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Comparing response of *Pinus edulis* tree-ring growth to five alternate moisture indices using historic meteorological data

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Abstract

Annual growth of semiarid tree species is generally limited by a period of water deficit and this relationship can be reflected in interannual variation in tree-ring width of semiarid species such as *Pinus edulis*, a piñon pine that is widely distributed across the southwestern United States. Tree-ring width of *P. edulis* and other semiarid tree species is most frequently related to annual precipitation amount alone or to the Palmer drought severity index (PDSI). But water deficit and associated variation in moisture can also be described using numerous other indices such as the standardized precipitation index (SPI), and a comparison of the performance of several indices that relate historical climate data to tree-ring variation in *P. edulis* is lacking. We compared abilities to predict radial tree-ring growth of *P. edulis* using five metrics of water availability: PDSI, two indices based on precipitation alone (total precipitation and SPI), and two indices that factor in temperature to determine water deficit (based on Walter climate diagrams that use monthly precipitation and temperature). Each metric was evaluated over three commonly used time periods (water year, calendar year, and June–August) using the limited available data from *P. edulis* sites in the southwestern USA where co-located tree-ring and weather data were available. Our results indicate that PDSI was the best predictor of *P. edulis* ring widths, regardless of time period, and provide a first comparative test of PDSI with SPI and Walter indices that can be further tested as larger data sets become available.

Keywords: Palmer drought severity index (PDSI, Palmer index); *Pinus edulis*; Pinyon; Standardized precipitation index (SPI); Tree-rings; Walter index

1. Introduction

Semiarid environments by definition have seasonal periods of water deficit annually. Tree growth in semiarid environments often reflects interannual variation related to climate and associated water deficit through variation in tree-ring widths (Fritts, 1976; Vaganov et al., 2006). Although many studies focus on

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precipitation alone as limiting radial plant growth for semiarid trees, other metrics might more accurately reflect the amount of water available to plants, such as timing of precipitation events, variance from relevant means and corresponding temperature dynamics (Loik et al., 2004; Schwinning and Sala, 2004; Schwinning et al., 2004). A variety of climate metrics describing water availability could be relevant predictors of tree-ring widths (Table 1). Precipitation totaled over a year is perhaps the most direct metric. However, variations from mean precipitation and variations in the seasonal distribution of precipitation, as well as the intervals between major precipitation inputs, affect the overall water available to a plant. Various metrics reflect these additional factors to some extent and highlight the importance of water surplus and/or deficit (Fritts, 1976). The most commonly used metric other than total precipitation is the Palmer drought severity index (PDSI; Alley, 1984; Guttman, 1999). PDSI includes a variable-length memory, in that the calculation of water availability dates to the last period of established drought or wetness, and requires specific assumptions about evapo-transpiration and seasonal vegetation dynamics affecting ground cover (Alley, 1984).

Several other metrics of moisture availability arguably could be more relevant to prediction of ring-width responses and/or could require fewer assumptions than PDSI. Of particular note is the standardized precipitation index (SPI; Table 1; Edwards and McKee, 1997; Hayes, 2003; McKee et al., 1995), which some climatologists consider a more useful metric than PDSI, particularly for assessing short-term precipitation effects and soil moisture assessment (Guttman, 1999; Sims et al., 2002). SPI is a normalized index in which precipitation events or periods of interest are compared using deviations from a norm based on 30 years or more of continuous precipitation record (Edwards and McKee, 1997).

Water deficit might be more accurately reflected by metrics that include the timing and magnitude of temperature relative to the timing and magnitude of precipitation. One of these metrics is the Walter climate index (Breckle, 2002), in which monthly temperature and precipitation are evaluated concurrently to identify periods of relative water surplus and deficit. These types of diagrams have been very useful to ecologists in that the temperature curve approximately replaces the curve of potential evaporation and can thus be used to relate the water balance to precipitation, thereby providing a more ecohydrological perspective. Although the Walter climate index has been usually applied using long-term monthly means for a site, it might also be applied to evaluate time series, providing a dynamic perspective of water balance (Breshears et al., unpublished manuscript). Indices that consider temperature effects in this way do not require the more detailed assumptions like those of PDSI, but the predictive ability of the Walter climate indices have not been tested.

