Journal of Hydrology (2007) **340**, 12–24

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Different responses of MODIS-derived NDVI to root-zone soil moisture in semi-arid and humid regions

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Received 7 June 2006; received in revised form 26 March 2007; accepted 30 March 2007

KEYWORDS
Root zone soil moisture;
NDVI;
Correlation analysis;
Regression model

Summary Surface representation of the root-zone soil moisture is investigated so that feasibility of using optical remote sensing techniques to indirectly map root-zone soil moisture is assessed. Specifically, covariation of root-zone soil moisture with the normalized difference of vegetation index (NDVI) from Moderate Resolution Imaging Spectroradiometer (MODIS) is studied at three sites (New Mexico, Arizona, and Texas) selected from the Soil Climate Analysis Network (SCAN). The three sites represent two types of vegetation (shrub and grass) and two types of climate conditions: semi-arid (New Mexico and Arizona) and humid (Texas). Collocated deseasonalized time series of soil moistures at five depths (5 cm, 10 cm, 20 cm, 50 cm, and 100 cm) and NDVI (8-day composite in 250 m resolution) during the period of February 2000 through April 2004 were used for correlation analysis. Similar analysis was also conducted for the raw time series for comparison purposes. The linear regression of both the deseasonalized time series and the raw time series was used to estimate root-zone soil moisture. Results show that (1) the deseasonalized time series results in consistent and significant correlation (0.46–0.55) between NDVI and root-zone soil moisture at the three sites; (2) vegetation (NDVI) at the humid site needs longer time (10 days) to respond to soil moisture change than that at the semi-arid sites (5 days or less); (3) the time-series of root-zone soil moisture estimated by a linear regression model based on deseasonalized time series accounts for 42–71% of the observed soil moisture variations for the three sites; and (4) in the semi-arid region, root-zone soil moisture of shrub-vegetated area can be better estimated using NDVI than that of grass-vegetated area.

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0022-1694/$ - see front matter
doi:10.1016/j.jhydrol.2007.03.022

Introduction

Soil moisture is a critical boundary condition in the interaction between land surface and atmosphere. Information of distributed soil moisture at large scale with reasonable spatial and temporal resolution is required for improving climatic and hydrologic modeling and prediction, particularly for the distributed models (Western et al., 2002). Various approaches have been developed to estimate soil moisture: from ground-based gravimetric sampling (e.g., Wilson et al., 2003), time-domain reflectometry (e.g., Topp et al., 1980; Roth et al., 1990), to air/space-borne remote sensing techniques (e.g., Engman and Chauhan, 1995; Dubois et al., 1995; Schmugge et al., 2002; Narayan et al., 2004).

Ground-based methods are point measurements, and only a limited number of samples can be made within limited areas (Western and Grayson, 1998), such as the NASA Cold Land Processes Field Experiment (CLPX) at three 25-km × 25-km Meso-cell Study Areas in northern Colorado between September 2001 and April 2003 (Cline and Elder, 2004), soil moisture experiment (SMEX) in Southern Great Plains region in July 1999 (SGP1999) (Njoku et al., 2002), SMEX02 in Iowa between June 25th and July 12th 2002 (Narayan et al., 2004), SMEX03 in June in Little Washita, Oklahoma, and SMEX04 in Walnut Gulch region, Arizona, etc. (Cosh et al., 2006; http://hydrolab.arsusda.gov/smex05/). These ground-based measurements are usually for campaign-style field experiments and impractical for soil moisture estimation at a basin or watershed scale (Wilson et al., 2003; Narayan et al., 2004). Furthermore, local scale variations (vertical or horizontal heterogeneity) in soil properties, topography, and vegetation type and coverage make selection of representative field sites difficult if not impossible (Goward et al., 2002). Thus, extrapolating these isolated measurements to produce spatially and representatively distributed soil moisture is often difficult.

Remote sensing has provided thriving perspective for spatial and instantaneous measurement of soil moisture content for three decades (Wang and Schmugge, 1980; Jackson and Schmugge, 1989; McVicar and Jupp, 1998; Cashion et al., 2005). Passive microwave radiometry and active microwave radar have been widely and actively used for mapping large-area surface soil moisture (Jackson et al., 1995; Chen et al., 1997; Njoku and Li, 1999; Schmugge et al., 2002; Njoku et al., 2002; Wigneron et al., 2003; Narayan et al., 2004), such as SGP1999 (Njoku et al., 2002), SMEX02 (Bindlish et al., 2006; Narayan et al., 2004), SMEX03, and SMEX04, etc., (Cosh et al., 2006; http://hydrolab.arsusda.gov/smex05/). Among these investigations, passive and active L and S band (C and X band also being used) sensors have been successfully used to retrieve the surface soil moisture, but as the signal only penetrates the soil surface to several centimeters, soil moisture mapped by these sensors only represents the top few centimeters. Besides, these sensors become less sensitive to soil moisture in vegetated regions as the vegetation water content increase (Narayan et al., 2004).

Most hydrological and agricultural interests are in the root-zone soil moisture, which is much deeper than the top several centimeters and cannot be penetrated by current microwave remote sensors. Is it possible to estimate the root-zone soil moisture using optical remote sensing measurements? In vegetated regions, root-zone soil moisture is a link between surface phenology and subsurface water storages, and it strongly influences surface water balance and energy partitioning due to evapotranspiration (Song et al., 2000). Root-zone soil moisture also controls surface vegetation health conditions and coverage, especially in arid and semi-arid areas, where water is one of the main controlling factors for vegetation growth (Magagi and Kerr, 2001). Thus, surface vegetation density and status are often a function of local climate and soil property which control water availability. It is observed that a shrub—grass—juniper—ponderosa pine ecotone develops along a climate gradient in central New Mexico (Sandvig, 2005). Within one ecosystem, vegetation self-adjusts its spatial density to match the local climate condition and water availability (Wu et al., 1985; Walker et al., 1989; Miina and Pukkala, 2002). For example, it is observed that vegetation density increase from 20% to 50% along a climate gradient on the eastern slope of Los Pinus Mountain, New Mexico (Wilson and Guan, 2006). In a natural ecosystem, vegetation may develop quasi-equilibrium within a local climate condition, leading to similar root-zone soil moisture in the climate gradient zone. The long-term mean root-zone soil moisture in such a system follows a general seasonality forced by long-term mean local climate and vegetation life cycles, which is predictable. However, varying climatic conditions at various temporal scales result in temporal deviation of soil moisture from its long-term mean conditions. This soil moisture deviation from the mean condition affects vegetation and cause a change in vegetation characteristics (either by leaf condition, or by surface coverage) from the mean condition. This temporal vegetation change could be captured by NDVI derived from optical remote sensing measurements, which is based on the spectral signature of vegetation in near infrared band and red band, associating with vegetation status and fractional vegetation cover. In a short time frame (hours), the NDVI may decrease due to sudden soil moisture increase (rainfall), since increasing top-layer soil moisture would result in a larger decrease of near-infrared reflectance compared to the red reflectance of vegetation. However, in a longer time frame (such as 8 days in this study), it is expected that NDVI increases as soil moisture increases over the growing season.

