Winter 2006

Soil moisture dynamics from satellite observations, land surface modeling, and field data

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SOIL MOISTURE DYNAMICS FROM SATELLITE OBSERVATIONS, LAND SURFACE MODELING, AND FIELD DATA

BY

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DISSERTATION

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Doctor of Philosophy
in
Civil Engineering

December, 2006

UMI Number: 3241640

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ACKNOWLEDGEMENTS

First, I would like to deeply appreciate my advisor, Dr. Jennifer M. Jacobs for her encouragement, guidance, and patience throughout my Ph.D. studies at UNH. It was a great opportunity to develop creative and independent thinking by her supreme advice. I would like to thank Drs. Michael Cosh (USDA) and Venkat Lakshmi (USC) for their thoughtful comments. I also would like to thank Drs. Thomas Jackson (USDA), David Bosch (USDA), and SMEX sampling teams for field data collection effort. I am very grateful to my committee, Drs. Scott Ollinger, Ernst Linder, Tom Ballestero, and Robert Roseen for their time and comments. Especially, I would like to show my deep appreciation to Dr. Yong Nam Yoon (KU) and Dr. S. Lawrence Dingman (UNH) for their teaching and advice to strengthen my hydrological concepts. Thanks go to colleagues, En-Ching Hsu, Ram Ray, and Su Youn Kim for sharing thinking and helping data analysis.

I would sincerely like to thank my parents and brothers for their incessant encouragement and support. I am extremely grateful to my wife and best friend, Dr. Bo-Young Lee for her encouragement and generosity. I'd love to thank my sweet daughter, Jia Choi for her smile to make me energetic. Finally, I am grateful to God for giving me wisdom and courage throughout my studies.

This work was supported by the NASA Grant (no. NNG04GL60G) to Dr. Jennifer M. Jacobs.

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ABSTRACT

SOIL MOISTURE DYNAMICS FROM SATELLITE OBSERVATIONS, LAND SURFACE MODELING, AND FIELD DATA

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Knowledge of soil moisture variability is essential to understand hydrologic processes at a range of scales. In this study, spatio-temporal variability of soil moisture and inter-comparison among different soil moisture products were analyzed. The variability patterns were well characterized by negative exponential fitting as function of observed sampling extent scale. The simple physical soil moisture dynamics model was identified as an alternative approach to characterize statistical soil moisture variability. The soil moisture variability was strongly related to physical properties including rainfall and topography.

Normal and log-normal distributions were recognized as the most efficient probability density functions to capture soil moisture variability patterns for all conditions. Further, these variability patterns were well maintained for root zone profile and surface soil moisture time stable characteristics can be used to upper boundary for sub-surface time stability.

Through inter-comparison analysis, average soil moisture from remotely sensed measurements, ground-based measurements, and land surface model results showed excellent agreement. However, remotely sensed soil moisture had little variation, especially during the growing season. There were complementary benefits with low random errors for the land surface model and low system errors for the remotely sensed data.

The error characteristics of remotely sensed measurements can enhance the utility of satellite observations. The remote sensing measurements can provide relative soil moisture conditions to improve runoff predictions and analyze land surface-atmosphere interactions for regional climate predictions in data limited areas. However, their extremely limited variations must be refined prior to direct application in hydrological processes.

Overall, the identified soil moisture variability patterns provide a new understanding of soil moisture dynamics and spatio-temporal variability patterns as related to physical variables. These organized characteristics are essential to predict land-atmosphere interactions, rainfall-runoff processes, and groundwater recharge processes. Practically, these findings can be used to calibrate land surface models and to estimate heterogeneity effects of land surface processes. Additionally, statistical information as a function of scale is critical to develop up-scaling and down-scaling methodologies without significant loss of information. This dissertation's findings provide critical insight to hydrologic processes related to soil moisture at a range of scales.

INTRODUCTION

Soil moisture is a significant hydrological and ecological variable that controls the exchange of water and heat energy between the land surface and the atmosphere. It has an important role for partitioning of precipitation into runoff, infiltration, and surface storage. It also has major effects on the partitioning of incoming solar radiation and long wave radiation into outgoing long wave radiation, latent heat flux, ground heat flux, and sensible heat flux (Pachepsky et al., 2003).

Recently, aircraft and satellite instruments have been used to provide mean surface soil moisture (0 - 5 cm) values at broad spatial scales (Jackson et al., 1995, 1999; Schmugge et al., 2002). These instruments measure the natural thermal emission of the land surface and the intensity of this emission as a brightness temperature (T_B). Surface soil moisture is retrieved from T_B observations (Jackson et al., 1995, 1999). Even if remotely sensed soil moisture has many advantages, it cannot describe hydrology at the watershed or field scale because its scale is too large (Mohanty and Skaggs, 2001; Jacobs et al., 2004). Additionally, remotely sensed soil moisture measurements are limited to a shallow depth and are not responsive at heavy vegetation cover (Schmugge et al., 2002; Margulis et al., 2002).

Soil moisture variability across spatial-temporal scales must be understood to validate, calibrate, and downscale remotely sensed data. However, the satellite soil moisture product validation is complicated by the scale mismatch between satellite footprint (1 – 50 km) and ground based in-situ measurement (1 – 5 cm) as soil moisture is highly heterogeneous (Cosh et al., 2004). Thus, a large number of distributed soil moisture measurements within the footprint are required to accurately estimate mean values. There are two approaches available to provide a large number of ground based in-situ samples. The first is intensive field experiments such as Washita'92, SGP97, SGP99, SMEX02, and SMEX03 (Jackson and Schiebe, 1993; Jackson et al., 1999; Mohanty et al., 2002; Bosch et al., 2006). These experiments were conducted to provide validation data for satellite and aircraft based microwave remote sensing instruments over a wide range of vegetation conditions during short-term periods as a part of an integrated set of hydrological data. Moreover, these intensive field experiments allow us to develop effective approaches to monitor soil moisture variability in applicable areas as well as provide validation data (Mohanty and Skaggs, 2001; Jacobs et al., 2004; Cosh et al., 2004). The second validation approach uses in-situ networks such as the soil climate analysis network (SCAN) operated by Natural Resources Conservation Service (NRCS) (Cosh et al., 2004) and Steven-Vitel Hydra probes networks operated by USDA-ARS Southeast Watershed Research Lab (SEWRL) (Bosch et al., 2006). These networks provide a continuous longer-term dataset of soil moisture profiles. Even if ground-based measurements can provide more reasonable and direct values, the network's density is very sparse aside from the intensive field experiments (Reichle et al., 2004).

An alternative approach is to carefully select representative sampling sites. If Vauchaud et al.'s (1985) time stability concept demonstrates a constancy of spatial soil moisture patterns, then the number of observations may be minimized without considerable loss of information. Since the time stability concept was introduced, several studies have analyzed the temporal variability of soil moisture (Grayson and Western, 1998; Mohanty and Skaggs, 2001; Jacobs et al., 2004; Cosh et al., 2004). Grayson and Western (1998) found that a few time stable sites can represent mean soil moisture in small watersheds. Jacobs et al. (2004) and Cosh et al. (2004) validated the time stability concept in the SMEX02 (Soil Moisture Experiment 2002). Based on observations from the Little Washita watershed during SGP97 (Southern Great Plains Hydrology 1997), Mohanty and Skaggs (2001) pointed out that further studies are required to understand soil moisture dynamics with related to soil, topography, vegetation, and climate in a variety of places and over a large range of scales. Jacobs et al. (2004), during the SMEX02, also found that physical characteristics, soil texture, vegetation, land-cover, and topography could be used to understand of time stable soil moisture patterns.

At broad spatial scales, the improved assessment of land surface water and energy fluxes, and water storage is a key factor in understanding the complex interactions between the land surface and the atmosphere (Kustas et al., 1996; Moulin et al., 1998; Boegh et al., 2004). Here, remotely sensed soil moisture and in-situ measurement provide two means to characterize regional soil water storage. Another approach is to use soil - vegetation - atmosphere transfer (SVAT) models at a regional or watershed scale (Lohmann et al., 1998; Liang et al., 1998; Dai et al., 2003). SVAT schemes use the water and energy balances to combine land surface and atmosphere processes (Sellers et al., 1986; Dickinson et al., 1993). For robust assessment of water and energy flux, a more physical parameterization is required (Mohr et al., 2000). However, in-situ measurement of physical parameters outside of intensive field experiment is generally sparse. Thus, an alternative approach is the careful selection of SVAT models, which have adequately sophisticated parameterization for accurate simulation (Whitfield et al., 2006). The ability to apply SVAT models over a range of field conditions may improve our understanding of land-atmosphere interactions in data-limited regions.

Each of these soil moisture datasets has useful information and limitations. Effective soil moisture estimations may be conducted by data assimilation systems (i.e., data merging procedure) from remotely sensed measurements, ground-based measurements, and models (Margulis et al., 2002; Reichle et al., 2004). There have been significant advances in assimilation methodologies, but a fundamental requirement is the characterization of error statistics from available sources for optimal soil moisture estimation (Crow and Wood, 2003; Reichle and Koster, 2003). Bias estimation by comparisons among different data types is effective for understanding the data errors and identifying significant obstacles to data assimilation.

The first objective of this study is to broadly examine the variability of soil moisture as related to physical properties across a variety of landscapes. In this study, we address major issues; 1) How do soil moisture variability patterns differ by soil depth?; 2) How can we characterize the relationship between mean soil moisture and spatial variability of soil moisture measurements?; 3) What statistical distributions are appropriate to capture soil moisture variability by depth?; 4) What are the key physical parameters that control spatial-temporal dynamics of soil moisture at a range of scales?; 5) Is time stability a robust sampling design for surface and root zone soil moisture?; and 6) How well can a simple physical dynamics model predict variability patterns?

This study's second objective is to examine the conformity of different data types (i.e., remotely sensed measurements, ground-based measurements, and models) at Little River, GA. For this study, we address major issues; 1) How do soil moisture estimates compare among sources at regional scale?; 2) How well do soil - vegetation - atmosphere transfer (SVAT) models simulate spatial and temporal variability of surface soil moisture?; 3) How well does Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) on Aqua satellite replicate surface soil moisture patterns?; and 4) How can we characterize error statistics by bias estimation from the three data source?

CHAPTER 1.

SOIL MOISTURE VARIABILITY OF ROOT ZONE PROFILES WITHIN SMEX02 REMOTE SENSING FOOTPRINTS

Abstract

Remote sensing of soil moisture effectively provides soil moisture at a large scale, but does not explain highly heterogeneous soil moisture characteristics within remote sensing footprints. In this study, field scale spatio-temporal variability of root zone soil moisture was analyzed. During the Soil Moisture Experiment 2002 (SMEX02), daily soil moisture profiles (i.e., 0-6, 5-11, 15-21, and 25-31 cm) were measured in two fields in Walnut Creek watershed, Ames, Iowa, USA. Theta probe measurements of the volumetric soil moisture profile data were used to analyze statistical moments and time stability and to validate soil moisture predicted by a simple physical model simulation. For all depths, the coefficient of variation of soil moisture is well explained by the mean soil moisture using an exponential relationship. The simple model simulated very similar variability patterns as those observed.

As soil depth increases, soil moisture distributions shift from skewed to normal patterns. At the surface depth, the soil moisture during dry down is log-

normally distributed, while the soil moisture is normally distributed after rainfall. At all depths below the surface, the normal distribution captures the soil moisture variability for all conditions. Time stability analyses show that spatial patterns of sampling points are preserved for all depths and that time stability of surface measurements is a good indicator of subsurface time stability. The most time stable sampling sites estimate the field average root zone soil moisture value within ± 2.1% volumetric soil moisture.

Introduction

Soil moisture is a significant variable in hydrologic and biologic processes. It is a controlling variable in the exchange of water and energy between the land surface and the atmosphere through evaporation and transpiration. It determines the partitioning of precipitation into runoff, infiltration, and surface storage, as well as the partitioning of incoming solar radiation and long wave radiation into outgoing long wave radiation, and latent heat, ground heat, and sensible heat fluxes (Pachepsky et al., 2003).

Aircraft and satellite instruments (i.e., various active and passive microwave sensors), which provide mean surface soil moisture (0 - 5 cm) values at large spatial scales, are only recently available (Jackson et al., 1995, 1999; Schmugge et al., 2002). Microwave sensors have many advantages including the ability to directly measure soil moisture regardless of weather conditions or time of day (Jackson, 1993; Jackson and Schmugge, 1995). However, sub-pixel variability at the surface layer is still not well understood (Mohanty and Skaggs, 2001; Jacobs et al., 2004). Furthermore, retrieved soil moisture products can not describe variability at depths below the surface, as only a shallow depth (0 - 5 cm) is observed (Schmugge et al., 2002).

An understanding of soil moisture variability across spatial-temporal scales is essential to validate, calibrate, and downscale remotely sensed soil moisture products. Information characterizing spatio-temporal variability of soil moisture within remote sensing footprints can provide a blueprint to design ground-based experiments and networks and to efficiently use remote sensing measurements (Famiglietti et al., 1999; Ryu and Famiglietti, 2005). To characterize soil moisture variability within remote sensing footprints, a large number of ground-based in-situ samples were gathered during Washita'92, SGP97, SGP99, SMEX02, and SMEX03 (Jackson and Schiebe, 1993; Jackson et al., 1999; Mohanty et al., 2002; Narayan et al., 2004). Soil Moisture Experiments (SMEX) are a series of soil moisture field experiment conducted annually from 2002 to 2005 (SMEX02 - SMEX05) to validate aircraft and satellite soil moisture measurements, to provide datasets of hydrologic processes and land-atmosphere interactions, and to evaluate new instrument technologies for soil moisture remote sensing (Mohanty and Skaggs, 2001; Jacobs et al., 2004; Cosh et al., 2004).

For most practical applications, knowledge of soil moisture must be understood for layers deeper than the thin surface layers observed using remote sensing instruments. Entire soil moisture profiles provide an enhanced characterization for hydrologic applications (Western et al., 1998) and a more integral understanding of soil moisture dynamics (Bloschl and Sivapalan, 1995). Moreover, the dynamics of soil moisture at deeper layers may significantly influence surface soil moisture variability (Jacques et al., 2001). Most previous studies of soil moisture variability are restricted to a shallow depth (0-5 cm) with only a few studies considering different soil depths (i.e., 0-100 cm) (Kachanoski and Jong, 1988; Hupet and Vanclooster, 2002; Martinez-Fernandez and Ceballos, 2003). Hupet and Vanclooster's (2002) and Martinez-Fernandez and

Ceballos' (2003) investigations of spatio-temporal root zone soil moisture dynamics showed that patterns vary with depth. However, none of these studies were conducted during large scale experiments.

The relationship between mean soil moisture and variability within a footprint has been investigated to identify appropriate statistical distributions and physical parameters for soil moisture dynamics, to minimize the number of sampling sites, and to determine the sampling periods required to limit error (Famiglietti et al., 1998, 1999; Hupet and Vanclooster, 2002; Ryu and Famiglietti, 2005). While numerous studies have characterized soil moisture field statistics (Famiglietti and Wood, 1991, 1994; Famiglietti et al., 1998, 1999; Wilson et al., 2003; Ryu and Famiglietti, 2005), there is still no consensus as to which probability density function (PDF) is suitable. There is also no agreement as to whether soil moisture variability is positively (Hills and Reynolds, 1969; Henninger et al., 1976; Bell et al., 1980; Robinson and Dean, 1993; Famiglietti et al., 1998; Martinez-Fernandez and Ceballos, 2003) or negatively (Famiglietti et al., 1999; Hupet and Vanclooster, 2002) correlated to mean soil moisture content. Teuling and Troch's (2005) simple soil moisture model provided a preliminary link between physical processes and statistical variability patterns.

