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Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring

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Abstract

Drought is one of the major natural hazards that bring about billions of dollars in loss to the farming community around the world each year. Drought is most often caused by a departure of precipitation from the normal amount, and agriculture is often the first sector to be affected by the onset of drought due to its dependence on water resources and soil moisture reserves during various stages of crop growth. Currently used drought indices like the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI) have coarse spatial (7000–100,000 km^2) and temporal resolution (monthly). Hence, the distributed hydrologic model SWAT was used to simulate soil moisture and evapotranspiration from daily weather data at a high spatial resolution (16 km^2) using GIS. Using this simulated data the drought indices Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) were developed based on weekly soil moisture deficit and evapotranspiration deficit, respectively. SMDI was computed at four different levels, using soil water available in the entire soil profile, then soil water available at the top 2 ft. (SMDI-2), 4 ft. (SMDI-4), and 6 ft. (SMDI-6). This was done because the potential of the crop to extract water from depths varies during different stages of the crop growth and also by crop type. ETDI and SMDI-2 had less auto-correlation lag, indicating that they could be used as good indicators of short-term drought. The developed drought indices showed high spatial variability (spatial standard deviation ~1.00) in the study watersheds, primarily due to high spatial variability of precipitation. The wheat and sorghum crop yields were highly correlated ($r > 0.75$) with the ETDI and SMDI's during the weeks of critical crop growth stages, indicating that the developed drought indices can be used for monitoring agricultural drought.

Keywords: Drought index; PDSI; SPI; Soil moisture; Evapotranspiration; Crop yield

1. Introduction

1.1. Drought

Drought is one of the major natural hazards that bring about billions of dollars in loss to the farming community around the world every year. According to the U.S. Federal Emergency Management Agency (FEMA), droughts occur almost every year across a portion of the nation, and the United States loses $6–8 billion annually on average due to drought (FEMA, 1995). During the 1998 drought, Texas alone lost a staggering $5.8 billion (Chenault and Parsons, 1998), which is about 39% of the $15 billion annual agriculture revenue of the state (Sharp, 1996). In spite of the economic and the social impact of drought, it is the least understood of all natural hazards due to the complex nature and varying effects

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of droughts on different economic and social sectors (Wilhite, 2000).

Agriculture is often the first sector to be affected by the onset of drought due to dependence on water resources and soil moisture reserves during various stages of crop growth. The droughts of the 1930s, 1950s, 1980s and 1990s emphasize the vulnerability of the agricultural sector to drought and the need for more research to understand and determine the impacts of agricultural drought. Understanding and developing tools to predict and monitor drought would help in planning to mitigate the impacts of drought.

1.2. Drought indices

Federal and State government agencies use drought indices to assess and respond to drought. A drought index integrates various hydrological and meteorological parameters like rainfall, evapotranspiration (ET), runoff and other water supply indicators into a single number and gives a comprehensive picture for decision-making. Among various drought indices, the Palmer Drought Severity Index (PDSI) (Palmer, 1965), Crop Moisture Index (CMI) (Palmer, 1968), Standardized Precipitation Index (SPI) (McKee et al., 1993), and Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) are used extensively for water resources management, agricultural drought monitoring and forecasting. Each of these drought indices, their strengths and limitations are explained briefly in the following section.

1.2.1. Palmer Drought Severity Index (PDSI) and Crop Moisture Index (CMI)

One of the most widely used drought indices is the PDSI (Palmer, 1965). PDSI is primarily a meteorological drought index formulated to evaluate prolonged periods of both abnormally wet and abnormally dry weather conditions. Hence, PDSI responds slowly to detect short-term dry spells which could be deteriorating during critical stages of crop growth. Hence, Palmer (1968) developed the CMI as an index for short-term agricultural drought from procedures within the calculation of the PDSI. PDSI is calculated from precipitation deficits for monitoring long-term drought conditions, whereas CMI is calculated from evapotranspiration deficits for monitoring short-term agricultural drought conditions that affect crop growth.

PDSI and CMI have similar limitations in that, the model assumes that parameters like land use/land cover, and soil properties are uniform over the entire climatic zone (7000–100,000 km^2). However, in reality, parameters like land use/land cover and soil properties vary widely. In addition to the large spatial lumping of physical parameters, several studies have highlighted various limitations of PDSI and CMI (Akinremi and McGinn, 1996; Alley, 1984; Guttman, 1998; Narasimhan, 2004), which are outlined below:

- In PDSI, potential evapotranspiration (ET) is calculated using Thornthwaite's method. Thornthwaite's equation for estimating ET is based on an empirical relationship between evapotranspiration and temperature (Thornthwaite, 1948). Jensen et al. (1990) evaluated and ranked different methods of estimating ET under various climatic conditions and concluded that the poorest performing method overall was the Thornthwaite equation. Palmer (1965) also suggested replacing Thornthwaite's equation with a more appropriate method. Thus, a physically-based method like the FAO Penman-Monteith equation (Allen et al., 1998) must be used for estimating ET.
- The water balance model used by Palmer (1965) is a two-layer lumped parameter model. Palmer assumed an average water holding capacity of the top two soil layers for the entire region in a climatic division (7000–100,000 km^2). However, in reality, soil properties vary widely on a much smaller scale. The rainfall is also highly variable spatially in arid and semi-arid climatic zones. This often makes it difficult to spatially delineate the areas affected by localized drought events. Further, PDSI and CMI do not account for the effect of land use/land cover on the water balance.
- Palmer (1965) assumed runoff occurs when the top two soil layers become completely saturated. In reality, runoff depends on soil type, land use, and management practices. However, Palmer (1965) does not account for these factors while estimating runoff.

1.2.2. Standardized Precipitation Index (SPI)

SPI (McKee et al., 1993) is primarily a meteorological drought index based on the precipitation amount in a 3, 6, 9, 12, 24 or 48 month period. In calculating the SPI, the observed rainfall values during 3, 6, 9, 12, 24 or 48 month period are first fitted to a Gamma distribution. The Gamma distribution is then transformed to a Gaussian distribution (standard normal distribution with mean zero and variance of one), which gives the value of the SPI for the time scale used.

Unlike PDSI and CMI, SPI takes into account the stochastic nature of the drought and is therefore a good measure of short- and long-term meteorological drought. However, SPI does not account for the effect of soil, land use characteristic, crop growth, and temperature anomalies that are critical for agricultural drought monitoring.

1.2.3. Surface Water Supply Index (SWSI)

The SWSI (Shafer and Dezman, 1982) was primarily developed as a hydrological drought index with an intention to replace PDSI for areas where local precipitation is not the sole or primary source of water. The SWSI is calculated based on monthly non-exceedance probability from available historical records of reservoir storage, stream flow, snow pack, and precipitation.

The purpose of SWSI is primarily to monitor the abnormalities in surface water supply sources. Hence it is a good measure to monitor the impact of hydrologic drought on urban and industrial water supplies, irrigation and hydroelectric power generation. However, there is a time lag before precipitation deficiencies are detected in surface and subsurface water sources. As a result, the hydrological drought is out of phase from agricultural drought. Because of this phase difference, SWSI is not a suitable indicator for agricultural drought.

Agricultural crops are sensitive to soil moisture. The soil moisture deficit in the root zone during various stages of the crop growth cycle will have a profound impact on crop yield. For example, a 10% water deficit during the tasseling, pollination stage of corn could reduce the yield by as much as 25% (Hane and Pumphrey, 1984). Hence, the development of a reliable drought index for agriculture requires proper consideration of vegetation type, crop growth and root development, soil properties, antecedent soil moisture condition, evapotranspiration, and temperature. The existing drought indices currently used for drought monitoring do not give proper consideration to the aforementioned variables. Hence, a better tool for agricultural drought monitoring is essential for the farming community and the decision-makers.

Meyer et al. (1993a,b) developed a comprehensive crop-specific drought index (CSDI) for corn by taking into account the water use during specific periods of crop growth, using a simple water balance model, at the spatial scale of a crop reporting district. Wilhelmi et al. (2002) developed a GIS based agricultural drought vulnerability assessment method for the state of Nebraska and found the seasonal crop moisture deficiency to be a useful measure for spatial characterization of the state's agroclimatology.

As precipitation and soil properties have high degree of spatial variability, the current study aims to develop drought indices, based on weekly soil moisture deficit – SMDI and ET deficit – ETDI, at a much finer spatial resolution using a comprehensive hydrologic model coupled with a crop growth model and GIS. The consideration of spatial variability of hydrological parameters related to soil type and land cover and meteorological parameters such as rainfall and temperature is a better approximation of the hydrologic system and will improve our ability to monitor soil moisture deficit/drought at a much better spatial resolution. For this study, a spatial resolution of 16 km^2 was chosen to capture adequate spatial variability of hydrological and meteorological parameters over a large watershed and for future integration studies with WSR-88D radar precipitation that has a similar spatial resolution. At present, drought indices like PDSI or CMI are reported for the entire climatic zone at a spatial resolution ranging from 7000 to 100,000 km^2 on a monthly time scale. The increased temporal resolution (weekly) and spatial resolution (16 km^2) may give the farming community, water managers and policy makers a better tool for assessing, forecasting and managing agricultural drought on a much finer scale.

2. Methodology

2.1. Hydrologic modeling

A spatially distributed hydrologic model is essential for developing the drought index. In this study, the hydrologic model Soil and Water Assessment Tool (SWAT) was used. SWAT is a physically based basin-scale continuous time distributed parameter hydrologic model that uses spatially distributed data on soil, land cover, Digital Elevation Model (DEM), and weather data for hydrologic modeling and operates on a daily time step. Major model components include weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management. A complete description of the SWAT model components (Version 2000) is found in Arnold et al. (1998) and Neitsch et al. (2002). A brief description of the SWAT hydrologic component is given here.

