Forecasting of Lower Colorado River Basin Streamflow using Pacific Ocean Sea Surface Temperatures and ENSO

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Abstract
The lower Colorado River basin is located in an area of known El Niño-Southern Oscillation (ENSO) influence. A streamflow forecast is developed using Pacific Ocean Sea Surface Temperatures (SSTs) as predictors in addition to a traditional ENSO predictor, such as the Southern Oscillation Index (SOI). Significant regions of SST influence on streamflow were determined using linear correlations (LC). These significant SST regions are then used as predictors in a statistically based exceedance probability model previously applied to streamflow stations in Australia and the U.S. Long lead-time (3 and 6 month) streamflow forecasts were developed for El Niño, La Niña and non-ENSO years for the winter-spring (January-February-March – JFM) season. The use of the SSTs resulted in improved forecasts, based on cross-validated skill scores, when compared to forecasts using the SOI. Additionally, forecast lead-times were increased when using the SSTs as predictors due to the inability of the SOI to provide an acceptable forecast. Also, the use of SSTs provided an improved forecast for all lead times for non-ENSO seasons when compared to the SOI forecasts. Following the methodology presented, water resource planners in ENSO influenced areas are provided a useful tool for forecasting streamflow.

Introduction
One of the most well understood atmospheric/oceanic patterns relevant to climate variability in the western United States is the El Niño-Southern Oscillation (ENSO). ENSO refers to the interaction of El Niño, defined as the periodic large scale warming of the central-eastern equatorial Pacific Ocean, with the Southern Oscillation, the large scale climate variations existing in the tropical Pacific (Philander, 1990). ENSO phenomenon causes, simultaneously, droughts in Australia, New Zealand, and Southern Africa and devastating floods in North America, Peru, and Ecuador (Ropelewski and Halpert 1987).

In the western United States, El Niño events are associated with below-normal streamflow in the Pacific Northwest, while at the same time there is above-normal streamflow in the southwest (e.g., Cayan and Peterson, 1989; Redmond and Koch, 1991; Piechota and Dracup, 1996). The variability of the snowpack in the Colorado River Basin during El Niño and La Niña years has been investigated by Clark et al. (2001) and McCabe and Dettinger (2002). Clark et al. (2001) found mixed signals where the Upper Basin had slightly below-normal snow pack during El Niño years and Lower Basin rivers had above-normal streamflow. The opposite conditions were observed for La Niña years.

The study presented here focuses on the influence of climate variability (Pacific Ocean sea surface temperatures and ENSO) on streamflow in the lower Colorado River basin. The study will first identify SST regions that influence winter-spring streamflow. Next, the study will assess if an acceptable long-range (3 to 6 month) forecast for all years for the winter-spring streamflow can be developed using these SST regions as predictors. Additionally, the SOI will be used as a predictor to determine if it can provide an acceptable long-range forecast. The study will then determine how the quality of the forecast varies based on the seasonal strength of ENSO for the predictor. Finally, a winter-spring forecast will be developed based on the seasonal strength of ENSO.

Data

The major datasets used to develop the relationships between climate variability and streamflow are historical streamflow data for the San Francisco and Salt Rivers and historical climate / oceanic data for the Pacific Ocean.

Streamflow Data

Streamflow data were obtained from the U.S. Geological Survey (USGS) NWISWeb Data retrieval (http://waterdata.usgs.gov/nwis/) for two USGS streamflow stations in the lower Colorado River basin (Table 1 and Figure 1). The lower Colorado River basin is primarily undeveloped and considered to be a semi-arid region. USGS station #09444500 represents the San Francisco River (referred to in this paper as SF). The San Francisco River is located along the western New Mexico and eastern Arizona borders. The river flows southwesterly into the Gila River. The total watershed contributing to the streamflow station is 2,763 square miles. USGS station #09497500 represents the Salt River (referred to in this paper as SR). The Salt River is located in southern Arizona and flows westerly into the Gila River. The total watershed contributing to the station is 2,849 square miles. The average monthly streamflow rate (in cubic feet per second – cfs) for the winter-spring season (January, February and March - JFM) is averaged and converted into streamflow volumes (acre feet) by multiplying the seasonal average rate values times the total number of days in the season (with proper conversions). For the predictand (winter-spring streamflow), the (0) notation [i.e. JFM(0)] represents the current year. This season was selected since, typically, a high number of winter frontal storms occur, and, generally, March has the highest streamflow. Sixty years of monthly streamflow data covering a period from 1942 to 2001 are used.

