Development and Evaluation of Soil Moisture-Based Indices for Agricultural Drought Monitoring

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ABSTRACT

Agricultural drought is characterized by low soil moisture levels that negatively affect agricultural production, but in situ soil moisture measurements are largely absent from indices commonly used to describe agricultural drought. Instead, many indices incorporate weather-derived soil moisture estimates, which is necessary, in part, because the relationships between in situ soil moisture and agricultural-drought impacts are not well quantified. Our objective was to use in situ soil moisture data from monitoring networks in Oklahoma and West Texas to identify a soil moisture-based agricultural drought index that is (i) strongly related to crop-yield anomaly across networks, (ii) comparable across time and space, and (iii) readily understandable. Candidate indices included soil matric potential (MP), soil water storage (SWS), and fraction of available water capacity (FAW), with indices assessed in their raw form and after climatological (i.e., anomalies) or statistical standardization. At the county level, indices related similarly to crop-yield anomaly, with soil moisture-yield anomaly correlation coefficients averaging 0.63, 0.76, and 0.76 for winter wheat, hay, and cotton, respectively. However, standardization was essential to maximize temporal and spatial comparability, and at the regional level, standardized indices were more highly correlated with crop-yield anomaly than non-standardized indices. Our findings show that existing in situ soil moisture datasets can underpin regional drought-monitoring systems. The SWS-anomaly may be the preferred index because it is comparable across space and time, has units that are readily understandable (e.g., mm or inches), and can be broadly applied using data from the many in situ soil-moisture monitoring networks across the world.

Core Ideas

- In situ soil moisture data were used to develop agricultural-drought indices.
- Promising indices were directly linked to drought impacts (i.e., lower crop yield).
- Preferred indices, formulated as anomalies, were comparable across time and space.
- These can be derived from in situ soil moisture data common to networks worldwide.
- Our methodology is transferrable to other regions with in situ soil moisture data.

Published in Agron. J. 111:1–15 (2019)
doi:10.2134/agronj2018.09.0558

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Drought is among the most damaging of all natural disasters, with complex economic, environmental, and social effects that are often far-reaching and long-lasting (Wilhite et al., 2007), but soil moisture, the primary variable by which agricultural drought is defined (Mishra and Singh, 2010), is generally underused for drought monitoring. Worldwide, natural disasters impacted more than half a billion people in 2016, of which more than 69% suffered from the impacts of drought (Guha-Sapir et al., 2017). In the United States, the historic drought of 2011 and 2012 covered more than half the country, making it the most widespread drought since the 1950s (Rippey, 2015). The effects of drought are often felt first in the agricultural sector (Narasimhan and Srinivasan, 2005), and crop failure caused by inadequate soil moisture is the hallmark of agricultural drought. In this respect, the impact of the 2011 to 2012 drought was historic. In 2011, agricultural losses reached US$1.6 billion in Oklahoma (Stotts, 2011) and $7.6 billion in Texas (Fannin, 2012), and nationwide in 2012, more than $30 billion in primarily agricultural damages occurred (Rippey, 2015).

Unlike other natural disasters, drought can develop slowly, with effects that are often felt only long after drought onset. It is therefore not surprising that considerable effort has been spent on developing tools to detect and quantify the magnitude of drought, and in fact, more than 100 drought indices currently exist (Zargar et al., 2011). Among the most prominent of these are the Palmer drought severity index (PDSI), (Palmer, 1965), the standardized precipitation index (SPI) (McKee et al., 1993) and the United States Drought Monitor (Svoboda et al., 2002). Even though soil moisture is the central variable by which agricultural drought is defined, in situ soil moisture data are not explicitly used to construct these and other widely used drought indices, which often merely incorporate soil moisture as a weather-derived variable (Woli et al., 2012). Only recently

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Abbreviations: AWC, available water capacity; ePDF, empirical probability; FAW, fraction of available water capacity; FWI, fractional water index; ISMN, International Soil Moisture Network; KDE, kernel density estimate; MP, matric potential; NASMD, North American Soil Moisture Database; PAW, plant available water; PDSI, Palmer drought severity index; SFAW, statistically standardized fraction of available water capacity; SMP, statistically standardized matric potential; SPI, standardized precipitation index; SSWS, statistically standardized soil water storage; SWC, soil water content; SWD, soil water deficit; SWS, soil water storage.

have drought indices based on situ soil moisture been developed (Hunt et al., 2009; Martínez-Fernández et al., 2015; Torres et al., 2013), and to our knowledge, no studies linking these new indices to agricultural drought impacts exist.

The absence of in situ soil moisture from drought indices was once unavoidable because of a lack of data, but the situation changed with the advent of large-scale monitoring networks that began in the 1990s (Ochsner et al., 2013). For example, the North American Soil Moisture Database (NASMD) contains a catalog of in situ soil moisture data that covers more than 1800 sites from 33 monitoring networks in North America, with some networks having data records that span more than 20 yr (Quiring et al., 2016). Similarly, the International Soil Moisture Network (ISMN) contains a rapidly expanding database of worldwide in situ soil moisture measurements, with data from more than 400 sites from 14 networks outside of North America (Dorigo et al., 2011). The wealth of information available in new resources like the NASMD and ISMN creates unprecedented opportunities for improved drought monitoring using in situ soil moisture data, thus the absence of measured soil moisture from drought monitoring tools is an important, but solvable, problem.

Several key challenges currently limit the use of in situ soil moisture data for drought monitoring and inhibit its translation into actionable information for producers. First, few studies have evaluated the potential role of existing large scale soil moisture networks for drought monitoring (Hunt et al., 2009; Mozny et al., 2012), and despite recent advances (Krueger et al., 2015; Torres et al., 2013), there remains a general lack of understanding of how soil moisture data from these networks is related to actual drought impacts. Evidence suggests that soil moisture-based drought indices may better reflect potential drought impacts than indices derived from meteorological variables (Krueger et al., 2017; Narasimhan and Srinivasan, 2005). Likewise, measured soil moisture may be better for early drought detection than the United States Drought Monitor (Ford et al., 2015). Still, while the evidence to support the use of measured soil moisture in agricultural drought monitoring is tantalizing, the absence of statistical models quantitatively linking soil moisture to drought impacts remains a primary impediment (Ochsner et al., 2013). There is a clear need to link drought to its agricultural impacts using existing in situ soil moisture data sets.

There is also no consensus regarding how to best formulate soil moisture-based drought indices. For example, a basic index may simply represent soil matric potential (MP), volumetric soil water content (SWC), or SWC summed across some soil depth (soil water storage, SWS) (Dutra et al., 2008). Or it may be formulated to represent moisture that is available to plants, an increase of index complexity that requires either estimation (Hunt et al., 2009) or measurement of soil physical properties (Scott et al., 2013) for each measurement location. For these types of indices, soil moisture may be expressed as plant available water (PAW), the difference between measured SWC and SWC at permanent wilting point (Scott et al., 2013), or as soil water deficit (SWD), the difference between SWC at field capacity and measured SWC (Torres et al., 2013).

Furthermore, the index may be subjected to a normalization procedure, one method of which uses the physical properties of the soil. For example, PAW and SWD may be normalized by dividing values by the available water capacity (AWC) (Hunt et al., 2009; Martínez-Fernández et al., 2015), where AWC is the difference between SWC at field capacity and wilting point. The ratio of PAW to AWC is the fraction of available water capacity (FAW) and has been used in recent wildfire—drought research (Krueger et al., 2015, 2016, 2017). Regardless of formulation, indices may also be standardized by comparing values against the long-term average (anomaly) (Narasimhan and Srinivasan, 2005) or by using more complex statistical standardization (Carrão et al., 2016; Dutra et al., 2008). One statistical method is to fit soil moisture data to a probability density function that defines the relationship between soil moisture values and their probabilities, and then translate probabilities to a normal distribution to obtain standard normal values. Each of these options has inherent strengths and weaknesses, but conclusive evidence to support one over the other is lacking.

Because agricultural drought is defined as insufficient soil moisture for agricultural production, an ideal agricultural drought index is one with soil moisture data at its core, but the challenges described above currently hinder the use of soil moisture data in this context. We attempt to overcome these challenges by using soil moisture data from the densely monitored Oklahoma Mesonet (McPherson et al., 2007) and West Texas Mesonet (Schroeder et al., 2005) systems to develop and compare soil moisture-based drought indices that link drought to its agricultural impacts. Our objective was to identify a soil moisture-based agricultural drought index that is (i) strongly related to crop-yield anomaly across networks with differing soil moisture sensing technologies, (ii) comparable across time and space, and (iii) readily understandable. We evaluated a variety of indices including soil matric potential (MP), a fundamental measurement of soil moisture status; soil water storage (SWS), data for which is generally more widely available and understood; and fraction of available water capacity (FAW), which incorporates the impact of soil physical properties on soil water availability. Each index was evaluated before and after climatological or statistical standardization. Relationships with yield were assessed by correlating crop-yield anomaly in Oklahoma and Texas with drought index values at the county level. For maximum temporal and spatial comparability, drought indices should be absent of seasonality and able to represent agricultural drought across wet and dry regions. Temporal comparability was assessed by quantifying the autocorrelation of the candidate indices, and the strong climate gradient across our study area allowed us to assess spatial comparability of the indices. This work is directed toward overcoming the obstacles that currently limit the use of in situ soil moisture for agricultural drought monitoring where long-term in situ soil moisture data are available, and our methodology presents a framework by which these or other indices can be evaluated worldwide.

