Commonly Used Drought Indices as Indicators of Soil Moisture in China

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ABSTRACT

Soil moisture shortages adversely affecting agriculture are significantly associated with meteorological drought. Because of limited soil moisture observations with which to monitor agricultural drought, characterizing soil moisture using drought indices is of great significance. The relationship between commonly used drought indices and soil moisture is examined here using Chinese surface weather data and calculated station-based drought indices. Outside of northeastern China, surface soil moisture is more affected by drought indices having shorter time scales while deep-layer soil moisture is more related on longer index time scales. Multiscalar drought indices work better than drought indices from two-layer bucket models. The standardized precipitation evapotranspiration index (SPEI) works similarly or better than the standardized precipitation index (SPI) in characterizing soil moisture at different soil layers. In most stations in China, the Z index has a higher correlation with soil moisture at 0–5 cm than the Palmer drought severity index (PDSI), which in turn has a higher correlation with soil moisture at 90–100-cm depth than the Z index. Soil bulk density and soil organic carbon density are the two main soil properties affecting the spatial variations of the soil moisture–drought indices relationship. The study may facilitate agriculture drought monitoring with commonly used drought indices calculated from weather station data.

1. Introduction

Drought is a climatic hazard that may cause many negative influences to food security and economic and social stability. Recent studies show increasing global drought from both observations and models (Dai 2012). Thus, it is urgent to understand the current and future drought situations in different regions of the world. Effective drought monitoring, usually based on meteorological observations, plays an important role in drought assessment and alleviation.

Drought can be monitored from meteorological, agricultural, and hydrological considerations (Dracup et al. 1980; Wilhite and Glantz 1985). Meteorological drought is usually quantified by the rainfall anomaly occurring over a time period (Olukayode Oladipo 1985; Mezehausken 2004). Agricultural drought, probably the most important aspect of drought, is often characterized by the shortage of soil moisture within a period that influences crop production (Palmer 1965). Hydrological drought occurs with the reduction in streamflow and reservoir levels occurring over the longest time scales. Various drought indices derived from widely available climatic data from weather stations (e.g., precipitation P and temperature) have been most commonly used. There are basically two categories of these drought indices. The first category contains the multiscalar drought indices based on the characterization of wetness and dryness by statistical probability, for example, the standardized precipitation index (SPI; McKee et al. 1993) and the standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al. 2010). The SPI is defined by precipitation anomalies occurring over different time scales and is often used for drought
monitoring because of its simplicity (Guttman 1998). The SPI has great potential in risk assessment and decision making. The SPEI is also a multiscalar drought index that evaluates the balance between precipitation and potential evapotranspiration PET. The other category contains the drought indices generated from two-layer bucket models, for example, the Palmer drought severity index (PDSI; Palmer 1965), the Z index (Palmer 1965), and the self-calibrating Palmer drought severity index (scPDSI; Wells et al. 2004).

Monthly calculation of these commonly used drought indices can be easily realized with publicly available data sources. Compared with these drought indices, agriculture drought is relatively hard to quantify because of the lack of ground soil moisture observations. What is more, the soil moisture retrieved from climate models has very large uncertainties in showing trend and variability (Li et al. 2007). As an alternative, microwave remote sensing can retrieve soil moisture, but it can only sense the surface soil depth, usually within 0–5 cm (Owe et al. 2001; Dorigo et al. 2010), and estimation in highly vegetated regions is uncertain or missing (Jackson 1997; Wagner et al. 1999).

Commonly used drought indices from climatic data can potentially work as indicators of soil moisture, and there are some studies on the relationship between drought indices and soil moisture in different regions of the world. For example, Sims et al. (2002) show the SPI to be more representative of short-term precipitation and soil moisture variation in North Carolina. Mika et al. (2005) show that the PDSI has a higher correlation with soil moisture from November to April than from May to October in the Great Hungarian Plain. Dai et al. (2004) show that the PDSI in most parts of China has a significant correlation with soil moisture within a 1-m depth. These studies mainly focused on the relationship between mean soil moisture (usually within 1-m depth) and drought indices. The variations of soil moisture at different layers and its responses to meteorological drought are not quite clear.

