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The value and skill of seasonal forecasts for water resources management in the Upper Santa Cruz River basin, southern Arizona

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ABSTRACT

The potential for adaptive water resources management based on seasonal forecasts in the arid Upper Santa Cruz River, southern Arizona was examined. We demonstrated that seasonal forecasts can be used to optimize water resources management and increase supply. Using El Nino Southern Oscillation (ENSO) to forecast the wet seasons (winter and summer) can provide information during extreme ENSO. We found that ENSO is a better indicator for dryer than normal winters during La Nina and dryer than normal summers during El Nino. As in indicator of wetter than normal seasons (i.e. El Nino and La Nina in the winter and summer, respectively) ENSO is often not a consistent predictor and moreover, on several occasions the wetter than normal rainfall did not yield above normal seasonal flows. We also examined the seasonal precipitation forecasts for the region from the Climate Forecast System (CFS). The CFS showed reasonable predictive skill for the winter that extends up to four months lead-time. The only CFS skill for forecasting summer rainfall was observed for predicting above normal rainfall in July with one-month lead-time. Seasonal forecasts can substantially improve water resources management but currently requires considerations of large uncertainties in the operationally available forecasts.

1. Introduction

Improvement of water supply reliability by optimizing the existing water resources management practices can provide a considerable benefit in water-stressed arid regions. One potential optimization strategy is to implement adaptive management scheme that is based on seasonal weather forecasts. For example, by predicting an approaching above normal wet season the existing water reservoirs can be further exploited and anticipated to be replenished, on the other hand, a prediction of a below normal wet season may activate conservative management measures to conserve reservoirs' carry over for the next season. Many studies have assessed the use of seasonal forecasts in conjunction with hydrological models for adaptive water resources management in various climatic and hydrologic regions worldwide (e.g. Georgakakos et al., 2012a; Georgakakos et al., 2012b; Gong et al., 2010; Graham et al., 2006; Chiew et al., 2003). The recurring challenge in this adaptive management strategy is to manage the risk and benefits that emanate from uncertain forecasts. Therefore, a useful adaptive management strategy has to balance risk and benefits by considering the skill and utility of the available forecasts.

The value of seasonal forecasts for the Upper Santa Cruz River (USCR), southern Arizona was previously recognized for mitigation of floods (Sprouse and Vaughan, 2003). In this study, we evaluate the potential benefit and the skill of seasonal forecasts to water resources management in the USCR. The water resources system in this arid environment is reliant on the highly variable local climate and has to be carefully managed in order to sustain the riparian vegetation ecosystem along the river.

The objectives of this study are two fold, first, to evaluate whether seasonal weather forecasts can benefit the water resources management practices in the region, and second, to evaluate whether the operationally readily available forecasts are sufficiently skillful to support adaptive management strategy in the region. The two forecast sources that were assessed herein are the observed sea surface temperature index El Nino Southern Oscillation (ENSO) during the transition to the wet seasons and the precipitation forecasts for the region from the Climate Forecast Model (CFS) The National Centers for Environmental Prediction (NCEP) National Oceanic and Atmospheric Administration (NOAA).

Following section 2 that describes the study area, in Section 3 we assess the value of seasonal forecast to the management of

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water resources in the USCR. This assessment is carried out by using a hydrologic modeling framework that was developed for the region and enables assessment of various management scenarios (Shamir et al., 2007a; 2015). In Section 4, we examine the observed ENSO in the spring and fall seasons as a predictor for rainfall and streamflow during the summer and winter, respectively. In Section 6, the skill of the CFS precipitation forecasts for the region is examined and the discussion and conclusions Section is last.

2. Study area

The Santa Cruz River, a tributary of the Gila River that flows into the Colorado River, is mostly an ephemeral stream with some relatively short perennial and intermittent sections. The Santa Cruz flows southward into Mexico from its headwater in the San Rafael Valley, southern Arizona. About 50 km through Mexico, the river reenters Arizona, about 10 km east of the city of Nogales, Arizona. A U.S. Geological Survey streamflow gauge (USGS # 09480500) with drainage area of ~1400 km^2, of which approximately 1150 km^2 are in Mexico, has been operating on the Santa Cruz River at the border crossing (Fig. 1).

Downstream of the USGS gauge the ephemeral channel overlays a series of four relatively shallow, highly permeable and with limited storage capacity alluvial aquifers that are bounded by the low permeability Nogales Formation (Erwin, 2007; Page et al., 2016). These shallow aquifers, often referred to as the microbasins (MB), extend along the channel of the river for about 25 km to the confluence with Nogales Wash near the International Wastewater Treatment Plant (IWTP) (Fig. 1).

Recent studies suggest the existence of a highly permeable deeper layer below the stream alluvium (Nelson, 2010; Page et al., 2016). It is evident that during long dry periods with no streamflow to recharge the aquifer, the water level in the MB dropped considerably. In addition, the rate of groundwater flow to the downstream northern aquifer is likely to be higher than the receiving underflow that crosses from Mexico.

The main groundwater recharge mechanism of the MB is the infiltration in the alluvial channel during the occasional rain driven streamflow events on the Santa Cruz River. The dependence on streamflow events in conjunction with the net water loss of the MB compounds the impact of drought on water resources management in this region.

This relatively shallow aquifer (Depth to Water [DTW] ~3–15 m) is one of two sources of water to the City of Nogales, Arizona (population of over 20,000 people) (ADWR, 2012).

The second source of water to the City of Nogales is the Potrero wellfield along the Potrero Creek on the west side of the city. It is a deeper aquifer (~80–100 m DTW) and the sources of recharge for this aquifer are not yet well understood. Thus, a continuous and unmanaged withdrawal from this aquifer may cause an incurable decline in water levels. The City's annual consumption during 1990–2009 was about 4200 acre-feet per year (5.2 million m^3 yr^{-1}) split approximately evenly between the Potrero wellfield and the MB. The 2025 water demand for the city of Nogales is projected to

