ESTIMATION OF ROOT-ZONE SOIL MOISTURE USING MODIS-DERIVED NDVI IN SEMIARID AND HUMID CONDITIONS

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ABSTRACT

In semiarid or arid conditions, the change of root-zone soil moisture can be almost instantaneously reflected by vegetation through biophysical process. This study investigated feasibility of mapping root-zone soil moisture using MODIS-derived NDVI via statistic approach at three sites (New Mexico, Arizona, and Texas) selected from the Soil Climate Analysis Network (SCAN). These 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 time series of soil moistures at 5 depths (5, 10, 20, 50, and 100 cm) and NDVI (8-day composite in 250 m resolution) during February 2000 through December 2004 were used. Results show that (1) During the growing season, root-zone soil moisture can be effectively estimated by a bivariate linear regression model using deseasonalized NDVI; (2) In semi-arid region, root-zone soil moisture can be better estimated using NDVI in shrub-vegetated area than in grass-vegetated area; (3) The performance of the estimation of soil moisture using NDVI in grass vegetation at the semiarid site in NM and at the humid site in TX does not display observable difference.

INTRODUCTION

Soil moisture, defined as the ratio of liquid water content to the soil in percentage of volume or weight, is a heritage and memory of previous precipitations. In vegetated regions, root-zone soil moisture is a link between surface phenology and subsurface water storages; it strongly influences surface water balance and energy partitioning due to evapotranspiration (Song, et al., 2000). Soil moisture also controls surface vegetation health conditions and coverage, especially in arid and semi-arid areas where water is a controlling factor for vegetation growth (Magagi & Kerr, 2001). As it is a critical boundary condition in the interaction between land surface and atmosphere, accurate mapping of soil moisture at large scale with reasonable resolution is thus imperative for climatic and hydrologic modeling and prediction (Western et al., 2002).

Various approaches have been developed to estimate soil moisture: from point-based gravimetric sampling (Wilson et al., 2003), time-domain reflectometry (TDR) (Topp et al., 1980; Roth et al., 1990), to space-borne remote sensing techniques such as passive microwave radiometry (Engman & Chauhan, 1995), and imaging radar (Dubois et al., 1995). Gravimetric sampling is a direct and accurate method of determining soil moisture; however, it is time and labor consuming to undertake. Other ground-based methods, such as time-domain reflectometry (TDR) and neutron probe etc., are indirect and soil property-depended, which must be calibrated against gravimetric samples. Among them, TDR is considerately reliable and portable methods for determining soil moisture content without destructing soil moisture (Roth et al., 1990). However, all these ground-based methods are point measurements and labor-intensity, and only relatively limited number of samples can be made within a limited scale (Western & Grayson, 1998). They are impractical for soil moisture estimation at a basin or watershed scale (Wilson et al., 2003). For these typical field methods, 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, extrapolation of these measurements to spatial distributed soil moisture is often problematic.

Remote sensing methods have offered great perspectives for spatial and instantaneous measurement of soil moisture content in recent three decades (Wang & Schmugge, 1980; Jackson & Schmugge, 1989; Cashion et al., 2005). Imaging radar has the potential to map surface soil moisture at high resolution over large areas (Dubois et al., 1995). The measurements of soil moisture using synthetic aperture radar (SAR) depend on the interpreting of backscatter signal to obtain the component due to variations in soil dielectric constant (Wilson, et al., 2003). Various studies indicate that the accuracy of active microwave surface soil moisture estimate depends on bare soil types, and that vegetation type, fractional vegetation cover and land surface roughness also negatively impact the accuracy of soil moisture estimates (Cashion et al., 2005). Recently, passive microwave radiometer (PMR) has been widely and actively used for mapping large-area surface soil moisture (Jackson et al., 1995; Njoku & Li, 1999; Chen et al., 1997).

