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The association between climate teleconnection indices and Upper Klamath seasonal streamflow: Trans-Niño Index

Adam M. Kennedy,[1,3]* David C. Garen[2†] and Roy W. Koch[3]
[1] *Department of Forest Science, Oregon State University, Corvallis, Oregon, USA*
[2] *US Department of Agriculture, Natural Resources Conservation Service, National Water and Climate Center, Portland, Oregon, USA*
[3] *Environmental Sciences and Resources, Portland State University, Portland, Oregon, USA*

Abstract:

This research investigates large-scale climate features affecting inter-annual hydrologic variability of streams flowing into Upper Klamath Lake (UKL), Oregon, USA. UKL is an arid, mountainous basin located in the rain shadow east of the crest of the Cascade Mountains in the northwestern United States. Developing accurate statistical models for predicting spring and summer seasonal streamflow volumes for UKL is difficult because the basin has complex hydrology and a high degree of topographic and climatologic variability. In an effort to reduce streamflow forecast uncertainty, six large-scale climate indices—the Pacific North American Pattern, Southern Oscillation Index, Pacific Decadal Oscillation (PDO), Multivariate El Niño-Southern Oscillation Index, Niño 3·4, and a revised Trans-Niño Index (TNI)—were evaluated for their ability to explain inter-annual variation of the major hydrologic inputs into UKL.

The TNI is the only index to show significant correlations during the current warm phase of the PDO. During the warm PDO phase (1978–present), the averaged October through December TNI is strongly correlated with the subsequent April through September streamflow ($r = 0{\cdot}7$) and 1 April snow water equivalent ($r = 0{\cdot}6$). Regional analysis shows that this climate signal is not limited to UKL but is found throughout the northwestern United States.

Incorporating the TNI variable into statistical streamflow prediction models results in standard errors of forecasts issued on the first of February and earlier that are 7–10% smaller than those for the models without the TNI. This, coupled with other enhancements to the statistical models, offers a significant increment of improvement in forecasts used by water managers.

KEY WORDS Trans-Niño Index; hydro-climatology; streamflow forecasting; El Niño; teleconnections; climate variability; water supply; principal components regression

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INTRODUCTION

The United States Bureau of Reclamation (USBR) operates many dams, power plants, and canal systems throughout the western United States. One project notable and highly publicized in recent years is the Klamath Irrigation Project, located in southern Oregon and northern California, USA (Figure 1). Here, the USBR faces an array of challenges regarding water-related management, including recurring drought, decreasing water quality in Upper Klamath Lake, and public and political pressure to restore healthy populations of several threatened and endangered fish species (Lost River Sucker, Shortnose Sucker, and Coho Salmon; NRC, 2004). Complicating water management issues are numerous competing water interests that include agricultural growers, municipal utilities, Native American tribes, and wildlife refuge and habitat management, both at the lake's outlet and downstream at sites along the Lower Klamath River.

A primary water management tool in the basin is seasonal streamflow forecasts, which are issued by the Natural Resources Conservation Service (NRCS), an agency of the US Department of Agriculture, in cooperation with the US National Weather Service. The official monthly forecasts begin in January preceding the seasonal snowmelt and end in June. These models rely on a principal components based regression model (Garen, 1992) to predict future streamflow relying on current snow water equivalent (SWE), fall and spring precipitation, antecedent streamflow, groundwater, and climate indices. Existing models, however, are not as accurate as water managers would like. Many of the reasons for this forecast uncertainty have to do with the physical characteristics of the basin, that is, high topographic and climatologic variability, which makes it difficult to obtain integrated forcings from a point observation network; groundwater influences mute the seasonal snowmelt signal; lake dynamics such as evaporation and groundwater interactions change the actual amount of water stored in the lake; and there are ungauged inputs into the lake from local drainages. The other major source of forecast uncertainty is unknown future weather at the time forecasts are issued. The former sources of uncertainty are difficult to reduce given the existing data networks,

* Correspondence to: Adam M. Kennedy, Department of Forest Science, Oregon State University, 201K Richardson Hall, Corvallis, Oregon 97331, USA. E-mail: akennedy@coas.oregonstate.edu
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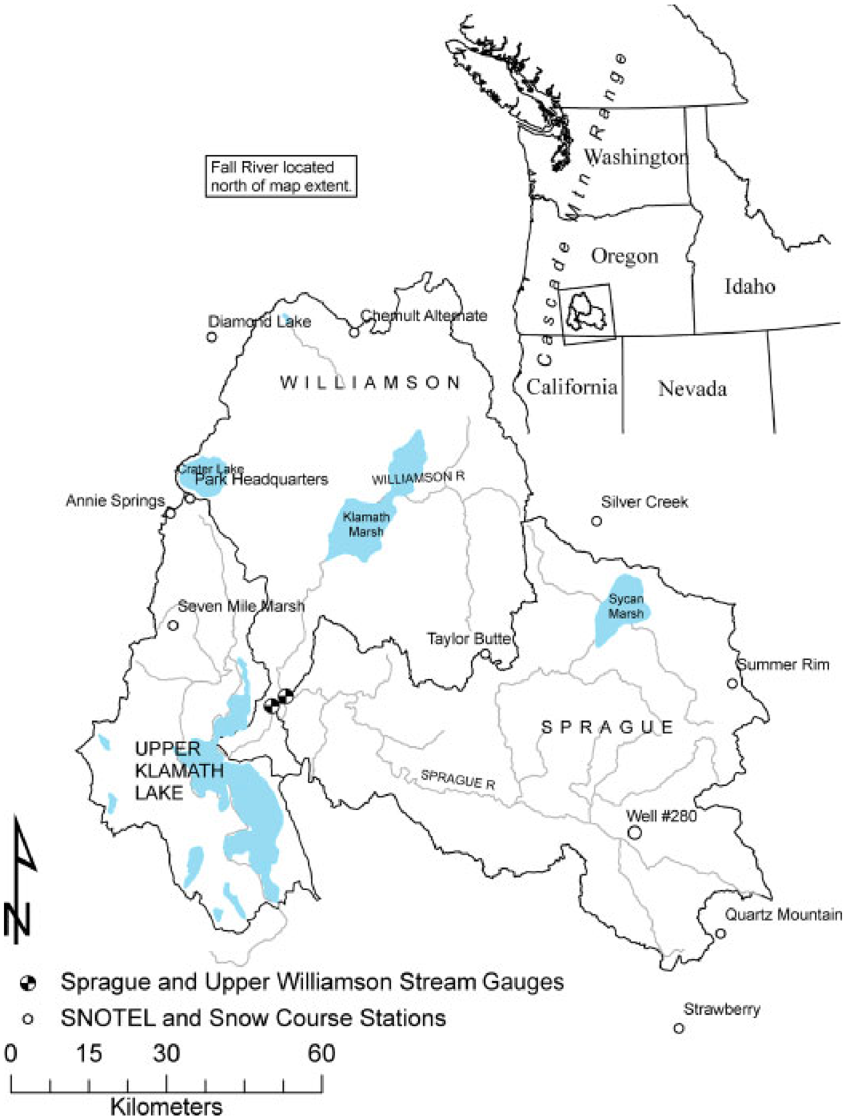

Figure 1. Upper Klamath Basin including Williamson, Sprague and Upper Klamath Lake drainages and climate and streamflow stations used in this research

although increments of improvement can be made with careful predictor variable selection and optimization. The latter source of forecast uncertainty has better prospects of being addressed, and this is the focus of the present study.