Table 1: List of USGS stations with unimpaired streamflow data.

River Basin	Site Name	USGS Site #	Years of Record
San Francisco	San Francisco River at Clifton, Arizona	09444500	1942-2001
Salt	Salt River near Chrysotile, Arizona	09180500	1942-2001

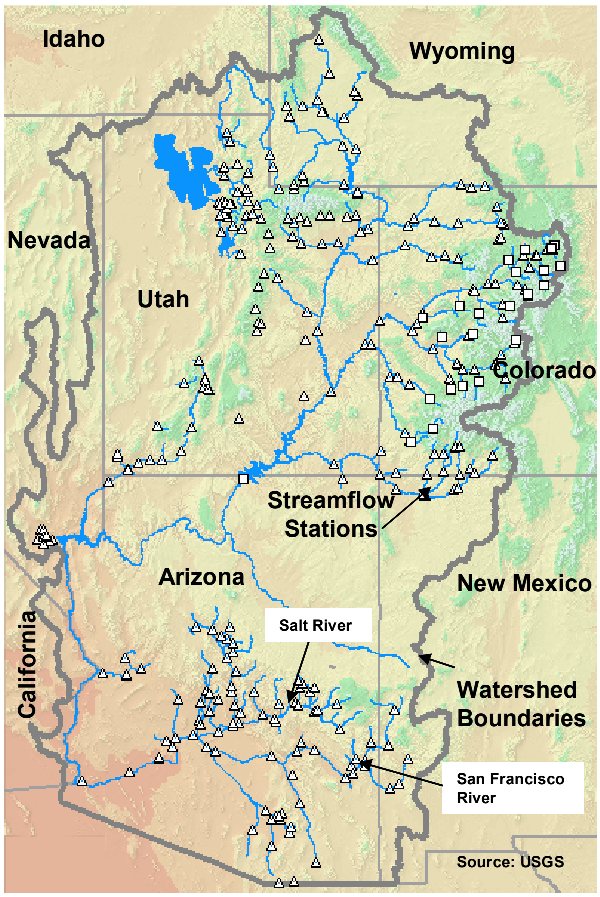


Figure 1: Select USGS streamflow stations for Lower Colorado River. The watershed boundaries of the Colorado River are displayed.

Climate and Oceanic Data

SOI data were obtained from the Australian Bureau of Meteorology (*http://www.bom.gov.au/climate/current/soi2.shtml*). The SOI is calculated from the monthly (or seasonal) fluctuations in the air pressure difference between Tahiti and Darwin. Sustained or long-term (6 to 18 month) negative values of the SOI often indicate El Niño episodes. These negative values usually reflect a sustained warming of the central and eastern tropical Pacific Ocean, a decrease in the strength of the Pacific Trade Winds, and an increase in rainfall over southwestern United States. Positive values of the SOI are associated with stronger Pacific trade winds and warmer sea temperatures to the north of Australia, popularly known as a La Niña episode. Waters in the central and eastern tropical Pacific Ocean become cooler during this time (Philander, 1990).

Pacific Ocean SST data were obtained from the National Climatic Data Center website (*http://lwf.ncdc.noaa.gov/oa/climate/research/sst/*). The SST data consists of average monthly values for a 2^{o} by 2^{o} grid cell (Smith and Reynolds, 2002). The range of Pacific Ocean SST data used for the analysis was Longitude 120^{o} West to Longitude 80^{o} East and Latitude 70^{o} South to Latitude 70^{o} North. This results in a grid with 81 cells in the x-direction and 71 cells in the y-direction. The SST predictors cover a period from 1941 to 2000.

