Evaluation of Drought Metrics in Tracking Streamflow in Idaho

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Jacob W. Wolf

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Major Professor: John T. Abatzoglou, Ph.D
This thesis of Jacob W. Wolf, submitted for the degree of Master of Science with a major in Geography and titled "Evaluation of Drought Metrics in Tracking Streamflow in Idaho," has been reviewed in final form. Permission, as indicated by the signatures and dates given below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor  
John T. Abatzoglou  
Date 7/25/12

Committee

Members  
Jae H. Ryu  
Date 7/25/12

Von P. Walden  
Date 7/26/12

Department

Administrator  
Karen S. Humes  
Date 7/10/12

Karen S. Humes

Discipline's

College Dean  
Paul Joyce  
Date 7/27/12

Final Approval and Acceptance by the College of Graduate Studies  
Date

Jie Chen
Abstract

Changes in streamflow across the western US illustrate a need to better understand how drought indices derived from climate data track streamflow. Three drought metrics, the Standardized Precipitation Index (SPI), Standardized Precipitation-Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI) were correlated to water-year runoff for fourteen drainage basins in Idaho from 1950-2010. Two common methods of estimating potential evapotranspiration (PET), the Thornthwaite and Penman-Monteith methods, were considered in both the SPEI and PDSI. Results show that no single metric is universally superior, but rather that correlations vary seasonally and in heterogeneous fashion across the watersheds. Overall, the 9-month SPEI during the spring months most consistently exhibited the highest correlation to streamflow for most regions, particularly the snow-domination basins, while the PDSI exhibited the highest correlation to streamflow in two of the three rain-dominated basins. There was a slight increase in correlation to streamflow for both PDSI and SPEI using PET estimated with the Penman-Monteith method over the Thornthwaite method. Lastly, correlation using a 31-year moving window shows correlations have improved over time for all three metrics, with improvements most notable in drought indices that account for PET.
Acknowledgements

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I. Introduction

Water resources of the western United States depend upon winter snowpack as a natural reservoir and are sensitive to an array of atmospheric drivers (McCabe and Dettinger, 2002; Clark, 2010). Large inter-annual variability in winter precipitation across the western United States, where the majority of precipitation falls during the winter months (McCabe and Dettinger, 2002) and the increase in water demand is coupled with a growing population (Wilhite et al., 2007) make the region susceptible to water limitations. The complex topography of mountain watersheds pose additional challenges to water resources as snowpack in lower elevations near the 0°C isotherm is highly sensitive to changes in temperatures during snow accumulation and melt stages (Pagano et al., 2004; Halmet et al., 2007; Cayan et al., 2009). Similarly, coupled atmospheric-ecohydrological processes have been shown to influence evapotranspiration and are an important aspect of residual surface water supply (Jarvis, 1976; McEvoy et al., 2012).

Because the western US is generally more arid than the eastern United States and the population relies heavily on a small seasonal window of precipitation, the region must address its finite water supply and moreover its susceptibility to drought. Drought is most simply defined as the difference between water supply and water demand (Redmond, 2002). Droughts are manifested in both surface water supply resources (such as soil moisture, ground water, snowpack, river discharge, and reservoir storage) and pose a variety of impacts including those to ecology, agriculture and energy generation (IPCC-SREX, 2012). Drought is a natural hazard with a slow onset and wide spatial domain; it is often said that drought is the most complex of all natural hazards, and more people are affected by it than any other hazard (Heim, 2002; Wilhite et al., 2007). As vulnerability to drought increases because of
mounting pressure on water and other natural resources, the scientific community faces a significant challenge to produce timely and more comprehensive assessments of the utility of drought indices (Wilhite et al., 2007; Mishra and Singh, 2010).