A key objective of this study, then, is to improve the existing streamflow forecast models by including a climate teleconnection index to represent future weather (particularly for the winter) and to evaluate the skill of forecasts that include a climate teleconnection index against those that do not. Other studies have looked at the relationship between large-scale climate teleconnections and weather or hydrologic phenomena (e.g. Mantua *et al.*, 1997; McCabe and Dettinger, 2002; Beebee and Manga, 2004; Gedalof *et al.*, 2004; Grantz *et al.*, 2005; Tootle *et al.*, 2005; Bonsal *et al.*, 2006; Kingston *et al.*, 2006, 2007), but these have either not explicitly studied the Klamath Basin, or those that have considered the region have not found a related teleconnection index. In the present study, a teleconnection index related to the hydrology of the Klamath Basin has been found and incorporated into statistical streamflow forecasting models.

SITE DESCRIPTION

This study focuses on Upper Klamath Basin, which is the drainage area flowing into Upper Klamath Lake, located just north of the California border in south central Oregon, USA (Figure 1). It is in the rain shadow at the base of the eastern slopes of the Cascade Range and lies on the western fringe of the Basin and Range physiographic province (Risley and Laenen, 1999). Its topographic features contribute to high spatial variability in precipitation and temperature. It is characterized by an extensive volcanic geology, which results in a large percentage of precipitation, especially in the western part of the basin, infiltrating into the regional groundwater system, thus integrating the climate signal over a 2–3 year period (Risley *et al.*, 2005).

Including the closed basin of Crater Lake (a caldera), Upper Klamath Basin has an area of 9772 km^2. It can be divided into three sub-basins—Williamson (3726 km^2), Sprague (4170 km^2), and Upper Klamath Lake (1874 km^2), the latter making up the remaining area of Upper Klamath Basin downstream of the Williamson and Sprague rivers. Elevation in the Upper Klamath Basin ranges from 1257 to 2865 m with a mean elevation of 1545 m. The Williamson and the Sprague rivers comprise about 50% of the total inflow into Upper Klamath Lake. The remainder is derived from precipitation over the lake, streamflow production from the local drainage area, and groundwater inflow.

HYDROLOGIC SENSOR NETWORK

Snow and precipitation data

The main source of data is the NRCS, which began installing meteorological stations in the vicinity during the early 1980s as part of their SnowTelemetry (SNOTEL) system. Most stations measure snow depth, SWE, precipitation, and temperature. SNOTEL provides a near real-time network with data arriving at the NRCS processing stations via meteor burst technology hourly and published online soon thereafter in both daily and monthly aggregations (http://www.wcc.nrcs.usda.gov/snow). The SNOTEL stations used in this study are shown in Figure 1. In addition, first-of-month SWE from one manually measured snowcourse, Park Headquarters, was also used as a predictor as well as precipitation from the adjacent Crater Lake station.

Streamflow data

Streamflow data were available from the US Geological Survey (USGS) for all months beginning in 1924 for both the Sprague (USGS gauge 11501000) and Williamson (USGS gauge 11502500) rivers. Because the Williamson gauge is located just downstream of the confluence with the Sprague, it is necessary to subtract the Sprague discharge from the Williamson to define the Williamson flow. This computed data series is referred throughout this paper as the Upper Williamson.

Unimpaired streamflow data

Data from the Hydro-Climatic Data Network (HCDN), a subset of USGS streamflow stations unaffected by major anthropogenic influences (Slack *et al*., 1993), were used for the regional analysis portion of this research. While the HCDN data set ended in 1988, no major dams or significant diversions have been built in the western US since then, so the records of streams originally included in the HCDN were updated from the USGS. The Sprague River was included in the original HCDN data network, while the Williamson was not even though the streamflow is largely unimpaired by diversions or dams.

Hydrogeology information

Risley *et al*. (2005) have shown that groundwater observations may be useful in characterizing large-scale climate variability and that this may have statistical importance in streamflow forecast models. For this study, water levels for Oregon state well #280, located in the eastern headwater region of the Sprague basin, and streamflow for Fall River [Oregon Water Resources Department (OWRD) gauge 14057500], located in the Deschutes Basin (adjacent to the Klamath Basin to the north), are used to quantify the observed decadal-scale hydrogeologic variability and base flow conditions.

HYDRO-CLIMATIC CHARACTERIZATION

Streamflow characteristics

While geographically adjacent, the Sprague and Upper Williamson basins have distinct streamflow regimes. The Sprague is a surface water dominated basin with a strong seasonal snowmelt signal. The Upper Williamson, however, is characterized by a significant groundwater component due to volcanic geology, and it has a large mid-basin marsh, both of which smooth much of the seasonal snowmelt streamflow. The Sprague, therefore, shows much more temporal streamflow variability than does the Upper Williamson, which is evident in the monthly time series plots in Figure 2.

Climate change/Shifting hydrograph

Global warming may influence seasonal runoff timing, with more winter precipitation falling as rain rather than snow and snowmelt occurring earlier (Parson *et al*., 2000; Regonda *et al*., 2005). A simple analysis of computing

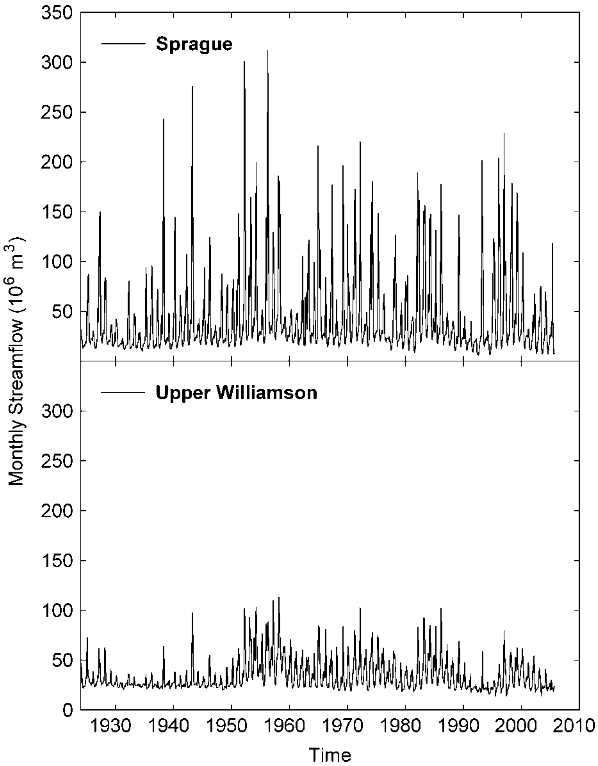

Figure 2. Monthly Upper Williamson and Sprague river streamflow time series (1924–2004)