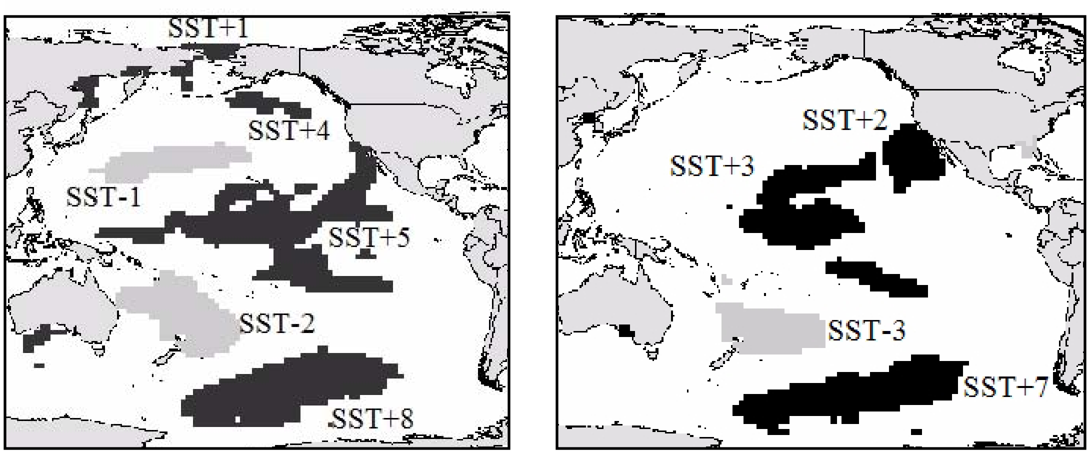
Like the predictand (streamflow), average monthly values of the SOI and SST predictors are averaged for each season: April-May-June (AMJ - spring season) and July-August-September (JAS – summer season). The (-1) notation [i.e. AMJ(-1)] represents the previous year.

Methodology
Linear correlations are performed between the seasonal [AMJ(-1) and JAS(-1)] Pacific Ocean SSTs and the SOI and winter-spring [JFM(0)] streamflow for the SF and SR (Figure 2).

Predictors (SSTs & SOI)			Predictand (Streamflow)
AMJ(-1)	**JAS(-1)**		**JFM(0)**

Figure 2: Seasonal predictors (SSTs & SOI) and predictand (streamflow).

The SST regions (Figures 3 and 4) represent areas in which the confidence level exceeded 99%, which corresponds to an R value > +0.30 or < -0.30.



(a) **(b)**

Figure 3: SST (a) AMJ(-1) and (b) JAS(-1) regions exceeding 99% when forecasting SF streamflow [JFM(0)]. "Black" cells represent positive correlations while "grey" cells represent negative correlations. Range identifiers (i.e. SST+2) for model input are provided.

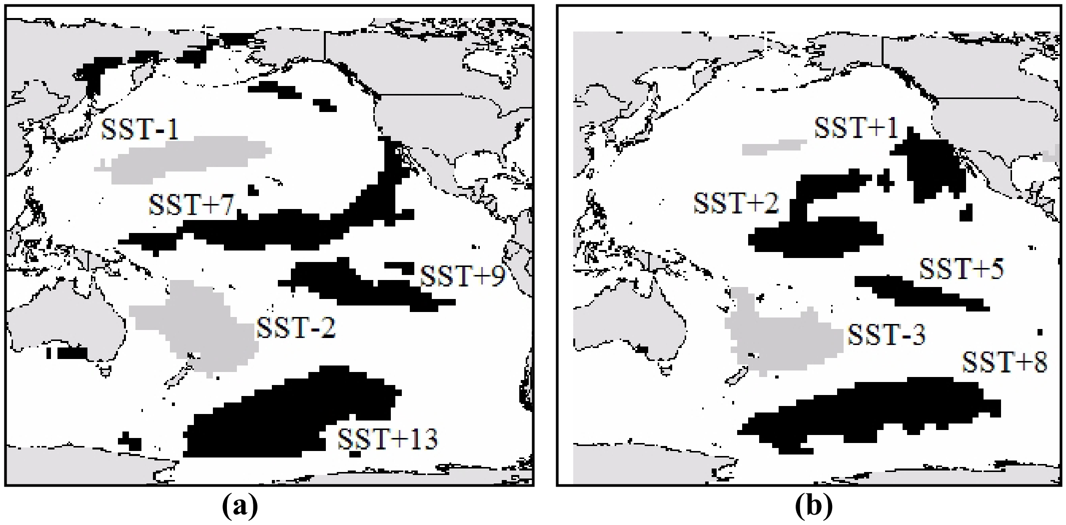


Figure 4: **SST (a) AMJ(-1) and (b) JAS(-1) regions exceeding 99% when forecasting SR streamflow [JFM(0)]. "Black" cells represent positive correlations while "grey" cells represent negative correlations. Range identifiers (i.e. SST+2) for model input are provided.**

Once the seasonal SST ranges are identified, yearly (1941-2000) averages for each seasonal SST range are determined. For example, there are six seasonal SST ranges (four positively correlated and two negatively correlated) identified for AMJ(-1) when predicting SF JFM(0) streamflow (Figure 3a). The yearly average seasonal SST values for each range are individually (one predictor) input into an exceedance probability model. This is repeated, for this example, six times such that only a single seasonal SST range is input into the model. Finally, seasonal values of SOI are individually input into the model. A streamflow forecast is developed for each of these predictors.

