

University of Nevada, Reno

An Evaluation of Multi-Scalar Drought Indices in Nevada and Eastern California

A thesis submitted in partial fulfillment of the requirement for the degree of Master of
Science in Atmospheric Science

by

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Abstract

Nevada and eastern California are home to some of the driest and warmest climates, most mountainous regions, and fastest growing metropolitan areas of the United States. Throughout Nevada and eastern California snow-dominated watersheds provide most of the water supply for both human and environmental demands. Increasing demands on finite water supplies have resulted in the need to better monitor drought and its associated hydrologic and agricultural impacts. Two multi-scalar drought indices, the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI), are evaluated over Nevada and eastern California regions of the Great Basin using standardized streamflow, lake and reservoir water surface stages to quantify wet and dry periods. Results show that both metrics are significantly correlated to surface water availability, with SPEI showing slightly higher correlations over SPI suggesting that the inclusion of a simple water balance demand in SPEI is useful for characterizing hydrologic drought in arid regions. These results also highlight the utility of multi-scalar drought indices as a proxy for summer groundwater discharge and baseflow periods.

Acknowledgements

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1. Introduction

Increasing water demands and climate variability in the face of finite water supply are of particular concern in Nevada and eastern California, and across the greater southwestern U.S. Drought is a complex phenomenon that can have several different meanings; for example, a simple precipitation (P) deficit is commonly referred to as meteorological drought, while hydrologic and agricultural drought refer primarily to the availability of surface and ground water, and soil moisture (Palmer 1965, Redmond 2002, Wilhite and Buchanan-Smith 2005). Developing and validating drought indices that adequately account for different characteristics of drought has been a major area of research for many meteorologists and hydrologists (Oladipo 1985, Keyantash and Dracup 2002). While much research in the past has been devoted to identifying drought in agricultural and densely populated regions (Meyer et al. 1991, Wu et al. 2004, Mavromatis 2007), this study examines drought in Nevada and eastern California, an arid region with minimal agriculture and population, and sparse water availability.

One of the first and most highly used drought indices is the Palmer Drought Severity Index (PDSI; Palmer 1965), which is based on a simplified soil water balance. While the PDSI has been well established for adequately explaining many observed wet and dry climate cycles, it has some limitations due to the many parameterizations of the calculation, and lack of ability to detect drought for a wide range of time scales (Alley 1984, Karl 1986, Guttman 1998, Vicente-Serrano et al. 2010). With the development of the self calibrated PDSI (sc-PDSI; Wells et al. 2004) many of the limitations of the original PDSI were overcome by replacing empirically derived constants with values that

are based on the climatic data of a given location. While the sc-PDSI is an improvement over the original PDSI, it still lacks the ability to depict drought at multiple time scales. More recently, drought indices have been developed that take into consideration the multi-scalar properties. A multi-scalar index allows the user to examine wet and dry periods over a range of time scales. This is extremely important when monitoring hydrologic drought within a system that contains many surface water resources that each respond to accumulated P at different time scales. The standardized precipitation index (SPI; McKee et al. 1993) is based solely on accumulated P (Guttman 1999). It was the first widely accepted drought index to account for dry conditions at short time scales (i.e., one to three months) in regions otherwise experiencing wet conditions at longer time scales (i.e., 24-48 months). The main limitation of the SPI is that it is based entirely on P and ignores other variables which effect atmospheric water demand such as temperature (T), wind speed, solar radiation, and vapor pressure deficit. In an effort to improve upon the SPI, the standardized precipitation evapotranspiration index (SPEI) was recently developed (Vicente-Serrano et al. 2010), which incorporates T based potential evapotranspiration (PET) (Thornthwaite 1948). Vicente-Serrano (2010) demonstrated that the SPEI was able to better characterize recent drought over SPI in the arid regions that experienced significant warming over the last century. However, little research has been conducted directly comparing the performance of the SPI against the SPEI, particularly as it relates to hydrologic metrics of drought in arid regions of the United States.

Most of the municipal water supplies in the Great Basin are derived from spring snowmelt runoff, groundwater recharge, and storage, all of which have large temporal variability due to climate variability. Therefore, it is crucial for water resource managers and developers to understand how drought conditions, on both long and short timescales, will affect water availability. Drought indices such as the PDSI and the SPI have been used in the past by water resource managers and incorporated into drought management plans (Wilhite and Buchanan-Smith 2005).

Currently, the state of Nevada relies on the U. S. Drought Monitor (USDM) as its primary monitoring system along with the judgment of experts in the field to declare drought throughout the state (Nevada Division of Water Resources 2012). The USDM, one of the most widely accepted and heavily used drought monitoring tools in the United States (Svoboda et al. 2002, Anderson et al. 2011), combines several drought metrics including SPI and PDSI, along with a consensus of federal and academic scientists to produce weekly maps classifying drought in the U.S. Due to its ease of use and straightforward classification system, the USDM is being used by a number of sectors including state and federal agencies, agriculture and media (Svoboda et al. 2002). With development continuing to increase in metropolitan and rural areas and pending major inter-basin groundwater transfers planned from eastern to southern Nevada (Nevada Bureau of Land Management 2011), resolving drought metrics that track water availability is of significant interest in this region.

The primary focus of this paper is to evaluate which multi-scalar index, SPI or SPEI, is most suitable for hydrologic drought monitoring throughout Nevada and eastern

California regions of the Great Basin. This determination is accomplished by examining the relationships between SPI, SPEI and independent observations of lake and reservoir stage, and streamflow. Given the multi-scalar characteristics of the drought metrics of interest, we also seek to identify the time scale where the linkages between purely atmospheric and hydrologic observations are found within the study area. Finally, we discuss how drought has changed over the last century, and the importance of choosing a drought index that can account for potential impacts of climate change in arid regions.

2. Study Area and Climatology

The study area lies primarily within the western hydrologic Great Basin located in northern Nevada and including a portion of the eastern Sierra Nevada front in California (Figure 1). The basin and range topography and varying elevations create widespread T and P gradients, for example, annual P in mountainous areas can exceed 1250 mm, while nearby valleys receive less than 200 mm. The Great Basin is an ideal location to compare SPI and SPEI due to the fact that evapotranspiration is by far the largest outflow component of the hydrologic budget. Additionally, because of the lack of P and available soil moisture, PET greatly exceeds actual evapotranspiration (ET), as net radiation is primarily partitioned into sensible heat (i.e. heating of the air) rather than latent heat (i.e., evapotranspiration) (Huntington et al. 2011). Examining SPEI over complex terrain in an arid region can reveal useful information regarding the effects of T and PET on drought conditions that are often overlooked.