METHODS

Study Area

The availability of long-term, in situ soil moisture data from the Oklahoma Mesonet, which began intensive soil moisture monitoring in 1994 (McPherson et al., 2007), and the West Texas Mesonet, which began in 1999 (Schroeder et al., 2005), make this part of the southern Great Plains ideal for our study. The Oklahoma and West Texas Mesonet systems are two of the most densely measured, large-scale soil moisture monitoring

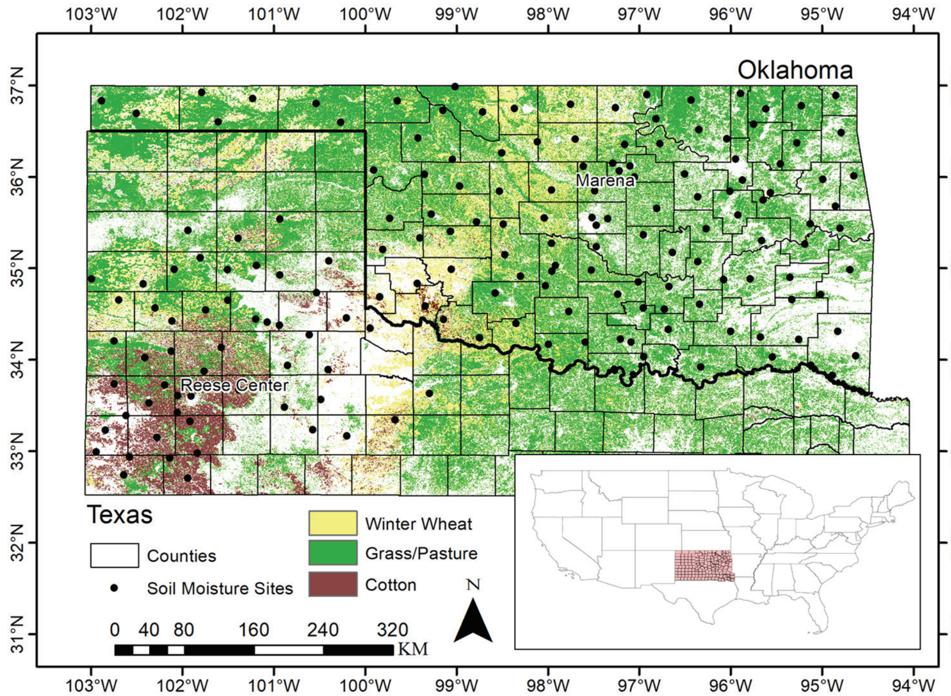

Fig. 1. Map of the study area including locations of Oklahoma Mesonet and some West Texas Mesonet stations as well as wheat, grass/pasture, and cotton land cover in Oklahoma and part of Texas in 2016. Inset shows the location of the study area inside the continental United States.

networks in the world, contiguously covering all of Oklahoma and most of the Texas Panhandle (Fig. 1) and having a total area of around 274,900 km^2 (Ochsner et al., 2013). Currently, soil moisture in Oklahoma is recorded at more than 100 stations at the 5- and 25-cm depths, with 76 of those stations also having long-term soil moisture data records at the 60-cm depth (McPherson et al., 2007). Soil moisture is measured at 5, 20, 60, and 75 cm at 75 stations by the West Texas Mesonet. These networks span a diversity of climate conditions, with precipitation increasing from west to east and temperature increasing from north to south across the study area (PRISM Climate Group, 2017). The climate is primarily semiarid in the Texas portion of the study area and temperate over most of Oklahoma (Peel et al., 2010). Annual average precipitation (1981–2010) varies from less than 400 mm in the southwestern Texas Panhandle to more than 1500 mm in eastern Oklahoma (PRISM Climate Group, 2017). Temperature varies roughly from northwest to southeast, with an annual average of about 12°C in northwest Oklahoma to about 18°C in southeast Oklahoma.

Crop Yield

Soil moisture-yield relationships were assessed at the county level using annual yield data for wheat, cotton, and non-alfalfa hay from 2000 to 2016 in Oklahoma and 2002 to 2016 in Texas (USDA-NASS, 2017a). Oklahoma ranks second nationally for winter wheat production and third for non-alfalfa hay production (USDA-NASS, 2017b). In 2012, wheat accounted for 52% of harvested area in Oklahoma, and hay accounted for 32% (USDA-NASS, 2014a). Texas is the top cotton producing state in the United States (USDA-NASS, 2017b), with the majority of Texas production in the panhandle region that is covered by the West Texas Mesonet (USDA-NASS, 2014b). In 2012, cotton accounted for about 42% of harvested area in the Texas Panhandle, while wheat accounted for 23% (USDA-NASS, 2014b). Because wheat is important in both Oklahoma and West Texas, cross-state comparisons of soil moisture-yield relationships were possible for this crop.

We used yield data from non-irrigated land when possible. In Texas, non-irrigated yield data were available for wheat and cotton, but in Oklahoma, separate irrigated and non-irrigated yield data for these crops were available only for the years 2000 to 2009. For hay in Oklahoma, separate irrigated and non-irrigated yield data were not available for any part of the study period. We used several strategies to overcome this limitation. For wheat, irrigated and non-irrigated yield data from 2000 to 2009 were used to identify counties where irrigated wheat production was most common. Irrigated wheat accounted for more than 5% of total wheat production in only three Oklahoma counties, and these were excluded from further analysis. The proportion of irrigated cotton was relatively high in all major cotton producing counties in Oklahoma, ranging from 12 to 75% of total production. Cotton was therefore excluded from further analyses for Oklahoma. For hay, we assumed that irrigated hay was only a small part of total production and proceeded with data as received. This assumption was supported by 2012 Agricultural Census data that indicated that less than 2% of non-alfalfa hay produced in Oklahoma was irrigated (USDA-NASS, 2014a). Annual county-level hay yield is not recorded in Texas.

Counties were included in soil moisture-yield analyses only if the yield data record was at least 50% complete. For counties that met this threshold, as well as an additional soil moisture data completeness threshold described below, county-level yield data completeness in Oklahoma from 2000 to 2016 was 91% for wheat and 80% for hay (Table 1). Likewise, in Texas from 2002 to 2016, data completeness was 64% for wheat and 80% for cotton. For retained counties, yield values were converted to yield anomalies by subtracting average yield for the period of our study from each annual value. Example time series of

Table 1. Summary of the county level crop yield data completeness (USDA-NASS, 2017a) for wheat, hay, and cotton in Oklahoma from 2000 to 2016 and the Texas Panhandle from 2002 to 2016.

State	Crop	Number of counties	Number of years	*n*	Data completeness, %
Oklahoma					
	Wheat	46	17	714	91
	Hay	58	17	792	80
Texas Panhandle					
	Wheat	13	15	125	64
	Cotton	20	15	242	80

yield anomalies for Payne County Oklahoma, which contains the Marena Mesonet site (Fig. 1), and Lubbock County, Texas, which contains the Reese Center Mesonet site (Fig. 1), can be seen in Fig. 2. The Mann-Kendall test for trend (Mann, 1945) was applied to yield data for each retained county-crop combination. Of the 137 county-crop combinations (Table 1), crop yield showed a significant trend for only 6 combinations, and therefore no detrending procedure was applied.

Soil Moisture

In situ soil moisture data were obtained from the Oklahoma Mesonet Daily Data Retrieval webpage (https://www.mesonet.org/index.php/weather/daily_data_retrieval) and from the West Texas Soil Moisture webpage (http://www.mesonet.ttu.edu/WeatherData.html). We chose to construct our agricultural drought indices using in situ rather than satellite derived soil moisture data because the in situ data were available for multiple depths within the plant root zone, whereas satellite data are limited to the near soil surface. However, we recognize that remotely sensed soil moisture data can form the basis of effective agricultural drought indices (Martínez-Fernández et al., 2016; Mishra et al., 2017), may be an important alternative in regions without large-scale in situ data, and may be complementary where both in situ and remotely sensed data are available. Data from the Oklahoma Mesonet are from 1996 to 2016 and those from the West Texas Mesonet are from 2002 to 2016. The retrieved data were daily averages of soil moisture recorded under vegetation every 30 min by the Oklahoma Mesonet or every 15 min by the West Texas Mesonet. While not crop specific, these data instead offer a general accounting of soil moisture conditions. In this way, the data are somewhat similar to satellite-based soil moisture measurements, which are an aggregate measurement across a variety of land use types (Martínez-Fernández et al., 2016). It is important to note that because soil moisture data were collected under natural vegetation, they may not quantitatively reflect soil moisture under crops during parts of the year. This discrepancy is likely most pronounced for wheat because of the marked temporal differences in water use between it and natural vegetation (Patrignani and Ochsner, 2018). Therefore potentially weaker soil moisture-yield relationships may exist for this crop than for hay and cotton. On the other hand, there is likely little discrepancy between soil moisture under hay and measured soil moisture under grassland vegetation at the monitoring sites because of the similar growth patterns of these land cover types. Furthermore, the water use pattern of cotton in the Texas Panhandle (Chen et al., 2015, 2018) is similar to that we observed under natural vegetation at West Texas Mesonet Sites. Soil moisture shows rapid depletion during late spring and early summer before reaching a minimum in late summer, although soil moisture depletion in cotton may lag that in grassland (Chen et al., 2015).

Data from the Oklahoma Mesonet were received as reference temperature difference (Illston et al., 2008) measured using heat dissipation sensors (Model 229, Campbell Scientific Inc., Logan, UT) at the 5- and 25-cm soil depths. Reference temperature difference was used to calculate matric potential (MP), which in turn was used to calculate volumetric soil water content (SWC), and finally fraction of available water capacity (FAW). Data from the West Texas Mesonet were received as SWC (Schroeder et al., 2005) at the 5- and 20-cm depths. SWC was measured using a water content reflectometer (Model 615-L, Campbell Scientific Inc., Logan, UT), the output of which is converted to soil water content based on a calibration equation unique to each site and measurement depth. For the West Texas Mesonet, it was not possible to calculate MP because of the underlying soil moisture measurement technique, and the absence of the necessary soil physical property information precluded us from calculating FAW.

For Oklahoma, reference temperature difference was converted to MP using a known calibration function (Illston et al., 2008). Matric potential was then converted to SWC using soil water retention parameters obtained from the Rosetta pedotransfer function based on soil physical properties measured on samples collected at each Mesonet station (Scott et al., 2013). The soil water retention parameter database (MesoSoil v. 1.3) is available from the Dep. of Plant and Soil Sciences at Oklahoma State University (http://soilphysics.okstate.edu/data/). The SWC was then used to calculate plant available water (PAW) as:

$$\mathrm{PAW} = (\vartheta - \theta_{\mathrm{WP}})d \quad [1]$$

where θ is measured SWC, θ_{WP} is SWC at the permanent wilting point, and d is the thickness (mm) of the layer represented by the measurement. The FAW was next calculated by normalizing PAW as the ratio of PAW to maximum possible PAW, or available water capacity (AWC), as:

$$\mathrm{FAW} = (\vartheta - \theta_{\mathrm{WP}})/(\vartheta_{\mathrm{FC}} - \theta_{\mathrm{WP}}) \quad [2]$$

where θ_{FC} is volumetric water content at field capacity. For calculations of PAW and FAW, we defined permanent wilting point as the volumetric water content corresponding to a matric potential of −1500 kPa (Scott et al., 2013) and, based on visual inspection of matric potential data, we defined field capacity as the volumetric water content corresponding to a matric potential of −10 kPa. Our preliminary soil moisture-yield anomaly analyses included MP, SWC, PAW, SWD, and FAW, but PAW and SWD showed no clear benefit over the other indices and were excluded from further analyses.

