ELSEVIER

Journal of Hydrology 199 (1997) 74–87

Journal of Hydrology

Annual precipitation and river discharges in Florida in response to El Niño- and La Niña-sea surface temperature anomalies

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Received 28 November 1995; revised 25 September 1996; accepted 9 October 1996

Abstract

Statistical analysis proves that El Niño and La Niña are responsible for up to 40% of annual precipitation variations and up to 30% of river discharge variations in Florida. The analysis is based on 44-year records of precipitation from more than 30 gauge stations and stream discharge from 20 gauge stations distributed all across Florida Peninsula. The cross-correlation coefficients for both the sea surface temperature (SST) and precipitation data series, the SST and river data series are calculated after the SST data series, precipitation and river data series are prewhitened by an autoregressive moving average (ARMA) model (0, 1). The cross-correlations between the SST anomalies and both the precipitation and river discharge are positively significant. The conclusion is that a higher annual precipitation amount (a 'wet' year) is expected from an El Niño year, and a lower precipitation amount (a 'dry' year) is expected from a La Niña year. Large amounts of fresh water recharge into the estuary in an El Niño year and less fresh water recharges into an estuary in a La Niña year. Also a higher groundwater table is expected in an El Niño year, and a lower groundwater table is expected in a La Niña year. Assuming that SST anomalies are the input signals for a time-series analysis, the impulse response weights of both precipitation and river discharge to SST signals can be calculated due to their positive correlations. The impulse response weights can be used to build the linear transfer functions of precipitation, river discharge and SST signals. The annual precipitation and stream discharge amount therefore can be predicted from the SST anomalies. This can provide some guidance for the water management policy and planning.

1. Introduction

A persistent high pressure zone exists along the eastern South Pacific and an equally

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0022-1694/97/$17.00
PII S0022-1694(96)03303-3

persistent low pressure zone exists along the west South Pacific (Vogel, 1989). The exchange of pressures between west and east is known as the Southern Oscillation and is caused by the interannual sea surface temperature (SST) variation in the tropical Pacific (Philander, 1990; Quinn and Neal, 1987). This exchange is the most notable signal in interannual climatic variations (Rasmussen and Carpenter, 1987). El Niño is a warm anomaly event and La Niña is a cool anomaly event in the tropical Pacific Ocean, respectively. They are considered as significant perturbations of general atmospheric circulation (Philander, 1990; Quinn and Neal, 1987).

Broad spectra of events are thought to be related with El Niño and La Niña cycles. They range from flood and drought, coastal marine life loss to cloudiness (Angell and Korshover, 1987) and earthquake (Walker, 1995). It has been widely demonstrated that the hydrometeorology cycles are certainly affected by El Niño and La Niña (Ropelewski and Halpert, 1987; Kahya and Dracup, 1993). The amount of precipitation is related with El Niño and La Niña (Ropelewski and Halpert, 1987; Horel and Wallace, 1981), but the amplitude and phase of the hydrologic response might be different in different regions. Severe drought might be related with El Niño events in Australia and Indonesia, but high flood events might be related with El Niño in South America (Philander, 1990; Simpson and Cane, 1993). These extreme water events depend on the moisture-laden atmospheric circulation in certain geographical location. Most of the studies relating the hydrometeorology to El Niño and La Niña are in broad scales and are more focused on extreme water events, i.e. floods or droughts instead of the total discharge of the year.

Geographically, Florida Peninsula is located in the mid-low latitude. It has broad coastal regions. There are unique properties in Florida hydrometeorology. Most of the river streams are gaining streams in Florida. There are strong fluctuations in the amount of annual precipitation. The stream flow, which filters noisier precipitation fields, is the integral form of land and atmospheric processes (Kahya and Dracup, 1993). Because most of the stream flows in Florida are gaining water from aquifers, the stream discharge is a direct reflection of the groundwater table. The higher the groundwater table, generally, the stronger the stream flows. All the streams eventually discharge into estuaries in Florida. Therefore, the estuary water salinities are greatly affected by the amounts of the stream discharge. The salinity in the estuary directly affects the offshore oyster and other sea food production, the offshore wetland environments and ecological cycles. In a 'wet' year, there is a high stream discharge, high groundwater table and more fresh water intrusion into the bay. In a 'dry' year, there is less stream discharge, a low groundwater table and high saline water in the estuary. Therefore examining and understanding the effect of El Niño and La Niña on the water system in Florida is an important issue to the coastal environments. Understanding the influence of El Niño and La Niña on the water system, and the short period prediction of a 'wet' or 'dry' season based on the SST anomalies can provide guidance for the water management planning and policy making and help us to better understand all the mechanisms that might affect the Florida coastal environments.