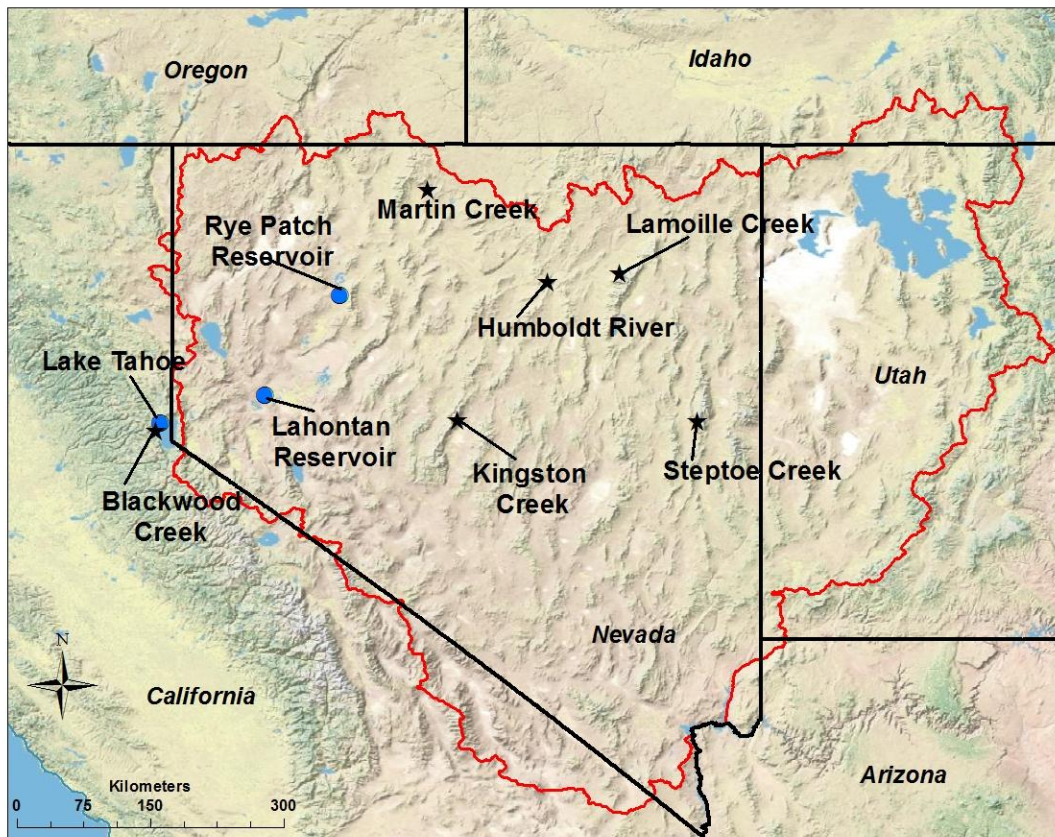


Figure 1. Study area with hydrologic Great Basin perimeter (red line), USGS lake and reservoir gages (blue dots) and USGS streamflow gages (black stars).

3. Data and Methodology

3.1 Climate data

Monthly gridded data sets of total P and maximum and minimum T at 4-km spatial resolution from the Parameter-elevation Regression on Independent Slopes Model (PRISM; Daly et al. 1994) were used in this analysis with a period of record (POR) from 1895-2010. PRISM incorporates orographic effects on P , and T inversions that are common in valley floor areas. It has been shown to outperform other available long-term

gridded climate datasets across much of the sparsely monitored landscape of central and eastern Nevada (A. Lutz, Desert Research Institute, personal communications).

3.2 Hydrologic data

Previous work has shown that hydrologic variables can serve as good indicators of drought (Chang and Kleopa 1991), and show strong relationships to SPI and SPEI at different time scales (Vicente-Serrano and López-Moreno 2005, Lorenzo-Lacruz et al. 2010, Vicente-Serrano et al. 2011a and 2011b). The timescale with the highest correlations will depend on the type and characteristics of the water body (i.e., lake or stream) and the surrounding watershed (i.e., managed/unmanaged, drainage area, etc.). To evaluate the correlations between SPI and SPEI and hydrologic states and fluxes, several streams, lakes, and reservoirs throughout the study area were chosen for analysis. Hydrologic data of water stage and streamflow were obtained from the United States Geologic Survey (USGS), and site characteristics are summarized in Table 1. Two reservoirs, one lake, five streams and one river (Table 1, Figure 1) were chosen and a *POR* of 1960-2010 was used everywhere except for Kingston Creek and Steptoe Creek, where observations began in 1966, and a *POR* of 1966-2010 was used. Although water releases from lakes and reservoirs are anthropogenically controlled, natural wet and dry cycles are still clearly evident in the historical time series.

Station Name and Type	Period of Record Used	Gage Elevation (m)	Hydrologic Parameter
Lake Tahoe at Tahoe City, CA (lake)	1960-2010	1,896	gage elevation (ft.)
Blackwood Creek near Tahoe City, CA (stream)	1960-2010	1,900	streamflow (cfs)
Rye Patch Reservoir near Rye Patch, NV (reservoir)	1960-2010	1,255	gage elevation (ft.)
Lahontan Reservoir near Fallon, NV (reservoir)	1960-2010	1,268	gage elevation (ft.)
Humboldt River at Palisade, NV (river)	1960-2010	1,471	streamflow (cfs)
Martin Creek near Paradise Valley, NV (stream)	1960-2010	1,433	streamflow (cfs)
Kingston Creek below Cougar Canyon near Austin, NV (stream)	1966-2010	1,975	streamflow (cfs)
Lamoille Creek near Lamoille, NV (stream)	1960-2010	1,902	streamflow (cfs)
Steptoe Creek near Ely, NV (stream)	1966-2010	2,268	streamflow (cfs)

Table 1. Summary of USGS stations used in study

3.3 Drought index calculations

Input variables required for computing each index include a time series of total monthly P for SPI, P minus PET for SPEI, and average monthly lake or reservoir stage and streamflow for standardized hydrologic variables. Following the approach of Vicente-Serrano et al. (2010) for computing SPEI, monthly PET was calculated using the Thornthwaite equation (Thornthwaite 1948), which relies on average monthly T and latitude to calculate monthly average day length. Other methods for computing PET , which incorporate more physically based parameters including wind speed, solar radiation and vapor pressure deficit (e.g., Penman-Monteith (Allen et al. 1998)), are desirable for use in the SPEI. Unfortunately, lack of reliable long-term data prohibits an accurate calculation of the Penman-Monteith over a long POR , which is why the T -based Thornthwaite approach was used (Vicente-Serrano et al. 2010).

The SPI and SPEI are multi-scalar in nature meaning that they can be examined across a spectrum of time scales. For example, a 6-month SPI for October would require input of P accumulated between May thru October, while a 12-month SPEI for October would require input of P minus PET accumulated over the previous 12 months. For this study SPI and SPEI were calculated at time scales of 1 through 12-, 15-, 18-, 24-, 30-, 36-, 48-, 60-, and 72-months. Standardized hydrologic variables were only calculated at the 1-month time scale, so no aggregation of the monthly time series was necessary.

All drought indices were calculated following the same procedure: standardization of the probability distribution of each aggregated time series. Various probability distributions have been tested extensively and used in the past to compute SPI such as the two parameter Gamma distribution (McKee et al. 1993), the Pearson III distribution (Guttman 1999, Vicente-Serrano and Lopez-Moreno 2005) and the three parameter log-logistic distribution (Vicente-Serrano et al. 2011b). The log-logistic distribution has also been used to compute SPEI (Vicente-Serrano et al. 2010) and standardized streamflow (Vicente-Serrano et al. 2011a). Therefore, we chose to use the log-logistic distribution following Singh et al. (1993) and Vicente-Serrano (2010) to standardize all of our variables in order to obtain accurate comparisons. The probability weighted moments (Greenwood et al. 1979, Hosking 1990) were first obtained in order to calculate the parameters of the probability distribution function. The final step was to standardize the probabilities using an inverse normal function (Abramowitz and Stegun 1965, Vicente-Serrano 2010). The average value of each standardized time series is zero, negative values indicate drier than normal conditions, and positive values indicate wetter

than normal conditions. Each standardized hydrologic time series was then correlated with corresponding SPI and SPEI using Pearson's linear correlation coefficient. Spatially averaged SPI and SPEI data from within the watershed boundaries of each water body were used in the correlations.

4. Results

When examining time series of SPI and SPEI at the 1-month time scale, it is evident that SPI reaches a maximum negative value consistently through time (Figure 2). This is due to the fact that the region near Mina, NV, approximately 200 km to the southeast of Lake Tahoe, regularly experiences months with no P , especially during the summer season. Therefore, the 1-month SPI values will not vary for as long as no P is recorded for that given month. At longer time scales of 12-, 48- and 72-months timescales SPI fails to capture the severity of the well known drought period that occurred during a portion of the first decade of the 21st century (e.g., Cook et al. 2004, Cook et al. 2007) that contributed to significant statewide reservoir depletions in Nevada along with vegetation mortality throughout much of the southwestern United States (Breshears et al. 2005, Mueller et al. 2005, Cook et al. 2007).