Soil moisture derived from microwave remote sensing data is generally just for the top several centimeters because active scattering or emission layer of microwave signals is limited in depth. However, the hydrological and agricultural interests are often in root-zone soil moisture, which is usually deeper than the top several centimeters, depending on vegetation types. Growth and productivity of vegetation is primarily determined by water availability in the root zone. On the other hand, health conditions, productivity, and coverage of vegetation are often characterized by using vegetation indices, which can be derived from multi-spectral optical remote sensing data (0.3 μm - 2.5 μm). Thus, it is believed that vegetation indices derived from remote sensing optical data may respond to the change of soil moisture to a certain degree (Sandholt et al., 2002). Utilizing multi-spectral imagery such as the Advanced Very High Resolution Radiometer (AVHRR), Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+), and Moderate Resolution Imaging Spectroradiometer (MODIS), etc., the normalized difference of vegetation index (NDVI) based on the vegetation sensitivity in near-infrared and red spectral bands can be derived. The study of Farrar et al. (1994) showed that NDVI was controlled by soil moisture of the concurrent month. NDVI derived from 8km NOAA/AVHRR data had different sensitivity to soil moisture change at 10~20 cm depth in different sub regions (Zhang et al, 2005). The relationship between NDVI and root-zone soil moisture was linear and a function of crop type (Narasimha et al, 1993). The study of Adegoke & Carleton (2002) showed that the maximum Pearson correlation coefficient (CC) between deseasonalized root-zone soil moisture (average of the top 30 cm and top 100 cm depth) and deseasonalized NDVI could ranged 0.3~0.42 during April to September (growing season). Sandholt et al. (2002) examined the relation between temperature-vegetation dryness index (TVDI), based on remotely sensed surface temperature and NDVI, and surface soil moisture simulated using an hydrological model, and pointed out that the TVDI was closely related to surface soil moisture. The study of Feng et al (2004) showed that it was practical to monitoring the farmland soil humidity in every ten days by long time-series NOAA/AVHRR-derived NDVI in China. Combining the measurements of Synthetic Aperture Radar (SAR-ESR2) and TM images, Wang et al (2004) developed a regression model among soil moisture, NDVI and $Ds_{wet\text{-}dry}$ via an optical/microwave synergistic model after reducing the surface roughness effect by using the temporal differential backscatter coefficient ($Ds_{wet\text{-}dry}$); then they used the built regression model to estimate soil moisture using TM-derived NDVI and ESR2-derived $Ds_{wet\text{-}dry.}$ They found that their results are valid for sparse and moderate vegetated area in semiarid region.

This is the second paper of a two-paper series. In the first paper (Wang et al, 2005), we examined the response of NDVI to soil moisture change at various root depths using the same dataset. It showed that deseasonalized soil moisture and MODIS-derived NDVI had moderate linear correlation (CC = ~0.5). In this second paper, we focus on mapping root-zone soil moisture using NDVI in different environments. Compared to NOAA/AVHRR, MODIS-NDVI has higher spatial and temporal resolution, which would provide better representation of vegetation status. The three sites in this study (New Mexico, Arizona, and Texas) were selected from the Soil Climate Analysis Network (SCAN) and represent different naturally vegetated surfaces in two climate conditions (semi-arid and humid). Collocated time series of soil moistures at 5 depths (5, 10, 20, 50, and 100 cm) and NDVI derived from 8-day 250 m × 250 m MODIS reflectivity products at three sites were used to develop a bivariate linear regression model. Two types of observed soil moisture were used to validate the soil moisture estimated via the bivariate regression model. Our results suggested that remotely-sensed NDVI can be used to estimate spatially distributed root-zone soil moisture in the grassland in sub-tropic region and both grassland and shrubland in semi-arid region as is demonstrated in our study.

STUDY SITES

The study sites are selected to be within two different climate regions, humid Texas coast and semi-arid New Mexico and Arizona: Adams Ranch (grass, New Mexico), Walnut Gulch (shrub, Arizona), and Prairie View (grass, Texas).

Adams Ranch site (SCAN site ID: 2015) lies in Lincoln County of New Mexico and belongs to semi-arid climate (mean annual rainfall about 400 mm). This site is located at an elevation of 1879 m, with a southeast-facing slope of 2.0 degree. The top 100 cm soil is dark brown (7.5YR 3/4) sandy clay loam, dry, moderately alkaline (pH = 8.0), and composed of 13.8% clay, 15.6% silt, and 70.6% sand. This site is characterized as homogeneous grassland. The major root zone is less than 60 cm depth (National Soil Survey Center, 2005).