2. The annual precipitation and stream discharge in Florida in response to SST anomalies

SST data used in this study are the annual average Japanese Meteorological Agency

(JMA) index of sea surface temperature anomalies of the eastern tropic Pacific in tenths of a degree centigrade (i.e. 23 on the plot scale will be 2.3°C). They are the averaged measurements from latitude 4°N to 4°S and longitude 150°W to 90°W. The precipitation data are the annual average rainfalls in centimeters from the National Climate Center Database. The stream discharges are the average annual stream discharges from United States Geological Survey (USGS) water year report database and are in cubic meters per second (a year in this study is from January to December instead of the USGS water year). Thirty precipitation and 20 stream discharge data series, for which there have been more than 45 years continuous recording history, are chosen across the Florida peninsula (Fig. 1 and Table 1). The obvious peaks in the plot for the SST anomaly are associated with the El Niño events and the obvious valleys in the plot for the SST anomaly are associated with the La Niña events (Figs. 2 and 3). An obvious matching of the peaks and valleys between the annual SST anomaly and annual precipitation amount exists for most of the precipitation data series. A matching of peaks and valleys between the annual SST anomaly and annual stream discharge amount also exists with a half- to 1-year lag shift existing.

In order to statistically verify the relationships observed from these raw data plots for the annual precipitation and stream discharge in response to SST anomalies, the cross-correlation structure between the corresponding two series has been examined in this study. Because the input series may be autocorrelated, the direct cross-correlation function between the input and response series may give a misleading indication of the relation between the input and response series (Box and Jenkins, 1976; Zwiers, 1990). Therefore, a prewhitening process is conducted before the data are cross-correlated.

First we fit an Autoregressive integrated moving average (ARIMA) model for the input series SST anomalies sufficient to reduce the residuals to white noise:

$$X_t = m_x + (1 - 0.303\,B^2 + 0.314\,B^4)a_t \tag{1}$$

where X_t is annual SST anomalies at year t, m_x is the average value of the sample variable X_t from 1949 to 1992, B is the backshift operator with $BX_t = X_{t-1}$ and a_t is a random shock signal. The significance of the t-test for the first coefficient 0.303 is 2.07, and for the second coefficient 0.314 is –2.36.

Three annual data series (SST index, precipitation and stream discharge of 44 years records) are then prewhitened by the above moving average filter, the residual series produced are:

$$e_x = (X_t - m_x)(1 - 0.303\,B^2 + 0.314\,B^4)^{-1} \tag{2}$$

$$e_y = (Y_t - m_y)(1 - 0.303\,B^2 + 0.314\,B^4)^{-1} \tag{3}$$

$$e_z = (Z_t - m_z)(1 - 0.303\,B^2 + 0.314\,B^4)^{-1} \tag{4}$$

where e_x, e_y and e_z denote the 'residues' from the filtering. X_t, Y_t and Z_t denote the data series values and m_x, m_y and m_z denote the means for SST, precipitation and stream discharge, respectively. The residual series are then cross-correlated for precipitation and SST, stream discharge and SST by the cross-correlation equation defined below.