Stations recording soil moisture were retained in the analysis if the data record from 2000 through 2016 for the Oklahoma Mesonet or from 2002 through 2016 for the West Texas Mesonet was at least 80% complete, which resulted in 83 and 30 retained sites for the Oklahoma Mesonet and West Texas Mesonet, respectively. For counties with multiple soil moisture stations meeting this 80% data completeness threshold, daily county-level averages were calculated. To estimate how well our point-scale

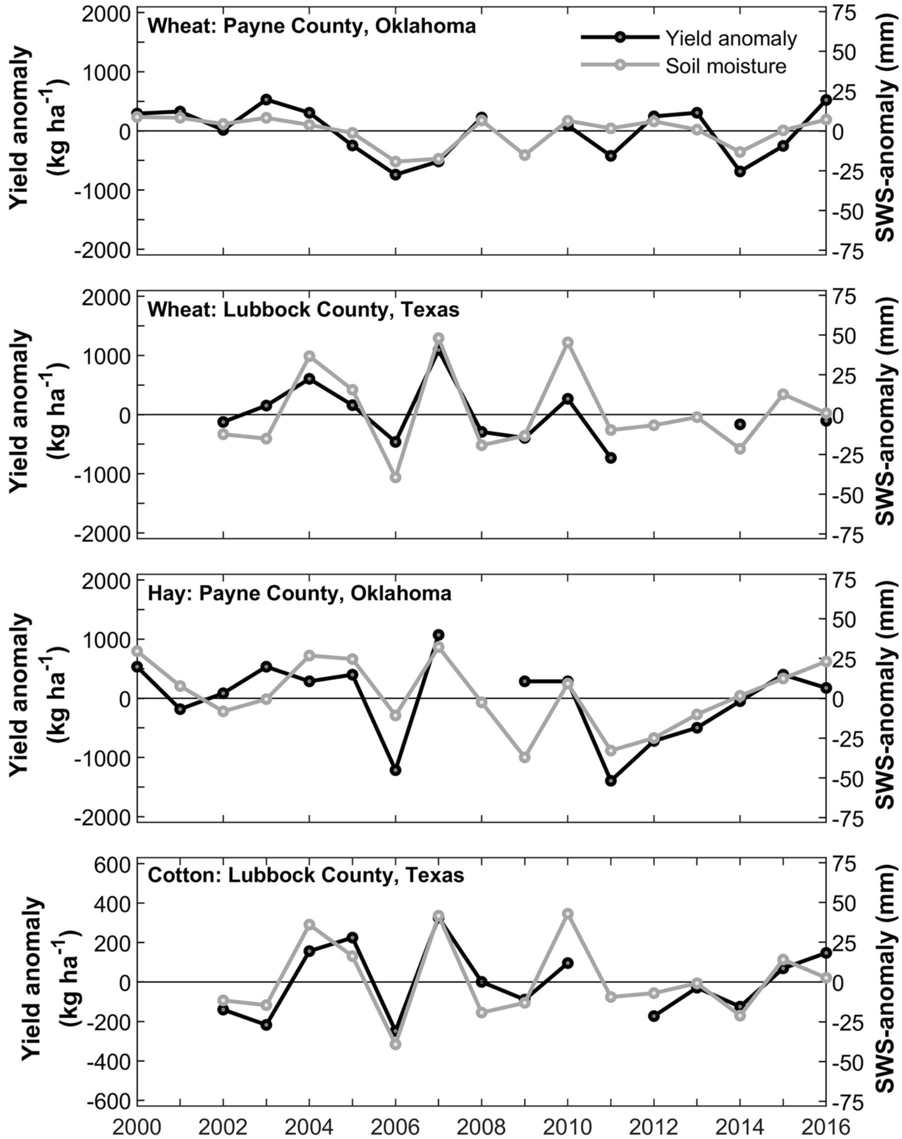

Fig. 2. Annual crop-yield anomaly and soil water storage (SWS)-anomaly for Payne County, Oklahoma from 2000 to 2016 and Lubbock County, Texas from 2002 to 2016.

soil moisture data represented soil moisture across a wider area, we calculated the Pearson correlation coefficient of daily SWS-anomaly at each station in Oklahoma with all other stations from 2000 to 2016, and similarly in the Texas Panhandle from 2002 to 2016. For each state, correlation coefficients were then compared to the distance between stations, and a line was fit to the coefficient-distance pairs following the method of Rico-Ramirez et al. (2015). In Oklahoma, we found that at distances of 25 and 50 km, the fitted correlation coefficients were 0.74 and 0.65. Likewise, in the Texas Panhandle, fitted correlation coefficients were 0.51 and 0.47 at these distances. For context, stations in the Oklahoma and West Texas Mesonet systems each represent an area of about 1681 km^2, or a square area with sides of about 41 km (Ochsner et al., 2013). Based on our observed correlation between stations at this spatial scale, we concluded that the point-scale soil moisture data from these networks were generally correlated with soil moisture conditions across surrounding areas. However, we also recognize that soil moisture is heterogeneous at scales as small as meters (Famiglietti et al., 2008), and that the soil moisture data in our analyses did not account for this fine scale variability.

Soil moisture for each network was integrated across a soil depth of 0 to 40 cm by calculating depth-weighted averages of sensors in this soil layer. Depth weighting was necessary because soil moisture measurements from the networks in our study, like other major networks (Quiring et al., 2016), are not evenly distributed throughout the soil profile. In Oklahoma, for example, in situ measurements at 5 cm are at the midpoint of the 0- to 10-cm soil layer, and measurements at 25 cm are the midpoint of the 10- to 40-cm soil layer. Therefore, each measurement represented a different volume of soil. To account for this, data recorded at 5 cm were weighted 0.25 and those at 25 cm (Oklahoma Mesonet) or 20 cm (West Texas Mesonet) were weighted 0.75 to obtain depth-weighted average SWC. Depth weighted MP and FAW were calculated similarly. Depth-weighted average SWC in the 0- to 40-cm layer was then multiplied by 400 to obtain soil water storage (SWS) in mm. Each index was assessed as a daily value, a daily value relative to soil moisture climatology (anomaly), and a daily value standardized using statistical techniques. After calculating the anomaly and statistically standardized values, the 1-wk moving average of each index was calculated as the average of the 7-d period ending on the current day. This timescale was chosen to capture important intra-monthly variation in soil moisture conditions that can be obscured by drought indices averaged over longer periods (Zhang et al., 2017). We were left with the following nine indices: MP, MP-anomaly, statistically standardized MP (MPS), SWS, SWS-anomaly, statistically standardized SWS (SSWS), FAW, FAW-anomaly, and statistically standardized FAW (SFAW). Of these, only those based on soil water content (SWS, SWS-anomaly, and SSWS) were available for the Texas Panhandle.

Soil moisture anomalies are important for drought monitoring because they represent soil moisture relative to normal levels for a specific time of year (Quiring et al., 2016) and therefore can account for soil moisture seasonality (Illston et al., 2004). We calculated daily anomalies by subtracting the long-term average value for each day of year from the daily values. For the Oklahoma Mesonet, average values were calculated for the 1996 to 2016 period, and for the West Texas Mesonet, average values were calculated for 2002 to 2016. The length of the 21- and 15-yr periods are in line with previous work where soil moisture anomalies were calculated (Quiring et al., 2016; Wu et al., 2002). Example time series of SWS-anomaly for Payne County, Oklahoma and Lubbock County, Texas are provided in Fig. 2. For statistical standardization, we followed the three-step procedure described by Carrão et al. (2016). With this approach, an empirical probability distribution function (ePDF) of daily values at each station was first produced using a kernel density estimator (KDE) (Silverman, 1986). Next, the empirical probability of each daily value was translated onto the normal cumulative distribution function curve to estimate the cumulative probability of each daily value. Finally, this cumulative probability was transformed to the standard normal value (mean = 0, variance = 1) for each drought index: SMP, SSWS, and SFAW. We chose to fit an empirical PDF to soil moisture data because it does not presuppose the form of the distribution of soil moisture data (Carrão et al., 2016), and because it is less susceptible to bias problems associated with small sample sizes (Sienz et al., 2012).

In step 1 of the statistical standardization procedure, the ePDF was fit to daily soil moisture data using a kernel density estimator (KDE). A unique ePDF was developed for each day of the year and soil moisture measurement location. For each station, the daily ePDF was based on 21 soil moisture values in Oklahoma (one for each year from 1996–2016) and 15 values in the Texas Panhandle (2002–2016), sample sizes that we determined to be large enough to create a stable sample distribution. Ford et al. (2016) previously reported 3 to 6 yr of soil moisture data were required to create stable sample distributions for daily soil moisture data aggregated to the monthly timescale. Because our data were at the daily timescale, we expected that a somewhat longer data record would be needed to create a stable sample distribution. We applied the method of Ford et al. (2016) to our daily data and found that, averaged across each station and day of the year, approximately 11 yr of data were required. We therefore concluded that the data record lengths in our study were sufficient to produce reliable ePDFs.

For a sample of $x_1, x_2, x_3, \ldots, x_n$, the KDE used to construct the ePDF is:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad [3]$$

where K is the kernel, and h is the smoothing parameter, or bandwidth. The KDE depends only mildly on the form of K (Liao et al., 2010), and as is usually done (see Silverman, 1986), we defined K as the normal probability density function:

$$K(x) = \frac{1}{\sqrt{2\pi}}\exp\left(\frac{-x^2}{2}\right) \qquad [4]$$

On the other hand, the KDE depends critically on the value of h (Liao et al., 2010). Because using a single bandwidth applied across the entire sample distribution creates KDEs that are vulnerable to noise in parts of the distribution where data are sparse (e.g., distribution tails) (Salgado-Ugarte et al., 1993), we instead used the variable bandwidth method described by Shimazaki and Shinomoto (2010). With this method, the bandwidth was smaller in parts of the distribution where data were dense and longer where data were sparse. The result is retention of fine details in dense regions of the data distribution and the elimination of spurious peaks in the final density estimate where data are sparse.

For each station and day, we calculated the bandwidth for 4096 equally spaced points on the interval of the minimum and maximum soil moisture values for that day. At each point, the optimal bandwidth was obtained by iteratively computing optimal fixed-size bandwidths for the local interval, with the optimization based on a principle of minimizing the expected least squares error loss function between the kernel estimate and an unknown underlying density function (Shimazaki, 2017). After bandwidth optimization, the KDE was calculated at each point, from which the KDE for each daily soil moisture value was obtained and the ePDF constructed (step 1). Then the ePDF was translated onto the normal cumulative distribution function (step 2), which was finally transformed to the standard normal value for each drought index: SMP, SSWS, and SFAW (step 3). SSWS is analogous to SPI (McKee et al., 1993) in that its units are in standard deviations and its range is from approximately −3 to 3. A value of −1 corresponds with a cumulative probability of 15.9%, and with similarly standardized indices, this value is often the threshold value for moderate drought (Carrão et al., 2016).

Statistical Analysis

Soil Moisture-Yield Anomaly Relationships

The relationship between soil moisture conditions, represented by each of nine drought indices, and county level crop-yield anomaly was assessed using Pearson's linear correlation. For each combination of drought index and crop, the correlation between daily soil moisture and county level yield anomaly was calculated for each day of the 1-yr period ending at the typical harvest date for that crop. For example, the most active period of wheat harvest in Oklahoma is from 6 June to 27 June and in Texas is from 1 June to 3 July (USDA-NASS, 2010). We therefore defined the "crop year" for wheat as the period from 1 July through 30 June. Soil moisture on 1 July of each year in the study period was then correlated with wheat yield anomaly for that crop year, followed by soil moisture on 2 July, and so on until a time series of 365 correlation coefficients was obtained. In Oklahoma, each correlation was based on up to 17 soil moisture-yield anomaly pairs (one for each year from 2000–2016), whereas up to 15 pairs were correlated for the Texas Panhandle (2002–2016). The maximum correlation coefficient and the day of year on which it occurred were recorded, and the analysis was repeated for all counties. For wheat, for example, there were 59 counties in Oklahoma and Texas with sufficient soil moisture and crop yield data for this analysis (Table 1), and therefore 59 maximum correlation coefficients for each drought index.