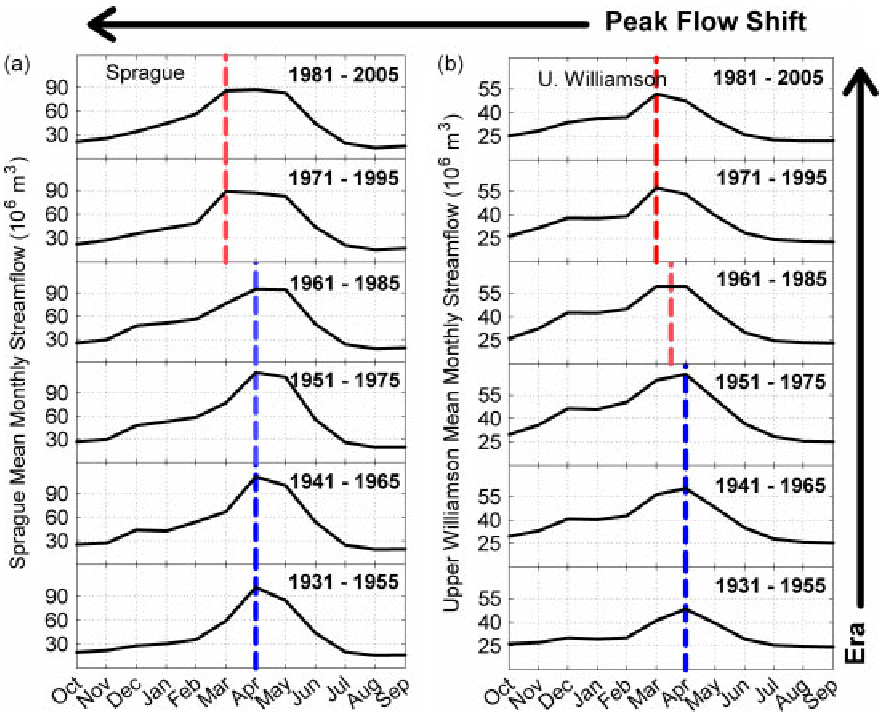

Figure 3. Twenty-five year moving window average monthly streamflow hydrographs for the (a) Sprague and (b) Upper Williamson rivers. Note peak monthly flow is occurring earlier

average monthly streamflow for moving 25-year windows shows clearly that even though total streamflow volumes have varied significantly through time, peak seasonal runoff has shifted from April to March in both the Upper Williamson and Sprague rivers (Figure 3). This trend is consistent with the findings for other rivers in western North America (Mote *et al*., 2005; Stewart *et al*., 2005). This shift in streamflow timing has important implications for streamflow forecasting models (season forecasted, calibration period) and for water management decisions. This issue is not studied in detail here, but it is important to keep in mind in further studies.

CLIMATE SIGNAL EVALUATION

Redmond and Koch (1991) were among the first to show the significant relationship between the El Niño-Southern Oscillation (ENSO) and streamflow in the western US. El Niño (La Niña) events are typically associated with anomalously low (high) winter precipitation totals in the Pacific Northwest (and the opposite for the desert Southwest). Since the work of Redmond and Koch (1991), the Southern Oscillation Index (SOI) has been widely used in water resource management to index future climate conditions.

While useful as a climate teleconnection index in much of the western US, the SOI signal is not observed in every basin throughout the West. Most notable is the absence of the SOI signal around the mid-latitude region (37–43 °N) of western North America (Redmond and Koch, 1991). This region lies between the typical storm tracks, which take a more southerly route during El Niño and a more northerly route during La Niña. It is this observation that motivates looking for a large-scale climate teleconnection index that explains hydrologic variability in regions removed from the typical ENSO signal.

Climate teleconnection indices

Six large-scale climate teleconnection indices—SOI, Niño 3·4, Pacific Decadal Oscillation (PDO), Multivariate El Niño-Southern Oscillation Index (MEI), Pacific North American (PNA) Index, and the Trans-Niño Index (TNI)—were investigated because they have been commonly used for climate monitoring in the western US (Wallace and Gutzler, 1981; Wolter, 1987; Mantua *et al*., 1997; Trenberth and Stepaniak, 2001).

The SOI is defined by the Climate Prediction Center, part of the US National Weather Service, as the difference between the standardized sea level atmospheric pressure observed at Tahiti and that at Darwin, Australia divided by the monthly standard deviation (http://www.cpc.ncep.noaa.gov/data/indices). Positive SOI values indicate La Niña, and negative values indicate El Niño.

The Niño 3·4 Index measures the area averaged sea surface temperature (SST) over the equatorial Pacific Ocean (5°N–5 °S) (170–120 °W) and is an appropriate proxy for Pacific mean equatorial SST (Trenberth and Stepaniak, 2001). The Niño 3·4 is negatively correlated with the SOI, that is, when mean Pacific SST is high, the SOI is generally low.

The PDO refers to the time history of the leading eigenvector of North Pacific SST (Mantua *et al*., 1997). Variability observed in the PDO appears to follow a decadal-scale pattern. That is, it is generally agreed that

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the PDO may be in either a cool phase (1945–1977) or a warm phase (1925–1944, 1978–present). Some suggest that the PDO changed phase during the mid 1990s (Mestas-Nuñez, 2006), but for lack of the specific evidence, it is assumed in the present study that a phase change did not occur.

The MEI is calculated as the first unrotated principal component of six observed variables over the tropical Pacific (Wolter, 1987). The variables measured include sea level pressure, zonal and meridional surface wind, SST, surface atmospheric temperature, and total cloudiness fraction of the sky. Negative MEI values indicate La Niña, while positive values indicate El Niño.

The PNA is based on 500-mb pressure patterns of the Northern Hemisphere (Wallace and Gutzler, 1981). It is strongly influenced by the ENSO, and it has been suggested that the PNA is a major mechanism directing storm tracks into the western US (Redmond and Koch, 1991).

The TNI is a measure of the standardized SST gradient between region Niño 1 + 2 and Niño 4 (Trenberth and Stepaniak, 2001). The Niño 1 + 2 region is located off the west coast of Peru and Ecuador, near the Galapagos Islands. The Niño 4 region spans the International Date Line in the equatorial Pacific (Figure 4). It is a relatively new index that was originally developed to characterize the evolution of an El Niño event, but it may also be useful for predictive purposes (Trenberth and Stepaniak, 2001).

