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Are drought indices and climate data good indicators of ecologically relevant soil moisture dynamics in drylands?

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ABSTRACT

Droughts are disproportionately impacting global dryland regions where ecosystem health and function are tightly coupled to moisture availability. Drought severity is commonly estimated using algorithms such as the standardized precipitation-evapotranspiration index (SPEI), which can estimate climatic water balance impacts at various hydrologic scales by varying computational length. However, the performance of these metrics as indicators of soil moisture dynamics at ecologically relevant scales, across soil depths, and in consideration of broader scale ecohydrological processes, requires more attention. In this study, we tested components of climatic water balance, including SPEI and SPEI computation lengths, to recreate multi-decadal and periodic soil-moisture patterns across soil profiles at 866 sites in the western United States. Modeling results show that SPEI calculated over the prior 12-months was the most predictive computation length and could recreate changes in moisture availability within the soil profile over longer periods of time and for annual recharge of deeper soil moisture stores. SPEI was slightly less successful with recreating spring surface-soil moisture availability, which is key to dryland ecosystems dominated by winter precipitation. Meteorological drought indices like SPEI are intended to be convenient and generalized indicators of meteorological water deficit. However, the inconsistent ability of SPEI to recreate ecologically relevant patterns of soil moisture at regional scales suggests that process-based models, and the larger data requirements they involve, remain an important tool for dryland ecohydrology

1. Introduction

Rising temperatures and shifting precipitation patterns are increasing the severity and frequency of droughts across the globe, the impacts of which are disproportionately affecting dryland ecosystems (Noy-Meir, 1973; Bradford et al., 2020). Drylands cover ∼ 40% of the land surface and provide essential ecosystem services to over 2.5 billion people globally (Reynolds et al., 2007; Prăvălie, 2016). However, future climate projections indicate pronounced shifts in aridity, especially in drylands, that require better understanding and ability to predict ecologically relevant impacts of climatic water balance, and better planning tools for scientists and resource managers (Kemp et al., 2015; Bradford et al., 2020).

Quantifying drought severity is essential to understand and manage the ecohydrological, agricultural, and social impacts of water scarcity (Reynolds et al., 2007; Slette et al., 2019; Slette et al., 2020). Numerous algorithms are available to estimate drought severity from climatic water-balance, but the ecological relevance of these indices is likely affected by the decoupling of relationships along the soil–plant-atmosphere pathway (McDowell et al., 2011; Hoover et al., 2017; Bradford et al., 2020). The generalized nature of drought indices make them applicable over larger spatial extents, but may also limit their accuracy at finer spatial resolutions (e.g., site, plot) where vegetation composition, soil characteristics, and disturbance history affect ecohydrological processes and necessitate more granular approaches to quantifying drought impacts (Feilhauer et al., 2018; Huang et al., 2020; Slette et al., 2020).

Seasonal variation in moisture availability has profound impacts on

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dryland ecohydrological niches through linkages between soil moisture and vegetation composition and functioning (Schlaepfer et al., 2012; Germino and Reinhardt, 2014; Biederman et al., 2018; James et al., 2019). Many drylands are characterized by moisture surpluses during winter and spring, followed by moisture deficits in summer and fall which vary over soil depths to influence plant development, water use, and reproductive strategies (Barnard et al., 2017; Szutu and Papuga, 2019; Knowles et al., 2020). Dryland shrub species such as big sagebrush (*Artemesia tridentata*) rely on winter precipitation for surface moisture availability in spring to promote seed germination and establishment, and for recharge of deeper soil moisture stores for transpiration when surface soil layers dry in summer (Germino and Reinhardt, 2014; Shriver et al., 2018; Szutu and Papuga, 2019; O'Connor et al., 2020). Physically-based models (such as SoilWat2; Schlaepfer et al., 2012; Bradford et al,. 2014b) estimate evapotranspiration and depth-resolved soil moisture and temperature dynamics quite well (Schlaepfer et al., 2012; Bradford et al., 2014a; Schlaepfer et al., 2017; Petrie et al., 2020), but due to model complexity, are limited in interpretability and must balance spatial resolution with data limitations and computational requirements.

The standardized precipitation-evapotranspiration index (SPEI) is a widely used drought index based on climatic water balance (difference between precipitation and potential evapotranspiration [pET]) and has proven to be especially useful for cross-site comparisons and climate-change studies (Vicente-Serrano et al., 2010; Zhao et al., 2021). The SPEI algorithm of drought severity can be computed over various record lengths to represent different hydrologic scales (e.g., site- to basin-scale hydrology; Vicente-Serrano et al., 2010; Li et al., 2015), and has be shown to be an excellent indicator of agricultural and ecohydrological processes including soil moisture, streamflow, tree-ring records, and crop yields (Vicente-Serrano et al., 2012; Tian et al., 2018; Babst et al., 2019). However, previous studies have focused primarily on moisture dynamics at discrete depths and considered only volumetric water content, indicating a knowledge gap in understanding depth-resolved dynamics across sites and regions, and with more ecologically relevant moisture metrics that account for soil texture differences on matric potential and field capacity such as soil water availability (SWA).