One semiarid tree species that is both widely distributed (West, 1999) and is particularly well-studied with respect to tree-ring chronologies is *Pinus edulis* (e.g., Adams and Kolb, 2004, 2005; Carson and Munroe, 2005; Gray et al., 2004; Hidalgo et al., 2001; Ogle et al., 2000; Ruel and Whitham, 2002; see also Fritts, 1976;

Table 1
Metrics related to moisture deficit and their assumptions

Metric	Use of temperature in addition to precipitation	Additional parameters	"Memory"	References
Raw precipitation	No	None	Fixed	–
PDSI	Yes	Seasonal vegetation ground cover, 25 mm evaporation, no snow relation	Variable	Guttman (1999), Alley (1984)
SPI	No	30 years of precipitation record, normalization	Fixed	Hayes (2003), Edwards and McKee (1977)
Water	Yes	Evaporative demand	Fixed	Modified from Breckle (2002)
Water deficit	Yes	Only negative values	Fixed	Modified from Breckle (2002)

We used three time periods for each index: Calendar year and two water relevant intervals, June–August and our defined Water Year. PDSI: Palmer Drought Severity Index; SPI: Standardized Precipitation Index. "Memory" refers to incorporation of lag effects from previous climate and is categorized as a fixed or variable period.

Vaganov et al., 2006). As noted above in a more general context, tree-ring width of *P. edulis* is most frequently related to annual precipitation amount alone or to the PDSI. But water deficit and associated variation in moisture can also be described using numerous other indices such as the SPI, and a comparison of the performance of several indices that relate historical climate data to tree-ring variation in *P. edulis* is lacking. Linking *P. edulis* response to historical meteorological data is important because it provides a means for developing an improved understanding of how the species responds to periods of varying water deficit, which can include periods of severe drought and, in some cases, tree mortality (Allen and Breshears, 1998; Breshears et al., 2005; Gitlin et al., 2006; Mueller et al., 2005; Shaw et al., 2005).

Here we evaluate five different metrics of moisture with respect to their ability to predict changes in tree-ring width of *P. edulis*: PDSI, two indices based on precipitation alone (total precipitation and SPI), and two that factor in temperature to determine water deficit. The two temperature-related metrics, detailed as follows, are based on Walter climate diagrams that use monthly precipitation and temperature. Each of the five metrics was evaluated over three time periods relevant for plant growth: water year (November 1–October 31 of the following calendar year), calendar year, and June–August using the limited data from *P. edulis* sites in southwestern USA where co-located tree-ring and weather data were available. Note that we used climate measures to predict radial growth rather than the more traditional approach used in dendrochronology, where growth is used to reconstruct climate. We discuss how our results, which indicate that PDSI was the best predictor of *P. edulis* ring widths regardless of time period, provide a first comparative test of PDSI with SPI and Walter indices that can be further tested as larger data sets become available.

2. Materials and methods

2.1. Study area and data

We used five study sites for which ring width and meteorological data sets could be directly paired to determine radial growth response to weather. In pairing sites, we used published instrumental data from a pool of 5525 metrological stations (Contributors to the Western Regional Climate Center, 2004, http://www.wrcc.dri.edu/index.html) and 75 *P. edulis* ring-width sites in Colorado, New Mexico, Arizona, Utah, and Nevada (Contributors of the International Tree-Ring Data Bank, 2004; http://www.ngdc.noaa.gov/paleo/treering.html). We used ArcInfo to match stations within 20 km of a ring-width site, and ArcMap to check for slope and aspect similarities among all matches. From this set, we selected pairs of ring width and weather station sites that were less than 5 km radial separation and less than 60 m elevation difference (Table 2; Fig. 1). Although these constraints resulted in a relatively small number of study sites, they allowed us to be more confident that relationships between tree-ring widths and weather patterns were not confounded by additional spatial variability in weather.

We used published monthly precipitation totals and average monthly temperatures from meteorological stations provided by the Western Regional Climate Center site (Contributors to the Western Regional Climate Center 2004, http://www.wrcc.dri.edu/index.html) to calculate total precipitation and the Walter-based indices.

Table 2
Sites with paired meteorological and ring width used for analyses

State	Meteorological station	Elevation (m)	Latitude	Longitude	Period of analysis	Ring width site	Elevation (m)	Latitude, longitude	Distance between sites (m)	Elevation difference (m)
AZ	Betatakin Clines	2198 2198	36.68	110.53	1951–1972	Tsegi Point Road	2196	36.68, 110.53	<100	−2
NM	Corners El Morro	[OBMI]	35.05	105.68	1970–1982	Clines Corner	2225	35.08, 105.65	4800	27
NM	Natl. Monument Mimbres	2204	35.05	108.35	1948–1972	El Morro Mimbres	2225	35.03, 108.35	1900	21
NM	Ranger Stn. Tajique 4	1905	32.93	108.01	1957–1982	Junction Tajique	1925	32.93, 108.01	<100	20
NM	NW	2131	34.80	106.30	1949–1969	Canyon	2103	34.76, 106.31	4000	−28