Statistical design

Each climate signal was evaluated independently for its usefulness in explaining the inter-annual hydrologic variability of major observed hydrologic variables within Upper Klamath Basin. Following Koch and Fisher (2000), the period of record for each variable was stratified on the basis of PDO phase. That is, western US large-scale climate was considered temporally homogeneous during the cool PDO phase 1945–1977 and homogeneous during the warm phases of 1925–1944 and 1978–present. The time period analysed was 1951–2004, the beginning of this period being determined by the readily available data record for the teleconnection indices. Pearson correlation coefficients were computed to determine if an association existed between the selected climate teleconnection indices and major hydrologic variables within Upper Klamath Basin. Statistical significance was defined by values established in Helsel and Hirsh (2002). Because the main objective of this evaluation was to identify climate teleconnection indices valuable in their predictive ability, a lag period of up to eleven months prior to the time of the hydrologic variable observation was used. The teleconnection indices were analysed both at a monthly and a three-month time step, but because there were no significant differences between the two analyses, only the results of the three-month aggregates are discussed here.

Results

Of the climate teleconnection indices evaluated during this research, the TNI was the only index having a statistically significant signal during the current warm PDO phase (Figure 5). During the entire period of record, the TNI shows moderate positive correlations with seasonal Klamath streamflow, 1 April SWE, and Nov–Mar precipitation. That is, when the late fall/early winter multi-month TNI value is positive, above normal winter precipitation and snow accumulation is expected, leading to above normal subsequent seasonal streamflow. The reverse is true when the late fall/early winter multi-month TNI value is negative. During the cool PDO phase, however, these relationships are much weaker. During the current warm PDO phase, these relationships are strongest, with correlation coefficients reaching a maximum during September through January prior to the snowmelt runoff season. This lag time ranging from 3 to 8 months prior to the seasonal runoff period beginning in April makes the TNI useful as a predictor variable in a statistical streamflow forecast model because it is available prior to the main period of snow accumulation.

Figure 4. Geographic scope of Niño 1 + 2 and Niño 4 regions used to compute the TNI

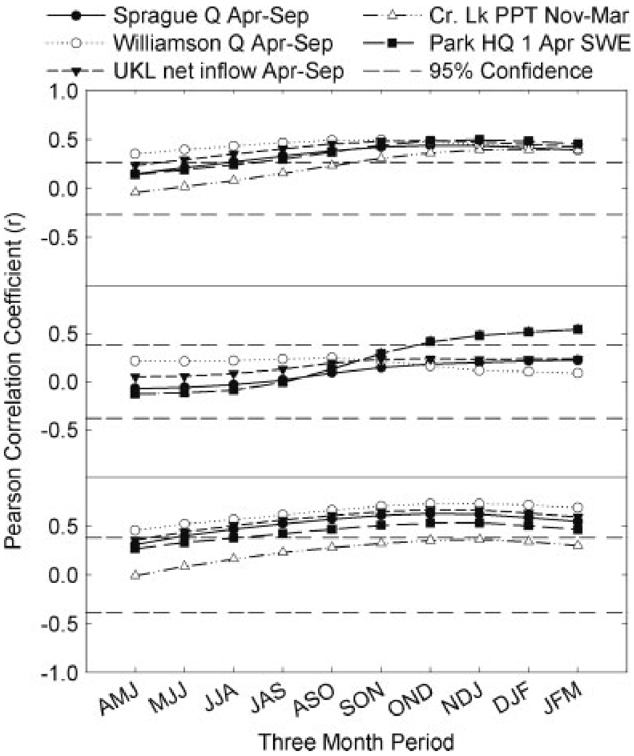

Figure 5. Pearson correlation coefficients between the three-month average TNI and subsequent seasonal hydrologic variables. Q = streamflow volume, Cr. Lk. = Crater Lake, PPT = precipitation, 95% confidence = confidence threshold over which the r-value is statistically different than zero

Discussion

These results suggest that during the current warm PDO phase, 1978 through the present, the most important measure of large-scale climate variability within the Upper Klamath Basin is the equatorial Pacific Ocean SST gradient. This gradient may be appropriately expressed by using the TNI climate teleconnection. This numerical representation of equatorial sea surface east-west temperature gradient has not been previously applied directly to model hydrologic variability, but the results presented here suggest that there is some potential predictive ability in the TNI. An index such as the TNI could be used to reduce the uncertainty of streamflow forecast models by providing a variable that indexes future climate and weather variability.

Given the potential utility of the TNI to improve streamflow forecasts, the remainder of this study focuses on the methods required to incorporate this climate index into operational forecast models. Revisions are necessary to update the TNI to convert it into an index useable in real-time applications. These revisions are discussed in the following section.

REVISED TRANS-NIÑO INDEX

Evaluation of the algorithm developed by Trenberth and Stepaniak (2001) to compute the TNI identified two computational issues that needed to be addressed before the TNI would be useful in a real-time streamflow forecast model. First, Trenberth and Stepaniak (2001) used a five-month centered averaging (current month plus the two previous and two future months) to smooth the monthly Niño region temperature data prior to standardization, following the tradition set by the National Center for Environmental Prediction (NCEP) monthly Climate Diagnostics Bulletin (Trenberth and Stepaniak, 2001). This works well for evaluation purposes but it is not appropriate for a real-time model where all data must be known at the time the forecast is published. This requires the TNI algorithm to be adjusted so the final form does not include future climate information.

Trenberth and Stepaniak (2001) also employed a climatologic period of 1950–1979 to standardize the final index. The present study requires the TNI to represent both the past climate regime (1950–1977) and the current climate regime (1978–present). While the previous climate regime began around 1945, as defined by the PDO, this research uses only the published SST data for the regime, which began in 1950. Revising the TNI algorithm with a climatologic period that began in January 1950 and ended in December 2004 captures the large-scale atmospheric circulation character leading up to and following the 1976/1977 PDO phase shift.

Revised TNI calculation methods

The methods used to compute the revised TNI are as follows: (1) Obtain the Niño 1 + 2 and Niño 4 area averaged monthly SST time series. These data are available online from NCEP (http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices). NCEP publishes these monthly data within 2 weeks after the end of each month. (2) Compute the monthly means over the complete period of record (January 1950 through December 2004 for this study). (3) Subtract monthly means from monthly data to obtain the monthly anomalies. (4) Divide monthly anomalies by the standard deviation of anomalies (all months considered together). (5) Subtract the standardized Niño 4 from the standardized Niño 1 + 2 to obtain monthly TNI series. This algorithm yields a revised monthly TNI for the 1950–present period of record. This revised TNI will from this point on be referred to as TNI*.