In this study, we combined 36 years (1979–2015) of weather data, SPEI estimates, landscape characteristics, and estimates of soil water availability to model long-term and seasonal variability in soil moisture dynamics at 866 sites across the western United States using machine learning. Specifically, our objectives were to test gridded weather data, SPEI estimates, and the length over which SPEI was calculated, to assess SPEI and moisture dynamics for correlations with depth-resolved and event-specific soil water availability (SWA) including surface availability in spring, and deep soil recharge from winter precipitation. We apply a machine learning framework (random forests) to quantify the importance of predictor variables and account for potential interactions and collinearity among predictors.

2. Materials and methods

2.1. Spatial data and multi-scalar drought index

We calculated the SPEI index at 866 sites (Fig. 1) using the 'SPEI' package in R (Beguería et al., 2017) over the period of 1979–2015 across the western United States. We used monthly averages of precipitation and potential evapotranspiration (pET) extracted from the University of Idaho Gridded Surface Meteorological Dataset (GridMET; Abatzoglou, 2013) for 1979–2014 at a 4 km resolution. Pixel-level vegetation type was aggregated from 30 m resolution 2011 National Landcover Database images (Homer et al., 2015). SPEI estimates of drought severity were computed at periods ranging from one to 48 months and tested individually as indicators of soil moisture dynamics to determine which interval would be most predictive for further modeling (see section 3.2 below).

2.2. Ecohydrological modeling

Daily SWA was simulated at all 866 sites using SoilWat2 (Version

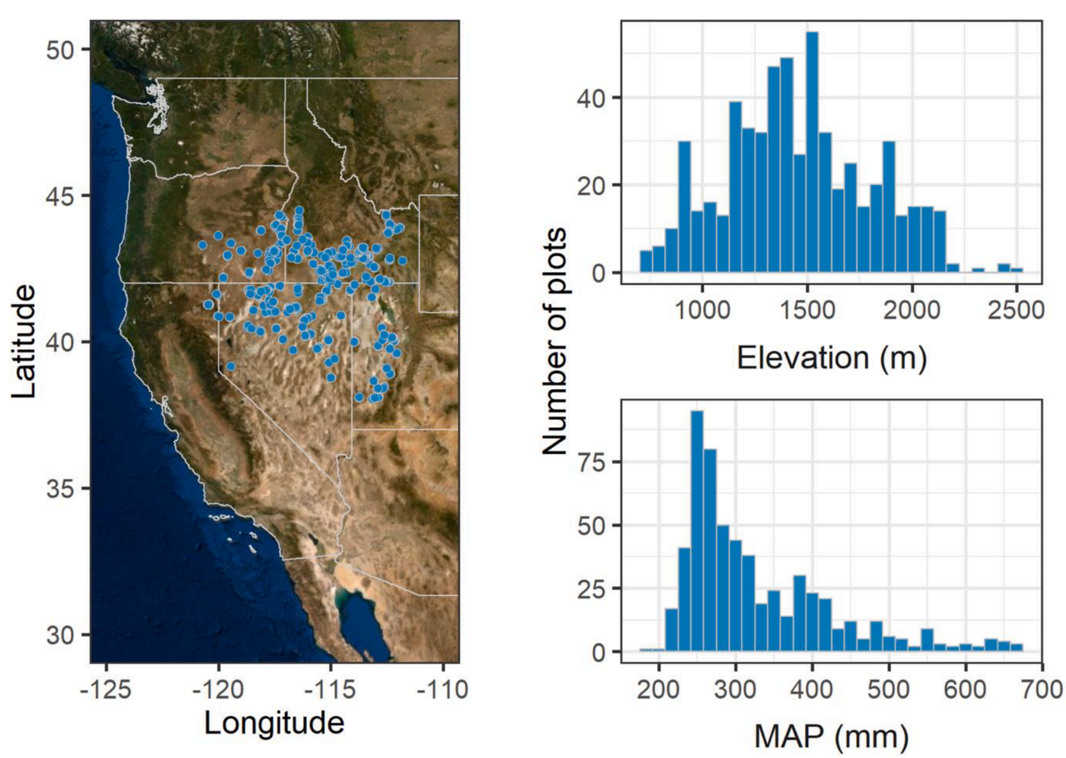

Fig. 1. Geographic locations and elevation and mean annual precipitation (MAP) distributions of the 866 sites of vegetation and soil measurements and modeling of soil water availability.

