Evaluating the Utility of Drought Indices as Soil Moisture Proxies for Drought Monitoring and Land–Atmosphere Interactions

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ABSTRACT

There are a variety of metrics that are used to monitor drought conditions, including soil moisture and drought indices. This study examines the relationship between in situ soil moisture, NLDAS-2 soil moisture, and four drought indices: the standardized precipitation index, the standardized precipitation evapotranspiration index, the crop moisture index, and the Palmer Z index. We evaluate how well drought indices and the modeled soil moisture represent the intensity, variability, and persistence of the observed soil moisture in the southern Great Plains. We also apply the drought indices to evaluate land–atmosphere interactions and compare the results with soil moisture. The results show that the SPI, SPEI, and Z index have higher correlations with 0–10-cm soil moisture, while the CMI is more strongly correlated with 0–100-cm soil moisture. All the drought indices tend to overestimate the area affected by moderate to extreme drought conditions. Significant drying trends from 2003 to 2017 are evident in SPEI, Z index, and CMI, and they agree with those in the observed soil moisture. The CMI captures the intra- and interannual variability of 0–100-cm soil moisture better than the other drought indices. The persistence of CMI is longer than that of 0–10-cm soil moisture and shorter than that of 0–100-cm soil moisture. Model-derived soil moisture does not outperform the CMI in the 0–100-cm soil layer. The Z index and CMI are better drought indices to use as a proxy for soil moisture when examining land–atmosphere interactions while the SPI is not recommended. Soil type and climate affect the relationship between drought indices and observed soil moisture.

KEYWORDS: Atmosphere; Drought; Atmosphere-land interaction; Climatology; Hydrometeorology; Surface observations

1. Introduction

Drought is a recurring climate feature characterized by a deficiency of precipitation over a protracted period of months, years, or even decades. Drought can cause environmental damage and economic losses through its influence on organisms, ecosystems, economy, and society (Heim 2002). A large number of drought indices have been developed to quantify drought severity and impacts. These drought indices use a variety of approaches to measure drought conditions (Quiring 2009). Wang et al. (2015) identified two main categories of drought indices: those that are purely based on statistical probability, such as the standardized precipitation index (SPI; McKee et al. 1993), and those that are based on a combination of a water balance model and statistical probability, such as the Palmer drought severity index (PDSI; Palmer 1965). The various drought indices do not always agree regarding the degree of dryness/wetness because each index is designed for a different purpose and/or to describe a different type of drought. For example, the SPI is commonly used to represent meteorological drought, while the PDSI is commonly used to represent agricultural and hydrological drought (Quiring 2009).

Soil moisture, reflecting the water content of soil, can also be used to represent different types of drought. Previous research has shown that soil moisture can be used to describe meteorological drought conditions. For example, Sims et al. (2002) compared the SPI and PDSI with soil moisture from 1994 to 1999 in North Carolina and found that short-term variations in soil wetness more closely match the SPI than the PDSI. Tian et al. (2018) demonstrated that soil moisture has good agreement with 1-month SPEI in the southern United States. Halwatura et al. (2017) also found that meteorological drought indices can accurately represent soil moisture drought in eastern Australia. Other studies have found...
that soil moisture is useful for representing agricultural drought (Martínez-Fernández et al. 2016; Narasimhan and Srinivasan 2005). For example, Narasimhan and Srinivasan (2005) found that their soil moisture–based drought index was highly correlated with wheat and sorghum crop yields. Martínez-Fernández et al. (2016) also found a good relationship between soil moisture and annual cereal production. Despite of the importance of soil moisture for monitoring agricultural and meteorological drought, direct measurements of soil moisture are not sufficiently dense for drought monitoring in all regions of the United States. In fact, many studies use drought indices (Kumar et al. 2016) or model-simulated soil moisture (Narasimhan and Srinivasan 2005; Samaniego et al. 2018) because of the lack of soil moisture measurements. This potentially limits our understanding of drought because it assumes that drought indices are a good proxy for in situ soil moisture measurements. One of the reasons that there is low confidence in global drought trends is because of the lack of direct measurements, such as soil moisture and runoff (Hartmann et al. 2013).

In addition to drought monitoring, soil moisture is also important because it influences temperature and precipitation on subdaily (Ford et al. 2015b) to seasonal time scales (Meng and Quiring 2010). Soil moisture affects the surface energy and water balance (Seneviratne et al. 2010). Dry soil limits evapotranspiration and increases the near-surface air temperature (Guo and Dirmeyer 2013; Teuling et al. 2010). The relationship between soil moisture and precipitation is more complicated and less direct. Both positive and negative soil moisture–precipitation feedbacks are observed. A positive feedback means that dry soils will limit evapotranspiration, leading to less moisture in the atmosphere, which may decrease precipitation. In contrast, a negative feedback means that reduced evapotranspiration will increase near-surface air temperature and this decreases convective inhibition; enhancing the probability of convective precipitation over drier soils (Ford et al. 2015a, 2018; Tuttle and Salvucci 2016). Hence, soil moisture is a critical variable for both characterizing drought conditions and for investigating land–atmosphere interactions.

Drought indices have been used to characterize near-surface moisture conditions in some land–atmosphere interaction studies because of the lack of available soil moisture measurements. For example, Hirschi et al. (2010) used the SPI as a proxy for soil moisture and applied quantile regression to identify the relationship between the SPI and summer temperature extremes in southeastern Europe. Their results indicated that extreme heat tended to intensify over dry soils. Ford et al. (2017) also used the SPI to represent soil moisture deficits and identify the long-term variability of soil moisture–maximum temperature coupling over the continental United States. They found that the strength of land–atmosphere coupling varies over time and that it is modulated by remote sea surface temperature forcing. However, neither of these studies evaluated the suitability of using the SPI as a proxy for soil moisture. Therefore, it is not clear how sensitive their results are to using an indirect estimate of soil moisture.