For streamflow forecasting purposes or other environmental modelling applications requiring a leading climate signal, it is useful to compute an aggregated or seasonal TNI* series that reflects the seasonal character of the Pacific Ocean SST gradient. This captures the overall character of the ocean better than the snapshot provided by a single month. To obtain a seasonal TNI* value: (6) Perform correlations with the variables of interest to identify months that contain the predictive signal. (7) Compute a seasonal TNI* by averaging the months well correlated to selected variables. (8) Finally, divide the seasonal TNI* by its respective multi-month standard deviation to reach the final standardized multi-month TNI*.

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Revised TNI calculation results

Once the TNI was revised and updated, the TNI* was evaluated to re-check that the modifications did not remove the predictive signal. The results of the monthly correlation analysis confirm that the TNI* signal strength during the warm PDO phase peaks during the Oct–Dec period prior to the beginning of the peak snowmelt season (Figure 6). From visual inspection, the most notable signal is the correlation between the Oct–Dec TNI* and the subsequent Apr–Sep streamflow volume for the Upper Williamson ($r = 0{\cdot}73$) and the Sprague ($r = 0{\cdot}65$) as well as the Apr–Sep net inflow for Upper Klamath Lake ($r = 0{\cdot}67$; not shown). Furthermore, the Oct–Dec TNI* is moderately correlated with 1 Apr SWE at the Park Headquarters ($r = 0{\cdot}51$) and Summer Rim ($r = 0{\cdot}61$) snow measuring sites. These two sites are high elevation stations located in the vicinity of Upper Klamath Basin and are useful variables to include in streamflow prediction models.

Because the Oct–Dec multi-month TNI* is identified to be the most valuable aggregation, a cursory evaluation of its historical character is instructive. The Oct–Dec TNI* appears to have a homogeneous period prior to 1977 with low variability and a homogeneous period beginning 1978 with high variability (Figure 7), which coincides well with the North Pacific circulation phase shift of 1976/1977 and other reports of increasing hydrologic variability throughout the West (Stewart *et al.*, 2005). However, the high variability during the current warm phase does not appear in the previous warm phase (1925–1944), signaling that the 1977 climate shift is related to more than just the PDO behavior and perhaps to more far-reaching climate change, another fundamental mechanism (Ebbesmeyer *et al.*, 1991), or as van Oldenborgh and Burgers (2005) suggest, variability of statistical noise.

REGIONAL TNI* SIGNAL

A question of interest is whether the TNI* signal has regional importance and if the regional signal behaves

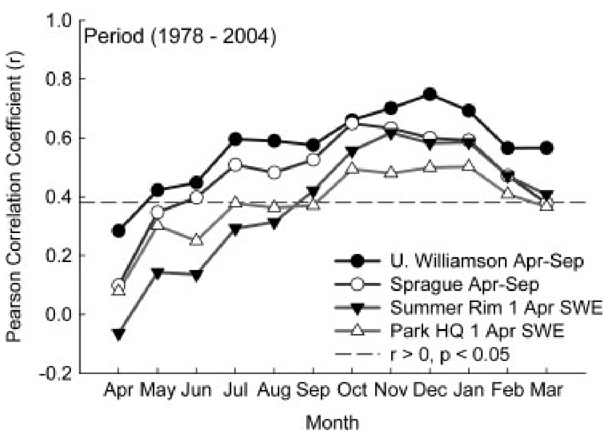

Figure 6. Pearson correlation coefficients between the monthly TNI* and the subsequent seasonal hydrologic variable

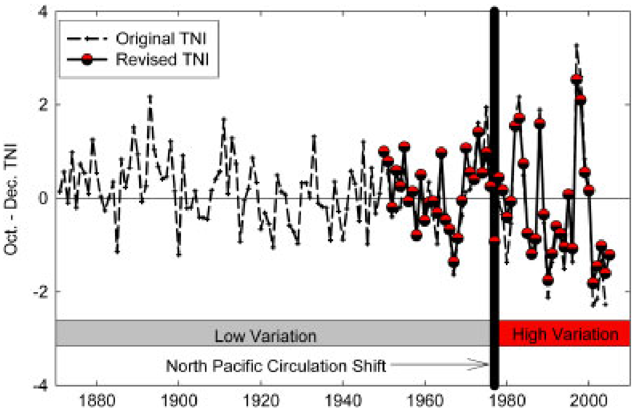

Figure 7. Time series plot of the original and revised TNI values. Note increased variance following the 1976/1977 climate shift

similarly to its expression in the Klamath Basin. To determine whether the TNI* signal is regionally distributed, correlation coefficients were calculated with HCDN streamflow records and with NRCS SNOTEL SWE data.

Methods

Initial analyses employed an online statistical model called Climate Explorer (http://climexp.knmi.nl), developed through the Royal Netherlands Meteorological Institute (KNMI), to identify all western US streamflow stations that exhibit an association with the TNI*. This helped define the areal domain in which to focus a more in-depth evaluation. The Climate Explorer model allows efficient data acquisition and processing of a variety of statistical procedures including lead/lag correlation analysis (van Oldenborgh and Burgers, 2005) and stores numerous hydrologic data sets for online processing. The TNI* was uploaded into the Climate Explorer model and correlated with Apr–Sep HCDN streamflow and 1 Apr NRCS SWE, which are both built into the KMNI model, for all stations in the western US during 1950–1988 and 1981–2004 respectively.

After the general signal extent was determined, 68 stream gauges taken from the preliminary analysis with the TNI* were selected and updated to 2004 using historic USGS streamflow data. Each station was then evaluated to determine if variation in signal strength coincided with the decadal-scale PDO phase. The records for each station were stratified into three categories—cool PDO era (1950–1977), warm PDO era (1978–2004), and the entire period (1950–2004)—then were evaluated to determine the strength of the correlation coefficient between the Oct–Dec TNI* and the subsequent seasonal Apr–Sep streamflow volume. The correlation coefficients for each period were then plotted as points on a map allowing a visual representation of the TNI* signal extent.

Results

Preliminary regional scale correlations between the Oct–Dec TNI* with the subsequent Apr–Sep streamflow and 1 Apr SWE for all stations within the geographic scope of this research suggests the TNI* signal is present throughout the northwestern US from southern Oregon, east into Idaho, and north into Washington (Figures 8 and 9 respectively). Final results suggest that while the overall extent of the TNI* signal varies depending on which time period is evaluated, the main signal band is located near the border of Oregon and California east of the Cascade Mountains, regardless of PDO phase (Figure 10).