Although drought can be constructed across many disciplines, the primary attributes that determine surface water supply and drought include precipitation (P), potential evapotranspiration (PET), snow water equivalent (SWE) and soil moisture. Not only do the overall quantities of these terms matter, but also the timing and duration associated with them. Drought indices such as the Standardized Precipitation Index (SPI, McKee et al., 1993) and Standardized Precipitation-Evapotranspiration Index (SPEI, Vicente-Serrano et al. 2010) have been developed to accommodate the multi-scalar properties of drought that is temporally flexible and applicable to different types of drought. The SPI assumes that the variability in P is much greater than other parameters such as PET and only accounts for P, whereas SPEI accounts for atmospheric demand through a simplified moisture balance by using P minus PET. The Palmer Drought Severity Index (PDSI, Palmer 1965) is a very common drought index based on soil water balance equations that considers PET and P in addition to available water holding capacity of the soil (AWC). Subsequent improvements to the PDSI, including the Self Calibrated PDSI, or SC-PDSI (Wells et al., 2004), have overcome some of the limitations of the PDSI. In this study, the application of the SC-PDSI over the PDSI offered little to no improvement and was not used (differences noted in Figure 6). However, the failure of the PDSI to account for snow dynamics makes it less attractive and not physically representative of areas that receive the majority of P as snow including much of the western US (Alley 1984; Guttman et al. 1992; Nkemdirim and Weber 1999; Steinmann et al. 2005). Similarly, there are a comparable number of ways to estimate PET using climatologi-
Two frequently used methods for estimating PET include a simple temperature based approach using the Thorthwaite method (Thornthwaite, 1948) and an energy-balance approach using the Penman-Monteith method (Allen, 1998). Although previous studies have shown that drought indices are insensitive to the choice of PET method (Dai, 2011), no known study has evaluated the sensitivity of PET methods for tracking drought at high-resolution spatial scales (e.g. 4km by 4km) relevant to watersheds in the western United States.

Numerous previous studies have evaluated the utility of drought indices to track measured hydrological, agricultural, ecological indicators (e.g., Ellis et al., 2010; van der Schrier et al., 2011; McEvoy et al., 2012). The study region of Idaho was selected given its strong north/south dichotomy in climate and topography. Also important was the availability of long term data from unregulated stream gauge stations. Finally, the complex mountainous terrain located in the northern portion of the state offered complexity to the work. While a thorough evaluation of drought indices is a much-needed step prior to application of such indices in decision-making, the ground-truthing of drought indices can be complicated by the variety of measured impacts (Redmond, 2002).

In this study we utilize streamflow from 14 unregulated long-term stream gauges across the state of Idaho as a measured indicator of water supply given the importance of hydrologic drought on surface water availability (Idaho Drought Plan, 2001). The study region of Idaho was selected given its strong north/south dichotomy in climate and topography. Also important was the availability of long term data from unregulated stream gauge stations. Finally, the complex mountainous terrain in the northern portion of the state offered complexity to the work. We aim to evaluate how drought indices capture water-year streamflow
across the different basins within the state, identify which drought index performs best in which season, as well as explore why such differences arise across different watersheds. In a manner similar to that used by Redmond (2002), we hypothesize there is no panacea for drought indices, but rather the utility of such metrics vary heterogeneously across the diverse watersheds of the western U.S. due to differences in seasonality of P, the fraction of P incorporated into the snowpack, and the influence of PET on the local water balance. Finally, given observed changes in the timing of streamflow (Stewart et al., 2005) coincident to widespread regional warming and questions of non-stationarity of hydrology in a changing climate, we examine whether relationships between indices and streamflow have changed over the period of record (1950-2010).

II. Data and Methodology

The study area selected in this paper has fourteen observed United States Geological Survey (USGS) [downloaded from: waterdata.usgs.gov/nwis/uv last accessed March 2012] unregulated stream gauges with high quality records (both in duration, and percent of complete records) across the state of Idaho (Table 1). Hydrology within the state of Idaho is driven by snow-dominated and transient watersheds (Clark, 2010) with basins located across the state at various elevations, thus making it a suitable test bed for evaluating a suite of drought indices. Station selection stems from familiarity of stations from previous efforts and drainage basin runoff patterns, dominated by snowmelt runoff with lower-elevation drainage basins in the northern and southwestern parts of Idaho subject to intense winter or early spring rainstorms that can trigger rain-on-snow events (Clark, 2010). We specifically examined water year streamflow following Clark (2010) as the summation of observed daily streamflow (cfs) over the October-September months for 61 water-years (1949-1950 to 2009-
We calculate a Standardized Runoff Index (SRI, Shukla and Wood, 2008; Elsner, 2010) for each stream gauge by applying the statistical transform of McKee et al., (1993).