To date, there have only been a few studies that have examined the performance of drought indices using in situ soil moisture measurements because in situ soil moisture stations are too sparse or unevenly distributed and their observation records are not sufficiently long to support this type of analysis. Soil moisture is highly spatially heterogeneous because it is influenced by climate, land cover, topography and soil property (Crow et al. 2012). Either sparse or unevenly distributed soil moisture sites can limit the ability of observation on capturing the spatial variation. For example, the U.S. Climate Reference Network (USCRN; Diamond et al. 2013) has 114 stations over the contiguous United States with an averaged distance of 265 km between nearby sites. This is too sparse to capture the spatial variations of regional drought and soil moisture patterns. Temporally, Ford et al. (2016) demonstrated that between 3 and 15 years of data are required to produce stable soil moisture distributions. Globally, there are very few regions with in situ soil moisture observations that can meet requirements of both spatial and temporal coverage. Sims et al. (2002) found that the SPI represents soil moisture better than the PDSI at short time scales (~1–3 months) in North Carolina. Wang et al. (2015) showed that in China the SPEI has a higher correlation with soil moisture than the SPI. Tian et al. (2018) examined the correlation between six drought indices and 0–60-cm soil moisture in the southern United States and found that the SPEI is the drought index that best represents soil moisture conditions in this region. These evaluations of the relationship between drought indices and soil moisture focused exclusively on correlation analysis. Therefore, they may not provide a comprehensive assessment of all of the characteristics, such as intensity, variability, and persistence, that are important when it comes to drought monitoring and land–atmosphere interactions.

There are three main knowledge gaps in the current literature: 1) the similarities and differences between different drought indices and in situ soil moisture in terms of their ability to detect different drought characteristics are not fully understood, 2) the sensitivity of using different drought indices as soil moisture proxy in land–atmosphere interactions has not been evaluated, and 3) there are few studies that examine how variations
in soil and climate characteristics influence the relationship between observed soil moisture and drought indices. This study will fill these knowledge gaps by providing a comprehensive assessment of the relationship between in situ soil moisture and four commonly used drought indices at the state level in SGP. We evaluate how well each drought index represents the intensity, variability and persistence of drought. Also, we investigate the land–atmosphere interactions by using different drought indices and soil moisture. The data and methods used in this study are presented in section 2, and this is followed by a comprehensive evaluation of that ability of drought indices to represent soil moisture conditions in section 3. In section 4, the discussion of results and limitations are summarized. Last, we will conclude by presenting the key findings in section 5.

2. Materials and methods

a. Study area

Our study region covers Oklahoma and northwestern Texas (Fig. 1), which we refer to as the southern U.S. Great Plains (SGP). This is one of the main agricultural areas in the United States and the annual value of agricultural production in Oklahoma and Texas is >16 billion U.S. dollars (Steiner et al. 2018). As shown in Fig. 1a, northwestern Texas is the largest cotton producing area in the United States and Oklahoma is one of the main winter wheat growing regions. The SGP was selected for this study because it has a dense network of in situ soil moisture observations that have a relatively long period of record (>15 years of record, Fig. 1a). Ford et al. (2016) demonstrated that between 3 and 15 years of data are required to produce stable soil moisture distributions. Therefore, we removed all sites with less than 15 years of observations. The SGP region is also an area that is frequently affected by drought. For example, in 2011 the SGP region experienced extreme drought and it caused more than 9 billion U.S. dollars in economic losses (Tian et al. 2018). Additionally, the SGP has frequently been identified as a hotspot for land–atmosphere interactions in both modeling and observational studies (Ford and Quiring 2014a; Ford et al. 2015a; Koster et al. 2004).

b. In situ soil moisture measurements

We focus on the warm season (April–September) in this study because accurately measuring soil water
content in frozen soils is difficult (Xia et al. 2015a). Daily in situ soil moisture data from 2003 to 2017 were obtained from the National Soil Moisture Network (NSMN, http://nationalsoilmoisture.com/), which aggregates data from a large number of in situ networks (Quiring et al. 2016). Data from 206 stations representing three observational networks—Oklahoma Mesonet (OKM; McPherson et al. 2007), West Texas Mesonet (WTM; Schroeder et al. 2005), and Soil Climate Analysis Network (SCAN; Schaefer et al. 2007)—are used in this study (Fig. 1b). Detailed information about these three networks is shown in Table 1. Since each of these networks uses different instruments to measure soil moisture, we did not compare the results among these three networks in this study. We used volumetric water content (VWC) in two layers, 0–10 and 0–100 cm. The soil moisture in the 0–10-cm layer is represented by the VWC measured at 5 cm. For 0–100-cm VWC, we used a depth-weighted average to combine the measurements from multiple sensors within the top 100 cm of the soil column. In this study, we used the daily average replacement method (Ford and Quiring 2014b) to fill data gaps when there were fewer than 10 consecutive days that are missing in a month. Daily soil moisture measurements are then averaged to monthly and warm-season values to assess variability and trends. For those months with more than 10 consecutive days of missing data, we flagged that month as “missing.” Spatially, we aggregated the station-based measurements to 1/8° grid cells using a simple spatial averaging method to match the spatial resolution of drought indices. In our study area, the number of stations in each grid cell varies from 0 to 2. Those grid cells with no stations located within them are not considered in our analyses. This approach has been widely used in previous studies (Albergel et al. 2012; Robock et al. 2003; Xia et al. 2015b), and it reduces some of the bias associated with the point-versus-gridscale mismatch.

c. Model-simulated soil moisture

Model-simulated soil moisture (in 0–10- and 0–100-cm soil layers) from 2003 to 2017 was also evaluated in this study because it represents an independent data source that can provide soil moisture estimates. Model-simulated soil moisture data are derived from phase 2 of the North American Land Data Assimilation System (NLDAS-2) (Xia et al. 2012). NLDAS is a project developed by multiple organizations to construct land surface model datasets. Soil moisture is simulated at 1/8° spatial resolution by four land surface models: Mosaic, Noah, Sacramento (SAC), and Variable Infiltration Capacity (VIC). Mosaic and Noah provide simulated soil moisture in the 0–10- and 0–100-cm soil layers. VIC simulates soil moisture in three layers. The first layer has a constant depth (0–10 cm), while the second and third layers have variable depths. In our study area, layers 2 and 3 are consistently set to 10–40 and 40–140 cm. SAC model is a conceptual water storage model. NLDAS-2 uses a physically based heat transfer component (Koren et al. 2010) to convert SAC water storage to soil moisture in 0–10-, 10–40-, and 40–140-cm soil layers. More details on the postprocessing techniques used for SAC are described by Xia et al. (2012). A depth weighted average is then applied to VIC and SAC to produce a model-estimate soil moisture in the 0–100-cm layer. In this study, modeled soil moisture is compared with in situ soil moisture in the same layers.

