Station 02323500 (SR1), for Winter [JFM(0)], Streamflow Using Summer [JAS(-1)], Climate Predictors. Observed streamflow values (dark circles), climatology forecast, and cross validation LEPS scores (percent) are also provided.

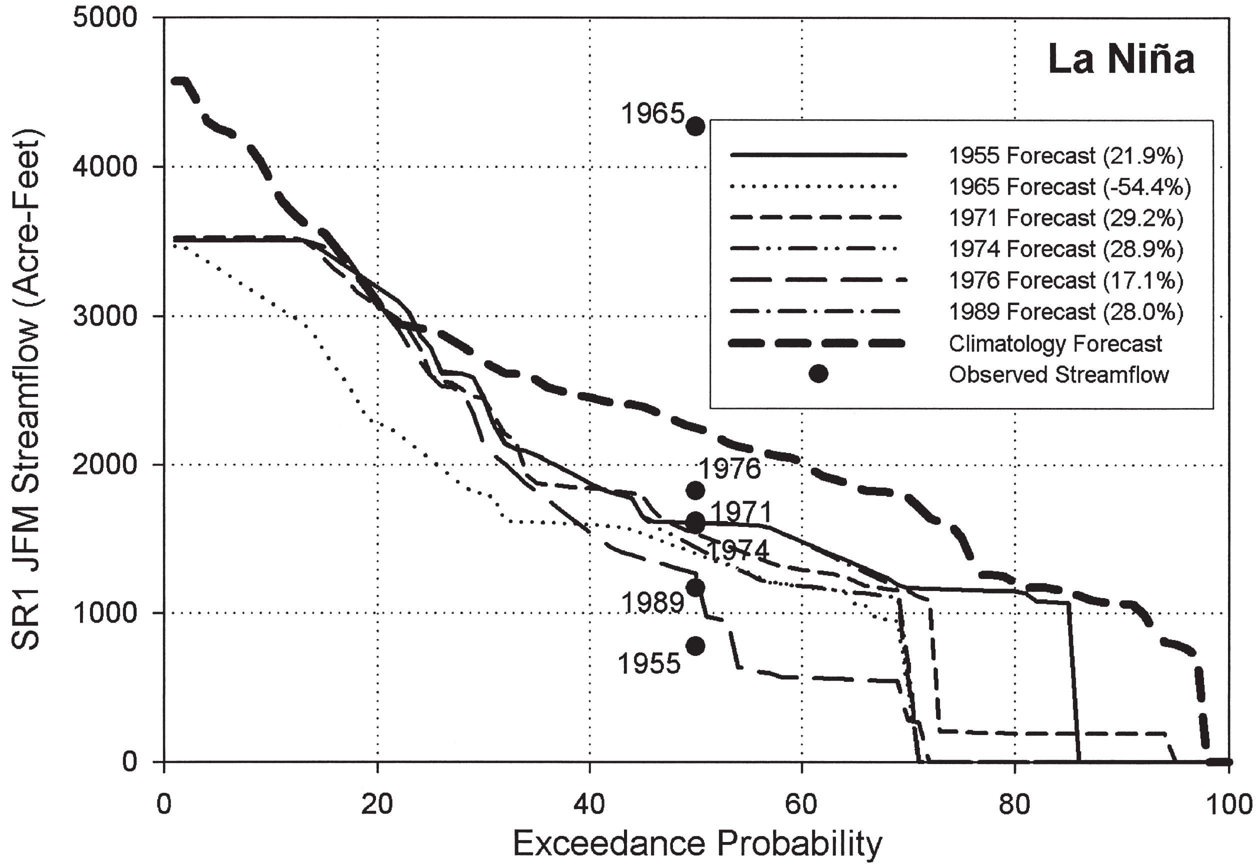

Figure 3. Exceedance Probability Forecasts for La Niña Years Between 1951 and 1996 for the Suwannee River, Station No. 02323500 (SR1), for Winter [JFM(0)] Streamflow Using Summer [JAS(-1)] Climate Predictors. Observed streamflow values (dark circles), climatology forecast, and cross validation LEPS scores (percent) are also provided.

Cross validation LEPS scores are significantly higher for El Niño/La Niña years, again showing the strong ENSO signal. These results can be used to predict winter/spring streamflow in ENSO years by first identifying in the summer JAS(-1) that an El Niño or La Niña event is occurring, based on the average MEI value. The model can produce an exceedance probability forecast for JFM(0) using these climate data. AMJ(0) can then be forecasted based on persistence, that is, the JFM(0) streamflow.

CONCLUSIONS

A method for developing an exceedance probability streamflow forecast using multiple predictors is presented here and applied to the Suwannee River. Because the exceedance probability forecast is continuous, it allows the forecast user to evaluate the forecast amount of streamflow at different levels of risk. For instance, past studies show that El Niño events produce more rainfall and more streamflow, while La Niña events produce less rainfall and less streamflow. Referring to Figure 2, JFM(0) streamflow for an El Niño year can be forecast based on the JAS(-1) value of the predictor MEI because 100 percent of the weight was placed on this predictor by the model (see Table 1). Although the climatology forecast for the median (50 percent) exceedance probability shows a value of approximately 2,200 acre-feet, the model's forecasts range from approximately 2,400 to 3,000 acre-feet. The seasonal streamflow for four of the six El Niño events for this period of study exceeded the climatology forecast. These forecasts can provide water resource planners and local communities with sufficient lead times to prepare for greater flows and possible flooding of the Suwannee River. The opposite occurs for La Niña years (see Figure 3). While the climatology forecast for the average (50 percent) exceedance probability again shows a value of approximately 2,200 acre-feet, the model's forecasts range from approximately 1,000 to 1,500 acre-feet. The seasonal streamflow for five of the six La Niña events for this period of study were below the climatology forecast. Again, these forecasts can provide hydrologists and biologists the necessary lead time to institute conservation practices to prevent negative impacts to wetlands and environmentally sensitive areas. Low flows of the Suwannee River will likely result in increased concentrations of pollutants and contaminants due to lack of dilution.