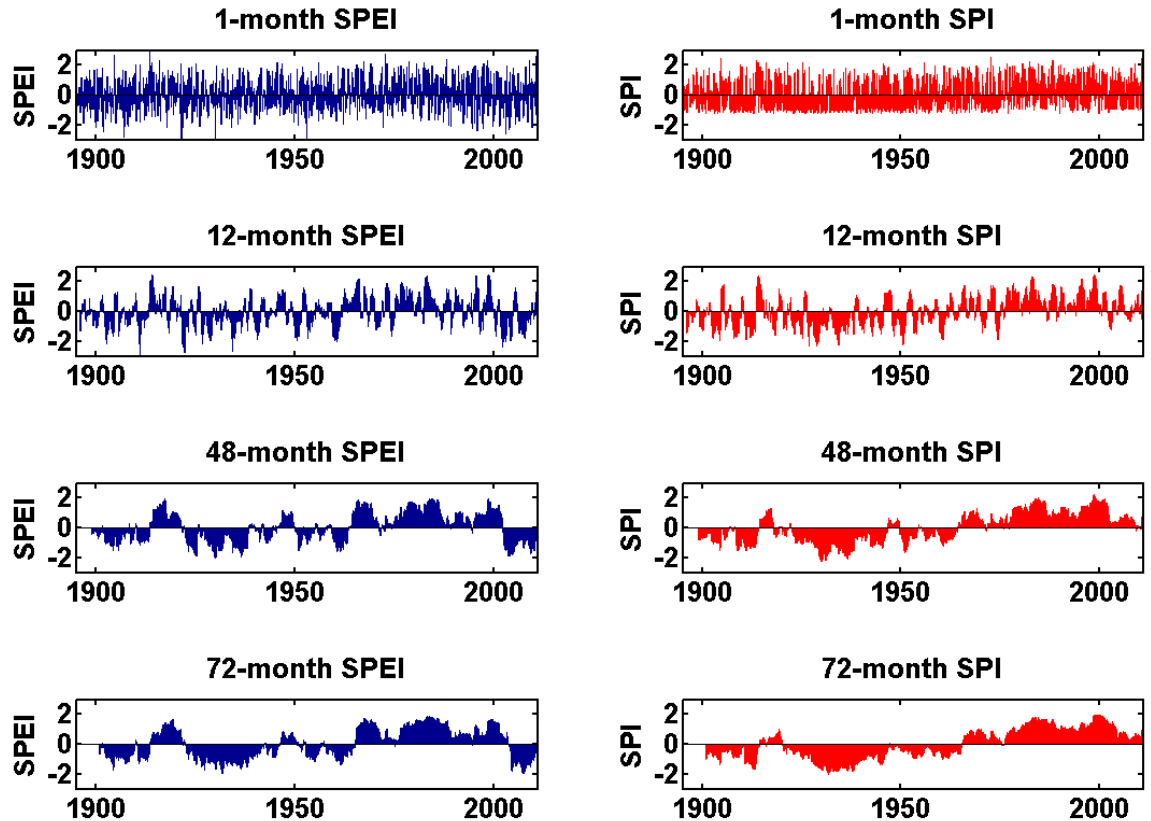


Figure 2. Historical time series of SPEI (blue) and SPI (red) near Mina, NV at 1-, 12-, 48- and 72- month time scales.

The anomalously high T that contributed to a greater atmospheric water demand played a significant role in causing severe drought conditions in the early 2000's when compared with droughts throughout the 20th century (Breshears et al. 2005, Weiss et al. 2009) that are clearly distinguished with SPEI. This can be seen in the 6-month SPEI and SPI for August 2007 shown in Figure 3. During the spring and summer (March through August) of 2007, the western U.S. experienced record warmth (Figure 3d; Levinson and Lawrimore 2008) that contributed to high PET values over the study area, and is reflected in the severity of SPEI (Figure 3a) when compared to SPI (Figure 3b). The differences

shown in Figure 3c highlight the sensitivity of SPEI to T in the arid (i.e., more water-limited) regions of west-central Nevada and eastern California, while small differences are found over the most energy-limited (i.e., higher P) mountainous regions of the Sierra Nevada range. Based on Guttman's (1999) SPI classification system, the differences shown in Figures 3c suggest that in the most water-limited regions of the study area SPEI and SPI are signaling different drought classes with SPEI indicating more severe drought conditions.

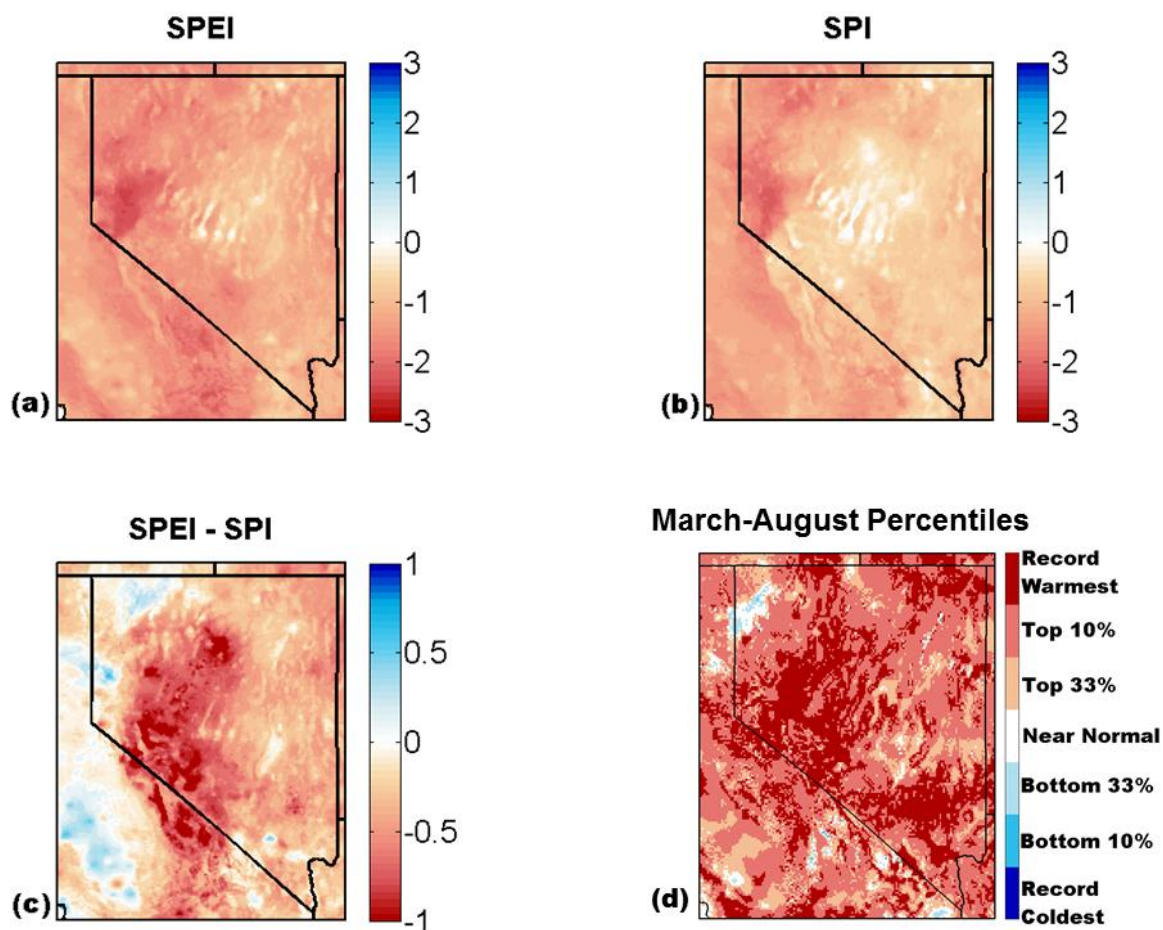


Figure 3. August 2007 6-month SPEI (a), SPI (b), and SPEI – SPI (c). The March-August 2007 mean temperature percentiles are displayed in Figure 3d. The percentile rankings are based on data from 1895-2010.