Each model has different strengths and biases in terms of its ability to simulate soil moisture. In general, Noah and VIC soil moisture tends to be wetter than the observations, while Mosaic and SAC are drier than the observations (Xia et al. 2015b). In this study, we calculated a four-model ensemble mean to represent model-simulated soil moisture. We adopted the approach that Wang et al. (2009) used to calculate the multimodel ensemble mean, rather than using a simple average. This approach normalizes soil moisture in each model grid, then averages these normalized values for all four models. Wang et al. (2009) demonstrated that the simple averaging method may miss some extreme events because different models may not reach extreme values at the same time. The hourly model-simulated soil moisture data were averaged to daily, monthly and annual values.

d. Drought indices

Four drought indices are evaluated in this study: SPI, standardized precipitation and evapotranspiration index (SPEI), crop moisture index (CMI), and Palmer Z index (Z index). These four drought indices are selected because 1) they are based on different calculation methods: the SPI and SPEI are based on probability distributions, whereas the CMI and Z index are forms of the PDSI, which is a water balance model; 2) they are typically used for different types of drought: the SPI and SPEI are used for

<table>
<thead>
<tr>
<th>In situ network</th>
<th>No. of stations in the study area</th>
<th>Type of sensor</th>
<th>Measurement depths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma Mesonet</td>
<td>136</td>
<td>Campbell Scientific 229-L</td>
<td>5, 10, 25, and 60 cm</td>
</tr>
<tr>
<td>West Texas Mesonet</td>
<td>70</td>
<td>Campbell Scientific 615-L</td>
<td>5, 20, 60, and 75 cm</td>
</tr>
<tr>
<td>Soil Climate Analysis Network</td>
<td>2</td>
<td>Stevens HydraProbe</td>
<td>5, 10, 20, 50, and 100 cm</td>
</tr>
</tbody>
</table>

Table 1. Summary of in situ networks providing soil moisture data.
describing meteorological drought, whereas the CMI and Z index are agricultural drought indices; and 3) they are all time independent (i.e., calculated using only meteorological inputs from the current month without relying on any data from previous months). Detailed descriptions of these indices are given below. Considering the time scales that are suitable for both drought evaluation and land–atmosphere interactions, the four drought indices are calculated at both the daily and monthly time scale. Drought indices at these time scales have been used as soil moisture proxy in the previous studies (Ford and Quiring 2019; Hirschi et al. 2010; Tian et al. 2018), and they are incorporated with soil moisture by the U.S. Drought Monitor to support drought monitoring. Also, the impacts of soil moisture on the atmosphere usually occur at relatively short time scales (Ford et al. 2017; Hirschi et al. 2010). The daily drought indices (based on the mean of 7 days prior to the target date) are only used for calculating persistence and the impacts of the land surface on convective initiation, while all of the other evaluations of drought index performance are based on the monthly time scale.

1) SPI AND SPEI: STATISTICAL PROBABILITY INDICES

The SPI (McKee et al. 1993) is calculated by standardizing the probability of precipitation for a user-specified time period (typically months). A precipitation record is fit by a probability density function and then transformed to a normal distribution (Guttman 1999). In this study, we used the gamma distribution to calculate the SPI. Compared with normal distribution, the gamma distribution provides a better fit (Guttman 1999; Wu et al. 2007) and so it has been recommended as the best approach by the National Drought Mitigation Center (NDMC; drought.unl.edu).

In the SPEI, precipitation is replaced by the difference between precipitation and potential evapotranspiration (PET) (Vicente-Serrano et al. 2010), where PET represents water demand. Similar to the SPI, the gamma distribution is used to calculate SPEI.

2) CMI AND Z INDEX: WATER BALANCE INDICES

The CMI (Palmer 1968) and Z index (Palmer 1965) were developed based on the PDSI. The PDSI uses a simple two-layer water balance model to estimate the actual and potential values of evapotranspiration, recharge to soils, runoff, and water loss to the soil layers. The amount of water needed to maintain “normal” conditions is represented by the climatically appropriate for existing conditions (CAFEC). As shown in Eq. (1),

\[ \hat{P} = \alpha_P E + \beta_P R + \lambda_P R O - \delta_L, \]

where \( \hat{P} \) is the CAFEC; PE is potential evapotranspiration; PR is potential recharge to soils; PRO is potential runoff; \( L \) is potential water loss; and \( \alpha_P, \beta_P, \lambda_P, \) and \( \delta_L \) are water-balance coefficients, equaling to the ratio of actual values over potential values.

The Z index is given in Eq. (2):

\[ Z = (P - \hat{P})K, \]

where \( P \) is actual precipitation and \( K \) is a climatic characteristic coefficient. Detailed formulas can be found in Yuan and Quiring (2014).

The CMI is the sum of the evapotranspiration anomaly index and the wetness index. The CMI is given in Eq. (3):

\[ CMI_i = EAI_i + WI_i, \]

where EAI is the evapotranspiration anomaly index, which is computed as deficit of actual evapotranspiration [in Eq. (2)] to “expected” evapotranspiration (i.e., long-term mean evapotranspiration); WI is the wetness index combines recharge to soils [in Eq. (2)] and runoff [in Eq. (2)]. Detailed descriptions of the CMI can be found in Palmer (1968). The Z index and CMI are designed for relatively short time scales (1–3 months).

e. PET

The SPEI, CMI, and Z index all require an estimate of PET as part of their calculation. In the original PDSI, PET is estimated by the Thornthwaite equation (Thornthwaite 1948). However, subsequent studies have shown that the Thornthwaite equation is sensitive to air temperature and this may cause an overestimation of PET (Damberg and AghaKouchak 2014; Sheffield et al. 2012; Yuan and Quiring 2014). Therefore, in this study, PET is estimated using the Penman–Monteith equation, as given by the Food and Agricultural Organization (Allen et al. 1998):

\[ \text{PET} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_a - e_d)}{\Delta + \gamma (1 + 0.34U_2)}, \]

where \( R_n \) is net radiation at the crop surface, \( G \) is soil heat flux density, \( T \) is mean air temperature at 2-m height, \( U_2 \) is wind speed at 2-m height, \( e_a \) is saturation vapor pressure, \( e_d \) is actual vapor pressure, \( \Delta \) is slope of vapor pressure curve, and \( \gamma \) is psychrometric constant.