3.2) (Schlaepfer et al., 2012; Bradford et al., 2014b). SoilWat2 is a daily time-step process-based model that simulates soil moisture pools and fluxes across discrete soil layers and accounts for interactions between vegetation, climate, and soil conditions by incorporating Penman-Monteith energy-balance evapotranspiration estimates (Monteith, 1965). SoilWat2 accuracy has been verified in sagebrush ecosystems to observations of soil water potential and eddy covariance measurements of evapotranspiration (Schlaepfer et al., 2012) and daily volumetric moisture content (Bradford et al., 2014a). Further, soil temperature has been validated at multiple depths in several ecosystems (Petrie et al., 2020) and SoilWat2 estimates of mean monthly soil moisture patterns showed agreement with multiple global circulation models (Schlaepfer et al., 2017). Meteorological forcings, including daily maximum and minimum air temperature and daily precipitation amounts, were extracted from the GridMET data set (Abatzoglou, 2013). Soil textural inputs were characterized to 50 cm depths using field-collected soil samples, when available, and up to 250 cm depths using matching soil map units from the SSURGO soils database (Staff, 2017). For this study, daily soil moisture content values were simulated for soil layers terminating at 5, 10, 20, 30, 40 ,50, 70, 90, 110, 130 and 150 + cm. To characterize the influence of vegetation biomass on evapotranspiration and soil moisture fluxes, plant cover by species was measured using line-point intercept measurements (3 spoke-in-wheel transects; Herrick et al., 2005). Potential biomass was then estimated at each plot for the entire record length using algorithms included within SoilWat2 (Bradford et al., 2014b). We report SWA instead of volumetric water content because it is reported in mm or water depth (similar to ET) and because it incorporates aspects of soil characteristics, effectively normalizing moisture availability across multiple soil types.

2.3. Predictive models of soil moisture dynamics

We used random forest algorithms to develop models of soil moisture dynamics from SPEI and meteorological variables due to their ability to handle large datasets, assess parameter interactions, and variables by importance based on their influence on model accuracy (Barnard et al., 2019). Specifically, we used permuted variable importance which measures the importance of a predictor by recording a baseline model accuracy on an out-of-bag sample, permuting the predictor variable, and passing test samples back through the random forest. Variable importance is then determined as the difference in accuracy between the baseline model and that with the permuted variable importance.

We developed models of (1) soil moisture dynamics across the entire record length, (2) recharge of deep soil moisture (>50 cm) for each water year (October to September), and (3) surface soil moisture (<20 cm) availability in early spring (March and April). For the whole record length, we specifically modeled *changes* in monthly soil moisture over the entire record length (not monthly absolute values of SWA) to minimize violating model assumptions of independence that would occur with temporally-autocorrelated data. Deep soil moisture recharge was calculated as the maximum positive change in SWA during the 1-Oct to 31-Sept water year. Spring soil moisture availability was determined as the average SWA during March and April, the months during which surface soil moisture availability is most important for seedling germination and emergence in arid shrublands (DiCristina and Germino, 2006; James et al., 2019; O'Connor et al., 2020).

3. Results

3.1. SPEI variability: Hotspots for drought?

Over the period of 1979–2015, average SPEI using a 12-month computation length was lowest and indicated greater drought severity in the western portion of the United States (Fig. 2). Drought was more severe in southern Colorado, northern New Mexico, the basin and range region of Nevada, the rain shadow of the Cascade Range and Sierra Nevada (central Washington and Oregon and Nevada) and the Northern Rocky Mountains. There was persistently higher drought severity on the New Mexico and Arizona border just south of the four-corners region and the inland Northwest (central Idaho, western Montana, eastern Washington and Oregon). Interestingly, areas with mean SPEI closest to zero typically had the greatest variability in SPEI over the record length (standard deviation of SPEI).

Changes in annualized SPEI (ΔSPEI) from 1978 to 2015 were most negative (i.e. increasing drought over record length) in the western United States and corresponded linearly to average SPEI ($R^2 = 0.91$; Fig. 1). Specifically, the four-corners region of the Desert Southwest, and western Nevada had the greatest increases in drought severity, whereas the upper Midwest and Northeast regions of the US generally had decreases in drought severity. The ΔSPEI was related to the standard deviation of SPEI in a parabolic fashion similar to how mean SPEI relates to the standard deviation of SPEI.