Farrar et al.'s study (1994) shows that NDVI was controlled by surface soil moisture of the concurrent month. Liu and Kogan (1996) found that NDVI highly couples with water deficit and rainfall for grassland and open woodland. Adegoke and Carleton (2002) assessed the relation between root-zone soil moisture and AVHRR-derived NDVI (pixel size: 1 km × 1 km) at 17 Illinois Climate Network sites covered with crop and forest during 1990—1994, and suggested that (1) the maximum Pearson correlation coefficient (R) between deseasonalized root-zone soil moisture (average of the top 30 cm and top 100 cm depth) and deseasonalized NDVI (biweekly) is 0.3—0.42 during April to September (growing season); and (2) R reaches a maximum as NDVI lags soil moisture for 2 weeks and keeps relatively stable as NDVI lags soil moisture up to 8 weeks. Sandholt et al. (2002) examined the relation between temperature-vegetation dryness index (TVDI) derived from remotely sensed surface temperature and NDVI and surface soil moisture simulated using a hydrological model, and concluded that the TVDI was closely related to surface soil moisture. Both raw (Wang et al., 2003; Cashion et al., 2005; Jackson et al., 2004; Li et al., 2005) and deseasonalized (Wang et al., 2001; Adegoke and Carleton, 2002; Li et al., 2005) time series have been commonly used in literature for correlation analysis, though, physically, the seasonal cycle of time-series should be removed.

The objective of this paper is to develop and test the potential of an optical remote sensing approach for estimating root-zone soil moisture. Specifically, we will answer the following questions through data analysis and comparison with ground observations: (1) what is the difference of using raw and deseasonalized time series for correlation analysis between NDVI and soil moisture? (2) what is the depth at which soil moisture in different vegetation types and climate regimes is best reflected in the surface vegetation's NDVI? and (3) what is the time lag for NDVI to respond to the change of root-zone soil moisture? Is there any difference of time lag in terms of vegetation type and climate regime?

Study sites

The study sites are selected to be within two climate regions, humid Texas coast and semi-arid New Mexico and Arizona: Adams Ranch (grass, New Mexico), Prairie View (grass, Texas) and Walnut Gulch (shrub, Arizona) (Table 1). The three sites are naturally and intensively vegetated land with almost flat topography and single type of vegetation and soil. Thus, the point and area sampling difference between ground measurements and satellite sensor (MODIS) is minimized.

Data source and quality

MODIS reflectivity and NDVI

The MODIS on board the Terra satellite was launched in December 1999. The atmospherically corrected surface reflectance product MOD09Q1 used in this study is a two-band product: band 1 centered at 648 nm and band 2 at 858 nm. This is a level 3, 8-day composite product with 250 m spatial resolution in sinusoidal projection. Eight-day periods begin on the first day of the year, continue consecutively and extend a few days (3 days for a regular year and 2 days for a leap year) into the next year. For a predefined 8-day period, fewer than 8 days (2–7 days) are used to calculate the 8-day product when fewer than eight daily files corresponding to the 8-day period are available for various reasons, such as MODIS shutdown or data loss on the satellite platform (Zhou et al., 2005). The MODIS data from February 2000 through April 2004 (tile h09v05 covering the New Mexico and Texas sites and h09v04 covering the Arizona site) were used for the study.

To derive the NDVI from the MOD09Q1 reflectance product, we developed an automated procedure similar to the one developed for MODIS snow cover retrieval (Zhou et al., 2005). The NDVI (or average NDVI) is calculated by using the Eq. (1) in three different scales of 1, 5, and 9 pixels. The SCAN station site is always in the center (near center) of the 1, 5, or 9 pixel patches.

$$\mathrm{NDVI} = \frac{R_{b2} - R_{b1}}{R_{b2} + R_{b1}} \tag{1}$$

where R_{bx} is the reflectivity of the 1-pixel patch or average reflectivity of the 5-pixel or 9-pixel patch; b_1 and b_2 are the MODIS band 1 and band 2, respectively. Our preliminary analysis indicates that there is little difference of R between soil moisture and NDVI from any of the three different sized pixel patches. So the influence of mismatch of image registration between one MODIS pixel and one SCAN site is negligible, and NDVI time series of one-pixel scale where the SCAN site located is used for the following analyses.

Soil moisture

Neutron probe measurements of volumetric soil water content (also referred to soil moisture hereafter) were hourly measured at the soil climate analysis network (SCAN) sites (ftp://ftp.wccr.nrcs.usda.gov/data/scan/). Soil moisture was measured at five depths of 5 cm, 10 cm, 20 cm, 50 cm, and 100 cm. Daily soil moisture is the average of hourly soil moisture. Sampling method, uncertainties and variability associated with SCAN data are documented at National Soil Survey Center (1995).

To study the correlation between NDVI and soil moisture, the daily time series of soil moisture data have to be processed to match the 8-day NDVI. Following the convention

Table 1 Information of study sites

Study sites	Location	Climate	Vegetation	Soil type (%)			General description
				Clay	Silt	Sand	
Adams Ranch (2015) New Mexico	34°15′8.00″N 105°25′10.00″W	Semi-arid	Grassland	13.8	15.6	70.6	pH 7.7 slope 2.0 drainage class: well
Walnut Gulch (2026) Arizona	31°44′0.60″N 110°3′0.00″W	Semi-arid	Shrub land	15.2	27.8	57.0	pH 8.4, slope 8.0 drainage class: well
Prairie View (2016) Texas	30°5′41.00″N 95°58′18.00″W	Humid	Grassland	22.1	24.8	53.1	pH 6.0 slope 1.0 drainage class moderately well

Source. National Soil Survey Center (2005). 2015, 2026 and 2016 are the universal SCAN ID. pH is the average of top 100 cm deep soil sample.

in creating MODIS 8-day reflectance and NDVI datasets, the 8-day average soil moisture is defined as the average value of the day and those of the succeeding 7 days. Therefore, the 8-day soil moisture corresponds to the MODIS 8-day NDVI product.

Data quality control and Q-test

Data preparation, cleaning, reduction, and quality control are extremely important steps in large data analysis. Analyzing data that has not been carefully screened for specific problems can produce highly misleading results, in particular in predictive data (Westphal and Blaxton, 1998). In this study, Dixon's *Q*-test was performed for the highest and lowest value in a moving window of three continuous data. It will screen any potential data outliers caused by random error (e.g. instrument faults) and environmental contaminations (e.g., clouds, rainfall, and aerosols for NDVI), etc. (Miller and Miller, 1993). Any outlier will be replaced by the average of two closest neighbor data (i.e. one from each side).

Methods

Seasonality and differencing series

Most time-series variables have a characteristic of serial dependencies or autocorrelation, which requires to be removed in order to identify underlying relationship between two variables by differencing the series (Kendall and Ord, 1990), although both raw and deseasonalized time series are simultaneously used in literatures (Wang et al., 2001, 2003; Cashion et al., 2005; Jackson et al., 2004; Li et al., 2005; Adegoke and Carleton, 2002). To determine the seasonal component of time series variables, there are many methods such as moving average, time-series average, kernel smoothing, etc. (Shumway and Stoffer, 2000). Seasonality calculation through time-series average is one of the methods that can reflect the true seasonal cycle of time series variables. Realizing time series average requires a long term data set, for this study, there is only a four-year dataset, so a simple moving average based on the time-series average of the four-year dataset is used to identify the seasonal components: 23-point moving average for the daily soil moisture and 3-point moving average for the 8-day NDVI. Deseasonalized time series is then produced by subtracting seasonal time series from raw time series.