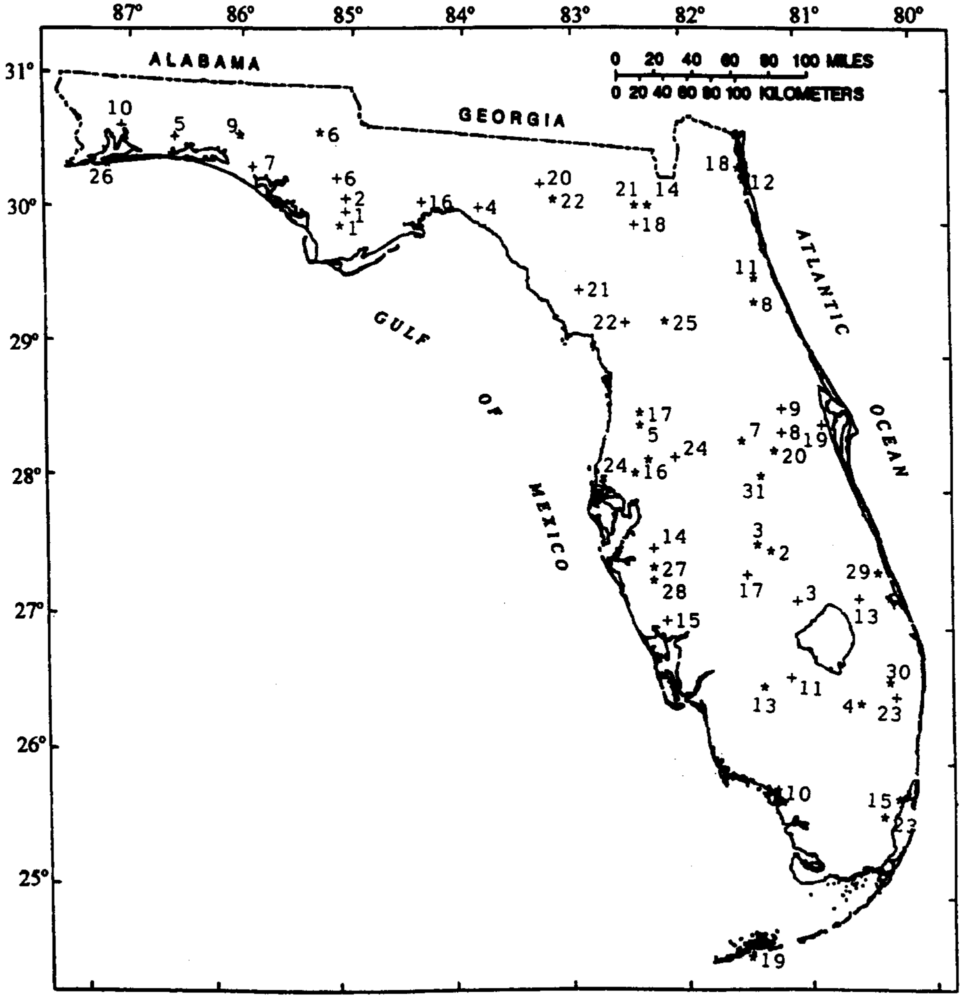

Fig. 1. Location of precipitation and river gauge stations used in this study corresponding to Table 1. An '*' is a precipitation gauge station, and a ' + ' is a river gauge station.

The population cross-correlation coefficient for variables X_t and Y_t is defined as:

$$P_{xy}(k)=\frac{r_{xy}(k)}{s_x s_y} \quad k=0,\ \pm 1,\ \pm 2\ldots \tag{5}$$

where s_x and s_y denote the sample standard deviations of X_t and Y_t, respectively, $r_{xy}(k)$ denotes the sample cross-covariance between x and y at lag k, and is defined as:

$$r_{xy}=E[(x_t-m_x)(Y_{t+k}-m_y)] \tag{6}$$

where E denotes the sample expectation.

The cross-correlation coefficients are calculated by using the SAS ARIMA procedures

Table 1

A name list of precipitation and river gauge stations corresponding to the numbers in Fig. 1

Precipitation stations		River gauge stations	
*1. Apalachicola	*17. Inverness	+ 1. Apalachicola R. Near Sumatra	+ 17. Peach R.
*2. Avon Park	*18. Jacksonville	+ 2. Apalachicola R. Near Wewahitchka	+ 18. Santa Fe R.
*3. Bartow	*19. Key West	+ 3. Arbukle Creek	+ 19. St. Johns R.
*4. Belle Galde	*20. Kissimmee	+ 4. Aucilla R. Near	+ 20. Suwannee R. St Ellaville
*5. Brooksville	*21. Lake City	+ 5. Blackwater R. Near Baker	+ 21. Suwannee R. Near Wilcox
*6. Chipley	*22. Madison	+ 6. Chipola R. Near Altha	+ 22. Waccasassa R. Near Gulf Hsmmock
*7. Clemont	*23. Miami Beach	+ 7. Choctawhatche Near Bruce	+ 23. West Palm Beach Canal
*8. Crescent	*24. Naples	+ 8. Cypress Creek	+ 24. Withlacoochee R. At Trilby
*9. De Funiak Springs	*25. Ocala	+ 9. Econlockhatchee R.	
*10. Everglades Scanlon	*26. Pensacola	+ 10. Escambia R. Near Century	
*11. Federal Point	*27. St. Petersburg	+ 11. Fisheating Creek at Paldale	
*12. Fernandia	*28. Tampa	+ 12. Hillsborough R. Near Tampa	
*13. Fort Myers	*29. Vero Beach	+ 13. Kissimmee R.	
*14. Glen St. Mary	*30. West Palm Beach	+ 14. Little Manatee Creek	
*15. Hialeah City	*31. Winter Heaven	+ 15. Myakka R. Near Sarasota	
*16. Hillsborough		+ 16. Ochlockonee R.	