For spatially explicit parameterization, SWAT subdivides watersheds into sub-basins based on topography, which are further subdivided into hydrologic response units (HRU) based on unique soil and land cover characteristics. Four storage volumes represent the water balance in each HRU in the watershed: snow, soil profile (0–2 m), shallow aquifer (2–20 m), and deep aquifer (>20 m). The soil profile can be subdivided into multiple layers. Soil water processes include surface runoff, infiltration, evaporation, plant water uptake, inter (lateral) flow, and percolation to shallow and deep aquifers.

SWAT simulates surface runoff using the modified SCS curve number (CN) method (USDA Soil Conservation Service, 1972) with daily precipitation data. Based on the soil hydrologic group, vegetation type and land management practice, initial CN values are assigned from the SCS hydrology handbook (USDA Soil Conservation Service, 1972). SWAT updates the CN values daily based on changes in soil moisture.

The excess water available after accounting for initial abstractions and surface runoff, using SCS curve number method, infiltrates into the soil. A storage routing technique is used to simulate the flow through each soil layer. SWAT directly simulates saturated flow only and assumes that water is uniformly distributed within a given layer. Unsaturated flow between layers is indirectly modeled using depth distribution functions for plant water uptake and soil water evaporation. Downward flow occurs when the soil water in the layer exceeds field capacity and the layer below is not saturated. The rate of downward flow is governed by the saturated hydraulic conductivity.

The Penman-Monteith (Monteith, 1965) method was used in this study for estimating reference crop ET (Alfalfa). SWAT computes evaporation from soils and plants separately as described in Ritchie (1972). Soil water evaporation is estimated as an exponential function of soil depth and water content based on reference crop ET and a soil cover index based on above ground biomass. Plant water evaporation is simulated as a linear function of reference crop ET, leaf area index (LAI), root depth (from crop growth model), and soil water content.

The crop growth model used in SWAT is a simplification of the EPIC crop model (Williams et al., 1984). A single model is used for simulating both annual and perennial plants. Phenological crop growth from planting is based on daily-accumulated heat units above a specified optimal base temperature for each crop, and the crop biomass is accumulated each day based on the intercepted solar radiation until harvest. The canopy cover, or LAI, and the root development are simulated as a function of heat units and crop biomass.

The hydrology of six watersheds located in major river basins across Texas (Fig. 1) was modeled using SWAT by Narasimhan (2004) using historical weather data (1901–2002). Each watershed was divided into several sub-basins of 4 km × 4 km each. SWAT was calibrated and validated using measured stream flow at 24 USGS stream gauging stations distributed across six watersheds in Texas. Measured stream flow data from 24 USGS streamgage stations with combined station years of about 125 and 490 years of stream flow data were used for model calibration and validation, respectively. The overall R^2 and coefficient of efficiency

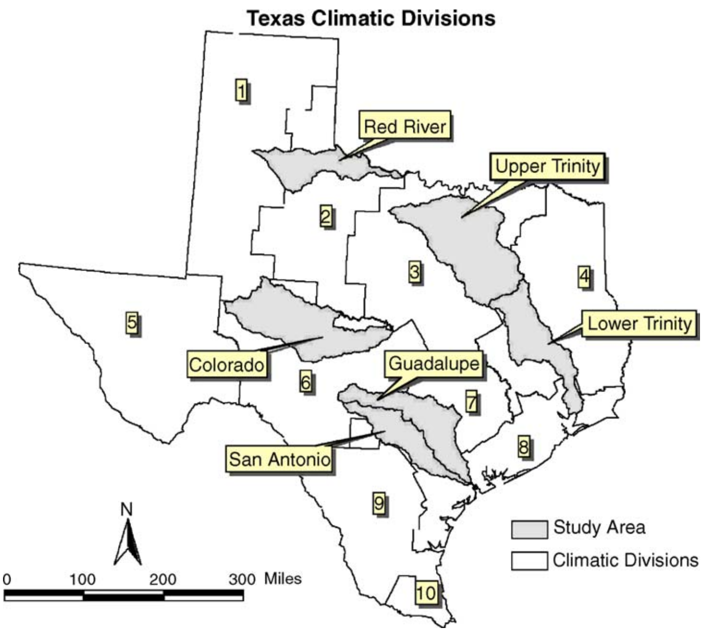

Fig. 1. Texas climatic divisions and locations of six watersheds.

(E) values for the calibration period was 0.75, and the validation period was 0.70 (Narasimhan, 2004). However, in the current study, soil moisture is the hydrologic component of interest. DeLiberty and Legates (2003) studied the seasonal and interannual variability of soil moisture in Oklahoma and observed that SWAT simulations compared well with observed soil moisture data at the two sites in central Oklahoma. Due to a lack of measured soil moisture data, the simulated soil moisture data was analyzed using the Normalized Difference Vegetation Index (NDVI), measured from satellite during the active growing season (April to September) from 1983 to 1998. The soil moisture simulated by SWAT was positively correlated with NDVI for agriculture and pasture land cover types ($r \sim 0.6$), indicating that the model could simulate the soil moisture changes with reasonable accuracy. Off these six watersheds, Red River and Colorado River watersheds were selected for this study due to the high percentage of cropland in these watersheds. The historical soil moisture and evapotranspiration simulated by Narasimhan et al. (2005) in these two watersheds was used in this study for developing the agricultural drought indices.

2.2. Characteristics of a Drought Index

Before elaborating on the development of the drought index, it is essential to discuss the characteristics of a drought index. They are:

1. The index must be able to reflect developing short-term dry conditions, thus responding to agricultural drought.
2. The index should not have any seasonality (i.e., the index should be able to indicate a drought irrespective of whether it is summer or winter).
3. The drought index should be spatially comparable, irrespective of climatic zones (humid or arid).

These characteristics were taken into account in the development of the two drought indices, the Soil Moisture Deficit Index (SMDI) and the Evapotranspiration Deficit Index (ETDI).

2.3. Soil Moisture Deficit Index (SMDI)

The daily model output of available soil water in the root zone was averaged over a 7-day period to get weekly soil water for each of the 52 weeks in a year for each sub-basin. The long-term soil moisture for each week in a year was obtained by taking the median of the available soil water for that week during a 70-year period (1911–1980). The median was chosen over the mean as a measure of ''normal'' available soil water because median is more stable and is not influenced by few outliers. The maximum and minimum soil water for each week was also obtained from the 70-year data. Using this long-term median, maximum and minimum soil water, weekly percentage soil moisture deficit or excess for 98 years (1901–1998) was calculated as:

$$\mathrm{SD}_{i,j} = \frac{\mathrm{SW}_{i,j} - \mathrm{MSW}_j}{\mathrm{MSW}_j - \min SW_j} \times 100, \quad \text{if } \mathrm{SW}_{i,j} = \mathrm{MSW}_j$$

$$\mathrm{SD}_{i,j} = \frac{\mathrm{SW}_{i,j} - \mathrm{MSW}_j}{\max SW_j - \mathrm{MSW}_j} \times 100, \quad \text{if } \mathrm{SW}_{i,j} > \mathrm{MSW}_j \tag{1}$$

where $\mathrm{SD}_{i,j}$ is the soil water deficit (%), $\mathrm{SW}_{i,j}$ the mean weekly soil water available in the soil profile (mm), MSW_j the long-term median available soil water in the soil profile (mm), max.SW_j the long-term maximum available soil water in the soil profile (mm), and min.SW_j is the long-term minimum available soil water in the soil profile (mm) (i = 1901–1998 and j = 1–52 weeks).

By using Eq. (1) the seasonality inherent in soil water was removed. Hence, the deficit values can be compared across seasons. The SD values during a week range from −100 to +100 indicating very dry to very wet conditions. As the SD values for all the sub-basins were scaled between −100 and +100 they are also spatially comparable across different climatic zones (humid or arid).

The SD value during any week gives the dryness (wetness) during that week when compared to long-term historical data. Drought occurs only when the dryness continues for a prolonged period of time that can affect crop growth. As the limits of SD values were between −100 and +100, the worst drought can be represented by a straight line with the equation:

$$\sum_{t=1}^{j} Z_t = -100t - 100 \tag{2}$$

where t is the time in weeks. If this line defines the worst drought (i.e., −4 for the drought index to be comparable with PDSI), then SMDI for any given week can be calculated by:

$$\mathrm{SMDI}_j = \frac{\sum_{t=1}^{j} \mathrm{SD}_t}{25t + 25} \tag{3}$$

Now we are faced with a complicated task of choosing the time period (weeks) over which the dryness values need to be accumulated to determine drought severity. In order to overcome this and take the time period into account indirectly, the drought index was calculated on an incremental basis as suggested by Palmer (1965):

$$\mathrm{SMDI}_j = \mathrm{SMDI}_{j-1} + \Delta\mathrm{SMDI}_j \quad (4)$$

In order to evaluate the contribution of each month to drought severity, we can set $i = 1$ and $t = 1$ in Eq. (3) and we have:

$$\mathrm{SMDI}_1 = \frac{\mathrm{SD}_1}{50} \quad (5)$$

Since this is the initial month:

$$\mathrm{SMDI}_1 - \mathrm{SMDI}_0 = \Delta\mathrm{SMDI}_1 = \frac{\mathrm{SD}_1}{50} \quad (6)$$

A drought will not continue in the extreme category if subsequent months are normal or near normal. Therefore, the rate at which SD must increase in order to maintain a constant value of SMDI depends on the value of SMDI to be maintained. For this reason, an additional term must be added to Eq. (6) for all months following an initial dry month:

$$\Delta\mathrm{SMDI}_j = \frac{\mathrm{SD}_j}{50} + c\,\mathrm{SMDI}_{j-1} \quad (7)$$

where

$$\Delta\mathrm{SMDI}_j = \mathrm{SMDI}_j - \mathrm{SMDI}_{j-1}$$

Eq. (7) can now be solved for c. By assuming SMDI is -4 during subsequent time steps, then SD_i should be -100:

$$\Delta\mathrm{SMDI}_j = \frac{-100}{50} + c(-4.0), \quad 0 = -2 - 4c,$$

$$c = -0.5$$

Therefore, drought severity in any given week is given by:

$$\mathrm{SMDI}_j = \mathrm{SMDI}_{j-1} + \frac{\mathrm{SD}_j}{50} - 0.5\mathrm{SMDI}_{j-1}$$
$$\mathrm{SMDI}_j = 0.5\mathrm{SMDI}_{j-1} + \frac{\mathrm{SD}_j}{50} \quad (8)$$

SMDI during any week will range from -4 to +4 representing dry to wet conditions. SMDI was computed at four different levels, using soil water available in the entire soil profile, then soil water available at the top 2, 4, and 6 ft. that are represented as SMDI, SMDI-2, SMDI-4, and SMDI-6, respectively. This was done because the potential of the crop to extract water from depths varies during different stages of crop growth and by crop type.