Data required to calculate drought indices is derived from two primary sources. First, monthly P and maximum, minimum, and dew point temperature at 4-km spatial resolution is acquired from the Parameter-elevation Regression on Independent Slopes Model (PRISM; Daly et al., 1994) from [1895 to 2010]. Secondly, due to the lack of long-term observations of downward solar radiation and 10-meter wind speed, we bilinearly interpolate climatological monthly downward surface shortwave radiation and 10-m wind speed from the North American Land Data Assimilation System (NLDAS-2) (Mitchell et al., 2004) to the 4-km PRISM grid. Finally, AWC data was retrieved from the State Soil Geographic Data Base (STATSGO) at the 250 cm level [http://www.soilinfo.psu.edu/index.cgi] from Kangas and Brown (2007).

While prior studies have examined the sensitivity of PET approaches in the context of drought indices (Dai 2010, 2011; Lu et al., 2005), the utility of each method as incorporated into drought indices has not been fully vetted in regions of complex terrain or at spatial scales of individual watersheds. Redmond (2002) noted the need to better evaluate drought indices at smaller scales where impacts are manifested and in particular across the western United States given the complexity of climate gradients. The Thornthwaite method is advantageous and widely used as it requires only inputs of latitude and temperature such that PET is a function of mean monthly temperature. The Penman-Monteith method of calculating PET is a more processed-based energy-balance approach for PET and requires inputs of temperature, latitude, elevation, wind speed, radiation, albedo, and vapor pressure deficit. The Penman-Monteith equation was further modified for monthly mean temperatures less than 5°C using a
hyperbolic tangent equation determined by Dai (2008) that accounts for unrealistic variations in the surface energy budget when snow cover exists or prior to the onset of the growing season and active transpiration when temperature is a limiting factor (Jarvis, 1976). While both methods are accepted and actively used to estimate PET, several authors have demonstrated large disparities between the two approaches (e.g. Van der Schrier et al., 2011). These disparities are particularly pronounced across the western US as shown by the climatological annual sum of Thornthwaite and Penman-Monteith PET 1981-2010 (Fig. 2). The large diurnal temperature range and subsequent larger vapor pressure deficit during the summer months over the interior West in summer is not accounted for by the Thornthwaite equation, thereby explaining the significantly higher PET estimated through the Penman-Monteith approach. Averaged over the western US, the Penman-Monteith annual climatology (1981-2010) value is approximately 90% greater than the Thornthwaite method and likely to significantly alter terms in the water budget. By default, the Penman-Monteith PET method is used for the SPEI and PDSI unless otherwise stated.

We use the SPI, SPEI and PDSI as drought indices in this analysis. Both the SPI and SPEI are calculated monthly by considering the cumulative P, or cumulative P minus cumulative PET, respectively, over the past number of months relative to historical conditions that is then transformed into a Gaussian distribution using Box-Cox transformation techniques (Box and Cox, 1964; Shapiro and Francia, 1972). The SPI and SPEI are multi-scalar indices, such that they can be used to examine a multitude of time scales. For example, the 6-month SPEI for June would require the difference of P minus PET accumulated from January through June. The time steps used in this study were 1, 2, 3, 4, 5, 6, 9, 12, 24, and 36 months. The PDSI has been widely used and shown to correlate strongly with both hydrolog-
ical (Dai 2011) and ecological (Westerling et al. 2003) variables; however, the failure of the PDSI to discriminate the phase of $P$ potentially limits its applicability in snow-dominated and transient watersheds that define the hydrology of the western U.S. (Alley 1984; Dai 2004; van der Shrier 2007). The PDSI relies on a two-bucket soil moisture storage scheme that assumes the top layer has a storage capacity of 1-in (25.4 mm) and the bottom layer has a storage capacity dependent the AWC of the soils at that location. As such, it uses a soil moisture balance model that accounts for the amount and sequence of supply and demand.