An approach to characterize mean footprint using minimal measurements for the spatio-temporal variability of soil moisture is the time stability concept (Vauchaud et al., 1985). Grayson and Western (1998), Mohanty and Skaggs (2001), Jacobs et al. (2004), and Cosh et al. (2004) demonstrated that a few time stable sites well represent the mean soil moisture within small watersheds.

During SGP97 (Southern Great Plains Hydrology 1997), Mohanty and Skaggs (2001) validated the time stability concept. Jacobs et al. (2004) and Cosh et al. (2004) also validated the time stability concept in the SMEX02 (Soil Moisture Experiment 2002). However, these studies only examined time stability for near surface soil moisture. Little is known about the concept's validity for other depths or the relationship between surface time stability and profile time stability.

The main objective of this study is to better understand field scale soil moisture dynamics for two fields in central Iowa. This study (1) investigates how variability patterns differ by soil depth; (2) characterizes the relationship between mean soil moisture and spatial variability of soil moisture measurements over time; (3) tests a physical dynamics model to predict variability patterns; (4) identifies appropriate statistical distributions by depth; and (5) examines the temporal stability concept of soil moisture for a soil water profile.

Study Region

SMEX02 was conducted in cooperation with National Aeronautic and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA), and United States Department of Agriculture (USDA). Detailed descriptions of SMEX02 can be found at http://hydrolab.arsusda.gov/smex02/. The Walnut Creek watershed (100 km^2) in Ames, Iowa was the site for intensive investigations of soil moisture and hydro-meteorological samples during SMEX02. Approximately 95% of the watershed is used for row crop agriculture (corn and soybean). The climate is nearly humid and average annual rainfall is 835 mm. The heaviest rainfall usually occurs in May and June and amounts to about one third of the annual total. There are 20 recording rain gauges at 1-mile intervals in the watershed. The topography is characterized by low relief and poor surface drainage, resulting from prairie potholes that are water-holding depressions of glacial origin. The representative soils are loams and silty clay loams and have relatively low permeability (Iowa State University, 1996).

During the SMEX02 field campaigns, sampling was conducted between June 23 to July 12, 2002 in the Walnut Creek watershed and regional sites near Ames, Iowa. In the watershed sampling, ground sampling was conducted at 33, approximately 800 × 800 m, fields (WC01 - WC33) for ESTAR/2D-STAR/PSR aircraft remote sensing validation (Figure 1-1 (a)). For this study, we selected two watershed fields (WC11 and WC13) (Figure 1-1 (b)) whose locations and field attributes are given in Table 1-1. While both fields had similar relief and soils, WC11 had a corn crop with a small area of soybean planted near the western edge of the field and WC13 had a soybean crop. Average crop root zone depths of corn and soybean are between 12 and 18 inch during second growth stage of vegetative growth and development (Smajstrla, 1990). The soil moisture of from 0 to 31 cm depth should capture most of the root zone water dynamics during the SMEX02.

Soil moisture content was measured almost daily from June 26 to July 10, 2002 at 25 points in the WC11 field and from June 27 to July 8, 2002 at 31 points in the WC13 field. Measurements were conducted between 1200 and 1600 local time (CDST). Sampling points were located at 100 m intervals along four transects oriented east-west and north-south within each field (Figure 1-1 (b)). During the experiment, volumetric soil moisture contents were measured using theta probes (Dynamax, Inc., Texas). More detailed information for the theta probes can be found at http://www.dynamax.com. The theta probe measures the average dielectric constant using 6 cm length tines. For subsurface measurements, an auger was used to extract soil to the required soil depth (i.e., 5, 15, 25 cm) and the theta probe was pushed into the soil until the tines were fully covered. The average soil moisture from 0 to 31 cm was estimated by averaging the 4 measurements, 0-6, 5-11, 15-21, and 25-31 cm. In this study, we abbreviate theta probe measured soil moisture at 0-6 cm as 0 cm, 5-11 cm as 5 cm, 15-21 cm as 15 cm, and 25-31 cm as 25 cm.

Methods

Statistical Analysis

Statistical moments, mean, standard deviation, coefficient of variation, and skewness of soil moisture measurements were calculated daily by field and soil depth. Probability density functions (PDFs) were fit using the method of moments. The normal distribution and log-normal distribution were analyzed as they are the most widely used PDFs in hydrologic systems (Li and Avissar, 1994; Crow and Wood, 2002; Haan, 2002; Ryu and Famiglietti, 2005).

Probability plot correlation coefficient (PPCC) tests (Looney and Gulledge,1985; Vogel, 1986) were conducted to determine whether the data follow normal or lognormal distributions. In the PPCC test, if the correlation coefficient (r) between the data and standardized quantile for the specified distribution is smaller than the critical r*, the null hypothesis, Ho (Ho: the data are drawn from the named distribution) is rejected. A large α level (i.e., 0.1) was applied to increase the power to detect non-normality, especially for small sample sizes (Helsel and Hirsch, 2002).

Physical Soil Moisture Dynamics Model

A simple physical dynamics model was used to examine how well the observed statistical variability was predicted by physical soil moisture dynamics. For this study, the physical model is based on the previous studies (Guswa et al., 2002; Teuling and Troch, 2005). Additional model parameter details are provided by the previous studies. The basic soil moisture dynamics equation (Guswa et al., 2002; Teuling and Troch, 2005) is defined as

$$\frac{d\theta}{dt} = \frac{1}{L}(I - q - S) \tag{1-1}$$

where θ is the average volumetric soil moisture over a depth, L is the root zone depth, I is the infiltration rate, q is the drainage, and S is the root water uptake.

Infiltration is calculated as the minimum of precipitation minus interception and unsaturated depth of the root zone (Guswa et al., 2002). Drainage is estimated by Darcy's law and is parameterized by Campbell (1974) as

$$q = k_{sat}(\frac{\theta}{\phi})^{2b+3} \tag{1-2}$$

where k_{sat} is the saturated hydraulic conductivity, ϕ is the porosity, and b is the pore size distribution index. The porosity (ϕ) and pore size distribution index (b) were fitted by linear relationship with natural logarithm of the saturated hydraulic conductivity (k_{sat}) ($\phi = -0.0147\ln(k_{sat}) + 0.545$ and $b = -1.24\ln(k_{sat}) + 15.3$) (Clapp and Hornberger, 1978).

The root water uptake is defined by Teuling and Troch (2005) as

$$S = f_r\beta\{1 - \exp(-c\varepsilon)\}E_p \tag{1-3}$$

where f_r is the root fraction, β is the soil moisture stress function, c is the light use efficiency parameter, ε is the leaf area index (LAI), and E_p is the potential evapotranspiration [mm/day].

The root fraction (f_r) was set equal to one and light use efficiency parameters (c) were 0.55 and 0.50 in WC11 and WC13, respectively (Teuling and Troch, 2005). The soil moisture stress function (β) was modeled following Teuling and Troch (2005). Table 1-1 lists soil parameter values obtained from Iowa State University (1996) and LAI values from Anderson et al. (2004). Atmospheric forcing data (precipitation and evapotranspiration) were obtained from available data (SMEX02 datasets).

Both the leaf area index (ε) and the natural logarithm of the saturated hydraulic conductivity (k_{sat}) were assumed to follow a normal distribution (Teuling and Troch, 2005). One thousand samples were generated by Monte-Carlo simulations (Haan, 2002) based on the statistical mean and standard deviation for leaf area index (ε) during three measurements periods (Anderson et al., 2004) and the natural logarithm of the saturated hydraulic conductivity (k_{sat}) (Clapp and Hornberger, 1978) (Table 1-1).

Time stability analysis

Vachaud et al. (1985)'s time stability concept characterizes the time-invariant association between spatial location and statistical parametric values of a given soil property. In order to analyze the time stability of a soil moisture field, two statistical metrics, the mean relative difference and the root mean square error of mean relative difference, are determined. The field mean soil moisture ($\bar{\theta}_{j,t}$), the mean relative difference ($\bar{\delta}_{i,j}$), and the variance of the relative difference ($\sigma(\delta)_{i,j}{}^2$) for each sampling point (Vachaud et al., 1985) are defined as

$$\bar{\theta}_{j,t} = \frac{1}{n_{j,t}} \sum_{i=1}^{n_{j,t}} \theta_{i,j,t} \tag{1-4}$$

$$\bar{\delta}_{i,j} = \frac{1}{n_t} \sum_{t=1}^{n_t} \frac{\theta_{i,j,t} - \bar{\theta}_{j,t}}{\bar{\theta}_{j,t}} \tag{1-5}$$

$$\sigma(\delta)_{i,j}{}^2 = \frac{1}{n_t - 1} \sum_{t=1}^{n_t} \left(\frac{\theta_{i,j,t} - \bar{\theta}_{j,t}}{\bar{\theta}_{j,t}} - \bar{\delta}_{i,j}\right)^2 \tag{1-6}$$

where t is the number of dates, j is the number of fields, i is the number of sample points within field j at time t, $\theta_{i,j,t}$ is a volumetric soil moisture at location i in field j and time t.

The mean relative difference indicates whether a soil moisture measurement of a particular sample point is greater or less than the average soil moisture of the field. The mean relative difference plot, drawn by rank with an error boundary of one standard deviation of the relative difference, determines which sample points are the best time stable locations in the field.

The root mean square error (RMSE) of mean relative difference, which includes both bias and precision metrics (Jacobs et al., 2004), is defined as

$$RMSE_{i,j} = (\bar{\delta}_{i,j}{}^2 + \sigma(\delta)_{i,j}{}^2)^{1/2} \tag{1-7}$$

This combination statistic identifies time stable locations in a field as those having low RMSE values.

Results and Discussion

Statistical analysis

The time series of precipitation and the mean, standard deviation, and skewness of volumetric soil moisture by depth and field are shown in Figure 1-2. The mean soil moisture shows a dry down phase from the initiation of the SMEX02 campaign. After rainfall events, the mean soil moisture increases. The mean soil moisture content is highly dependent on depth, while the standard deviation and skewness of soil moisture are less dependent. The dependency may be related to surface evaporation, root water uptake, and soil properties. Deeper layers typically have somewhat less variability than shallower layers. Several environmental factors (i.e., evaporation and rainfall) may cause higher variability at the surface than the subsurface. During the experiment, the mean soil moisture varied by 23.5% at 0 cm, 18.8% at 5 cm, 16.2% at 15 cm, and 14.5% at 25 cm in WC11. Smaller ranges, 14.6, 9.5, 7.6, and 6.8% at 0, 5, 15, and 25 cm depths were observed in WC13 (Figures 1-2(a) and 1-2(d)). The mean soil moistures changes were greater in shallower layers than in deeper layers.

The maximum standard deviations of the soil moisture were 8.0 and 10.1% at WC11 and WC13, respectively. Between fields differences for the maximum standard deviation were likely caused by highly heterogeneous rainfall on June 30 and July 1. That the maximum standard deviation occurred during the dry down may be related to hysteresis effects (Figures 1-2(b) and 1-2(e)). Average soil moisture standard deviation values of 4.6, 5.7, 5.6, and 5.5% at 0, 5, 15, and 25 cm depths were observed in WC11. Higher average values, 5.8, 7.5, 7.1, and 6.5% at 0, 5, 15, and 25 cm depths, were observed in WC13. While soil moisture standard deviation tended to decrease as soil depth increased, the maximum standard deviation of the soil moisture did not occur at the surface, but at 5 cm.

The largest skewness occurred at or near the surface during the initial dry down (Figures 1-2(c) and 1-2(f)). For deeper depths, skewness was typically near zero or negative. Average soil moisture skewness of 0.18, 0.23, 0.00, and -0.10% at 0, 5, 15, and 25 cm depths were observed in WC11. Higher average values, 0.62, 0.36, -0.07, and -0.36 at 0, 5, 15, and 25 cm depths, were observed in WC13. Overall, WC13 had higher variability (i.e., standard deviation and skew) than WC11. The WC13's higher sand content and lower vegetative cover of soybean likely enhanced variability. The soybean's lower Normalized Difference Vegetation Index (NDVI) reflects a partial canopy cover as compared to corn (WC11) and more spatially varied soil water loss by evaporation (Jacobs et al., 2004).

Figures 1-3(a) and 1-3(d) show the relationship between the mean soil moisture and the standard deviation by soil depth. While considerable scatter exists, negative relationships are evident for all soil depths. Interestingly, the relationship between the mean soil moisture and the standard deviation of soil moisture at 0 cm depth showed a transition to a positive relationship with drier conditions (10-15%) in both fields. Overall, soil moisture variability showed the highest values at moderate moisture conditions (15-25%) and reduced values for drier and wetter conditions for all depths. Using 154 field scale samples of surface soil moisture for the SGP97 experiment, Ryu and Famiglietti (2005) also found that 20% mean soil moisture content showed the highest variability.

For surface measurements, our negative relationships are consistent with the previous study of Famiglietti et al. (1999) who found negative relationships between surface mean soil moisture and standard deviation of soil moisture content for six fields in SGP97. However, many previous studies found a positive relationship between the mean surface soil moisture content and the standard deviation of soil moisture (Hills and Reynolds, 1969; Henninger et al., 1976; Bell et al., 1980; Robinson and Dean, 1993; Famiglietti et al., 1998). These previous studies postulated that variability peaked under wet soil moisture conditions, because soil heterogeneity would be maximized after rainfall events (Famiglietti et al., 1998). Contradictory relationships may be also influenced by combined physical effects of soil texture, hysteresis effects, vegetation, topography, and sampling scale (Famiglietti et al., 1998). For the subsurface depths, our negative relationships are consistent with Hupet and Vanclooster's (2002) finding that the standard deviation of soil moisture decreased with increasing mean soil moisture (20-45%) at depths from 0 to 125 cm in agricultural maize cropped field. However, Martinez-Fernandez and- Ceballos (2003) found a positive relationship between soil moisture mean (10-30%) and variance at depths from 0 to 100 cm for crops grown in sandy soils (cereals and vineyards). This difference may be caused by their site's sandy soils and fortnightly sampling that likely resulted in rapid drainage and relatively dry conditions.

The relationships between the coefficient of variation and the mean soil moisture content for the different depths are shown in Figure 1-3(b) and 1-3(e). The coefficient of variation exponentially decreases as the mean soil moisture increases for all depths. This result is consistent with the previous studies of Bell et al. (1980), Owe et al. (1982), Charpentier and Groffman (1992), and Famiglietti et al. (1999) for surface soil moisture. Jacobs et al. (2004) characterized the negative relationship between the surface mean soil moisture content and the coefficient of variation using an exponential fit for four fields of the SMEX02. Here, the profile results are well characterized by the exponential fit $CV = Ce^{B\theta}$ (Table 1-2) with B and C varying by depth. The 0 cm depth has the least negative relationship (i.e., smallest B, C parameters, and R^2) in both fields, with deeper layers having more obvious negative relationships. These small variability patterns for the 0 cm depth are affected by the high variation of mean soil moisture at the surface. WC13 had higher relative variability under dry conditions and more rapidly declining relative variability with increasing mean soil moisture for all depths as compared to WC11. This higher variability may be related to WC13's relatively high sand content, low vegetation cover, and high topographic relief as compared to WC11 (Table 1-1). For both fields, the relationships converge under wet conditions.