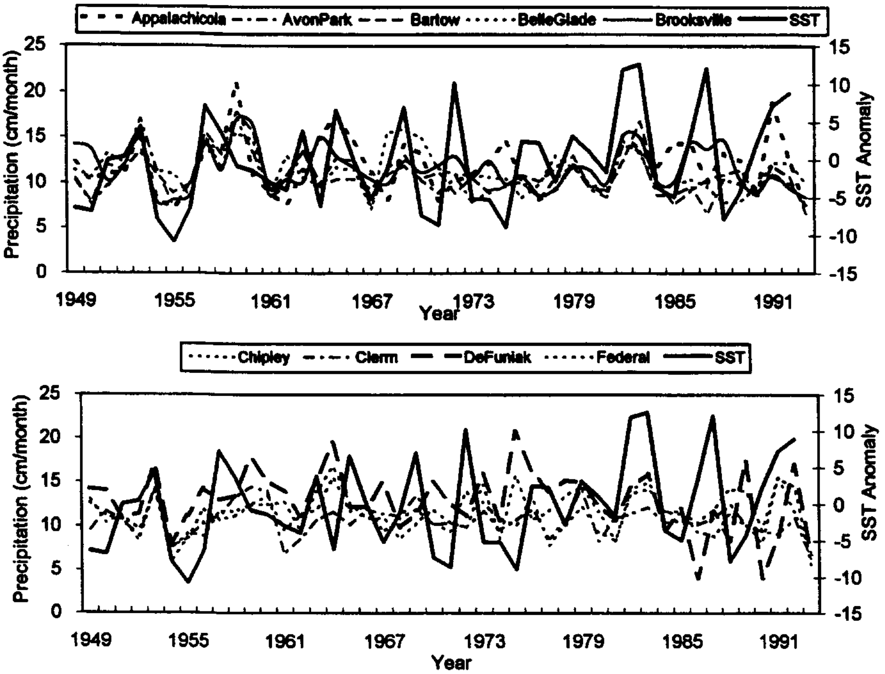

Fig. 2. Representative annual precipitation data (in cm month^{-1}) vs annual average SST data.

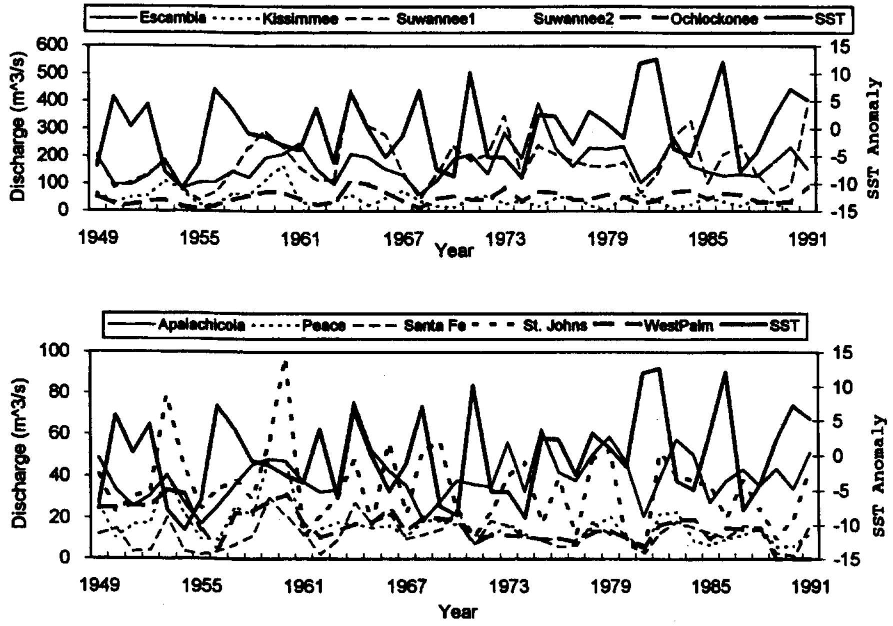

Fig. 3. Representative annual stream discharge vs annual average SST data.

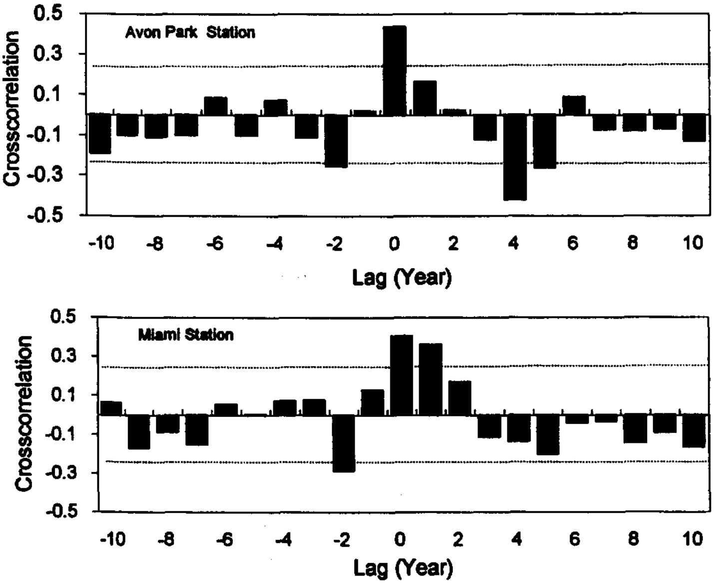

Fig. 4. Cross-correlation of precipitation vs SST anomaly. Note that the dotted lines are about the two standard error lines.