Correlation analysis

The Pearson Product Moment Correlation (Korin, 1975; Balsley, 1978) is used for correlation analysis using deseasonalized time series of NDVI and soil moisture, while correlation analysis between raw time series of NDVI and soil moisture are used for comparison. Time lag is also considered in our analyses. For example, in a 5-day time lag, the NDVI of the 8th day (which is actually a composite from the 8th to the 15th day of the month) is compared with soil moisture of the 3th day, which is constructed from averaging daily soil moisture from the 3th to 10th day. In order to assess the statistical significance of *R* between soil moisture and NDVI, the null hypothesis is used to evaluate the significance of *R* (Balsley, 1978).

Bivariate linear regression model and validation

Regression analysis is a traditional exploratory data analysis technique. In this study, root-zone soil moisture is estimated by NDVI through bivariate least square regression model through Eqs. (2)–(5) (MathWorks, 2004).

$$Y = X\beta + \varepsilon \tag{2}$$

$$\beta = (X'X)^{-1}X'Y \tag{3}$$

$$\hat{Y} = X\beta \tag{4}$$

$$\mathrm{Est}M = \mathrm{Seas}M + \hat{Y} \tag{5}$$

where Y is an $n \times 1$ vector of observed raw (or deseasonalized) soil moisture from a particular soil depth, X is an $n \times 2$ matrix composed of 1 and raw (or deseasonalized) NDVI, β is a regression function vector calculated from X and Y, ε is the random error component, $\hat{Y}$ is an estimated (raw or deseasonalized) soil moisture ($n \times 1$ vector). For the deseasonalized time series, the estimated soil moisture is given in Eq. (5).

Similar to correlation analysis, both raw and deseasonalized time series of soil moisture and NDVI are used for regression analysis and validation. For simplicity, in the following discussion, we refer the method using raw time series data for regression analysis and validation as *raw method*, while using deseasonalized time series data as *delta method*. The raw method uses the raw time series to derive regression functions (β) in Eqs. (3) and (4), and then using this β and X (ie. NDVI) to directly estimate soil moisture in Eq. (4). The delta method consists of three steps: (1) use deseasonalized NDVI and deseasonalized soil moisture to derive β; (2) use this β and delta NDVI (i.e. raw time series minus seasonal time series) to calculate delta soil moisture; and (3) add the estimated delta soil moisture back to seasonal soil moisture to obtain estimated soil moisture via Eq. (5).

Three variables are used to validate the model: *R*, root of mean squared error (RMSE), and mean relative difference (κ) between estimated soil moisture and observed soil moisture. Large *R*, small RMSE, and small κ together can guarantee a best performance of estimation (Habib et al., 2001).

A set-aside method was used to construct a new subset, by taking every other data point aside from the complete raw/deseasonalized time series, for validation of the regression model established by using the remaining subset after the set-aside subset.

Results

Characteristics of the time series of soil moisture profiles

As an example, the 8-day soil moisture and NDVI during January 1, 2001 through December 31, 2001 and seasonal soil moisture and NDVI in the period of 2000–2004 at the three sites are shown in the left and right panels of Fig. 1, respectively. As expected, high frequency variations are seen in the time series of soil moisture at 5 cm, 10 cm, and 20 cm

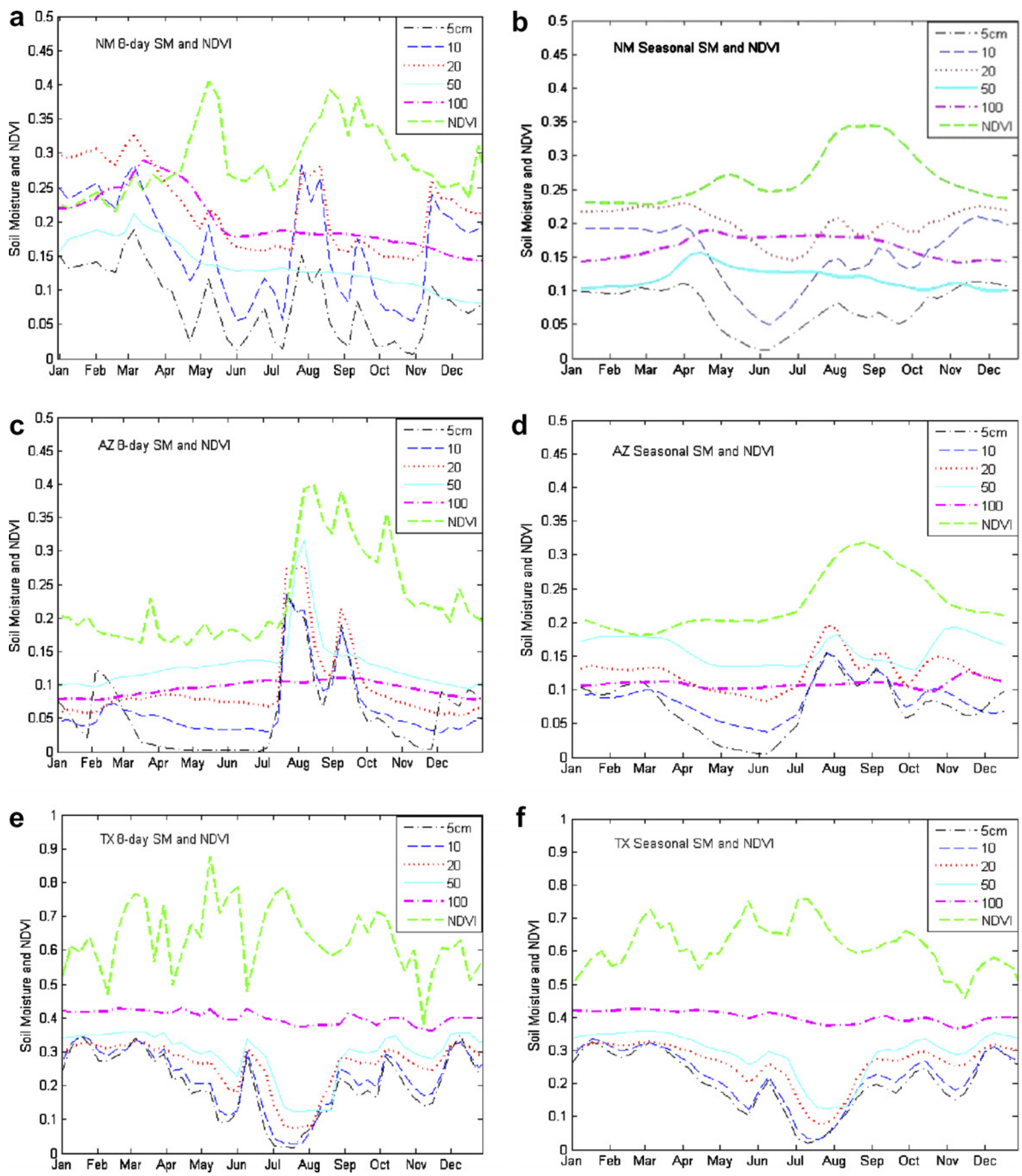

Figure 1 The time-series soil moisture and NDVI of 8-day (left panel) in 2001 and seasonal (right panel) in the period of 2000–2004 for three sites: Adams Ranch in NM (top panel), Walnut Gulch in AZ (middle panel) and Prairie View in TX (bottom panel). Soil moisture is volumetric ratio of liquid water to soil. Both soil moisture and NDVI have no unit. The marker label of *X*-axis is month, but actually it is Julian day and every 8 days.

