Adopting drought indices for estimating soil moisture: A North Carolina case study

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[1] Soil moisture availability has a significant impact on environmental processes of different scales. Errors in initializing soil moisture in numerical weather forecasting models tend to cause errors in short-term weather and medium range predictions. We study the use of two drought indices: Palmer Drought Severity Index (PDSI) values and Standardized Precipitation Index (SPI) for estimating soil moisture. SPI and PDSI values are compared for three climate divisions: western mountains, central piedmont, and the coastal plain in North Carolina, USA. Results suggest SPI to be more representative of short-term precipitation and soil moisture variation and hence a better indicator of soil wetness. A regression equation that uses SPI is proposed to estimate soil moisture. *INDEX TERMS:* 1866 Hydrology: Soil moisture; 1812 Hydrology: Drought; 1894 Hydrology: Instruments and techniques; 3322 Meteorology and Atmospheric Dynamics: Land/atmosphere interactions

1. Introduction

[2] Soil moisture is an important surface variable that modulates the atmospheric surface energy balance and hence has a significant impact on the vertical distribution of turbulent heat fluxes, as well as the boundary layer structure [*Alapaty et al.*, 1997]. Accurate soil moisture representation is also known to significantly enhance climate outlook projection and precipitation predictability [*Koster et al.*, 2000]. However, regionally representative soil moisture is a difficult parameter to estimate. Soil moisture measurements are limited, point-based, and show significant spatial variability. Therefore development of a simple approach for estimation of soil moisture on a regional scale is of immediate importance.

[3] Here we report the potential use of drought indices for estimating soil moisture. Two drought indices: Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI) are evaluated for representing soil moisture in this study.

[4] PDSI and SPI are generally used to assess the drought conditions across the United States [*Palmer*, 1965; *Alley*, 1984; *McKee et al.*, 1993]. PDSI is defined as:

$$PDSI_i = 0.897\, PDSI_{i-1} + (1/3)z_i, \qquad (1)$$

where i is the current month (period), and z_i is the difference between total precipitation and the potential evapotranspiration and runoff/recharge [*Hu et al.*, 2000]. Estimation of PDSI is based on monthly precipitation, temperature, and local "available water content" (AWC) [*Heddinghaus and Sabol*, 1991]. Despite its popularity, PDSI has several limitations as reviewed in *Alley* [1984] and *Guttman et al.* [1992]. These include an inherent time scale that reflects Palmer's study, and the uncertainty of the index to the AWC for different soil types. The Standardized Precipitation Index (SPI), proposed by *McKee et al.* [1993], is an alternative to PDSI. SPI represents a statistical z-score or the number of standard deviations (following a gamma probability distribution transformed to a normal distribution) above or below that an event is from the mean [*Edwards and McKee*, 1997]. It was designed to quantify precipitation deficit on multiple time scales and eliminate some of the disadvantages of using PDSI. One advantage of SPI is that it can be tailored to specific needs. For example, SPI are routinely calculated for 1-, 3-, and 6- month periods [*McKee et al.*, 1995]. The premise of this study is that drought indices are available and there is a potential to use them to infer regional soil moisture status, which in turn can be used for several applications including short and medium range weather predictions and for providing seasonal climate outlooks [*Pielke*, 1998; *Koster et al.*, 2000].

2. Data

[5] Precipitation data were obtained for three climate divisions (CDs) in North Carolina: divisions 1, 4, and 8 (indicated in Figure 1). The three CDs represent different land-use and topographical features (Division 1 is mountainous, 4 is semi-urban, and 8 corresponds to the coastal region). Monthly PDSI values for these CDs were obtained from the National Climatic Data Center (NCDC) and the National Drought Mitigation Center (NDMC). SPI values were obtained using the precipitation data from select stations in these regions and with the use of the method suggested by *Edwards and McKee* [1997]. Daily, weekly, biweekly, and monthly SPI were determined in an attempt to find the best fit for anomalous precipitation data sets. Precipitation anomalies were developed by removing the average precipitation amount from the individual precipitation events for the specified time period. Soil moisture observations were obtained from automated agro-meteorological towers available as a part of the North Carolina AgNet using time-domain reflectometery [*Niyogi et al.*, 1998; *Noborio*, 2001].