Drought indices are calculated for each stream-gauge site averaging the 4km by 4km PRISM pixels within the upstream drainage basin. The drainage basins for each station are generated from the USGS stream gauge site using ESRI ArcMap software that takes into account the elevation of the surrounding terrain, the stream gauge point location, and the HUC watershed to generate the drainage basin that feeds into the specific station. Finally, we characterize attributes of each basin using (i) basin size, (ii) the fraction of accumulated $P$ remaining as SWE on 1 April, hereafter referred to as SWE:$P$ ratio (Pierce et al. 2008), (iii) the ratio of water year $P$ that falls during spring (April-June, using 1981-2010 climatology, hereafter referred to as $P_{AMJ}$) and (iv) total $P$ (1981-2010 climatology) during the water year. The SWE:$P$ ratio is computed as the ratio April 1 SWE to October-March $P$ using calculated SWE output from the Variable Infiltration Capacity (VIC) model (Liang et al. 1994) at 1/8 degree spatial resolution from 1981-2010. The basins are then classified similar to Elsner et al. (2010) as rain-dominated basins having SWE:$P$ less than 0.3, transient as 0.3-0.6, and snow-dominated as 0.6-1.0 (Figure 1). Basin characteristics are provided in Table 1.

Several types of analyses are then used to test the main hypotheses of our work. (i) The primary analysis involved calculation of Pearson’s correlation coefficients between wa-
ter-year SRI and both SPI and SPEI at the 1, 2, 3, 4, 5, 6, 9, 12, 24, and 36-month time step in addition to PDSI for January through September of the water year. (ii) We also calculate correlations of the aforementioned SPEI and PDSI using both PET methods to gauge SRI. (iii) To better explain heterogeneity in the ability of drought indices to track SRI across the watersheds, we calculate total basin size, SWE:P ratio, $P_{AMJ}$, and total annual precipitation for each basin. (iv) Ultimately, to examine our final question of whether there have been any changes in the utility of drought indices to track SRI, we compute correlation coefficients as previously stated using a 31-year moving window.

III. Results

A time series of SRI of the Salmon River at White Bird, Idaho (See Table 1) along with PDSI, 6-month SPI and SPEI for the month of April averaged over the upstream watershed are shown in Figure 3. It is possible to discern how the metrics and SRI track each other inter-annually, and how each metric successfully captures, to some degree, drought and pluvial events. This example characterizes the relationships between SRI and drought indices seen across many of the gauges in the study area. It also suggest that such metrics, to first-order, track water year SRI, but also shows that the ability of individual metrics to track measured hydrology vary, thus necessitating a thorough evaluation across all timescales, basins and metrics.

Matrices of the mean squared correlation coefficient $(\overline{r^2})$ between SRI and the various timescales of SPI and SPEI for the months of January through September averaged across all 14 basins are shown in Figure 4 along with a difference matrix $(\overline{r^2_{SPI}} - \overline{r^2_{SPEI}})$. The results shown in Figure 4 illustrate that SPI and SPEI are comparable at each time step and month. There is a strong correlation between SRI and both SPI and SPEI in spring (April-
June) with April performing best, for time scales of 6-9 months as this coincides with the period of predominant precipitation. The degradation of correlations to SRI for 12-month SPI and SPEI in July-September over the 9-month versions of these metrics from April-July suggests that summer precipitation has negligible relationship to SRI. The 9-month time step exhibited the strongest correlations for both the SPEI and SPI and subsequent analysis focuses on this time scale.