To gain a better understanding of the sensitivity of SPEI to T , we also examined 6-month SPEI (Figure 4a) and SPI (Figure 4b) for February 1960, when below to near normal T was present in most of the region.

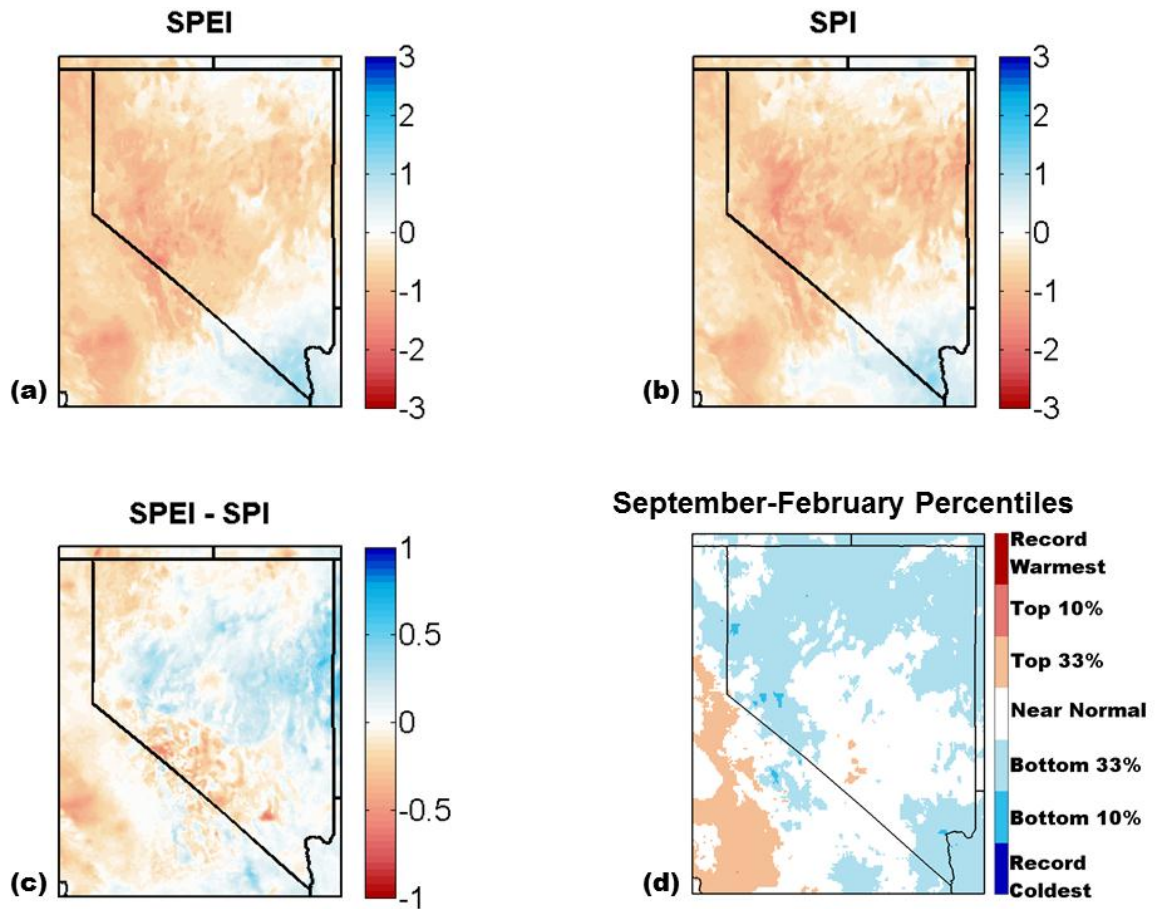


Figure 4. February 1960 6-month SPEI (a), SPI (b), and SPEI – SPI (c). The September-February 1960 mean temperature percentiles are displayed in Figure 4d. The percentile rankings are based on data from 1895-2010.

Both SPEI and SPI indicate moderate drought conditions over most of the central portion of the study area; however, in contrast to Figure 3c, Figure 4c reveals much smaller difference between SPEI and SPI. Some small isolated areas of larger differences (SPEI – SPI approaching -1) do exist, but the area covered is significantly smaller than during

the summer of 2007 drought and positive differences ($SPEI > SPI$) are much more widespread. One similarity between Figure 3c and Figure 4c is that small differences between SPEI and SPI were found over the Sierra Nevada range. This indicates that in the higher elevations with much higher P and lower T than the valley floors, using a drought index that includes PET is not as crucial. These results suggest that the differences between a T driven SPEI and SPI will continue to grow and SPEI will continue to indicate greater drought severity if the increasing surface T trend continues in the western U.S. as predicted by regional climate models (e.g., Rauscher et al. 2008), especially in arid regions.

Figure 5 illustrates the continuous correlations between standardized stage for Lake Tahoe (Figure 5a), Rye Patch Reservoir (Figure 5b), Lahontan Reservoir (Figure 5c), and derived SPI and SPEI for all time scales. The time series of each standardized stage along with SPEI and SPI at the time scale when maximum continuous correlations were found are shown in Figure 6. Similar results were found at Lake Tahoe and Rye Patch where SPEI showed slightly better correlations for all time scales. The highest correlation ($R = 0.88, p < 0.05$) with SPEI was found at Lake Tahoe at the 48-month time scale (Figure 5a and 6a), however high correlations ($R > 0.8, p < 0.05$) were also found at time scales of 30-60 months. At Rye Patch reservoir correlations were lower, with the highest SPEI correlations ($R > 0.60, p < 0.05$) occurring at time scales of 24-36 months. These results show that in general Lake Tahoe and Rye Patch reservoir take several years to respond to drought (2-4 years), and both SPEI and SPI have the ability to characterize this response; however, SPEI offers a slight advantage.

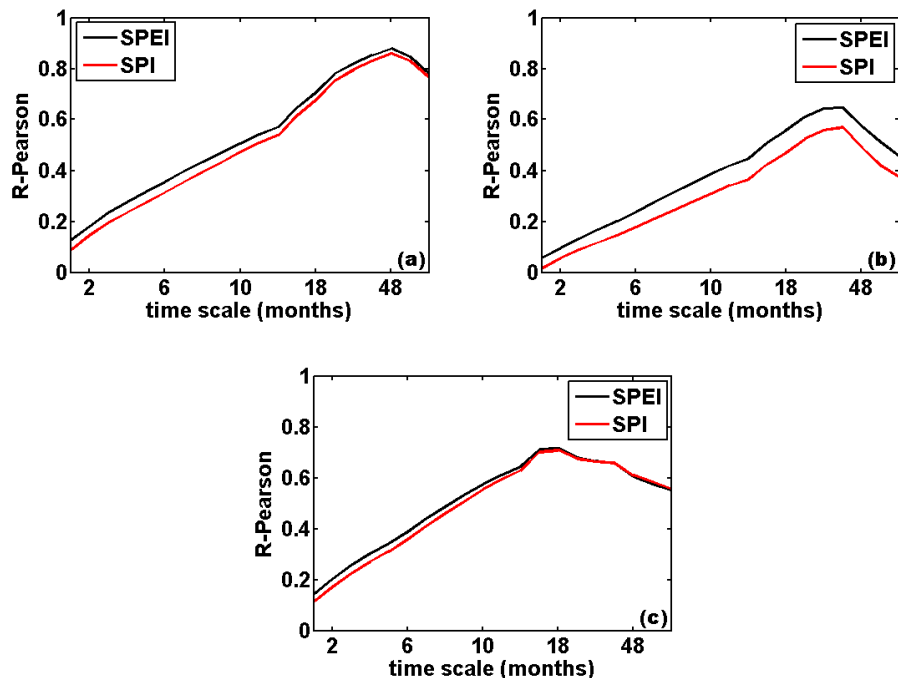


Figure 5. Correlations between standardized lake and reservoir stages at Lake Tahoe (a), Rye Patch Reservoir (b), Lahontan Reservoir (c) and PRISM based drought indices. SPEI and SPI were computed at time scales of 1 through 12-, 15-, 18-, 24-, 30-, 36-, 48-, 60- and 72- months.