(Figs. 4 and 5). Twenty out of 30 precipitation series show significant correlation between annual SST and precipitation data at zero lags. This result is considered significant with 95% confidence from the t-test, $t = r_{xy}/s(r_{xy})$, where $s(r_{xy})$ is a sample standard error. Five out of 30 stations do not show significant cross-correlation coefficients after prewhitening

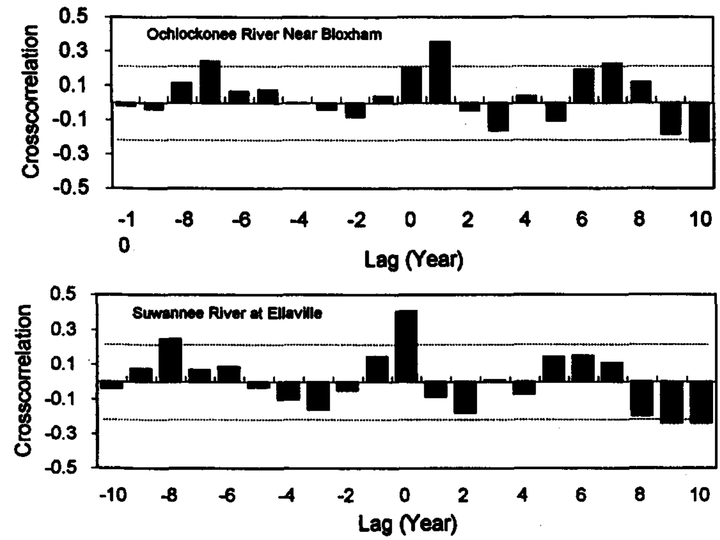

Fig. 5. Cross-correlation of discharge vs SST anomaly. Note that the dotted lines are about the two standard error lines.

both series. Another five out of 30 show some mixed patterns, such as significant coefficients existing at negative two and zero lags. These results demonstrate that a statistically significant correlation exists between the SST anomalies and the annual precipitation data in Florida.

The same procedure is performed for the cross-correlation of SST and stream discharge. Both SST series and stream discharge are filtered by the moving average filter (Eq. (1)) before the cross-correlation coefficients are calculated. Ten out of 20 selected stream data series show a significant positive cross-correlation between the SST and the discharge. Six out of 20 show that a marginally significant inverse cross-correlation exists at negative two lag between SST and discharge. The positive cross-correlation implies that the annual stream discharge is significantly affected by the SST anomalies. Because the El Niño cycle is approximately 3.8 years, the inverse correlation at negative lag two implies that the higher water amount is also at approximately zero lag in corresponding with the SST cycles. The inverse coefficients at negative two lag are also shown in a few of the precipitation coefficients (Fig. 4).

In general, the cross-correlation between SST and annual precipitation is stronger than the coefficients between SST and stream discharge in Florida. Precipitation is directly controlled by atmospheric circulation; whereas the stream is partially controlled by precipitation. Stream flow is affected by the reservoir effect, which here refers to water stored in natural reservoirs and aquifers, being replenished through precipitation and being slowly released into the streams. Therefore, not only the SST anomalies, but also the previous soil water conditions, vegetation cover and the size of drainage area also affect the stream discharge amount.

3. Linear transfer function modeling

Satellite technology and modeling are pivotal for prediction of the SST anomaly (Liu et al., 1995). Therefore, the statistical relationship between precipitation, streamflow and SST anomalies allows for extended hydrologic predictions. One of the important steps for prediction from one data series to another data series is to build the dynamic transfer function model. The first step of building the dynamic transfer function model is to determine the impulse response function. In a time series study, the output series (Y_t) responds to a change in the input (X_t) with a time lag. We assume that this distributed lag is linear, with the transfer function $f(X_t)$ as a linear combination of current and the past X_t values:

$$Y_t = f(X_t) = v_0 X_t + v_1 X_{t-1} + v_2 X_{t-2} + \ldots \tag{7}$$

Coefficient V_0 is a weight that states how Y_t is responding to a change in X_t; coefficient V_1 is a weight that states that how Y_t responds to a change in X_{t-1}. The V weights can be positive or negative, and the higher the absolute value of the v, the larger the response of Y_t to a change in X_{t-k}. The true transfer function underlying a sample data set may not be linear. But the linearity assumption is used because (1) it simplifies the statistical analysis considerably; (2) despite their relative simplicity, linear models have proven to be useful in a wide variety of situations; (3) a linear model is often a useful first step or approximation (Pankratz, 1991).

Table 2
Impulse response weights, the AR and MA terms of precipitation and SST and their t-tests