There are subtle differences between the SPEI and SPI as shown in Figure 4c. The SPEI provides slightly more explanatory power over the SPI from March to September for time scales of 9-months and less. This period roughly coincides with months where temperatures are above freezing and when snow melt and PET become more important to the local hydrology. The SPEI exhibited statistically significant increases in correlations in May (typically peak timing of streamflow) in 7 basins, while the SPI has 0, and there is no significant correlation to SWE:P ratio by basin. By contrast, the 24 and 36 month SPI exhibits a stronger correlation than the SPEI in months January through April; however, given the lower overall correlations, these differences are not pertinent to the focus of this work. Finally, although beyond the scope of the current analysis, this hints that SPEI may be superior metric to SPI for low-flow conditions and may suggest that the SPEI performs better than the SPI under warmer conditions as it addresses the role of moisture demand that the SPI does not.

We expand upon our regional correlation analyses by examining relationships between 9-month SPI and SPEI to SRI at individual gauges. Figure 5 shows the 9-month SPEI and 9-month SPI and their respective significant differences at the various stations A-N (Table 1). It is possible to see that the correlations with streamflow vary by station with
some basins having strong correlations of $r^2$ near 0.9. The strongest correlations include the primary period of precipitation during the late winter and spring months as seen by the band emanating from 4-month metrics January through 12-month metrics in summer. This band captures the multi-scalar nature of both metrics, as the metrics contain consistent strength while time increases and the metric duration increases.

Figure 6 shows the $r^2$ for PDSI with the stations ranked by SWE:P ratio, the SC-PDSI, and their differences. As mentioned previously, there was little improvement with the SC-PDSI; as such, the PDSI was used for analysis. The PDSI has the strongest correlation in April. The PDSI drought metric performs differently than the SPEI and SPI in reference to the timing of maximum correlation as well as the magnitude of correlation explained. PDSI correlation is weaker than SPEI and SPI for the months of July through September, but may be slightly better prognostically as indicated by the significant correlation in the months of March and April for rain-dominated stations. Comparable to the SPI and SPEI, SWE:P again does not seem to indicate any role in determining station correlation strength and station heterogeneity is visible in previous figures.

Correlation matrices for PDSI and SPEI using PET calculated from both the Penman-Monteith and Thornthwaite methods and their difference, are shown in Figure 7. Correlation matrices to SRI using the different PET estimates are largely unchanged confirming the results of Dai (2011). The large disparity across the western landscape between the two PET methods suggests that metrics using different PET methods should also differ greatly. While there is a large difference primarily in the southwest portion of the country, the differences across Idaho are much less. This suggests that the nuances of PET are not fully vetted across this particular study area. The Penman-Monteith method accounted for 3.5% more variance
explained over the Thornthwaite from March-July when averaged across all basins for the 9-month SPEI. The Penman-Monteith PDSI also correlates slightly higher than the Thornthwaite across several stations and may be the preferred option for calculating metrics more closely based on local water balance. The similarity in the standardized PET in the SPEI suggests that either metric is acceptable, but that the Thorthwaite method may be preferred if data access is limited.

A scatter plot of computed correlations for PDSI and 9-month SPEI and SPI for the months of April and July versus the different basin characteristics is shown in Figure 8. In April, PDSI performs comparably to the 9-month SPEI and 9-month SPI correlation coefficients across all 14 basins. Correlations across SWE:P in April indicate that 9-month SPI, 9-month SPEI, and PDSI perform quite well, with all stations exhibiting an $r^2 > 0.7$. Another feature to note in April is the performance of the PDSI exceeds that of the 9-month SPEI and 9-month SPI in rain-dominated drainage basins (Table 1). Small to moderate-sized basins ($<4000$ km$^2$) indicate stronger correlation than larger basins using SPEI and SPI. All metrics perform better with a lower $P_{AMJ}$%, in April, indicating that some of the heterogeneity in correlations across the 14 basins is due to the seasonality of $P$. When correlated to total $P$, correlations do not indicate a strong dependence on overall amount; however it is interesting to note that the two driest basins have lowest correlations in April. It would be necessary to examine a broader range of basins to verify this result. In July there exists a marked decrease in performance in PDSI across all 14 gauges, with $r^2 > 0.6$ and far below that of both SPI and SPEI. For SPI and SPEI there is a trend towards decreasing correlation values with basin size. Substituting the Thornthwaite PET method does not provide any marked improvement
over the Penman-Monteith, as shown in Figure 9 which displays the SPEI and PDSI Penman-Monteith-Thornthwaite PET correlations.