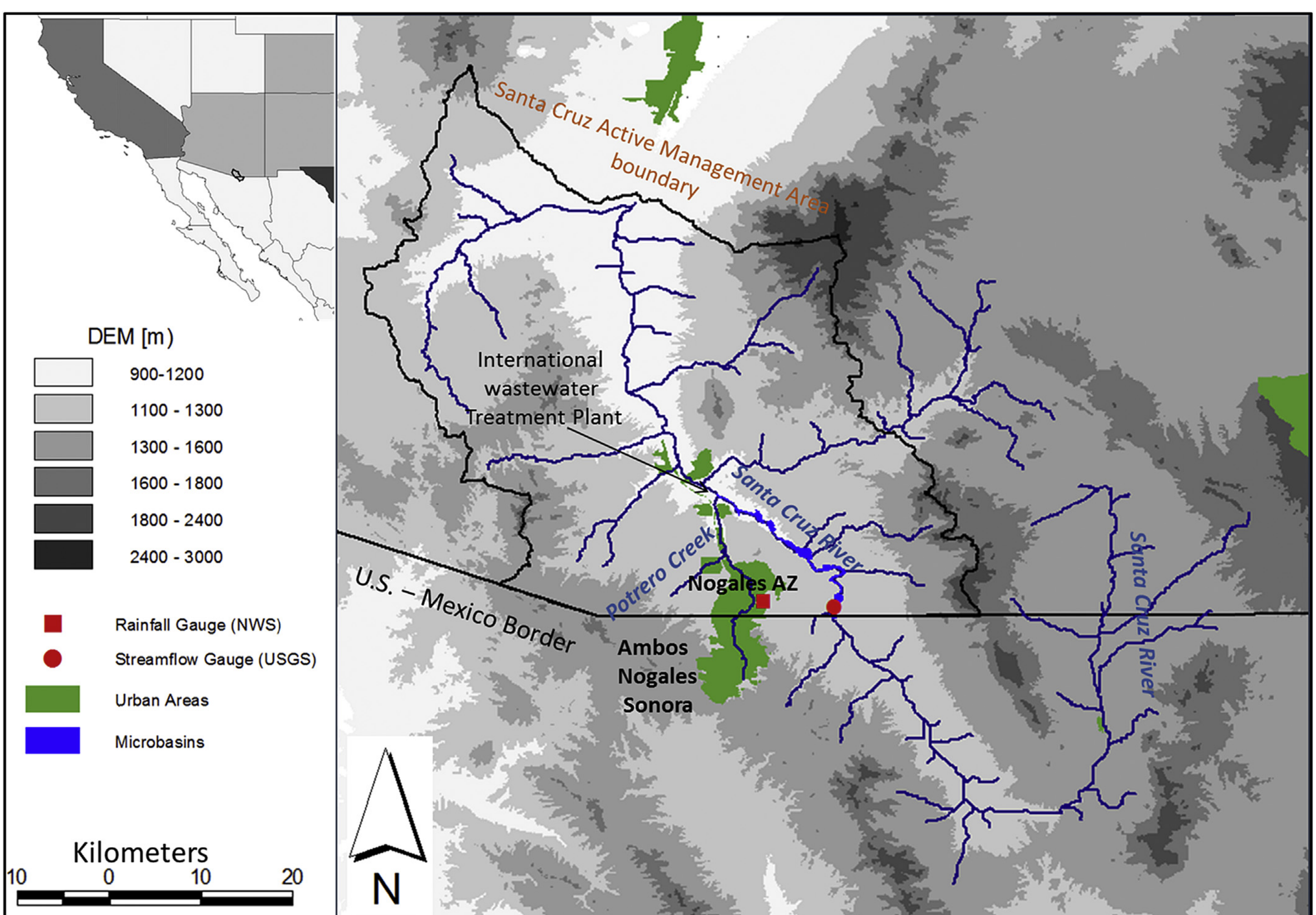

Fig. 1. A regional map.

remain below 5000 acre-feet per year (6.2 million Mm^3 yr^{-1}) (ADWR, 2012).

Water managers in the region prefer to maximize the use of water from the MB because of its substantial cheaper pumping cost, seasonal replenishment, and better water quality. The water from several of the Potrero wells requires additional treatment to reduce the arsenic concentration below the U.S. federal drinking water standard. Although the MB is the preferred source of water for the region, it requires a careful management in order to sustain a healthy riparian ecosystem.

The region has two wet seasons: summer (July–September) and winter (December–March). The spring (April–June) is mostly dry and fall (October–November) is commonly dry with infrequent intense rainfall events. The summer storms, influenced by the North American monsoon, consist of isolated convective cells that produce intense local short-lived rainfall events. Winter storms are commonly caused by large-scale low-pressure frontal systems approaching from the west and southwest that yield wide spread rainfall events that often last for a few days.

3. The value of Seasonal forecasts

An accurate forecast of dryer than normal wet seasons - either winter or summer - can potentially guide water resources managers to conservatively manage the MB in order to sustain the health of the riparian corridor. In this Section however, we evaluate the potential benefit from accurate forecasts of above normal wet summers and/or wet winters. We conduct this evaluation by using the previously developed modeling framework that includes several operational management schemes and tracks changes in the groundwater levels. The hydrologic modeling framework is presented in Shamir et al. (2007a, 2015) and it is succinctly described below.

3.1. Modeling framework

The hydrologic modeling framework consists of a stochastic rainfall generator module that produces sequences of likely to occur hourly rainfall events. These rainfall sequences are used as input to a hydrologic model that simulates hourly streamflow in the Santa Cruz River at the international border. The streamflow is then conveyed along the river channel sections that overlay the MB and groundwater recharges into each of the MB are calculated. In addition, the storages and levels at the four MB are dynamically updated. This framework was used to experiment with various prescribed water withdrawal rates to conduct risk-based assessment for various water resources management strategies (Eden et al., 2016; Shamir et al., 2015, 2007a,b; 2005; Nelson, 2010).

Herein, we selected one of the management scenarios presented in Shamir et al. (2015). In this management scenario, a monthly varying withdrawal rate of 5000-acre feet per year was applied. In order to manage for sustainable and healthy riparian vegetation along the river corridor, in occasions that the DTW in one of the MB dropped below 3-m, the simulation of withdrawal from this MB was ceased. In the cases that the withdrawals have ceased, it is assumed that water demand is satisfied from the alternative Potrero well field. In order to test the value of the seasonal forecast we added the following management rule to this strategy: In case that a forecast for above normal wet conditions in winter or summer has been issued, the withdrawal from the MB can continue up to DTW of 6 m. This relaxation of the DTW threshold is based on the assumption that the upcoming above normal wet season will be associated with streamflow events that will replenish the depleted aquifer and therefore minimize the stress to the riparian vegetation. This relaxation of the rule can potentially increase the portion of water delivered from the MB. In addition, creating the larger storage capacity by increasing the withdrawal from the MB can potentially increase the amount of water recharged into the MB with water that otherwise be flowing downstream of the MB river section (Shamir et al., 2015).

It is important to note that the above presented management strategy is not necessarily being followed in the current management practices of the MB. The water resources management in the region has not been formalized and the decisions are driven by the needs of the operators to optimize water consumption, regulatory constraints, economic considerations, and protection of the river's riparian corridor.

Sustaining healthy riparian vegetation requires careful management to prevent severe long-term groundwater decline. Several studies were conducted in the region to identify resiliency of various riparian vegetation species to a variety of stressors (e.g. Stromberg et al., 2012; Lite and Stromberg, 2005). However, up to date there are no official guidelines for the Santa Cruz region to inform groundwater management practices in order to sustain healthy riparian environment. The DTW (3–6 m) thresholds that were selected for this study are perceived as conservative values that are within the ranges reported in the scientific literature for various riparian tree species (e.g. Lite and Stromberg, 2005).

An important stipulation in the hydrologic modeling framework described above is the simplified groundwater model that considers each of the four shallow aquifers as a single storage unit. As such, changes in the water levels are uniformly distributed without regard for the spatial distribution within the aquifer units and the exact locations of the extraction wells. A detailed groundwater model for the region was developed by ADWR (Erwin, 2007; Nelson, 2010). Nelson (2010) implemented the groundwater model in an ensemble mode, using monthly time steps, to evaluate the potential future water level decline due to increase groundwater withdrawal. The incorporation of the ADWR groundwater model in the current study required substantial additional development that was beyond the scope of this study. Therefore, herein a simplified version of the groundwater model as developed in Shamir et al. (2005, 2007a) modified herein for hourly runs (Shamir et al., 2015) was used. Notice that the simplified model was developed to replicate the results of the ADWR model and the parameters for this model were estimated from the aquifer characteristics reported in Erwin (2007). The simplified model provides an interim tool that enables the explorations and comparisons among various management strategies under various climatic regimes.

We applied the modeling framework with the above-described management strategy using a sequence of 100 years of likely hourly rainfall that is based on historic analysis with eight different treatments. The differences among the eight treatments are in the time of issuance of the forecasts and the prescribed skill for these forecasts (Table 1).

In Fig. 2, the yearly gain of additional withdrawal from the MB that can be achieved using forecasts of above normal winter and/or summer relatively to the standard reference (no forecast) treatment (A) are presented as box plots (the Box plot interpretation is described in the Figure's caption). Clearly, in this example, the monthly forecasts provide substantial gains. For instance, treatment B of a perfectly accurate forecast for above-normal winter and summer that is issued with a one-month lead-time, resulted in a 7.1% annual average increase of pumpage from the MB; and in some years, the gain exceeded 40%. In treatment C, where the perfect forecasts are available two months in advance, the average annual gain is 8.3% and in some years exceeded 45%. Although apparently only a slight gain is realized from the 2-month lead-time forecast, the benefits are pronounced during some specific years.