The correlation analysis was repeated for cotton and hay, with the crop year for cotton defined as 1 January through 31 December and that for hay as 1 October through 30 September. Using the maximum daily correlation coefficients recorded for each county, the performance of each drought index was compared using analysis of variance (ANOVA) with multiple comparison ($P \leq 0.05$). Continuing with the wheat yield anomaly example, the ANOVA compared the 59 maximum correlation coefficients recorded for each drought index. Prior to ANOVA, correlation coefficients were submitted to Fisher's z-transformation (Fisher, 1921):

$$z' = 0.5\left(\ln\frac{1+r}{1-r}\right) \quad [5]$$

The transformation was necessary because the sampling distribution of the correlation coefficient is non-normal (Lane et al., 2016). Throughout the manuscript, any mention of average correlation coefficients or statistical procedures applied to correlation coefficients refers to values that were transformed, averaged, and then back transformed. Maps displaying correlation strength were used to demonstrate the spatial variability of the soil moisture-yield anomaly relationship, with maximum correlation coefficients between SWS-anomaly and yield anomaly of each crop displayed for counties meeting data completeness requirements.

Temporal Comparability of Drought Indices

Time-series plots of correlation coefficients were used to highlight the temporal variability of soil moisture-yield anomaly relationships. The time series was constructed by calculating the average and standard deviation of county-specific correlation coefficients between SWS-anomaly and crop-yield anomaly for each day of the crop year. Only counties where soil moisture-yield anomaly relationships were significant were included. Further assessment of the temporal variability was conducted using autocorrelation with lags of up to 1825 d. The significance of autocorrelation is generally assessed as $\pm 2/n^{0.5}$, where n is sample size (Dente et al., 2013). Because the sample size for our soil moisture time series were large, the correlation coefficient corresponding to significant autocorrelation was as low as 0.03. Autocorrelation values at this level are unlikely to be of practical importance, but values as low as 0.2 to 0.5 may be useful for anticipating future conditions (Walsh et al., 2005). We therefore used $r = 0.2$ as the threshold for important autocorrelation.

Spatial Comparability of Drought Indices

Unlike for the initial correlation analysis where soil moisture-yield anomaly data pairs were correlated individually for each county, to assess the ability of each index to represent agricultural drought across space, soil moisture-yield anomaly data pairs from all counties were combined into a single correlation analysis. For example for wheat, there were up to 839 soil moisture-yield anomaly pairs in the single correlation analysis (46 Oklahoma counties × 17 yr × 91% data completeness + 13 Texas counties × 15 yr × 64% data completeness). The calculation was performed for each crop. Differences between drought indices were identified by comparing the 90% confidence intervals on correlation coefficients for each drought index-crop combination. The 90% confidence interval was chosen to more easily detect differences between indices, albeit at increased risk of incorrectly identifying differences compared with using a 95% confidence interval. Confidence intervals were calculated by submitting correlation coefficients to Fisher's z transformation to obtain z', which is normally distributed and has a standard error of:

$$\sigma_{z'} = \frac{1}{\sqrt{n-3}} \quad [6]$$

where n is the sample size. Confidence intervals were calculated as:

$$z' \pm z \cdot \sigma_{z'} \quad [7]$$

where z is 1.645 (Lane et al., 2016) and then back-transformed for comparison. All statistical analyses were conducted with Matlab R2018a (MathWorks, Inc., Natick, MA).

RESULTS

Soil Moisture-Yield Anomaly Correlation

Soil moisture is the central variable by which agricultural drought is defined, but the relationships between measured soil moisture and drought impacts remain understudied, and there is no consensus regarding how to best formulate soil moisture-based drought indices. We calculated the daily county-level correlation of each of three drought indices, as well as their anomaly and statistically standardized values, with wheat, hay, and cotton yield anomalies and found that county-level yield anomaly was positively related to soil moisture for all indices. For a given crop, the correlation strength for all indices and in all forms (raw values, anomalies, and statistically standardized) was similar, suggesting that at the county level, the differing formulations and standardizations of these candidate drought indices did not affect the strength of relationship with crop-yield anomaly. The maximum correlation averaged across counties and indices was 0.66 for wheat, 0.76 for hay, and 0.76 for cotton. Thus, yield anomalies of warm-season cotton were more strongly correlated ($P \leq 0.05$) with soil moisture conditions than were the yield anomalies of cool-season winter wheat. Hay may include both warm- and cool-season species. The lower average correlation for wheat may result from the fact that soil moisture measured under grassland vegetation as in our study does not accurately represent that under winter wheat (Patrignani and Ochsner, 2018).

For wheat, the strength of the soil moisture-yield anomaly relationship generally decreased from west to east, with correlation coefficient values >0.74 for most counties in the Texas Panhandle and >0.48 for most counties in western Oklahoma (Fig. 3). Note that while Fig. 3 (as well as Fig. 4, discussed in the following paragraph) displays results for SWS-anomaly, for discussion we use the general term "soil moisture" since within-county results were similar for each index we considered. The spatial pattern in correlation strength follows a trend of generally increasing precipitation and decreasing evaporative demand from west to east across the study area (Lollato et al., 2017). Wheat yields in Oklahoma are generally not water limited when growing season precipitation is greater than 400 mm (Patrignani et al., 2014), which occurs roughly east of 98° W longitude. Here, temperature is a more likely environmental driver of wheat yield

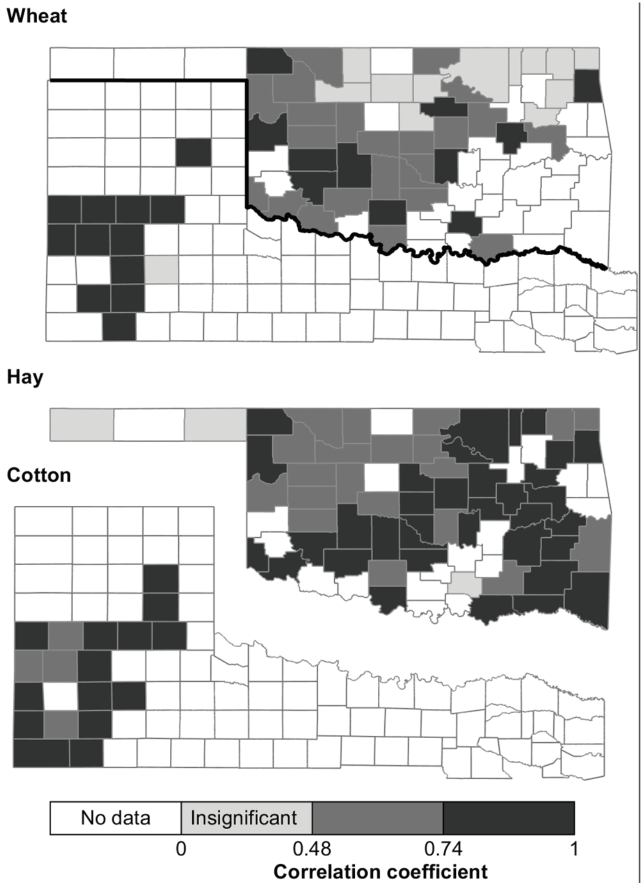

Fig. 3. Correlation between soil water storage anomaly (SWS-anomaly) and wheat, hay, or cotton yield anomaly for individual counties in Oklahoma (2000–2016) and the Texas Panhandle (2002–2016). Correlation coefficients (*r*) are for the day of year on which *r* was greatest, which varied by county. White colored counties were excluded from the analysis because of insufficient soil moisture or yield data. For wheat, correlation strength generally decreased from west to east, roughly corresponding with the spatial gradient of average annual precipitation across the region, which increase from west to east.

(Lollato et al., 2017), and therefore wheat yield anomalies were not highly correlated with soil moisture in this region.

Because of the unique water requirements of each of the crops in our study, it is not surprising that the timing of peak soil moisture-yield anomaly correlation varied by crop (Fig. 4). For wheat, the dominant cool season crop in the region, the soil moisture-yield anomaly relationship was highest around 25 March, which roughly corresponds with the period when most wheat in Oklahoma is undergoing stem elongation (USDA-NASS, 2016a) and when soil moisture under wheat typically begins a period of rapid decline (Patrignani and Ochsner, 2018). Given the similar temporal pattern of wheat development in Oklahoma and Texas (USDA-NASS, 2016b, 2016c), this likely also holds true for Texas. This finding corroborates previous work reporting that stem elongation is a critical period for drought induced yield losses in wheat (Salter and Goode, 1967). In Oklahoma, the 10- to 40-d period after winter dormancy (approximately the month of March) is known to be of critical importance for wheat yield determination (Raun et al., 2001), and field-scale wheat yield predictions have been improved by incorporating in situ soil moisture measured during this time (Walsh et al., 2013).

Where wheat production is water limited, our findings suggest that soil moisture may be a useful tool for key early-spring management decisions. For example, unfavorable soil moisture conditions may discourage producers from spring nitrogen fertilizer application, which occurs in February and March in Oklahoma for split nitrogen systems (Mohammed et al., 2013). Likewise, soil moisture information may be valuable in dual-purpose wheat systems, where wheat is grazed by cattle during its vegetative stages before their removal for production of a wheat grain crop. The optimal time for cattle removal is at the initiation of wheat stem elongation, or first hollow stem, which often occurs around the first week of March (Taylor et al., 2015). Unfavorable soil moisture conditions at this time may encourage producers to "graze-out" the wheat crop and forego any potential grain production.

For hay, the soil moisture-yield anomaly relationship did not display clear spatial patterns, with correlation coefficient values >0.48 for all but two counties in Oklahoma (Fig. 3). The absence of a spatial pattern in correlation strength suggests that hay yield is limited by available soil moisture throughout the state, which may be a reflection of the timing of the peak soil moisture-yield anomaly relationship strength. This summer peak in correlation strength, which was from 21 June through 11 July (Fig. 4), suggests that hay's demand for soil moisture is greatest at a time when soil moisture is generally below the threshold for moisture stress in plants in Oklahoma (Krueger et al., 2016). This is in contrast to wheat, where the impact of soil moisture on yield was greatest during a time when soil moisture is generally high.

While correlation strength peaked during the summer, the soil moisture-hay yield anomaly correlation was statistically significant during most months from December through July (Fig. 4). Unlike wheat and cotton, for which yield is from a single plant species, hay yield represents the combined yields of warm and cool season perennial and annual species (Arnall et al., 2017), and therefore the timing of peak correlation was not as distinct for hay as the other crops. Each species has unique yield distribution characteristics (Hancock et al., 2014; Rogers et al., 2012) that contribute to a long harvest season beginning in April and proceeding through October (USDA-NASS, 2010). Hay from cool season species can account for a substantial part of total hay production, with, for example, small grain hay accounting for 20% of non-alfalfa hay production in Oklahoma in 2012 (USDA-NASS, 2014a). The secondary peak in correlation strength ending around mid-February may be a reflection of the influence of soil moisture on small grain hay yield.