Station name	Mu	Num1, 0	$t1$	Num1, 1	$t2$	MA1	t_a	AR1	t_r
Apalachicola	4.73	0.075	2.92	−0.06	−2.32	0.48(4)	3.01	–	–
Avon Park	4.18	0.053	2.98	–	–	−0.49(6)	−2.82	0.23	1.45
Bartow	4.39	0.068	3.67	−0.047	−2.46	−0.25(3)	−1.46	0.21	−1.46
Belle Glade	4.50	0.047	2.38	–	–	–	–	0.29	1.95
Brooksville	4.62	0.075	3.40	−0.032	−1.53	–	–	–	–
Chipley	4.64	0.017	0.74	−0.032	−1.45	–	–	–	–
Everglades	4.32	0.061	2.67	−0.051	−2.30	−0.28	−1.56	–	–
Federal	4.43	0.041	2.35	–	–	0.27(5)	1.53	–	–
Fernandina	4.23	0.062	2.45	0.157	0.66	–	–	–	–
Lake City	4.55	0.034	1.25	0.052	−2.46	0.28(2)	1.25	–	–
Madison	4.31	0.054	2.44	−0.025	−1.17	0.24(3)	1.41	–	–
Miami	3.85	0.070	3.66	−0.047	−2.44	–	–	0.21	1.27
Naples	4.41	0.057	3.16	–	–	0.36(5)	2.30	–	–
Ocala	4.37	0.049	3.49	−0.020	−1.35	−0.76(6)	−3.76	–	–
West Palm B.	5.07	0.085	4.13	−0.070	−3.39	–	–	–	–
Winter Haven	4.10	0.049	2.98	−0.036	−2.13	–	–	–	–

Mu, mean of the data series; Num1, 0, response weight lag 0; Num1, 1, response weight at lag 1; AR1, first order autoregressive term; MA1, moving average term with () the shift term; t_a, t-test value for the moving average; t_r, t-test value for the autoregressive term.

We can write a linear distributed lag transfer function in a backshift form by defining $V(B)$ as:

$$V(B) = V_0 + V_1B + V_2B^2 + V_3B^3 + \dots \quad (8)$$

where B is the backshift operator defined such that $B^kX_t = X_{t-k}$. Using Eq. (8), Eq. (7) will become: $Y_t = V(B)X_t$. The individual weights in $V(B)$, (V_0, V_1, V_2) are called the impulse response weights. The entire set of V weights is called the impulse response function.

Eq. (8) represents a free-form distributed lag model. The order of $V(B)$ is often chosen arbitrarily. Generally the k is chosen to include the longest time-lagged response expected to be important. The V weights are estimated by using the regression method based on the maximum likelihood estimation of the SAS package (SAS, 1993). The established ν-weight pattern will be the estimated impulse response, which relates the change of the output signal to the input signal's current and past change.

The dynamic linear transfer modeling will be applied to the data series having significant cross-correlations only at non-negative lags, because the transfer function models for data series with significant cross-correlations at negative lags require complex state space modeling which will complicate the interpretation of the modeling result.

Both the data series of the SST and precipitation are generally stationary. Streamflow is pre-processed through log transformation to reduce the variance. The cross-correlation analysis shows that the positive significant cross-correlation generally exists only at lag zero, marginally significant at lag one for precipitation and the SST anomaly. The significant positive cross-correlations exist at zero and one lag for stream discharge and SST. Therefore, the impulse response weight estimations are expected to be simple. Only the

Table 3
Impulse response weights, MA and AR terms of the stream discharge and SST and their t-tests

River name	Mu	Num1, 0	$t1$	Num1, 1	$t2$	MA1	t_a	AR1	t_r
Apalachicola	7.21	0.008	1.16	− 0.019	− 2.75	–	–	0.16	1.74
Little Mana.	4.98	0.021	1.96	− 0.024	− 2.27	–	–	–	–
Myakka River	5.35	0.025	2.44	− 0.021	− 2.01	–	–	–	–
Ochlockonee	7.35	0.023	2.23	− 0.034	− 3.26	–	–	0.42	2.83
Santa Fe	5.87	0.027	1.62	− 0.048	− 2.83	–	–	0.22	1.35
Suwanne Ell.	8.62	0.038	3.36	0.011	− 1.06	–	–	0.40	2.50
Suwanne Wil.	9.16	0.012	2.07	− 0.032	− 5.48	0.37	2.20	0.51	3.55
West Palm B.	6.33	0.023	2.54	− 0.022	− 2.40	–	–	0.53	3.61

Parameters are the same as in Table 2.

linear response weights at no more than three lags are estimated with the maximum likelihood by the autoregressive fitting. The parameter estimation result of the modeling and the t-tests of these parameters are listed in Tables 2 and 3. The best fittings of the model are achieved when the residual autocorrelation, partial correlation and inverse autocorrelation coefficients lay well within the two standard errors. The parameter findings also follow the parsimony and the non-redundant principles of the Box–Jenkins theories (Box and Jenkins, 1976; Pankratz, 1991). The linear transfer functions are established according to the estimated parameters (Tables 4 and 5).