3. Comparing SPI, PDSI, and Precipitation Anomalies

[6] Intuitively, soil moisture values depend on precipitation amounts. However, precipitation has significant spatial variability and a co-varying factor is needed to develop the soil moisture estimates. The drought indices such as SPI and PDSI, are also dependent on the precipitation occurrence, and can be hence considered to co-vary with soil moisture.

[7] One-month SPI were calculated from 1994 to 1999 and compared with the monthly average precipitation anomalies from CDs 1, 4, and 8. Corresponding monthly PDSI values were also compared to the precipitation anomalies for the same period. These are overlaid with the CD1 SPI and precipitation anomaly time–series in Figure 2. For all the three CDs, the SPI values are in phase with the precipitation anomalies and followed the curve closely. This is expected, since SPI can be considered as a measure of precipitation anomaly; but the coherent and in-phase variations are particularly encouraging. In comparison, PDSI values, though

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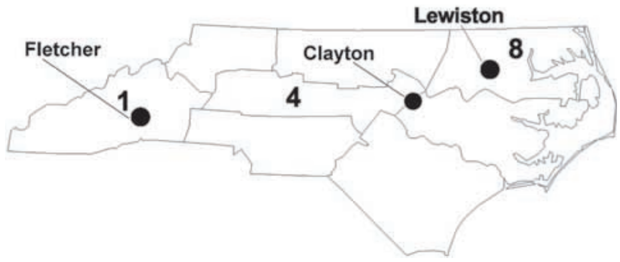

Figure 1. A map of North Carolina showing the different climate divisions. Divisions 1, 4, and 8 are used in this study. The sites of the soil moisture measurements are also indicated.

generally are in phase, do not follow the precipitation anomaly as closely as the SPI values for the same period. The amplitude for PDSI values is damped as compared to the precipitation anomalies. That is, PDSI follows the general trend of precipitation changes but does not capture the extremes as well. Results for divisions 4 and 8 yield similar results (not shown) between the SPI, PDSI, and precipitation anomaly as for CD1 (Figure 2).

[8] The PDSI response time appears to lag behind the respective SPI and the precipitation anomaly variations. This lag is more evident when comparing data from CDs 4 and 8 (typical lag of the order of 3 months behind the precipitation anomaly). The occurrence of a precipitation anomaly is not apparent from the PDSI variation (but is seen in SPI). To address the issue of temporal and phase changes further, fast fourier transforms (FFT) of the two drought indices and precipitation time series were calculated for each CD. The FFT estimates clearly identified seasonal, semi annual and annual peaks in the precipitation time series for all the CDs. A sample plot for CD1 is shown in Figure 3. The significant peaks became less distinguishable for the coastal region (not shown). This could be related to higher precipitation frequency as expected from events such as coastal storms, coastal fronts, and sea breeze occurrences along the coast. As discussed in *Guttman et al.* [1992], PDSI is better suited for semiarid and dry

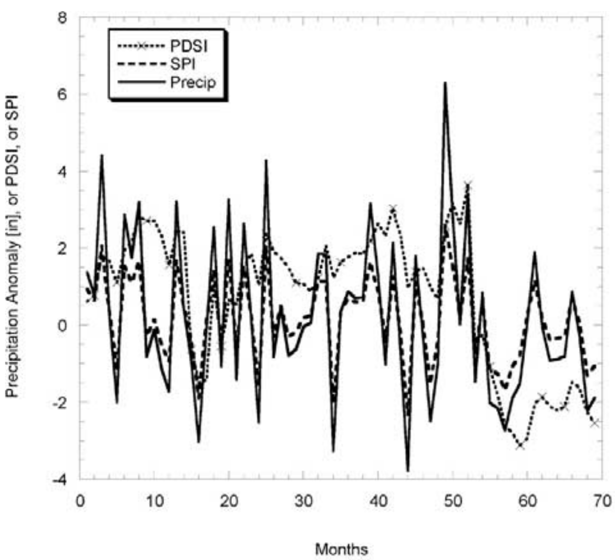

Figure 2. Monthly PDSI, SPI, and precipitation anomalies for climate division 1. The time series is indicated by months beginning in January 1994 and continuing through December 1999. The vertical axis corresponds to precipitation anomaly (in), SPI and PDSI values. Overall, SPI is in-phase with the precipitation anomalies while PDSI has a slower response time.