For cotton, the primary warm season crop in the region, there was no apparent spatial pattern in soil moisture-yield anomaly correlation strength (Fig. 3). Correlation coefficient values were >0.74 for most counties in the Texas Panhandle. As with hay, the absence of spatial patterns in correlation strength indicates that cotton production is limited by water availability throughout this region. The soil moisture-yield anomaly relationship was significant or nearly significant from February through May, with a peak value of 0.65 on 18 March (Fig. 4). There remains some debate regarding the most critical period for drought stress in cotton, but the flowering period, approximately July through mid-August, is generally agreed to be critical (Loka et al., 2011; Salter and Goode, 1967). We found soil moisture was poorly related to cotton yield anomaly after May, with a maximum

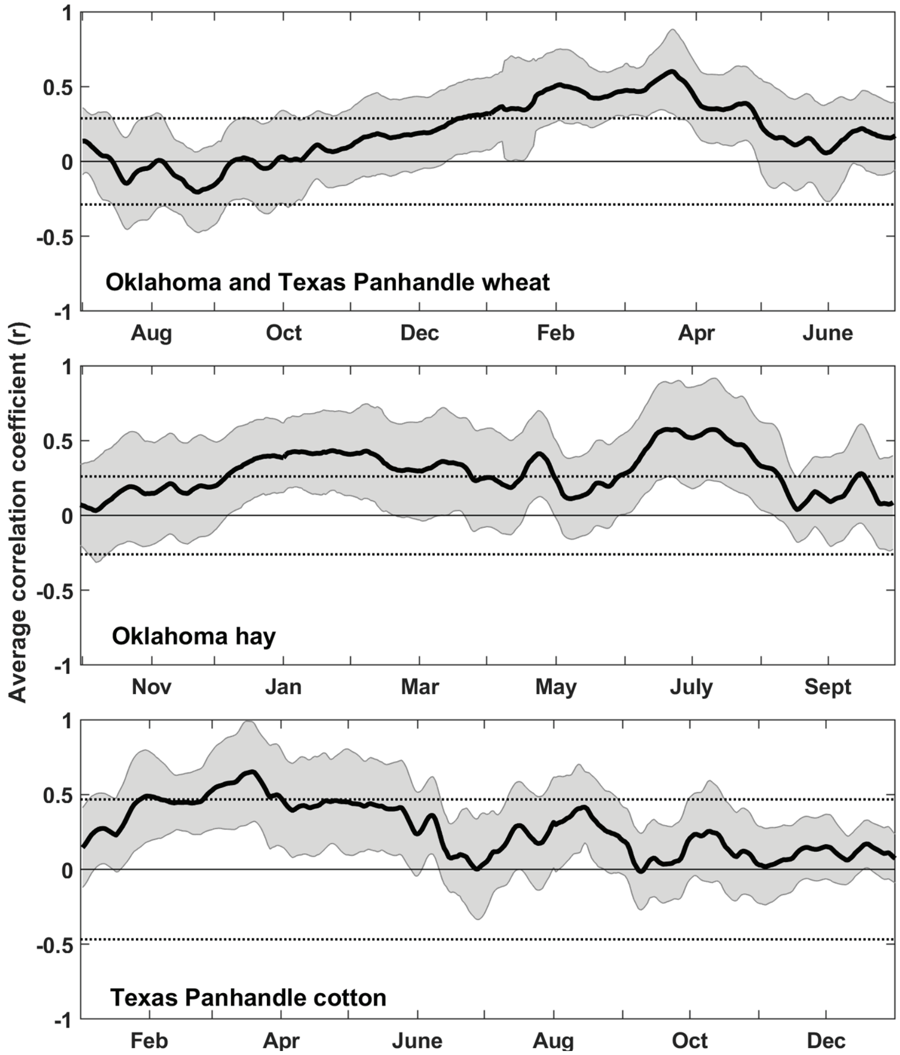

Fig. 4. Average correlation between SWS-anomaly and wheat, hay, or cotton yield anomaly for counties in Oklahoma (2000–2016) and the Texas Panhandle (2002–2016). The black line represents the across-county average correlation coefficient (*r*) for each day of year for counties with significant soil moisture-yield anomaly relationships, and the shaded area around each line represents one standard deviation. The dashed lines are the limits of significant correlation ($P \leq 0.05$), which varied by crop because the number of counties in the analysis varied (n = 47 for wheat, 57 for hay, and 18 for cotton).

correlation coefficient of 0.42 during the typical flowering period. Instead, we found that the critical period occurred before cotton planting, which is generally between 15 May and 20 June in the Texas Panhandle (Warrick et al., 2002). Several factors may account for this finding. Adequate soil moisture at planting is known to help ensure uniform cotton stands and encourage deep root growth (Warrick et al., 2002). High soil moisture at planting also provides water for early season growth and may make cotton plants less susceptible to later drought stress. It should also be noted that West Texas Mesonet soil moisture data are collected under natural vegetation and may not reflect soil moisture under cotton, with soil moisture depletion under cotton lagging that in grassland (Chen et al., 2015). It is possible that this mismatch in crop water use accounts for the absence of significant correlation during July and August. Regardless of the explanation, our finding that soil moisture levels before cotton planting influence yield may have important management implications. Data currently available through the West Texas Mesonet may cue producers to assess conditions in individual fields and adjust planting and other management decisions accordingly.

Soil Moisture Temporal and Spatial Comparability

It is essential that an agricultural drought index reflect the potential impacts of drought on crop yield, and our initial analyses showed that the indices we assessed did this equally well at the county level. For regional-level application, however, an agricultural drought index must also represent drought similarly throughout the year and across differing climates. To assess the temporal comparability of the drought indices, we compared soil moisture time series and correlograms for soil moisture values (SWS) and standardized soil moisture (SWS-anomaly and SSWS). In locations such as central Oklahoma where annual precipitation is relatively high and follows a seasonal cycle, SWS showed distinct seasonality (Fig. 5a), whereas seasonality was less pronounced in the drier Texas Panhandle (Fig. 5b). Seasonality was removed by standardizing SWS, either by calculating its anomaly (Fig. 6c) or through statistical standardization (Fig. 6e). Standardization also improved spatial comparability, with standardized indices showing consistently stronger correlation with crop-yield anomaly when data from all counties were combined into a single regional-level correlation analysis (Fig. 7).

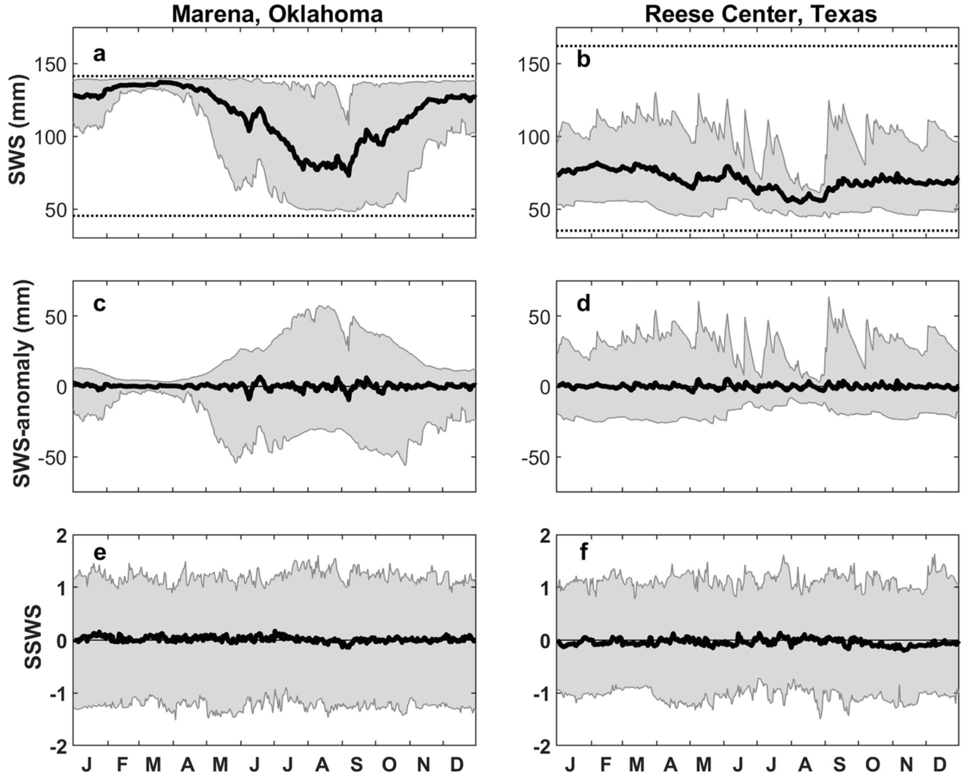

Fig. 5. Time series of soil water storage (SWS), SWS-anomaly, and standardized SWS (SSWS) for the Marena Oklahoma Mesonet station near Stillwater, Oklahoma from 2000 to 2016 and the Reese Center West Texas Mesonet station near Lubbock, Texas from 2002 to 2016. The solid black lines represent mean values for each day of the year, and the shaded region is the area between 10th and 90th percentile values. For SWS, maximum and minimum values are represented by dashed lines. Soil moisture at Marena shows strong wet and dry seasonality (a), while at Reese Center, soil moisture is generally low and punctuated by irregular high periods (b).

We first assessed the temporal comparability of indices with and without standardization by comparing time series of daily mean SWS, SWS-anomaly, and SSWS at the Marena Oklahoma Mesonet station near Stillwater, Oklahoma, and the Reese Center West Texas Mesonet station near Lubbock, Texas (Fig. 5). These sites lie near the southwestern and northeastern eastern edges of the wheat production area in our study (Fig. 1), and have markedly different annual precipitation, with the Reese Center station receiving 513 mm and the Marena station receiving 924 mm (PRISM Climate Group, 2017). Maximum and minimum soil water storage at these sites is similar (Fig. 5a and b), although soil at the Reese Center site is a lighter texture (sandy loam) (NRCS, 2017) compared with the Marena site (loam). Average SWS for each day of the year at the Marena site demonstrated a seasonal cycle (Fig. 5a) that is typical of soil moisture throughout Oklahoma (Illston et al., 2004), where soil moisture is depleted during the summer and recharged during the fall and winter (Krueger et al., 2016). At the Marena site, SWS often averaged more than 125 mm, near the maximum value of 141 mm for this site, and reached a low near 73 mm in the summer. In contrast, this seasonal cycle was less apparent at the Reese Center site, with average SWS for each day of the year only ranging from a low of 55 mm in late summer to a high of 82 mm late winter (Fig. 5b).