4. Discussion of the model result and forecast

The coefficients are considered to be significant if t-test values exceed the approximate

Table 4
The linear transfer functions of the precipitation and SST

Apalachicola	$Y_t = 4.73 + (0.075 + 0.063\,B)X_t + (1 - 0.48\,B^4)a_t$
Avo Park	$Y_t = 3.23 + 0.053\,X_t + (1 + 0.49\,B^6)a_t/(1 - 0.23\,B)$
Bartow	$Y_t = 3.47 + (0.068 + 0.047\,B)X_t + (1 + 0.25\,B)a_t/(1 - 0.21\,B)$
Belle Galde	$Y_t = 3.17 + 0.047\,X_t + a_t/(1 - 0.29\,B)$
Brooksville	$Y_t = 4.62 + (0.076 + 0.032\,B - 0.04\,B^2)X_t + a_t$
Chipley	$Y_t = 4.64 + (0.017 + 0.032\,B)X_t + a_t$
Everglades	$Y_t = 4.32 + (0.061 + 0.051\,B)X_t + (1 + 0.28\,B)a_t$
Federal Point	$Y_t = 4.43 + 0.041\,X_t + (1 - 0.27\,B)a_t$
Fernandina	$Y_t = 4.23 + (0.062 - 0.028\,B^2)X_t + a_t$
Lake City	$Y_t = 4.55 + (0.034 + 0.05\,B)X_t + (1 - 0.21\,B)a_t$
Madison	$Y_t = 4.31 + (0.054 + 0.025\,B)X_t + (1 - 0.24\,B)a_t$
Miami Beach	$Y_t = 3.04 + (0.07 + 0.05\,B)X_t + a_t/(1 - 0.21\,B)$
Naples	$Y_t = 4.40 + 0.057\,X_t + (1 - 0.36\,B)a_t$
Ocala	$Y_t = 4.37 + (0.049 + 0.0\,B)X_t + (1 + 0.76\,B)a_t$
West Palm B.	$Y_t = 5.07 + (0.085 + 0.07\,B)X_t + a_t$
Winter Haven	$Y_t = 4.10 + (0.049 + 0.035\,B)X_t + a_t$

Z_t, stream discharge values at year t; X_t, SST anomalies at year t; a_t, random shock; B, backshift operator.

Table 5
Linear transfer function models for the stream discharge and SST

Apalchicola	$Z_t = 7.21 + (0.008 + 0.019\,B)X_t + a_t/(1 - 0.27\,B)$
Little Manatee	$Z_t = 4.98 + (0.021 + 0.024\,B)X_t + a_t$
Myakka	$Z_t = 5.36 + (0.026 + 0.021\,B)X_t + a_t$
Santa Fe	$Z_t = 4.6 + (0.027 + 0.048\,B)X_t + a_t/(1 - 0.22\,B)$
Suwanne at Ell.	$Z_t = 8.6 + (0.037 - 0.012\,B)X_t + a_t/(1 - 0.22\,B)$
Suwanne N. Wil.	$Z_t = 9.17 + (0.012 + 0.032\,B)X_t + (1 - 0.37\,B)a_t/(1 - 0.51\,B)$
West Palm B.	$Z_t = 6.33 + (0.023 + 0.022\,B)X_t + a_t/(1 - 0.51\,B)$

The parameters are the same as Table 4.

5% critical value of 2.0 (Pankratz, 1991). More than half of the t-test values for all the impulse response weights for the first two terms (Tables 2 and 3) are above the critical value of 2.0. This result proves that both annual precipitation and stream discharge are affected by the SST anomalies with 95% confidence. The t-tests of the impulse response weights for precipitation average 2.4 at zero lag, and are less than 1.50 at one lag (Table 2). Therefore, the impulse response of the precipitation is concurrent with SST anomalies. For the stream discharge, the t-test at 1 year lag is larger than at zero lag for the impulse response weights (Num1, 0 and Num1, 1 in Table 3). This means that the stream discharge lags SST 0.5 to 1 year. For the linear transfer function model of precipitation and SST anomalies, the t-test proves that the moving average (MA) term dominates the autoregressive (AR) term (Table 2). For the linear transfer function model of stream discharge, the AR term dominates the MA term. The MA term reflects the seasonal trend, and the AR term reflects the system persistence itself.

The half- to 1-year delay to the SST signal and the persistence of the stream discharge may be associated with the reservoir effect of stream flow. Most rivers in Florida are gaining water from the aquifer for all seasons; therefore, the discharge also depends on the groundwater table which contributes to the delay and longer persistence in the stream's response.

The dynamic regression forecasts of Y_t (Tables 4 and 5) are a weighted sum of inputs plus a weighted average of the estimated perturbation series; the perturbation is interpreted as the one-step ahead forecast errors that would occur if we used only the transfer function part of the model to forecast. For a given SST data series, the one-step (which is 1 year) forward precipitation and stream discharge can be forecasted from the above linear transfer function models (Figs. 6 and 7). The upper and lower 95% confidence intervals are also plotted with the forecast values. A 1-year forward forecast of the linear transfer function models with SST anomalies as input signal matches most of the measured data peaks and valleys in trends. The R^2 value for the precipitation model ranges from 0.218 (Apalachicola Station) to 0.397 (West Palm Beach Station), and increases down to the south in general. This indicates that up to 40% of the annual precipitation variations in Florida may be explained by El Niño and La Niña occurrences. R^2 for stream discharge ranges from 0.12 to 0.27 which indicates that El Niño and La Niña occurrences explain only up to 30% of the annual stream discharge variation. The 1-year lead predicted data series generally smoothed the extreme peaks and valleys compared with the observed data series.