depths in Adams Ranch (Fig. 1a), 5 cm, 10 cm, 20 cm, and 50 cm depths in Walnut Gulch (Fig. 1c) and Prairie View (Fig. 1e), and low frequency variation at the 50 cm and 100 cm depths in Adams Ranch and at 100 cm depth in Walnut Gulch and Prairie View. Overall, NDVI has similar variation in pattern with soil moisture, while time lag of NDVI to soil moisture is particularly seen at the humid TX site; For example, there is a large time lag of about 10–15 days from later May to early June, 2001. Time lag here refers to the time delay that NDVI responds to soil moisture.

Seasonal soil moisture at Adams Ranch (Fig. 1b) increases generally from 5 cm, 10 cm, to 20 cm depth, then dramatically decreases at 50 cm depth and finally increases again from 50 cm to 100 cm depth. The largest seasonal soil moistures are at the 20 cm depth except in June when the soil moistures of 100 cm are larger than those of 20 cm; the lowest values are at the 5 cm depth. There is a significant decrease of soil moisture at the top three depths from April through May, reaching a minimum by the early to end of June. The cause for this decrease is likely due to the continuous evapotranspiration and low rainfall. The soil moisture of these three depths increases dramatically from the end of June to early August due to the intense monsoonal rainfall in this area (Xie et al., 2006). From September to the end of November, the soil moisture increases gradually due to decreased evapotranspiration, although there are some fluctuations due to occasional monsoonal rain storms during this period. From December, the soil moisture decreases gradually and then increases a little bit from January to the end of March before dramatic decrease starting from April due to the stratiform rainfall in winter and dry weather in early spring (Xie et al., 2006). At the 50 cm and 100 cm depths, the soil moisture has little fluctuation through a year compared with the larger fluctuation in the root zone. This means that soil moisture at 50 and 100 cm depth at this site is less affected by rainstorm events or evapotranspiration, representing the long-term trend of rainfall and other climatic factors.

Seasonal soil moisture at Walnut Gulch (Fig. 1d) increases from 5 cm, 10 cm, 20 cm, to 50 cm depths, and decreases at 100 cm depth. Overall, the soil moisture at the Walnut Gulch site (shrub) is lower than that at the Adams Ranch site (grass), which may indicate the higher drought-resistivity of shrub than grass. We also notice that there are some exceptional large values at the 20 cm depth during July and September (larger than those at the 50 cm depth), which is likely caused by intense monsoonal rainfall storms. Similar to the New Mexico site, at the top 50 cm (5 cm, 10 cm, 20 cm, and 50 cm), soil moisture experiences a large decrease from early March to early June, then a rapidly increases from the end of June to end of July due to the monsoonal rainfalls. There are some significant fluctuations from August to November due to monsoonal convective thunderstorms and high evapotranspiration. At the 100 cm depth, the soil moisture is almost in a flat line, representing the long-term trend of rainfall and other climatic factors. Comparing the New Mexico and Arizona sites, we can see that they are very similar, though the Arizona site is drier and has deeper root zone system evidenced by the 50 cm seasonal soil moisture variation at the AZ site but not the NM site.

The Prairie View site in TX, however, is different from the Adam Ranch site in NM and the Walnut Gulch site in AZ. The time series of the seasonal soil moisture (Fig. 1f) increases from the 5 cm, 10 cm, 20 cm, 50 cm, to the 100 cm depth, while the soil moisture at the 100 cm depth is much higher than others. Overall, the seasonal soil moisture at any depth and NDVI at the Texas site are much higher than those of the corresponding depths and NDVI at the New Mexico and Arizonan sites. Similarly, temporal pattern of soil moisture at the top four depths (5 cm, 10 cm, 20 cm, and 50 cm depths) at this site is also different from the other two sites. The soil moisture has a decrease trend from early March to middle (end) of July, with an outstanding peak in early June, due to the first rainfall season. The increase of soil moisture from August to early October is due to the second rainfall season. There is a big drop of soil moisture in mid October, an increase again in the end of November, and then a slightly changes until early march. These differences are understandable since this site in Texas lies in the humid coastal area (Gulf of Mexico) with mean annual rainfall over 1000 mm, compared to 350 mm and 400 mm in Arizona and New Mexico sites, respectively. Similar to the Arizona site, the soil moisture of 100 cm depth is almost in a flat line, representing the long-term trend of rainfall and other climatic factors.

A trend of time lag on soil moisture change from 5 cm to 100 cm depth can be clearly seen from Fig. 1f of the Texas site. The similar trend is also visible from the semi-arid New Mexico and Arizona sites (Fig. 1b and d).

Cross correlation between soil moisture and NDVI

Correlation analysis was carried out between the deseasonalized time series of NDVI and soil moisture, and between the raw time series of NDVI and soil moisture. During the non-growing season, most vegetation is dormant, and NDVI derived from satellite image cannot reflect the underlying status of soil moisture. Thus, we focus on growing seasons. The starting and ending points of the growing season are site-dependent and are generally difficult to define. Given that the water availability in the root zone is one of the main controlling factors for vegetation status which can be represented in NDVI (Martyniak et al., 2007), we define the duration of growing season as the period during which the NDVI is best correlated with the soil moisture. For example, at the New Mexico and Arizona sites, it is found that deseasonalized NDVI and deseasonalized soil moisture have a stronger correlation during May through September than other periods, while at the Texas site, it is from May to October.

During the growing seasons of four years, there are about 76 samples ($(153 \text{ days} \times 4 \text{ year})/8 = 76$, one sample per 8-day) at Adams Ranch site in NM, 53 samples at Walnut Gulch site in AZ, and 92 samples in Prairie View site in TX. At a 95% confidence level ($P = 0.05$), large sample Z-value from the Table of Areas of the Normal Curve (Appendix VII in Balsley, 1978, p. 498) is 1.96σ. If Z-value is less than 1.96σ, the null hypothesis is true, then R is zero (Balsley, 1978). Using $Z = 1.96\sigma$, the R threshold to reject the null hypothesis is 0.23, 0.27, and 0.21 for Adams Ranch, Walnut Gulch, and Prairie View site, respectively. This means that, if R is less than 0.23 at New Mexico site, 0.27 at Arizona site, and 0.21 at Texas sites, Z-value will be less than $1.96\ \sigma$, suggesting no significant linear correlation between NDVI and soil moisture.