2.4. Evapotranspiration Deficit Index (ETDI)

ETDI was calculated using a procedure similar to the one explained above for SMDI, except that the water stress ratio given by Eq. (9) was used instead of using ET alone. The daily model output of actual evapotranspiration and reference crop evapotranspiration were cumulated over a 7-day period to get weekly actual and reference crop evapotranspiration for each of the 52 weeks in a year for each sub-basin. Water stress ratio for the week is calculated as:

$$\mathrm{WS} = \frac{\mathrm{PET} - \mathrm{AET}}{\mathrm{PET}} \quad (9)$$

where WS is the weekly water stress ratio, PET the weekly reference crop evapotranspiration, AET the weekly actual evapotranspiration.

WS values range from 1 to 0, with 1 indicating no evapotranspiration and 0 indicating evapotranspiration occurring at the same rate as reference crop ET. The long-term water stress for each week in a year was obtained by taking the median of the water stress for that week during a 70-year period (1911–1980). The maximum and minimum water stress ratio for each week was also obtained from the 70-year data. From the long-term median, maximum and minimum water stress, percentage water stress anomaly during any week for 98 years (1901–1998) is calculated as:

$$\mathrm{WSA}_{i,j} = \frac{\mathrm{MWS}_j - \mathrm{WS}_{i,j}}{\mathrm{MWS}_j - \mathrm{minWS}_j} \times 100, \quad \text{if } \mathrm{WS}_{i,j} = \mathrm{MWS}_j$$
$$\mathrm{WSA}_{i,j} = \frac{\mathrm{MWS}_j - \mathrm{WS}_{i,j}}{\mathrm{maxWS}_j - \mathrm{MWS}_j} \times 100, \quad \text{if } \mathrm{WS}_{i,j} > \mathrm{MWS}_j \quad (10)$$

where WSA is the weekly water stress anomaly, MWS_j the long-term median water stress of week j, $\mathrm{max.WS}_j$ the long-term maximum water stress of week j, $\mathrm{min.WS}_j$ the long-term minimum water stress of week j, and WS is the weekly water stress ratio (i = 1901–1998 and j = 1–52 weeks).

The water stress anomaly during any week ranges from -100 to +100 indicating very dry to very wet conditions with respect to evapotranspiration. Adopting a similar cumulating procedure of SMDI, drought severity due to evapotranspiration deficit is given by:

$$\mathrm{ETDI}_j = 0.5\mathrm{ETDI}_{j-1} + \frac{\mathrm{WSA}_j}{50} \qquad (11)$$

Using Eqs. (8) and (11), Soil Moisture Deficit Index (SMDI) at 2, 4, and 6 ft. and Evapotranspiration Deficit Index (ETDI) were calculated for 98 years of simulated soil moisture and evapotranspiration data from 1901 to 1998.

3. Results and discussion

3.1. Time-series characteristics

An auto-correlation analysis was done to study the characteristics of the drought index based on soil and land cover characteristics. The correlogram of simulated soil water available in the root zone for one of the sub-basin is shown in Fig. 2a. From the correlogram, we observed that soil water available in the root zone was highly auto-correlated. This is because soil water in the current time step depends on the soil water available during previous time steps. The sinusoidal pattern of the correlogram indicates that soil water was also highly seasonal, fluctuating according to seasonal precipitation and evapotranspiration. Hence, the soil water was differenced with median long-term weekly soil water to remove the seasonality. The correlogram of SMDI (Fig. 2b) derived from the differenced soil water showed that the seasonal differencing effectively removed the seasonality, which is ideal for drought monitoring, irrespective of season.

Incidentally, Eqs. (8) and (11), derived for calculating drought index from soil moisture and evapotranspiration deficits, respectively, are also analogous to the first order auto-correlation process with white noise represented by the SD and WSA terms (dryness or wetness during the week compared to historical data). The auto-correlation lags (i.e., the lag at which the correlation is less than $\pm 2/\sqrt{N}$, where N is the number of data points) for individual sub-basins for different drought indices are shown in Fig. 3. The auto-correlation lag seems to closely depend on the available water holding capacity of the soil with the lag increasing with water holding capacity. This was expected because if the water holding capacity of the soil is high, then the current soil water and evapotranspiration will be affected by events (precipitation and evapotranspiration) that happened in the distant past rather than for the soils with low water holding capacity.

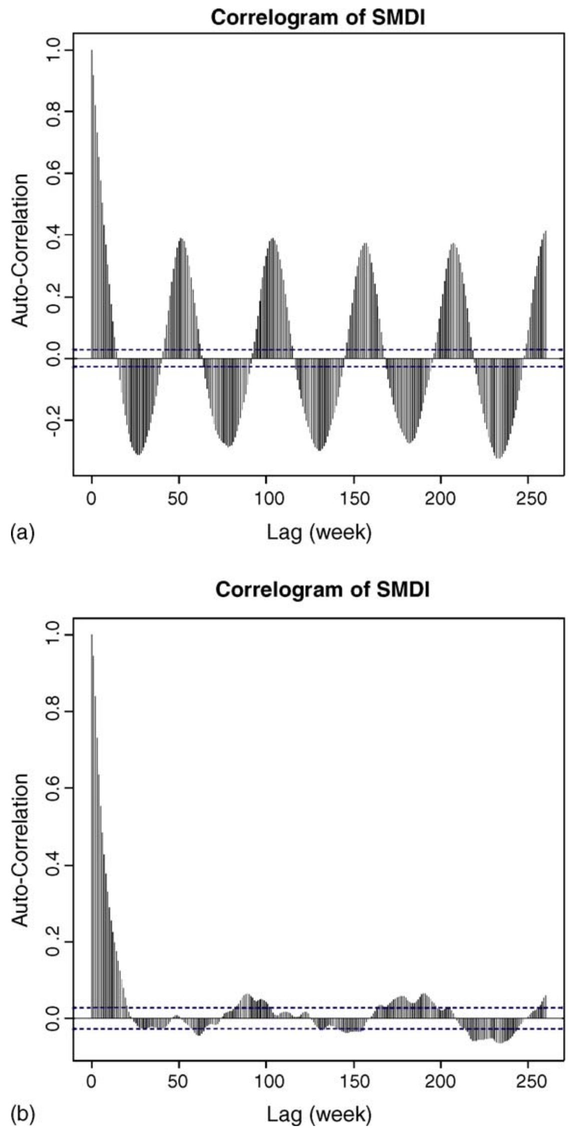

Fig. 2. Correlogram (a) soil moisture and (b) Soil Moisture Deficit Index (SMDI).

The lag also increases with depth due to increase in total available water holding capacity. Lag does not seem to depend much on the land cover type. However, among different land cover types, agricultural lands have the largest lag. This is because most of the agricultural lands are primarily located on soils with high water holding capacity.

Among different drought indicators, SMDI-2 ft had the lowest auto-correlation lag (12 weeks; approximately 3 months). This is because the top 2 ft. of the soil profile very actively participate in the evapotranspiration of available soil water. Most of the pasture and agriculture crops have shallow root systems that