The seasonality of SWS observed at the Marena site was removed by standardization, with average values of SWS-anomaly and SSWS near zero each day of the year (Fig. 5c and e). However, the standardized indices (SWS-anomaly and SSWS) displayed different patterns in the distribution of their values throughout the year, with SWS-anomaly (Fig. 5c) showing a variable distribution and SSWS (Fig. 5e) having a distribution that was relatively constant. For example, the distribution of SWS-anomaly at the Marena site, represented by 10th and 90th percentile values, is relatively narrow during the winter and spring and is wide during summer. This pattern, also evident for SWS, indicates soil moisture conditions that are usually wet during the winter and highly variable during the summer. In contrast, at the Reese Center site, soil moisture distribution is relatively wide most of the year, but more narrow during the summer (Fig. 5d), a pattern suggestive of generally dry conditions during the summer and variable conditions at other times. Average daily SWS and SWS-anomaly were almost always nearer the 10th percentile than the 90th at the Reese Center site, which is indicative of soil moisture climatology that is predominantly dry with occasional wet periods. These temporal patterns in the distribution of the soil moisture data were generally absent from the SSWS time series (Fig. 5f) because the statistical standardization procedure involves transforming measured soil moisture into a standard normal value.

To more rigorously assess these seasonal patterns, we next calculated the autocorrelation time series of SWS, SWS-anomaly, and SSWS for the Marena and Reese Center sites. The seasonality that was apparent for SWS at the Marena site was manifested as a sinusoidal pattern of autocorrelation (Fig. 6a). Correlation coefficient values were greater than 0.2 or less –0.2 at 1-yr intervals, with autocorrelation persisting at least 5 yr. Autocorrelation was removed through standardization, with the autocorrelation coefficient permanently falling below 0.2 after 54 d for SWS-anomaly (Fig. 6c) and 92 d for SSWS (Fig. 6e). At the

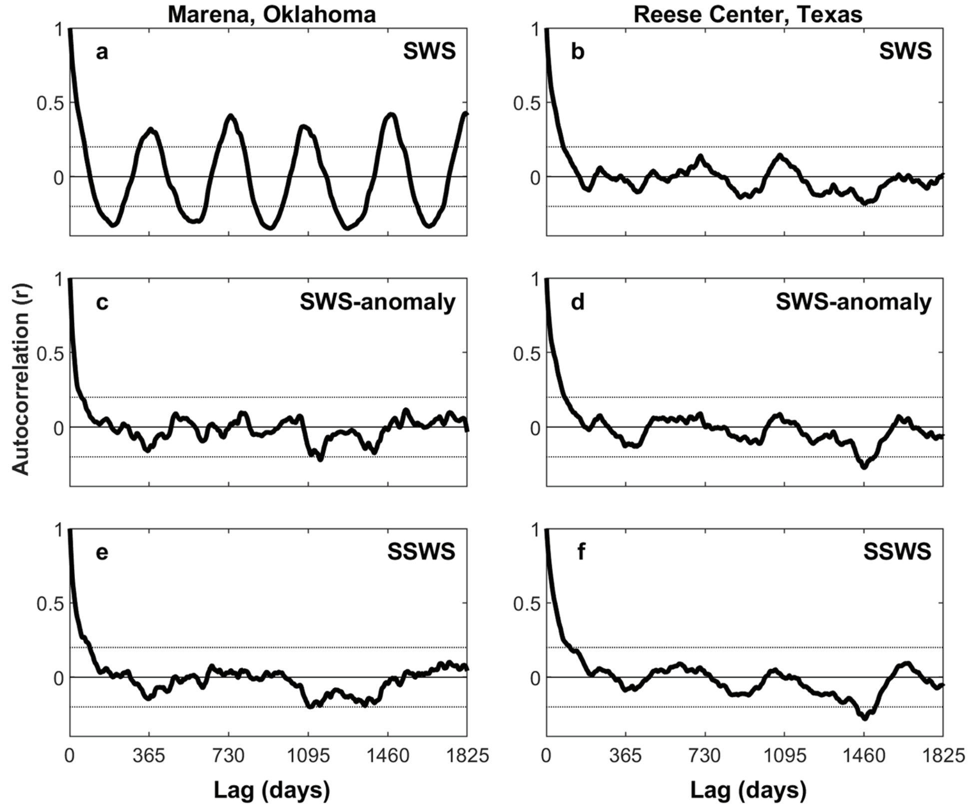

Fig. 6. Correlograms for soil water storage (SWS), SWS-anomaly, and standardized SWS (SSWS) for the Marena Oklahoma Mesonet station near Stillwater, Oklahoma from 2000 to 2016 and the Reese Center West Texas Mesonet station near Lubbock, Texas from 2002 to 2016. Dashed lines are included at ±0.2 as an estimate of the limit of practically meaningful autocorrelation. SWS at Marena shows strong seasonality, with autocorrelation that persists for at least 5 yr (a), but seasonality is removed by calculating SWS-anomaly (c) or SSWS (e). None of the indices shows seasonality at Reese Center (b, d, and f).

Reese Center site, where seasonality was absent from the SWS time series (Fig. 5b), the sinusoidal pattern was also absent, and autocorrelation fell below 0.2 after 79, 85, and 109 d for SWS, SWS-anomaly, and SSWS, respectively (Fig. 6b, d, and f). The high degree of autocorrelation for SWS that we observed is consistent with previous work in Oklahoma (Dente et al., 2013), and its removal through standardization is ideal for inter-seasonal drought monitoring (Narasimhan and Srinivasan, 2005).

We found that standardized indices were also more effective than non-standardized indices for monitoring agricultural drought across differing climates. Unlike for the county level analysis where all drought indices were similarly related to crop-yield anomaly, when soil moisture and yield anomaly data for all counties were combined into a single regional-level analysis, the standardized indices were more strongly related to crop-yield anomaly than non-standardized indices (Fig. 7). There was also a general tendency toward stronger correlation for statistically standardized indices than anomalies, although the difference was significant for only MP-anomaly and SMP. On the other hand, the formulation of the index (i.e., MP, SWS, or FAW) did not matter for a given standardization procedure (anomaly or statistical) and crop. This is an important result because, for example, quantifying the necessary soil physical properties to allow for the calculation of FAW can be costly and time consuming. Our findings show that in the context of identifying agricultural drought, simpler measures of soil moisture like MP and SWS may suffice.

Our standardized indices related similarly to crop-yield anomaly as other soil moisture based drought indices (Narasimhan and Srinivasan, 2005; Zhang et al., 2017), but they generally outperformed weather derived indices (Tian et al., 2018). In Texas, for example, correlation between weekly modeled soil moisture and wheat yield anomaly was as high as 0.81 at the watershed scale (Narasimhan and Srinivasan, 2005). Similarly, when aggregated across Oklahoma, correlation between wheat yield anomaly and fractional water index (FWI) was 0.53 (Zhang et al., 2017). The FWI is a normalized measure of the sensor response for in situ soil moisture measured by the Oklahoma Mesonet. FWI has a range of 0 to 1 (Illston et al., 2008), and is somewhat comparable to the non-standardized indices in our study. At the county level in Oklahoma, on the other hand, the median correlation between weather-derived drought indices and wheat ranged from 0.29 to 0.47 and for cotton it ranged from 0.30 to 0.44 (Tian et al., 2018). The higher correlations that we observed may result because growing conditions are more accurately represented by measured soil moisture than by weather-derived indices. It is also possible that the critical period of soil moisture stress in crops is better captured by daily soil moisture, as we used in our study, than indices aggregated at the monthly time step

It is clear from our analyses that standardization is essential for a drought index to be comparable across time and space. At the regional level, standardization by calculating anomalies or using statistical techniques removed seasonality from soil moisture time series and improved the relationship between soil moisture and crop-yield anomaly. The statistically standardized indices had the benefit of a data distribution that was consistent throughout the

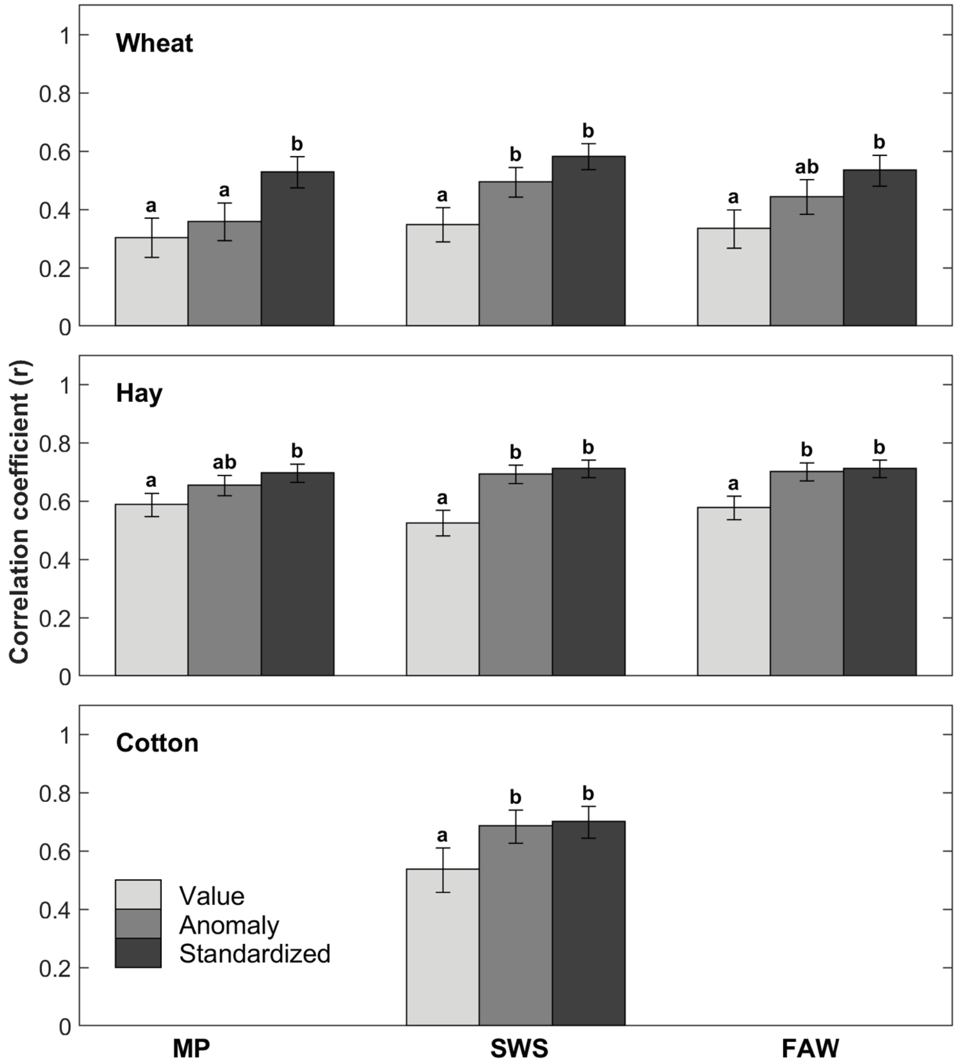

Fig. 7. Correlation coefficients (*r*) between drought indices and wheat, hay, or cotton yield anomaly. County-level data for counties with significant soil moisture-crop yield anomaly relationships were combined into a single correlation analysis for each drought index-crop combination. Oklahoma data were from 2000 to 2016 and Texas Panhandle data were from 2002 to 2016. Drought indices included matric potential (MP), soil water storage (SWS), and fraction of available water capacity (FAW), and *r* is shown for index values, anomalies, and statistically standardized indices. Error bars are 90% confidence intervals, and columns with different lowercase letters are significantly different at $P \leq 0.10$. Anomaly and statistically standardized indices were generally more strongly related to crop-yield anomaly than index values.

year, and they showed slightly better relationships with crop-yield anomaly than anomalies in some cases. Therefore, at the regional level, agricultural drought assessments based on statistically standardized soil water storage (SSWS) may be preferred.