Table 1
Treatments for evaluation of above normal seasonal forecasts.

	Treatments	Avg. annual withdrawal gain/loss (%) from the MB
A	Standard reference (no forecast)	0
B	Perfect forecasts for wet summers and winters are given with a month lead time (1 June and 1 November)	7.1
C	Perfect forecasts for wet summers and winters are given with two months lead time (1 May and 1 October)	8.3
D	70% success forecasts for wet summers and winters are given with a month lead time (1 June and 1 November)	7.8
E	Perfect forecasts for wet winters are given with a month lead time (1 November)	0.7
F	70% success forecasts for wet winters are given with a month lead time (1 November)	1.5
G	Perfect forecasts for wet summers are given with a month lead time (1 June)	6.4
H	70% success forecasts for wet summers are given with a month lead time (1 June)	6.4

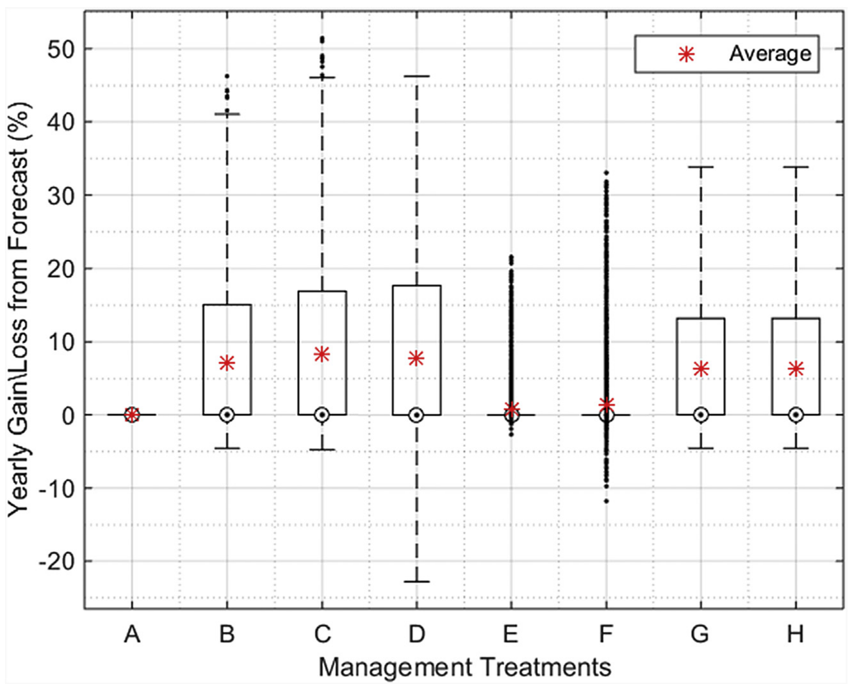

Fig. 2. A box plot of the total annual gain/loss of withdrawal from the MB compared to the standard reference run (A) of the eight management treatments (see Table 1). In the box plot the central marks (target) are the median, edges of the boxes are the 25th and 75th percentiles, whiskers are the 5 and 95 percentiles and the dots are below and above the whiskers percentiles, respectively. The averages of the distribution are indicated as red asterisk. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The consequence of imperfect forecast is shown in treatment D in which 70% of the above normal forecasts are correct and the other 30% are realized as either normal or below normal wet season. The cases of the false alarms for above normal winter or summer can cause lasting overdrafts (below the 3 m DTW). The consequences of the lasting overdraft below the selected threshold should be investigated to understand and quantify the risk for riparian vegetation die-off. It is seen that the benefit are comparable to the ones with perfect forecasts although occasionally the groundwater level drop below the threshold.

About 90% of the annual gain due to 1-month lead-time forecast is due to summer flows. It is possible to gain from an above normal forecast during the winter, however, only in some of the years. Wetter than normal summers usually imply frequent rainfall events that cause frequent small to medium flow events. These relatively small and frequent flow events are effectively recharged into the MB. On the other hand, wetter than normal winters are usually winters with one or a few very large rainfall events that cause large streamflow evens. These large winter events have substantial volumes that are conveyed downstream of the MB and unavailable for recharge.

In summary, it is demonstrated that seasonal forecasts with 1 or 2 months lead times can substantially increase the amount of water withdrawal from the MB. The major gain is from the prediction of above normal summers but also from the occasional above normal winters.

4. El Nino Southern Oscillation [ENSO] analysis

El Niño Southern Oscillation (ENSO) is a term used to describe both warm (El Niño) and cool (La Niña) ocean-atmosphere events in the tropical Pacific. El Niño and La Niña occur when sea surface temperatures in the Pacific Ocean near the equator and the west coast of South America are unusually warm (El Niño) or cold (La Niña) for an extended period of time. A strong winter El Nino suppresses the jet stream further south and likely to bring above normal wet winters to the Southern U.S. while a weak ENSO signal (La Nina) is likely to be associated with below normal dry conditions (e.g. Redmond and Koch, 1991; Cayan and Webb, 1992; Dettinger and Diaz, 2000).

Because of ENSO's seasonal low frequency dynamic the observed ENSO values during the transition period to the wet seasons (spring and fall) are often indicative of the ENSO conditions during the wet seasons and therefore can potentially be used to forecast the wetness of the upcoming wet season. Current and forecasted ENSO values are routinely available from the Climate Prediction Center (NOAA) (CPC: (http://www.cpc.ncep.noaa.gov/), the International Research Institute for Climate and Society (IRI: http://iri.columbia.edu/), and specific interpretation and discussion are routinely provided for the Southwest U.S. by the Climate Assessment for the Southwest, University of Arizona (CLIMAS: http://www.climas.arizona.edu/).

In the fall of 2015, during the development of this study, an extreme El Nino had been in the making and was accurately predicted by the CPC to mature into the largest El Nino ever observed during the winter of 2016. The winter of 2016 turned out to be warm and dryer than normal in the southwestern U.S with precipitation pattern that shifted to the North Pacific, a spatial pattern that resembles the expected rainfall during La Nina conditions.

Fig. 3 is a scatter plot of the winter (Dec–Mar) rainfall in Nogales station [1949–2016] (Fig. 3A) and streamflow on the Santa Cruz River for the same duration (Fig. 3B) as a function of the observed ENSO3.4 anomaly index in the fall (Sep–Oct). It is seen that all the years with Sep–Oct ENSO3.4 anomaly that were greater than 1.5 °C, excluding 2015–2016, had above normal winter rainfall. The dashed horizontal lines in the Figures indicate the 33.3 and 67 percentiles. On the other hand, during very strong Sep–Oct La Nina [ENSO3.4 < -1 °C], except from one year, the winter rainfall were below normal. Winter rainfall had no clear association during years with Sep–Oct ENSO3.4 being in between these extreme high and low. Looking at the streamflow in Fig. 3b, it appears that all the strong negative ENSO3.4 were normal or below normal while the strong positive ENSO3.4 were not always translated to above normal flow, despite the fact that the rainfall was above average (e.g. 1997–1998). This is likely because of variation in the precipitation patterns that control the generation of runoff such as rainfall intensity, duration of the storms, and duration among storms.

Similar to Figs. 3 and 4 is a scatter plot for the summer (Jul–Sep) rainfall (Fig. 4A) and streamflow (Fig. 4B) as a function of the observed ENSO3.4 anomaly in June. As reported in Castro et al. (2012) the ENSO3.4 association with the summer rainfall is inverse to the winter association. During negative ENSO the rainfall was above normal and during positive ENSO the rainfall was normal or below normal. Notice however, that the wettest summers in the records are seen in years with neutral ENSO signals. Looking at the streamflow, the positive (negative) ENSO had low (high) summer flows. In the Santa Cruz region, the ENSO summer signal association with rainfall and streamflow is comparable or maybe even more pronounced than the association with the winter.