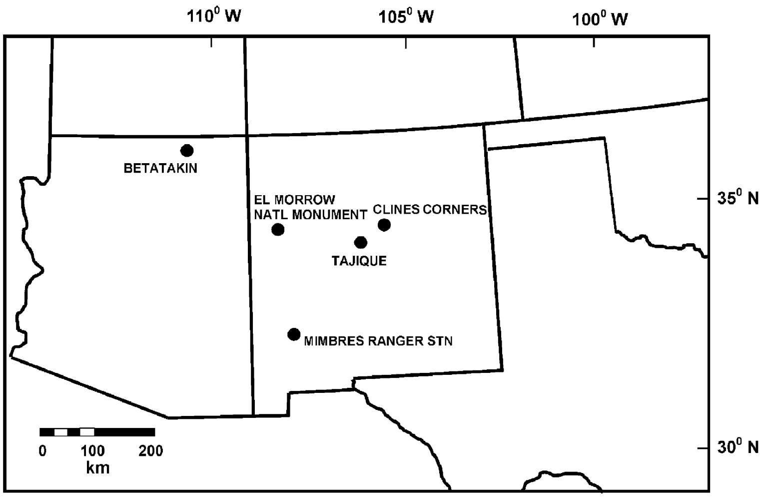

Fig. 1. Study site locations where existing tree-ring chronologies for *Pinus edulis* were co-located with meteorological data.

The Walter index within a given month is calculated as

$$\left(\frac{\text{Precipitation (mm)}}{2}\right) - \text{Temperature } (^\circ\text{C}).$$

(Note this relationship uses the more commonly applied ratio of 2 mm precipitation per 1 °C, rather than a ratio of 3 mm precipitation per 1 °C that has applied in some cases for steppes and prairies; Breckle, 2002 and references therein.) The Walter index for a period sums all Walter monthly indices within the period, whereas the Walter Deficit sums only monthly values that are negative, which correspond to periods of water demand, during the period of interest. For PDSI and SPI, we used analyses from the same meteorological stations obtained through queries submitted to online computations and algorithms hosted by the National Agricultural Support System site hosted by the University of Nebraska Lincoln (USDA, 2004; http://nadss.unl.edu).

We obtained published standardized ring-width site chronologies from the World Data Center for Paleoclimatology tree-ring site (Contributors of the International Tree-Ring Data Bank, 2004; http://www.ngdc.noaa.gov/paleo/treering.html). We used the standardized ring widths, which are normalized averages for a stand of trees representing the percentage of mean growth observed for each year over the entire stand. The index values are scaled by a factor of 10 so that mean growth = 1000 and no growth = 0 (this index does not have a defined maximum).

2.2. Time periods and analysis

We evaluated all indices over three ecologically relevant time intervals: the calendar year, a commonly used interval for evaluating tree growth; summer months of June–August (JJA), when water stress is often greatest; and a water year from November 1–October 31 of the following year, which more directly reflects the time period over which an entire annual growth ring is formed. We evaluated the performance of different climate indices for predicting standardized ring-width increments using mixed model regression (Littell et al., 1996). Models had the following structure, which allows each location to have a unique intercept and slope:

$$y_{ij} = \alpha + a_i + (\beta + b_i)x_{ij} + \varepsilon_{ij},$$

where y_{ij} are standardized ring-width increments at location i for time j; a and β are fitted population average intercept and slope, respectively; a_i are random location effects on the intercepts; and b_i are random location effects on the slopes, and ε_{ij} are residual errors. Residual errors were assumed to be normally distributed with σ^2_{e} and first order temporal autocorrelation (ρ). Random intercept and slopes were also assumed to be randomly distributed with σ^2_{a} and σ^2_{b}, respectively and with covariance $\sigma_{\mathrm{a,b}}$. Our primary parameters of interest are the population average slope (β) and intercept (α); the random effects are necessary to account for repeated measurements within locations. We also constructed quadratic and cubic polynomial models to test for non-linearity. The sample size adjusted form of Akaike's Information Criteria (AICc; Akaike, 1973) was used to assess the relative performance of different climate indices and time scales (Burnham and Anderson, 2002). Models with the smaller AICc values have more support within a set of competing models. We used differences between the AICc of competing models (ΔAICc) to further compare models. Thus a model with ΔAICc $= 0$ is the best model within a group, and ΔAICc values <2 also have strong evidence for describing the data accurately. We also computed R^2 values relative to the residual variance from baseline random intercepts model to provide supplemental information on relative model performance. The model parameters were estimated by maximum likelihood (SAS, 2001; mixed procedure).