Walnut Gulch (2026) site lies in Walnut Gulch Watershed, Lucky Hills in Cochise County of Arizona (mean annual rainfall about 350 mm). This site locates at an elevation of 1372 m, with fan-terrace physiography and 8.0 degree slope. The top 100 cm soil is yellowish red (5YR 4/6) loam, dry, moderately alkaline (pH = 8.4), and composed of 15.2% clay, 27.8% silt and 57.0% sand. This site is characterized as homogeneous shrub land. The major root zone is less than 81 cm depth (National Soil Survey Center, 2005).

Prairie View (2016) site lies in Waller County of Texas, in the southeast of Gulf Coast Prairies, and belongs to sub-tropic climate (annual rainfall about 1000 mm). This site locates at an elevation of 82 m, with southwest facing slope of 1 degree. The top 100 cm soil is brown (10YR 4/3) fine sandy loam with a parent material of loamy marine sediments and composed of 22.1% clay, 24.8% silt and 53.1% sand. The water table is about 2 m. This site is characterized as grassland. The major root zone is less than 64 cm depth (National Soil Survey Center, 2005).

DATA

Soil Moisture

Neutron probe measurements of volumetric soil water content (also referred to soil moisture hereafter) were made hourly at the SCAN sites (ftp://ftp.wcc.nrcs.usda.gov/data/scan/). Soil moisture was measured at 5 depths of 5 cm, 10 cm, 20 cm, 50 cm, and 100 cm.

MODIS Reflectivity

The product MOD09Q1 used in this study is a level 3, 8-day composite, and 250 m spatial resolution product in sinusoidal projection. It is temporally composed of MODIS level-2G products to provide an estimate of the surface spectral reflectance of band 1 (red) and band 2 (near infrared) as it would be measured at ground level in the maximum absence of atmospheric scattering or absorption and cloud contamination. 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). In this study, MODIS tile h09v05 covers the New Mexico and Texas sites, and tile h09v04 covers the Arizona site. The data from February 2000 through December 2004 were ordered through the EOS data gateway.

METHODS

Derivation of NDVI from MODIS Reflectivity Product

To derive the NDVI, 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 equation (1) in one pixel, where the SCAN station site locates.

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

where R is the reflectivity of the 1-pixel patch; b_1 and b_2 are the MODIS band 1 and band 2, respectively.

Seasonality and Differencing Series

Most time-series variables have a characteristic of serial dependencies or autocorrelation, which needs to be removed in order to identify the real correlation between two variables by differencing the series (Kendall & Ord, 1990). There are many methods, such as moving average, time-series average, kernel smoothing, etc., to determine the seasonal components of time series variable (Shumway & Stoffer, 2000). This study combines the time-series average and simple moving average to identify the seasonality of soil moisture and NDVI. Here we use 23-point simple moving average for the daily soil moisture and 3-point simple moving average for the 8-day mean NDVI. Deseasonalized time series or stationary time series was produced by subtracting the raw time series with seasonal time series.

Bivariate Regression Model and Validation

Regression analysis is a traditional exploratory data analysis (EDA) technique and the final step of data mining to some degree, which is oriented towards number applications other than the basic nature of the underlying phenomena, just like a "black box" (Westphal, 1998). Our preliminary analysis shows that NDVI can respond to the change of soil water content and has a considerable correlation with root-zone soil moisture; therefore, root-zone soil moisture will be estimated through bivariate least square regression model through equations (2)-(4) (Chatterjee et al., 1986; MathWorks, Inc., 1997).

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

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

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

where Y is an n×1 vector of observed soil moisture, X is an n×2 matrix composed of 1 and NDVI, β is a p×1 regression function vector calculated from X and Y, ε is the random error component, $\hat{Y}$ is an estimated n×1 vector.

Both raw and deseasonalized time series of soil moisture and NDVI were used for regression analysis. Here we refer the raw time series data for regression analysis as raw method, and the deseasonalized time series data for regression analysis as delta method. The raw method uses the raw time-series NDVI and raw time-series soil moisture to develop regression model/functions (β) in equations (3) and (4), and then using the developed regression model (β) and new NDVI to directly calculate soil moisture in equation (4). The delta method consists of three steps: (1) use deseasonalized NDVI and deseasonalized soil moisture to develop regression model/ function (β); (2) use the developed regression model/function (β) and new delta NDVI to calculate delta soil moisture; and (3) add the estimated delta soil moisture back to the soil moisture seasonality to obtain soil moisture.