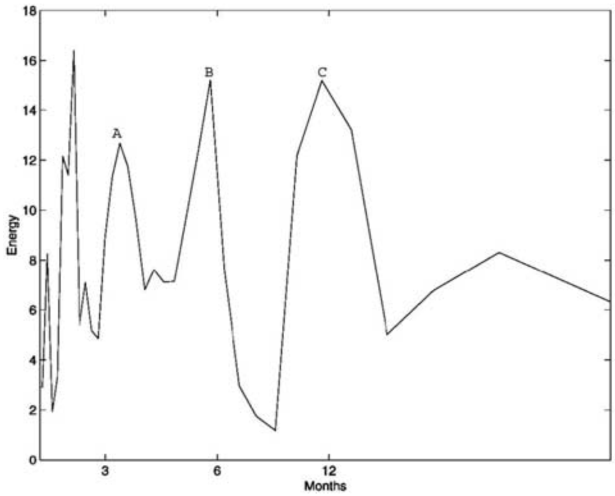

Figure 3. Fast Fourier Transforms (FFT) of precipitation over a 6-year period for climate division 1 using SPI as the indicator. The x-axis corresponds to the months showing the seasonal, semi-annual, and annual peaks (labeled as A, B, and C, respectively). The y-axis (unitless) shows the relative energy associated the significant peaks.

climate regions and hence, as seen in our results, the ability for PDSI to represent the anomaly appears to be inversely related to the precipitation frequency. *Heddinghaus and Sabol* [1991] also discuss such conditions where anomalous precipitation may be enough to end a drought period defined by PDSI. Further, an anomalous precipitation event can affect PDSI values for several months, even though the actual dry period may not have ended.

[9] Overall, SPI appears to be better suited, compared to PDSI, for representing precipitation variability and hence resulting soil moisture changes at a short time scale (weeks to months). Accordingly, daily and weekly SPI were also calculated and compared to the respective precipitation anomalies (not shown). These short time scale SPI variations were also in phase with precipitation changes. Interestingly, although the phase is the same for the SPI and the precipitation changes, SPI gives some erroneous spikes and is offset (positive bias) from the precipitation anomaly time-series. This suggests there could be a temporal lower limit (order of a week) for the derivation of meaningful quantitative relationships such as soil moisture from SPI.

4. Analysis of SPI, PDSI, and Soil Moisture Variations

[10] Soil moisture and precipitation data were obtained from the North Carolina Agricultural Network (AgNet) stations [*Niyogi et al.*, 1998]. The locations of the monitoring sites used in this study are shown in Figure 1. Monthly and biweekly SPIs, and monthly PDSI values were obtained for the same time period. We test the hypothesis that SPI can be used as a surrogate for estimating soil wetness. This hypothesis stems from the assumption that, for a short time scale, a positive precipitation anomaly can generally be indicative of higher soil moisture and vice versa.

[11] For comparison, SPI and PDSI were normalized by offsetting the time series such that the minimum value corresponds to zero; and then dividing by the new (offset) maximum value. Thus, an independent scale for normalizing these offset SPI (OSPI) is considered as:

$$NSPI_{i,j} = \frac{OSPI_{i,j}}{\max\left(OSPI_{i,j}\right)}, \qquad (2)$$

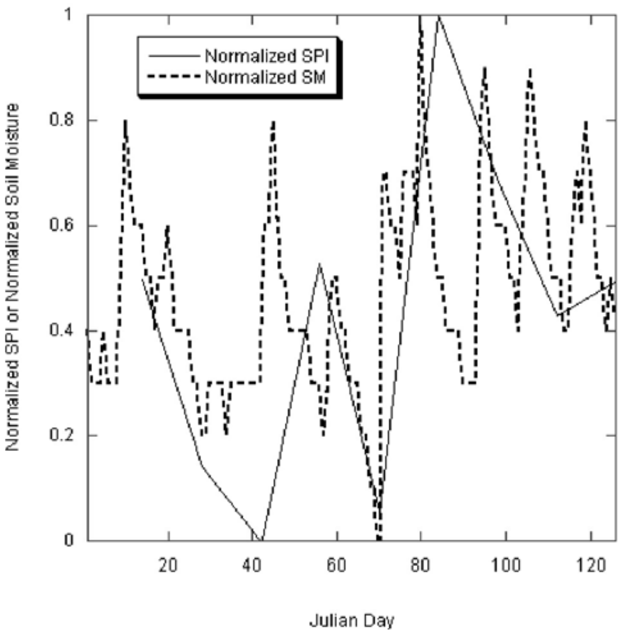

Figure 4. Variability of the normalized soil moisture, and biweekly SPI at Fletcher, NC. The solid line corresponds to normalized biweekly SPI (Normalized SM), while the dashed line is the normalized soil moisture. Though there is a phase lag, the overall variability in the soil moisture is captured.

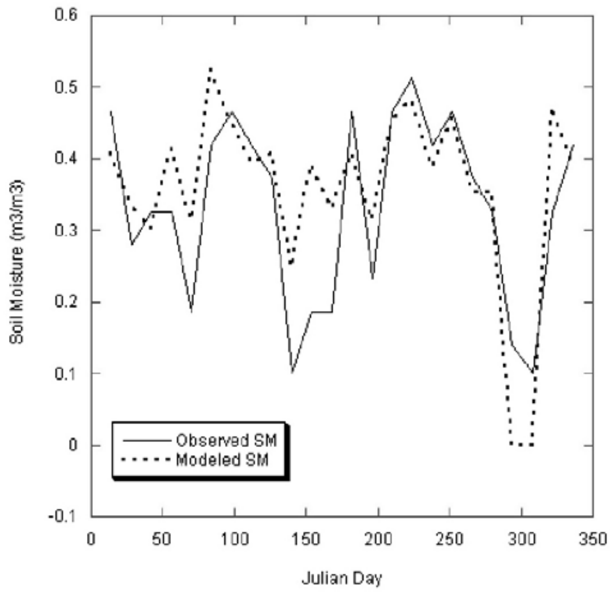

Figure 6. Observed and 'modeled' soil moisture at Fletcher, NC. The observations were taken continuously at a depth of 10 cm (every hour and then averaged to a day). The 'modeled' value is estimated as 75% of the SPI (normalized as discussed in the text), multiplied by the saturation limit of the soil (taken as 0.7 m^3 m^{-3} for this site).

where $OSPI_{i,j}$ is the offset SPI at time i and location j [and equals $SPI_{i,j} - \min(SPI_{i,j})$] and $NSPI_{i,j}$ is the normalized $OSPI_{i,j}$. Similar normalization was performed for PDSI. The soil moisture observations were normalized with the consideration of wilting and saturation as the minima and maxima, respectively [e.g., *Alapaty et al.*, 1997]. This normalization was performed to simply compare the time series variations between similar scales (0 to 1).