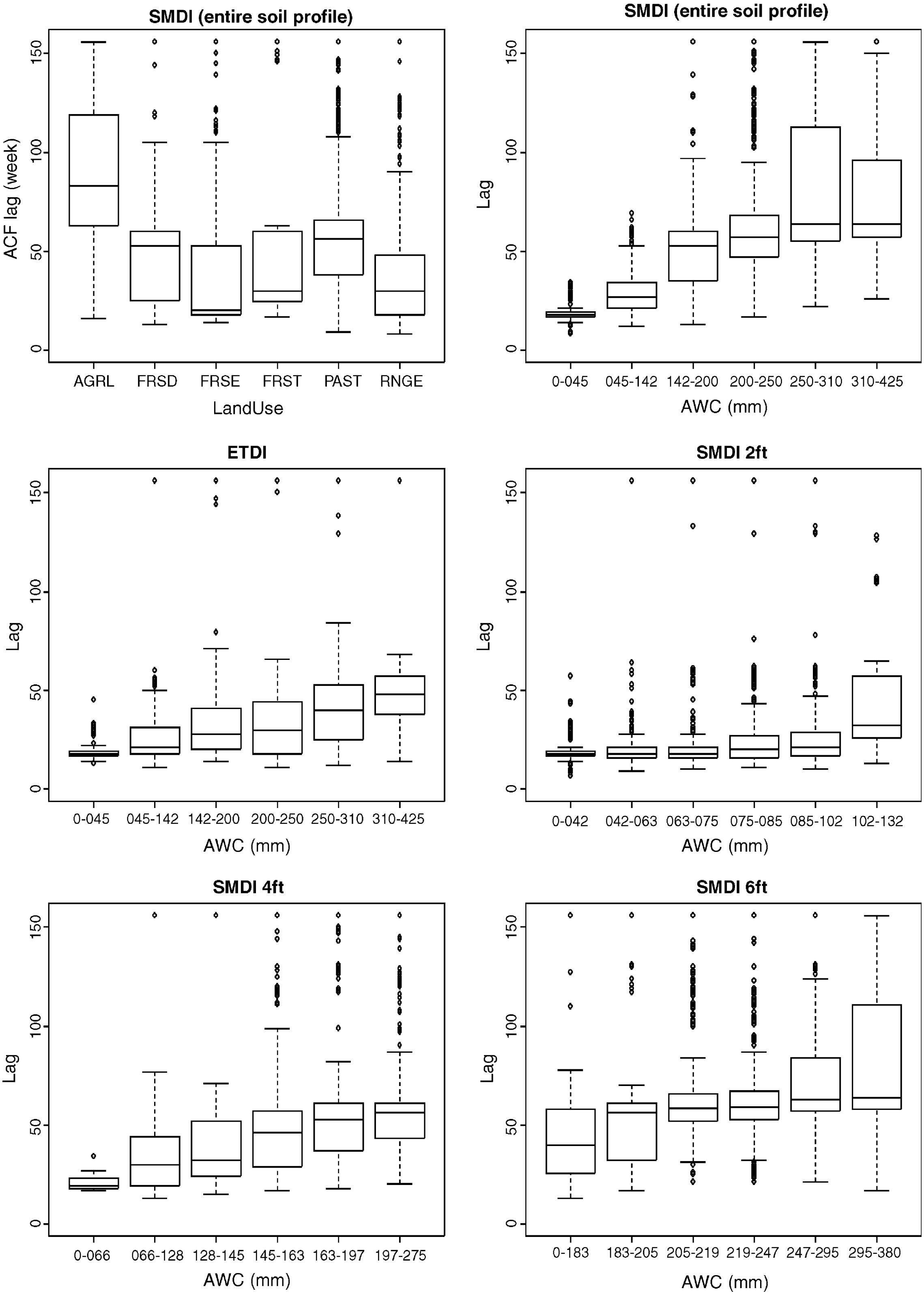

Fig. 3. Auto-correlation lags of drought indices based on available water holding capacity of soil and land cover type.

primarily use the soil water available at the top 2 ft. of the soil profile. For the same reason, the ETDI also have smaller auto-correlation lags when compared to SMDI, derived from an entire soil profile, which has a lag of approximately 1.25 years. Hence, ETDI and SMDI-2 could be useful indicators of short-term drought conditions, whereas SMDI derived from an entire soil profile could be a good indicator of long-term drought conditions.

3.2. Spatial variability

A spatial variability analysis was done to study the effect of the spatially distributed model along with distributed model parameters on soils, land cover and topography, and weather variables like precipitation and temperature on the drought index. Standard deviation of the drought index, calculated in space from the drought index of hundreds of subbasins within the watershed during each time step, was used as a measure of spatial variability of the drought index. The spatial standard deviation was calculated for each week for 98 years from 1901 to 1998. For both watersheds, irrespective of the drought index, the spatial standard deviation was above 1.0. Considering that the range of drought indices is from −4 to +4, a standard deviation of 1.0 indicates that the spatial variability of the drought index is high. The distribution of standard deviation for 52 weeks during the 98-year period for Red river and Colorado, is shown in Figs. 4 and 5.

The mean and standard deviation of weekly precipitation and reference crop ET for each watershed were also analyzed to determine the reason for spatial variability in the drought index. Analysis of 98 years of precipitation data showed that the precipitation distribution in a year was bimodal. For both watersheds, with high precipitation occurring during late spring and mid fall seasons. Precipitation was the highly variable component both spatially and temporally during different years for the same season. Reference crop

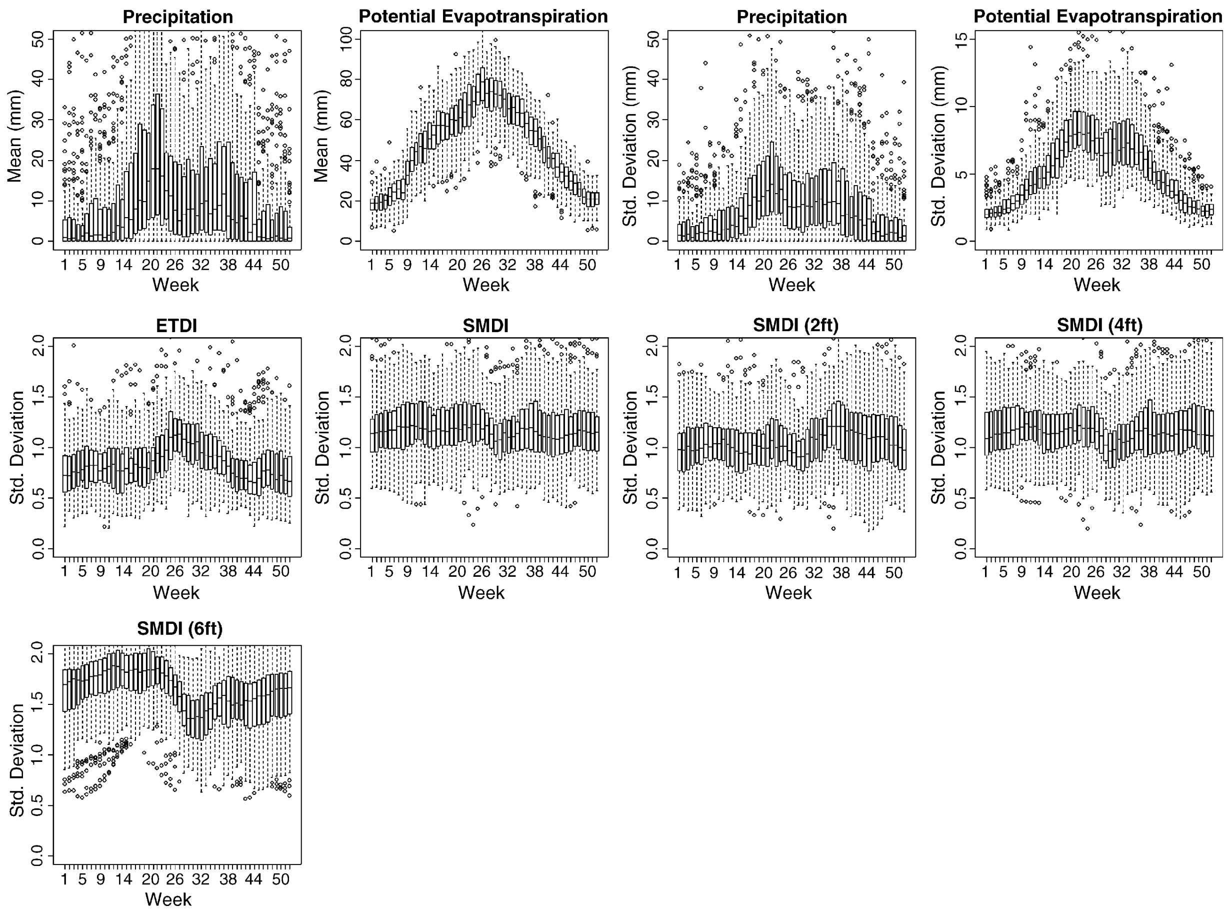

Fig. 4. Distribution of spatial standard deviation of precipitation, evapotranspiration and drought indices for 98 years during each week in Red River.

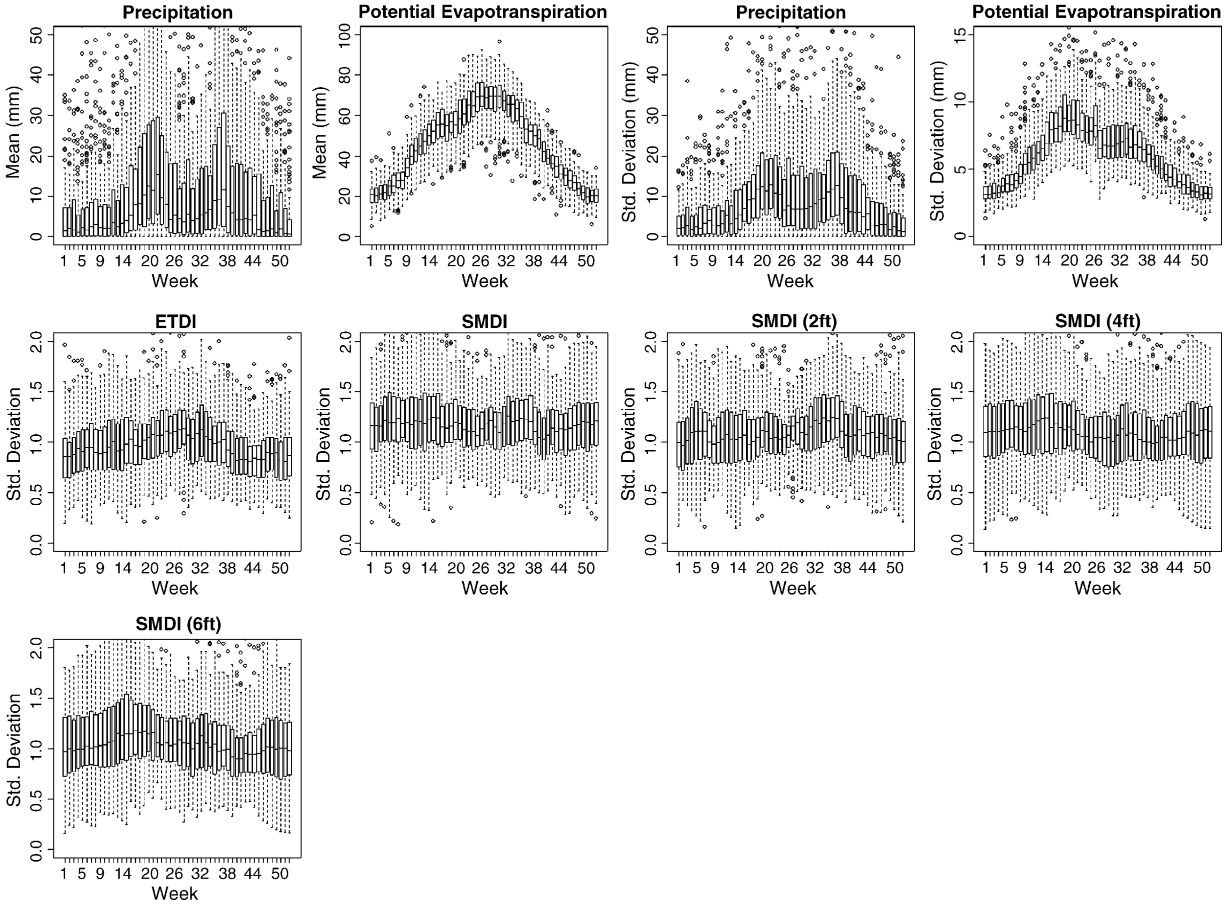

Fig. 5. Distribution of spatial standard deviation of precipitation, evapotranspiration and drought indices for 98 years during each week in Colorado River.