China feeds about 22% of the world’s population with only ~7%–8% of its arable land. Crop production and food security in China has been a major concern because of increasing drought threats in many cultivated areas in recent years (Piao et al. 2010). Studies that can improve agricultural drought monitoring are of special significance in China. There are relatively few studies on the soil moisture response, at different depths, to commonly used drought indices in China. In this study, we focus on the following issues to enhance our understanding of commonly used drought indices as indicators for agriculture drought monitoring in China: 1) the relationship between the time scale of drought and soil layer depth, 2) finding a physical interpretation for the soil moisture–drought indices relationship, 3) determination of which commonly used drought index (SPI, SPEI, Z index, PDSI, and scPDSI) best characterizes soil moisture at different soil depths, and 4) comparison of different drought indices as indicators of soil moisture.

2. Data and methods

We referred to soil moisture data at 40 stations (Li et al. 2005), as shown in Fig. 1, and climatic data at 756 weather stations from China’s meteorological sharing service system (http://cdc.cma.gov.cn/). We selected the nearest weather stations within 0.5° lat/lon (32 stations). The data from the station with the open circle are used in Fig. 2. Due to the spatial distribution of soil moisture stations, the islands in the South China sea are not displayed, similarly hereinafter.

![Fig. 1. Spatial distribution of soil moisture stations in China. Black dots denote the location of 40 soil moisture stations in China. Stations with plus signs are those collocated with meteorological and soil moisture observations within 0.5° lat/lon (32 stations). The data from the station with the open circle are used in Fig. 2. Due to the spatial distribution of soil moisture stations, the islands in the South China sea are not displayed, similarly hereinafter.](image-url)
humidity were downloaded. According to the FAO’s Penman–Monteith method (Allen et al. 1998), monthly total sunshine hours need be changed to monthly mean daily sunshine hours. Monthly mean daily wind speed $U$ needs be converted from 10- to 2-m height (i.e., from $U_{10}$ to $U_2$, respectively) before calculation by the following equation:

$$U_2 = 4.87U_{10}/\ln[67.8(10 - 5.42)].$$  \hspace{1cm} (1)

In calculating the PDSI, one important parameter of the soil “bucket” model is available water content (AWC). In this study, we obtained soil AWC for each station within the top 1-m depth from the Global Gridded Surfaces of Selected Soil Characteristics dataset, part of the International Geosphere–Biosphere Programme Data and Information Systems (IGBP-DIS), that has a spatial resolution of $5 \times 5$ arc-min (available at www.daac.ornl.gov).

The soil properties data for China (Wei et al. 2013) are from Beijing Normal University (http://globalchange.bnu.edu.cn/). The data contain six layer divisions, and we adopt the $5 \times 5$ arc-min soil property data of the 0–83-cm layers, which are close to the soil moisture for the 0–80-cm (respectively) layers that are used here. Sand percentage (%), clay percentage (%), bulk density (g cm$^{-3}$), and soil organic carbon (SOC) density (t ha$^{-1}$) were used to interpret the multisite variations of soil moisture response to drought indices, as these four have proven to be influential factors of the soil water content (Cosby et al. 1984; Rawls et al. 2003).

The SPI uses precipitation as the sole input to quantify drought severity, while the SPEI uses the difference between precipitation and PET, potentially reflecting the influence of temperature variations on drought, as PET is dominated by surface air temperature, wind speed, solar radiation, and humidity. The SPI and SPEI at different time scales are calculated with historical data following gamma and log logistic distribution, respectively. The standardized values of these indices have an average value of zero and a unit standard deviation. One of the important characteristics of the SPI and SPEI lies in their multiple time scales that can be used to evaluate drought from the viewpoint of temporal accumulation of moisture anomalies. The PDSI is based on a water budget model from the water balance equation (Palmer 1965) that incorporates precipitation, evapotranspiration, runoff, and recharge. The PDSI itself depends on a two-layer bucket model of the soil. The top layer of soil is assumed to hold an inch of soil moisture. In the PDSI calculation, the Climatically Appropriate For Existing Conditions (CAFEC) are used to obtain the potential index values:

$$\alpha_i = \frac{\bar{E}_i}{\bar{P}_i}, \quad \beta_i = \frac{\bar{RE}_i}{\bar{P}_i}, \quad \gamma_i = \frac{\bar{RO}_i}{\bar{PRO}_i}, \quad \text{and} \quad \delta_i = \frac{\bar{L}_i}{\bar{PE}_i}.$$  \hspace{1cm} (2)

where water balance coefficients $\alpha$, $\beta$, $\gamma$, and $\delta$ of each month $i$ can be calculated by average values of evapotranspiration $\bar{E}$; recharge to soils $\bar{RE}$; runoff $\bar{RO}$; water loss to the soil layers $\bar{L}$; and their potential values $\bar{PE}$, $\bar{PRE}$, $\bar{PRO}$, $\bar{PL}$, respectively. The amount of precipitation to maintain normal soil moisture level, which is also called CAFEC precipitation $P_c$, can be expressed as

$$P_c = \alpha_i \bar{PE} + \beta_i \bar{PRE} + \gamma_i \bar{PRO} + \delta_i \bar{PL}.$$  \hspace{1cm} (3)

This leads to the $Z$ index, which is based on the difference between the actual precipitation in a given month and the computed $P_c$ for the same month:

$$Z = K(P - P_c),$$  \hspace{1cm} (4)

where $K$ is the climatic characteristic coefficient. Finally, the PDSI of month $i$ can be calculated:

$$\text{PDSI}_i = 0.897\text{PDSI}_{i-1} + \frac{Z_i}{3}.$$  \hspace{1cm} (5)

In the calculation of scPDSI, $K$ in Eq. (4) and 0.897 and $\frac{1}{3}$ in Eq. (5) are replaced with values automatically calculated based on the historical climatic data of a given location.

There are two commonly used methods to calculate evapotranspiration: the Thornthwaite method for PET and the Penman–Monteith method for reference evapotranspiration $ET_o$. Van der Schrier et al. (2011) show that PDSI values based on the two methods are very similar in showing drought trend, intensity, and duration. Dai (2011) also proves that the choice of different methods has little effect on PDSI and scPDSI results, while Sheffield et al. (2012) pointed out that the drought trends from the Thornthwaite and Penman–Monteith methods have strong differences. McVicar et al. (2012) also pointed out that variability of the atmospheric water demand in China is not only driven by dynamics in the average temperature but mostly by changes in other climatic factors. To quantify evapotranspiration more accurately, we use the Penman–Monteith method for calculation of $ET_o$ in SPEI, $Z$ index, PDSI, and scPDSI. The calculation of SPI and SPEI was implemented in R using the “SPEI” package (Beguería et al. 2013). The calculation of $Z$ index, PDSI, and scPDSI was implemented in C++ using the code provided by Wells et al. (2004). We revised part of the code to replace the Thornthwaite method with the FAO’s Penman–Monteith method to calculate the $ET_o$ (Allen et al. 1998). In the calculation, the reference surface is a hypothetical
grass reference crop with an assumed height of 0.12 m, a fixed surface resistance of 70 s m\(^{-1}\), and an albedo of 0.23.

3. Results

a. Time-scale effect of drought indices on soil moisture

Ji and Peters (2003) show that a 3-month SPI has the highest correlation with vegetation growth on croplands and grasslands of the midlatitude U.S. Great Plains. Five drought moisture indices are similarly compared here (Fig. 2), as an example, to the observed 10–20-cm depth soil moisture values at Nanchong station in south-central China. The indices include the 3-month SPI, SPEI, Z index, PDSI, and scPDSI. Fluctuations in the 3-month SPI and SPEI are similar over the period of record but do not adequately replicate the wet soil conditions early in the record. The Z index has
higher-frequency variations in its record and some similarities to the SPI and SPEI. The PDSI and scPDSI of a given month can represent an accumulation of drought over the previous few months; thus, their curves are smoother than the 3-month scales of the SPI and SPEI. All drought indices explain roughly the same amount of soil moisture variance at the chosen station ($p < 0.001$).

![Fig. 3](image1.png)  
**FIG. 3.** The optimum time scale of SPI for a soil layer depth of (a) 0–5 and (b) 90–100 cm. (c),(d) As in (a),(b), but for SPEI. The circles without color filling are those for which the soil moisture observations in a given layer cover less than 40 months or for which the correlation is not significant at $p = 0.05$.