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). A detailed description of the methodology and model can be found in Piechota et al., (2001) and Piechota et al., (1998). The model is statistically based and applies a kernel density estimator (Silverman, 1986 and Piechota et al., 1998) to develop a probability density function for each climate predictor.

The skill of the forecast was measured using the Linear Error in Probability Space (LEPS) score. The LEPS 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 (non-exceedance 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 is calculated for calibration and cross-validation (CV) analyses. CV provides a robust measure of skill since a forecast is developed for each year. The use of CV eliminates spurious predictors and artificial skill. A 10% or greater value is generally considered a LEPS score with good skill.

The model will produce a JFM(0) streamflow forecast for each seasonal predictor (SST or SOI). This forecast is referred to as the all years forecast. The all years forecasts are then re-ranked, based on the seasonal (predictor) value of the SOI for each year. For the predictor seasons [AMJ(-1) and JAS(-1)], El Niño, non-ENSO and La Niña years for each season are determined based on the average seasonal SOI value. An SOI <= -5.0 is considered an El Niño year for that season; an SOI >= +5.0 is considered a La Niña year for that season, and -5.0 to +5.0 are considered a Non-ENSO year for that season (Table 2). This will allow the user to determine an average CV LEPs score for all El Niño, La Niña and non-ENSO years for each predictor season [AMJ(-1) and JAS(-1)] for the streamflow predictand [JFM(-1)] season.

Table 2: Seasonal El Niño, Non-ENSO and La Niña years from 1941 to 2000.

ENSO Season	AMJ(-1) 1941 – 2000	JAS(-1) 1941 – 2000
El Niño Years	1941, 1946, 1947, 1949, 1953, 1965, 1966, 1969, 1972, 1977, 1980, 1982, 1987, 1991, 1992, 1993, 1994, 1995, 1997	1941, 1946, 1951, 1953, 1957, 1965, 1969, 1972, 1976, 1977, 1982, 1987, 1991, 1993, 1994, 1997
Non-ENSO Years	1942, 1943, 1944, 1945, 1948, 1951, 1952, 1954, 1957, 1958, 1959, 1960, 1961, 1963, 1967, 1970, 1973, 1976, 1978, 1979, 1981, 1983, 1984, 1985, 1986, 1988, 1990, 1998	1942, 1944, 1948, 1949, 1952, 1958, 1959, 1961, 1962, 1963, 1966, 1967, 1968, 1970, 1978, 1979, 1980, 1983, 1984, 1985, 1986, 1989, 1990, 1992, 1995, 1999, 2000
La Niña Years	1950, 1955, 1956, 1962, 1964, 1968, 1971, 1974, 1975, 1989, 1996, 1999, 2000	1943, 1945, 1947 1950, 1954, 1955, 1956, 1960, 1964, 1971, 1973, 1974, 1975, 1981, 1988, 1996, 1998

Results

The forecast model results (CV LEPS scores) are displayed in Tables 3 – 6. The best CV LEPS score for all years, El Niño, non-ENSO and La Niña years is highlighted. A discussion of each streamflow station's results is provided. Additionally, an exceedance probability forecast for El Niño, non-ENSO and La Niña years for SR JFM(0) streamflow is provided for the 6 month [AMJ(-1)] lead-time (Figure 5).

San Francisco River

For the AMJ(-1) prediction (Table 3), SST-2 (+2.6%) displayed a slight improvement when compared to the SOI (+1.7%) for the all years forecast. The most significant result was the non-ENSO forecast. SST-1 (+8.8%) far exceeded the SOI (-6.1%). SST-2 (+9.6%) again displayed a slight improvement when compared to the SOI (+9.0%) for La Niña years. The SOI (+8.2%) is the best predictor during an El Niño year. Although none of the CV LEPS scores exceeded 10%, the model displayed good predictability for AMJ(-1) El Niño years (use the SOI, +8.2%), non-ENSO years (use SST-1, +8.8%) and La Niña years (use SST-2, +9.6%).