Results from Table 1 suggest that PDSI is preferred over the SPEI and SPI in rain-dominated basins while the SPEI is best in snow-dominated basins. SPEI is best in 9 of 14 stations, and the 9-month is best in 9 of 14 stations. Also shown in Table 1 is the indication if the Penman-Monteith or Thornthwaite PET method was used in the peak correlation for the SPEI metrics. It is possible to see that in only 1 peak metric correlation did the Thornthwaite produce a higher peak correlation over the Penman-Monteith.

Finally, correlations between SRI and 9-month SPI and SPEI as well as PDSI using 31-year moving windows are shown in Figure 10 to examine whether these relationships have changed over the study period. The Penman-Monteith in both the SPEI and PDSI indicate stronger correlations through time. Our results suggest correlations between these three drought indices and SRI have increased, suggesting a potential closer coupling between drought indices and hydrology over time. The SPEI has increased its explained variance over SPI by nearly 4% over 30 year time period. Figure 11 shows the April correlation trends for the PDSI Penman-Monteith and Thornthwaite, as well as the 9-month SPEI with the Penman-Monteith and Thornthwaite, and the 9-month SPI. There exists an interesting trend of change between the different PET methods for both the PDSI and 9-month SPEI, and requires further analysis for a thorough explanation. This performance by the SPEI may indicate a more appropriate metric in a warming scenario over the PDSI given that SPEI was a superior diagnostic over PDSI in April.
IV. Conclusions

This analysis evaluated spatial and temporal differences in the PDSI, SPI, and SPEI across fourteen watersheds in Idaho. While all metrics performed adequately with $r^2$ to SRI greater than 0.6 during the months of March through September, the SPEI provided the best overall proxy for streamflow in Idaho and, therefore, may also perform well in other regions of the western U.S. The stronger relationships to SPEI over SPI suggest that the inclusion of atmospheric demand in drought indices is advantageous, reinforcing the results of McEvoy et al., (2012) across the complex hydrology of the northern Great Basin and Northern Rocky mountains of Idaho. The stronger correlations to SPI and SPEI are most likely due to the multi-scalar nature of these indices and potentially PDSI’s treatment of all precipitation as liquid in the water balance. We speculate that PDSI’s treatment of all precipitation as liquid, and subsequent earlier depletion of soil moisture is at the root of the declining correlation through late spring into summer. Efforts to establish a new PDSI-based metric that explicitly account for snowpack dynamics (e.g., van der Schrier et al., 2007) may provide a more physically representative water-balance drought metric. The Penman-Monteith SPEI offers improvement over the SPI and results similar to Dai (2011) and van der Schrier et al. (2011) in that the difference in PDSI using the Penman-Monteith or Thornthwaite method of PET is limited; however, the Penman-Monteith indicates increases in correlation over time with 3% more variance explained in the 9-month SPEI and 5% more variance explained in the PDSI.

The results of this study also demonstrate changing seasonal relationships between drought indices and water-year runoff and suggest that relying solely on one metric throughout a complete season may provide a proxy that is less than optimal. For example, while the PDSI performed best in April in rain-dominated basins, the 9-month SPI and SPEI explained
a greater amount of variance in June and July. This suggests that one may be able to successfully use the PDSI as a prognostic tool for water year runoff while using SPEI or SPI are more adequate for diagnostic monitoring. Following Redmond (2002), this study verifies that no one metric is best for any situation and depends on the needs of the user and timing of analysis.