Discussion

A thorough evaluation of the association between the TNI* and both local and regional hydrologic variables surrounding Upper Klamath Basin determined that the TNI* is significantly, positively associated with northwestern US hydrology. From a management perspective, incorporating some of the underlying climate processes should become a necessary component of a comprehensive adaptive water management plan. Since the scope of this research is mountain derived hydrology and streamflow forecast uncertainty, incorporating the TNI* into statistical seasonal streamflow prediction models becomes a priority and is therefore considered in the following section.

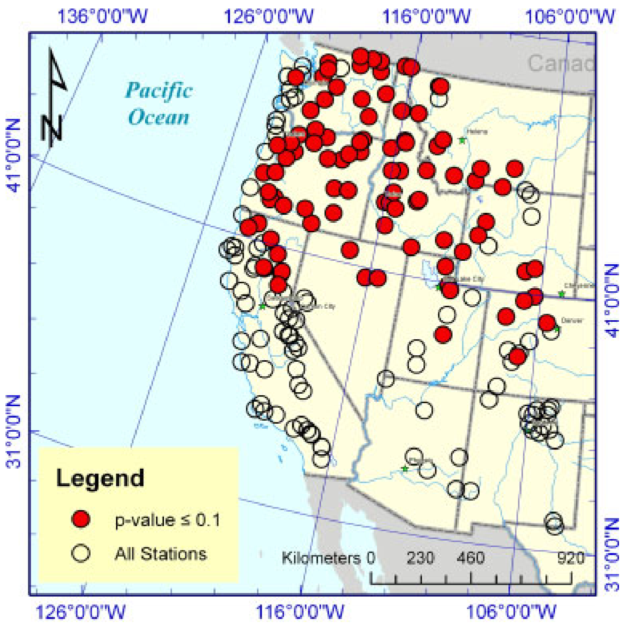

Figure 8. Preliminary Pearson correlation coefficients of Oct-Dec TNI* with Apr–Sep HCDN streamflow stations. Filled circles represent a significant correlation (p-value $\leq 0{\cdot}1$) (1951–1988)

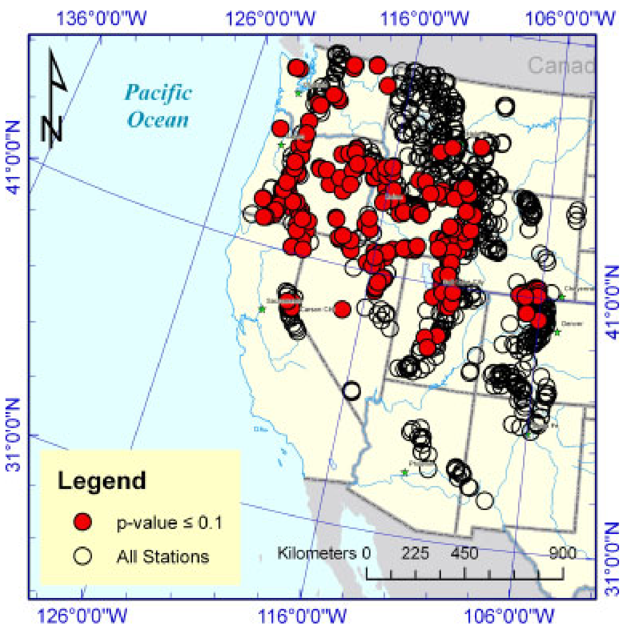

Figure 9. Preliminary Pearson correlation coefficients of Oct—Dec TNI* with 1 Apr NRCS SNOTEL/snow course stations. Filled circles represent a significant correlation (p-value $\leq 0{\cdot}1$) (1981–2003)

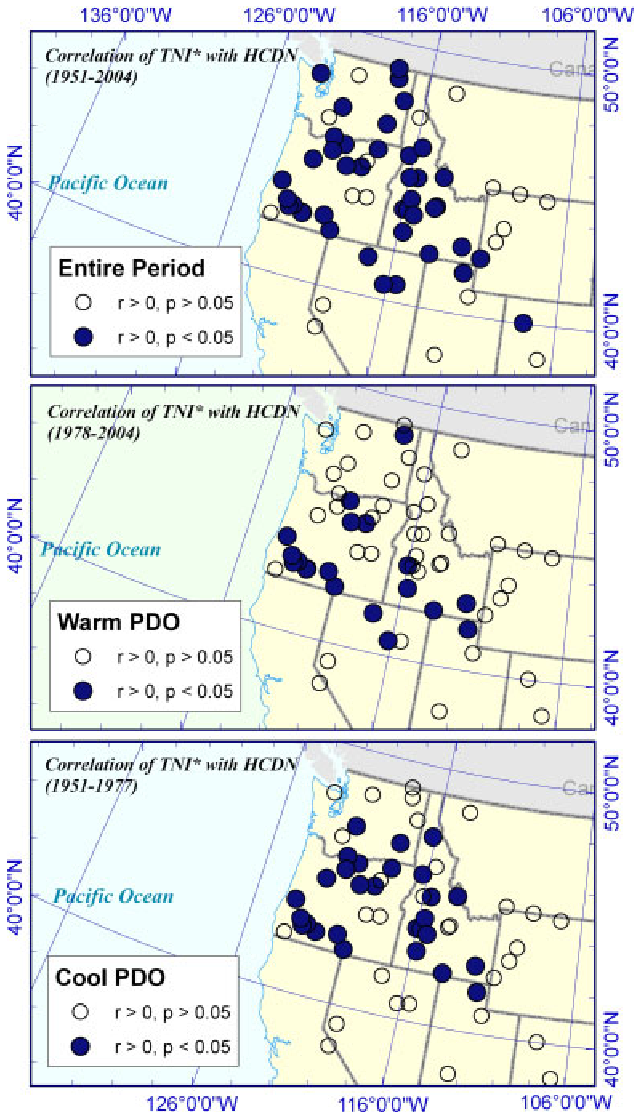

Figure 10. Final Pearson correlation coefficients between the Oct–Dec TNI* with Apr–Sep HCDN streamflow

SEASONAL STREAMFLOW PREDICTION MODELS

In the western US, seasonal weather is generated to a large degree from sea surface conditions originating in the tropical and extratropical regions of the Pacific Ocean. Quantifying the conditions of these regions prior to the period of western US maximum snow accumulation, usually occurring around March and April, may provide improved accuracy in statistical streamflow prediction models.

To improve seasonal streamflow prediction models, recent research has suggested including large-scale climate indices, particularly those derived from equatorial Pacific Ocean SST and atmospheric circulation processes, in streamflow forecast models (Grantz *et al.*, 2005). These large-scale indices are not intended to capture the natural chaotic component of weather but have been shown to characterize the offshore marine atmosphere, which in the western US drives the seasonal onshore weather patterns. Past research has shown that certain large-scale climate variables have a significant relationship to western US hydrology (Mantua *et al.*, 1997; McCabe and Dettinger, 2002; Beebee and Manga, 2004; Gedalof *et al.*, 2004; Grantz *et al.*, 2005; Tootle *et al.*, 2005; Bonsal *et al.*, 2006; Kingston *et al.*, 2006; Kingston *et al.*, 2007).