![Fig. 4](image2.png)  
**FIG. 4.** Correlation between the optimum time scales (1–12 months) and soil depth for the full soil layer of 0–100 cm using (a) SPI and (b) SPEI. Significant correlations at the $p = 0.05$ level are represented by filled colors. The circles centered with black dots denote a negative correlation. The depth was quantified by the mean value of each layer, for example, 95 cm represents the 90–100-cm layer. The circles without filling are those for which the soil moisture observations in a given layer cover less than 40 months or for which the correlation is not significant at $p = 0.05$. 
In this study, the optimum time scale of the SPI and SPEI is defined as the monthly time-scale period of the drought indices that has the most significant correlation with soil moisture at a specific soil layer. Pearson correlation coefficients $r$ between different monthly periods of the drought indices (SPI and SPEI) and the soil moisture at a specific layer were calculated in order to find the optimum time scale for this soil layer. The correlation between optimum time scale and layer depth is shown in Fig. 3. The majority of stations (20 of 29 in SPI and 20 of 29 in SPEI) have an optimum time scale of 1–3 months with soil moisture depths of 0–5 cm (Figs. 3a,c), although some stations have much longer time scales of 6–12 months, especially in northeastern China. In contrast, 14 of 23 in SPI and 14 of 22 in SPEI had optimum time scales of 9–12 months with soil moisture depths of 90–100 cm (Figs. 3b,d). This suggests a direct relation between the length of the index time scales and the related layer depths. Figure 4 shows more generally that the full 100-cm soil depth and the optimum time scale have positive a correlation at most stations (17 of 23 in SPI and 17 of 20 in SPEI). Most of the exceptions are in northeastern China.

Based on Eq. (5), the PDSI value for a given month is influenced by that occurring for the previous month. However, PDSI has no series of monthly time scales (like SPI or SPEI) over which it can be calculated, as there is no scale parameterization in the model outputs. To try and evaluate the PDSI time-scale relationship further, Figs. 5a and 5b show the optimum time scale for the PDSI at each location relative to the monthly time-scale SPI and SPEI values. In most parts of China, the PDSI best characterizes droughts of 9–12 months (23 of 32 relative to the SPI and 22 of 32 relative to the SPEI). Compared with the PDSI, Eq. (3) shows that the $Z$ index has no inherent memory from the previous month. Figures 5c and 5d show that the $Z$ index can only characterize drought of a 1-month time scale.

Figure 6 shows the correlation magnitude between the PDSI and soil moisture and between the $Z$ index and soil moisture for two soil layers. The $Z$ index has a higher correlation with soil moisture than the PDSI in most
stations within 0–5 cm soil depth while the PDSI has a higher correlation with soil moisture than the Z index in most stations within 90–100 cm. This result is consistent with Figs. 3 and 5, which shows that deep soil moisture is more correlated with longer time scales of drought indices and that the Z index can only represent the 1-month scale of drought well.

b. Comparisons of different drought indices as indicators of soil moisture

Table 1 shows the number of stations characterized by the highest correlation between drought indices and soil moisture at different layers. The SPEI has the best correlation with soil moisture in both the surface (0–5 cm) and deepest layers (90–100 cm) at 44% and 45% of stations, respectively. In the middle layer (40–50 cm), the percentage of the best correlations is roughly similar for both the SPEI and SPI. The number of stations where the SPI and SPEI have the best correlation to soil moisture of the 0–100 cm layer is roughly the same.

Using the soil moisture for the full 0–100 cm depth with 11 layer divisions at the 32 Chinese stations, Fig. 7 shows the variance of correlation coefficients between soil moisture and different drought indices along the soil depth from 0 to 100 cm. Within 0–100-cm depth, multiscale drought indices can represent soil moisture better than drought indices from a two-layer bucket model. As for multiscale drought indices, the SPEI has a higher mean correlation with soil moisture within 0–20 cm depth than SPI while the variance of correlation coefficients between SPI and soil moisture is smaller within the full 0–100 cm soil depth. In drought indices from a two-layer bucket model, the Z index has a higher correlation with soil moisture within 0–10 cm depth than either the PDSI or scPDSI, while PDSI and scPDSI have a higher correlation with soil moisture within 30–100 cm depth than the Z index. Our analysis also shows that PDSI has a higher correlation with soil moisture within 0–100 cm than scPDSI in China.