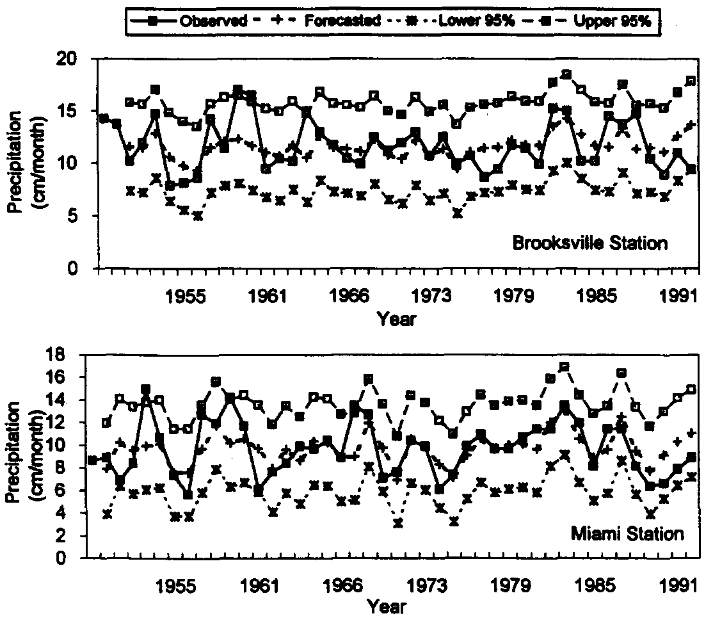

Fig. 6. Comparison of observed and 1-year lead forecast of annual precipitation from 1949 to 1992.

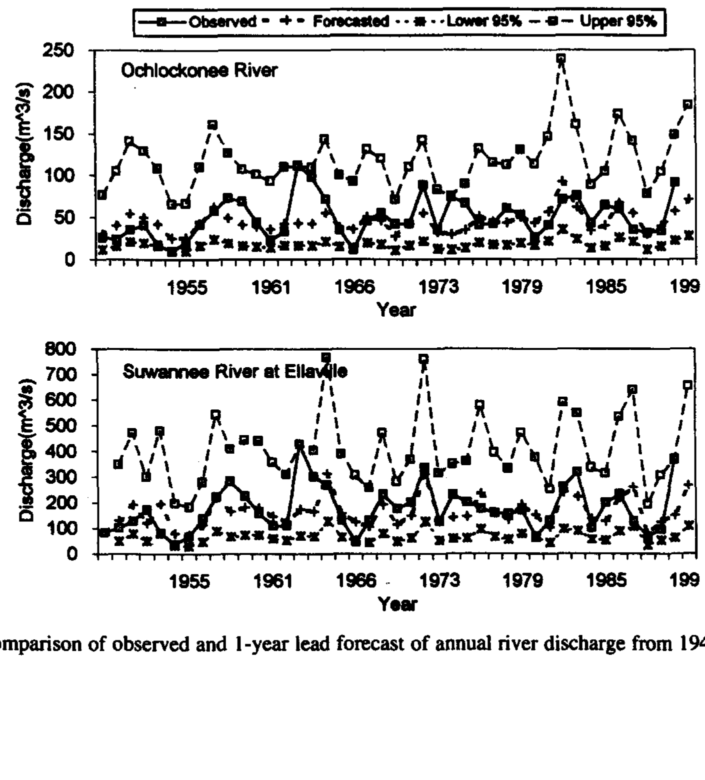

Fig. 7. Comparison of observed and 1-year lead forecast of annual river discharge from 1949 to 1992.

5. Conclusions

SST anomalies are partially responsible for the amounts of annual precipitation and annual stream discharge in Florida. Significant cross-correlations exist between the SST and precipitation, SST and stream discharge. The annual responses of precipitation are in phase with the SST anomalies, with no yearly delay. The reservoir effects might cause a half- to 1-year delay in the annual stream discharge's response to SST signals. The response of annual stream discharge is weaker than the response of the precipitation to SST due to the same reason. Generally, a 'wet' year and higher stream discharge are expected in an El Niño year, and a 'dry' year and lower stream discharge are expected in a La Niña year in Florida. Therefore, higher groundwater table and more fresh water are expected in an estuary along the coastal area in an El Niño year, and lower groundwater table and more saline water is expected in a La Niña year. The linear transfer function model can be established for the SST anomalies, precipitation and stream discharge for forecasting purposes. The forecasted data series tend to smooth the peaks and valleys of the annual water data series.

Acknowledgements

The authors are grateful to S. Akula from Northwest Water Management District, Florida, and one of the anonymous reviewers for their very helpful comments and editing. The authors also want to thank M. Koch from Temple University for his discussion. The authors further acknowledge X. Niu of the Statistical Department, Florida State University, for his help.

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