In order to examine the ENSO signal with respect to water resources the winter and summer streamflow are plotted as a function of the seasonal rainfall in Fig. 5. For the winter during La Nina years, with no exception, the seasonal streamflow were lower than normal. During El Nino years, large variability of seasonal flow was observed while the largest seasonal flow occurred during neutral ENSO years. For the summer, El Nino conditions were associated with low flows and La Nina conditions were associated with above normal flow. In fact, the highest seasonal flows were seen in La Nina years although the rainfall values were not the highest. This comparison points to the fact that total seasonal precipitation may not necessarily be a sufficient index for water resources management. The precipitation pattern that controls the generation of runoff and streamflow (e.g. inter-arrival of storms, magnitude) should be considered as well as the antecedent moisture conditions of the land surface.

5. CFS reforecast

The National Centers for Environmental Prediction (NCEP), NOAA have been routinely producing seasonal outlooks using the coupled forecast system model (CFSv2) (Saha and coauthors 2010, 2014). The operational seasonal forecasts are produced four times daily at 00, 06, 12, and 18 UTC and at each time four ensemble-members that are varied by their initial conditions are produced.

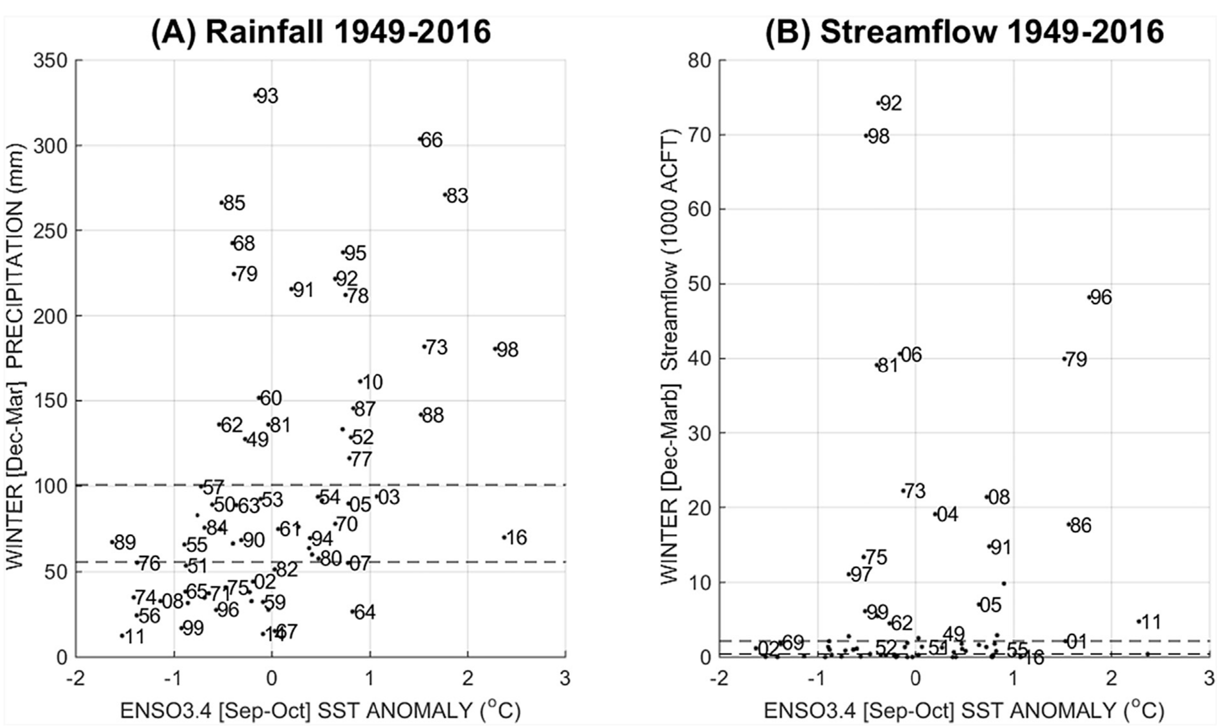

Fig. 3. Winter (December–March) rainfall (left Panel) and streamflow (right panel) as a function of ENSO3.4 anomaly in September–October. Dashed lines indicate the distributions' terciles.

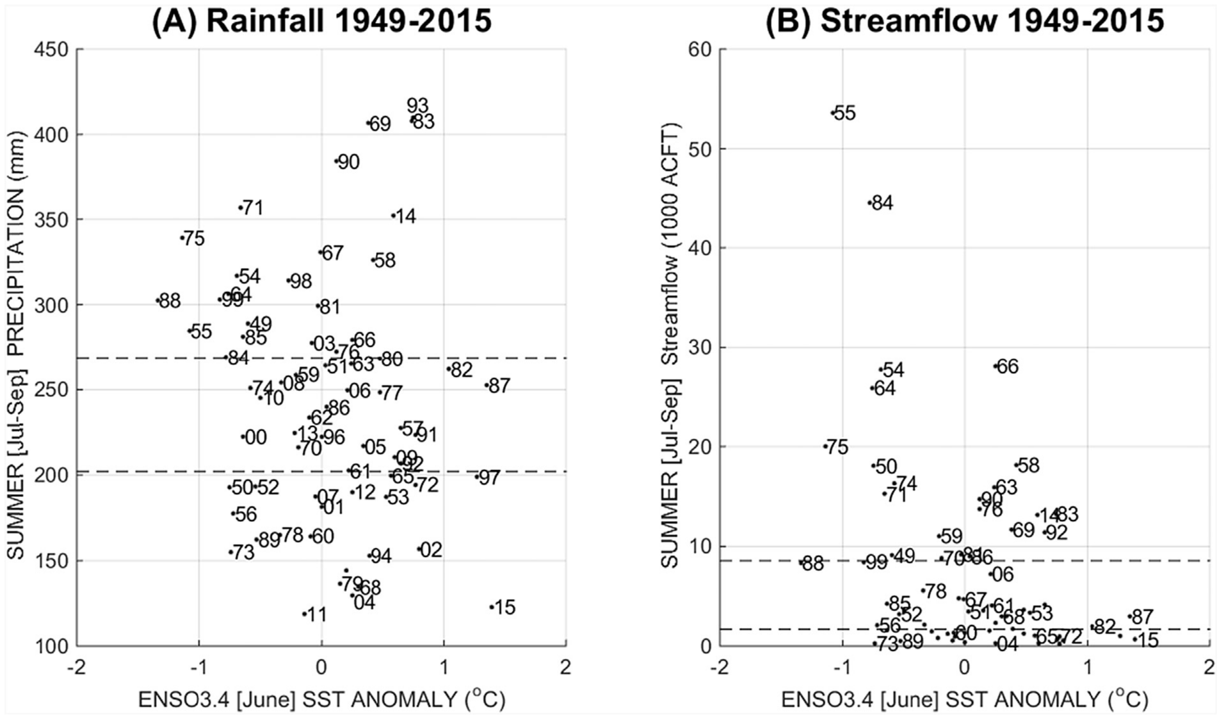

Fig. 4. Summer (July–September) rainfall (left panel) and streamflow (right panel) as a function of June ENSO3.4 anomaly. Dashed lines indicate the distributions' terciles.