This analysis found only a weak relationship between basin characteristics (e.g., SWE:P) and drought index-streamflow correlations; however, the strong performance of PDSI in April for the 4 lowest-ranked SWE:P watersheds compared to the 9-month SPI and 9-month SPEI may indicate an inability of the PDSI to properly account for snowpack. A more thorough analysis that characterizes upstream geology and vegetation may help discern the heterogeneity in drought-streamflow relationships across the basins. Another complicating factor is the paucity of long-term climate stations across the study area that may provide different levels of data quality within each basin.

Figure 9 shows a 31-year moving average window for each metric averaged across the 14 basins. It is possible to see an increasing explanation of SRI by the multiple drought metrics as time progresses. A thorough explanation for recent strengthening in the coupling between drought indices and SRI is beyond the scope of this work and should be examined across a broader study area. We suggest several hypotheses for this increase: (i) increasing data quality and spatial representation of climate datasets in complex terrain (Daly, 1994), (ii) decreasing fraction of precipitation falling as snow (Eckhardt and Ulbrich, 2003; Abatzoglou, 2010) altering snow hydrology and increasing the utility of drought indices that only account for liquid precipitation, and (iii) changes in precipitation seasonality.
The need to accurately monitor drought is increasingly important in a changing climate in water limited regions. Tracking interannual variability in water resources for the western U.S. has also been heightened due to changes in streamflow (e.g., Clark, 2010) and the decline in the streamflow of the bottom quartile of years (Luce and Holden, 2009). The inclusion of an atmospheric demand term in SPEI was found to improve correlations with streamflow across Idaho, and a broader analysis across more diverse basins is needed to establish where this demand term is critical in terms of drought monitoring. While PET methods produce stark differences (Figure 2), there is relatively little difference in the sensitivity of the SPEI or PDSI to the method of PET used. The PDSI and 9-month SPEI improve over the SPI at a faster rate, reaching a difference in correlation of 5.7% and 4%, respectively. Finally, the improvement shown here in using metrics that contain moisture balance calculations (SPEI, PDSI) suggests that additional analyses of the suitability of drought indices in a changing climate should be performed given the future hydrologic changes (Barnett et al., 2005).
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Table 1: List of stations and their basin properties as described in the text (adapted from Clark, 2010).