A fairly consistent relationship between soil moisture skewness and mean soil moisture was observed (Figures 1-3(c) and 1-3(f)). As soil dried, a few sites remained wet resulting in a positive skew. These wet sites typically had higher clay content (30-31%) and were located in lower elevations. Following rainfall events, a few relatively dry sites caused a negative skew. These dry locations typically had a relatively high sand content (30-33%) and were located at hilltops. While, the average skewness of WC13 (0.62, 0.36, -0.07, and -0.36 at 0, 5, 15, and 25 cm depths) is relatively large compared to that of WC11 (0.18, 0.23, 0.00, -0.10 at 0, 5, 15, and 25 cm depths), the decreasing skewness with soil depths is similar to those.

Statistical results agree with observations of enhanced normality with increasing soil depth. Table 1-3 summarizes field statistics and the results of the PPCC test for normal and lognormal distributions. While the surface distributions were positively skewed during the inter-storm period, they were negatively skewed after rainfall events. The surface distributions were relatively well described by the log-normal distribution during the dry down phase, and by the normal distribution after rainfall. The distributions at other depths (i.e., 5, 15, 25, and 0-31 cm) differed from those at the surface. While positively skewed patterns decreased and normal patterns increased with increasing soil depth before rainfall events, the distributions showed normal or negatively skewed patterns after rainfall events.

Sixty six percent of the distributions were well described by both the normal and log-normal distributions. Normal and log-normal distributions were appropriate for 83 and 77% of the datasets, respectively. Neither a normal, nor a log-normal distribution was appropriate for 6% of the datasets. For the 0-31 cm profile, either the normal or the log-normal distributions can be used in all cases. These results are consistent with Famiglietti et al. (1999) who found normal patterns in the mid-range of mean soil moisture and positive/negative skewed patterns in the dry and extremely wet conditions at the surface, respectively for the SGP97 area. Ryu and Famiglietti (2005) also found that the normal distribution was appropriate to represent sub-pixel soil moisture variability under wet conditions for the SGP97 area. This study extends their findings and shows that the normal distribution captures the variability for all 0-31 cm profiles.

Physical soil moisture dynamics

Figure 1-4 shows the results from the simple dynamics model simulation. The simulated mean soil moisture versus day of year (DOY) plots for WC11 and WC13 show good agreement with observed surface (0 cm) and root zone (0-31 cm) measurements (Fig 1-4(a) and 1-4(c)). The RMSE of simulated mean soil moisture for the surface and the root zone were 6.6 and 4.4% for WC11 and 1.8 and 3.4% for WC13. WC11's high RMSE reflects a large overestimation on July 10. Overestimated mean soil moisture on a rainy day is likely caused by a high infiltration estimate because the bucket model only uses a mean saturation amount regardless of the soil moisture spatial distribution (Guswa et al., 2002).

The mean soil moisture and the coefficient of variation for the observed data and simulated results are shown in Figure 1-4(b) and 1-4(d). The simulated patterns are similar to those observed for the surface and the root zone. Both are well characterized by the exponential fit (Table 1-2). The model results successfully capture the higher variability patterns in WC13 as compared to WC11. The differences in variability appear to be primarily driven by LAI differences, because topographic processes were not considered in the physical model and the soil parameters were quite similar. Overall, these results support Teuling and Troch's (2005) finding that a simple physically-based model can capture the relationship between mean soil moisture and variability.

Time stability of the soil moisture

Figures 1-5 and 1-6 show the time stability results by depth. Negative mean relative differences indicate that corresponding sites have drier spatial patterns compared to the field mean soil moisture while positive mean relative differences indicate that corresponding sites have wetter spatial patterns compared to the field mean soil moisture. The error bars, standard deviation of the mean relative difference, and RMSE values are also indicators as to which sites capture the best field mean soil moisture. The best locations have a mean relative difference and RMSE close to zero. The most stable locations in WC11 and WC13 represent field mean soil moisture for all soil depths within ± 1.1% and ± 2.1%

volumetric soil moisture (VSM), respectively. In both fields, time stability improved with increasing depth. The average values of standard deviation and RMSE decrease gradually with increasing soil depth. For example, the average values of standard deviation and RMSE decreased from 21.9 and 27.8 at the surface to 14.9 and 21.4% at 25 cm depth in WC11. While WC13 had greater variability at most levels than WC11, the variability at 25 cm was much lower than that at the surface. The WC11 shows better time stability than WC13 for all depths.

Figures 1-5(f) and 1-6(f) show the mean relative difference values for all depths at each sampling location. Sampling locations are ordered by the 0-31cm rank. In WC11, sampling points 13, 21, 70, 79, and 83 are the five most stable sampling locations for root zone soil moisture (0-31 cm). The most locations in WC13 are 17, 54, 58, 75, and 136 (Figure 1-1(b)). Figures 1-5(f) and 1-6(f) show that each site maintains its spatial patterns regardless of soil depth. A comparison of the mean relative difference rankings between soil depths was conducted using a paired t-test and the signed rank test, a non parametric procedure used to identify differences in paired observations using the sign and magnitude of the differences (Helsel and Hirsch, 2002). Here, a pair is two depths at a single point and the stability ranks corresponding to those depths are compared. All possible combinations of depths were examined (e.g., 0 and 5 cm, 0 and 15 cm, 0 and 25 cm, etc.). The paired t-test and signed rank test indicated that there was no significant difference in rank for any combination of depths. This result shows that time stable locations identified using surface measurements are also time stable for the root zone profiles under conditions of no significant soil type variability by soil depths.

Temporal mean soil moisture of each sampling point for the best stable sampling sites had a relatively low standard deviation value for all depths. Here, we note that time stability is closed to zero as standard deviation and relative variability decreases. The majority of five most stable sampling points for root zone were located in hill slopes (Figure 1-1(b)). These results extend Jacobs et al.'s (2004) finding that mild slopes exhibit time stable characteristics for surface soil moisture. Hupet and Vanclooster (2002) found that dry periods had poor stability characteristics for depths from 0 to 125 cm. However, Martinez-Fernandez and Ceballos's (2003) experiment in sandy soils found that for comparable absolute values of the mean relative differences, dry sites had lower standard deviations than wetter sites at all soil depths (i.e., 0 to 100 cm). Jacobs et al. (2004) and Mohanty and Skaggs (2001) confirmed this finding for surface soil moisture measurements. In our study, while the drier sites had lower standard deviations at the surface, this was not the case at many deeper depths at both sites. Based on this finding, recommended time stable sampling sites may include either slightly drier or wetter sites when root zone soil moisture is to be estimated.

Conclusion

In this study, variability and time stability of soil moisture were considered for different soil depths in two fields in the Walnut Creek watershed, Iowa. The coefficient of variation of soil moisture decreased exponentially with increasing mean soil moisture content for all soil depths. The surface depth showed the least negative relationship between mean soil moisture and the coefficient of variation of soil moisture. Surface soil moisture was well described by a normal distribution, except during dry down phases when it is positively skewed. At deeper depths, the normal distribution generally captured the soil moisture variability. A simple physical model can provide insight to statistical relationships necessary to disaggregate physically based land surface model predictions. The most stable station represented the field mean soil moisture content within ± 1.1% and ± 2.1% volumetric soil moisture (VSM) for WC11 and WC13 fields, respectively. The time stability patterns were maintained regardless of the soil depth. However, in contrast to earlier studies, better time stability is not always found at drier sites, as the deeper soils showed much poorer time stability. Here, the best sampling sites were either slightly drier or wetter sites. Earlier studies' results regarding surface time stability may provide valuable insight to root zone time stability prediction.

This study also found less variability at deeper depths as compared to surface soil moisture observations. Surface soil moisture variability and skewness may be used as an upper boundary for the root zone variability and skewness. Thus, care should be taken in extrapolating statistics from surface measurements to the entire root zone.

Table 1-1. Geographic locations and field characteristics for the WC11 and WC13 fields (Note: Values in parenthesis are the standard deviations)

Field	UTM coordinates of the NE corner of the field	No. of sampling points	Average soil texture		Crop type	Average K_{sat} (mm/day)	Average LAI			Max elevation difference (m)
			Sand (%)	Clay (%)			6/28	7/2	7/8	
WC11	442,616(E) 4,647,323(N)	25	24.5	28.6	Corn	351.7 (190.5)	2.44 (0.41)	2.74 (0.45)	3.72 (0.44)	3.7
WC13	443,524(E) 4,645,315(N)	31	26.3	28.6	Soybeans	424.9 (196.7)	0.65 (0.26)	0.92 (0.28)	1.70 (0.52)	6.1

Table 1-2. Regression relationship between the coefficient of variation and the mean soil moisture of observed and simulated for the different soil depths in WC11 and WC13 fields where $CV = Ce^{B\theta}$

		In-situ			Simulated		
Field	Depth	C	B	R^2	C	B	R^2
WC11	0 cm	0.80	-0.061	0.80	0.47	-0.059	0.79
	5 cm	2.07	-0.092	0.92			
	15 cm	1.84	-0.087	0.90			
	25 cm	1.92	-0.086	0.81			
	0-31 cm	1.49	-0.086	0.91	0.56	-0.050	0.67
WC13	0 cm	1.58	-0.091	0.81	1.22	-0.079	0.94
	5 cm	2.86	-0.099	0.87			
	15 cm	4.02	-0.110	0.88			
	25 cm	9.75	-0.138	0.85			
	0-31 cm	3.38	-0.114	0.96	0.67	-0.047	0.87

Table 1-3. Summary of field statistics and PPCC test (Fitness of PDF lists which probability density functions are appropriate.)

Site	Depth	Date	Number of Samples	Mean (%)	Std.Dev. (%)	CV	Skewness	PPCC Normal	PPCC Lognormal	Fitness of PDF N = normal LN = Lognormal
WC11	0 cm	6/26	25	16.73	6.73	0.40	0.67	Accept	Accept	N/LN
		6/27	25	15.00	5.91	0.39	1.26	Reject	Accept	LN
		6/28	25	16.93	6.31	0.37	0.68	Accept	Accept	N/LN
		6/29	25	12.66	4.04	0.32	0.31	Accept	Accept	N/LN
		6/30	25	13.24	4.44	0.34	0.44	Reject	Accept	LN
		7/1	25	10.40	3.09	0.30	-0.14	Accept	Reject	N
		7/3	25	12.31	5.03	0.41	1.07	Reject	Accept	LN
		7/5	25	25.87	4.19	0.16	-0.44	Accept	Accept	N/LN
		7/7	25	28.72	5.37	0.19	-1.53	Reject	Reject	-
		7/8	25	25.18	3.57	0.14	-0.53	Accept	Reject	N
		7/9	25	21.77	3.86	0.18	0.40	Accept	Accept	N/LN
		7/10	25	33.85	2.89	0.09	-0.06	Accept	Accept	N/LN
	5 cm	6/26	25	20.91	6.06	0.29	0.06	Accept	Accept	N/LN
		6/27	25	20.10	7.07	0.35	0.15	Accept	Reject	N
		6/28	25	21.23	7.09	0.33	0.52	Accept	Accept	N/LN
		6/29	25	24.03	5.02	0.21	0.19	Accept	Accept	N/LN
		6/30	24	19.09	7.99	0.42	0.30	Accept	Accept	N/LN
		7/1	23	17.73	6.40	0.36	0.47	Accept	Accept	N/LN
		7/3	24	17.07	6.11	0.36	0.49	Accept	Accept	N/LN
		7/5	25	25.59	5.18	0.20	0.58	Accept	Accept	N/LN
		7/7	25	29.80	5.42	0.18	-0.29	Accept	Accept	N/LN
		7/8	25	25.72	4.40	0.17	-0.17	Accept	Accept	N/LN
		7/9	25	22.86	5.59	0.24	0.41	Accept	Accept	N/LN
		7/10	25	35.85	2.24	0.06	0.01	Accept	Accept	N/LN
	15 cm	6/26	25	21.87	7.09	0.32	0.02	Accept	Accept	N/LN
		6/27	25	23.78	6.01	0.25	0.02	Accept	Accept	N/LN
		6/28	25	23.42	5.45	0.23	-0.02	Accept	Accept	N/LN
		6/29	25	19.77	6.60	0.33	0.52	Accept	Accept	N/LN
		6/30	24	20.13	6.33	0.31	0.03	Accept	Accept	N/LN
		7/1	23	20.96	6.21	0.30	0.23	Accept	Accept	N/LN
		7/3	24	18.81	6.60	0.35	0.39	Accept	Accept	N/LN
		7/5	25	25.47	4.92	0.19	-0.24	Accept	Accept	N/LN
		7/7	25	25.29	5.59	0.22	0.00	Accept	Accept	N/LN
		7/8	25	25.24	3.70	0.15	-0.07	Accept	Accept	N/LN
		7/9	25	24.90	4.99	0.20	-0.40	Accept	Reject	N
		7/10	25	34.96	3.25	0.09	-0.43	Accept	Accept	N/LN
	25 cm	6/26	25	24.47	7.69	0.31	-0.76	Reject	Reject	-
		6/27	25	25.81	5.39	0.21	0.19	Accept	Accept	N/LN
		6/28	25	26.34	6.15	0.23	-0.28	Accept	Reject	N
		6/29	25	24.53	5.73	0.23	-0.28	Accept	Reject	N
		6/30	24	23.66	6.41	0.27	0.01	Accept	Reject	N
		7/1	23	23.66	5.07	0.21	0.10	Accept	Accept	N/LN

Table 1-3. Summary of field statistics and PPCC test (Fitness of PDF lists which probability density functions are appropriate.) (Continued)

		7/3	24	20.61	5.60	0.27	0.48	Accept	Accept	N/LN
		7/5	25	26.36	4.92	0.19	0.05	Accept	Accept	N/LN
		7/7	25	25.56	5.91	0.23	0.19	Accept	Accept	N/LN
		7/8	25	25.68	4.91	0.19	-0.13	Accept	Accept	N/LN
		7/9	24	25.73	4.94	0.19	-0.46	Accept	Reject	N
		7/10	25	35.08	3.03	0.09	-0.29	Accept	Accept	N/LN
	Total	6/26	25	21.40	5.69	0.27	-0.03	Accept	Reject	N
		6/27	25	21.85	5.45	0.25	0.16	Accept	Accept	N/LN
		6/28	25	22.49	5.63	0.25	0.25	Accept	Accept	N/LN
		6/29	25	20.77	4.94	0.24	0.17	Accept	Accept	N/LN
		6/30	24	19.59	5.68	0.29	0.14	Accept	Accept	N/LN
		7/1	23	18.99	4.67	0.25	0.24	Accept	Accept	N/LN
		7/3	24	17.59	5.06	0.29	0.49	Accept	Accept	N/LN
		7/5	25	25.80	4.23	0.16	-0.12	Accept	Accept	N/LN
		7/7	25	27.06	4.68	0.17	0.22	Accept	Accept	N/LN
		7/8	25	25.46	3.42	0.13	-0.20	Accept	Accept	N/LN
		7/9	24	24.29	4.27	0.18	-0.19	Accept	Accept	N/LN
		7/10	25	35.01	2.32	0.07	0.12	Accept	Accept	N/LN
WC13	0 cm	6/27	30	14.49	7.65	0.53	0.77	Reject	Accept	LN
		6/28	31	11.04	5.65	0.51	1.41	Reject	Accept	LN
		6/29	31	10.14	4.76	0.47	0.66	Accept	Accept	N/LN
		6/30	31	13.24	8.88	0.67	1.37	Reject	Reject	-
		7/1	28	13.45	7.82	0.58	1.49	Reject	Accept	LN
		7/3	23	9.83	5.84	0.59	1.19	Reject	Accept	LN
		7/5	24	22.46	4.02	0.18	-0.09	Accept	Accept	N/LN
		7/6	31	21.96	4.39	0.20	0.30	Accept	Accept	N/LN
		7/7	31	24.44	5.39	0.22	-0.99	Reject	Reject	-
		7/8	31	21.05	3.35	0.16	0.12	Accept	Accept	N/LN
	5 cm	6/27	31	20.69	6.82	0.33	0.31	Accept	Accept	N/LN
		6/28	31	20.91	7.85	0.38	0.41	Accept	Accept	N/LN
		6/29	31	20.24	7.14	0.35	0.30	Accept	Accept	N/LN
		6/30	31	16.33	8.48	0.52	1.10	Reject	Accept	LN
		7/1	27	19.71	10.14	0.51	0.39	Reject	Reject	-
		7/3	23	16.74	9.34	0.56	0.60	Reject	Accept	LN
		7/5	22	22.98	5.70	0.25	0.36	Accept	Accept	N/LN
		7/6	31	23.24	6.39	0.28	-0.07	Accept	Accept	N/LN
		7/7	31	25.79	5.98	0.23	0.11	Accept	Accept	N/LN
		7/8	30	23.28	6.87	0.29	0.12	Accept	Accept	N/LN
	15 cm	6/27	31	27.00	6.18	0.23	-0.70	Accept	Reject	N
		6/28	31	25.16	6.56	0.26	-0.76	Accept	Reject	N
		6/29	31	24.04	7.33	0.30	-0.70	Accept	Reject	N
		6/30	31	19.84	9.72	0.49	0.32	Reject	Accept	LN
		7/1	28	20.66	9.18	0.44	0.37	Reject	Accept	LN
		7/3	23	20.80	8.40	0.40	0.12	Accept	Reject	N
		7/5	22	22.82	6.31	0.28	0.11	Accept	Accept	N/LN
		7/6	31	25.83	6.15	0.24	0.20	Accept	Accept	N/LN
		7/7	31	27.47	5.25	0.19	-0.01	Accept	Accept	N/LN
		7/8	30	23.86	5.53	0.23	0.34	Accept	Accept	N/LN