Fig. 2 shows the correlation at 5 depths for deseasonalized time series (left panel) and raw time series (right panel) versus time lag of NDVI to soil moisture, respectively. Fig. 2a is for the Adams Ranch site. From the analysis of null hypothesis, the correlation between soil moisture and NDVI is statistically significant at the 5 cm, 10 cm, and 20 cm depths (near surface and major root zone). At the 50 cm and 100 cm depths, however, the correlation is not statistically significant. The correlation is very similar (about 0.46–0.48) at 5 cm, 10 cm, and 20 cm depths when NDVI lags soil moisture 5 days. This suggests that grass can respond to the change of soil moisture almost immediately and can keep a fairly short memory of root-zone soil moisture in semi-arid regions. During the cold period (October–April), the correlation between NDVI and soil moisture (not shown) is much lower than that of the growing season, and the correlation is

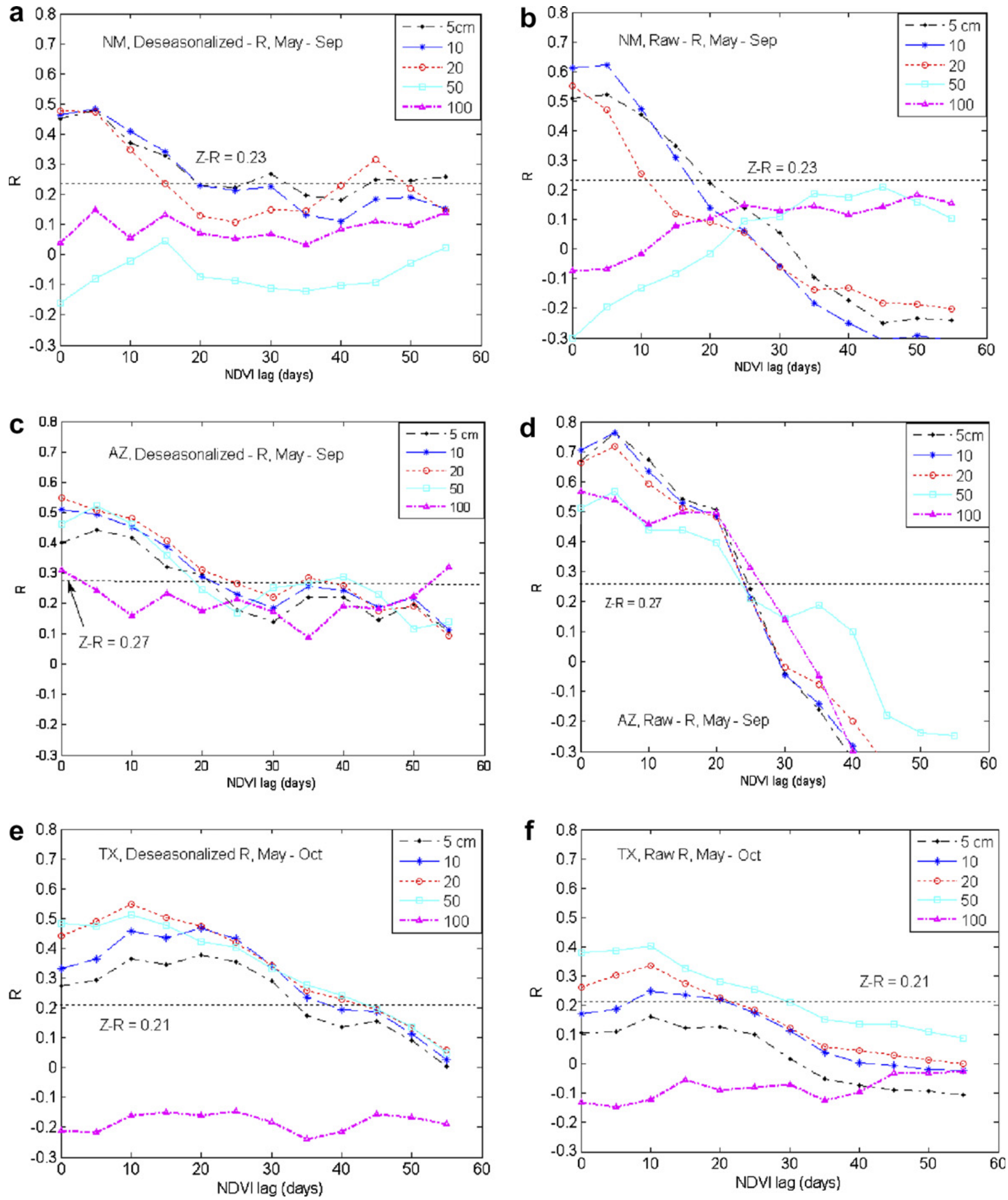

Figure 2 Correlation coefficient between soil moisture (at five depths) and NDVI versus time lag of NDVI during growing season for deseasonalized time series (left panel) and raw time series (right panel). *Z*—*R* is a threshold of *R* that can reject the null hypothesis.

not statistically significant. The correlation of raw time series display similar patterns (Fig. 2b) as the deseasonalized series, but with larger *R* values.

Fig. 2c is for the Walnut Gulch site. All *R* values at the 5 depths reject the null hypothesis, indicating statistically significant correlation between NDVI and soil moisture, although the *R* value at the 100 cm depth (below-root zone) is much smaller than those at the root zone system. Their *R* values at the 5 cm and 50 cm depths gently increase and reach maxima when NDVI lags soil moisture for 5 days, then decreases when NDVI lags soil moisture for more than 5 days. At the 10 cm and 20 cm depths, the *R* gently decreases when NDVI lags soil moisture. This result may suggest that at this semi-arid shrub site, remotely sensed NDVI for shrub almost immediately responds to soil moisture of 10 cm and 20 cm depths, while to 5 cm and 50 cm depths, there is about 5 days delay to reach the maximum *R*. During the cold period (October—April), the *R* between NDVI and soil moisture is much lower (not shown) than those during the growing season and is not statistically significant. The *R* of raw time series displays similar patterns (Fig. 2d) as the deseasonalized series, but with larger *R* values.

Fig. 2e is for the Prairie View site in TX. The R values at the 5 cm, 10 cm, 20 cm, and 50 cm depths reject the null hypothesis, suggesting statistically significant correlation between soil moisture and NDVI at those depths. Their R values increase gently and reach maxima when NDVI lags soil moisture for up to 10 days and then decrease with longer time lag. This suggests that grass in humid region responds to the change of soil water content for about 10 days delay and that it can keep a fairly ''longer'' memory of root zone soil water content than grass in semi-arid region where NDVI responds to the change of soil moisture much faster. The R at the 100 cm depth is not statistically significant and suggests that soil moisture at this depth and NDVI are decoupled. During the period other than the growing season, i.e., November to April, their R values at the 5 cm, 10 cm, 20 cm, and 50 cm depths are lower than that during the ''growing season'' but still statistically significant (not shown). This may suggest that the NDVIs response to soil moisture in Texas site may extend well beyond this identified growing season (May—October). The most difference from the two semi-arid sites is that, in the Texas humid site, the R of raw time series (Fig. 2f) is smaller than the R of deseasonalized time series (Fig. 2e). In the raw time series, only the R at 20 cm and 50 cm depths are statistically significant.