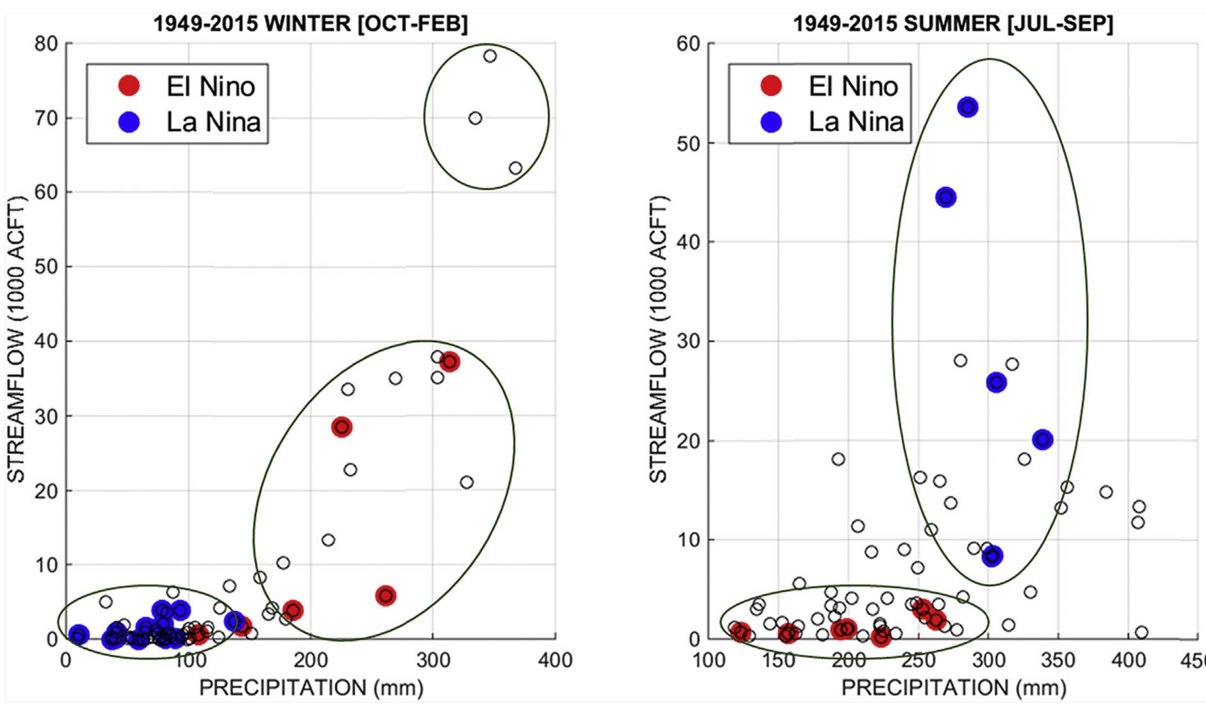

Fig. 5. Winter (left) and summer (right) streamflow as a function rainfall. The red and blue dots indicate strong El Nino and La Nina, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The forecasts' numerical output (1°x1°; 6-hourly intervals) extend up to 9 months and include an array of variables at various levels throughout the atmosphere, radiative and energy fluxes at the surface, and surface variables. NCEP also produced a dataset of retrospective forecasts from the CFSv2, often termed reforecast. The reforecast dataset consists of seasonal (9-month) forecasts every 5 days during 1982–2010 with 4 forecasts per day (00, 06, 12, and 18 UTC). The CFS reanalysis (CFSR) dataset was also retrospectively produced by NCEP to provide spatially congruent initial model states for the atmosphere, ocean, land, and sea ice (Saha and Coauthors, 2014).

In this study four CFSv2 grid-cells in the study domain [31-31.5°

North latitude;-111.0–111.5° East Longitude] were aggregated. The results from the four grid-cells aggregation were compared to aggregation of up to 16 CFS grid-cells to find no considerable differences.

5.1. Historic and climatological data

An essential step to evaluate a forecast model is to assess whether it simulates well the inter-annual variability of the large-scale synoptic conditions that control the rain bearing events and the mesoscale physical processes interaction with the local terrain to influence the rainfall spatial and temporal distributions (Castro et al., 2012). A complete assessment of the physical components of the model is beyond the scope of this study but in the following, we assess the performance of the CFSR monthly rainfall for the study region. Monthly climatological gridded dataset was retrieved from 0.5° Global Precipitation Climatology Center (GPCC) (Schneider et al., 2014; available from: http://www.esrl.noaa.gov/psd/). The GPCC dataset is based on 67,200 quality-controlled worldwide stations with records that exceed 10 years. A comparison between the monthly median (1982–2010) CFSR and the GPCC for the study area is in Fig. 6. Although slightly overestimated during July–August, the CFSR matches well the observed annual cycle. Monthly total scatter plots of the CFSR and GPCC for 1982–2010 (Fig. 7) indicates an overall good agreement during the winter (Dec–Mar, R: 0.85–0.95) with weaker agreement during the summer months (Jul–Sep, R: 0.35–0.86).

5.2. Evaluation of reforecast skill

A plethora of tests and indices exist to evaluate the skill of the seasonal meteorological forecasts (e.g. Wilks, 2006). In the following, we present a ROC (Relative Operating Characteristics) curve analysis, a visual method to inspect the forecasts' skill, a method that is often used for meteorological forecast verification (e.g. Mason and Graham, 1999; Stanki et al., 1989; WMO, 2000). The ROC curve analysis assesses the degree of correct probabilistic discrimination in a set of forecasts. Determination here refers to the forecasts' capacity to distinguish among different categorical outcomes.

ROC curve analysis of hit and false alarm rates provides value to

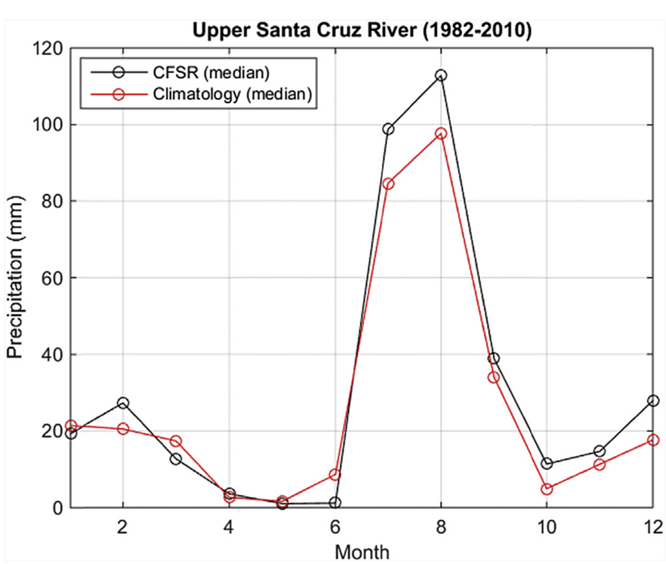

Fig. 6. Monthly medians 1982–2010 of GPCC and CFSR.

the user by knowing the probability of an event occurring given that a warning has provided or the probability that event will occur when warning is not issued. The ROC curve analysis requires the development of a contingency table to summarize the success of a forecast-based decision making that is based on two alternatives. These two alternatives in meteorological forecasts are often the ability provide a warning (W) to the occurrence or nonoccurrence of a predefined event (E). An event in this study is defined as the total rainfall in a given month being wetter than a percentile threshold of this month inter-annual distribution of forecasts. The analysis is then repeated with a month identified as being dryer than a percentile threshold. A warning for an above (or below) normal month will be issued following an assessment of an ensemble of forecasts to a categorical statement of whether the defined event is expected or not expected to occur. A two by two contingency table for a categorical (warning/no warning) forecast system is shown in Table 2.

In Table 2, n is the number of observations, e and e' are the total events and nonevents, respectively, w and w' are the total of warnings and no warnings, respectively, h, f, m and c are the number of hits, false alarms, misses, and correct rejections, respectively.