3. Results

In addressing the model performance of our five moisture indices' ability to predict interannual tree-ring-width variation, we found that PDSI was a better linear predictor of standardized ring widths than any of the four other indices, regardless of time interval (water year, calendar year, June–August; Fig. 2). The Walter index and total precipitation were much better predictors of radial growth than was the Walter deficit index, and both were consistently better than the SPI (Fig. 2). More specifically, we did not detect important between-location variation for mean width increment (σ_a^2), for location-specific variation in slopes (σ_b^2), or temporal autocorrelation when climate indices were used to model standardized ring-width increments (AICc <2 when compared to simpler models). Parameter estimates of these variance components were never different from zero and variation between locations accounted for only 6% of the total variation in relative growth in our data set; we, nonetheless, retained the random location effect in all models to account for the nested data structure. No significant quadratic or cubic effects were detected among the climate indices.

In addressing the model performance of our five moisture indices' ability to predict interannual tree-ring-width variation with respect to the different time intervals studied, we found that the water-year time interval

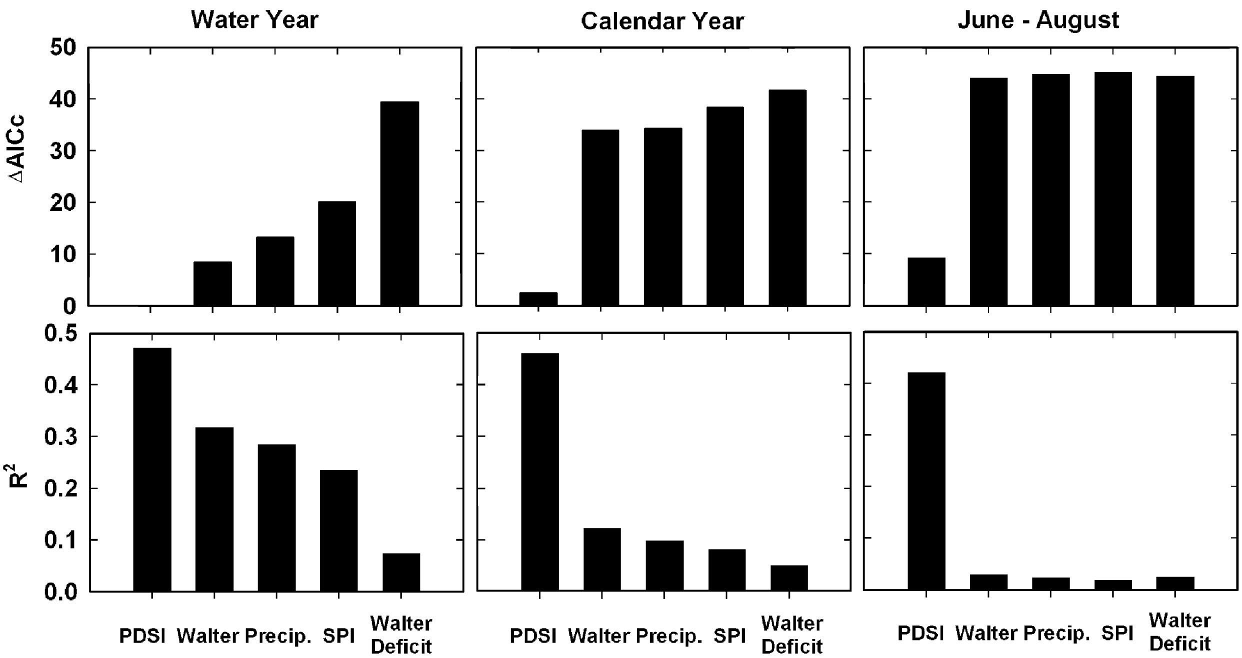

Fig. 2. Comparison of five moisture indices for predicting standardized ring widths of *P. edulis* computed at three time scales in terms of ΔAICc and R^2 values. Comparison of five water-related index values for each of three time periods (water year, calendar year, and June–August), and evaluated in terms of their ability to predict tree-ring widths, ranked by ΔAICc (top row; see Section 2), and R^2 (bottom row). The ΔAICc provides a metric for ranking alternative models. Models with smaller ΔAICc values have the most support. The R^2 provides an index of how much variation is explained by the model.