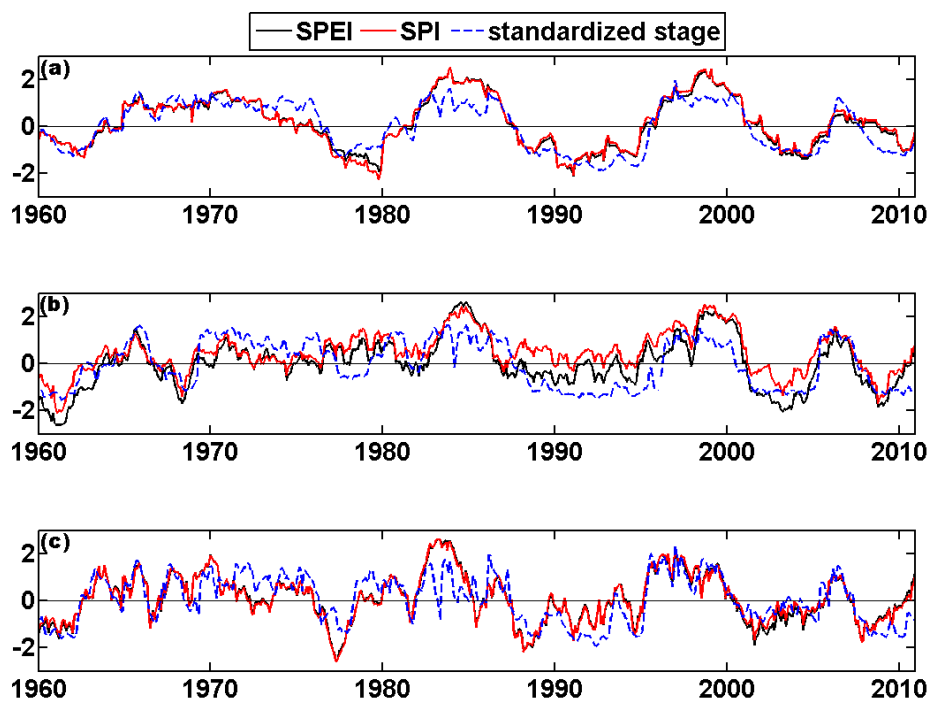


Figure 6. Continuous time series of SPEI (black) and SPI (red) at the 48-month time scale for Lake Tahoe (a), 30-month time scale for Rye Patch Reservoir (b) and 18-month time scale for Lahontan Reservoir (c). Continuous time series of monthly standardized lake and reservoir stage is displayed in blue.

The low correlations found at short time scales (< 6-month) are a reflection of the corresponding high frequency signals of SPEI and SPI. While these shorter time scale indices are still important for drought monitoring, they do not reflect the hydrologic drought conditions of the lakes and reservoirs described in this paper.

Clearly evident in Figures 6a and 6b are the anthropogenic impact from water releases during wet periods, where the standardized stage of Lake Tahoe and Rye Patch reservoir is typically below the SPEI and SPI. Controlled releases of stored water due to limited capacity prevents the continued rise of lake and reservoir stages, making for lower standardized stage during extended wet periods of the mid 1980s and late 1990s. A similar pattern is seen during dry periods, when standardized lake and reservoir stage is higher than SPEI and SPI. In these cases water conservation efforts correspond with minimum releases and fairly steady minimum stages, which typically persist until the next wet period. The exception to this is during the early 1990s when Lake Tahoe reached its lowest level on record. During this extended dry period the lake fell below its natural rim, and no water was able to be released into the Truckee River for an extended period of time. Lahontan Reservoir maximum correlations (Figures 5c and 6c) were found at small time scales (15-24 months), which is a result of the small storage volume of Lahontan compared to Lake Tahoe.

Figure 7 shows the monthly correlations between SPEI and standardized lake and reservoir stage at various time scales. Maximum monthly correlations were found at similar time scales to the continuous correlations at Lake Tahoe (Figure 7a) and Rye Patch Reservoir (Figure 7b) and small variations were seen month to month when

correlations were strongest. This makes sense since high correlations were found at time scales greater than one year. The lower frequency signals of SPEI at these time scales (30-48 month) along with the stage levels do not vary significantly from month to month. At Lahontan Reservoir (Figure 7c) the highest monthly correlations were found at the 10-15 month time scales, which differ from the continuous correlations found in Figure 5c. Greater monthly variability in stage, which may be a result of significant management and upstream diversions along with the smaller storage volume of Lahontan, has led to more significant monthly differences in correlations with SPEI and stronger correlations during the late summer months.

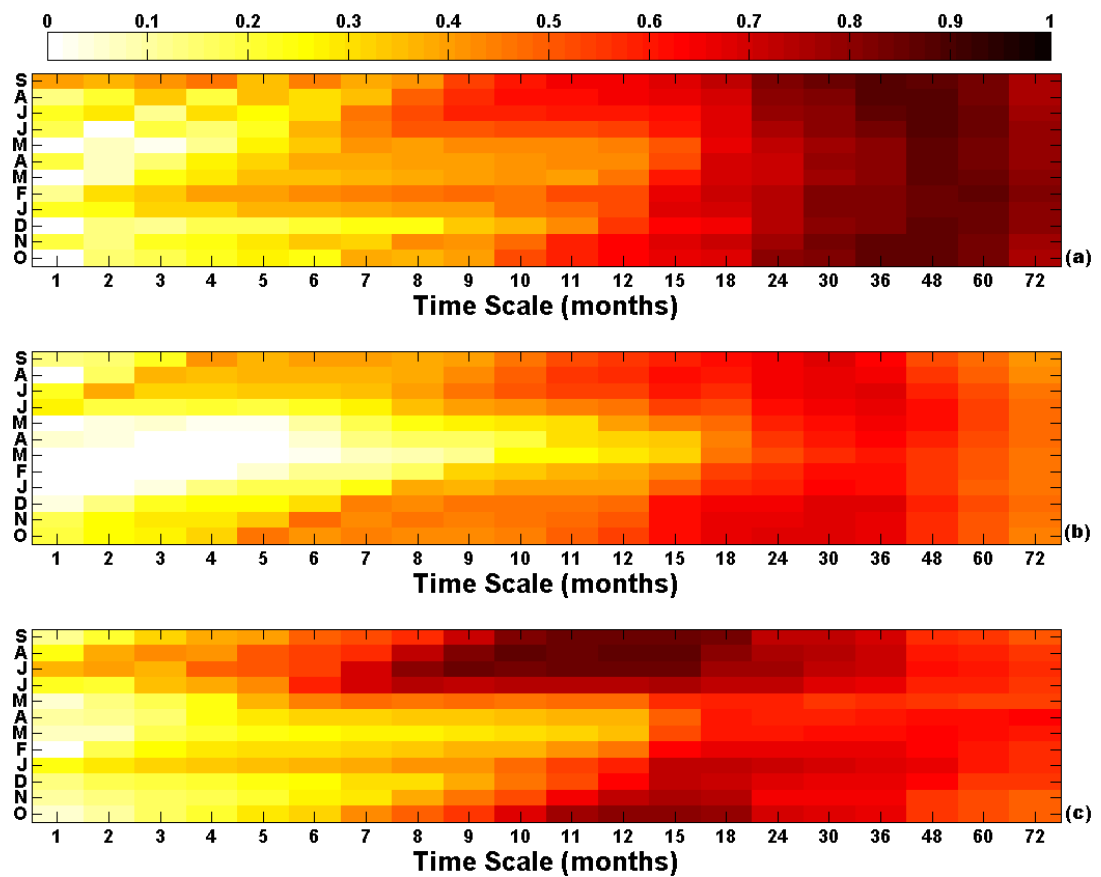


Figure 7. Monthly correlations between SPEI and standardized stage at Lake Tahoe (a), Rye Patch Reservoir (b), and Lahontan Reservoir (c) with the months of the water year (October-September) on the y-axis.