Table 1-3. Summary of field statistics and PPCC test (Fitness of PDF lists which probability density functions are appropriate.) (Continued)

25 cm	6/27	31	30.15	4.68	0.16	-0.95	Reject	Reject	-
	6/28	31	29.38	4.70	0.16	-0.47	Accept	Reject	N
	6/29	31	28.13	7.35	0.26	-1.53	Reject	Reject	-
	6/30	30	23.38	9.69	0.41	-0.11	Accept	Reject	N
	7/1	26	26.36	7.28	0.28	0.13	Accept	Accept	N/LN
	7/3	23	25.00	8.48	0.34	-0.83	Accept	Reject	N
	7/5	22	24.60	7.04	0.29	-0.13	Accept	Accept	N/LN
	7/6	30	28.61	5.23	0.18	0.04	Accept	Accept	N/LN
	7/7	31	29.36	4.75	0.16	0.37	Accept	Accept	N/LN
	7/8	29	26.56	5.31	0.20	-0.10	Accept	Accept	N/LN
Total	6/27	30	24.04	5.54	0.23	0.05	Accept	Accept	N/LN
	6/28	31	22.72	5.52	0.24	0.29	Accept	Accept	N/LN
	6/29	31	21.71	6.14	0.28	-0.55	Accept	Reject	N
	6/30	31	18.97	7.39	0.39	0.68	Accept	Accept	N/LN
	7/1	25	20.56	7.45	0.36	0.63	Reject	Accept	LN
	7/3	23	18.96	7.29	0.38	0.33	Accept	Reject	N
	7/5	22	23.28	5.12	0.22	0.22	Accept	Accept	N/LN
	7/6	30	25.28	4.87	0.19	0.22	Accept	Accept	N/LN
	7/7	31	27.01	4.43	0.18	0.54	Accept	Accept	N/LN
	7/8	31	24.09	4.84	0.20	0.20	Accept	Accept	N/LN

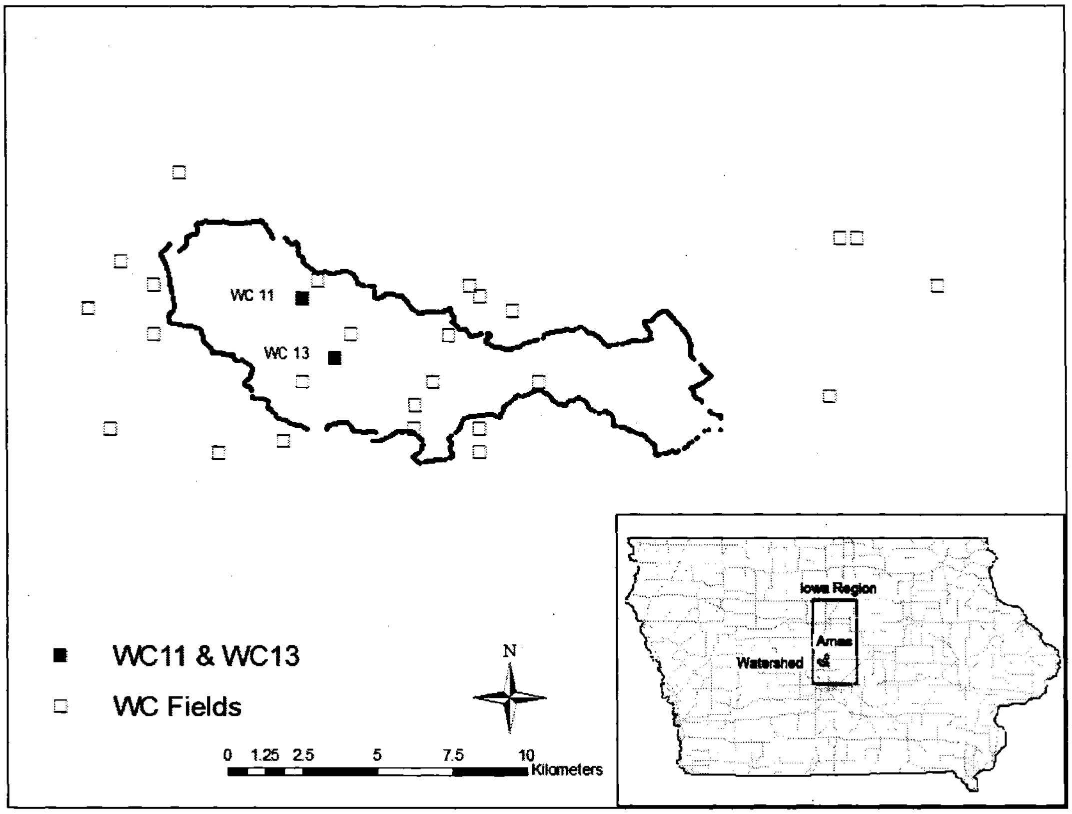

Figure 1-1(a). Walnut Creek Watershed for the SMEX02

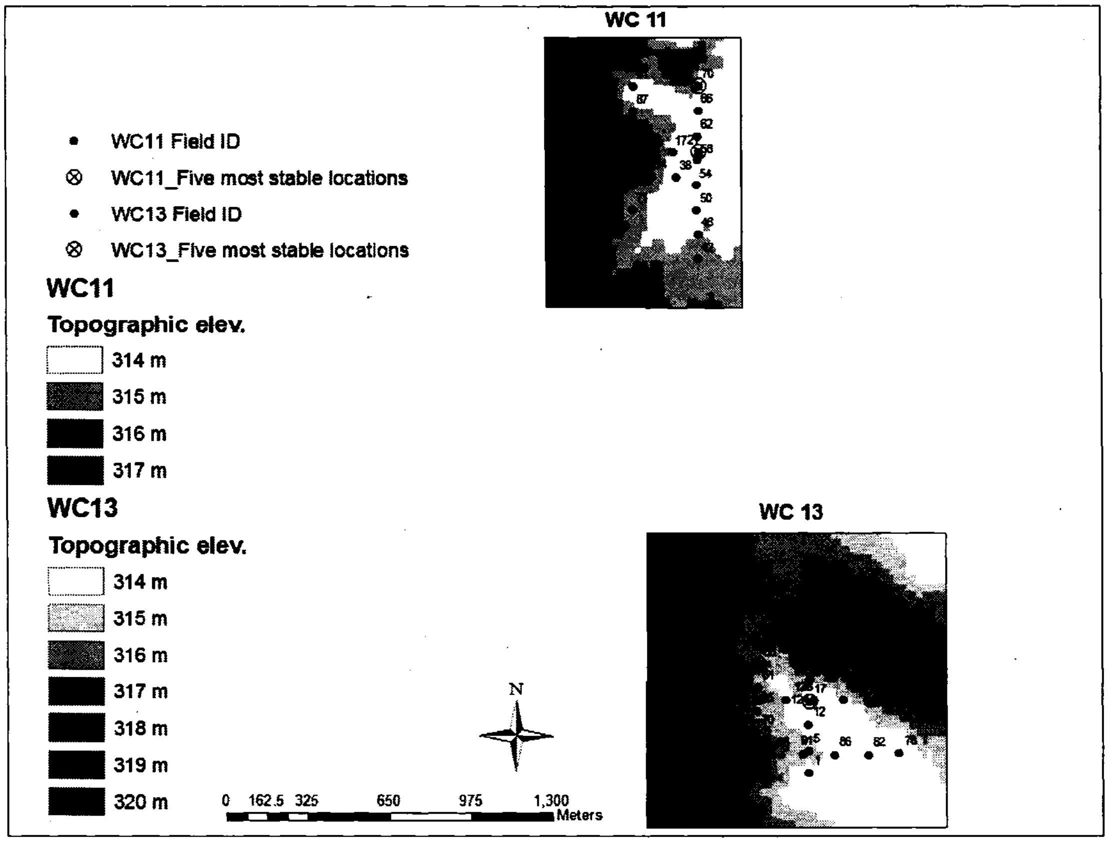

Figure 1-1(b). Sampling locations in the WC11 (25 sampling points) and WC13 (31 sampling points) fields

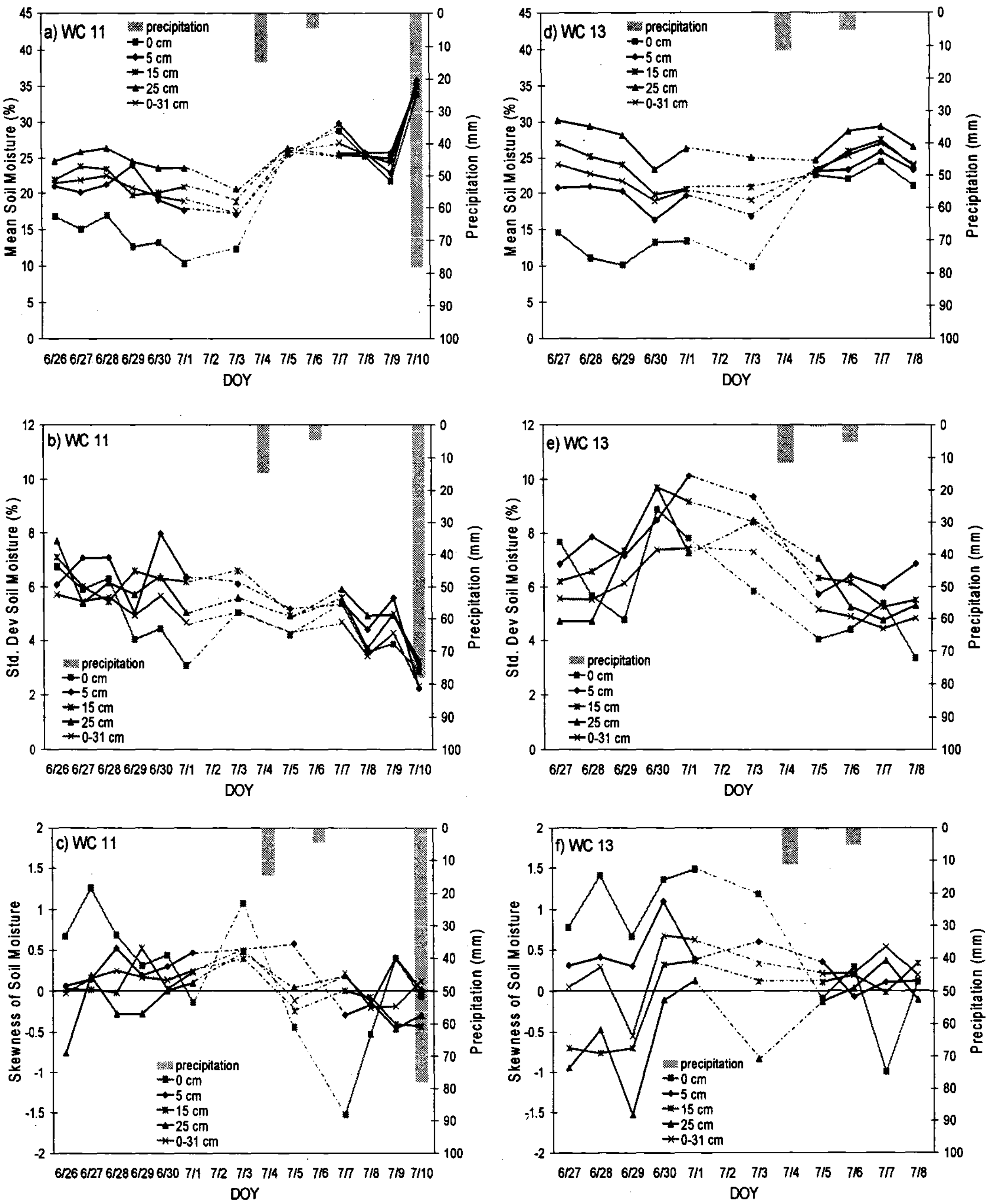

Figure 1-2. Soil moisture statistics and precipitation for fields WC 11 and WC 13 by day of year (Note: Dashed lines aid the visual inspection at the missing data points)