Table 3: Cross-validated LEPS scores for SSTs and SOI [AMJ(-1)] when forecasting SF [JFM(0)] streamflow for All, El Niño, Non-ENSO and La Niña years.

Predictor	All Years	El Niño Years	Non-ENSO Years	La Niña Years
SST+1	+2.3%	+5.1%	+0.8%	+1.4%
SST+4	+0.3%	-2.7%	+0.4%	+4.5%
SST+5	+2.0%	+5.4%	-1.3%	+4.0%
SST+8	-0.5%	+1.3%	-4.5%	+5.5%
SST-1	+6.2%	+7.0%	**+8.8%**	-0.3%
SST-2	**+2.6%**	-1.0%	+1.8%	**+9.6%**
SOI	+1.7%	**+8.2%**	-6.1%	+9.0%

For the JAS(-1) prediction (Table 4), SST+3 (+12.0%) provided a slightly improved forecast when compared to the SOI (+11.2%) for El Niño years. SST+7 (+0.7%) provided an improved forecast for non-ENSO years when compared to the SOI (-3.7%). The SOI provided the best forecast for all years (+4.3%) and La Niña years (+10.4%).

Table 4: Cross-validated LEPS scores for SSTs and SOI [JAS(-1)] when forecasting SF [JFM(0)] streamflow for All, El Niño, Non-ENSO and La Niña years.

Predictor	All Years	El Niño Years	Non-ENSO Years	La Niña Years
SST+2	+0.6%	-4.2%	-0.1%	-1.8%
SST+3	+1.8%	**+12.0%**	-5.8%	+4.2%
SST+7	-2.2%	-2.4%	**+0.7%**	-6.5%
SST-3	-1.7%	-3.6%	-1.6%	-0.2%
SOI	**+4.3%**	+11.2%	-3.7%	**+10.4%**

Salt River

For the AMJ(-1) prediction (Table 5), SST-1 (+8.7%) provides a significant improvement when compared to the SOI (+2.4%) for the all years forecast. The results are more significant for the non-ENSO years forecast where SST-1 (+9.7%) provided a significant improvement when compared to the SOI (-5.1%). SST-1 (+14.4%) continues to out perform the SOI (+10.0%) for the La Niña years forecast. The SOI (+8.2%) is the best predictor for the El Niño years forecast. The model displays good predictability for AMJ(-1) El Niño years (use the SOI, +8.2%), non-ENSO years (use SST-1, +9.7%) and La Niña years (use SST-1, +14.4%).

Table 5: Cross-validated LEPS scores for SSTs and SOI [AMJ(-1)] when forecasting SR [JFM(0)] streamflow for All, El Niño, Non-ENSO and La Niña years.

Predictor	All Years	El Niño Years	Non-ENSO Years	La Niña Years
SST+7	+1.9%	+3.2%	-1.8%	+8.0%
SST+9	+0.4%	+0.5%	-2.9%	+7.4%
SST+13	-0.6%	+0.5%	-4.7%	+6.6
SST-1	**+8.7%**	+3.3%	**+9.7%**	**+14.4%**
SST-2	-1.0%	-2.1%	+1.4%	+14.0%
SOI	+2.4%	**+8.2%**	-5.1%	+10.0%

For the JAS(-1) prediction (Table 6), SST-3 (-1.2%) provides an improved forecast when compared to SOI (-5.1%) for non-ENSO years. However, the SOI provides the best forecast for all years (+2.3%), El Niño years (+8.2%) and La Niña years (+8.6%).

Table 6: Cross-validated LEPS scores for SSTs and SOI [JAS(-1)] when forecasting SR [JFM(0)] streamflow for All, El Niño, Non-ENSO and La Niña years.

Predictor	All Years	El Niño Years	Non-ENSO Years	La Niña Years
SST+1	-0.7%	+2.3%	-5.1%	+3.4%
SST+2	+1.3%	+7.6%	-4.0%	+3.7%
SST+5	+1.1%	+6.3%	-6.4%	+8.2%
SST+8	-1.4%	+2.1%	-3.0%	-2.3%
SST-3	+1.6%	+3.3%	**-1.2%**	+4.7%
SOI	**+2.3%**	**+8.2%**	-5.1%	**+8.6%**

Exceedance Probability Forecasts

The LEPS score by itself does not demonstrate the usefulness of the model results. Instead, a plot of the exceedance probability versus the streamflow demonstrates the information that would be presented to a water resource manager. Figure 5 presents the AMJ(-1) season when predicting SR JFM(0) streamflow. The SOI is used for El