The strength of the soil moisture-yield-anomaly relationship at the regional scale was somewhat lower than at the county level, highlighting the influence of local conditions on the soil moisture-yield anomaly relationships. Average correlation across standardized indices at the regional level was of 0.49, 0.69, and 0.69 for wheat, hay, and cotton, respectively, whereas at the county level, the average correlation for wheat was 0.63, average correlation for hay was 0.76, and that for cotton was 0.76. This poorer regional-level performance underscores the importance of considering local conditions when translating soil moisture data into actionable information. This point can be further clarified by way of example. The day of year when the soil moisture-wheat yield anomaly relationship was greatest was similar for Payne County Oklahoma (21 March) and Lubbock County Texas (18 March), the southwestern and northeastern eastern edges of the wheat production area in our study. But the duration over which soil moisture was significantly related to yield anomaly differed markedly for these counties, with a significant soil moisture-wheat yield anomaly relationship in Payne county from 7 February through 27 March and in Lubbock county from 12 March through 12 June. The period of significance in Payne County includes the critical time for wheat grazing termination and spring nitrogen application in that area, facts that were clear only after considering the data at a smaller spatial scale.

CONCLUSION

A wealth of in situ soil moisture data exists throughout the United States and in a growing number of nations around the world, but key challenges currently limit the use of these data for agricultural drought monitoring and prevent translation of the data into actionable information for producers. Using in situ soil moisture data from the Oklahoma and West Texas Mesonet systems, we found that crop-yield anomaly was positively correlated with soil moisture for each index and crop that we studied, a finding that highlights the potential value of the many existing in situ soil moisture data sets for agricultural drought monitoring. The significant soil moisture-yield anomaly relationships occurred despite the fact that soil moisture data were collected under natural vegetation, and may therefore not reflect crop-specific soil moisture conditions during parts of the year. These differing land cover conditions may partially explain the weaker soil moisture-yield relationships observed for winter wheat than for other crops. We also found that the formulation of the index was relatively unimportant, with matric potential (MP), soil water storage (SWS), and fraction of available water capacity (FAW) relating similarly to crop-yield anomaly at each spatial scale that we considered. This important result is evidence that, in the context of agricultural drought monitoring, existing data sets can be important drought monitoring tools with little further resource input, that is, without extensive sampling campaigns to determine soil properties at the monitoring stations. To maximize temporal and spatial comparability, however, it was essential that drought indices be standardized, either by calculating data anomalies or using statistical techniques. Standardization not only removed seasonality from soil moisture time series, but also improved index comparability across different climates.

We recommend SWS-anomaly as a particularly promising drought index because, in addition to the previously mentioned benefits of standardization, SWS-anomaly has units that are immediately recognizable to users (i.e., mm or inches of soil moisture above or below average). The fact that these units are directly comparable with precipitation units is a further advantage that may promote correct thinking about the soil water balance and the amount of precipitation needed to alleviate agricultural drought. Because county-level soil moisture-yield anomaly relationships were stronger than those at the regional level, we conclude that drought assessments derived from local data may more precisely translate soil moisture data into actionable information, but at the cost of some added complexity. Regional or county-specific drought assessments informed by soil moisture-based drought indices could form the foundation of powerful decision support tools for wheat, cotton, and hay producers in the southern Great Plains, and our methods are a framework by which similar indices can be evaluated and applied across the world.

ACKNOWLEDGMENTS

The authors would like to thank the Oklahoma Mesonet and West Texas Mesonet for providing daily weather and soil moisture data. We would also like to thank Shanshui Yuan of The Ohio State University for assistance with map preparation. Support for this work was provided by the Department of Interior (DOI) South Central Climate Science Center (G15AP00151), the USDA National Institute of Food and Agriculture, Agriculture and Food Research Initiative competitive grant nos. 2012–02355 and 2013–69002–23146, Hatch project OKL02918, and the Division of Agricultural Sciences and Natural Resources at Oklahoma State University. The Oklahoma Mesonet is jointly operated by Oklahoma State University and the University of Oklahoma. Continued funding for maintenance of the network is provided by the taxpayers of Oklahoma.

REFERENCES

Arnall, B., T. Hanks, J. Jones, J. Payne, C. Penn, B. Pugh, et al. 2017. Oklahoma forage and pasture fertility guide. E-1021. Oklahoma Coop. Ext. Serv., Stillwater, OK.

Carrão, H., S. Russo, G. Sepulcre-Canto, and P. Barbosa. 2016. An empirical standardized soil moisture index for agricultural drought assessment from remotely sensed data. Int. J. Appl. Earth Obs. Geoinf. 48:74–84. doi:10.1016/j.jag.2015.06.011

Chen, Y., S. Ale, N. Rajan, C.L.S. Morgan, and J. Park. 2015. Hydrological responses of land use change from cotton (*Gossypium hirsutum* L.) to cellulosic bioenergy crops in the Southern High Plains of Texas, USA. Glob. Change Biol. Bioenergy 8:981–999. doi:10.1111/gcbb.12304

Chen, Y., W.G. Marek, H.T. Marek, E.J. Moorhead, R.K. Heflin, K.D. Brauer, et al. 2018. Assessment of alternative agricultural land use options for extending the availability of the Ogallala Aquifer in the Northern High Plains of Texas. Hydrology 5. doi:10.3390/hydrology5040053

Dente, L., Z. Vekerdy, R. de Jeu, and Z. Su. 2013. Seasonality and autocorrelation of satellite-derived soil moisture products. Int. J. Remote Sens. 34:3231–3247. doi:10.1080/01431161.2012.716923

Dorigo, W.A., W. Wagner, R. Hohensinn, S. Hahn, C. Paulik, A. Xaver, et al. 2011. The International Soil Moisture Network: A data hosting facility for global in situ soil moisture measurements. Hydrol. Earth Syst. Sci. 15:1675–1698. doi:10.5194/hess-15-1675-2011

Dutra, E., P. Viterbo, and P.M.A. Miranda. 2008. ERA-40 reanalysis hydrological applications in the characterization of regional drought. Geophys. Res. Lett. 35:L19402. doi:10.1029/2008GL035381

Famiglietti, J.S., D. Ryu, A.A. Berg, M. Rodell, and T.J. Jackson. 2008. Field observations of soil moisture variability across scales. Water Resour. Res. 44. doi:10.1029/2006WR005804

Fannin, B. 2012. Updated 2011 Texas agricultural drought losses total $7.62 billion. Texas A&M Univ., College Station, TX. https://today.agrilife.org/2012/03/21/updated-2011-texas-agricultural-drought-losses-total-7-62-billion/ (accessed 6 Dec. 2017).

Fisher, R.A. 1921. On the "probable error" of a coefficient of correlation deduced from a small sample. Metron 1:205–235.

Ford, T.W., D.B. McRoberts, S.M. Quiring, and R.E. Hall. 2015. On the utility of in situ soil moisture observations for flash drought early warning in Oklahoma, USA. Geophys. Res. Lett. 42:9790–9798. doi:10.1002/2015GL066600

Ford, T.W., Q. Wang, and S.M. Quiring. 2016. The observation record length necessary to generate robust soil moisture percentiles. J. Appl. Meteorol. Climatol. 55:2131–2149. doi:10.1175/JAMC-D-16-0143.1

Guha-Sapir, D., P. Hoyois, P. Wallemacq, and R. Below. 2017. Annual disaster statistical review 2016. The numbers and trends. Centre for Research on the Epidemiology of Disasters (CRED), Brussels, Belgium.

Hancock, D.W., R.C. Lacy, and R.L. Stewart, Jr. 2014. Forage systems for stocker cattle. Univ. of Georgia. Athens, GA.

Hunt, E.D., K.G. Hubbard, D.A. Wilhite, T.J. Arkebauer, and A.L. Dutcher. 2009. The development and evaluation of a soil moisture index. Int. J. Climatol. 29:747–759. doi:10.1002/joc.1749

Illston, B.G., J.B. Basara, and K.C. Crawford. 2004. Seasonal to interannual variations of soil moisture measured in Oklahoma. Int. J. Climatol. 24:1883–1896. doi:10.1002/joc.1077

Illston, B.G., J.B. Basara, C.A. Fiebrich, K.C. Crawford, E. Hunt, D.K. Fisher, et al. 2008. Mesoscale monitoring of soil moisture across a statewide network. J. Atmos. Ocean. Technol. 25:167–182. doi:10.1175/2007JTECHA993.1

Krueger, E.S., T.E. Ochsner, J.D. Carlson, D.M. Engle, D. Twidwell, and S.D. Fuhlendorf. 2016. Concurrent and antecedent soil moisture relate positively or negatively to probability of large wildfires depending on season. Int. J. Wildland Fire 25:657–668. doi:10.1071/WF15104

Krueger, E.S., T.E. Ochsner, D.M. Engle, J.D. Carlson, D. Twidwell, and S.D. Fuhlendorf. 2015. Soil moisture affects growing-season wildfire size in the Southern Great Plains. Soil Sci. Soc. Am. J. 79:1567–1576. doi:10.2136/sssaj2015.01.0041

Krueger, E.S., T.E. Ochsner, S.M. Quiring, D.M. Engle, J.D. Carlson, D. Twidwell, et al. 2017. Measured soil moisture is a better predictor of large growing-season wildfires than the Keetch–Byram drought index. Soil Sci. Soc. Am. J. 81:490–502. doi:10.2136/sssaj2017.01.0003

Lane, D.M., D. Scott, M. Hebl, R. Guerra, D. Osherson, and H. Zimmer. 2016. Introduction to statistics. Rice Univ., Houston, TX. http://onlinestatbook.com/2/ (16 Sept. 2016).

Liao, J.G., Y. Wu, and Y. Lin. 2010. Improving Sheather and Jones' bandwidth selector for difficult densities in kernel density estimation. J. Nonparametr. Stat. 22:105–114. doi:10.1080/10485250903194003

Loka, D.A., D.M. Oosterhuis, and G.L. Ritchie. 2011. Water deficit stress in cotton. In: D.M. Oosterhuis, editor, Stress physiology in cotton. Cotton Foundation, Cordova, TN. p. 37–72.