Three parameters are used to validate the estimated soil moisture from NDVI based on raw or delta method. They are correlation coefficient (CC), root of mean squared error (RMSE) and mean relative difference (κ) between estimated soil moisture and observed soil moisture. Large CC, small RMSE, and small κ together can guarantee a best performance of estimation (Habib et al., 2001).

In the course of validation, time series of soil moisture and NDVI were constructed into two datasets in both raw and deseasonalized time series for regression analysis (raw method and delta method). Then the CC, RMSE, and κ were calculated based on estimated soil moisture and observed soil moisture. The first set of data was a subset of data constructed from the complete raw or deseasonalized time series of soil moisture and NDVI using a so-called set-aside method that every other data point are dropped. The retained sub dataset were used to establish the regression model, and the dropped sub dataset were used to validate the model. The second dataset was the time series of soil moisture and NDVI in 2004. This dataset was used to validate the predicted soil moisture of 2004 using the model established based on data of previous years (2000-2003).

RESULTS

The vertical profile characteristics of soil moisture distribution and the correlation between soil moisture of different depths and MODIS-derived NDVI were described in our first paper (Wang et al, 2005). This paper mainly focused on the estimation of root-zone soil moisture using NDVI.

Our preliminary analysis shows that the estimated soil moisture of root zone, particularly at 10 cm and 20 cm depth, is significant, and that the estimated soil moisture at top surface (5 cm) or below root zone (100 cm) is not ideal. Figures 1, 2 and 3 display the estimated soil moisture versus the observed soil moisture at 10 cm and 20 cm depth for three sites using both delta method and raw method.

Figure 1 is for the Adams Ranch site in NM. Cases A and B use delta method and cases C and D use raw method. A, B, C, and D were during May to September in 2000-2003 using the first type of dataset; E and F use delta method during May to September in 2004 using the second type of dataset. Overall, the estimated soil moisture (10 cm & 20 cm depth) in 2000-2003 using both methods matches the observed soil moisture with CC of 0.56~0.71, mean absolute difference (RMSE) of 0.04~0.06 and mean relative difference (κ) of 16%~60%. The delta method, which has higher CC and smaller κ and RMSE, displays better performance than the raw method. The predicted soil moisture for year 2004 (see cases E and F) using delta method does not match the observed soil moisture with CC of 0.50~0.54, RMSE of 0.08~0.12 and κ of 56%~135%, as well as the estimated soil moisture in 2000-2003 (see cases A and B). The predicted soil moisture at 10 and 20 cm depths in 2004 is smaller than the observed soil moisture, particularly at 20 cm depth. The predicted soil moisture using raw method in 2004 has worse performance than the delta method (not shown).

Figure 2 is for the Walnut Gulch site in AZ during May to September in 2000-2003. Cases A and B use delta method, and cases C and D use raw method. Overall, the estimated soil moisture (10 cm & 20 cm depth) in 2000-2003 using both methods matches the observed soil moisture with CC of 0.64~0.84, RMSE of 0.03~0.05 and κ of 16%~32%. Similarly as at Adams Ranch site, the delta method, which has higher CC, smaller k and RMSE, shows better performance than raw method. The estimated soil moisture, which has higher CC and smaller κ and RMSE, is better than that at Adams Ranch site. Because of the bad quality of soil moisture in 2004, the predicted soil moisture in 2004 can not be validated and has not been shown here.