ET also showed some spatial variability with high variability occurring during the summer season.

The spatial variability (standard deviation) of the drought indices, especially ETDI, during different seasons closely followed the variability in precipitation and evapotranspiration across seasons. In order to get a sense of how the standard deviation reflects the spatial distribution of drought indices, SMDI derived during 46th week of 1988 and 24th week of 1990 with standard deviations of 1.0 and 1.5, respectively, are shown in Fig. 6a and b. As the standard deviation increased, the spatial variability of the drought index also increased considerably.

The spatial standard deviation of ETDI increased from 0.75 during the spring season to as much as 1.5 at the end of the summer season (Figs. 4 and 5). This was because evapotranspiration was high during summer, following a season of high precipitation during spring that recharged the available soil water to varying degrees of saturation depending on the spatial distribution of precipitation and soil properties. The precipitation amount also gradually decline during summer and has high spatial and temporal variability. This affects actual evapotranspiration that depends on the amount of water already in the soil profile, soil physical properties and land cover characteristics. Hence, the spatial variability of ETDI increases during the summer season.

The spatial variability of SMDI for all soil depths was above 1.0 during most of the seasons, for both watersheds. The SMDI-6 for Red River had the highest standard deviation (~1.5) during most of the season and had a different seasonal pattern than SMDI-2 and SMDI-4. This is because Red River watershed covers a range of precipitation zones from 488 mm in the west to 748 mm in the east and soils with more than 6 ft depth are scattered across these zones. The standard deviation of SMDI-6 decreased during the summer because this part of the season was characterized by less precipitation (less spatial variability) and high evapotranspiration (soils

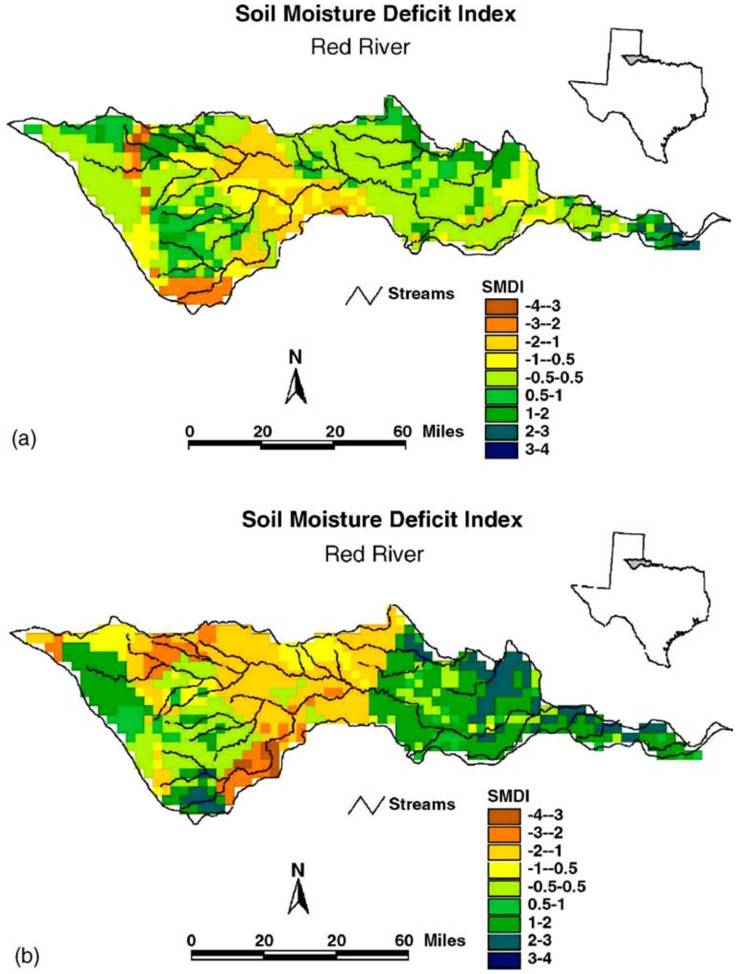

Fig. 6. Spatial distribution of Soil Moisture Deficit Index (SMDI). (a) 46th week of 1988 with standard deviation of 1.00 and (b) 24th week of 1990 with a standard deviation of 1.5.

become mostly dry), and thus, the spatial variability of SMDI reduced during summer. The spatial analysis of ETDI and SMDI indicate considerable spatial variability in drought across the region depending on the weather, soil and landuse characteristics.

3.3. Comparison with other drought indices

The drought indices SMDI and ETDI developed in this study were compared with other drought indicators currently in use, such as the PDSI (Palmer, 1965) and the SPI (McKee et al., 1993). PDSI and SPI are reported at the spatial scale of climatic divisions (Fig. 1) and at a monthly temporal resolution. However, the drought indices developed in this study have a spatial resolution of 4 km × 4 km (Fig. 6) and a weekly temporal resolution. Hence, the drought indices ETDI and SMDI need to be aggregated at spatial and temporal scales for comparison with PDSI and SPI.

Because ETDI and SMDI's were integrated measures of past weather conditions, instead of averaging the index temporally over the entire month, only the drought index calculated during the last week of every month was spatially averaged over the entire watershed for comparison with monthly PDSI and SPI. The spatially-averaged, monthly ETDI and SMDI's for 98 years (1901–1998) were compared with PDSI and SPI reported for climatic divisions in which major portions of each of the study watersheds are located. The correlation (*r*) matrix of the drought indices developed in this study (ETDI and SMDI's) with PDSI and SPI's published for 1, 3, 6, 9, and 12 month precipitation amounts for the two watersheds, Red River and Colorado, are presented in Tables 1 and 2. ETDI and

Table 1
Correlation matrix of drought indices—Red River

	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6	PDSI	SPI-1	SPI-3	SPI-6	SPI-9	SPI-12
ETDI	1.00										
SMDI	0.79	1.00									
SMDI-2	**0.94**	0.86	1.00								
SMDI-4	0.83	0.99	0.91	1.00							
SMDI-6	0.73	0.99	0.81	0.97	1.00						
PDSI	0.58	0.65	0.58	0.64	0.63	1.00					
SPI-1	0.69	0.43	0.61	0.47	0.38	0.44	1.00				
SPI-3	**0.72**	0.64	**0.73**	**0.67**	0.59	0.65	0.60	1.00			
SPI-6	0.54	**0.66**	0.59	0.66	**0.64**	0.79	0.40	0.72	1.00		
SPI-9	0.47	0.64	0.50	0.62	0.63	**0.82**	0.35	0.59	0.83	1.00	
SPI-12	0.42	0.59	0.44	0.56	0.59	**0.82**	0.29	0.50	0.73	0.89	1.00

SMDI's were positively correlated with PDSI and SPI's ($r > 0.7$) for both watersheds. This suggests that the dry and wet periods indicated by the ETDI and SMDI's were in general agreement with PDSI and SPI. However, the duration of the dryness or wetness and the intensity of drought measured by each index are different depending on the inherent characteristic of each drought index. The maximum correlations of ETDI and SMDI's to PDSI and SPI's for each watershed are indicated in bold font in Tables 1 and 2.

The ETDI and SMDI-2 were well-correlated with SPI-1 or SPI-3 ($r \sim 0.75$). This was expected because ETDI and SMDI-2 had lesser auto-correlation lag (Fig. 3) and thus depend on short-term weather conditions when compared to SPI's of higher duration or PDSI that are indicators of medium to long-term drought conditions. ETDI and SMDI-2 were also highly correlated with themselves ($r \sim 0.95$) because most of the active evapotranspiration takes place at the top 2 ft. of soil profile and they both are complementary to each other.

SMDI derived from the entire soil profile and SMDI-6 were well-correlated with PDSI, SPI-3 and SPI-6. For Colorado River, only 40% of the watershed had soils greater than 2 ft. deep. Hence, similar to SMDI-2, SMDI of Colorado River watershed had high correlation with SPI-1 ($r \sim 0.68$). However, for soils with depth greater than 6 ft. in Colorado River Watershed, SMDI-6 was well correlated with SPI-6 ($r \sim 0.67$). Hence, SMDI and SMDI-6 are good measures of long-term drought conditions. For both watersheds, SMDI-4 was well-correlated with SPI-3 ($r \sim 0.7$), suggesting that SMDI-4 could be a good intermediate measure between rapidly responding ETDI/SMDI-2 and slow evolving SMDI/SMDI-6.