Niño years while SST-1 is used for non-ENSO and La Niña years. The El Niño, non-ENSO and La Niña years exceedance probability forecasts represent the average of the forecasts (years) of streamflow, when it occurred (Table 2). It is clear from the three forecasts that, when forecasting JFM(0) streamflow, a AMJ(-1) El Niño will most likely produce more streamflow than a AMJ(-1) La Niña. As expected, the non-ENSO forecast lies between the El Niño and La Niña forecasts. Even at the 50% exceedance probability, the streamflow forecast, given the occurrence of a AMJ(-1) El Niño, is approximately 60% greater than if a AMJ(-1) La Niña had occurred.

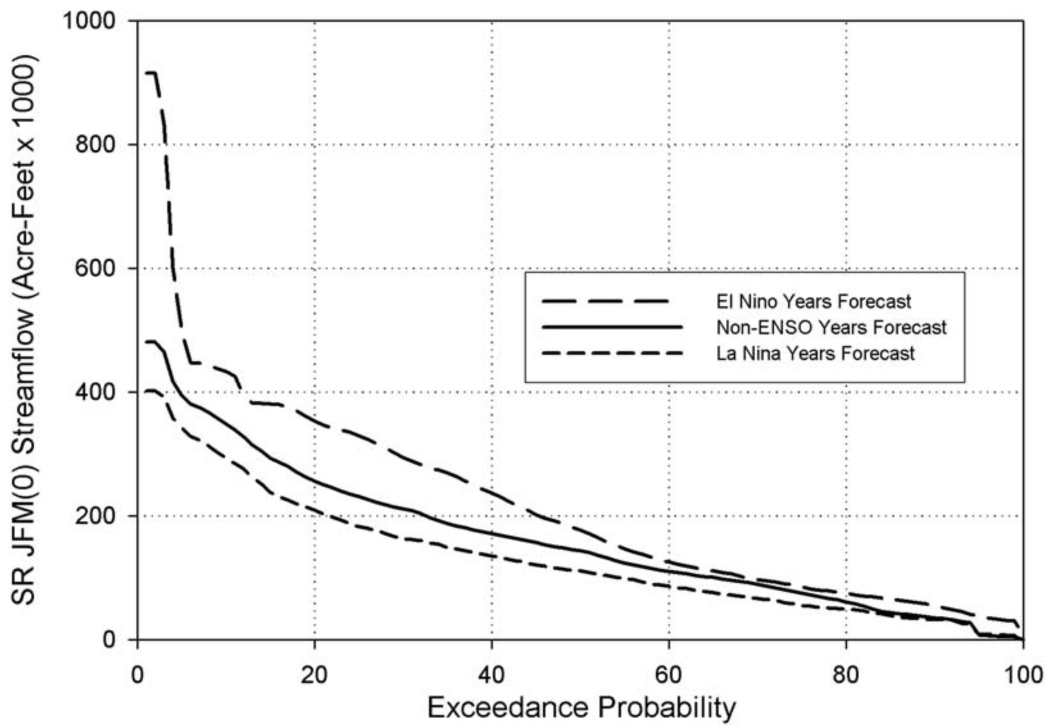


Figure 5: **Exceedance probability forecast, AMJ(-1) to predict JFM(0) Salt River streamflow for El Niño, Non-ENSO and La Niña years.**

Conclusions

There are several noteworthy observations from the study presented here.

- The use SSTs improved the forecast by showing increased values of CV LEPS scores when compared to the SOI for longer (6 month) lead-times. The SOI appears to be a better short lead-time (3 month) predictor while SSTs are a better long lead-time (6 month) predictor. This could be attributed to the short cycle time of ENSO. Ocean temperature variability may be slow in development and "lag" behind climate indices. This may account for the improvement in prediction when using SSTs for longer lead-times.
- SSTs provided an improved forecast for non-ENSO years for all predictor periods. Although the streamflow stations are in a region of ENSO influence, the SOI is a poor predictor for non-ENSO seasons.

- This methodology can be applied to other ENSO influenced streams. Water planners, knowing the seasonal SOI, can then (a) determine if a prediction can be made and, (b) what predictor (SSTs or SOI) to use.
- Future research could include combining the best seasonal predictors and determining if the “combination” forecast is an improvement over the single predictor forecast.

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