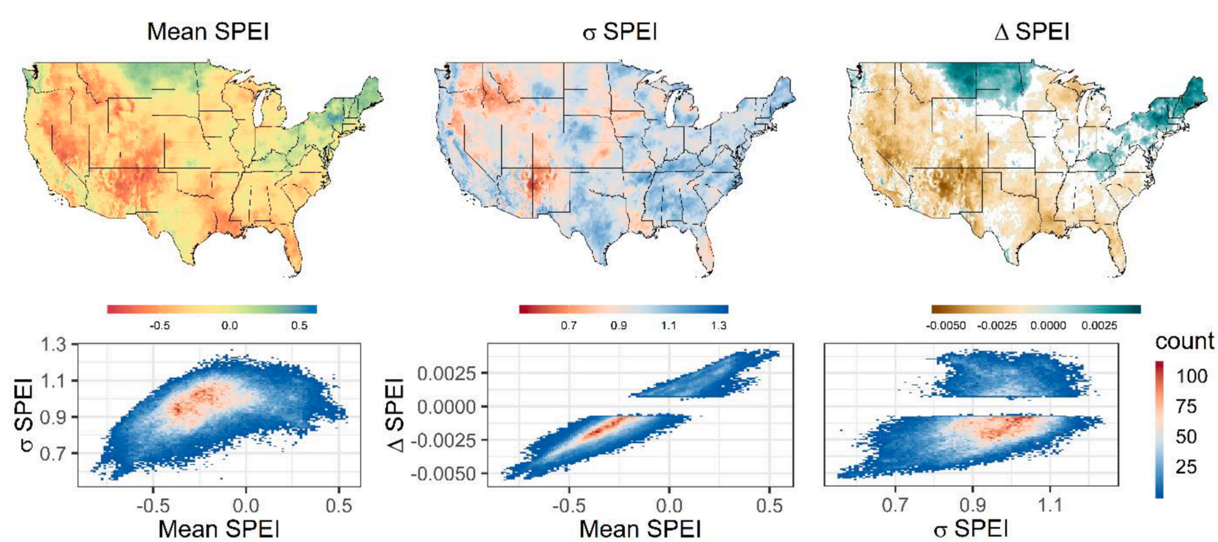

Fig. 2. Maps and correlations of mean, standard deviation among years (σ), and change (Δ) in the standardized precipitation-evapotranspiration index (SPEI), calculated over a rolling 12-month period, for the 1978–2015 period. White pixels in the ΔSPEI panel indicate no significant slope in a linear model of SPEI over time from 1978 to 2015 ($p < 0.05$). Smaller or more negative values of SPEI indicate a smaller water balance and drier conditions. Note, most Δ SPEI values near zero did not have a significant linear trend (at $p < 0.05$) and are omitted from scatter plots.

3.2. Comparison of SWA, SPEI, and weather data

The correlation of SPEI and SWA across a wide range of elevations and precipitation regimes was dependent on the SPEI computation length and soil depth (Figs. 1, 3). Overall, correlations of SWA and SPEI were greater in shallow and deep soils (<20 and > 50 cm, respectively) than at intermediate depths (Fig. 3). Correlations between SWA and SPEI in shallow soils were greatest with SPEI computed on time periods equal to or <4 months, compared to 4–64 months prior to the date for which SWA was estimated. In contrast, correlations between SWA in 20 cm or deeper soils and SPEI were greatest with SPEI computed on longer time periods preceding the date of SWA estimated, specifically 12–60 months (Fig. 3). The correlation between SWA and SPEI was greatest using a 12-month time frame for SPEI calculation for either intermediate soil depths (20–50 cm) and bulk SWA averaged across the entire vertical soil profile (Fig. 3), hence 12-month SPEI was used for subsequent modeling.

Although SWA across the soil profile generally covaried with SPEI over time, we observed different, and oftentimes counter-intuitive relationships between weather and SWA during different drought events with similar severity and duration (Fig. 4).

For example, in a representative site in northern Nevada, average monthly SPEI was −0.38 during an extended arid period 1988–1994 (lower left panels, Fig. 4. However, SWA was much lower across soil layers than a different drought period (1999–2005; right hashed-box) that had a more droughty mean SPEI of −1.05 but with higher SWA across soil layers (lower right panels, Fig. 4). A key difference among the two time periods was in the seasonality of precipitation: winter precipitation was 5.96 cm above average for this site in the 1999–2005 drought versus 27.83 cm below average for the 1988–1994 drought. Interestingly, the SPEI values in winter were only moderately different for drought periods, specifically winter SPEI was −0.48 in the 1990 s drought having a severe shortfall of winter precipitation, compared to winter SPEI of −0.24 for 1999–2005 drought in which winter precipitation was above average. The differences in winter precipitation apparently led to 22% higher SWA estimates in the soil profile during the 1999–2005 compared to 1988–1994 drought, despite drastically different SPEI averages for the periods.

3.3. Model performance and key variables

Machine learning models explained 64% of the variance in monthly changes in SWA across soil depths at all 866 sites (Fig. 5). The models consistently selected SPEI as the most important variable to explaining SWA, and calendar month as the second most important variable (Fig. 5). Explained variance was greatest (up to 88%) for the soil depths of 0–5 cm and 70–110 cm. Explanatory power of the surrogate models was also high for intermediate depths (50–90 cm) but with SPEI being the most important predictor. Models of SWA variability for the remaining soil layers explained from 54% (20 cm depth) to 67% (130 + cm depths) of variance. Shallow to medium depth soils (10–40 cm) were the least well estimated by the variables, with $\leq$ 62% of variance explained. Calendar time, represented by the month of each datum, was the most predictive variable for soil water from 10 to 40 cm depths.

The importance of SPEI, precipitation, and pET to explaining SWA varied with the time frame over which they were calculated, specifically for surface SWA in spring and deeper SWA that is annually recharged by winter precipitation (Fig. 6). The models explained 31% more variability in deep moisture recharge compared to spring moisture of near-surface soils. Precipitation was consistently the most important variable explaining spring moisture variability near the soil surface, especially when summed over the 4–5 months prior to March/April. Conversely, pET, the second most predictive variable, was more important when considered over the months prior to spring. SPEI was the least predictive