For both watersheds, PDSI was well-correlated with SPI-9 and SPI-12 ($r \sim 0.85$), suggesting that PDSI is an indicator of long-term weather conditions. This was consistent with the observation made by Guttman (1998) that PDSI and SPI are in phase only at a period of about a year. The correlation of PDSI with SPI-9 and SPI-12 was greater than 0.84 for most of the watersheds, which was higher than the correlation of SPI's with ETDI and SMDI's that varied between 0.71 and 0.78, suggesting that precipitation is the dominant factor in

Table 2
Correlation matrix of drought indices—Colorado River

	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6	PDSI	SPI-1	SPI-3	SPI-6	SPI-9	SPI-12
ETDI	1.00										
SMDI	0.96	1.00									
SMDI-2	**0.98**	0.98	1.00								
SMDI-4	0.81	0.90	0.84	1.00							
SMDI-6	0.78	0.88	0.80	0.99	1.00						
PDSI	0.54	0.58	0.52	0.66	0.66	1.00					
SPI-1	**0.73**	**0.68**	**0.70**	0.52	0.50	0.48	1.00				
SPI-3	0.66	0.67	0.66	**0.68**	0.65	0.72	0.62	1.00			
SPI-6	0.52	0.58	0.52	**0.68**	**0.67**	0.85	0.45	0.76	1.00		
SPI-9	0.44	0.52	0.44	0.64	0.66	**0.87**	0.38	0.65	0.87	1.00	
SPI-12	0.38	0.46	0.37	0.58	0.61	0.83	0.32	0.55	0.77	0.91	1.00

PDSI. Precipitation was the dominant factor in ETDI and SMDI's as well; however, as the spatial variability analysis showed, the spatial variability in precipitation, ET, soil, and land cover characteristics not accounted for by PDSI or SPI, were also critical in ETDI and SMDI for identifying localized drought conditions.

3.4. Performance of the drought indices during major drought events

The drought indices ETDI and SMDI were also compared with existing drought indices during major drought events of 1930s, 1950s, 1980s, and the 1990s. ETDI was compared with SPI-1 to evaluate the short-term drought events and SMDI-6 was compared with SPI-6 and PDSI to evaluate the long-term drought events. These drought indices were chosen for comparison as they showed high correlation with each other (Tables 1 and 2) as discussed in the previous section. The time-series plots (Figs. 7–10) show that ETDI and SMDI developed in this study agreed well with SPI and PDSI most of the time during major drought events. It should be noted that ETDI and SMDI range between −4 and +4, whereas SPI between −3 and +3 and PDSI between −6 and +6.

All the drought indices showed that both Red River and Colorado River watersheds were worst affected by the drought of the 1950s than the other drought events. The drought of the 1980s and 1990s was longer and severe in Colorado River watershed than in Red River watershed. The short-term drought indices ETDI and SPI-1 compared well with each other. The difference between these short-term drought indices is mainly due to the difference in their formulation; ETDI based on a complete water balance model and SPI based only on rainfall. The long-term drought index SMDI-6 compared well with SPI-6 than with PDSI. This is because PDSI has a long-memory and is an indicator of drought longer than 9 or 12 month period. For example, in the Red River watershed (Fig. 7b) both SMDI-6 and SPI-6 showed short periods of wetness during 1954 and 1955. However, PDSI being a long-term index showed severe drought continuously from 1951 to 1957. Unlike SMDI-6 for Red River watershed, SMDI-6 for Colorado River

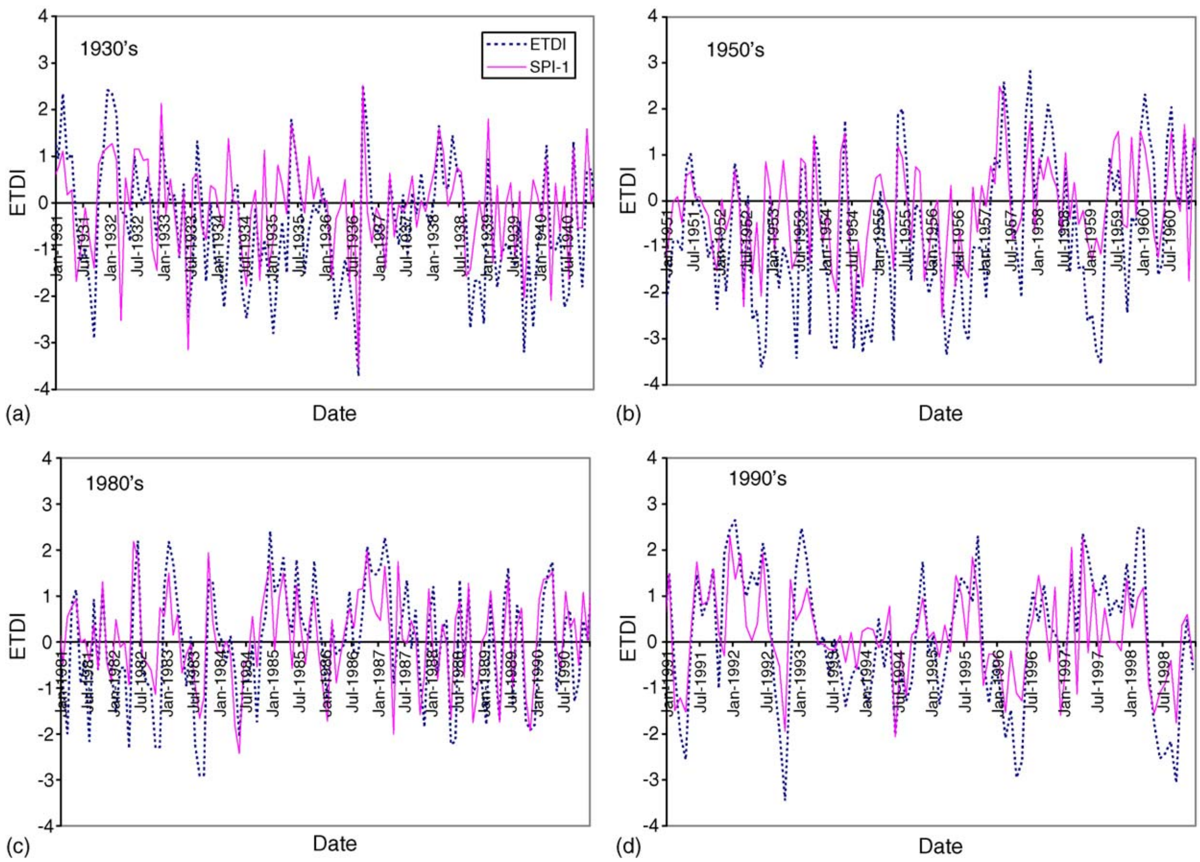

Fig. 7. Comparison of short-term drought indices ETDI and SPI-1 for the Red River watershed.

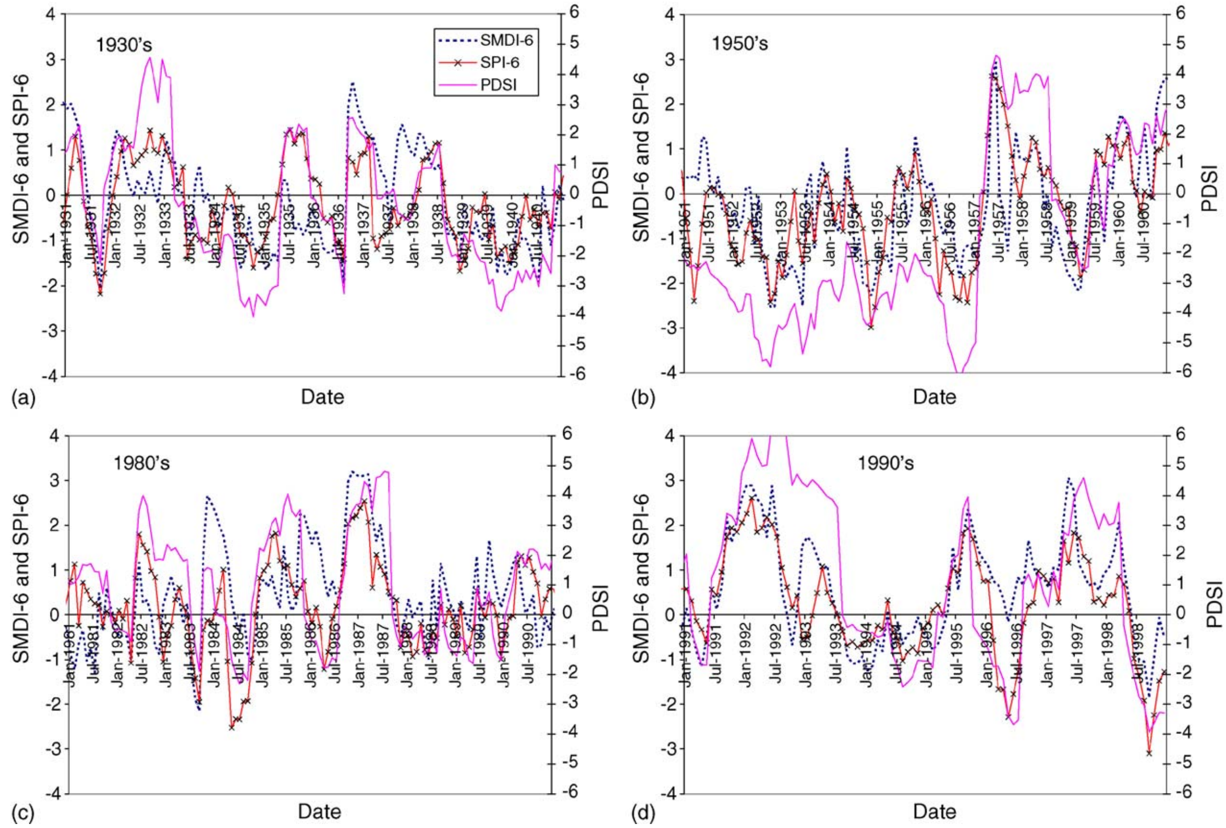

Fig. 8. Comparison of long-term drought indices SMDI-6, SPI-6 and PDSI for the Red River watershed.

watershed showed more fluctuation especially during the drought of the 1950s. Analysis of the data showed that the rainfall events during the 1950s drought where not enough to fill the entire soil profile and only the top 2–4 ft. of soil had moisture storage. Hence, SMDI-6 fluctuated more and behaved like SMDI-2 or SMDI-4 during the drought of the 1950s.