f. Meteorological data

Gridded temperature and precipitation data are used to calculate the drought indices. These data were obtained from the NLDAS-2 forcing data, which were
derived from NOAA Climate Prediction Center (CPC) gauge-based precipitation data. This dataset was adjusted by Parameter-Elevation Regressions on Independent Slopes Model (PRISM) to reduce the bias over high-elevation areas (Cosgrove et al. 2003). NLDAS-2 temperature data are derived from the NCEP North American Regional Reanalysis (NARR). The NLDAS-2 forcing data are hourly and have a 1/8° spatial resolution. Precipitation data are accumulated from hourly to daily, monthly, and annual values; temperature data are averaged to daily, monthly, and annual values. Other meteorological data, such as solar radiation, air pressure, wind speed, and humidity, are also obtained from NLDAS-2 forcing data. These data are necessary for calculating PET.

Convective initiation data from 2005 to 2007 are used to investigate the atmospheric response to land surface conditions. These data are generated using the Thunderstorm Observation by Radar Algorithm (ThOR; Houston et al. 2015), a Lagrangian method to automatically identify and track convective events. Detailed descriptions of this method are provided in Houston et al. (2015). These data have been used to assess the relationship between soil moisture and convective initiation in the previous studies (Ford et al. 2018; Yuan et al. 2020). However, because ThOR is computationally intensive, we only used 3 years of ThOR data in this study. To better examine the relationship between soil moisture and convective initiation, we focused on the weakly forced events, which excludes any days with large-scale synoptic forcing. There are a total of 1903 warm season weakly forced afternoon convective events over the SGP from 2005 to 2007, as shown in Fig. 1c, and 1528 of them occurred within a 50-km distance from in situ soil moisture sites.

g. Intensity, variability, and persistence

The drought indices are compared with soil moisture percentiles based on their ability to accurately represent drought characteristics: intensity (or severity), frequency, duration, variability, and persistence. Percentiles are calculated for both the soil moisture measurements and the drought indices using an empirical cumulative distribution function (ECDF). This approach has been used to develop soil moisture indices in previous studies (Samaniego et al. 2013; Sheffield et al. 2004) and has been adopted to describe drought severity by U.S. Drought Monitor. Krueger et al. (2019) evaluated matric potential (MP), soil water storage (SWS), and fraction of available water capacity (FAW) and compared the performance of the raw values of each of these soil moisture–based indices to soil moisture anomalies and percentiles. They found that the anomaly and percentile-based indices had a statistically significant stronger relationship with agricultural drought than the raw values. They concluded that using soil moisture percentiles removed seasonality from soil moisture time series and strengthened the relationship between soil moisture and crop yield. Therefore, we have adopted soil moisture percentiles in this study. We used a 15-day moving window to calculate the percentiles. The degree of similarity between the soil moisture and drought index percentiles is evaluated using the correlation coefficient. Additionally, the area experiencing drought, spatially averaged drought duration, and frequency are calculated for each drought category [e.g., moderate (D1), severe (D2), and extreme (D3) drought]. The drought categories are determined using the percentiles defined by U.S. Drought Monitor (Table 2). We did not consider mild (D0) or exceptional (D4) droughts. Only the grid cells with in situ stations are used to calculate drought area, duration and frequency. Drought area is calculated as the percentage of total grid cells that experiences drier then D1, D2, or D3 conditions. Drought duration is calculated based on the number of consecutive months when conditions are drier than the D1, D2, or D3 thresholds, respectively. Drought frequency is defined as the number of times a drought of a given intensity (e.g., D1, D2, or D3) occurs during the study period.

The interannual variability is assessed using the mean absolute delta ranking \( R \), as given in Eq. (5):

\[
R = \frac{1}{n-1} \sum_{i=1}^{n-1} |R_{i+1} - R_i|,
\]

where \( R_i \) is the ranking of \( i \)-th-year drought based on the descending order of drought index value. The interannual variability indicates year-to-year variations in moisture conditions. This is particularly important when some climate phenomenon (with a multiyear cycle) influences hydroclimatic conditions, such as ENSO. The intra-annual variability of drought indices and soil moisture is represented using the standard deviation. The standard deviation of all months within a given year represents the intra-annual variability of that year.

Persistence is quantified using the lagged autocorrelation of the daily time series. For each grid cell or

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Percentiles that are applied to soil moisture: VWC, SPI, SPEI, ( Z ) index, and CMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>Moderate</td>
<td>11%–20%</td>
</tr>
<tr>
<td>D2</td>
<td>Severe</td>
<td>6%–10%</td>
</tr>
<tr>
<td>D3</td>
<td>Extreme</td>
<td>&lt;5%</td>
</tr>
</tbody>
</table>

Table 2. U.S. Drought Monitor drought categories (D1–D3) and the associated percentiles.
station, lagged autocorrelations \( (r) \) are calculated at lags ranging from 1 to 90 days. The lagged correlation is calculated using two datasets: 1) all \( \text{day}_{-1} \) values, and 2) all \( \text{day}_{-1+n} \) values. For example, the lagged 1-day correlation is based on all 1 April values and all 2 April values. Robock et al. (1995) and Dirmeyer et al. (2016) used linear functions \( \text{e.g., } \ln(r) \) to determine persistence and we adopt the same approach. Therefore, in this study, persistence is measured as the number of days until \( \ln(r) = -1, \) \( r = 1/e. \)

**h. Land–atmosphere interactions**

We use drought indices and soil moisture (in situ observed and model simulated) to describe land surface conditions and to quantify its impact on air temperature and convective initiation. For temperature, we adopt the same approach used in Ford et al. (2017) to assess the coupling strength. This is based on calculating the correlation between soil moisture/drought indices in a given month and maximum temperature in the following month. For convective initiation, we assess the moisture conditions at the time and location when a convective storm initiates and compare it with randomly selected moisture conditions from a nonconvective time and location. This approach has been previously used to examine the interactions between afternoon convection and soil moisture (Ford et al. 2018; Taylor et al. 2012; Yuan et al. 2020). Specifically, we use soil moisture percentiles from in situ sites that are within a 50-km distance from each initiation. These are compared with soil moisture percentiles that are generated by randomly selecting an equal number of events from times and locations without convective initiation. The random selection process is repeated 1000 times using bootstrapping resampling method with replacement. For the drought indices and model simulated soil moisture, the locations and times that are used match the in situ soil moisture.