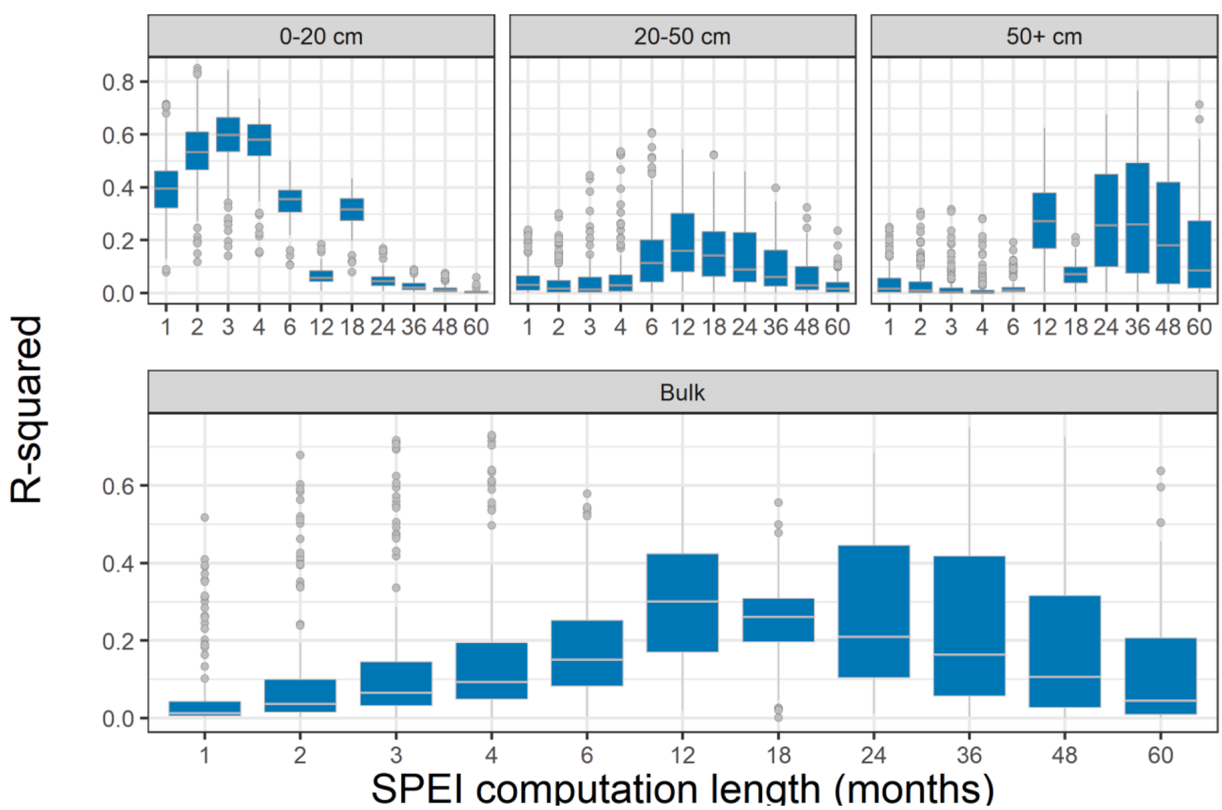

Fig. 3. Proportion of variation explained (r^2) between (SWA) and standardized precipitation-evapotranspiration index (SPEI) over the period of 1979–2015 at three soil depth bins (top panels) and averaged across the bulk soil column (lower panel) for different time frames for SPEI calculation (number of months preceding the date that SWA was estimated.