The hit rate (H_r) (sometimes also referred to as the probability of detection) represents the probability that an event will be forewarned:

$$H_r = h/(h+m) = h/e = \mathrm{p}(\mathrm{W}|\mathrm{E}) \qquad (1)$$

The false-alarm rate (FA_r) represents the probability that warnings will be issued to an event that did not occur:

$$FA_r = f/(f+c) = f/e' = \mathrm{p}(\mathrm{W}|\mathrm{E}) \qquad (2)$$

In a probabilistic forecast system, a warning is issued when the forecast of a predefined event exceeds a threshold. The ROC curve is a line that connects the hit and false alarm rates from contingency tables that correspond to a range of predefined warning thresholds. The plot is bounded by a case that warning never issued (hit and false-alarm rates of 0%) and a case that warning always issued (hit and false-alarm rates of 100%). For a skillful forecasting system, the hit rate exceeds the false alarm rate [$H_r > FA_r$] and thus the ROC curve will lie above the 45° line. When the curve lies close to the diagonal, the forecast system does not provide skillful information. A negative skill is shown for curves that bend below the diagonal line.

In Fig. 8, the probability that warning would have been issued with a 1-month lead-time by the reforecast CFS for a month to be below or above normal was examined, using the gauge observations to indicate the monthly outcomes. In this Figure the area under the above normal (A_a, black) and below normal (A_b, red) ROC curves are also indicated. A perfect forecast system will have an area of 1, and 0 will be a perfectly bad system.

As mentioned above, the reforecast dataset consists of a forecast that is issued every 5-days, and in each forecast-day, 4 forecasts are produced from different initial times (00:00, 06:00, 12:00, and 18:00 UTC). For instance, the rainfall forecast for February 2000 with one-month lead-time is considered as the ensemble of forecasts that were made during January 2000 (Jan 1, 6, 11, 16, 21, 26, and 31). Each day a forecast was issued with four initial times (7 days × 4 times a day = 28 forecast realizations).

Below and above normal warnings are assigned for a range of percentile thresholds. For example for the 30% threshold, a below normal warning is issued if the forecast is below the 30% of the distribution of all the January forecasts of the total rainfall in February for 1982–2010. This analysis is carried for each of the forecast realization and the decision to issue a warning (or not) is

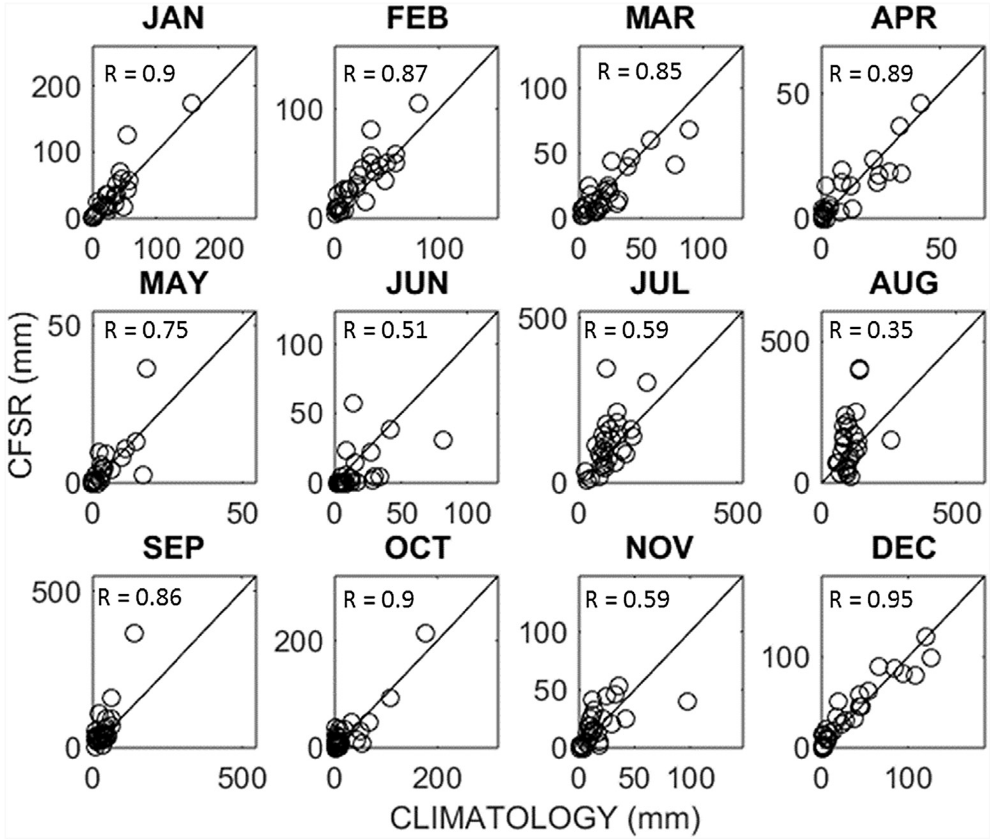

Fig. 7. Monthly scatter plots 1982–2010 of GPCC climatologies and CFSR. Correlation coefficients are indicated in the upper right corners.

Table 2
Contingency table structure for verification of a binary forecast system.

		Forecasts		Total
		Warning (W)	No Warning (W′)	
Observed	Event (*E*)	*h*	*M*	*e*
	Nonevent (*E*′)	*f*	*C*	*e*′
	Total	*w*	*w*′	*n*

based on the highest count of the realizations that are above or below the thresholds. The hit versus false alarm rates of this threshold constitutes a one point on the ROC curve.

A notable conclusion from Fig. 8 is that, compared to the summer, the CFS performs better in the winter (Dec–Mar) for both predicting above and below normal rainfall. The highest skill is shown for February for both above and below normal conditions. January had the best skill for above normal with negative skill for below normal conditions. A considerable skill to forecast above normal conditions is also shown for June. Although commonly a dry month, infrequently the onset of the monsoon season occurs during June. In the summer, on the other hand (Jul–Sep), the CFS performance is lacking accept from some skill in July to predict above normal conditions. This is consistent with Castro et al. (2012) that found CFS predictions of summer rain to be better in the beginning of the summer; because the atmospheric circulation in the beginning of the summer is tightly linked to the Pacific SST.

In Table 3, the letters P (positive, $A > 0.6$) and N (negative, $A < 0.4$) indicate the forecast skills base on the area (A) under the ROC Curves for the winter and summer months with 1, 2, 3 and 4 months forecast lead-times.

It is seen that predicting above normal rainfall in July with one-month lead-time is the only skillful CFS forecast for the summer. In the winter, as expected the skill is declining with lead-time. However, even with 4-month lead-time some forecast skills are observed. For Jan–Feb, the skill to forecast above normal conditions is carried up to 4-months lead-time and the skill to predict below normal is lacking. A good predictive skill is also seen for March while the 1-month lead-time December skill is not shown for the longer lead-times.

5.3. Evaluation during strong El Nino

Last, we evaluate the CFS performance in winters with strong El Nino. Evaluation of the CFS during El Nino events is essential because of the highly anticipated wet season that occasionally have not realized, as in the winter of 2015–2016. In Table 4, we look at forecast issued in four El Nino years for the winter months (Dec–Mar). The above normal (A), normal (N) and below normal (B) are determined as the terciles of the monthly reforecast distribution, while the observed monthly outcome is based on the gauge precipitation.

It is interesting to see that the CFS performed fairly well during the 2015–2016 El Nino (October forecasts are unavailable). January which was above normal was accurately predicted in December and February, albeit the strong El Nino, was accurately predicted to be below normal month in Nov, Dec and Jan. The CFS failed to predict the categorical wetness outcome in December and March. During the other El Nino years the CFS failed to predict the dry January in 97/98, wet December in 87/88 and the wet January in 82/83. Overall, the trend of the forecasts in these extreme El Nino years resembles the conclusion from the analysis of all the years, with high (low) skills in predicting February (January).