Soil moisture estimation and model validation

Correlation analysis above shows that the correlation between root-zone soil moisture and NDVI is significant, particularly at 10 cm and 20 cm depths in the New Mexico site, 10 cm, 20 cm, and 50 cm at both the Arizona and Texas sites. Both raw and delta methods are tested for regression analysis and validation. Figs. 3—5 display the estimated soil moisture versus the observed soil moisture at 10 cm, 20 cm, and 50 cm depths for the three sites.

Fig. 3 is for the Adams Ranch site in NM for year 2000—2003. The estimated soil moisture in 2000—2003 using both methods matches the observed soil moisture with R of 0.57—0.71, RMSE of 0.04—0.06 and κ of 16—60%. The delta method results in higher R and lower κ than the raw method.

Fig. 4 is for the Walnut Gulch site in AZ during May to September in 2000—2003. The estimated soil moistures in

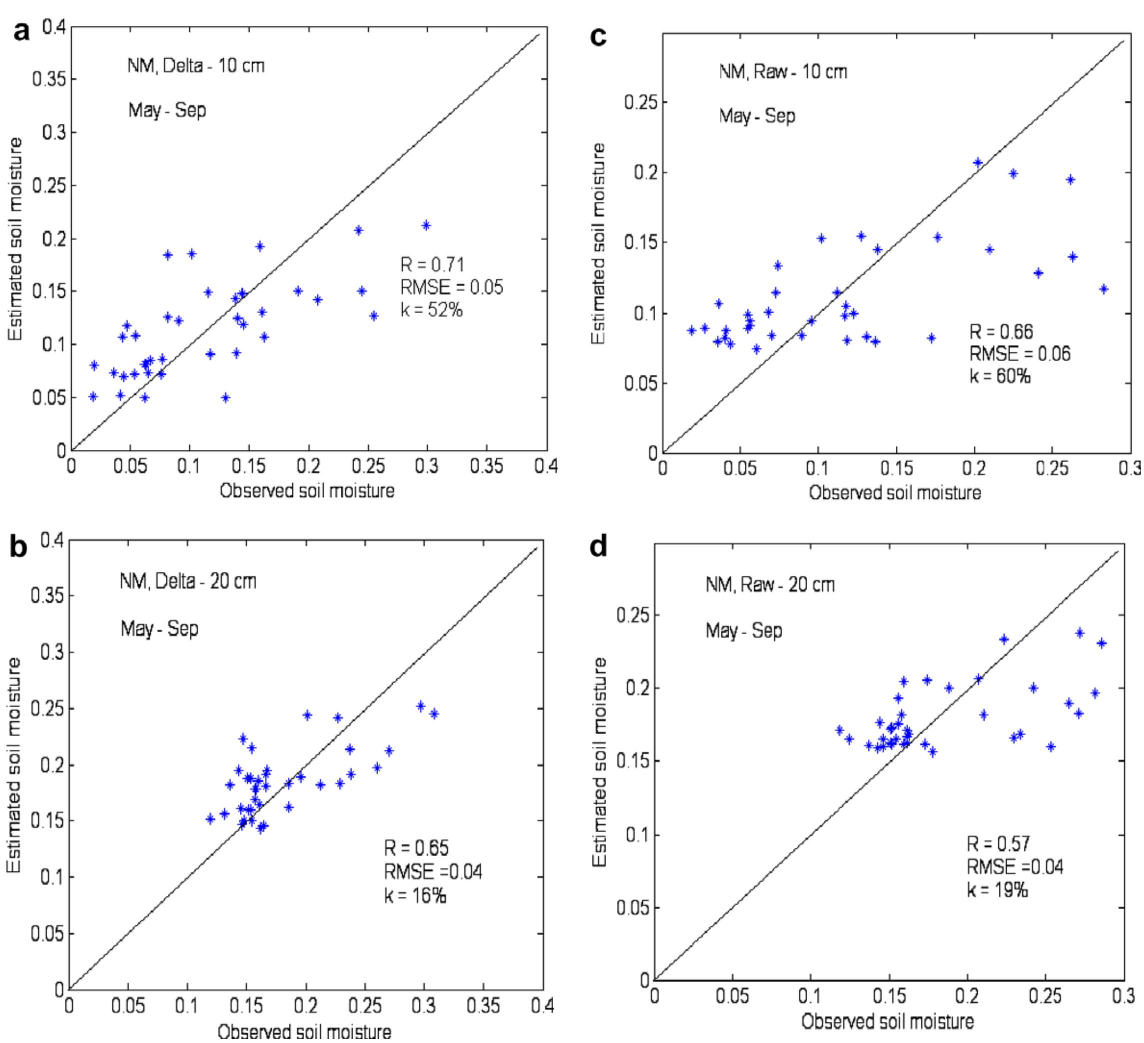

Figure 3 Estimated versus observed soil moisture at the 10 cm and 20 cm depths during May to September of 2000—2003 at the Adams Ranch site (NM) using delta method (left panel) and raw method (right panel).