The above application of the forecasting generally shows that ENSO is the most important predictor for winter and spring streamflow. There is potential for making streamflow forecasts with a six-month lead time using ENSO indicators and persistence. These forecasts are especially useful to water resources planners. The ability to predict above normal (flood) years can provide communities the necessary lead time to protect life and property. The ability to predict below normal (drought) years will provide hydrologists the necessary lead time to protect sensitive wetlands and protect endangered and threatened species.

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LITERATURE CITED

Drosdowsky, W. and L. Chambers, 1998. Near Global Sea Surface Temperature Anomalies as Predictors of Australian Seasonal Rainfall. Bureau of Meteorology Research Centre, Australia, Research Report 65.

Elsner, J.B. and C.P. Schmertmann, 1994. Assessing Forecast Skill Through Cross Validation. Weather and Forecasting 9:619-624.

Hanson, K. and C.A. Maul, 1991. Florida Precipitation and the Pacific El Niño, 1895-1989. Florida Scientist 54:160-168.

Giese, G.L. and M.A. Franklin, 1996. Magnitude and Frequency of Floods in the Suwannee River Water Management District, Florida. U.S. Geological Survey Water Resources Investigations Report 96-4176.

Kahya, E. and J.A. Dracup, 1993. U.S. Streamflow Patterns in Relation to the El Niño/Southern Oscillation. Journal of Water Resources Research 29(2):491-503.

Kiladis, G.N. and H.F. Diaz 1989. Global Climatic Anomalies Associated With Extremes in the Southern Oscillation. Journal of Climate 2(1):69-90.

Mantua, N.J., S.R. Hare, Y. Zhang, J.M. Wallace, and R.C. Francis, 1997. A Pacific Interdecadal Climate Oscillation With Impacts on Salmon Production. Bulletin of the American Meteorological Society 78:1069-1079.

Michaelsen, J., 1987. Cross-Validation in Statistical Climate Forecast Models. Journal of Climate and Applied Meteorology 26:1589-1600.

NOAA (National Oceanic and Atmospheric Administration), 2003. Climate Diagnostics Center (CDC), International Comprehensive Ocean-Atmosphere Data Set (ICOADS). *Available at* http://www.cdc.noaa.gov/~kew/MEI/mei.html. *Accessed in* February 2003.

Piechota T.C., F.H.S. Chiew, J.A. Dracup, and T.A. McMahon, 2001. Development of Exceedance Probability Streamflow Forecast. Journal of Hydrologic Engineering 6(1):20-28.

Piechota T.C., J.A. Dracup, F.H.S. Chiew, and T.A. McMahon, 1998. Seasonal Streamflow Forecasting in Eastern Australia and the El Niño-Southern Oscillation. Journal of Water Resources Research 34(11):3035-3044.

Potts, J.M., C.K. Folland, I.T. Jolliffe, and D. Sexton, 1996. Revised "LEPS" Scores for Assessing Climate Model Simulations and Long-Range Forecasts. Journal of Climate 9:34-53.

Ropelewski, C.F. and M.S. Halpert, 1986. North American Precipitation and Temperature Patterns Associated With the El Niño/Southern Oscillation. Monthly Weather Review 114(2):352-362.

Ropelewski, C.F. and M.S. Halpert, 1989. Precipitation Patterns Associated With the High Index Phase of the Southern Oscillation. Journal of Climate 2:268-284.

Schmidt, N., E.K. Lipp, J.B. Rose, and M.E. Luther, 2001. ENSO Influences on Seasonal Rainfall and River Discharge in Florida. Journal of Climate – Notes and Correspondence 14:615-628.

Silverman, B.W., 1986 . Density Estimation for Statistics and Data Analysis. Chapman and Hall, New York, New York.

State of Florida, 2003. Florida Administrative Code. Chapter 62-302.700.

Sun, H. and D.J. Furbish, 1997. Annual Precipitation and River Discharges in Florida in Response to El Niño- and La Niña-Sea Surface Temperature Anomalies. Journal of Hydrology 199:74-87.

USGS (U.S. Geological Survey), 2003. National Water Information System Website (NWISWeb) for the Nation, Surface Water Statistics – Monthly. *Available at* http://nwis.waterdata.usgs.gov/usa/nwis/monthly. *Accessed in* February 2003.

Ward, N.M. and K.K Folland, 1991. Prediction of Seasonal Rainfall in the North Nordeste of Brazil Using Eigenvectors of Sea-Surface Temperature. International Journal of Climatology 11:711-743.

Waylen, P.R., 1991. Modeling the Effects of Tropical Cyclones on Flooding in the Santa Fe River Basin, Florida. GeoJournal 23:361-373.

Wolter, K. and M.S. Timlin, 1998. Measuring the Strength of ENSO – How Does 1997/98 Rank? Weather 53:315-324.

Zorn, M.R. and P.R. Waylen, 1997. Seasonal Response of Mean Monthly Streamflow to El Niño/Southern Oscillation in North Central Florida. Professional Geographer 49:51-62.