### 3. Results

**a. Intensity comparison**

Figure 2 shows scatterplots of spatially averaged in situ soil moisture percentiles, drought-index percentiles, and model-simulated soil moisture percentiles. In 0–10-cm soil layer, the SPI, SPEI, and Z index tend to systematically underestimate the percentiles on the wet end, especially when the observed soil moisture percentiles are >0.80. In comparison, the CMI and NLDAS percentiles have little systematic bias with respect to the in situ soil moisture percentiles. In 0–100-cm soil layer, none of the drought indices show systematic bias. From 2003 to 2017, the modeled soil moisture and all of the drought indices, except the SPI, have a statistically significant \( (p < 0.05) \) correlation with in situ soil moisture in both 0–10- and 0–100-cm soil layers. The SPI, SPEI, and Z index have higher correlations with observed soil moisture in the 0–10 cm layer than soil moisture in the 0–100-cm layer. On the other hand, the CMI has higher correlations \( (r = 0.80) \) with the 0–100-cm soil moisture than the 0–10-cm soil moisture \( (r = 0.78) \). Among the four drought indices, the CMI has the highest correlation with soil moisture in both soil layers, followed by the Z index, SPEI, and SPI. The modeled 0–10-cm soil moisture has slightly higher correlations \( (r = 0.79) \) with the observed 0–10-cm soil moisture than all the drought indices. In the 0–100-cm soil layer, modeled soil moisture has slightly lower correlations than the CMI, but higher correlations than the Z index, SPEI, and SPI.

The spatial patterns of correlations over the SGP are shown in Fig. 3. We first examine the results based on the 0–10-cm soil moisture (left panel of Fig. 3). The SPEI, CMI, and Z index have correlations > 0.7 with in situ soil moisture at 57.8\%, 65.0\%, and 59.2\% stations, respectively, while no stations have correlations > 0.7 between the SPI and soil moisture. The SPEI, CMI, and Z index have similar spatial patterns of correlation, as shown in Figs. 3c, 3e, and 3g. In west central Texas and northeast Oklahoma, the correlations are lower than those in western Oklahoma and northern Texas. The correlation between the SPI and the observed 0–10-cm soil moisture (Fig. 3a) is generally lower than the other drought indices and there is no clear spatial pattern over the majority of study area. High correlations \( (r > 0.8) \) between the modeled and observed 0–10-cm soil moisture (Fig. 3i) are found in a few locations in northern Texas and western Oklahoma. In the 0–100-cm soil layer (right panel of Fig. 3), only CMI has high correlations with soil moisture, while the rest of drought indices show weak correlations. The SPEI and Z index show a substantial decrease in the number of stations with correlations > 0.7 from the top 10-cm soil layer to the 0–100-cm soil layer and the SPI consistently has low correlations at all stations. In contrast, the CMI has correlations > 0.7 at 95\% of sites in 0–100-cm soil layer, but correlations > 0.7 at only 65\% of sites in the 0–10 cm soil layer. The spatial pattern in this layer indicates a west-to-east gradient in the correlations, from low to high, for the SPI, SPEI, and Z index. The CMI has high correlations \( (r > 0.8) \) over the majority of Oklahoma. There is not a pronounced spatial pattern to the correlations between modeled and observed soil moisture in 0–100-cm soil layer. Compared with those in the 0–10-cm soil layer, there are fewer statistically significant correlations.
FIG. 2. Scatterplots of drought indices and model-derived soil moisture vs in situ soil moisture in the (left) 0–10- and (right) 0–100-cm soil layers. The drought indices include the 1-month SPI, SPEI, CMI, Palmer’s $Z$ index ($Z$), and NLDAS-2 model-simulated soil moisture. Each dot represents monthly mean conditions over the SGP during the warm season (April–September 2003–17). The correlation coefficient is reported in the lower-right-hand corner of each plot. An asterisk denotes a statistically significant correlation at the 95% confidence level.
between modeled and observed soil moisture in Texas, than in Oklahoma in the 0–100-cm soil layer.

The area, duration, and frequency of drought are also important drought characteristics. We examined these three indicators based the D1, D2, and D3 drought categories that are used by the U.S. Drought Monitor (Table 2). The drought area in each year is calculated by the number of soil moisture sites showing drought over the total number of soil moisture sites. The mean value of multiyear percentage is shown in Fig. 4a. The SPI shows a greater area that experienced D1, D2, and D3 drought conditions than the SPEI, CMI, and Z index. All of the drought indices overestimate drought area. However, CMI shows results that are most similar to the observed 0–100-cm soil moisture. Modeled soil moisture also slightly overestimates drought area in most cases, except for the D1 drought area based on 0–10-cm soil moisture.

Drought duration and frequency are calculated at each soil moisture site. The spatially averaged results are

“.” denotes statistically significant correlation at 95% confidence level

FIG. 3. Spatial patterns of the correlation coefficient between drought indices modeled soil moisture and (left) in situ–observed 0–10-cm soil moisture and (right) in situ–observed 0–100-cm soil moisture during the warm season (April–September) from 2003 to 2017.
shown in Figs. 4b and 4c. There is not a statistically significant difference between simulated and observed soil moisture in capturing drought duration and drought frequency. The SPI significantly overestimates drought duration in all three categories, and drought frequency in D1 and D2 categories. The SPEI and Z index perform similar to each other. They both show longer drought durations than the in situ soil moisture in both layers and in all three categories. However, the SPEI and Z index show similar drought frequency with in situ soil moisture (i.e., there are no statistically significant differences) in both soil layers. The CMI performs the best among the four drought indices and it agrees well with in situ soil moisture in terms of drought duration and frequency. The only statistically significant difference is between the CMI and 0–10-cm in situ soil moisture in the D1 and D2 categories.