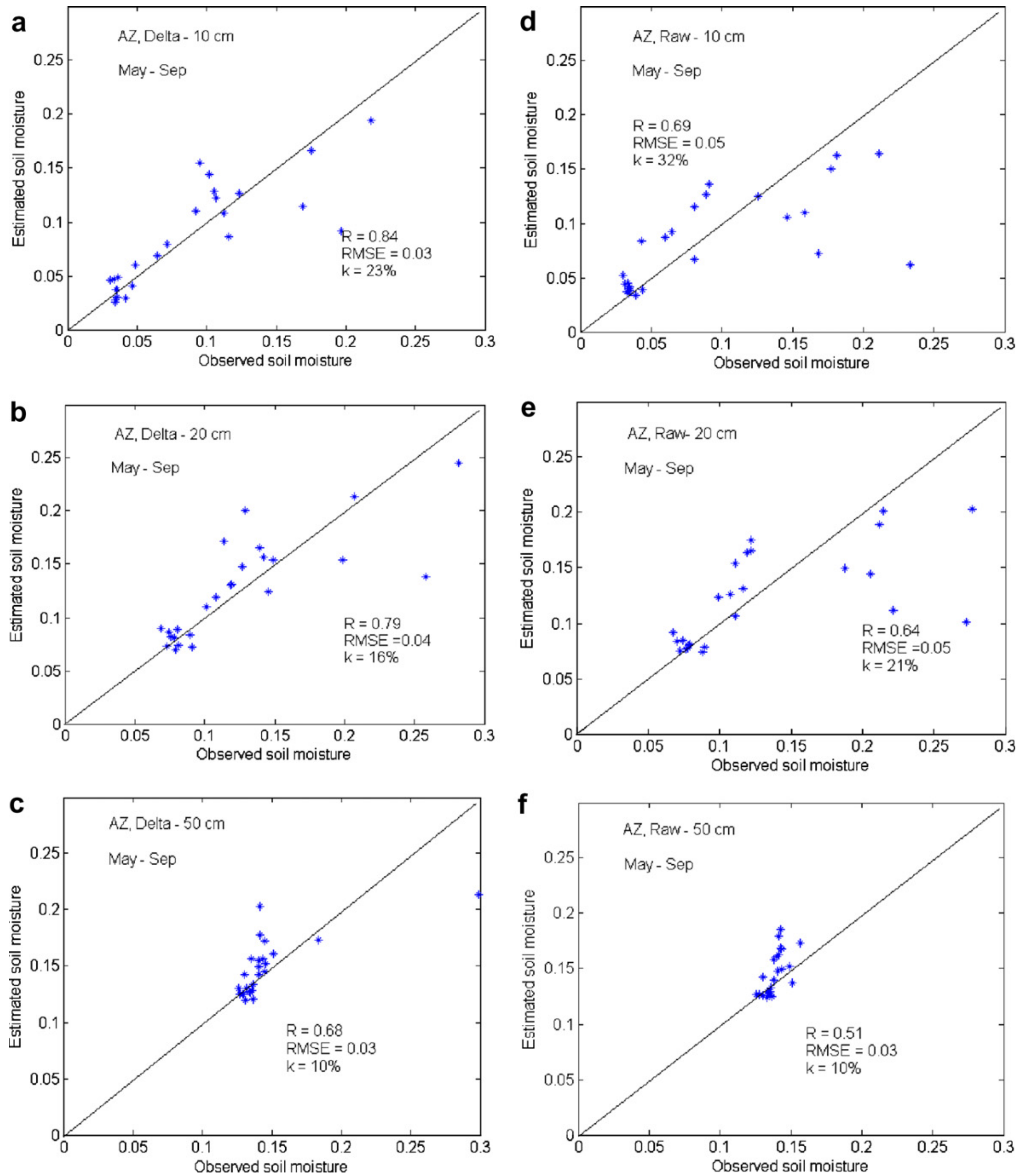

Figure 4 Estimated versus observed soil moisture at the 10 cm, 20 cm and 50 cm depths during May to September of 2000–2003 at the Walnut Gulch site (AZ) using delta method (left panel) and raw method (right panel).

2000–2003 using both methods match the observed soil moisture with R of 0.51–0.84, RMSE of 0.03–0.05, and κ of 10–32%. Similar to the results at the Adams Ranch site, the delta method produces higher R and lower k, indicating better performance than the raw method.

Fig. 5 is for the Prairie View site in TX during May to October in 2000–2003. The estimated soil moisture in 2000–2003 using the delta method matches the observed soil moisture with R of 0.68–0.74, RMSE of 0.05, and κ of 22–62%. However, the estimated soil moisture using the raw method does not match the observed soil moisture at all.

Discussion

Raw and deseasonalized time series

Both raw time series and deseasonalized time series have been frequently and simultaneously used in scientific research and data analyses since both can give good results in many cases. However, theoretically, raw time series contain seasonality or series correlation, which distorts the underlying correlation between variables, resulting in over- or under-estimates (Kendall and Ord, 1990). Therefore, cor-

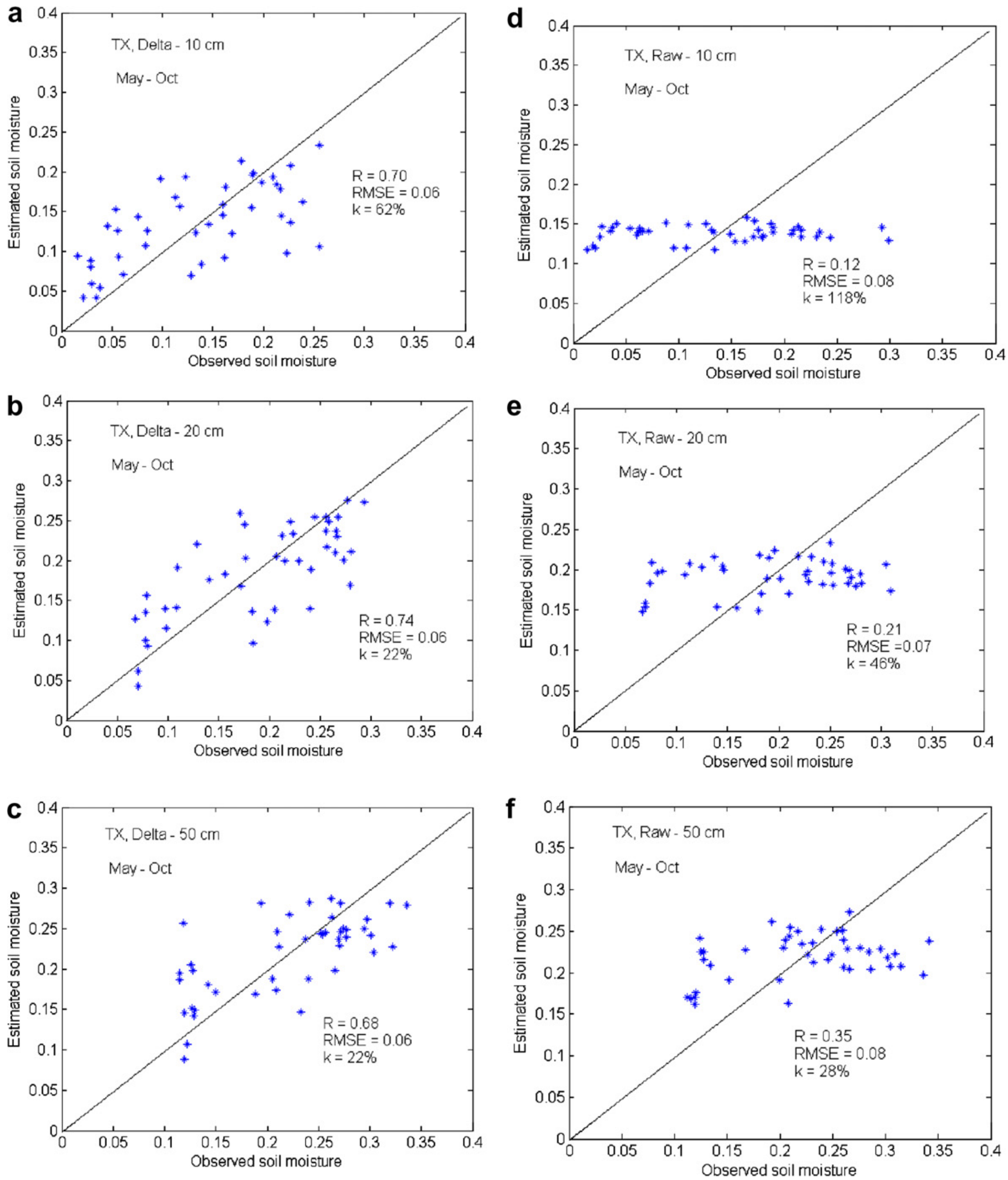

Figure 5 Estimated versus observed soil moisture at the 10 cm, 20 cm, and 50 cm depths during May to October of 2000—2003 at the Prairie View site (TX) using delta method (left panel) and raw method (right panel).