3.5. Correlation with crop yield

A correlation analysis was done with the drought indices and crop yield data to analyze if dryness during the critical period of crop growth affected the crop yield. Sorghum grown during summer (April to September) and wheat grown during winter (October to May) were selected for this analysis. The County crop yield data of sorghum and wheat during the past 26 years (1973–1998) were collected for various counties from the National Agricultural Statistical Service (NASS). Only the crop yields obtained under non-irrigated conditions were used for correlation analysis. From the 26 years of crop yield data for both sorghum and wheat, six years with best yield and six years with worst yield (12 years total) were selected for correlation analysis in each County for sorghum and wheat. The six best and six worst yields were selected because there are other factors like soil fertility, pests, diseases, water logging, and frost, in addition to soil moisture stress that can affect crop yield. By selecting these high and low yield years, we assume that the yield was affected primarily due to moisture stress experienced during different stages of crop growth. With the drought indices at a spatial resolution of 4 km × 4 km, the weekly drought indices were spatially averaged across the County, only for sub-basins with agricultural land cover, during each week for comparison with County crop yield data. The correlations of drought indices with sorghum yield during each week are given in Tables 3 and 4 and winter wheat yield correlations are given in Tables 5 and 6 for counties located in the study watersheds.

3.5.1. Sorghum

In major parts of Texas sorghum is planted during March to April and harvested in August to September. The critical growth stages of sorghum are tasseling,

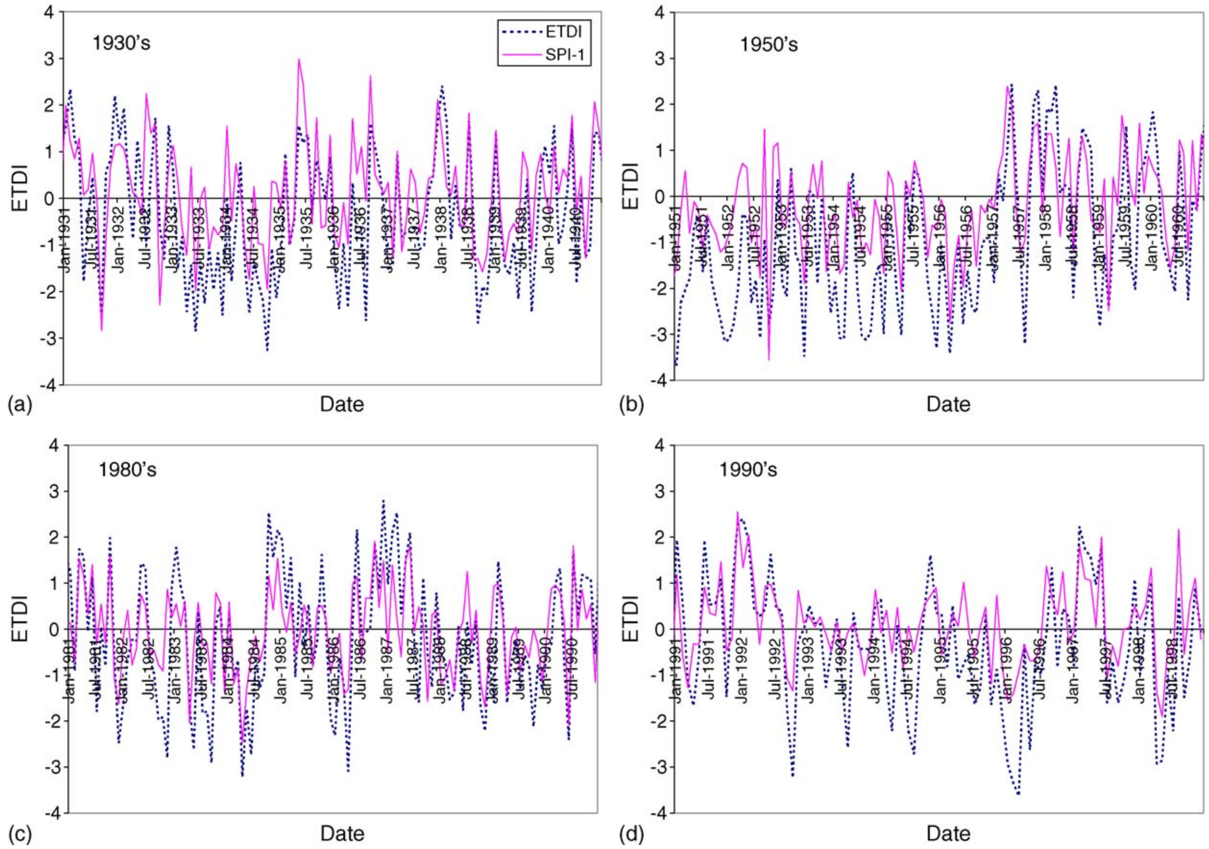

Fig. 9. Comparison of short-term drought indices ETDI and SPI-1 for the Colorado River watershed.

Table 3
Correlation of drought indices with sorghum yield during the crop growing season—Floyd County, Red River basin

Week	Month	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6
(a) ETDI and SMDI's						
14	4	0.17	0.72	0.69	0.66	0.68
15	4	0.40	0.75	0.72	0.68	0.71
16	4	0.66	**0.79**	**0.83**	0.75	0.75
17	4	0.41	**0.79**	0.81	**0.78**	**0.76**
18	5	0.10	0.78	0.72	0.77	0.74
19	5	−0.12	0.74	0.46	0.73	0.71
20	5	−0.16	0.66	0.20	0.63	0.65
21	5	0.30	0.71	0.26	0.67	0.70
22	6	0.35	0.72	0.27	0.64	0.69
23	6	0.46	**0.79**	0.34	0.67	0.75
24	6	0.36	0.74	0.22	0.60	0.72
25	6	0.47	0.72	0.24	0.59	0.70
26	6	0.59	0.71	0.35	0.59	0.69
27	7	0.71	0.70	0.37	0.58	0.69
28	7	0.88	0.74	0.45	0.65	0.71
29	7	**0.93**	0.76	0.55	0.69	0.73
30	7	0.91	0.75	0.52	0.69	0.72

Month	PDSI	SPI-1	SPI-3	SPI-6	SPI-9
(b) PDSI and SPI's					
4	0.65	0.23	0.43	0.44	**0.67**
5	0.54	0.15	0.31	0.32	0.65
6	0.64	**0.50**	0.52	0.49	0.54
7	**0.72**	0.43	0.45	0.56	0.57

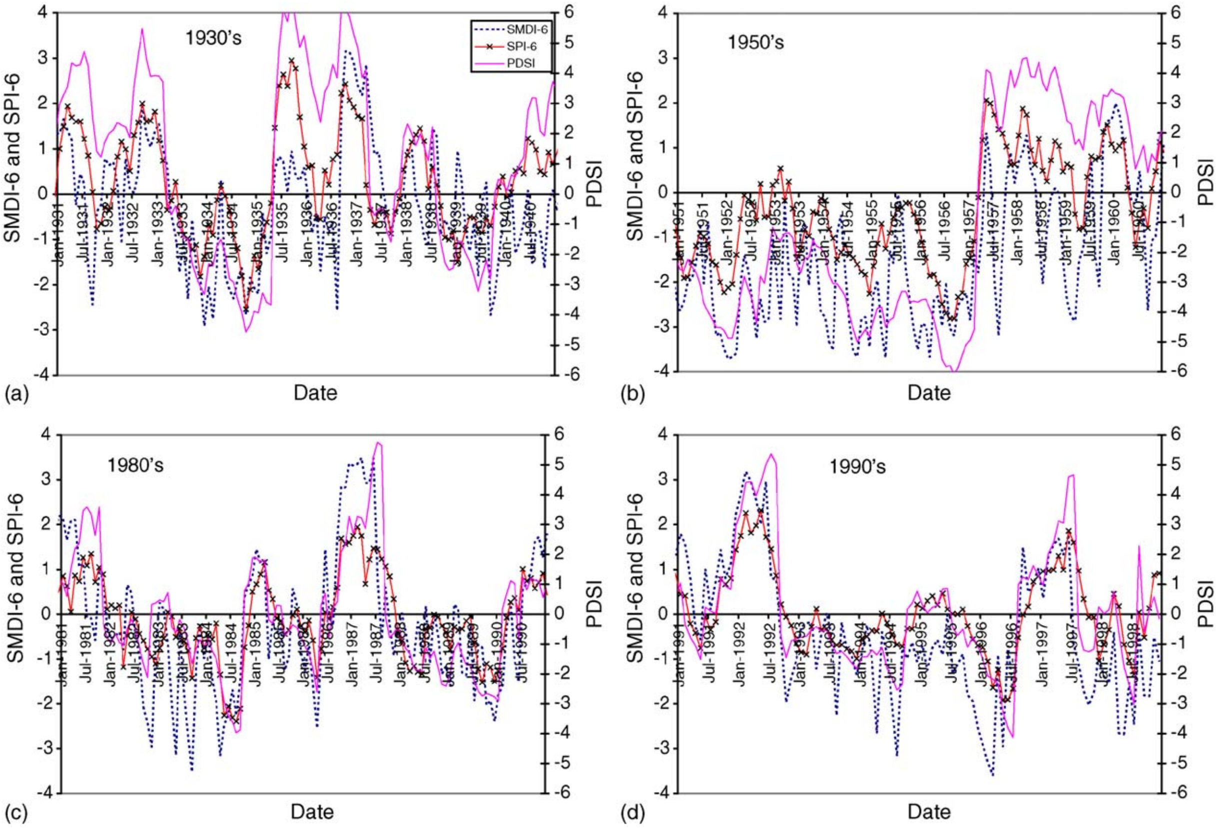

Fig. 10. Comparison of long-term drought indices SMDI-6, SPI-6 and PDSI for the Colorado River watershed.