We compare the time series of warm season drought indices and soil moisture in the SGP in Fig. 5. All drought indices, except the SPI, and both in situ and modeled soil moisture show statistically significant decreases between 2003 and 2017. This indicates that growing season conditions have experienced a pronounced drying trend in the SGP during this time period. The SPI indicates a different trend because it does not account for temperature changes and evapotranspiration (Yuan and Quiring 2014). Therefore, the difference between the SPI and other drought indices can be used to demonstrate that much of the drying trend is due to an increase in temperatures in the region, and therefore more evaporative demand, as opposed to a decrease in precipitation (i.e., less supply). Warmer temperatures tend to enhance evapotranspiration and this, in turn, leads to lower soil moisture and drier conditions in the SGP. Based on the in situ soil moisture, the drying trend is stronger in the 0–10-cm soil layer (−0.0085 yr\(^{-1}\)) than in the 0–100-cm soil layer (−0.0072 yr\(^{-1}\)). The differences indicated by the modeled soil moisture are smaller than the in situ soil moisture. When comparing these trends to the SPEI, CMI, and Z index, it is apparent that these drought indices tend to underestimate the drying trend in the SGP with respect to the in situ soil moisture. However, the CMI trend (−0.0069 yr\(^{-1}\)) is the most similar to that of the in situ soil moisture between 2003 and 2017, especially in the 0–100-cm soil layer. The trend in CMI also agrees very strongly with the modeled soil moisture trend. Since the length of record only covers 2003–17, the trends summarized in this study need further verification when longer time series are available.

b. Interannual/intra-annual variability of drought indices and soil moisture

Figure 5 illustrates the trend as well as the interannual variability. To quantitatively examine the interannual variability in drought indices and soil moisture, the mean absolute delta ranking is used. The mean absolute delta rankings for modeled and in situ soil moisture and each drought index have been calculated using each
month from the period of the record. The mean absolute delta ranking of in situ soil moisture in 0–100 cm (black dash line) is lower than that of soil moisture in 0–10 cm (black solid line) during the warm season (Fig. 6). Among the four drought indices, the SPI (green bars) shows the greatest variability from April to June, while the Z index (dark blue bars) has the greatest variability from July to September. The CMI (brown bars) has the least variability in all months and is the most similar to the 0–100-cm in situ soil moisture. The variability of modeled soil moisture in both layers is larger than that of in situ soil moisture. The difference is most pronounced in the 0–100-cm soil layer. The month-to-month variations in the delta ranking of the SPEI and Z index are similar to that of the modeled (in both layers) and 0–10-cm in situ soil moisture. The variability increases from April until August and then decreases in September. In April and May, the interannual variability of CMI is relatively low, but increases substantially in June and July, followed by decreases in August and September. This variability is very similar to that of the in situ soil moisture in the 0–100-cm soil layer.

We also assessed the intra-annual variability by calculating the standard deviation of all the warm season months in each year. The histograms of the standard deviations are shown in Fig. 7. As shown in Fig. 7c, the standard deviation of CMI is more evenly distributed than the other three drought indices. This distribution is similar to that of the standard deviation of the modeled and in situ soil moisture in the 0–100-cm soil layer (Figs. 7f,h). The shape of the histogram in 0–10-cm layer of soil moisture (Figs. 7e,g) is most similar to the SPEI

**Fig. 5.** Time series of spatially averaged warm season (April–September) percentiles of soil moisture and drought indices in the SGP from 2003 to 2017.

**Fig. 6.** Interannual variability of monthly soil moisture and drought indices (2003–17), as represented by the mean Δ ranking.
We also compare the multiyear averaged standard deviation (vertical lines) of each drought index and modeled soil moisture with in situ soil moisture. The multiyear averaged standard deviation of SPEI (0.243) and CMI (0.228) is smaller than soil moisture in 0–10-cm soil layer (0.257), while the standard deviation of the SPI (0.261) and \( Z \) index (0.267) is larger. The multiyear averaged standard deviation of modeled 0–10-cm soil moisture (0.251) is slightly larger than that of in situ soil moisture. All the differences described above are statistically significant based on a \( t \) test \( (p < 0.05) \). The mean standard deviation of soil moisture in the 0–100-cm soil layer (0.225) is smaller than that of all the drought indices and modeled 0–100-cm soil moisture. Only difference between observed soil moisture and the CMI is not statistically significant \( (p > 0.05) \). This again indicates that the CMI agrees most closely with observed soil moisture.

c. Persistence of drought and soil moisture

Soil moisture conditions vary over longer time scales than many atmospheric variables. This is known as soil moisture persistence or soil moisture memory (Wu and Dickinson 2004). Therefore, we examined the drought indices to see which were able to best capture this aspect of soil moisture. Figure 8 shows the lagged correlation based on 1–90-day lags. The lagged correlations of the SPI decrease most quickly, followed by the \( Z \) index, SPEI, and CMI. Not surprisingly, soil moisture persistence is weaker in the near-surface (0–10 cm) soil layer than in the 0–100-cm soil layer.

FIG. 8. Persistence of soil moisture and drought indices as measure by the lagged correlation coefficient as a function of time (days). The red line indicates the threshold used to determine the persistence (in days) for each drought index and measure of soil moisture.
We calculated the persistence of in situ and modeled soil moisture and each drought index across the study region (Fig. 9). Over the SGP, SPI (Fig. 9a) has consistently short persistence (<5 days), while both SPEI (Fig. 9b) and Z index (Fig. 9d) show similar spatial patterns. These indices have longer persistence (5–10 days) in west Texas and shorter persistence (<5 days) in the eastern part of the study region. The persistence of CMI (Fig. 9c) is much greater than the other three drought indices. It varies from 35 days in east Oklahoma to 60 days in west Texas. In comparison, the persistence of 0–10-cm in situ soil moisture (Fig. 9g) mostly varies from 15 to 25 days, while the persistence of NLDAS-2 soil moisture in the 0–10-cm layer (Fig. 9e) varies from 5 to 15 days. The persistence of in situ soil moisture in the 0–100-cm soil layer (Fig. 9h) is >70 days at all the locations. The persistence of NLDAS-2 0–100-cm soil moisture is between that of the CMI and in situ soil moisture, ranging from 35 to 70 days.

d. Sensitivity of using drought indices and soil moisture to evaluate land–atmosphere interactions

In this study, we calculated the coupling strength between in situ soil moisture and atmosphere conditions and assumed that this coupling strength is the benchmark. Therefore, we define coupling that is stronger or weaker than this benchmark as “error.” This is based on the assumption that the relationship between in situ soil moisture and atmospheric conditions represents the true coupling strength.