relation between deseasonalized time series is a physical based method and should always give consistent results. Our study supports this statement. All *R* values between deseasonalized root-zone soil moisture and NDVI are always significant and have similar maximum value (0.49—0.55) in semi-arid and humid conditions; in contrast, *R* values between raw root-zone soil moisture and NDVI are much higher in semi-arid conditions ($R_{max} = 0.78$) than in humid condition ($R_{max} = 0.40$). At the semi-arid Adams Ranch and Walnut Gulch sites, the *R* between the raw time series of soil moisture and NDVI is higher than those of deseasonalized time series (overestimate), while at the humid Prairie View site in Texas, the *R* between the raw time series of soil moisture and NDVI is lower than those of deseasonalized time series (underestimate). In the semi-arid environment, soil moisture is the major controlling factor for vegetation growth, and NDVI changes closely with soil moisture. NDVI and soil moisture have a similar seasonal pattern especially for the warm season. When this seasonal pattern is removed, the *R* between NDVI and root-zone soil moisture becomes smaller. At the humid site, however, the seasonal soil moisture is much higher than those in semi-arid regions;

soil water availability is not a major controlling factor for the vegetation growth; and NDVI and soil moisture have different seasonal pattern, thus the *R* between NDVI and soil moisture increases after the deseasonalization. Li et al. (2005) showed that the correlation between NDVI and soil moisture is higher after the seasonal cycle is removed, while Cashion et al. (2005) used the raw time series and concluded that there is little or no relationship between raw NDVI and soil moisture. Our results indicate that deseasonalized time series reveals consistent correlation between variables, while the raw time series either over- or under-estimates the underlying relation.

The *R* value (0.46–0.55) between deseasonalized time series of root-zone soil moisture and MODIS-derived NDVI at the three sites are higher than that (0.3–0.42) obtained by Adegoke and Carleton's (2002) using data from Illinois Climate Network and AVHRR-derived NDVI. Many factors may cause the difference such as higher spectral, radiometric and spatial resolution of MODIS instrument than those of AVHRR, different vegetation species and soil properties, etc. Results from this study also show that the response of NDVI to root-zone soil moisture change is almost independent of vegetation types (grass or shrub) and climate conditions (semi-arid or humid), though time lag is dependent on vegetation species and climate regimes.

As far as we know, this is the first study on the response of NDVI (or vegetation) to soil moisture at various soil depths from the top surface to well below the root zone for different vegetation types and at various climate regimes. Results show that NDVI has significant correlation with root-zone soil moisture at different depths for shrub and grass vegetation at humid and semi-arid conditions. The rooting depth of vegetation could be inferred from the significant *R* of soil moisture at different depths with NDVI. For example, our results indicate that shrub has deeper rooting depth than grass at the similar climatic condition, which matches with the actual situation (National Soil Survey Center, 2005). Our results also indicate that it needs more time delay for the NDVI to respond to the soil moisture change in humid regions (10 days) than in semi-arid regions (5 days or less). The drier the soil is, the shorter the lag time. These results are consistent with the study of Wang et al. (2003) in the central Great Plains.

Estimation of the root-zone soil moisture: raw and delta methods

Since we have identified the relationships between NDVI and root-zone soil moisture for grass and shrub in semi-arid and humid regions, we use these relationships to estimate the root-zone soil moisture using NDVI retrieved from MODIS reflectance product. From Figs. 3–5 and results in ''Soil moisture estimation and model validation'', we can see that the delta method (using deseasonalized time series) can be used to estimate the root-zone soil moisture in semi-arid and humid regions. Correlation analyses between estimated and observed soil moisture show that the soil moisture of shrub (Arizona) is better predicted than that of grass (New Mexico and Texas) using the relationships identified. It is also found that there is no significant difference on the prediction of soil moisture estimation for grasslands between semi-arid region (New Mexico site) and humid region (Texas site). However, it is found that the raw method cannot be used to estimate the root-zone soil moisture due to its inconsistency (an explanation offered in ''Raw and deseasonalized time series'').

Overall, the results suggest that regression models derived from delta method can be potentially used to produce a spatially distributed time series root zone soil moisture map (reflecting about 42–74% soil moisture variations), based on *in situ* soil moisture measurements and MODIS-derived NDVI time series for grassland in both semi-arid and humid regions and shrub land in semi-arid regions. In other words, the spatially dense remotely sensed NDVI is a good interpolator to interpolate the isolated temporally dense ground soil moisture to produce spatially dense soil moisture, similar with the method of normalized difference temperature index (NDTI) (McVicar and Jupp, 2002). This, however, may not be an easy task as the exact relationship depends also on vegetation species and climate regimes; a thorough validation study cross ''multiple vegetation gradients, spatio-temporal scales, and hydro-climatic regions'' must be done in order to verify this approach for its wide applications.

Summary and conclusions

This study examined the characteristics of soil moisture at the three selected SCAN sites in New Mexico, Arizona, and Texas from February 2000 to April 2004. The seasonal soil moisture at the semi-arid New Mexico and Arizona sites are much lower than at the humid Texas site. The major root-zone soil depth of shrub at Walnut Gulch is less than 100 cm (mainly between 20 cm and 50 cm), while the major root-zone soil depth of grass is between 5 cm and 20 cm at the semi-arid Adams Ranch site and 10–50 cm at the humid Prairie View site. Vertically, root-zone soil moistures increase with the increasing soil depth and are frequently affected by weather conditions (rainfall events, pressure, temperature, wind speed, etc.).

The cross correlation between time series (both raw and deseasonalized) soil moisture at various depths and remotely sensed NDVI were examined. Our results indicate that deseasonalized time series of soil moisture and NDVI show statistically significant correlations (*R*: 0.46–0.55) during growing season at all the three sites, while raw time series of soil moisture and NDVI distorts underlying biophysical relation between them, overestimating in semi-arid regions and underestimating in humid region. There is little difference of correlation in using deseasonalized time series for different vegetations (shrub and grass) in semi-arid regions and for different conditions (semi-arid and humid region) for grass vegetation. Through the significant correlation between deseasonalized time series of NDVI and soil moisture, it is possible for us to indirectly estimate the root zone depth for particular vegetation and climate conditions. Our results also indicate that a longer time lag is needed to allow the NDVI's response to the soil moisture change in humid regions (10 days) than in semi-arid regions (5 days or less).

Our results suggest that the delta method (using deseasonalized time series) can be applied to estimate the root-zone soil moisture (42–74% soil moisture variations) based on NDVI for grassland in both semi-arid and humid regions, and for shrub land in semi-arid region. As we discussed, mapping root-zone soil moisture is challenging because the relationship between NDVI and root-zone soil moisture is dependent on the vegetation species and climate zones. However, since the NDVI is significantly correlated with soil moisture at the whole root zone, NDVI derived from space-borne optical sensors may provide a good proxy for root-zone soil moisture mapping at large scale. To accomplish this task, further studies are needed to examine the correlation for other vegetation types and climate regimes as well as using longer time series when longer temporal MODIS data and *in situ* soil moisture measurements will be available.

Acknowledgements

Authors thank MODIS/Terra Science Teams and Natural Resources Conservation Service's Soil Climate Analysis Network (SCAN) for making the data free available. The first author thanks the UTSA's Environmental Science and Engineering PhD scholarship for financial support. This study was partly supported by the US Department of Education grant (P120A050061) to the second author. The authors would like to thank the three anonymous reviewers for their very helpful comments, suggestions, and corrections that substantially improved this paper.

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