Past Upper Klamath streamflow forecast models have not utilized large-scale climate teleconnection indices because the basin is located in a region absent of the conventional large-scale climate signals associated with regional precipitation and streamflow. New information resulting from this research suggests the TNI* can be a useful regional index added to the suite of forecast variables.

Model data

Streamflow forecast models that predict streamflow volume for the upcoming spring and summer period are regularly computed monthly beginning on 1 January and continuing until 1 June using those variables only available as of the prediction date. Candidate variables include SWE, water year precipitation to date, temperature for previous months, streamflow to date, groundwater levels, and climate teleconnections to date. For the models developed in this study, SWE data were obtained from the NRCS, streamflow data were obtained from the USGS, and groundwater level data were obtained from the OWRD. Rather than using station data for precipitation and temperature, monthly mean areal precipitation and temperature data derived from gridded fields estimated by the spatial interpolation model PRISM (Daly *et al.*, 1994; http://www.ocs.orst.edu/prism) were used, as these fields do a good job of representing the high spatial variability of these quantities.

Large-scale climate variation was represented by the TNI*. The TNI* is not available until around the second week after the first of each month, which is when the National Oceanic and Atmospheric Administration publishes its SST data, and this is after the official first-of-month forecasts are published. Therefore, the TNI* period used in a forecast model must be lagged by a month. For example, a 1 November forecast would include the Jul–Sep TNI*, and the 1 December forecast would include the Aug–Oct TNI*.

Statistical design

Climate and streamflow data were compiled from each station in the Upper Klamath vicinity and then pre-screened for missing or erroneous values. Missing climate data were estimated using a linear association between the station with missing data and a nearby station. Pearson correlation coefficients were computed to determine the association between each monthly climate series and subsequent seasonal (Apr–Sep) streamflow for the Upper Williamson and Sprague. Data from individual climate stations, in addition to computed mean areal precipitation and temperature data, well correlated with seasonal streamflow were identified and included in the final operational streamflow forecast candidate variable set, from which the final model variables were chosen.

Forecast model equations were developed with a principal components analysis (PCA) based regression model (Garen, 1992). PCA is a statistically robust procedure used to reduce the original set of variables into a smaller set of uncorrelated components that represent most of the information found in the original variables. By reducing the dimensionality, a few components rather than a large number of inter-correlated variables are used in the regression. For predictive purposes, principal components can be used as independent variables in regression equations (Garen, 1992).

The accuracy of each model was determined using a cross-validation procedure, which is inspired by the jackknife technique for statistical parameter estimation (Garen, 1992). This technique withholds one year from the calibration set, and coefficients from the model calibrated without this year are used with the data for the withheld year to predict the streamflow for that year. The withheld year is returned to the data set, and this process is repeated until all years have been withheld. Then, similar to the usual regression standard error, a cross-validation or jackknife standard error (JSE) is calculated. The JSE is used to measure the optimality of each model's variable combination.

The streamflow prediction models of 1 November through 1 May were developed for both the Sprague and Upper Williamson rivers (1 June models were not developed in this study). The final variables selected resulted from the use of a search algorithm (Garen, 1992) along with judgement to include the best predictor variables that were also physically meaningful and ensured month-to-month consistency in variable usage.

Results

Results show that including the TNI* in streamflow forecast models significantly reduces uncertainty, particularly for the earlier forecasts issued up through 1 February (Figure 11). For these early forecast months, the JSEs for the models containing the TNI* are 7–10% smaller than those for models that do not contain the TNI*. Final variables for the operational forecast models are shown in Tables I and II. Note that for the Sprague, there were no other variables besides the TNI* that were of value in

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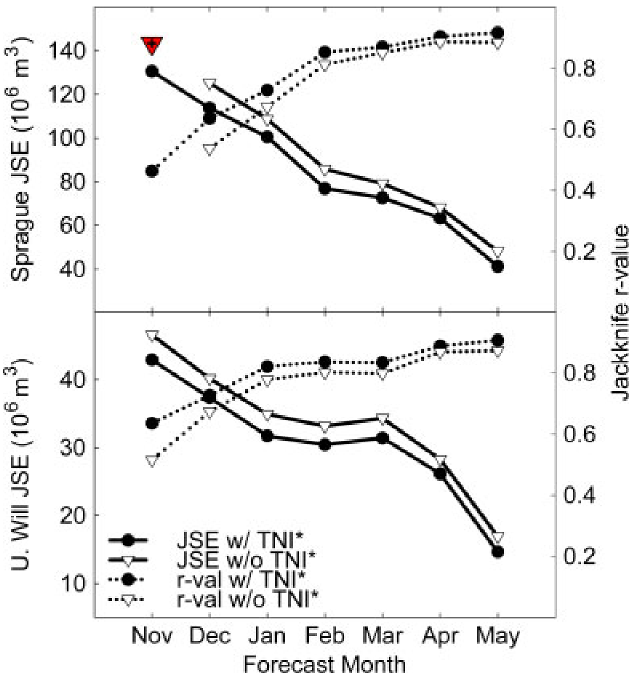

Figure 11. Sprague (upper) and Upper Williamson (lower) streamflow prediction model accuracy results. Note: November default forecast without the TNI* for the Sprague is denoted with solid triangle. JSE = jackknife standard error; r = Pearson correlation coefficient

the 1 November model, so the default 'forecast' without the TNI* is simply the long-term mean, and the standard error is the standard deviation of the Apr–Sep flow volume.

To determine the statistical significance of the difference between forecast uncertainty with and without the TNI*, one tailed paired-difference t-tests on the absolute errors of each annual prediction were used to determine if the equations that include the TNI* were statistically different from the equations that did not include the TNI*. While there was an improvement in all of the models that included the TNI* variable, statistically significant (p-value $\leq 0{\cdot}1$) differences were found in the equations for the December, January, and February forecast issue dates (Table III). The paired-difference t-test also showed significant differences in the April (Upper Williamson only) and May forecasts, but because this contradicts the perception that the TNI indexes winter precipitation and SWE, it may be preferable not to use the TNI* for these later forecasts, although it was used in this research.

SUMMARY AND CONCLUSIONS

Summary

The objective of this research was to identify a method that could be used to index future seasonal weather in the snowmelt-driven Upper Klamath Basin and ultimately reduce the uncertainty of seasonal streamflow prediction models. Because the volume of water available for irrigation, hydropower production, fish, and other uses is important in the Upper Klamath Basin, seasonal streamflow prediction models, beginning 1 November, were developed using the TNI* to predict the major inputs into Upper Klamath Lake—the Upper Williamson and Sprague rivers. Current trends in climate variability and shifts in hydrologic processes in the western US suggest that the inclusion of large-scale climate variables in regression-based streamflow models improves the accuracy and robustness of early season models during a time when total snow accumulation is incomplete.