Correlations between SPEI and SPI and standardized streamflows were consistent with results from lakes and reservoirs, where SPEI shows slightly better correlations than SPI; however, differences between SPEI and SPI are considerably smaller. The two highest correlations ($R = 0.78$ and $R = 0.76$, $p < 0.05$) were found between SPEI and Steptoe Creek (Figure 8c) and Kingston Creek (Figure 8d) at the 15-month time scale, respectively.

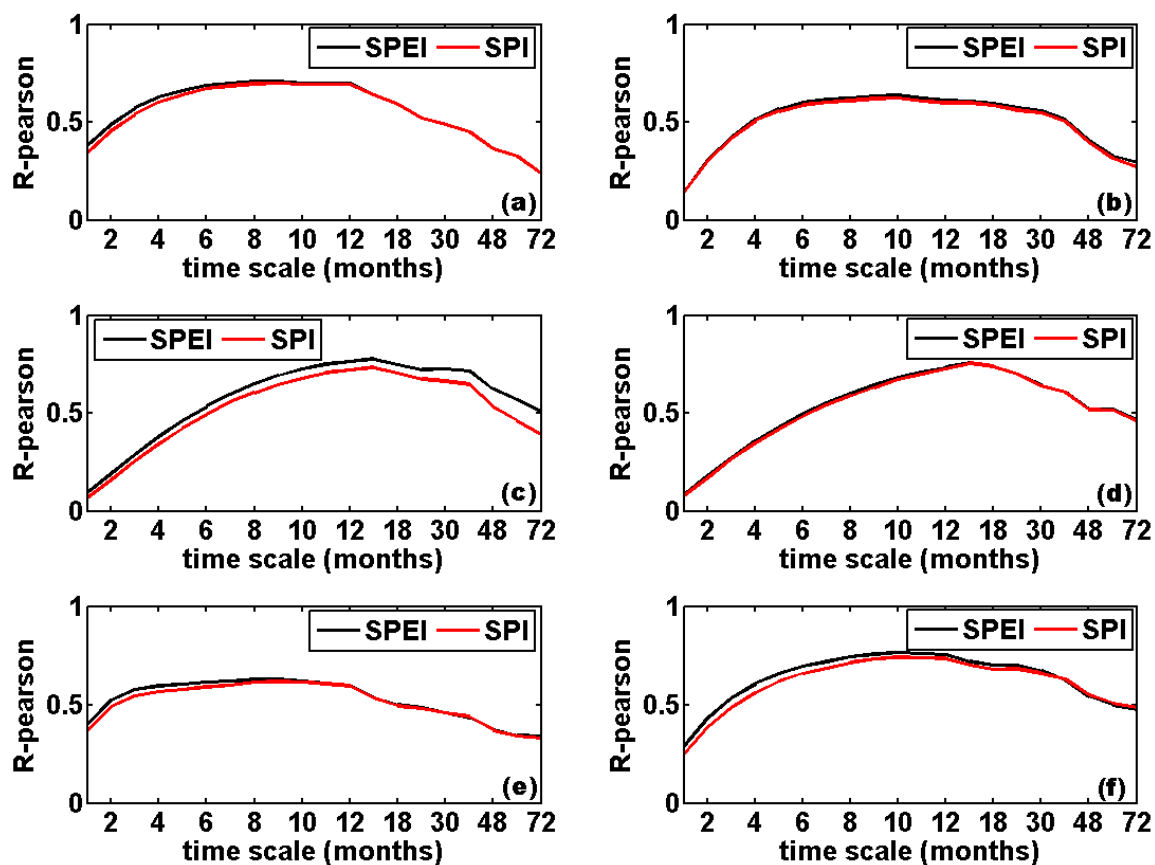


Figure 8. Correlations between PRISM based drought indices and standardized stream flow at Blackwood Creek (a), Lamoille Creek (b), Steptoe Creek (c), Kingston Creek (d), Martin Creek (e) and the Humboldt River (f).

In general, all of the highest correlations occurred between the 8-15 month time scales. This result is a fairly obvious one due to minimal watershed aquifer storage in crystalline mountain block and narrow alluvial valleys, making for a relatively fast hydroclimate response. Correlations were also examined for individual months to gain a better understanding of the watershed response to seasonal and annual climate variability. Figure 9 illustrates monthly correlations for different time scales at all streams. The general pattern shows the highest correlations occurring during June through August at the 8-12 month time scales.

Figure 10a illustrates the well correlated times series of August standardized streamflow and August 12-month SPEI for Blackwood Creek. This high correlation exists due to the fact that September – August cumulative P and groundwater recharge highly covaries with August groundwater discharge to streams (i.e., baseflow). On average 90 percent of the annual P in this region falls between the months of October and May, and the majority of groundwater recharge from snowmelt occurs between the months of March and June. Groundwater recharge discharges from the mountain block and thin alluvial aquifers to the stream as baseflow during the late summer and fall months of July-September. The magnitudes of these fluxes vary significantly from year to year as shown in Figure 10b, which illustrates the logarithm of streamflow to highlight the high variability in late summer and early fall baseflow periods.

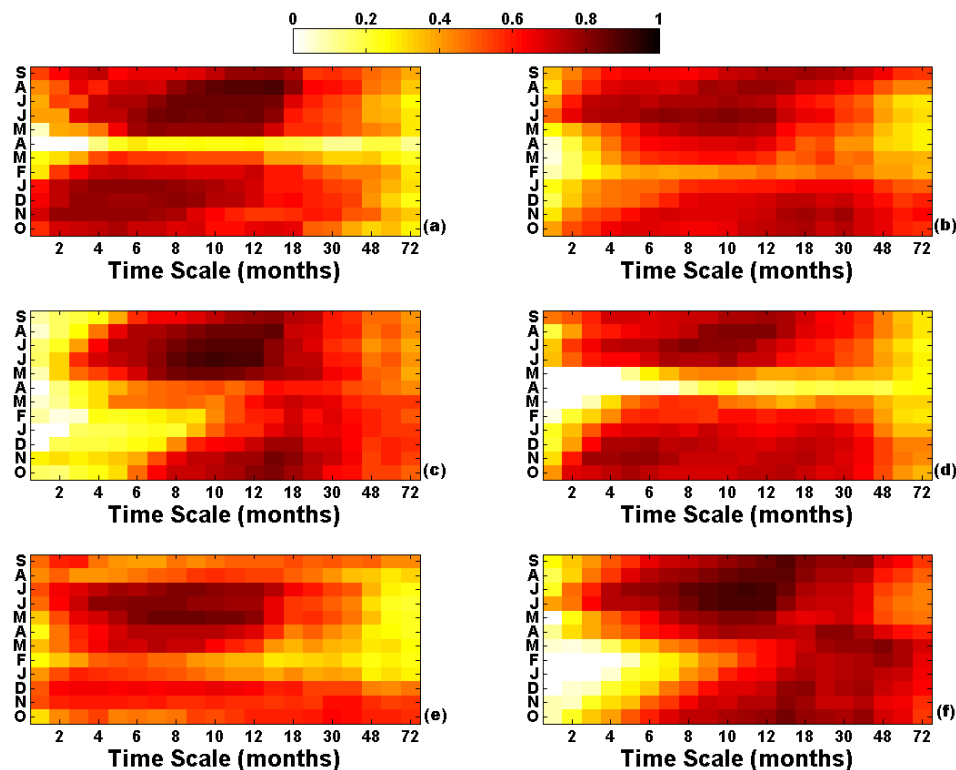


Figure 9. Monthly correlations between SPEI and standardized streamflow at Blackwood Creek (a), Humboldt River at Palisade (b), Kingston Creek (c), Lamoille Creek (d), Martin Creek (e) and Steptoe Creek (f) with the months of the water year (October-September) on the y-axis.