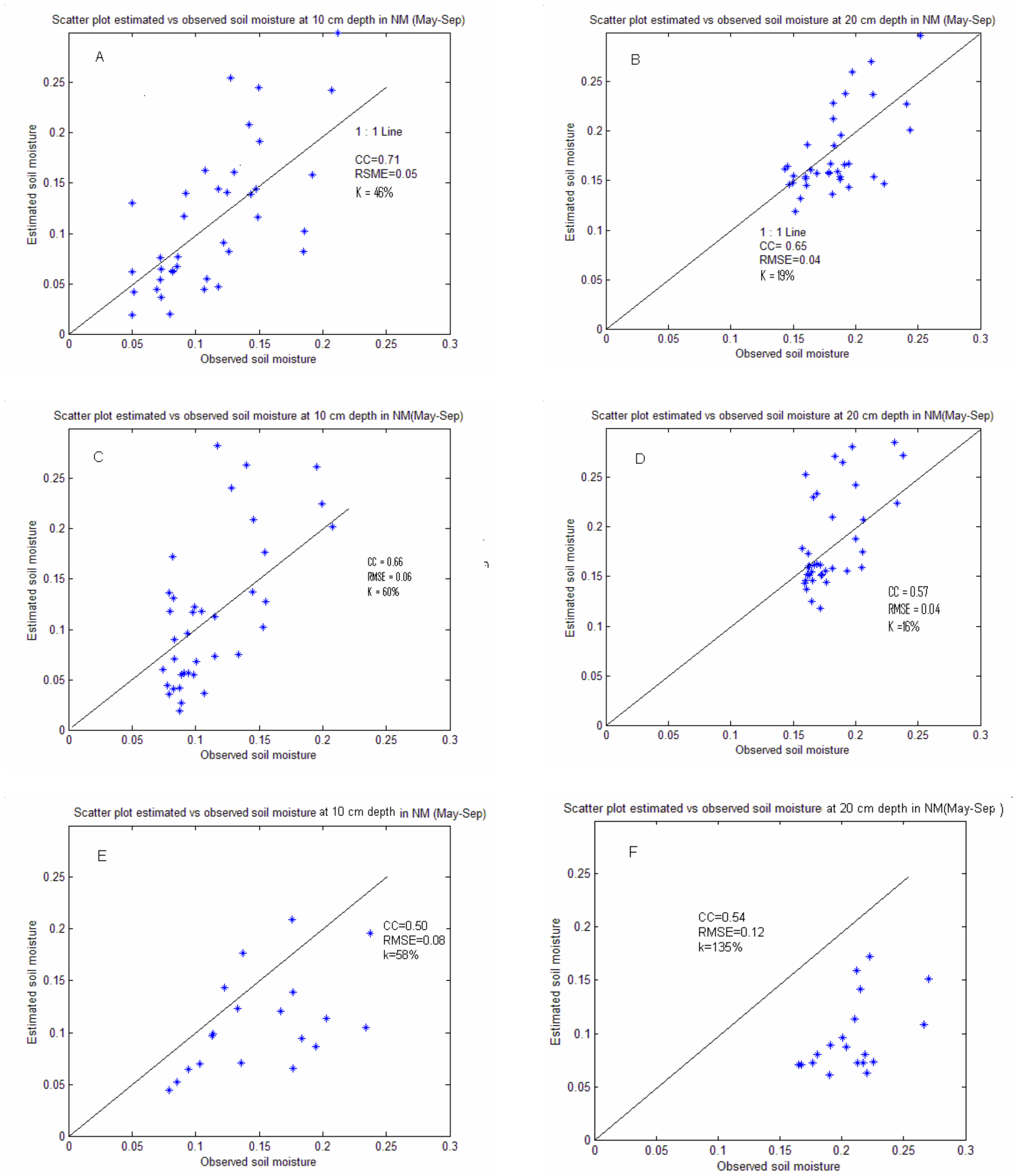


Figure 1. Estimated versus observed soil moisture at the 10 cm and 20 cm depths during May to September at the Adams Ranch site of NM. A and B, delta method; C and D, raw method. A, B, C, and D for 2000-2003; E and F, delta method for 2004 only.