<table>
<thead>
<tr>
<th>USGS station ID</th>
<th>Station Name</th>
<th>Basin Size (km²)</th>
<th>SWE:P</th>
<th>P$_{ann}$</th>
<th>Total PPT (mm)</th>
<th>Highest Metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Bruneau River near Hot Spring, ID</td>
<td>5,952</td>
<td>0.04</td>
<td>33.29</td>
<td>357.10</td>
<td>Jul PDSI</td>
</tr>
<tr>
<td>B</td>
<td>Weiser River near Weiser, ID</td>
<td>3,952</td>
<td>0.16</td>
<td>22.22</td>
<td>711.40</td>
<td>Apr PDSI</td>
</tr>
<tr>
<td>C</td>
<td>Salmon River at Salmon, ID</td>
<td>1,600</td>
<td>0.19</td>
<td>34.48</td>
<td>447.80</td>
<td>Mar SPEI 4 (PM)</td>
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<tr>
<td>D</td>
<td>Salmon River at White Bird, ID</td>
<td>2,144</td>
<td>0.33</td>
<td>28.13</td>
<td>853.60</td>
<td>Mar SPEI 6 (PM)</td>
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<tr>
<td>E</td>
<td>North Fork Coeur d'Alene River at Etna, ID</td>
<td>2,592</td>
<td>0.35</td>
<td>21.60</td>
<td>1195.70</td>
<td>May SPI 9</td>
</tr>
<tr>
<td>F</td>
<td>Boise River near Twin Springs, ID</td>
<td>368</td>
<td>0.38</td>
<td>20.93</td>
<td>705.40</td>
<td>Mar SPI 6</td>
</tr>
<tr>
<td>G</td>
<td>St. Joe River at Calder, ID</td>
<td>2,816</td>
<td>0.53</td>
<td>21.07</td>
<td>1265.80</td>
<td>Apr SPI 9</td>
</tr>
<tr>
<td>H</td>
<td>Selway River near Lowell, ID</td>
<td>2,720</td>
<td>0.56</td>
<td>26.09</td>
<td>1157.00</td>
<td>May SPEI 9 (TH)</td>
</tr>
<tr>
<td>I</td>
<td>Big Lost River near Chilly, ID</td>
<td>1,184</td>
<td>0.57</td>
<td>27.73</td>
<td>643.70</td>
<td>Jun SPEI 9 (PM)</td>
</tr>
<tr>
<td>J</td>
<td>North Fork Big Lost River at Wild Horse, ID</td>
<td>1,008</td>
<td>0.60</td>
<td>27.40</td>
<td>661.50</td>
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<tr>
<td>K</td>
<td>South Fork Boise River near Featherville, ID</td>
<td>1,728</td>
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<td>862.70</td>
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</tr>
<tr>
<td>L</td>
<td>South Fork Payette River at Lowman, ID</td>
<td>1,248</td>
<td>0.63</td>
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<td>983.90</td>
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<tr>
<td>M</td>
<td>Lochsa River near Lowell, ID</td>
<td>3,264</td>
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<td>22.86</td>
<td>1301.60</td>
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<tr>
<td>N</td>
<td>Johnson Creek at Yellow Pine, ID</td>
<td>928</td>
<td>0.75</td>
<td>21.36</td>
<td>1009.00</td>
<td>Jun SPEI 9 (PM)</td>
</tr>
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Figure 1: Map of the study area and 14 USGS stream gauges (black triangles) and their upstream watersheds. Watersheds are colored to represent their classification based on the ratio of April 1 snow water equivalent to precipitation (SWE:P). Letters correspond to Table 1.
Figure 2: Annual potential evapotranspiration averaged over the years 1981-2010 using (left) Penman-Monteith method and (right) Thornthwaite method. Units of mm.
Figure 3: Standardized streamflow and April PDSI, SPI-6, and SPEI-6 for the Salmon River at White Bird, Idaho 1950-2010.
Figure 4: Station-averaged $r^2$ values of metric duration for (a) SPI and (b) SPEI and their differences in (c) with only statistically significant values ($p<0.05$) shown.
Figure 5: Basin-specific $r^2$ values of (a) 9-month SPI and (b) 9-month SPEI ranked by SWE:P and (c) their differences, with differences less than 0.02 masked out.
Figure 6: Basin-specific $r^2$ values of (a) PDSI and (b) SC-PDSI ranked by SWE:P and (c) their differences, with differences less than 0.02 masked out.
Figure 7: Penman-Monteith 9-month SPEI (a), Thornthwaite 9-month SPEI (b) and (c) their differences, with differences less than 0.02 masked out. Penman-Montieth PDSI (d), Thornthwaite PDSI (e), and (f) their differences, with differences less than 0.02 masked out.
Figure 8: Penman-Monteith PDSI, 9-month SPEI, and 9-month SPI $r^2$ correlation to various basin metrics. Y-axis indicates $r^2$ correlation value.
Figure 9: PDSI and 9-month SPEI Penman-Montieth and Thornthwaite differences in correlation to various basin metrics. Y-axis indicates difference in $r^2$ correlation value between Penman-Monteith-driven indices and Thornthwaite-driven indices.
Figure 10: 31-year moving average correlations for 9-month SPI, Penman Monteith and Thornthwaite 9-month SPEI, PDSI. The years displayed on the x-axis are at the middle of the 31-year average and, therefore, ranges from 1965 to 1995. Black ticks represent month of peak correlation for the given year.
**Figure 11:** 31-year moving correlation trends of SRI and April PDSI (PM and TH), SPEI-9 (PM and TH) and SPI-9.