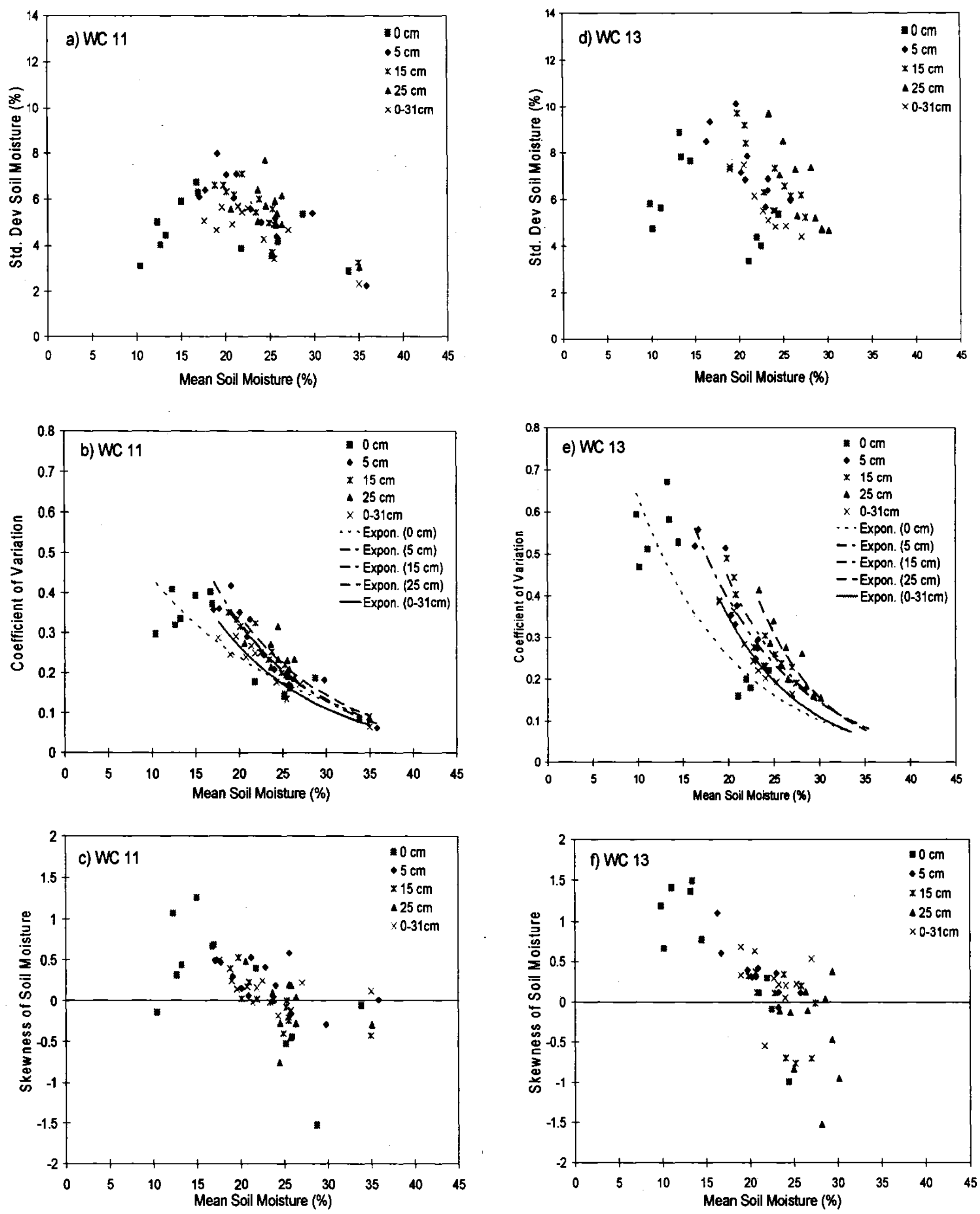

Figure 1-3. Relationships between volumetric soil moisture and statistics for WC11 and WC13

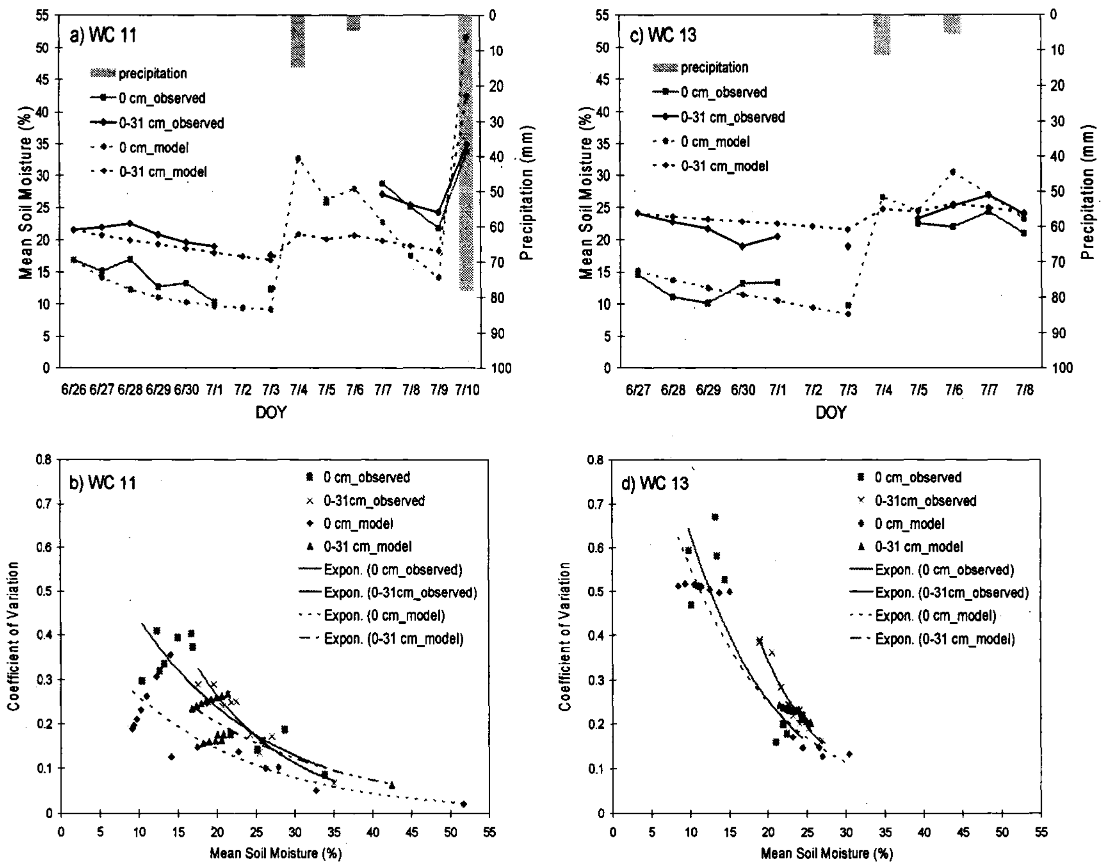

Figure 1-4. Observed and simulated mean soil moisture versus day of year (DOY) and relationships between volumetric soil moisture and statistics of observed data and simulated results for WC11 and WC13

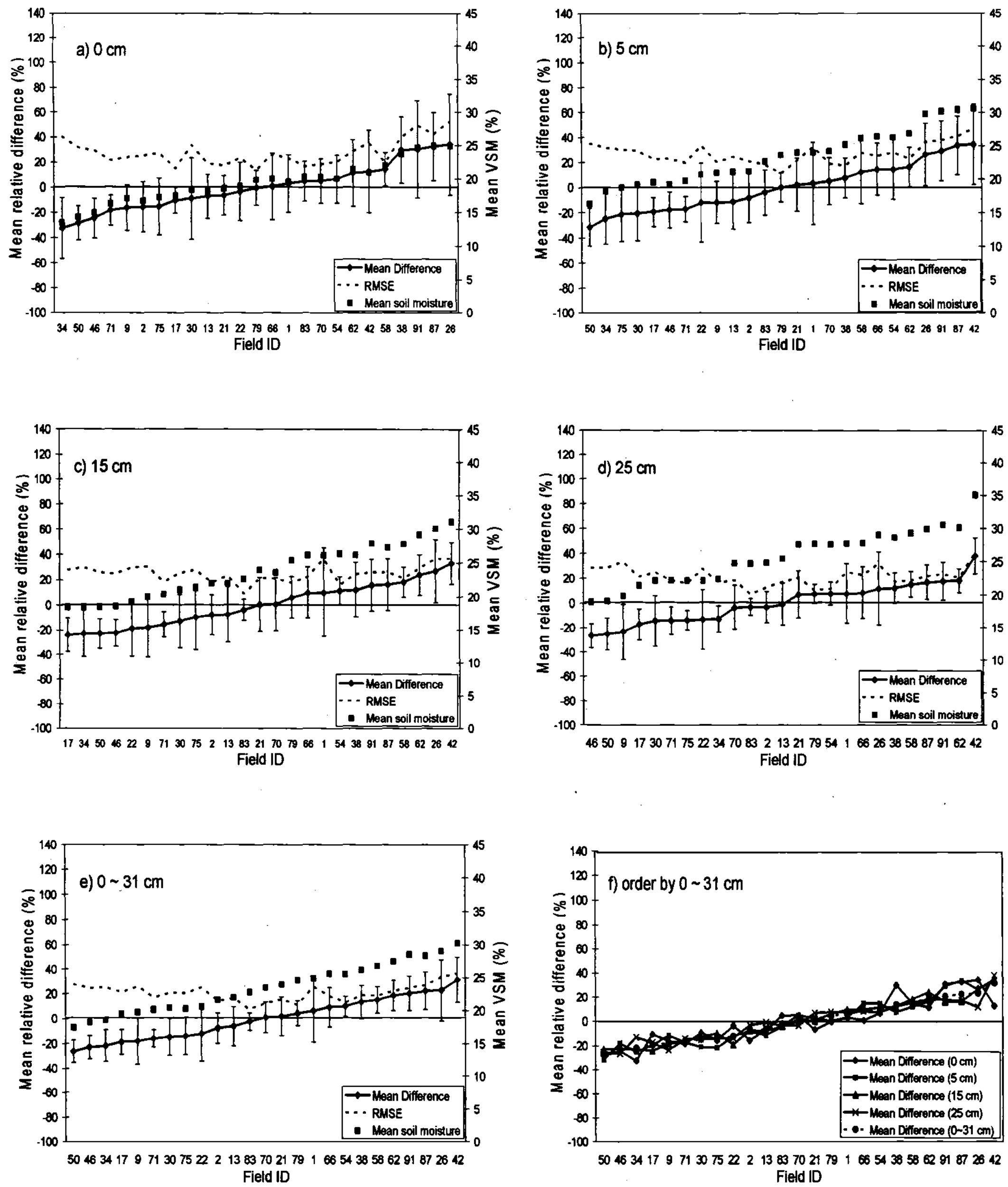

Figure 1-5. Rank ordered mean relative difference with standard deviation error bars, root mean square error, and mean volumetric soil moisture content for a) 0 cm, b) 5 cm, c) 15 cm, d) 25 cm, and e) 0-31 cm depths and f) mean relative differences for all depths where field ID is ordered by 0-31 cm depth ranking in WC11 field

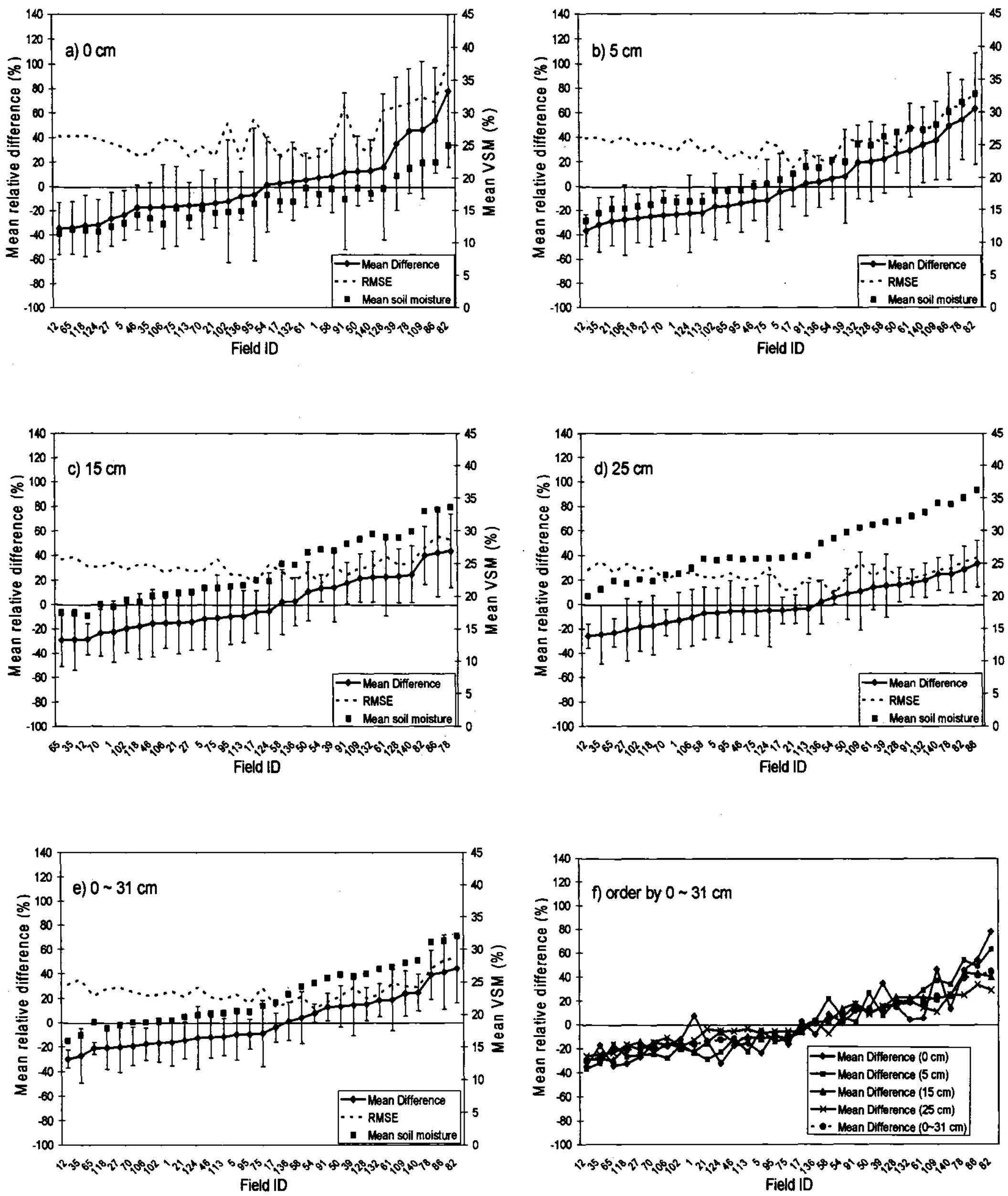

Figure 1-6. Rank ordered mean relative difference with standard deviation error bars, root mean square error, and mean volumetric soil moisture content (%) for a) 0 cm, b) 5 cm, c) 15 cm, d) 25 cm, and e) 0-31 cm depths and f) mean relative differences for all depths where field ID is ordered by 0-31 cm depth ranking in WC13 field

CHAPTER 2.

SCALED SPATIAL VARIABILITY OF SOIL MOISTURE FIELDS

Abstract

Knowledge of spatial soil moisture variability is essential to understand the spatial variability of the land surface hydrologic cycle at a range of scales. In this study, soil moisture spatial variability patterns are identified using measurements across different scales (i.e., field, watershed, and basin scales) and depths (i.e., from surface to root zone profile) from 18 different soil moisture field experiments. The spatial variability patterns are well represented by negative exponential functions between the mean and the coefficient of variation of soil moisture. Rainfall and topography are the most important physical parameters to understand how surface soil moisture variability changes as soils dry. Soil parameters control the maximum relative variability. The soil moisture variability typically decreases as sampling scale increases, while the soil moisture variability increases as soil depth increases. These common soil moisture variability patterns can provide a feasible methodology to validate land surface models.

Introduction

Knowledge of spatial soil moisture variability may provide the blueprint for future ground-based experiments and networks (Famiglietti et al., 1999; Ryu and Famiglietti, 2005). Moreover, its variability information is very crucial to understand and improve the parameterization for land surface hydrologic modeling (Giorgi and Avissar, 1997; Crow and Wood, 2002). However, soil moisture variability is not well understood over a range of scales and depth or across sites (Famiglietti et al., 1999; Martinez-Fernandez and Ceballos, 2003; Jacobs et al., 2004). Although numerous studies have characterized soil moisture, there is no agreement as to whether soil moisture variability is positively (Hills and Reynolds, 1969; Henninger et al., 1976; Bell et al., 1980; Robinson and Dean, 1993; Famiglietti et al., 1998; Martinez-Fernandez and Ceballos, 2003) or negatively (Famiglietti et al., 1999; Hupet and Vanclooster, 2002) correlated to mean soil moisture content.