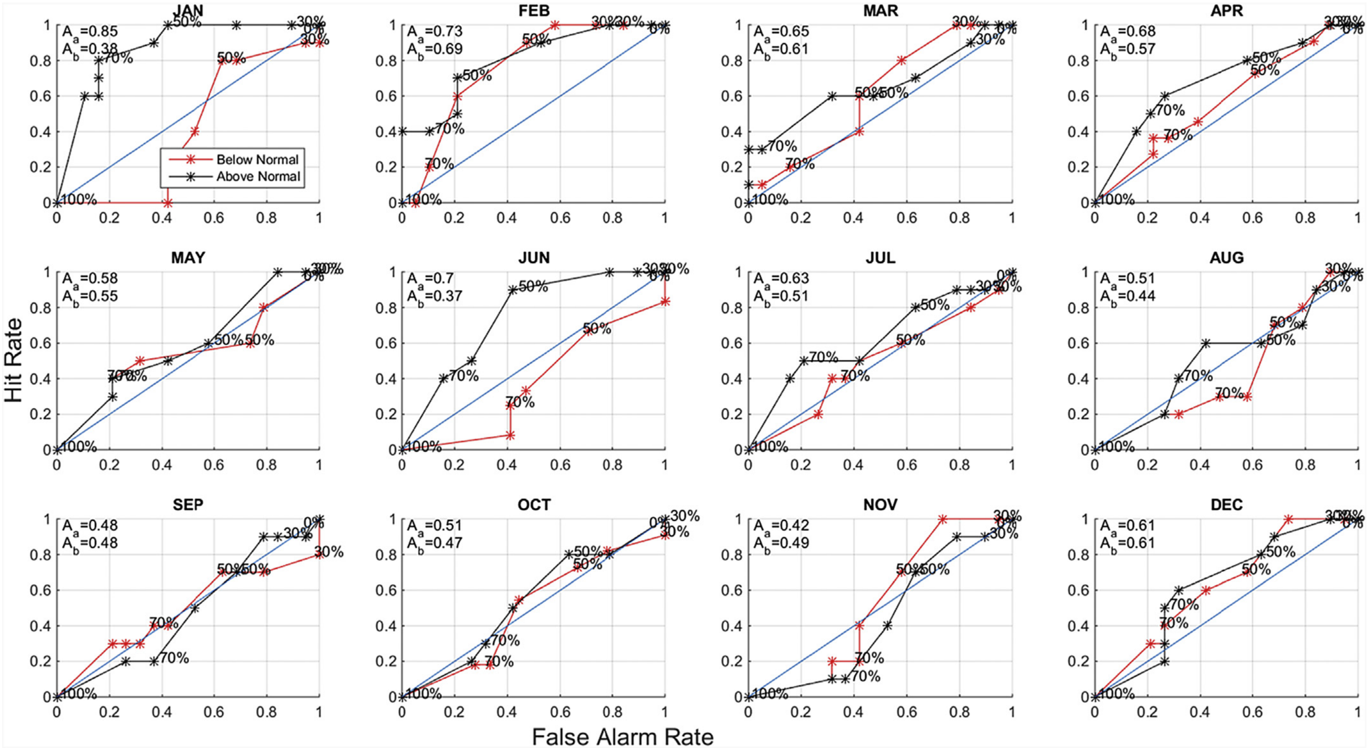

Fig. 8. Hit rates vs. false-alarm rates of the of the reforecasted CFS [1982–2010] monthly rainfall with one-month lead-time at the Upper Santa Cruz River compared to observed gauge precipitation. The red (black) lines are for the forecast to be above (below) normal. Also indicated the area under the curves for the for the above (A_a) and below (A_b) normal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Monthly rainfall forecasts skill evaluation with 1–4 months lead-time.

		1-month		2-months		3-months		4-months	
		Above Normal	Below Normal	Above Normal	Below Normal	Above Normal	Below Normal	Above Normal	Below Normal
Winter	Dec	P	P						P
	Jan	P	N	P	N	P	N	P	N
	Feb	P	P	P		P		P	
	Mar	P	P	P	P		P		P
Summ	Jul	P					N		
	Aug						N		N
	Sep								

*P – Positive ROC curve skill [Area ≥ 0.6] and N – Negative ROC curve skill [Area ≤ 0.4].

6. Summary and conclusions

In this study, we examined the potential benefits of adaptive water resources management driven by seasonal forecasts in the arid environment of the USCR region. The region's shallow groundwater reservoirs are being replenished by the infrequent flow events on the otherwise dry channel, during the two wet seasons that experience large inter-annual variability. Because of the limited storage capacity in these shallow aquifers, the efficiency of groundwater recharge rate during the flow events is highly dependent on the state of the aquifers. In addition, these climate sensitive aquifers require careful management in order to sustain the sensitive riparian ecology. In such a climate sensitive system that has a limited storage capacity, we demonstrated that by anticipating an upcoming wetter than normal season (winter or summer) with one or two months lead-time, an adaptive management approach can yield a significant gain by increasing the water withdrawal from the shallow aquifer. In the management strategy that was examined, the average annual expected gain is 7–8%, with some years exceeding 45% additional withdrawal from the MB. This gain represents a potential monetary benefit in addition to increase of water supply in the region. This gain was also realized while the forecast of wetter than normal season was correct 70% of the time. However, the inclusion of the forecast uncertainty yielded occasional long lasting drawdowns that may represents stress to the riparian ecosystem.

The skills of two-readily available seasonal forecasts products were evaluated. First, we evaluated the observed ENSO during the transition seasons as a predictor for the wet seasons. For the winter, we found the anticipated association of strong El Nino with wetter than normal winters although, with a few exceptions (e.g. 2015/16). The La Nina conditions in the fall, with no exceptions, were associated with below normal rainfall. The observed spring El Nino (La Nina) was associated with dryer (wetter) summers. Comparing the ENSO signal to the streamflow record showed that the wetter than normal El Nino during the winters and La Nina in the summers do

Table 4
CFS predictions of winter months during El Nino years. Parenthesis in the Target Forecast column indicates the observed outcome and bold font indicate a successful forecast.

Target forecast	Oct	Nov	Dec	Jan
Forecast issued during 2015–2016				
Dec (N)		B		
Jan (A)		N	**A**	
Feb (B)		**B**	**B**	**B**
Mar (B)			N	N
Forecast issued during 1997–1998				
Dec (A)	**A**	**A**		
Jan (B)	N	A	A	
Feb (A)		**A**	**A**	**A**
Mar (A)			N	**A**
Forecast issued during 1987–1988				
Dec (A)	B/N	N		
Jan (A)	B/N	B/N	**A**	
Feb (N)		**N**	B	**N**
Mar (N)			B	**N**
Forecast issued during 1982–1983				
Dec (A)	**A**	**A**		
Jan (A)	N	N	N	
Feb (A)		**A**	**A**	**A**
Mar (A)			**A**	N/A

not always produce large seasonal flows. This stresses the importance of the hydrologic regime in the basin that requires the consideration of the precipitation characteristics and the dynamic of the land surface conditions.

Second, the skill of the monthly rainfall forecasts available from the CFS NCEP, NOAA was examined. The CFS showed a fairly good skill for the winter months (mainly January–February) with skill extending up to 4-month lead-time. On the other hand, the only substantial skill that was discerned for the summer was the one-month lead-time for predicting above normal conditions in July.

The adoption of the adaptive strategy in this region should be further evaluated using a careful cost loss analysis to understand the region's resiliency to the consequences of false alarms for wetter than normal winters or summers. The study calls to motivate efforts to improve the seasonal forecasts capabilities and point to the importance of relevant hydrologic monitoring for water resources management and decision making in the region.