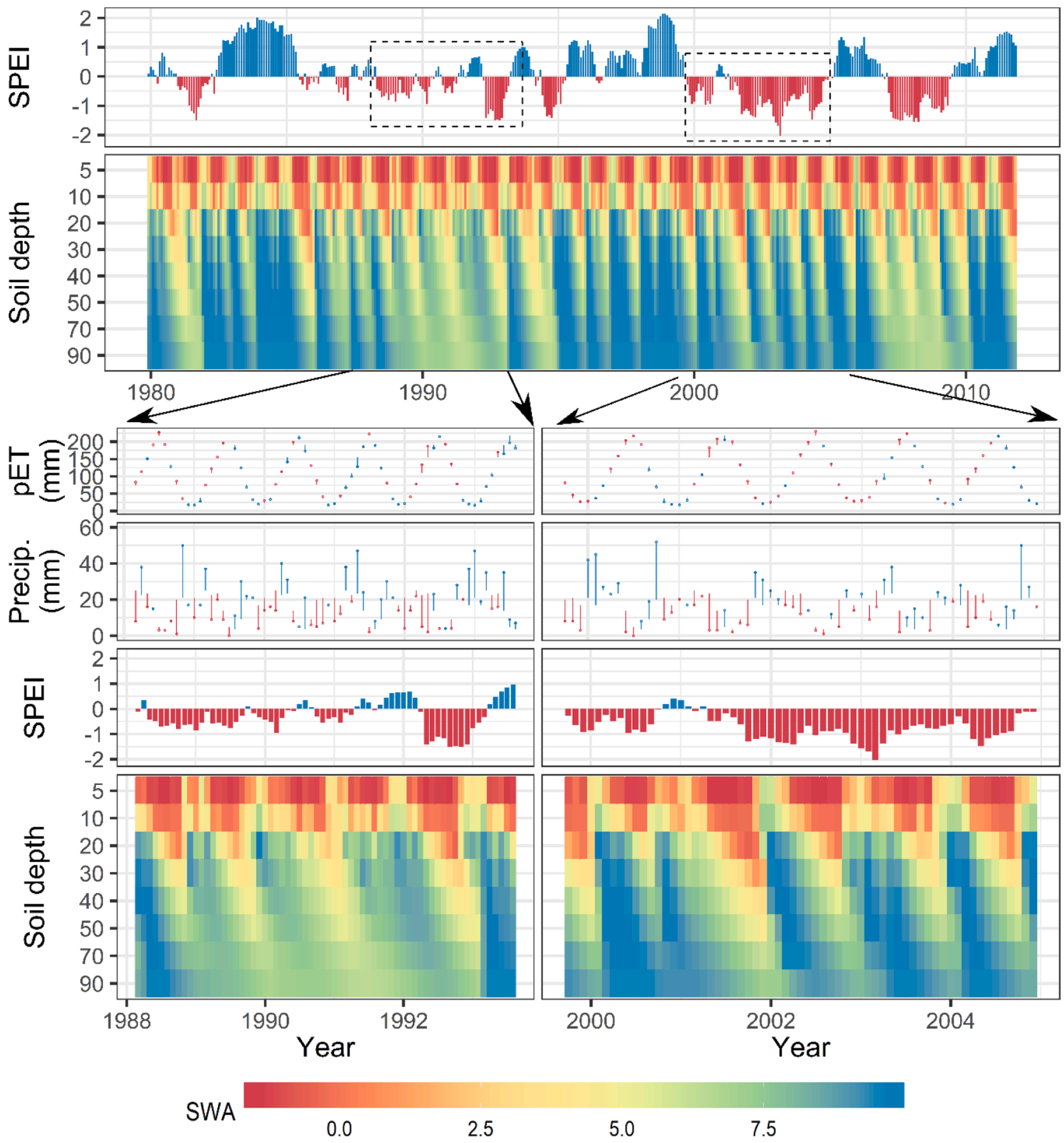

Fig. 4. Monthly time-series of standardized precipitation-evapotranspiration index (SPEI) and soil water availability (SWA), precipitation, and potential evapotranspiration (pET) across soil depths at an individual site in Northern Nevada USA. The top two panels are for the period 1979–2011, and lower three panels are for the period March 1988 through December 1994 (left column and left dashed box in top row) and September 1999 through April 2005 (right columns and right dashed box in top row) to show with better resolution the response of SWA to prolonged SPEI < 0. In the pET and Precip rows, the length of the line corresponds to the monthly anomaly for that estimate i.e. the line-end y-value with a circle represents monthly estimate and line end y-value without a circle represents average estimate for that month over the period of 1979–2015 (i.e. distance between the two is anomaly). Red lines and circles indicate a more arid month than normal (higher pET, lower precipitation). For the two SPEI rows, blue bars represent SPEI > 0 and red bars represent SPEI < 0. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of surface soil moisture in March/April regardless of computation length. For annual SWA recharge of deeper soil water, SPEI was consistently the most important predictor, especially at longer computation lengths (>8 months). Although summing precipitation over > 8 months increased its importance, it explained less variability in deep soil water recharge than pET.

4. Discussion

Estimating the availability of moisture in the places (soil depths) and times (seasons) that plants need it is critical for advancing earth-systems science, planning land management practices, and understanding the impacts of drought on ecosystems. Here, we characterized the ability of SPEI, meteorological variables, and landscape characteristics, to recreate longer-term and periodic patterns of soil moisture dynamics (SWA) across a dryland region. Our results highlight abilities and limitations of these predictors in recreating soil moisture dynamics and identify an important research need to develop more consistent methods to approximate soil moisture dynamics relevant to ecosystem functioning and resource management (Brabec et al., 2015; Chaney et al., 2017; Davidson et al., 2019). For example, annual recharge of deep soil moisture was recreated relatively well, with SPEI consistently emerging as the most important predictor (Fig. 6). Quantifying deep soil moisture recharge is important due to its impacts on watershed hydrology, forest growth and succession, annual forage productivity, and woody plant mortality (Allen et al., 2010; McDowell et al., 2013; Germino et al., 2018). However, our models, and SPEI as a predictor, were more challenged to recreate the availability of surface moisture in spring, which plays a vital role in agricultural production, and ecosystem functioning such as the success of post-fire ecosystem restoration treatments in