Figure 8 shows the seasonal variations of the correlation coefficient between the drought indices and mean
soil moisture within the 0–100-cm layer. In all seasons, the multiscalar drought indices (SPI and SPEI) have higher and more significant correlations with mean soil moisture than do drought indices from a two-layer bucket model (the Z index, PDSI, and scPDSI). The correlation differences between multiscalar drought indices and drought indices from a two-layer bucket model are noticeably higher in spring and winter.

4. Discussion

We depict agricultural drought from the viewpoint of soil moisture variations at 32 stations in the top 1-m (agricultural) layer in this study. The study was limited by the incompleteness of the soil moisture records at some stations, the effect of frozen surfaces in winter, and the depth of the evaluated layer. Future work might also incorporate Chinese crop yield data in further assessing regional soil moisture shortages, the actual severity of drought, and the usefulness of the drought indices. The study does show some of the basic regional patterns and characteristics of soil moisture variations associated with drought indices when facing the limited retrieval of soil moisture from either remote sensing data (only soil moisture at the surface layer <5 cm) or large uncertainties in soil moisture output from land surface models (Guo et al. 2004). The study may help meteorologists and ecologists to understand and monitor soil moisture and drought in agricultural areas of China.

The results suggest a preference to use multiscalar drought indices rather than drought indices from a two-layer bucket model, which need to incorporate more input parameters in their calculation. Determining the time scale of different drought indices is important. The basic pattern is that deeper soil moisture may be more effectively characterized by a drought index of longer time scales while soil moisture at the surface layer is affected by shorter time scales (Fig. 4). However, there are still very large spatial variations at different soil layers (Fig. 3). The optimum time scale of meteorological drought indices that characterize the mean soil moisture vary from region to region, which may be influenced by different factors along with the geographic variations. It is meaningful to build empirical models on soil moisture dynamics in response to multiscalar drought indices for different regions of China. This can help users monitor agricultural drought with widely available meteorological data from weather stations. At some stations in northeastern China, optimum time scale and soil depth have a negative correlation. These stations belong to the seasonally frozen region (Jin et al. 2000), where soil freezing and thawing happens regularly within a year. The soil moisture at the surface level is readily influenced by low temperatures in most months within a year, and there is little mobility of the water to greater soil depths once the surface is frozen. Unfortunately, none of the drought indices used in the study can quantify the influences of the snowpack on soil moisture because of the complex interactions between soil moisture and snow melting in cold and high-elevation regions in China. Future studies will explore the influence of snowpack on soil moisture dynamics in these regions from passive or active microwave remote sensing (Wiesmann and Mätzler 1999; Tsang et al. 2007).

The relationship between drought indices and soil moisture may be influenced by different soil properties. Figure 9 shows that soil organic carbon density at 0–83 cm positively influences the soil moisture–drought indices correlation with $p < 0.05$, while soil bulk density negatively influences the soil moisture–drought indices (Z index and scPDSI) correlation ($p < 0.15$). These soil properties may help interpret the cross-site variations of the soil moisture–drought indices relationship. Soil

| Table 1. Number of stations where soil moisture at different layers has the highest correlation with a specific drought index. Stations that have soil moisture observations of less than 40 months were not considered in calculations. |
|-----------------------------------------------|-----------|-----------|-----------|-----------|
| SPI                                          | 6         | 9         | 11        | 13        |
| SPEI                                         | 14        | 9         | 13        | 12        |
| Z index                                      | 7         | 1         | 1         | 0         |
| PDSI                                         | 3         | 8         | 1         | 2         |
| scPDSI                                       | 2         | 4         | 3         | 2         |

FIG. 7. The variance of correlation coefficients between soil moisture and different drought indices along the soil depth from 0 to 100 cm. The size of the circles denotes the variance of correlation coefficients between soil moisture and drought indices at 32 stations. The lines with different symbols represent the mean correlation coefficient between drought indices and soil moisture at 32 stations. Optimum time scales of SPI and SPEI were used to calculate correlation coefficients between soil moisture and drought indices at different layers.
texture (clay and sand percentage) does not influence the soil moisture–drought indices relationship with adequate significance.