Table 3 shows the correlation coefficient between spatially averaged antecedent soil moisture and drought indices and 1-month lagged monthly maximum temperature. All the soil moisture are negatively correlated with subsequent monthly maximum temperature, meaning...
drier than normal soil can be associated with anomalously warm conditions in the following month. Both in situ and modeled soil moisture suggest a moderate coupling strength with $T_{\text{max}}$. Soil moisture in the 0–10-cm layer is more strongly correlated with $T_{\text{max}}$ than soil moisture in 0–100-cm layer. All the drought indices indicate similar coupling strength with maximum temperature. The SPI shows the strongest relationship with $T_{\text{max}}$ ($r = 0.61$) and this is stronger than any of the soil moisture variable ($r < 0.5$). The SPEI and $Z$ index more closely represent the relationship between surface soil moisture and $T_{\text{max}}$, while the CMI more closely represents the relationship with the soil moisture in 0–100-cm soil layer.

The moisture conditions that are associated with convective initiation are shown in Fig. 10. Both in situ and NLDAS soil moisture suggest that warm-season afternoon convection initiates preferentially over dry soil. Convective initiation associated 0–10-cm soil moisture is slightly drier than 0–100-cm soil moisture. Among the four drought indices, the SPI shows the driest condition ($\mu = 0.27$), following by the SPEI ($\mu = 0.31$), $Z$ index ($\mu = 0.31$), and CMI ($\mu = 0.42$). The CMI is most similar to 0–100-cm soil moisture ($\mu = 0.40$), while the SPEI and $Z$ index are most similar to 0–10-cm soil moisture ($\mu = 0.36$).

4. Discussion

a. Selecting the best drought index to represent soil moisture

The SPI has the lowest correlation and shortest persistence among the four drought indices examined in this study. This contrasts with previous studies that concluded that the SPI is a better proxy for soil moisture than long-term drought indices, such as PDSI (Sims et al. 2002). The SPI has been previously used to represent soil moisture conditions (Ford et al. 2017; Hirschi et al. 2010), but our results suggest that the SPI may not be a good proxy for soil moisture as compared to other drought indices. Our analysis shows that the best drought index for representing soil moisture in the 0–100-cm soil layer is the CMI. The CMI was specifically designed for monitoring agricultural drought and it considers both evapotranspiration and runoff. Therefore, it provides a more complete representation of the soil water balance. The CMI has higher correlations with observed soil moisture and a linear trend and persistence that were more consistent with in situ soil moisture than the other drought indices.

One reason that the SPI is not the most suitable drought index for soil moisture is that it only considers moisture supply (i.e., precipitation), but not atmospheric demand (i.e., potential evapotranspiration). Therefore, it provides an incomplete accounting of the soil water balance. The drought indices that account for the influence of PET (e.g., SPEI, $Z$ index, and CMI) have been shown in this study to have better agreement with soil moisture than those that do not (e.g., SPI). This result confirms the findings of previous studies (Tian et al. 2018; Yuan et al. 2016).

b. External and internal factors that influence the agreement between drought indices and soil moisture

Our results demonstrate that there are substantial spatial variations in the degree of agreement (correlation) between drought indices and observed soil moisture. These variations are important because they indicate that the most appropriate drought index for representing soil moisture conditions may vary by location. In addition, these variations also indicate that drought indices do not capture all of the relevant factors that control variations in soil water content. For example, the observed variations are likely due, in part, to variations in climate conditions, land cover/vegetation, and soil properties (Crow et al. 2012). In this section we explore how climate factors, such as precipitation $P$ and PET, and soil properties influence the strength of the relationship between drought indices and soil moisture.

Each point in left plots of Fig. 11 represents one in situ site in the study region. The color of the point represents the strength of the correlation between the drought indices and soil moisture at that location. We found that the correlations vary as a function of both net precipitation ($y$ axis) and bulk density ($x$ axis). All four drought indices show that the correlations with soil moisture are higher...
under moderate net precipitation. When conditions get drier or wetter, the correlation between the drought indices and soil moisture decreases. Under drier conditions, soil moisture decrease occurs more slowly due to soil tension. Specifically, water molecules are bound more tightly to fine particles than to coarse particles. When the soil is saturated, there is more gravity water in the soil. As the soil dries, less gravity water exists in the soil and the impact of soil tension becomes more important. Drought indices do not account for soil physics; thus the low correlation with soil moisture. Under wetter conditions, either soil saturation or intense precipitation (larger than infiltration) will lead to the low correlation between the drought index and soil moisture. Only under moderate conditions, do changes in soil moisture correspond well to net precipitation.

Wang et al. (2015) found that soil properties can also influence the strength of the relationship between drought indices and soil moisture. They found that variations in bulk density of the soil had a modest influence ($r \sim 0.25$) on the strength of the relationship between soil moisture and drought indices. Therefore, in this study we explored how bulk density, together with net precipitation, influences the strength of the relationship between the drought indices and soil moisture.

The right figure of each subplot in Fig. 11 shows the correlation between bulk density and drought indices–soil moisture correlation, clustered by different net precipitation range. For example, the uppermost dot in the right plot of Fig. 11a shows the correlation between bulk density and SPI–soil moisture correlation at all the sites with net precipitation between $-0.5$ and $-1.0$. For the SPEI, CMI, and $Z$ index, we found that under low net precipitation conditions, bulk density has little impact on the strength of the soil moisture–drought index relationship. However, when conditions are wetter, bulk density appears to influence the strength of the soil moisture–drought index relationship. Theoretically, hydraulic conductivity is affected by bulk density and porosity. We only selected bulk density in this study because the spatial pattern of bulk density is negatively correlated with porosity (not shown), and both porosity and bulk density are determined by soil texture. Therefore, we conclude that soil texture can have an impact on the strength of the soil moisture–drought index relationship. Specifically, finer textured soils (i.e., those with a higher clay content) tend to have a weaker soil moisture–drought index relationship, while coarser-textured soils tend to have a stronger soil moisture–drought index relationship. This may be due to that the coarser textured soil has weaker tension, corresponding to faster soil drying.