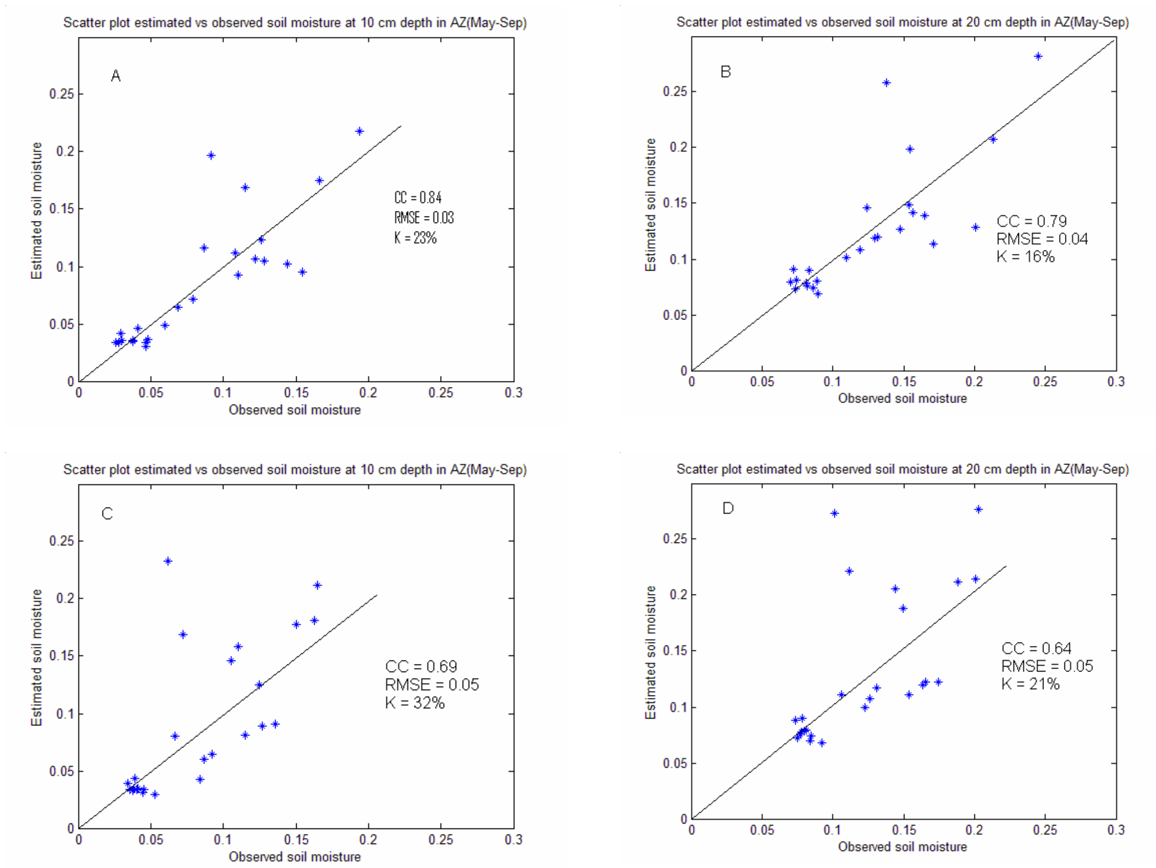


Figure 2. Estimated versus observed soil moisture at the 10 cm and 20 cm depths during May to September in 2000-2003 at the Walnut Gulch site of AZ. A and B, delta method; C and D, raw method.

Figure 3 is for the Prairie View site in TX during May to October in 2000-2003. Cases A and B use delta method; cases C and D use raw method. Overall, the estimated soil moisture (10 cm & 20 cm depth) in 2000-2003 using delta methods matches the observed soil moisture with CC of 0.7~0.74, RMSE of 0.05 and κ of 27%~62%. However, the estimated soil moisture using raw method does not match the observed soil moisture with CC of 0.12~0.21, RMSE of 0.06~0.07, and κ of 46%~116%. Similarly as at Walnut Gulch site, because of the bad quality of soil moisture in 2004, the predicted soil moisture in 2004 can not be validated and has not been shown here.

In short, the delta method can be used to effectively estimate the root-zone soil moisture using NDVI in both semi-arid and humid regions; whereas, raw method can only be used to estimate the root-zone soil moisture at semi-arid or arid regions. The estimated root-zone soil moisture using the delta method is better than that using the raw method. The estimated root-zone soil moisture at shrub vegetation is better than that at grass vegetation, while there is no significant difference on the performance of soil moisture estimation for grasslands in semi-arid region (New Mexico site) and humid region (Texas site).