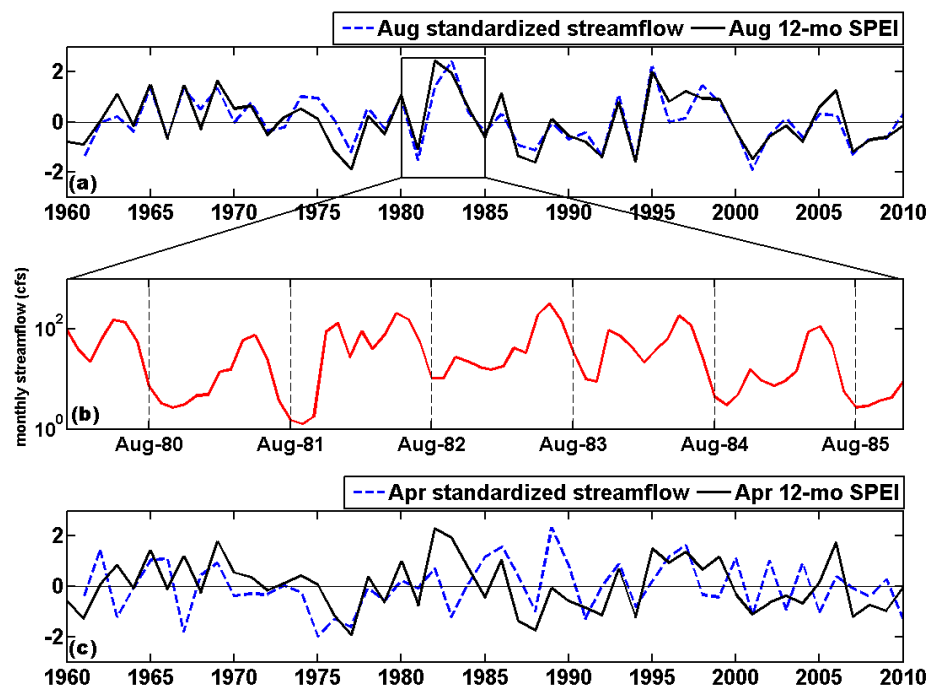


Figure 10. August standardized streamflow at Blackwood Creek and 12-month spatially averaged SPEI from corresponding watershed grid cells (a). Continuous monthly streamflow at Blackwood Creek between 1980 and 1985 (b). April standardized streamflow at Blackwood Creek and 12-month spatially averaged SPEI from corresponding watershed grid cells (c).

For example, the winter of 1980-81 was extremely dry and Blackwood Creek standardized streamflow, SPEI and baseflow (1.53 cfs) were quite low during August 1981 (Figure 10a and 10b). The following several winters were extremely wet, and are reflected in the August standardized streamflow, SPEI and baseflow (10.35 cfs in August 1982 and 36.13 cfs in August 1983). April clearly stands out as the only month with low correlations for all time scales at Blackwood Creek (Figure 9a) and Lamoille Creek (Figure 9d), and to a lesser degree at Kingston Creek (Figure 9c). All three of these sites are at similar elevation (1900-1975 m), and high alpine watersheds with shallow soils and thin alluvial aquifers feed flows at these gages. Another factor contributing to the low correlations is that April is a highly variable month for P and T throughout the study area, which can lead to rapid fluctuations of snow melt and streamflow. At Blackwood Creek, some winters like 1981-82 and 1982-83 can bring heavy snowfall and low T , which is reflected in the high 12-month April SPEI (Figure 10c). High snowpack and low April T contribute to low corresponding streamflow during these periods. Years with considerably less snowpack in April (e.g., April 1989) along with a dry month and high T will generate high stream flow throughout the month. These factors combined leads to a weak relationship between April streamflow and April SPEI or SPI. At Humboldt River (Figure 9b) and Martin Creek (Figure 9e), the two lower elevation (1433-1471 m) sites, consistently low correlations were found during the month of February indicating an earlier onset of highly variable streamflow.

5. Discussion and conclusions

This analysis evaluated spatial and temporal differences between SPEI and SPI, while comparing each index to standardized hydrologic variables throughout Nevada and eastern California. These multi-scalar indices were investigated because of their ability to detect a variety of drought types (Guttman 1999, McKee et al. 1993, Vicente-Serrano and Lopez-Moreno 2005, Vicente-Serrano et al. 2010), and overcome some of the limitations of the PDSI (Alley 1984, Karl 1986, Vicente-Serrano et al. 2010). Both indices appear to detect the major well-documented drought periods of the first half of the 20th century (Cook et al. 2004, Weiss et al. 2009); however, during the late 20th and early 21st century the magnitude of drought severity indicated by SPEI was not seen with SPI. Upon further inspection of the spatial patterns of SPEI and SPI during a cool period both indices were able identify drought periods and minor differences were found. While both SPEI and SPI were able to detect hydrologic droughts at different time scales when compared to standardized streamflow and lake and reservoir stage, SPEI consistently showed marginal improvement in correlations over SPI. Our results also highlight the inability of SPI at the 1-month time scale to detect the severity of drought indicated by SPEI in regions that regularly experience no *P* during some months of the year. During these periods, the SPI often indicated “neutral” drought conditions based on the classifications of Guttman (1999).

In summary, both SPEI and SPI proved to be useful for hydrologic drought monitoring at longer time scales, with SPEI offering some advantage over SPI. We have shown that computing drought indices at longer time scales (18-48 months) is important to the region when assessing hydrologic drought as available surface water in lakes and reservoirs can take several years to respond to accumulated precipitation. In addition, our

spatial analysis illustrates large differences between SPEI and SPI in and around valley floor areas, where most of the region's population resides. We suggest SPEI be considered as a regular input to the USDM, which is becoming heavily used by decision makers, as it can provide additional information regarding effects of atmospheric water demand on drought at longer time scales that cannot be found with PDSI, sc-PDSI or SPI.

While the strength of SPEI is the incorporation of T and PET , we have shown that it may be overly sensitive to T as a driver of PET . It has been suggested that empirical formulas for PET , similar to the Thornthwaite equation (1948) that ignores the full energy balance, could be more indicative of T trends as opposed to changes in water demand (Milly and Dunne 2011, Hobbins and Wood 2008). This leads to the question: is the severity of the 21st century drought as depicted by SPEI simply an indicator of the recent warm T trend, or does it represent a substantial decrease in the amount of water at the surface available for ET? Therefore, for future work it would be useful to examine physically based PET formulations for developing drought indices that incorporate vapor pressure deficit, downward solar radiation, aerodynamic considerations, land surface energy balance and near surface boundary layer feedbacks between actual ET and PET (Huntington et al. 2011, Anderson et al. 2011, Hobbins and Wood 2008).

This paper demonstrates that the inclusion of a simple water demand term in the SPEI can provide improved information in representing hydrologic drought variability in arid regions. While many drought indices exist to classify hydrological and agricultural drought, evaluation and future development of drought indices that are physically based and include land surface and atmospheric feedbacks will continually be an important aspect of research for assessing hydroclimatic variability and water availability.