Our analysis shows that commonly used drought indices are able to characterize the basic soil moisture dynamics at different layer depths. Multiscalar drought indices are more flexible in characterizing soil moisture dynamics with changing time-scale accumulation of climatic factors. The SPEI is found here to be better than the SPI in characterizing soil moisture within 0–20-cm depth in China (Fig. 7). The reason for this may well be that compared to the SPI, the SPEI incorporates the effect of temperature, wind, solar radiation, and humidity in the calculation of reference evapotranspiration. In addition, the SPEI has the flexibility to take into account different time scales of drought in comparison with the PDSI and Z index. Similar results can be found in other regions. For example, the SPEI was found to have a higher correlation with soil moisture than the SPI in the western and central United States (Vicente-Serrano et al. 2012). Beguería et al. (2013) pointed out that the SPEI can characterize severe drought events in Europe better than the SPI. A recent study by Scaini et al. (2015) also shows that the SPEI has a higher correlation than the SPI with soil moisture anomalies in Spain. The PDSI relates best to longer time scales (9–12 months) of the SPEI and SPI over different locations in China (Figs. 5a,b) and does not represent shorter time scales associated with shallow-layer soil moisture well, especially in central, western, and southern China, where soil water has higher mobility (Figs. 3a,c). This seems to make the PDSI better suited for analysis of hydrological rather than agricultural drought.

There are several other studies showing the weakness of the PDSI in drought characterization, mainly including its assumption that all the precipitation is rain, which makes values during winter months questionable (Keyantash and Dracup 2002; Mishra and Singh 2010), producing nonmultiscalarity (Vicente-Serrano et al. 2010) and complexity in its calculation (Paulo and Pereira 2006). Comparisons between the PDSI and other drought indices have been conducted in different regions of the world. Olukayode Oladipo (1985) pointed out that simple indices with rainfall as the only input

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**FIG. 8.** Correlation coefficient between mean soil moisture (0–100-cm layer) and drought indices in China in (a) spring (March–May; MAM), (b) summer (June–August; JJA), (c) autumn (September–November; SON), and (d) winter (December–February; DJF). Because of missing data at some soil stations, the effective stations used in boxplot are 20, 31, 31, and 8 for (a)–(d), respectively.
perform comparatively as well as the PDSI in depicting periods and intensity of drought in Nebraska. Dai et al. (2004) show that the PDSI is well correlated with soil moisture content during summer, while it is not a good soil moisture metric during the remainder of the year.

Previous studies show that the SPI is more suitable for monitoring droughts in East Africa than the PDSI because of its more consistent spectral patterns over the whole area and multiscale characteristics (Ntale and Gan 2003). Even so, the PDSI is still the most...
widely used drought index for monitoring droughts since its creation in 1965 by Palmer, as it has been well tested and verified in many cases (Heim 2002; Mishra and Singh 2010).

5. Conclusions

Our study compares commonly used drought indices in characterizing soil moisture variations in China and shows that these drought indices calculated with data from weather stations are good at quantifying soil moisture in most parts of China. Some conclusions can be drawn from the current research.

1) Multiscalar drought indices work better than drought indices from a two-layer bucket model in characterizing soil moisture at different layers. This is related to the flexibility of these indices in characterizing time-scale effect of climatic factors on soil moisture.

2) The analysis shows that in China, soil moisture at different depths is related to the time-scale length of the SPI and SPEI. The basic pattern is that soil moisture in deeper layers is related to drought indices of longer time scale. This fits well in areas of high soil moisture mobility. The Z index works better than the PDSI in most regions of China in characterizing soil moisture at surface layer (0–5 cm) while the PDSI works better in characterizing soil moisture of a deep layer (90–100 cm).

3) The SPEI works similarly or better than the SPI and PDSI through different soil layers from 0 to 100 cm, as it takes into account both the influences of temperature, wind, solar radiation, and humidity on drought as well as the changing time scale of drought. Thus, it has great potential to be used to monitor soil moisture shortages in China because of easy access to meteorological data from weather stations.

4) There are large spatial variations for soil moisture response to meteorological drought. The relationship between the drought indices and soil moisture is influenced by soil properties. Soil bulk density and soil organic carbon density are the two main properties influencing the relationship.

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