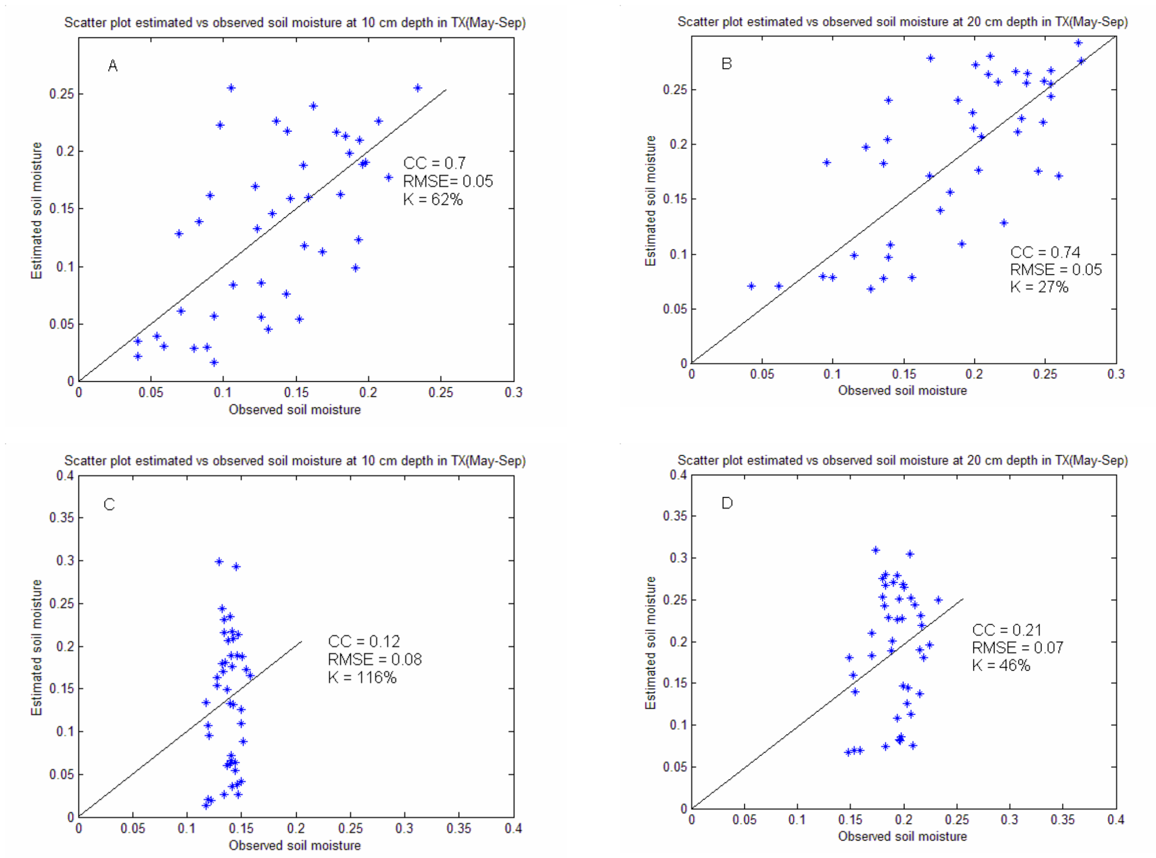
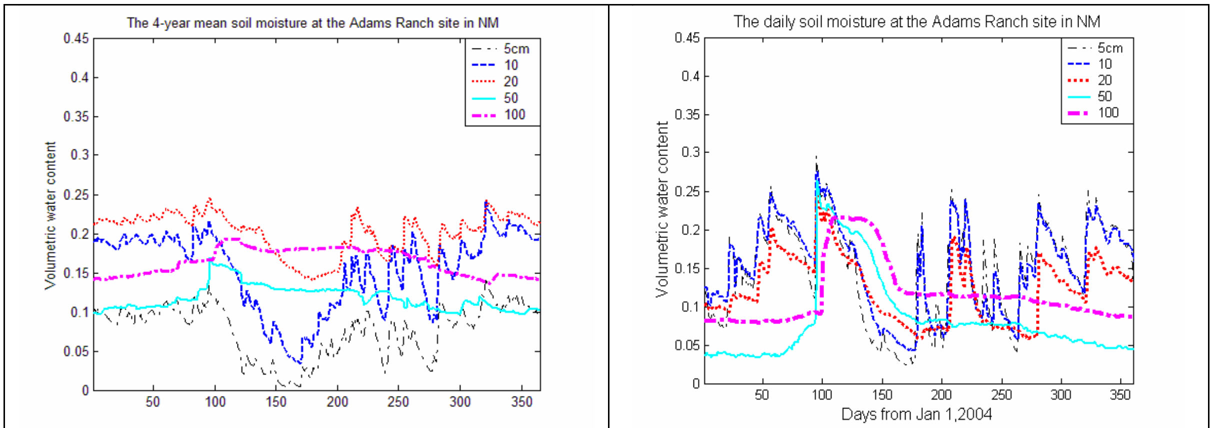


Figure 5. Estimated versus observed soil moisture at the 10 cm and 20 cm depths during May to September in 2000-2003 at the Prairie View site of TX. A and B, delta method; C and D, raw method.