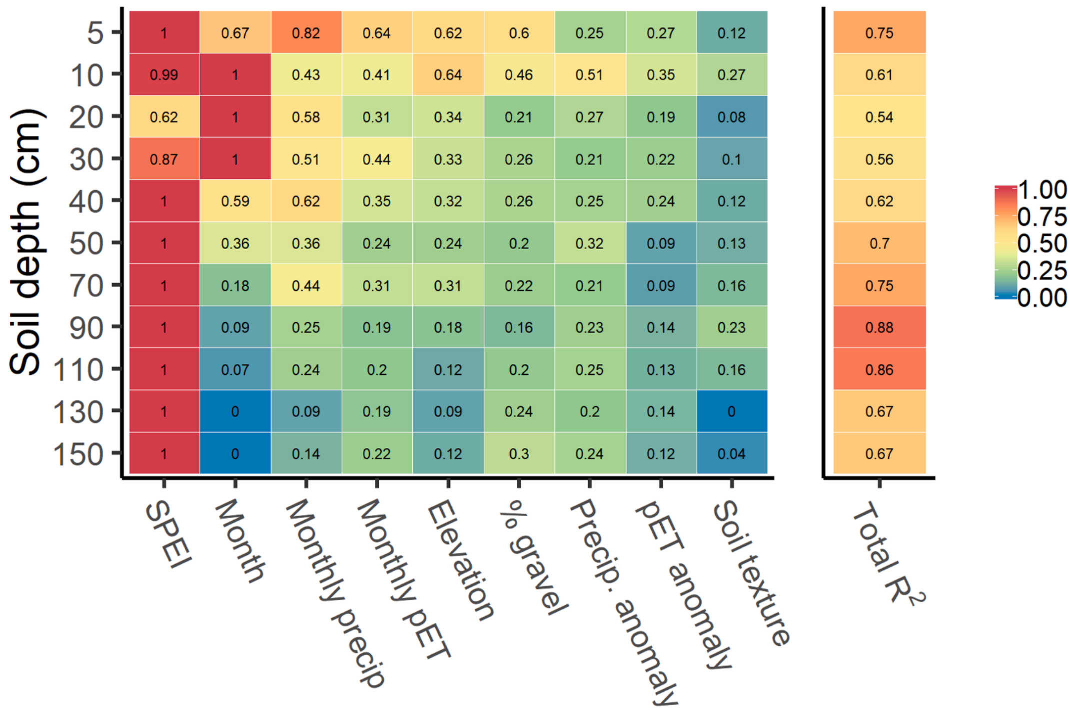

Fig. 5. Ranking of predictor variable contribution to model accuracy in a machine learning framework developed to predict changes in soil water availability across soil depths. Predictor variables are ranked by relative contribution (1 = greatest, 0 = least) to model performance from most predictive on the left of the x-axis (red fill), to least predictive on the right (green and blue fill). Right-most column reports total model R^2 for the soil depth layer. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

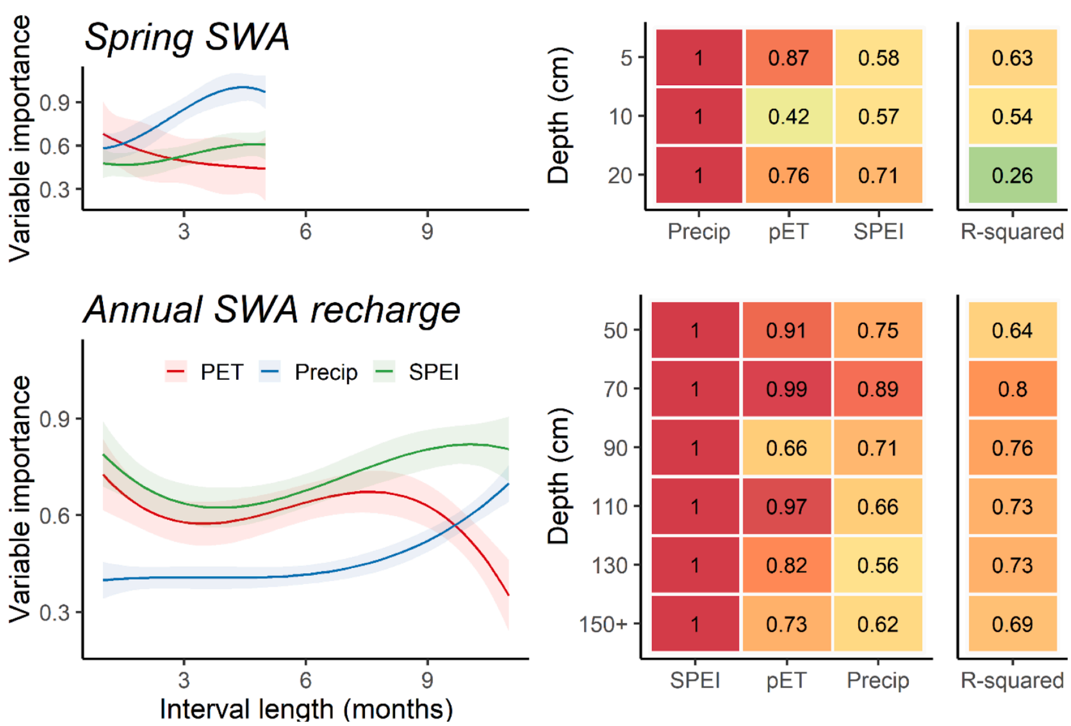

Fig. 6. Ranking of predictor variable importance changes with computation or sum length (left panels) for standardized precipitation-evapotranspiration (SPEI), potential evapotranspiration (pET), and precipitation (Precip), and by contribution to surface soil–water availability (SWA) in spring (top row) or contribution to annual recharge of deeper soil water availability (bottom row). Numbers within boxes in right panels indicates relative variable importance for machine learning models, and model R-squared from cross-validation.

shrublands (Roundy et al., 2018; Shriver et al., 2018; Tian et al., 2018; O'Connor et al., 2020). Improved ability to model surface soil moisture would also benefit scientific and management efforts in other arid systems such as predicting forest productivity, seed survival, and biocrust dynamics (Pakeman et al., 2012; Belnap et al., 2013; Winchell et al., 2016; Roundy et al., 2018).