The spatial soil moisture variability is mainly affected by physical properties such as climate, soil texture, vegetation, and topography in natural catchment or agricultural land (Grayson and Western, 1998). Jacobs et al. (2004) and Mohanty and Skaggs (2001) concluded that topography is a crucial physical factor to understand surface soil moisture variability. Teuling and Troch (2005) pointed out that soil and vegetation may be important factors that increase or decrease soil moisture spatial variance. They concluded that a simple soil moisture model provides a preliminary link between physical process and statistical variability patterns. Choi and Jacobs (2006) also concluded that a simple physical model provides insight to statistical relationships necessary to disaggregate physical land surface model predictions. Additionally, soil moisture variability may differ by spatial scale (Crow and Wood, 1999).

The objective of this study is to identify common patterns among soil moisture statistics across a variety of landscapes. Specifically, the relationships between mean soil moisture and spatial variability of soil moisture measurements are quantified. Spatial variability patterns are examined in light of local physical properties including climate, soil, topography, scale, and vegetation. This study differs from previous studies in that it 1) brings together measurements from 18 different experiments across the world, 2) includes both surface and root zone soil moisture, and 3) uses multivariate statistics to identify the effect of physical properties on soil moisture spatial variability.

Study Region

Table 2-1 identifies the 18 datasets (from 9 distinct field experiments) used in this study and provides detailed information for each study region and experiment. Additional information is available from the references listed in Table 2-1. Thirteen of the soil moisture datasets were obtained from the Southern Great Plains 1997 (SGP97) experiment and Soil Moisture Experiments 2002 (SMEX02), 2003 (SMEX03), 2004 (SMEX04), and 2005 (SMEX05) (Mohanty et al., 2002; Jacobs et al., 2004; Bosch et al., 2005; Cosh et al., 2006; Choi et al., 2005). SMEX are a series of soil moisture field experiment conducted annually from 2002 to 2005 (SMEX02 - SMEX05) in Iowa, Georgia, Alabama, Oklahoma, and Arizona. Additional datasets are from Florida, Belgium (Hupet and Vanclooster, 2002), and Spain (Martinez-Fernandez and Ceballos, 2003). The sites are predominantly agricultural lands with some forests, pastures, and clear cuts. Eleven datasets have only surface soil moisture measurements from approximately 0-6 cm. The remaining datasets include a profile of measurements in the root zone. All locations were sampled using in-situ devices, except the Iowa basin (Data ID E) which uses Polarimetric Scanning Radiometer (PSR) instrument.

Methods

Statistical Analysis

Statistical moments of soil moisture measurements, mean and coefficient of variation, were calculated by site, soil depth, and time. Jacobs et al. (2004) quantified the negative relationship between the surface mean soil moisture content and the coefficient of variation using an exponential fit for four fields from SMEX02. Exponential fits $CV = Ae^{B\theta}$ between mean soil moisture and coefficient of variation were conducted using observed standard deviation of soil moisture and temporal average standard deviation of soil moisture by site and soil depth. Comparisons between paired exponential fits using observed standard deviation of soil moisture and temporal average standard deviation of soil moisture at each site allow us to examine how fitting parameters, A and B, are significantly different from fitting parameters, A and B, using constant standard deviations.

Principal Component Analysis

A principal component analysis (PCA) was used to identify which physical properties were significant to understand hydrologic variability and how major principal components were related to surface soil moisture fitting parameters, A and B. The PCA is a multivariate statistics technique for data reduction and deciphering patterns within large sets of data (Stetzenbach et al., 2001; Farnham et al., 2003). It describes the variance-covariance structure of a number of variables by a few linear combinations of given variables (Johnson and Wichern, 2002). The principal components of the p random variables, $X_1, X_2, \ldots, X_P$ are determined by the p eigenvectors of the covariance matrix. The i^{th} principal component (Johnson and Wichern, 2002) is defined as

$$Y_i = e_i' X_i \tag{2-1}$$

where X_i are random vectors and e_i are eigenvectors. The variance of Y_i can be determined by

$$Var(Y_i) = e_i' \Sigma e_i = \lambda_i \tag{2-2}$$

where λ_i are eigenvalues of the covariance matrix. The maximum quantity of variance is explained by the first principal component (1st PC). Detailed descriptions for the PCA can be found in Johnson and Wichern (2002).

For this study, PCA was applied using standardized variables to ensure the same weight of each different physical parameter. Normalized scale, annual rainfall, soil porosity, wilting point, field capacity, percentage sand, leaf area index (LAI), and maximum difference of elevation for nine sites having sufficient physical parameters were used to conduct the PCA analysis (Table 2-1). Correlation coefficients between the first three principal components and the physical properties were calculated to quantify the physical variables' importance for the principal components. Correlation coefficients between the first three principal components and the fitting parameters, A and B, were also conducted to identify how the principal components are related to fitting parameters.

Results and Discussion

Figure 2-1 shows the relationships between the mean soil moisture and the coefficient of variation of soil moisture by datasets and measurement depth. Figure 2-1 also shows superimposed lines derived from a postulation that soil moisture has constant standard deviations (i.e., standard deviation values range from 1 to 13). The coefficient of variation exponentially decreases as the mean soil moisture increases for all data sources except the Duero surface data. This result is consistent with the previous studies at individual sites (Bell et al., 1980; Owe et al., 1982; Charpentier and Groffman, 1992; Famiglietti et al., 1999).

Table 2-2 lists the exponential fit $CV = Ae^{B\theta}$ including parameters A, B, and the correlation coefficient. The parameter A is related to the maximum relative variability, while the parameter B is related to the slope of the relative variability. The fitting parameters, A and B, vary by site and depth. The average values of A, B, and R^2 for all regions were 1.690, -0.061, and 0.656, respectively. All sites showed very strong correlations except Arizona (SMEX04), Boone County, and Duero. The magnitudes of A and B typically increase as the spatial scale decreases. For example, B values for surface measurement range from -0.091 to -0.061 for the field scale and from -0.037 to -0.001 at a watershed and basin scale, respectively in SMEX02. This result is explained by Rodriquez-Iturbe et al.'s (1995) finding that the soil moisture variance decreases according to a power function as the sampling scale increases. Crow and Wood (1999) found that soil moisture statistics differed for the field and watershed scales during the SGP97. Our study shows that the SGP97 field scale does have a greater relative decrease in variability than the watershed scale. However, a consistent negative relationship between mean soil moisture and coefficient of variation exists at both scales (Table 2-2).

The absolute values of A and B also increase as soil depth increases. The surface has the least negative relationship (i.e., A and B parameters closest to zero). These results extend Choi and Jacobs's (2006) finding that the surface has a smaller decrease in variability per change in soil moisture than the deeper layers.

Matched pair *t*-tests, commonly used to identify differences in paired observations, were conducted to determine if the exponential models using site specific constant standard deviation values differed from models derived from the observations. The null hypothesis, H_o was that the mean differences between a fitting parameter, A or B, from observational derived exponential model and that determining by fitting the average standard deviation were identical. Separate analyses were performed for each parameter, first using the 16 surface models parameters, then the 30 root zone models parameters (Table 2-2). At the surface, there was no significant difference for either A, or B (p values are 0.194 and 0.086, respectively). However, for the root zone, there was a significant difference for both the A and B parameters (p values are 0.002 and 0.007, respectively). These results indicate that root zone soil moisture spatial variability is more heterogeneous than surface soil moisture spatial variability and its variability across sites cannot be captured by the average standard deviation of soil moisture. That the *p* value of B at surface comparison also indicates the average standard deviation may be problematic to represent soil moisture variability at surface and root zone.

Differences of soil moisture variability among sites are quantified as the standard deviation of soil moisture. The PCA was used to characterize these differences related to physical properties including climate, soil, and vegetation and to identify how the fitting parameters are related to physical properties. The first three PCs, collectively, accounted for 93.15% of the total variance (Table 2-3), capturing most of physical properties' variability. Table 2-3 also shows that the most important controlling parameters for the first PC are porosity, wilting point, and field capacity, all soil factors. The second PC was equally well correlated with annual rainfall and the maximum difference of elevation. The third PC, highly correlated with scale, explains less of the variability. Famiglietti et al. (1995) and Syed et al. (2004) found that precipitation and potential evaporation were the major principal component to understand the spatial variability of hydrologic cycle in regional scale. Our results are consistent with these previous studies in that precipitation is one of the major principal components. In addition, our results provide another insight that soil related factors may be one of the most significant physical factors to understand hydrological variability.

The correlation between the major PCs and the surface soil moisture model fitting parameters shows that the A fitting parameter was most highly correlated with the first PC (Table 2-3). This indicates that soil parameters control the maximum coefficient of variation. The B fitting parameter was most strongly correlated with the second PC. The relative change in the soil moisture coefficient of variation with respect to mean moisture is better explained by rainfall and topography. Our results provide additional insight to Jacobs et al. (2004) and Mohanty and Skaggs (2001) findings that topography was the most important factor to understand surface soil moisture structure for the SMEX02 and SGP97 experiment. That they found soil related factors to be significant during inter-storm periods is supported by the correlation between soil properties and the A parameter, which controls the relative variance under dry conditions.

Conclusion

Our results show that the relationships between mean soil moisture and coefficient of variation are clearly explained by an exponential fit for a profile of soil moisture measurements. The surface soil moisture variability patterns characterized by the exponential fit are mostly affected by soil factors in terms of variability magnitude. The rainfall and topography are most significant factors to characterize how variability changes with mean surface soil moisture. Our statistical variability information is essential to identify appropriate statistical distributions and physical parameters for land surface hydrologic modeling over a range of scales (i.e., from sub-grid to whole grid scales). Further, the information on proper statistical distributions and parameter values can be used to validate land surface models' ability to characterize heterogeneity effects by scale and soil depth.

Table 2-1. Summary of field characteristics and data. Soil parameters are soil type, wilting point (θ_{wp}), field capacity (θ_{fc}), and porosity (ϕ) (Note: * indicates sites used for PCA analysis and ★ indicates physical properties used for PCA.)

Locations	ID	Sampling Approach					Site Description										Reference
		Scale ★ (km^2)	# of Points	Date	Frequency	Depth	Soil	θ_{wp} ★1	θ_{fc} ★1	ϕ ★2	Sand ★3 (%)	Relief	Max.Diff Elev. ★4	Land Use	LAI★	Annual Rainfall★ (mm)	
Iowa, US (SMEX02)	A*	Basin (5000)	48	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	22	Low	138	Agriculture	2.19	835	SMEX02 Dataset
	B*	Watershed (100)	33	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	2.65	835	SMEX02 Dataset
	C*	Field 11 (0.64)	25	6/02–7/02	Daily	Profile	Loam	0.15	0.35	0.48	29	Rolling	3.7	Corn	2.96	835	Choi & Jacobs, 2006
	D*	Field 13 (0.64)	31	6/02–7/02	Daily	Profile	Loam	0.15	0.35	0.48	29	Rolling	6.1	Soybeans	1.09	835	Choi & Jacobs, 2006
	E	Basin (5000)	10080	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	-	Low	-	Agriculture	-	835	SMEX02 Dataset
Georgia, US (SMEX03)	F*	Basin (3750)	49	6/03 – 7/03	Daily	Surface	Sand	0.05	0.10	0.40	75	Gently sloping	58	Forest, Pasture, Agriculture	1.89	1160	Bosch et al, 2005
	G*	Watershed (334)	17	6/03 – 7/03	Continuous	Profile	Loam	0.09	0.27	0.45	78	Gently sloping	32	Forest, Pasture, Agriculture	2.07	1160	Bosch et al, 2005
Arizona, US (SMEX04)	H*	Basin (3750)	40	8/04 – 8/04	Daily	Surface	Loam, Rock	0.09	0.27	0.45	41	Flat	568	Brush, Rangeland	0.44	350	SMEX04 Dataset
	I*	Watershed (150)	64	8/04 – 8/04	Daily	Surface	Loam, Rock	0.09	0.27	0.45	45	Flat	335	Brush, Rangeland	0.43	350	Cosh et al, 2006

Table 2-1. Summary of field characteristics and data. Soil parameters are soil type, wilting point (θ_{wp}), field capacity (θ_{fc}), and porosity (ϕ) (Note: * indicates sites used for PCA analysis and ★ indicates physical properties used for PCA.) (Continued)

Iowa, US (SMEX05)	J	Watershed (100)	32	6/05 – 7/05	Daily	Surface	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	-	835	SMEX05 Dataset
	K	Watershed (100)	10	6/05 – 7/05	Daily	Profile	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	-	835	Choi et al, 2005
Florida, US	L	Field (0.01)	40	2/98 – 3/98	Daily	Surface	Sand	0.05	0.10	0.40	92	Flat	5	Clear-cut	-	1315	Fischer, 1998
	M	Field (2.5×10^{-5})	72	2/98 – 3/98	Daily	Surface	Sand	0.05	0.10	0.40	92	Flat	5	Slash pine forest	-	1315	Fischer, 1998
Boone County, Iowa, US	N	Field (2×10^{-3})	30	5/00– 9/00	Weekly	Profile	Loam	0.15	0.33	0.47	37	Low	3.1	Agriculture	-	800	Irmak et al, 2002
Louvain-la-Neuve, Belgium	O	Field (6.3×10^{-3})	28	5/99– 9/99	Daily	Profile	Silty loam	0.13	0.33	0.49	6	Low	3.5	Agriculture	3.63	780	Hupet & Vanclooster, 2002
Duero, Spain	P	Basin (1285)	23	6/99 – 5/02	Fortnigh tly	Profile	Sandy loam	0.05	0.15	0.44	71	Flat	200	Agriculture	-	385	Martinez & Ceballos, 2003
Oklahoma,U S (SGP97)	Q*	Watershed (610)	23	6/97 – 7/97	Daily	Surface	Silt, Loam	0.09	0.22	0.44	58	Rolling	200	Rangeland, Pasture	2.30	750	Crow & Wood, 1999
	R	Field 21 (0.64)	49	6/97 – 7/97	Daily	Surface	Silty loam	0.13	0.33	0.49	35	Flat	-	Wheat, Grass	1.10	750	Crow & Wood, 1999

[1] Dunne and Leopold [1978]
[2] Clapp and Hornberger [1978]
[3] STATSGO (http://www.ncgc.nrcs.usda.gov/products/datasets/statsgo/)
[4] GTOPO30 (http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html)

Table 2-2. Regression relationship between the coefficient of variation and the mean soil moisture where $CV = Ae^{B\theta}$

Sites	Data ID	Scale (km^2)	In-situ Depth	A	B	R^2
SMEX02	A	Basin (5000)	surface	0.555	-0.036	0.729
	B	Watershed (100)	surface	0.474	-0.037	0.341
	C	Field WC11 (0.64)	surface	0.800	-0.061	0.801
			5cm	2.066	-0.092	0.914
			15cm	1.841	-0.087	0.904
			25cm	1.918	-0.086	0.815
	D	Field WC13 (0.64)	surface	1.581	-0.091	0.811
			5cm	2.858	-0.100	0.870
			15cm	4.019	-0.110	0.881
			25cm	9.751	-0.138	0.851
	E	Basin (5000)	surface	0.372	-0.001	0.003
SMEX03	F	Basin (3750)	surface	1.637	-0.087	0.924
	G	Watershed (334)	surface	0.885	-0.061	0.807
			20cm	1.539	-0.091	0.921
			30cm	0.914	-0.054	0.585
SMEX04	H	Basin (3750)	surface	0.943	-0.058	0.569
	I	Watershed (150)	surface	0.548	-0.021	0.202
SMEX05	J	Watershed (100)	surface	0.795	-0.066	0.845
	K	Watershed (100)	surface	0.873	-0.055	0.795
			5cm	2.077	-0.085	0.927
			10cm	2.445	-0.089	0.921
			15cm	2.863	-0.091	0.914
			25cm	8.152	-0.124	0.896