References

- Abramowitz, M. and I. A. Stegun, 1965: *Handbook of Mathematical Functions, with Formulas, Graphs, and Mathematical Tables*. Dover Publications, 1046 pp.
- Allen, R. G., L. S. Pereira, D. Raes, and M. Smith, 1998: Crop evapotranspiration, guidelines for computing crop water requirement. FAO Irrig. and Drain. Paper 56, Food and Agricultural Organization of the United Nations. Rome, Italy. 300.
- Alley, W. M., 1984: The Palmer drought severity index: limitations and applications. *J. Climate Appl. Meteor.*, **23**, 1100-1109.
- Anderson, M. C., C. Hain, B. Wardlow, A. Pimstein, J. R. Mecikalski, and W. P. Kustas, 2011: Evaluation of drought indices based on thermal remote sensing of evapotranspiration over the continental United States. *J. Climate*, **24**, 2025-2044.
- Breshears, D. D., N. S. Cobb, P. M. Rich, K. P. Price, C. D. Allen, R. G. Balice, W. H. Romme, J. H. Kastens, M. L. Floyd, J. Belnap, J. J. Anderson, O. B. Myers, and C. W. Meyer, 2005: Regional vegetation die-off in response to global-change-type drought. *Proc. Nat. Acad. Sci.*, **102**, 15144-15148.
- Cook, E. R., C. A. Woodhouse, C. M. Eakin, D. M. Meko, D. W. Stahle, 2004: Long-term aridity changes in the western United States. *Science*, **306**, 1015-1018.
- Cook, E. R., R. Seager, M. A. Cane, and D. W. Stahle, 2007: North American drought: reconstructions, causes, and consequences. *Earth-Science Rev.*, **81**, 93-134.
- Chang, T. J. and X. A. Kleopa, 1991: A proposed method for drought monitoring. *Water Resour. Bull.*, **27.2**, 275-281.
- Daly, C., R. P. Neilson, and D. L. Phillips, 1994: A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *J. Appl. Meteor.*, **33**, 140-158.
- Greenwood, J. A., J. M. Landwehr, N. C. Matalas, and J. R. Wallis, 1979: Probability weighted moments: definition and relation to parameters of several distributions expressible in inverse form. *Water Resour. Res.*, **15**, 1049-1054.
- Guttman, N. B., 1998: Comparing the Palmer drought index and the standardized precipitation index. *J. Amer. Water Resour. Assoc.*, **34**, 113-121.
- Guttman, N. B., 1999: Accepting the standardized precipitation index: a calculation algorithm. *J. Amer. Water Resour. Assoc.*, **35**, 311-322.

- Hobbins, M. T., A. Dai, M. L. Roderick, and G. D. Farquhar, 2008: Revisiting the parameterization of potential evaporation as a driver of long-term water balance trends. *Geophys Res Lett*, **35**, L12403, doi:10.1029/2008GL033840
- Hosking, J. R. M., 1990: L-moments: analysis and estimation of distributions using linear combinations of order statistics. *J. Royal Statistical Soc.*, **52B**, 105-124.
- Huntington, J. L., J. Szilagyi, S. W. Tyler, and G. M. Pohll, 2011: Evaluating the complementary relationship for estimating evapotranspiration from arid shrublands. *Water Resour. Res.*, **47**, 1-11.
- Karl, T. R., 1986: The sensitivity of the Palmer drought severity index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. *J. Climate Appl. Meteor.*, **25**, 77-86.
- Keyantash, J. A., and J. A. Dracup, 2002: The quantification of drought: an evaluation of drought indices. *Bull. Amer. Meteor. Soc.*, **83**, 1167-1180.
- Levinson, D. H. and J. H. Lawrimore, 2008: State of the climate in 2007. *Bull. Amer. Meteor. Soc.*, **89.7**, 179 pp.
- Lorenzo-Lacruz, J., S. M. Vicente-Serrano, J. I. López-Moreno, S. Beguería, J. M. García-Ruiz, and J. M. Cuadrat, 2010: The impact of droughts and water management on various hydrological systems in the headwaters of the Tagus River (central Spain). *J. of Hydrol.*, **386**, 13-26.
- Mavromatis, T., 2007: Drought index evaluation for assessing future wheat production in Greece. *Int. J. Climatol*, **27**, 911-924.
- McKee, T. B., N. J. Doesken, and J. Kleist, 1993: The relationship of drought frequency and duration to time scales. *8th Conf. on Applied Climatology*, Boston, MA, Amer. Meteor. Soc., 179-184.
- Meyer, S. J., K. G. Hubbard, and D. A. Wilhite, 1991: The relationship of climatic indices and variables to corn (maize) yields: a principal components analysis. *Agr. Forest Meteorol.*, **55**, 59-84.
- Milly, P. C. D. and K. A. Dunne, 2011: On the hydrologic adjustment of climate-model projections: the potential pitfall of potential evapotranspiration. *Earth Interact.*, **15**, doi: 10.1175/2010EI363.1

- Mueller, R. C., C. M. Scudder, M. E. Porter, R. T. Trotter III, C. A. Ghering, and T. G. Whitham, 2005: Differential tree mortality in response to severe drought: evidence for long-term vegetation shifts. *J. Ecology*, **93**, 1085-1093.
- Nevada Bureau of Land Management, 2011: *Clark, Lincoln, and White Pine counties groundwater development project draft environmental impact statement*. Vol. 1 A.
- Nevada Division of Water Resources, Division of Energy Management, and State Climate Office, 2012: *State of Nevada Drought Plan*. Reno, NV.
- Oladipo, E. O., 1985: A comparative performance analysis of three meteorological drought indices. *J. Climate*, **5**, 655-664.
- Palmer, W. C., 1965: Meteorological drought. U.S. Department of Commerce Weather Bureau Research Paper 45, 58pp.
- Rauscher, S. A., J. S. Pal, N. S. Diffenbaugh, and M. M. Benedetti, 2008: Future changes in snowmelt-driven runoff timing over the western US. *Geophys. Res. Lett.*, **35**, L16703, doi: 10.1029/2008GL034424.
- Redmond, K. T., 2002: The depiction of drought. *Bull. Amer. Meteor. Soc.*, **83**, 1143-1147.
- Singh, V. P., H. Guo, and F. X. Yu, 1993: Parameter estimation for 3-parameter log-logistic distribution (LLD3) by Pome. *Stochastic Hydrol. Hydraul.*, **7**, 163-177.
- Svoboda, M., D. LeCompte, M. Hayes, R. Heim, K. Gleason, J. Angel, B. Rippey, R. Tinker, M. Palecki, D. Stooksbury, D. Miskus and S. Stephens, 2002: The drought monitor. *Bull. Amer. Meteor. Soc.*, **83**, 1181-1190.
- Thornthwaite, C. W., 1948: An approach toward a rational classification of climate. *Geogr. Rev.*, **38**, 55-94.
- Vicente-Serrano, S. M. and J. I. López-Moreno, 2005: Hydrologic response to different time scales of climatological drought: an evaluation of the standardized precipitation index in a mountainous Mediterranean basin. *Hydrol. Earth Syst. Sci.*, **9**, 523-533.
- , S. Beguería, and J. I. López-Moreno, 2010: A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J. Climate*, **23**, 1696-1718.
- , J.I. López-Moreno, S. Beguería, J. Lorenzo-Lacruz, C. Azorin-Molina, and E. Morán-Tejada, 2011a: Accurate computation of a streamflow drought index. *J. Hydrol. Eng.*, doi:10.1061/(ASCE)HE.1943-5584.0000433.

- , J. I. López-Moreno, A. Drumond, L. Gimeno, R. Nieto, E. Morán-Tejeda, J. Lorenzo-Lacruz, S. Beguería, and J. Zabalza, 2011b: Effects of warming processes on droughts and water resources in the NW Iberian Peninsula (1930-2006). *Climate Res.*, **48**, 203-212.
- Weiss, J. L., C. L. Castro, and J. T. Overpeck, 2009: Distinguished pronounced droughts in the southwestern United States: seasonality and effects of warmer temperatures. *J. Climate*, **22**, 5918-5932.
- Wells, N., S. Goddard, and M. J. Hayes, 2004: A self-calibrating Palmer drought severity index. *J. Climate*, **17**, 2335-2351.
- Wilhite, D. A. and M. Buchanan-Smith, 2005: Drought as Hazard: Understanding the Natural and Social Context. *Drought and Water Crises: Science, Technology, and Management Issues*, CRC Press, Taylor and Francis Group, 3-29.
- Wu, H., G. H. Hubbard, and D. A. Wilhite, 2004: An agricultural drought risk-assessment model for corn and soybeans. *Int. J. Climatol.*, **24**, 723-741.