As a result of this research, a number of important findings have surfaced with regard to the hydrology of Upper Klamath Basin.

First, there appears to be a forward shift in the timing of peak seasonal streamflow for both the Sprague and Upper Williamson rivers. Increased winter temperatures associated with increased winter precipitation falling as rain are most likely responsible for this trend. A shift to earlier peak streamflow may lead to increased spring flooding in the event of a warm spring coupled with high seasonal snowmelt runoff. Additionally, decreased snow storage in the mountainous regions may reduce the availability of water later in the season, as reservoir storage of Upper Klamath Lake may not have the capacity to store increased spring and early summer runoff volumes. Because the USBR has traditionally based most of its seasonal water-related decisions on the 1 April forecast of the Apr–Sep streamflow volume,

Table I. Forecast variables (top row) used in the Sprague River forecast models. Prediction period is Apr–Sep except for the 1 May model, which is May–Sep

Prediction date	TNI*	Quartz Mountain SWE	Strawberry SWE	Taylor Butte SWE	Summer Rim SWE	Sprague MAP	Sprague MAT	Sprague River flow
1 Nov	Jul–Sep	—	—	—	—	—	—	—
1 Dec	Aug–Oct	Dec	—	—	—	Nov	—	Nov
1 Jan	Sep–Nov	Jan	Jan	Jan	Jan	Nov, Dec	—	Nov, Dec
1 Feb	Oct–Dec	Feb	Feb	Feb	Feb	Nov, Dec	—	Nov, Dec
1 Mar	Oct–Jan	Mar	Mar	Mar	Mar	Nov, Dec, Feb	—	Nov, Dec, Feb
1 Apr	Oct–Jan	Apr	Apr	Apr	Apr	Nov, Dec, Feb, Mar	Mar	Nov, Dec, Feb, Mar
1 May	Oct–Jan	—	—	—	May	Feb, Mar, Apr	Mar, Apr	Feb, Mar, Apr

SWE, snow water equivalent; MAP, mean areal precipitation; MAT, mean areal temperature.

Table II. Forecast variables (top row) used in the Upper Williamson River forecast models. Prediction period is except for the 1 May model, which is May–Sep

Prediction date	TNI*	Chemult Alt. SWE	Diamond Lake SWE	Park. HQ SWE	Taylor Butte SWE	Silver Creek SWE	Will. MAP	Will. MAT	U.Will. River flow	Well #280 depth	Fall River flow
1 Nov	Jul–Sep	—	—	—	—	—	Oct	—	Oct	—	Oct
1 Dec	Aug–Oct	Dec	Dec	—	—	—	Oct, Nov	—	Oct, Nov	—	Nov
1 Jan	Sep–Nov	Jan	Jan	Jan	Jan	Jan	Oct, Nov	—	Nov, Dec	Seas	Dec
1 Feb	Oct–Dec	Feb	Feb	Feb	Feb	Feb	Oct, Nov	—	Nov, Dec	Seas	Jan
1 Mar	Oct–Jan	Mar	Mar	Mar	Mar	Mar	Oct, Nov, Feb	—	Feb	Seas	Feb
1 Apr	Oct–Jan	Apr	Apr	Apr	Apr	Apr	Oct, Nov, Feb, Mar	—	Feb, Mar	—	Mar
1 May	Oct–Jan	—	—	May	—	—	Feb, Mar	Apr	Feb, Mar, Apr	—	Apr

Because water level observations from Well #280 are not taken on a regular basis, a seasonal index was computed from observations recorded during October, November, and December prior to the forecast season.
HQ, headquarters, SWE, snow water equivalent; MAP, mean areal precipitation; MAT, mean areal temperature.

Table III. T-values of paired-difference test between models that included the TNI* and those that did not

Month	Upper Williamson River	Sprague River
	t-stat (t-crit = 1·319, $df = 23$, p-value $<0{\cdot}1$)	
Nov	0.977	1.260
Dec	<u>2.181</u>	<u>1.950</u>
Jan	<u>2.073</u>	<u>1.401</u>
Feb	<u>1.958</u>	<u>1.461</u>
Mar	1.057	0.650
Apr	<u>1.497</u>	0.650
May	<u>2.036</u>	<u>2.198</u>

Underlined values indicate a statistically significant difference in forecast uncertainty.

this finding suggests that the 1 March forecast is now equally as important and that the March streamflow volume should also be included in the forecast period, with all other processes required to manage the water being shifted forward accordingly.

Second, a large-scale climate index, the TNI*, was identified as being significantly associated with seasonal streamflow and 1 April SWE within and outside of the Upper Klamath Basin. This association with Upper Klamath Basin hydrology is strongest during the current warm phase of the PDO (1978–present). The climate signal begins in June, 10 months prior to the onset of peak seasonal streamflow discharge, and peaks during the Oct–Dec season, which suggests including the TNI* in operational streamflow prediction models may improve early season forecasts.

Lastly, incorporating the TNI* into Upper Klamath Basin seasonal streamflow prediction models reduces the uncertainty of early season forecasts used by the USBR to manage water volumes of Upper Klamath Lake. Results suggest that the TNI* significantly reduces the early season forecast uncertainty in the 1 December, 1 January, and 1 February forecasts (p-value $\leq 0{\cdot}1$) for both the Sprague and Upper Williamson rivers. An early, more accurate streamflow prediction model should provide the USBR with better tools to make earlier decisions regarding water resource management in the basin.

Conclusion

While other authors have experimented with different large-scale climate indicators, employing the TNI* as a tool to characterize Pacific Ocean equatorial SST gradients and modelling its association with western hydrology are unique. Recent research has associated the TNI with the Niño 3·4 climate index (Trenberth and Stepaniak, 2001) so that, while the mechanism for the observed response in the Klamath was not identified here, there has been a recent evidence that suggests onshore atmospheric conditions are driven largely by the sea surface conditions (Trenberth *et al*., 2002a,b). Furthermore, the raw SST data used in the TNI* algorithm have been linked to La Niña and El Niño conditions (Hanley *et al*., 2002). These studies suggest that a physical mechanism exists and with further research may be identified.

Water management in the Klamath will always be challenging, largely because there is insufficient water for all competing uses, especially during dry years. Streamflow forecasts are key tools in helping to manage the water. The ability to produce a more accurate and robust streamflow forecast earlier in the season, which includes a large-scale climate feature, enhances the ability to manage the scarce resource. Together with basin-wide range management, crop selection, and land and water conservation methods, improved forecast tools and local climate understanding may greatly enhance the likelihood of agricultural sustainability in the basin.

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