Our findings compliment previous studies and fill knowledge gaps in terms of defining linkages between SPEI, meteorological metrics, and soil moisture dynamics. At the plot scale, SPEI has been shown to predict moisture trends in the top 1 m of soil using a quadratic function (Xingkai et al., 2016) and performed well to quantify agricultural drought impacts on yields of winter wheat, corn, and cotton (Tian et al., 2018). Wang et al. (2015) reported that SPEI outperformed other drought indices in predicting changes in soil moisture, concluding SPEI's multiscalar formulation allows for better representation of depth-resolved changes. Regional and continental scale studies in China using remotely sensed estimates of soil moisture show acceptable agreement with SPEI, but Scaini et al. (2015) found moisture *in situ* anomalies to exhibit higher correlations. Li et al. (2015) found SPEI to be approximately correlated with the Soil Moisture Condition Index (SMCI), but correlations decreased as longer computations lengths of SPEI were tested. Given that Li et al. (2015) focused only on the top 0–10 cm of soil moisture from Global Land Data Assimilation System Version 2.0 (GLDAS-2), the decreasing correlations agree with our findings of shorter SPEI computation lengths better representing shallow soils and longer computation lengths representing deeper soils.

We show strong spatial variability in continental-scale gradients in aridity and drought variability over the record length (Fig. 2). We also show relationships among drought trends, severity, and magnitude, suggesting that more drought-prone areas are not just increasing in aridity over time but are also prone to more and larger swings in aridity with implications for press- and pulse-drought dynamics (Hoover et al., 2015; Hoover and Rogers, 2016; Slette et al., 2019). These findings provide important insight and identify areas and regions that are currently impacted by water scarcity and may be more vulnerable to future drying trends. While long-term trends in drought may have limited application to resource managers, those seeking guidance on immediate conservation treatments, it provides significant insight into the spatial heterogeneity in aridity even within areas and regions that are otherwise considered similarly in terms of drought vulnerability. The strong spatial variation in the magnitude, variability, and trend in SPEI in the western United States with key hotspots of drought severity need to be considered when developing long-term plans for resource management including ecosystems services and development of hydrological infrastructure.

The strengths and weaknesses of SPEI as an indicator of soil moisture are accompanied by a tradeoff between the simplicity of meteorologically based drought indices, and the data needs and computational requirements of process-based soil moisture models or soil-moisture based drought indices. Despite the more intensive requirements of process-based models, and that they may not capture plot-specific soil physics processes (e.g., desiccation cracks, preferential flow paths, macropores), our results suggest that they may outperform meteorological metrics for understanding ecologically relevant drought dynamics. We do, however, acknowledge the potential for errors in process-based modeling, especially when models are run with coarse resolution geospatial datasets such as soils or gridded weather data that may have spatial inaccuracies and biases that may go unnoticed without field validation. Although this approach is common in larger-scale studies using process-based models (e.g., Eum et al., 2014; Pelletier et al., 2016; Shriver et al., 2019), future studies would benefit from assessing these errors when modeling soil moisture dynamics. Meteorological metrics, on the other hand, such as SPEI may provide useful predictions of qualitative changes in hydrologic water balance in longer time frames and provide general drought assessments of hydrological processes. Indeed, drought indices such as SPEI or the Palmer drought severity index (PDSI) are commonly leveraged for policy and management decisions, but the spatiotemporal limitations of their predictive ability need to be considered more critically when applied to smaller spatial scales (e.g., site, plot), shorter time periods (<1 year), or for modeling specific ecological outcomes.

5. Conclusions

In this study, we evaluated SPEI variability across CONUS, and assessed SPEI drought severity, meteorological conditions, and landscape characteristics as indicators of climatic water balance. We used a machine learning framework to model long term and periodic SWA dynamics across a broad range of dryland sites in the Great Basin, USA. SWA is an excellent metric to represent ecologically relevant soil moisture conditions in that it accounts for soil texture impacts on matric potential, is reported in mm, and thus normalizes moisture variability among sites with varying characteristics. Overall, long-term trends in SWA were modeled relatively well (up to 88% of variance explained, 64% average across soil depths) and twelve-month SPEI consistently emerged as the most important variable for model accuracy. Similarly, we found annual recharge of deep soil moisture to model quite well (up to 80% of variance explained, 73% average across soil depths > 50 cm), with SPEI again emerging as a key variable for model accuracy. Moreover, longer computation length SPEI were better indicators of deep SWA recharge than shorter computation lengths. However, we found the availability of surface SWA in spring, which is important for seedling germination and establishment in sagebrush steppe, was not modeled as well (up to 63% of variance explained, 48% averaged across the top 20 cm) and SPEI was consistently the least important parameters in these models. Instead, precipitation amounts from the previous 3–5 months were better predictors of SWA, suggesting a lagging influence of pET during the winter. While these results do show relatively positive outcomes in terms of modeling long-term and periodic soil moisture dynamics, potential error of models when averaged across events and soil layers, may limit their applicability as indicators for planning tool development. Instead, a reliance on process-based models may be more appropriate when enhanced precision in soil moisture dynamics are needed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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