Table 2-2. Regression relationship between the coefficient of variation and the mean soil moisture where $CV = Ae^{B\theta}$ (Continued)

			50cm	3.069	-0.108	0.619
Florida	L	Field Mize (0.01)	surface	0.563	-0.018	0.423
	M	Field Donaldson (2.5×10^{-5})	surface	0.456	-0.049	0.897
Boone County, Iowa	N	Field (2×10^{-3})	0-15cm	0.240	-0.017	0.172
			15-30cm	0.242	-0.003	0.090
			30-45cm	0.359	-0.011	0.378
			45-60cm	0.271	-0.004	0.028
			60-75cm	0.381	-0.018	0.304
			75-90cm	0.473	-0.021	0.868
			90-105cm	0.563	-0.024	0.820
			105-120cm	0.619	-0.027	0.703
Louvain-la-Neuve (Belgium)	O	Field (6.3×10^{-3})	0-20cm	1.436	-0.094	0.956
			25m	0.925	-0.079	0.967
			50cm	1.511	-0.100	0.917
			75cm	4.618	-0.123	0.937
			100m	5.136	-0.109	0.951
			125cm	2.206	-0.085	0.949
Duero (Spain)	P	Basin (1285)	surface	0.423	0.000	0.000
			25cm	0.497	-0.007	0.023
			50cm	0.590	-0.010	0.070
			100cm	0.557	-0.014	0.180
Oklahoma, US (SGP97)	Q	Watershed (610)	surface	1.035	-0.061	0.789
	R	Field LW21 (0.64)	surface	1.681	-0.084	0.921

Table 2-3. Correlation coefficients among the principal components, physical property, and fitting parameters, A and B, where $CV = Ae^{B\theta}$

Principal Component	Variance Explained	Correlation by Physical Property								Correlation by Fitting Parameter	
		Scale	Porosity	Rainfall	Wilting point	Field capacity	Sand	LAI	Max diff elevation	A	B
1^{st} PC	50.33	-0.613	**0.978**	-0.203	**0.982**	**0.964**	-0.802	0.203	-0.277	**-0.348**	0.178
2^{nd} PC	32.60	-0.265	-0.097	**0.934**	0.088	-0.130	0.326	0.818	**-0.925**	0.235	**-0.389**
3^{rd} PC	10.21	**0.718**	-0.036	0.097	0.089	0.012	-0.424	0.319	0.035	-0.168	0.101

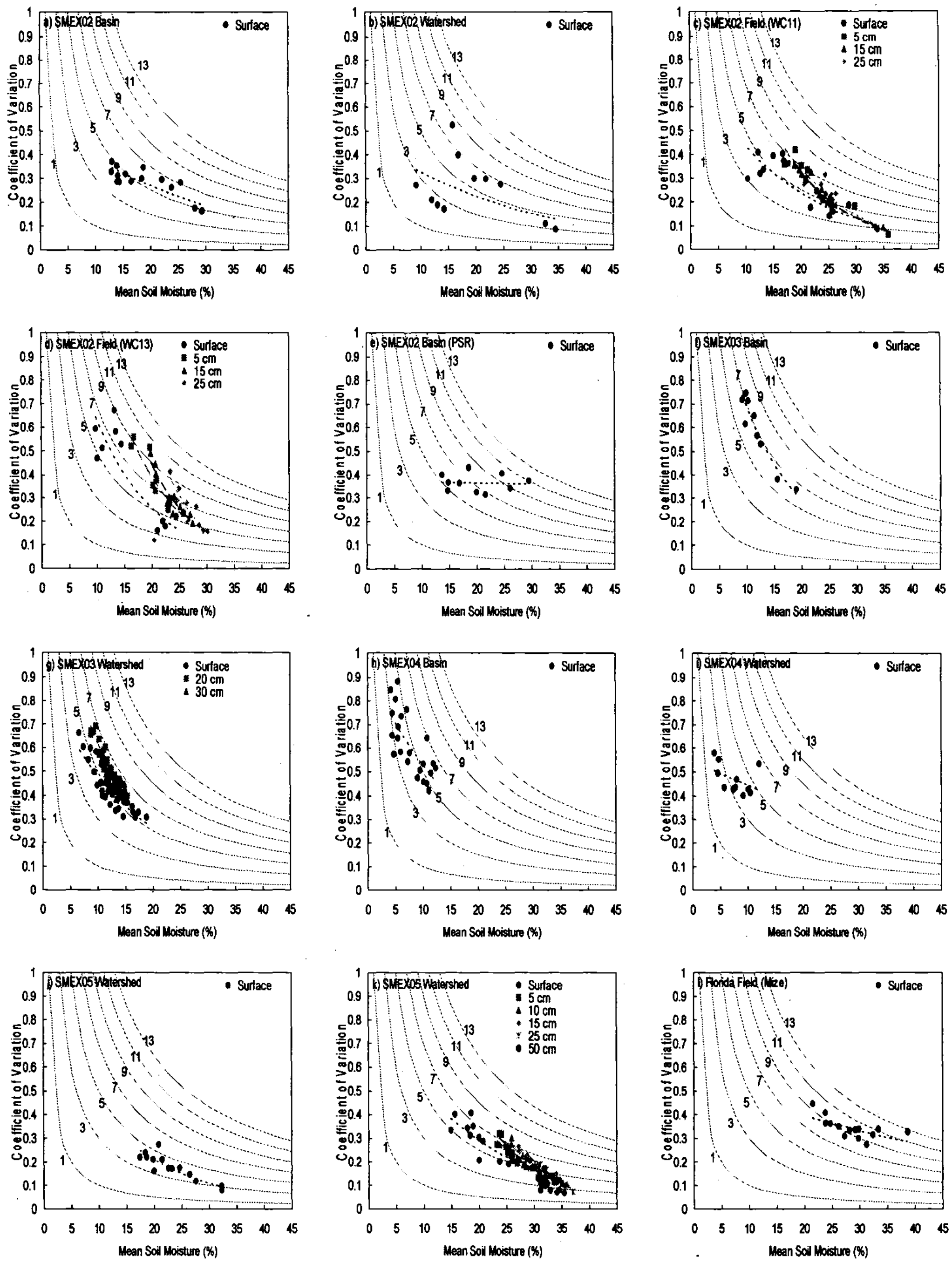

Figure 2-1. Relationship between mean soil moisture and coefficient of variation (a) SMEX02 Basin ~ (r) SGP97 Field (LW21) (Note: Superimposed lines are derived from constant standard deviation values, 1, 3, 5, 7, 9, 11, and 13)

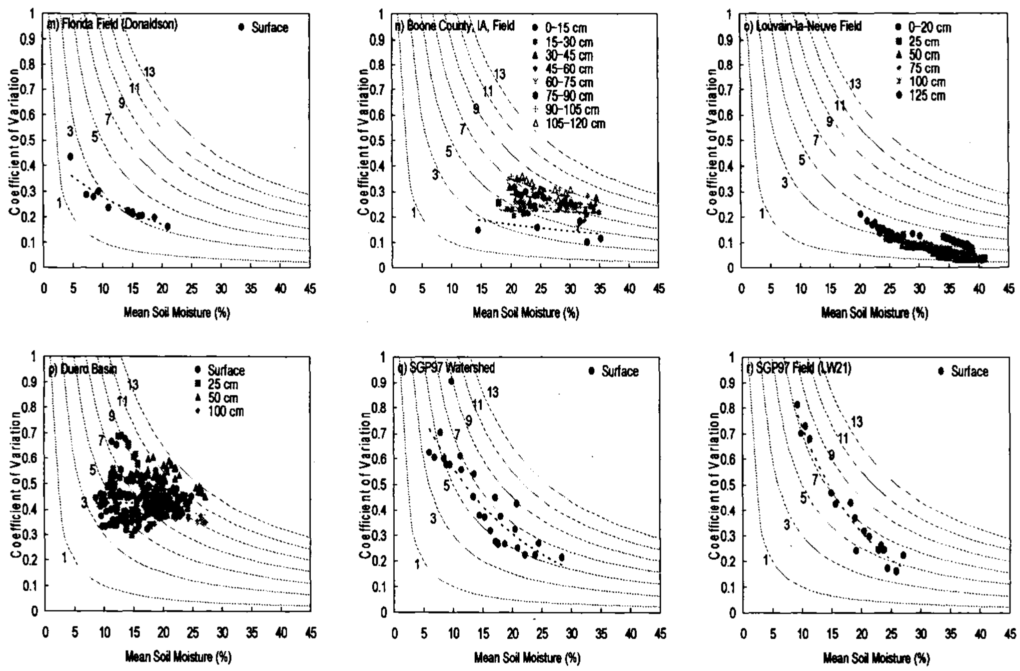

Figure 2-1. Relationship between mean soil moisture and coefficient of variation (a) SMEX02 Basin ~ (r) SGP97 Field (LW21) (Note: Superimposed lines are derived from constant standard deviation values, 1, 3, 5, 7, 9, 11, and 13) (Continued)

CHAPTER 3.

LONG TERM CONFORMITY OF SURFACE SOIL MOISTURE FROM REMOTELY SENSED DATA, LAND SURFACE MODEL, AND GROUDN BASED DATA: SMEX03 LITTLE RIVER REGION

Abstract

Optimal soil moisture estimation may be characterized by inter-comparisons among remotely sensed measurements, ground-based measurements, and land surface models. In this study, we compared soil moisture from Advanced Microwave Scanning Radiometer E (AMSR-E), ground-based measurements, and SVAT model (Common Land Model) at SMEX03 Little River region, GA. The comparison results showed that there is good agreement among different soil moisture products for short and long periods. The CLM reasonably replicated soil moisture patterns in dry down and wetting after rainfall though it had modest wet biases as compared to AMSR-E and ground data. While the AMSR-E average soil moisture agreed well with the other data sources, it had extremely low temporal variability, especially during the growing season from May to October. Overall, both CLM and AMSR-E had complementary strengths, low MAE and RMSE errors for CLM and very low biases for AMSR-E.

Introduction

Soil moisture is an important variable in hydrologic and biologic processes. It is a controlling variable in the exchange of water and heat energy between the land surface and the atmosphere through evaporation and transpiration. It determines the partitioning of precipitation into runoff, infiltration, and surface storage, as well as the partitioning of incoming solar radiation and long wave radiation into outgoing long wave radiation, latent heat flux, ground heat flux, and sensible heat flux (Pachepsky et al., 2003).

There are three approaches to characterize regional soil moisture; remote sensing observations, land surface models, and in-situ field measurements. Aircraft and satellite instruments (i.e., various active and passive microwave sensors) capable of providing mean surface soil moisture (0 - 5 cm) values at large spatial scales are recently available (Jackson et al., 1995, 1999; Schmugge et al., 2002). The ability to monitor soil moisture at large spatial scales by passive microwave sensors has many advantages including the ability to directly measurement soil moisture regardless of weather conditions or time of day (Jackson, 1993; Jackson and Schmugge, 1995).

Ground based in-situ samples typically capture spatial or temporal variability at a range of scales. Intensive field experiments such as Washita'92, SGP97, SGP99, SMEX02, and SMEX03 (Jackson and Schiebe, 1993; Jackson et al., 1999; Mohanty et al., 2002; Bosch et al., 2006) have provided validation data for satellite and aircraft based microwave remote sensing instruments over a wide range of vegetation conditions for short periods. In-situ networks such as the soil climate analysis network (SCAN) operated by Natural Resources Conservation Service (NRCS) (Cosh et al., 2004) and Steven-Vitel Hydra probes networks operated by USDA-ARS Southeast Watershed Research Lab (SEWRL) (Bosch et al., 2006) provide continuous longer-term datasets of soil moisture profiles.

Finally, soil - vegetation - atmosphere transfer (SVAT) models can characterize soil moisture at a range of scales (Lohmann et al., 1998; Liang et al., 1998; Dai et al., 2003). SVAT schemes combine land surface and atmosphere processes modeling using both the water and energy balances (Sellers et al., 1986; Dickinson et al., 1993). There have been extensive efforts to improve SVAT parameterization of the land-surface schemes during the past two decades including the Project for Inter-comparison of Landsurface Parameterization schemes (PILPS) (Yang et al., 1995; Shao and Henderson-Sellers, 1996; Pitman and Henderson-Sellers, 1998; Lohmann et al., 1998; Liang et al., 1998).

Each of the three methods has unavoidable limitations. Remotely sensed soil moisture cannot describe hydrology at the watershed or field scale because its retrieved soil moisture scale is too large (Mohanty and Skaggs, 2001; Jacobs et al., 2004). Another critical issue regarding remotely sensed soil moisture measurements is that the retrieved soil moisture is for a shallow depth and may not be correct for heavily vegetated areas (Schmugge et al., 2002; Margulis et al., 2002). Ground-based measurements can provide reasonable and direct values.

However, aside from the short duration, intensive field experiments, these measurements are very sparse and field or regional mean soil moisture is not properly represented (Reichle et al., 2004). Modeled soil moisture also has inevitable restrictions due to limited measurements of model physical parameters (Mohr et al., 2000; Whitfield et al., 2006) and input data errors (Reichle and Koster, 2004; Reichle et al., 2004).

Given the inherent restrictions caused by scaling mismatch, network density, parameterization, and data errors, ultimately the most effective soil moisture estimations may be accomplished through data assimilation (i.e., data merging procedure) of the remotely sensed measurements, ground-based measurements, and models (Margulis et al., 2002; Reichle et al., 2004). A fundamental principal of assimilation requires the characterization of error statistics from available sources to optimally estimate soil moisture (Crow and Wood, 2003; Reichle and Koster, 2003). Reichle and Koster (2004) and Reichle et al. (2004) showed that bias estimation by comparisons among different data types can be effective for understanding the data errors and identifying significant obstacles to data assimilation.

The objective of this study is to examine the conformity of different soil moisture products (i.e., remotely sensed measurements, ground-based measurements, and modeled results) at Little River, GA region for 2003 as well as during an intensive field experiment. For this study, we address a series of issues; 1) How do surface soil moisture estimates compare among sources? (i.e., satellite data, ground-based measurements, and model soil moisture); 2) How well do soil - vegetation - atmosphere transfer (SVAT) models simulate spatial and temporal variability of surface soil moisture?; 3) How well do Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) on Aqua satellite replicate surface soil moisture patterns?; 4) Are the results from the short duration field campaign robust?; and 5) What are the potential errors of different data sources for optimal soil moisture?

Study Area and Ground Based Measurements

The study region covered a 50 km by 75 km area that was divided into six 25 km by 25 km Equal-Area Scalable Earth Grids (EASE-Grids) (Figure 3-1). The Little River watershed (334 km^2) was included in this region. The watershed, near Tifton, GA, is managed by the USDA-ARS Southeast Watershed Research Lab (SEWRL) to collect hydrologic and climatic data. The Little River is a tributary of the Withlacoochee River, which is one of two main tributaries of the Suwannee River. In the watershed, land use is predominantly row-crop agriculture (40%), pasture (18%), forest (36%), and wetlands and residential (6%) (Bosch et al., 2006). The main crop types are cotton and peanuts with typical growing seasons from May to October. The climate is humid with average annual rainfall of 1160 mm. The soils are mostly sand and well-drained at surface and have relatively high permeability (Miller and White, 1998). More detailed information on study area is provided by Bosch et al. (2006).

For this study, four EASE-Grids A, B, C, and D (25 by 25 km EASE-Grids) that include the Little River watershed were selected (Figure 3-1). Table 3-1 describes the geographic locations and field attributes for four EASE-Grids. Major land uses for four EASE-Grids are cropland and pasture (58.1 – 71.8%), evergreen forest (18.0 – 35.8%), and wetland (4.3 – 8.0%). Surface soil texture for each EASE-Grid is almost identical (i.e., sand and clay contents are 78 and

6%, respectively). In each of the grids, soil moisture data are available from in-situ measurements, satellite observations, and SVAT model predictions.