The need for relevant hydrologic data for decision-making was acknowledged by Arizona Department of Water Resources and the Santa Cruz AMA Groundwater Users Advisory Council (Eden et al., 2016). ADWR provided funding for the development of the Water Resources and Climate Assessment Tool (WARCAT) in the Santa Cruz Active Management Area. WARCAT is a public web portal that gathers various datasets from multiple data provider agencies. The datasets include streamflow, rainfall and groundwater levels in conjunction with the CFS operational forecasts. These datasets are presented in an intuitive visual display of the current hydrologic conditions in comparison to historic conditions in order to provide a tool for stakeholders and decision makers for development of informed management practices. During the development of the WARCAT web portal, two workshops were conducted to solicit input and engage the stakeholders. As of October 2016, the website is publically available (url: https://warcat.hrcwater.org/SCAMA).

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References

ADWR, Arizona, July 2012. Department of Water Resources, 2012. Demand and Supply Assessment 1985–2025. Santa Cruz Active Management Area.
Castro, L.C., Chang, H.-I., Dominguez, F., Carrillo, C., Schemm, J.-K., Juang, H.-M.H., 2012. Can a regional climate model improve the ability to forecast the North American Monsoon? J. Clim. 25, 8212–8236.
Cayan, D., Webb, R., 1992. El niño-southern oscillation and streamflow in the western United States. In: Diaz, H.F., Markgraf, V. (Eds.), El Niño: Historical and Paleoclimatic Aspects of the Southern Oscillation. Cambridge University Press, Cambridge, pp. 29–68.
Chiew, F.H.S., Zhou, S., McMahon, L., 2003. Use of seasonal streamflow forecasts in water resources management. J. hydrology 270 (1–2), 135–144.
Dettingter, M.D., Diaz, H.F., 2000. Global characteristics of stream flow seasonality and variability. J. Hydrometeorol. 1, 289–310.
Eden, S., Megdal, S.B., Shamir, E., Chief, K., Mott Lacroix, E., 2016. Opening the black box: using a hydrological model to link stakeholder engagement with groundwater management. Water 8 (5), 216. http://dx.doi.org/10.3390/w8050216.
Erwin, G., 2007. Groundwater Flow Model of the Santa Cruz Active Management Area Microbasins International Boundary to Nogales International Wastewater Treatment Plant Santa Cruz County. Arizona Department of Water Resources. Modeling Report #15.
Georgakakos, K.P., Graham, N.E., Cheng, F.-Y., Spencer, C., Shamir, E., Georgakakos, A.P., Yao, H., Kistenmacher, M., 2012a. Value of adaptive water resources management in northern California under climatic variability and change: dynamic hydroclimatology. J. Hydrol. 412–413, 47–65.
Georgakakos, A.P., Yao, H., Kistenmacher, M., Georgakakos, K.P., Graham, N.E., Cheng, F.-Y., Spencer, C., Shamir, E., 2012b. Value of adaptive water resources management in Northern California under climatic variability and change: reservoir management. J. Hydrol. 412–413, 34–36.
Gong, G., Wang, L., Condon, L., Shearman, A., Lall, U., 2010. A simple framework for incorporating seasonal streamflow forecasts into existing water resource management practices. J. Am. Water Resour. Assoc. (JAWRA) 46 (3), 574–585. http://dx.doi.org/10.1111/j.1752-1688.2010.00435.x.
Graham, N.E., Georgakakos, K.P., Vargas, C., Echevers, M., 2006. Simulating the value of El Nino forecasts for the Panama canal. Adv. Water Resour. 29, 1665–1677.
Lite, S.J., Stromberg, J.C., 2005. Surface water and groundwater thresholds for maintaining Populus-Salix forests, San Pedro River, Arizona. Biol. Conserv. 125, 153–167.
Mason, S.J., Graham, N.E., 1999. Conditional probabilities, relative operating characteristics, and relative operating levels. Weather Forecast. 1999, 713–725.
Nelson, K., 2010. Risk Assessment of Pumping Impacts on Simulated Groundwater Flow in the Santa Cruz Active Management Area. ADWR Modeling Report No. 21, May 2010.
Page, W.R., Menges, C.M., Gray, Floyd, Berry, M.E., Bultman, M.W., Cosca, M.A., VanSistine, D.P., 2016. Geologic map of the rio rico and Nogales 7.5' quadrangles, Santa Cruz county, Arizona. U.S. Geol. Surv. Sci. Investig. Map 3354, 32 pp. pamphlet, 2 sheets, scale 1:24,000. http://dx.doi.org/10.3133/sim3354.
Redmond, K.T., Koch, R.W., 1991. Surface climate and streamflow variability in the Western United States and their relationship to large-scale circulation indices. Water Resour. Res. 27 (9), 2381–2399.
Saha, S., coauthors, 2014. The NCEP climate forecast system version 2. J. Clim. 27, 2185–2208. http://dx.doi.org/10.1175/JCLI-D-12-00823.1.
Saha, S., coauthors, 2010. The ncep climate forecast system reanalysis. Bull. Am. Meteorol. Soc. 90, 1015–1057.
Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., Rudolf, B., 2014. GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. Theor. Appl. Climatol. 115, 15–40. http://dx.doi.org/10.1007/s00704-013-0860-x.
Shamir, E., Megdal, S.B., Carrillo, C., Castro, C.L., Chang, H.-I., Chief, K., Corkhill, F.E., Eden, S., Georgakakos, K.P., Nelson, K.M., Prietto, J., 2015. Climate change and water resources management in the upper Santa Cruz River, Arizona. J. Hydrol. 521, 18–33. http://dx.doi.org/10.1016/j.jhydrol.2014.11.062.
Shamir, E., Wang, J., Georgakakos, K.P., 2007a. Probabilistic streamflow generation model for data sparse arid watersheds. J. Am. Water Resour. Assoc. 43 (5), 1142–1154.
Shamir, E., Graham, N., Meko, D., Georgakakos, K.P., 2007b. Hydrologic model for water resources planning in Santa-Cruz River, southern Arizona. J. Am. Water Resour. Assoc. 43 (5), 1155–1170.
Shamir, E., Graham, N.E., Wang, J., Meko, D.M., Georgakakos, K.P., December 2005. Stochastic streamflow scenarios for the Santa-Cruz River at the Nogales gauge,

prepared for the Arizona department of water resources. AMA, Hydrologic Research Center Technical Report No. 4, Santa Cruz. http://www.hrc-lab.org/projects/dsp_projectSubPage.php?subpage=santacruz.
Sprouse, T.W., Vaughan, L.F., 2003. Water resource management in response to El niño/southern oscillation (ENSO) droughts and floods the case of ambos Nogales. In: Diaz, H.F., Morehouse, B.J. (Eds.), Climate and Water Volume 16 of the Series Advances in Global Change Research, pp. 117–143.
Stanki, H.R., Wilson, L.J., Burrow, W.R., 1989. Survey of Common Verification Methods in Meteorology. Research Report No. 89–5. Atmospheric Environment Service, Forecast Research Division, 4905 Dufferin Street, Downsview, Ontario, Canada.
Stromberg, J.C., McCluney, K.E., Dixon, M.D., Meixner, T., 2012. Dryland Riparian Ecosystems in the American Southwest: Sensitivity and Resilience to Climatic Extremes. Ecosystems. http://dx.doi.org/10.1007/s10021-012-9603-3.
Wilks, S.D., 2006. Statistical methods in the atmospheric sciences. International Geophysics Series. Elsevier 467p.
WMO, 2000. Standardized Verification System (SVS) for Long Range Forecasts (LRF). World Meteorological Organization, Geneva, Switzerland.