Table 3
Regression models for predicting *P. edulis* standardized ring widths from Palmer Drought Severity Index (PDSI) using different time periods for PDSI

Time period	Model	ΔAIC_c	R^2
June–August	$y = 978 + 98.9 \times$ PDSI (46.3), (11.6)	9.3	0.42
Calender year	$y = 1011 + 126.4 \times$ PDSI (48.9), (13.7)	2.5	0.46
Water year	$y = 1001 + 115.9 \times$ PDSI (45.6), (12.2)	0.0	0.47

Standard errors for intercept and slope in parentheses below. Metrics for ranking models are ΔAIC_c, where models with smaller values have the most support, and R^2, where models with higher values have more support.

produced the strongest relationship with *P. edulis* radial growth for all five indices (Fig. 2). June–August intervals had the poorest fit for all indices. All three PDSI models predict average growth when the index values are at average moisture conditions (PDSI = 0 and fitted intercept values that are not different from 1000, Table 3). Although water-year PDSI has a slightly better fit to the data than calendar-year PDSI, the amount of variation explained is similar and the sensitivity of relative growth to changes in PDSI are similar for the two year types. Water-year PDSI has a slope of 116 compared to 126 for calendar-year PDSI, but the standard error estimates for the slopes are larger than the difference between them.

4. Discussion

Our assessment of the five different moisture indices indicates that PDSI explained the most variation in the trends of *P. edulis* radial growth. This finding was independent of the time period of interest (calendar year, water year, June–August). The growing acceptance and use of the SPI is associated with its ability to track short-term soil wetness (Guttman, 1999; Sims et al., 2002). Our results suggest PDSI is a better predictor of tree-ring growth for *P. edulis*, perhaps because PDSI is more accurately linked to the longer intervals of soil water dynamics that are relevant to tree growth. The stronger predictive ability of PDSI over SPI and the other metrics we evaluated, may be due to the variable-length window that is used in its calculation. That is, PDSI calculates water deficit over as long an interval as the deficit occurs, whereas the other metrics—both those based on precipitation alone and those based on precipitation and temperature—calculate water availability and water deficit in a fixed window. The use of a fixed window may inappropriately curtail a period of water deficit and associated stress experienced by a tree. Hence, PDSI may be a more direct metric for conditions of moisture availability and water deficit experienced by a tree.

The fact that two of the three indices that factor in temperature—PDSI and Walter index—perform so well highlights the importance of evaporative demand in affecting available moisture, consistent with more general concepts of vegetation biogeography (Breckle, 2002; Stephenson, 1990). Based on the ΔAICc values (Fig. 2), in most cases, water year is the best time interval for predicting tree growth. Because June–August does not include all the conditions a tree experiences over a year of growth, it is apparently a poor prediction interval. The difference in predictive power between the calendar year and the water year, which differ by only 2 months, demonstrates the importance of matching the growth cycle of a tree with the weather of that period.

Despite the relatively better performance of the PDSI over the other metrics, the R^2 values still only range from 0.42 to 0.47. These coefficients of determination highlight that considerable variation remains unaccounted for, and point to the limitations of weather-dependent indices for predicting tree growth. The metrics differentially approximate water deficit but still do not directly reflect soil moisture, which is likely a key driver of plant physiological responses and growth. Future research challenges include developing more direct metrics of plant-available water (Loik et al., 2004).

Overall, our results for several indices and time periods suggest that models based on precipitation alone do not share the same predictive power as PDSI for modeling radial growth in *P. edulis*. Although PDSI has the drawbacks of arbitrary assumptions and of requiring a more complex calculation, it most accurately models radial growth, likely due to its variable memory and its consideration of many environmental variables (Alley, 1984). Therefore, we suggest that future attempts to model radial tree growth in semiarid regions should mirror the PDSI and incorporate a variable memory index that is dependent on established periods of drought and wetness. Additional other indices that might be considered should still draw heavily on the variables of precipitation and evaporative demand. But improving model fit may depend on tying soil moisture directly to physiological response. In addition, new caution should be applied for all metrics with regard to what time period is used for calculation. The applicability of our results is, of course, constrained by the limited amount of data that were available for existing tree-ring data for *P. edulis* and historical data for co-located weather stations. In summary, our results indicate that PDSI was the best predictor of *P. edulis* ring widths, regardless of time period, and provide a first comparative test of PDSI with SPI and Walter indices that can be further tested as larger data sets become available.

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