Table 4
Correlation of drought indices with sorghum yield during the crop growing season—Tom Green County, Colorado River basin

Week	Month	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6
(a) ETDI and SMDI's						
14	4	0.56	0.81	0.64	0.83	0.81
15	4	0.54	0.82	0.65	0.84	0.82
16	4	0.68	0.85	0.71	0.87	0.85
17	4	0.74	0.85	0.74	0.87	0.85
18	5	0.73	0.86	0.75	0.88	0.86
19	5	0.69	0.86	0.75	0.88	0.86
20	5	0.72	**0.88**	0.79	0.89	**0.88**
21	5	0.78	**0.88**	**0.81**	**0.90**	**0.88**
22	6	**0.82**	0.87	0.80	0.89	0.87
23	6	0.79	0.81	0.61	0.83	0.81
24	6	0.70	0.74	0.49	0.76	0.74
25	6	0.75	0.72	0.56	0.74	0.72
26	6	0.76	0.74	0.68	0.77	0.74
27	7	0.77	0.76	0.70	0.79	0.76
28	7	0.74	0.77	0.63	0.81	0.77
29	7	0.74	0.78	0.73	0.86	0.79
30	7	0.73	0.79	0.70	0.83	0.80

Month	PDSI	SPI-1	SPI-3	SPI-6	SPI-9
(b) PDSI and SPI's					
4	0.68	0.68	0.63	0.55	0.77
5	0.70	0.46	0.75	0.74	**0.85**
6	**0.72**	**0.66**	**0.78**	**0.76**	0.83
7	0.71	0.04	0.63	0.74	0.69

Table 5
Correlation of drought indices with wheat yield during the crop growing season—Floyd County, Red River basin

Week	Month	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6
(a) ETDI and SMDI's						
1	1	0.72	0.76	0.61	0.77	0.77
2	1	0.71	0.77	0.65	0.78	0.77
3	1	0.72	0.79	0.68	0.79	0.78
4	1	0.73	0.79	0.71	0.79	0.78
5	2	0.56	0.77	0.68	0.77	0.77
6	2	0.62	0.77	0.66	0.76	0.77
7	2	0.62	0.75	0.64	0.75	0.76
8	2	0.57	0.74	0.66	0.74	0.75
9	3	0.57	0.74	0.67	0.75	0.76
10	3	0.61	0.77	0.71	0.76	0.79
11	3	0.59	0.81	0.75	0.79	0.83
12	3	0.58	0.82	0.74	0.81	0.84
13	3	0.59	0.81	0.69	0.80	0.84
14	4	0.70	0.82	0.70	0.81	0.84
15	4	0.74	0.83	0.74	0.83	0.86
16	4	**0.81**	0.85	**0.80**	0.86	0.89
17	4	0.71	0.89	0.80	**0.89**	0.92
18	5	0.45	**0.93**	0.72	0.88	**0.95**
19	5	0.20	0.91	0.49	0.83	0.92
20	5	−0.01	0.88	0.28	0.77	0.87
21	5	0.03	0.84	0.25	0.73	0.84

Month	PDSI	SPI-1	SPI-3	SPI-6	SPI-9
(b) PDSI and SPI's					
1	0.83	**0.77**	**0.80**	0.66	0.81
2	0.87	0.57	0.79	0.65	**0.85**
3	**0.88**	0.44	0.71	0.81	0.71
4	0.90	0.52	0.64	**0.84**	0.74
5	0.75	−0.25	0.34	0.61	0.58

pollination and yield formation (June to July), during which a water stress at the root zone can have a significant impact on the crop yield (Hane and Pumphrey, 1984). The correlation of weekly ETDI and SMDI's with the six best and six worst years of Sorghum yield also showed maximum correlation during the weeks in June and July (Tables 3a and 4a). For Floyd County in Red River basin, ETDI during the 29th week (July) had the highest correlation with crop yield ($r \sim 0.93$). However, for Tom Green County in Colorado River basin, high correlations of ETDI and crop yield were observed during the weeks of June. Because of differences in planting dates among various counties, this critical period of high correlation shifts between June and July. In Floyd County, the SMDI's were highly correlated with sorghum yield ($r > 0.75$) during the plant emergence and tillering phase as well (weeks 16 and 17). Tom Green County also showed high correlations of ETDI and SMDI's with sorghum yield ($r > 0.8$) during the plant emergence and tillering phase. This indicates that an adequate amount of soil moisture is needed during the sorghum crop establishment stage, as well as the tasseling and pollination stage, to have a better crop stand and increased crop yield.

The correlation with sorghum yield was also done on the monthly drought indices PDSI and SPI's reported for the climatic division (Tables 3b and 4b). Although PDSI and SPI's also showed good correlations with sorghum yield, ETDI and SMDI's have shown higher correlations ($r > 0.75$) than PDSI and SPI's during the critical growth stages. Hence, ETDI and SMDI could be useful indicators for monitoring soil moisture stress during critical growth stages of sorghum.

3.5.2. Winter wheat

In Texas, wheat is planted from mid September to October and harvested from mid May to June. The critical growth stages of wheat are head emergence, flowering and grain filling (March to April), during which a water stress at the root zone can have a significant impact on the crop yield (Hane and

Table 6
Correlation of drought indices with wheat yield during the crop growing season—Concho County, Colorado River basin

Week	Month	ETDI	SMDI	SMDI-2	SMDI-4	SMDI-6
(a) ETDI and SMDI's						
1	1	**0.74**	0.69	0.66	0.59	0.68
2	1	**0.74**	0.68	0.66	0.58	0.67
3	1	0.72	0.68	0.66	0.59	0.66
4	1	0.65	0.66	0.65	0.57	0.66
5	2	0.64	0.67	0.66	0.58	0.66
6	2	0.67	0.72	**0.71**	0.62	0.71
7	2	0.62	0.75	0.70	0.64	0.73
8	2	0.44	0.71	0.61	0.59	0.69
9	3	0.63	0.74	0.65	0.64	0.73
10	3	0.58	0.74	0.64	0.64	0.73
11	3	0.61	0.75	0.65	0.65	0.74
12	3	0.71	**0.80**	**0.71**	**0.70**	0.80
13	3	0.64	0.79	0.67	0.69	**0.81**
14	4	0.67	0.79	0.67	0.69	**0.81**
15	4	0.68	0.78	0.68	0.69	0.80
16	4	0.58	0.74	0.64	0.66	0.77
17	4	0.43	0.73	0.60	0.64	0.75
18	5	0.36	0.68	0.57	0.60	0.71
19	5	0.26	0.67	0.44	0.58	0.70
20	5	0.21	0.65	0.28	0.53	0.68
21	5	0.31	0.67	0.29	0.53	0.70

Month	PDSI	SPI-1	SPI-3	SPI-6	SPI-9
(b) PDSI and SPI's					
1	0.61	0.21	**0.79**	0.42	0.47
2	0.61	0.46	0.65	0.43	0.42
3	**0.66**	**0.66**	0.55	0.63	0.47
4	0.65	0.47	0.60	**0.78**	**0.53**
5	0.62	0.16	0.53	0.66	0.51

Pumphrey, 1984). For Floyd and Concho counties, ETDI and SMDI's showed high correlations ($r > 0.8$) with wheat yield during flowering and grain filling stages (March to April) (Tables 5a and 6a). Even though the correlations between wheat yield and drought indices were the highest during the critical period, the correlations were generally high ($r \sim 0.7$) during most of the wheat growing season. Analysis of the data showed that during the two best yields in record the soil was dry during the planting phase and during the two worst yields the soil was wet during the planting phase. This suggests that probably Wheat prefer somewhat dry soil during the planting phase for a good crop yield. However, further analysis with field level yield data is needed to confirm these observations.

In contrast to sorghum, where high correlations occurred mainly during the critical growth periods, the high correlations of drought indices with wheat yield were widely spread during the growing season. This indicates that a reasonable amount of soil moisture during most of the growing season will be favorable for wheat production. Compared to the summer crop sorghum, PDSI and SPI's were well-correlated with winter wheat. Similar to ETDI and SMDI's, PDSI and SPI also showed markedly high correlations during plant establishment – tillering stage and flowering – grain filling stage. However, ETDI and SMDI's have shown higher correlations with wheat yield with $r > 0.8$. Hence, ETDI and SMDI could be useful indicators for monitoring soil moisture stress during critical stages of wheat crop.

4. Summary and conclusions

Weekly soil moisture and evapotranspiration simulated by the calibrated hydrologic model SWAT was used to develop a set of drought indices – SMDI and ETDI, respectively. The drought indices were derived from soil moisture deficit and evapotranspiration deficit and scaled between −4 and 4 for spatial comparison of drought index, irrespective of climatic conditions.

- The auto-correlation lag of the drought indices, ETDI and SMDI, were closely related to the available water holding capacity of the soil, with lag increasing as a result of increased water holding capacity.
- ETDI and SMDI-2 had the lowest auto-correlation lag because the top 2 ft. of the soil profile very actively participate in the evapotranspiration of available soil water. Hence, ETDI and SMDI-2 could be good indicators of short-term agricultural droughts.
- The spatial variability of the drought indices was high with a standard deviation greater than 1.0 during most of weeks in a year, which was not apparent in the existing drought indices due to large scale spatial lumping.
- The high spatial variability in the drought indices was mainly due to high spatial variability in rainfall distribution.
- The spatial variability (standard deviation) of the drought indices especially ETDI during different seasons closely followed the variability in precipitation and evapotranspiration across seasons.
- ETDI and SMDI's were positively correlated with PDSI and SPI's for both watersheds. This suggests that the dry and wet period indicated by the ETDI and SMDI's were in general agreement with PDSI and SPI.
- For both watersheds ETDI and SMDI-2 were well-correlated with SPI-1 month ($r \sim 0.7$), indicating that ETDI and SMDI-2 are good indicators of short-term drought conditions suitable for agricultural drought monitoring.
- PDSI was highly correlated with SPI-9 and SPI-12 months ($r > 0.8$), suggesting that precipitation was the dominant factor in PDSI, and PDSI is an indicator of long-term weather conditions.
- The wheat and sorghum crop yields were highly correlated with the drought indices ($r > 0.75$) during the weeks of critical crop growth stages, indicating that ETDI and SMDI's can be used for agricultural drought monitoring.

The fine spatial resolution of ETDI and SMDI's combined with high temporal resolution will help in developing a better understanding of agricultural drought and would help in monitoring and planning to mitigate the impacts of drought.

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