Lollato, R.P., J.T. Edwards, and T.E. Ochsner. 2017. Meteorological limits to winter wheat productivity in the US Southern Great Plains. Field Crops Res. 203:212–226. doi:10.1016/j.fcr.2016.12.014

Mann, H.B. 1945. Nonparametric tests against trend. Econometrica 13:245–259. doi:10.2307/1907187

Martínez-Fernández, J., A. González-Zamora, N. Sánchez, and A. Gumuzzio. 2015. A soil water based index as a suitable agricultural drought indicator. J. Hydrol. 522:265–273. doi:10.1016/j.jhydrol.2014.12.051

Martínez-Fernández, J., A. González-Zamora, N. Sánchez, A. Gumuzzio, and C.M. Herrero-Jiménez. 2016. Satellite soil moisture for agricultural drought monitoring: Assessment of the SMOS derived Soil Water Deficit Index. Remote Sens. Environ. 177:277–286. doi:10.1016/j.rse.2016.02.064

McKee, T., N. Doesken, and J. Kleist. 1993. The relationship of drought frequency and duration to time scales. Proceedings of 8th Conference on Applied Climatology, Anaheim, CA. p. 179–184.

McPherson, R.A., C.A. Fiebrich, K.C. Crawford, J.R. Kilby, D.L. Grimsley, J.E. Martinez, et al. 2007. Statewide monitoring of the mesoscale environment: A technical update on the Oklahoma Mesonet. J. Atmos. Ocean. Technol. 24:301–321. doi:10.1175/JTECH1976.1

Mishra, A., T. Vu, A.V. Veettil, and D. Entekhabi. 2017. Drought monitoring with soil moisture active passive (SMAP) measurements. J. Hydrol. 552:620–632. doi:10.1016/j.jhydrol.2017.07.033

Mishra, A.K., and V.P. Singh. 2010. A review of drought concepts. J. Hydrol. 391:202–216. doi:10.1016/j.jhydrol.2010.07.012

Mohammed, Y.A., J. Kelly, B.K. Chim, E. Rutto, K. Waldschmidt, J. Mullock, et al. 2013. Nitrogen fertilizer management for improved grain quality and yield in winter wheat in Oklahoma. J. Plant Nutr. 36:749–761. doi:10.1080/01904167.2012.754039

Mozny, M., M. Trnka, Z. Zalud, P. Hlavinka, J. Nekovar, V. Potop, et al. 2012. Use of a soil moisture network for drought monitoring in the Czech Republic. Theor. Appl. Climatol. 107:99–111. doi:10.1007/s00704-011-0460-6

Narasimhan, B., and R. Srinivasan. 2005. Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. Agric. For. Meteorol. 133:69–88. doi:10.1016/j.agrformet.2005.07.012

NRCS. 2017. Web soil survey. USDA-NRCS, Washington, DC. https://websoilsurvey.nrcs.usda.gov/ (accessed 21 March 2017).

Ochsner, T.E., M.H. Cosh, R.H. Cuenca, W.A. Dorigo, C.S. Draper, Y. Hagimoto, et al. 2013. State of the art in large-dcale doil moisture monitoring. Soil Sci. Soc. Am. J. 77:1888–1919. doi:10.2136/sssaj2013.03.0093

Palmer, W.C. 1965. Meteorological drought. Research paper No. 45. US Dep. of Commerce. Washington, DC.

Patrignani, A., R.P. Lollato, T.E. Ochsner, C.B. Godsey, and J.T. Edwards. 2014. Yield gap and production gap of rainfed winter wheat in the southern Great Plains. Agron. J. 106:1329–1339. doi:10.2134/agronj14.0011

Patrignani, A., and T.E. Ochsner. 2018. Modeling transient soil moisture dichotomies in landscapes with intermixed land covers. J. Hydrol. 566:783–794. doi:10.1016/j.jhydrol.2018.09.049

Peel, M.C., T.A. McMahon, and B.L. Finlayson. 2010. Vegetation impact on mean annual evapotranspiration at a global catchment scale. Water Resour. Res. 46:1–16. doi:10.1029/2009WR008233

PRISM Climate Group. 2017. Oregon State Univ., Corvallis. http://prism.oregonstate.edu (11 Nov. 2017).

Quiring, S.M., T.W. Ford, J.K. Wang, A. Khong, E. Harris, T. Lindgren, et al. 2016. The North American soil moisture database: Development and applications. Bull. Am. Meteorol. Soc. 97:1441–1459. doi:10.1175/BAMS-D-13-00263.1

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, E.V. Lukina, W.E. Thomason, et al. 2001. In-season prediction of potential grain yield in winter wheat using canopy reflectance. Agron. J. 93:131–138. doi:10.2134/agronj2001.931131x

Rico-Ramirez, M.A., S. Liguori, and A.N.A. Schellart. 2015. Quantifying radar-rainfall uncertainties in urban drainage flow modelling. J. Hydrol. 528:17–28. doi:10.1016/j.jhydrol.2015.05.057

Rippey, B.R. 2015. The US drought of 2012. Weather Clim. Extrem. 10:57–64. doi:10.1016/j.wace.2015.10.004

Rogers, J.K., F.J. Motal, and J. Mosali. 2012. Yield, yield distribution, and forage quality of warm-season perennial grasses grown for pasture or biofuel in the southern Great Plains. ISRN Agron. doi:10.5402/2012/607476

Salgado-Ugarte, I.H., M. Shimizu, and T. Taniuchi. 1993. Exploring the shape of univariate data using kernel density estimators. Stata Tech. Bull. 16:8–19.

Salter, P.J., and J.E. Goode. 1967. Crop responses to water at different stages of growth. Commonwealth Agricultural Bureau, Farnham Royal, Buckinghamshire, UK.

Schroeder, J.L., W.S. Burgett, K.B. Haynie, I. Sonmez, G.D. Skwira, A.L. Doggett, et al. 2005. The West Texas Mesonet: A technical overview. J. Atmos. Ocean. Technol. 22:211–222. doi:10.1175/JTECH-1690.1

Scott, B.L., T.E. Ochsner, B.G. Illston, C.A. Fiebrich, J.B. Basara, and A.J. Sutherland. 2013. New soil property database improves Oklahoma Mesonet soil moisture estimates. J. Atmos. Ocean. Technol. 30:2585–2595. doi:10.1175/JTECH-D-13-00084.1

Shimazaki, H. 2017. Kernel density estimation with bandwidths locally adapted to data. MATLAB Central File Exchange. MathWorks, Inc., Natick, MA. https://www.mathworks.com/matlabcentral/fileexchange/37374-ssvkernel-x-tin- (accessed 29 Nov. 2017).

Shimazaki, H., and S. Shinomoto. 2010. Kernel bandwidth optimization in spike rate estimation. J. Comput. Neurosci. 29:171–182. doi:10.1007/s10827-009-0180-4

Sienz, F., O. Bothe, and K. Fraedrich. 2012. Monitoring and quantifying future climate projections of dryness and wetness extremes: SPI bias. Hydrol. Earth Syst. Sci. 16:2143–2157. doi:10.5194/hess-16-2143-2012

Silverman, B.W. 1986. Density estimation for statistics and data analysis. Chapman & Hall, London. doi:10.1007/978-1-4899-3324-9

Stotts, D. 2011. Oklahoma agricultural losses from drought more than $1.6 billion. Oklahoma State Univ., Stillwater, OK. http://water.okstate.edu/news-events/news/acs/oklahoma-agricultural-losses-from-drought-more-than-1.6-billion/ (accessed 6 Dec. 2012).

Svoboda, M., D. LeComte, M. Hayes, R. Heim, K. Gleason, J. Angel, et al. 2002. The drought monitor. B. Am. Meteorol. Soc. 83:1181–1190. doi:10.1175/1520-0477(2002)083<1181:TDM>2.3.CO;2

Taylor, K.W., F.M. Epplin, B.W. Brorsen, B.G. Fieser, and G.W. Horn. 2015. Optimal grazing termination date for dual-purpose winter wheat production. J. Agric. Appl. Econ. 42:87–103. doi:10.1017/S107407080000331X

Tian, L., S. Yuan, and S.M. Quiring. 2018. Evaluation of six indices for monitoring agricultural drought in the south-central United States. Agric. For. Meteorol. 249:107–119. doi:10.1016/j.agrformet.2017.11.024

Torres, G.M., R.P. Lollato, and T.E. Ochsner. 2013. Comparison of drought probability assessments based on atmospheric water deficit and soil water deficit. Agron. J. 105:428–436. doi:10.2134/agronj2012.0295

USDA-NASS. 2017a. Data and statistics-quick stats. USDA-National Agriculture Statistics Service, Washington, DC. http://quickstats.nass.usda.gov/ (accessed 6 Nov. 2017).

USDA-NASS. 2017b. Crop production 2016 summary. USDA-National Agriculture Statistics Service, Washington, DC.

USDA-NASS. 2016a. Oklahoma crop weather. Oklahoma Field Office, Cooperating with the Oklahoma Department of Agriculture, Food and Forest. Oklahoma City, OK.

USDA-NASS. 2016b. Oklahoma annual wheat review. Oklahoma Field Office, Oklahoma City, OK.

USDA-NASS. 2016c. Texas annual wheat review. Texas Field Office, Austin, TX.

USDA-NASS. 2014a. 2012 Census of agriculture. Oklahoma state and county data. USDA-National Agriculture Statistics Service, Washington, DC.

USDA-NASS. 2014b. 2012 Census of agriculture. Texas state and county data. USDA-National Agriculture Statistics Service, Washington, DC.

USDA-NASS. 2010. Field crops usual planting and harvesting dates. USDA-National Agriculture Statistics Service, Washington, DC.

Walsh, J.E., I. Shapiro, and T.L. Shy. 2005. On the variability and predictability of daily temperatures in the Arctic. Atmos.-ocean 43:213–230. doi:10.3137/ao.430302

Walsh, O.S., A.R. Klatt, J.B. Solie, C.B. Godsey, and W.R. Raun. 2013. Use of soil moisture data for refined GreenSeeker sensor based nitrogen recommendations in winter wheat (*Triticum aestivum* L.). Precis. Agric. 14:343–356. doi:10.1007/s11119-012-9299-9

Warrick, B.E., C. Sansone, and J. Johnson. 2002. Cotton production in West Central Texas. Texas A&M Agrilife Res. and Ext. Stn., San Angelo, TX.

Wilhite, D.A., M.D. Svoboda, and M.J. Hayes. 2007. Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness. Water Resour. Manage. 21:763–774. doi:10.1007/s11269-006-9076-5

Woli, P., J.W. Jones, K.T. Ingram, and C.W. Fraisse. 2012. Agricultural reference index for drought (ARID). Agron. J. 104:287–300. doi:10.2134/agronj2011.0286

Wu, W., M.A. Geller and R.E. Dickinson. 2002. The Response of soil moisture to long-term variability of precipitation. J. Hydrometeorol. 3:604–613. doi:10.1175/1525-7541(2002)003<0604:TROSMT>2.0.CO;2

Zargar, A., R. Sadiq, B. Naser, and F.I. Khan. 2011. A review of drought indices. Environ. Rev. 19:333–349. doi:10.1139/a11-013

Zhang, N., C. Zhao, S.M. Quiring, and J. Li. 2017. Winter wheat yield prediction using normalized difference vegetative index and agroclimatic parameters in Oklahoma. Agron. J. 109:2700–2713. doi:10.2134/agronj2017.03.0133