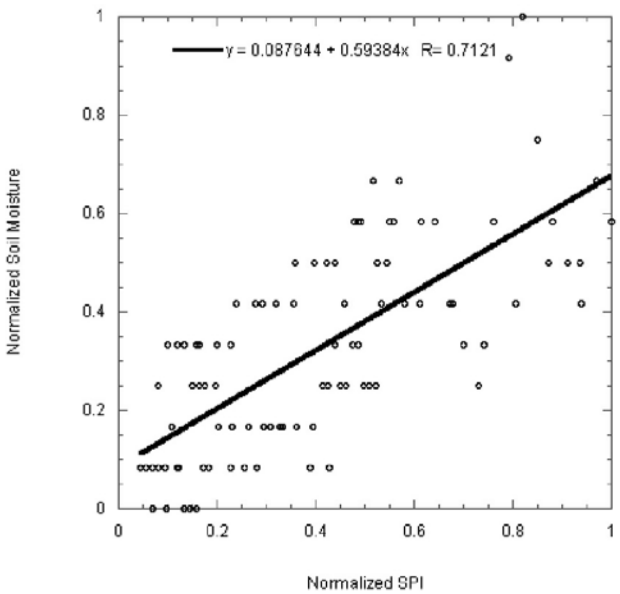

Figure 5. Relation between the normalized biweekly SPI and normalized soil moisture variation at Lewiston, NC. For this case, a correlation of 0.71 is obtained and suggests that soil moisture can be approximated as a fraction (typically 75% as discussed in the text) of normalized SPI.

[12] Figure 4 shows the plots of normalized soil moisture and normalized SPI for comparison. Because of the slow response time and the inability of PDSI to model the soil moisture, PDSI plots are not shown. The general pattern of the SPI variation follows the trend of soil moisture though a phase lag is evident. This result indicates that SPI values can be used as a potential indicator of soil moisture status.

[13] A scatter plot between normalized biweekly SPI values and normalized soil moisture is shown in Figure 5. Thus, soil moisture can be estimated as a linear function of SPI. This relation can be approximated as a fraction of the normalized biweekly SPI. Similar linear relations were obtained with different SPI lag times (weekly, biweekly, 1-, 3-, 6-, and 12- months) for different locations (e.g., Clayton in central NC, and Asheville in western NC). Overall, the results suggest that the normalized soil moisture can be approximated as about 75% of the normalized SPI. It should be emphasized that on comparing different cases it appears that this 75% is only an estimate and the actual value may vary from about 60 to 90% depending on the averaging period and location. This variability can be attributed to several factors but changes in soil types appear to be the main contribution and needs to be investigated further.

[14] Figure 6 shows the observed and SPI estimated soil moisture variation at Fletcher, NC. The soil moisture was observed at a depth of 10-cm. The soil moisture estimate ('modeled') was assumed as 75% of the normalized SPI. The resulting value was multiplied by the saturation soil moisture (considered as 0.7 m^3m^{-3} for this site) to obtain volumetric values.

[15] Overall, short-term averaging ($\sim$1 to 3 months) yielded the highest correlation between normalized SPI and normalized soil moisture (observed at the 10 cm depth). Deeper soil layers may show better correlation with longer averaging times and can be tested when data are available. Thus, the results indicate that SPI can be used as a surrogate for obtaining soil moisture information.

5. Conclusions and Future Applications

[16] This study suggests that drought indices can be used to develop soil moisture estimates. Specifically, SPI closely models precipitation anomalies on short-term time scales, and also appears to estimate soil moisture well. While PDSI values approximate the general trend of precipitation distribution, it is not representative of short-term time-scale variations. Results suggest that SPI appears to be better suited, than PDSI, for monitoring short-term surface soil moisture deficit (also an indicator of agricultural drought) in North Carolina and possibly southeast United States [see also *NDMC*, 1999].

[17] Developing SPI as a soil moisture indicator has some inherent advantages. SPI maps are routinely generated for the United States [*NDMC*, 1999] and can be constructed for other parts of the world. These maps can be used to initialize numerical weather forecasting models and developing 'area–averaged' (as against 'point') soil moisture estimates. Other important applications include using SPI based soil moisture analysis in near real time drought monitoring and region specific seasonal forecasting [e.g., *Koster et al.*, 2000]. This would provide a more mechanistic approach when developing a regional policy concerning drought. Climate models may also benefit from using SPI for initializing soil moisture into land surface model domains as discussed for example in *Pielke* [1998].

[18] The linear relationship suggested from the correlation between SPI and soil moisture values, needs additional analysis. Questions include, what SPI period (biweekly, monthly, 3 month, or 6 month) has the best signature of soil moisture variations; what is the influence of the soil type variability; and the correlation between SPI, PDSI, and other drought indices with deeper soil moisture values. However, our results do suggest that drought indices hold a promise to develop this information further.

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