DISCUSSION

Linear bivariate regression model requires a linear correlation between two sets of variable, even this correlation may be only a numeric relation and do not represent any specific biophysical or other association. Our result indicates that the linear correlation in the raw time series of soil moisture and NDVI is uncertain or unstable in different regions. For instance, it is found there is considerably high correlation in semi-arid regions (New Mexico and Arizona sites) but very low correlation in humid region (Texas site); the estimated results are also better in semi-arid regions than in humid regions. In contrast, the deseasonalized CC and corresponding estimations are stable regardless the types of vegetation and climate regimes. For example, there is moderate correlation between deseasonalized time series of soil moisture and NDVI no matter in semi-arid regions or humid regions; consequently, the estimated results using deseasonalized time series soil moisture and NDVI are nearly stable for same vegetation (grass) in different types of climate. In short, the results of this study indicate that it be better for bivariate regression model to use the deseasonalized time series of soil moisture and NDVI, i.e. the delta method in this paper.

Two sets of data have been used to validate the model. Overall, the predicted soil moisture through the second dataset in 2004 is not as good as that through the first dataset in 2000-2003 (section 5). This may be due to that the seasonal soil moisture constructed from 4 years of available data can hardly represent the long-term true seasonal value. This will lead to errors when adding the estimated delta soil moisture into the seasonal soil moisture as the total estimated soil moisture. Especially when we use it for prediction of soil moisture, the error could be larger. While for the first set of data in 2000-2003, the seasonal value of soil moisture is composed of the same soil moisture as used for validation. This will cancel out some errors caused by the seasonal soil moisture. For instance, for the second dataset, the κ is 135% at 20 cm depth (see figure 3-F) compared to the first dataset, whose k is usually lower than 20% at the 20 cm depth. A possible explanation for this exception is that it was due to an extremely wet year of 2004 compared to the years from 2000 to 2003, when the regression function β and seasonal soil moisture used were constructed by using these data. Comparing Figure 4 (a) and (b), we can see the difference of the daily soil moisture at the Adams Ranch site between periods from 2000 to 2003 and during 2004. It's quite wet in 2004, and the soil moisture at 5 cm and 10 cm has higher value than those at corresponding depths in previous years. This, thus, explains well that the estimated soil moisture at 10 cm and 20 cm using the regression function established by previous 4-year data is less than the observed soil moisture (Figures 1. E, F). In addition, it also indicates that it is reliable to estimate soil moisture in the same time period using NDVI via regression model, but it requires longer time period to predict future soil moisture using the same approach in order to mitigate the influence of seasonality of soil moisture.



a. Four-year mean soil moisture

b. Daily soil moisture in 2004

Figure 4. Mean soil moisture (2000-2003) and time-series of daily (2004) at Adams Ranch of NM.

SUMMARY

This study investigate the feasibility of estimating root-zone soil moisture using satellite (MODIS) derived NDVI by statistic method, least square linear regression model. We used two approaches to estimated soil moisture. One is raw time-series soil moisture and NDVI (raw method), and the other is the deseasonalized time-series soil moisture and NDVI (delta method). Meanwhile, we also used two types of dataset to validate the estimated soil moisture. Results show delta method is a more stable and reliable way for bivariate regression analysis. Root-zone soil moisture can be estimated by bivariate regression model using NDVI. The top surface (<5 cm) or below root-zone (>100 cm) soil moisture can not be estimated using NDVI due to the limitation of NDVI's response to soil moisture change. Raw method may also be used to estimate root-zone soil moisture at semi-arid or arid regions. In semi-arid regions, the estimated soil moisture using NDVI in shrub vegetation is better than that in grass vegetation. The performance of the estimation of soil moisture using NDVI in grass vegetation at the semiarid site in NM and at the humid site in TX does not display observable difference.

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