One limitation of our analysis is the limited number of in situ soil moisture sites. Therefore, the net precipitation clusters do not all have the same

FIG. 10. Mean and standard deviation of in situ (orange and yellow dots), model-derived (orange and yellow triangles) soil moisture and drought index (light blue) percentiles associated with weakly forced convective events ($n = 1528$). Green (SM 0–10 cm) and dark blue (SM 0–100 cm) points represent the mean and standard deviation of soil moisture percentiles of the random events. The randomization was repeated 1000 times.
sample size. This may influence our results. Significance testing is needed in the future when more soil moisture sites are available.

c. Limitations

There are a number of limitations to the approaches used in this study. First, in situ soil moisture was considered to be our target variable (ground truth) and was used to evaluate the four drought indices and NLDAS-2 modeled soil moisture. The four drought indices and modeled soil moisture data are spatially continuous and have a long period of record. However, the in situ data are relatively sparse spatially and have a relatively short period of record. Therefore, this study could be improved by including more in situ data and a longer period of record. Second, there are issues with the spatial resolution of the analysis. The in situ measurements provide soil moisture at a point, while the drought indices are based on a gridded dataset. Third, we used in situ data from three different networks in this study. There may be inconsistencies among these networks based on differences in the sensors used to measure soil moisture (Dirmeyer et al. 2016). We are currently developing methods to standardize/homogenize in situ measurements that are made using different sensors. Fourth, we did not include satellite observations in this study because they can only provide accurate estimation of surface soil moisture. However, as more assimilated soil moisture products using both in situ and satellite observations, future studies can include those products to evaluate drought indices. Finally, this study only evaluates four drought indices (SPI, SPEI, CMI, and Z index). These indices were selected because they are commonly used in the literature and they have previously been used as proxies for soil moisture. There are many other drought indices (e.g., drought indices with antecedent inputs) and approaches (e.g., the diagnostic soil moisture equations) that could be used to represent soil moisture conditions. Therefore, future studies should evaluate more drought indices. In addition, a number of these drought indices, such as SPI and SPEI, are multiscale. This study focused on monthly drought indices and did not examine other time scales.

5. Conclusions

Drought indices and soil moisture are both useful sources of information for drought monitoring. Soil moisture observations can be used to improve the development and application of drought indices. Drought indices can be used as soil moisture proxies to describe surface moisture conditions. In this study, we evaluated four short-term drought indices (1-month time scale) and model-estimated soil moisture by comparing them with in situ soil moisture measurements. The evaluation compared how three aspects of observed soil moisture
conditions (intensity, variability and persistence) are represented by the drought indices and modeled soil moisture.

Our results show that soil moisture percentiles in the 0–10-cm soil layer are more highly correlated with the SPI, SPEI, and Z index than soil moisture in 0–100-cm layer. We also found that the CMI is more highly correlated with soil moisture in the 0–100-cm soil layer than in the 0–10-cm soil layer. Overall, the CMI has the highest correlation with in situ soil moisture in the 0–100-cm soil layer, while modeled soil moisture has higher correlation with in situ observation than all the drought indices in the 0–10-cm soil layer. Spatially, lower correlation between soil moisture (0–100 cm) and drought indices tend to occur in west Texas regardless of the drought index or soil layer.

We did not find good agreement between the drought indices and soil moisture with respect to interannual variability. However, monthly variations in the interannual variability of CMI did agree well with those in the 0–100-cm soil layer. While modeled soil moisture is the most appropriate for capturing the intra-annual variability in the 0–10-cm soil layer. Overall, the CMI is the most appropriate drought index for capturing the intra-annual variability in the 0–100-cm soil moisture based on both the monthly variations and mean standard deviation.

The CMI is also the drought index that has the longest persistence, followed by Z index, SPEI, and SPI. However, the persistence of all of the drought indices is less than the observed soil moisture in the 0–100-cm layer.

In terms of investigating land–atmosphere interactions, the SPI tends to overestimate the coupling strength between the land surface and temperature or convective initiation. However, some drought indices are able to accurately capture land–atmosphere interactions. For example, the Z index can reproduce the correlation between 0- and 10-cm soil moisture and subsequent monthly maximum temperature and the CMI shows good agreement in terms of the 0–100-cm soil moisture conditions associated with convective initiation.

Currently, soil moisture simulated by land surface models, specifically NLDAS-2, provides the best alternative to the observed soil moisture in terms of estimating the soil water content in both surface and deep soil layers. Our results indicate that a good drought index can perform as well as a more complicated land surface model when it comes to representing drought frequency and intensity. The CMI is a drought index that is based on simple water balance model. It outperforms modeled soil moisture when it comes to representing drought characteristics. This finding is consistent with Ford and Quiring (2019) who showed that the simple CPC leaky bucket model performs as well (or better) than the NLDAS models and satellites for monitoring drought conditions in the United States. Therefore, for some specific applications, simple water balance–based drought indices such as the CMI can be used as a replacement for in situ soil moisture. They produce similar results and are easy to calculate.

Climate factors and soil properties influence the strength of the relationships between soil moisture and drought indices. Under moderate net precipitation condition, drought indices are highly correlated with soil moisture. However, when conditions are wetter, soil properties play a more important role in affecting the strength of the soil moisture–drought index relationship.

In summary, not all drought indices are appropriate for capturing soil moisture characteristics and therefore may not be good soil moisture proxies. Although the SPI has been used as a proxy for soil moisture in previous land–atmosphere interaction studies, our results demonstrate that it is not well suited for representing soil moisture conditions. Since the SPI was designed to measure meteorological drought, it does not account for the influence of ET. The three drought indices (SPEI, CMI, and Z index) that use PET are better suited for representing soil moisture conditions. Of the four drought indices we tested, the CMI is the best drought index to use for representing soil moisture conditions in the top 100 cm of the soil. This makes sense given that the CMI was designed for measuring agriculture drought and moisture available for crops (Palmer 1968). Although the findings of this study are based on a regional analysis, we expect that they are applicable in other regions around the world.

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