During SMEX03, intensive ground sampling was conducted at 49 regional sites within six EASE-Grids at Georgia region from June 20 to July 1, 2003 (Figure 3-1). The intensive grounding sampling was conducted daily during the satellite overpass (11:30 am to 2:30 pm EST). Seven or more sampling points were included in each EASE-Grid (Table 3-1). During the experiment, volumetric soil moisture content was measured using theta probes (Dynamax, Inc., Texas). The theta probe measures the average dielectric constant using 6 cm length tines. Of the 49 total sampling points, nine, seven, eight, and thirteen sampling points were averaged to determine the mean soil moisture for EASE-Grids A, B, C, and D, respectively (Table 3-1).

Hydra soil moisture sensors were installed at 19 in-situ network sites in or near the watershed (Figure 3-1). Soil moisture data were provided every 30 minutes at 5, 20, and 30 cm (Bosch et al., 2006). The Hydra probes measure the average dielectric constant using 6 cm length tines. Seven, three, one, and six in-situ network sites were include in EASE-Grids A, B, C, and D, respectively (Table 3-1). There is one Soil Climate Analysis Network (SCAN 2027) site in Grid D (Figure 3-1).

For the 2003 period, a representative in-situ network site was selected for each EASE-Grid based on the results of a previous study (Bosch et al., 2006). Thirteen of 19 network sites were drier than the regional mean soil moisture content. Based on time stability analysis (Vachaud et al., 1985) conducted separately for each EASE-Grid and data conditions, sampling locations that have the most time stable characteristics were identified. These sites, RG50, RG32, and RG16, that best represent EASE-Grids mean soil moisture were selected for EASE-Grid A, B, and D, respectively (Bosch et al., 2006). EASE-Grid C has only one existing in-situ network, RG67, measured from 05/29/2003 to 07/13/2003 (Figure 3-1).

Satellite Observations (AMSR-E)

The Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) on Aqua satellite was launched in May 2002. AMSR-E is a modified passive microwave radiometer deployed on Advanced Earth Observing Satellite-II (ADEOS-II) (Njoku et al., 2003). It provides brightness temperatures at six-frequencies ranging from 6.9 to 89.0 GHz in dual-polarized passive microwave radiometer systems. The 6.9 GHz (C band) and 10.7 GHz (X band) are the most useful channels to provide retrieved soil moisture products on a global scale at daily basis (Njoku et al., 2003). Currently, daily Level-3 land surface products in 25 km by 25 km EASE-Grids scale are accessible from the National Snow and Ice Data Center (NSIDC). These land surface products are stored in Hierarchical Data Format-Earth Observing System (HDF-EOS). Level-3 land surface products are regenerated to a global cylindrical 25 km EASE-Grids cell spacing by the time composition of Level-2B parameters for ascending and descending passes. The level-3 soil moisture product that has 25 km grid spacing and daily temporal resolution (1:30 pm EST overpass) was used in this study (Njoku et al., 2003).

Soil-Vegetation-Atmosphere Transfer (SVAT) Model

Common Land Model (CLM)

The Common Land Model (CLM) has been broadly examined with observation datasets over a wide range of fields (Dai et al., 2003). The CLM combines three existing models: Land surface model (LSM) (Bonan, 1996), Biosphere-atmosphere transfer scheme (BATS) (Dickinson et al., 1993), and Chinese academy of sciences institute of atmospheric physics LSM's 1994 version (Dai and Zeng, 1997).

The CLM requires preprocessed datasets of land surface type, soil and vegetation parameters, model initialization, and atmospheric boundary conditions as input (Dai et al., 2003). The energy and water balance are calculated for each tile at each time step using the general mosaic concept (Koster and Suarez, 1992). The tiles are divided by every sub-grid fraction and each tile contains a single land cover type. The energy and water balance solution of each time step are conserved and integrated by an implicit time-integration scheme. The CLM has a 10 layer soil profile and its thickness increases with depth. A weighted average of the three top layers (0-6 cm) that coincide with in-situ network (5 cm), SMEX03 (0-6 cm), and AMSR-E (0-2 cm) was used for this study.

In this study, the CLM is applied as a single column model using tiles based on land cover to estimate the quantification of energy and water balance.

The core single column of CLM can represent spatial extents as large as 28 km (0.25°) by 28 km (0.25°). The CLM's required parameters are longitude, latitude, soil texture profile (percentage of sand/clay/loam), soil color index, and percentages of land cover types (based on International Geosphere-Biosphere Programme (IGBP) classification).

Forcing Data

The forcing data that are required by the model are net downward solar radiation, net downward long wave radiation, air temperature, wind speed (U and V), air pressure, specific humidity, and precipitation. These data were obtained from the North American Land Data Assimilation System (NLDAS) (Cosgrove et al., 2003). The NLDAS data have an hourly temporal resolution and a 0.125° (~15 km) resolution. Meteorological variables are derived from Eta Data Assimilation System (EDAS) and Geostationary Operational Environmental Satellite (GOES) radiation data. Precipitation is a combination of EDAS, National Center for Environmental Prediction Climate Prediction Center (CPC) gauge-based data, and National Weather Service Doppler radar-based (WSR-88D) data (Cosgrove et al., 2003). For this study, the forcing data (15 km) at each NLDAS grid point was re-gridded to match the EASE-Grids spatial resolution (25 km). Table 3-1 summarizes the forcing data for the 2003 study period (from 01/01/2003 to 12/31/2003) by EASE-Grid. Forcing variables were similar across grids. Grid C had slightly more rain and Grid B had slightly less rain than the other grids.

Initialization and Parameterization

The initial subsurface soil temperature and moisture content values required by the model were obtained from the NRCS SCAN (2027) site, located in the southeast of the watershed (Figure 3-1). The SCAN site provides soil temperature and soil moisture content measured by Vitel Hydra Probe at 2, 4, 8, 20, and 40 inch depths.

The land cover classification was obtained from the 1:250,000 scale USGS GIRAS dataset (Mitchell et al., 1977). Land cover classification was predominantly cropland, evergreen forest, and wetland (Table 3-1). In each grid, the sub-grid tile fractions were based on the land use percentages.

Soil sand and clay percentages at the soil layers were obtained from the CONUS-SOIL database (Miller and White, 1998). The predominant soil texture is sand (~78%) and clay (~6%) for surface (Table 3-1). Sand percentage decreased as soil depth increased. Clay percentage increased as soil depth increased. Sand and clay percentages were about 55% and 20%, respectively, for bottom layer. Soil parameters in CLM are characterized by the soil texture i.e., sand and clay percentages. CLM estimates soil matric potential and hydraulic conductivity based on Clapp and Hornberger's (1978) relationship (Bonan, 1996).

Results

Soil moisture products were compared for SMEX03 study period (from 06/23/2003 to 07/02/2003) and 2003 study period (from 01/01/2003 to 12/31/2003). To match the time of soil moisture products (Aqua overpass (1:30 pm EST) and SMEX03 regional sampling (11:30 am to 2:30 pm EST)), network and CLM soil moisture values at 2:00 pm EST were used for the statistical analyses.

Comparison for SMEX03 Study Period

Figure 3-2 shows the time series of the four soil moisture products for the SMEX03 study period. The soil moisture time series showed surprisingly good agreements among four different sources and fairly consistent results across the grids. Statistical moments of the different soil moisture products for the SMEX03 time period are given by grid (Table 3-2). Average soil moisture (0.092-0.151) and standard deviation (0.012-0.051) of soil moisture showed excellent agreement among different data sources. However, AMSR-E's standard deviation values were much smaller than the other soil moisture values. All grids had a positive skew except for AMSR-E in Grid C.

Table 3-3 shows the bias estimation using various statistical measures among the four data sources for SMEX03 study period. The CLM and AMSR-E soil moisture was slightly wetter than the in-situ values for all grids except Grid A. The AMSR-E values were a little drier than the SMEX03 in Grid A. The AMSR-E biases were consistently less than those for CLM. The worst MAE and RMSE values, 0.054 and 0.059 [cm^3/cm^3], respectively for the CLM comparison to the SMEX03 in grid D, were quite low. The correlation coefficients showed very strong agreement among the different soil moisture products. As compared to the in-situ measurements, AMSR-E's correlation was similar to CLM when using the SMEX03 ground sampling sites, but much lower using the network data.

Overall, the CLM simulated soil moisture closely followed the drying and wetting patterns of the surface soil moisture measurements (Figure 3-2). While the CLM reasonably replicated dry down rate before rainfall and rapid rise after rainfall, it was consistently wetter than other soil moisture values (Tables 3-2 and 3-3). The AMSR-E average soil moisture also showed good agreement among other soil moisture products (Table 3-2). However, it did not capture the temporal variability of observed dry down and wetting for any of the grids (Figure 3-2). The AMSR-E soil moisture did have a small rise from 0.14 to 0.16 [cm^3/cm^3] after rainfall on Julian day 181; a comparable increase occurred during a period with no rain.

Comparison for 2003 Study Period

Figure 3-3 shows the time series of the four soil moisture products for the entire study period. The soil moisture time series agreed well in drying and wetting patterns among four different sources for all grids. Average soil moisture (0.122-0.167) had excellent agreement among the different data sources, though CLM and AMSR-E soil moisture were slightly wetter than ground based in-situ sampling (Table 3-2). As with the SMEX03 study period, the AMSR-E values had much lower variability than the other soil moisture values. With two exceptions, skew values were all positive.

Table 3-4 shows the biases using various statistical measures among three data sources for the entire year of 2003. The CLM and AMSR-E wet biases were typically less than 0.02 [cm^3/cm^3] and MAE values were less than 0.05 [cm^3/cm^3]. RMSE values were approximately 20-25% greater than the MAE values, which suggests significant differences for the wettest conditions. The correlation coefficients for the comparison between CLM and in-situ sampling (0.416-0.654) showed that soil moisture agreed well between the two data sources. However, correlation coefficients including AMSR-E soil moisture had much lower values (0.027-0.298). These low correlation coefficients are likely caused by the low variation in AMSR-E soil moisture. Overall, the biases, MAE, and RMSE for the entire year of 2003 had similar values to those during the SMEX03 study period, but the annual correlations were much weaker.

The CLM simulated soil moisture showed excellent agreement with surface soil moisture from the network at each EASE-Grid (Tables 3-2 and 3-4). However, the CLM simulated soil moisture was wetter than the observed soil moisture after rainfall events for all grids (Figure 3-3). While AMSR-E soil moisture was also within the range of the other data sources' soil moisture values, it had almost no variation during the growing season from May to October (approximately DOY 130-280) (Figure 3-3).

These results show that CLM and AMSR-E have complementary strengths. The CLM had relatively low MAE and RMSE errors. The AMSR-E typically had very low biases as compared to the network measurements. Additionally, the weak correlation between CLM and AMSR-E suggests that the two metrics are fairly independent.

Discussion

Based on our results, the CLM simulated soil moisture showed excellent agreement with ground based in-situ soil moisture for both the long and short periods (i.e., highest MAE and RMSE were 0.054 and 0.059 [cm^3/cm^3], respectively). Because there are inevitable limitations including scale mismatch and parameterization, a 5% error range for near surface volumetric soil moisture content is recognized as a reasonable error margin from previous studies (Shao and Henderson-Sellers, 1996; Mohr et al., 2000). Here, we notice that ground based in-situ sampling using impedance probes may also have 5% volumetric soil moisture error depending on the calibration methods (Cosh et al., 2005).

Several previous SVAT calibration/validation studies have identified typical errors and biases for different types of landscape and climate. Whitfield et al.'s (2006) comparison of two SVAT models, CLM and the Land Surface Process Model (LSP), showed that CLM's soil moisture was slightly drier than ground based measurements, while LSP's soil moisture was slightly wetter at field scale in southeastern U.S.. However, both the CLM and LSP provided reasonable soil moisture simulations (i.e., highest MAE and RMSE values were 0.032 and 0.033 [cm^3/cm^3], respectively). Dai et al. (2003) also found that CLM's soil moisture values were somewhat drier than observed ground data at a catchment in Russia for the period 1966-1983 even if its simulated soil moisture reasonably replicated observed soil moisture temporal variability. Mohr et al. (2000) demonstrated that the untuned PLACE model effectively simulated the spatio-temporal variability of soil moisture in Southern Great Plains Hydrology experiment (SGP97). Again, modeled soil moisture was slightly drier than ground based data. In contrast to these previous studies, CLM simulated soil moisture was slightly wetter than the ground based data for the long and short periods. This difference may be due to preferential siting of network sensors outside of active agricultural areas. This may result in soil type and vegetation differences between the EASE-Grid averaged values in CLM and the local values for the ground based data.

Several previous studies validated remote sensing measurements using SVAT models and ground based in-situ data for a variety field conditions and durations. Sahoo et al. (2006) showed similarly good agreement between the Noah land surface model and SMEX03 (r^2 = 0.72) and between AMSR-E and SMEX03 (r^2 = 0.56) as compared to our average values between CLM and SMEX03 (r^2 = 0.72) and between AMSR-E and SMEX03 (r^2 = 0.70). They also found that AMSR-E did not replicate the observed soil moisture temporal evolution as well during SMEX03 (Georgia) as during SMEX02 (Iowa) and SMEX04 (Arizona). Their Noah land surface model was consistently drier than AMSR-E and ground data during SMEX03. During the Southern Great Plains Hydrology 1997 (SGP97), Mohr et al. (2000) found that remotely sensed Electronically Scanned Thinned Array Radiometer (ESTAR) surface soil moisture had less temporal variation as compared to model and ground data. Reichle et al. (2004) found that SMMR soil moisture products had no agreement with NASA Catchment Land Surface model when Leaf Area Index (LAI) values exceeded unity. For lower LAI values, SMMR was able to capture the same global soil moisture patterns of wet and dry regions identified by models and ground data (1979-1987). These findings support our results that AMSR-E had limited variation annually and very poor agreement during the growing season.

Differences among soil moisture time evolutions are not readily apparent from standard statistics. AMSR-E had reasonable statistics and errors as well as temporal wetting and drying patterns that matched the CLM and ground based in-situ soil moisture values. However, AMSR-E had noteworthy less temporal variability compared to CLM and ground based in-situ soil moisture. A potential reason for the AMSR-E soil moisture's low temporal variations during the growing season is the passive microwave sensors' inability to capture reasonable brightness temperatures in densely vegetated surface conditions (Schmugge et al., 2002; Margulis et al., 2002). Another possible problem is that the sensitivity of AMSR-E retrieval algorithms may be reduced by vegetation and surface roughness effects (Njoku et al., 2003).

Conclusion

In this study, inter-comparisons of surface soil moisture from remotely sensed data (AMSR-E), land surface model (CLM), and ground data were conducted for SMEX03 study period and entire year of the 2003 at SMEX03 Little River region. Overall, our results show that there are good agreements among the different soil moisture products with CLM and AMSR-E having complementary benefits even if each data source has its own restrictions. These findings are consistent across the EASE-Grids. The CLM simulated soil moisture agreed well with ground based in-situ soil moisture for long and short periods within reasonable error ranges (i.e., highest MAE and RMSE were 0.054 and 0.059 [cm^3/cm^3], respectively). While AMSR-E provided an unbiased estimate of average soil moisture, it did not capture the full range of observed soil moisture. Additionally, AMSR-E had almost no variation from May to October. As with the year long period, AMSR-E did not capture observed soil moisture temporal variability during SMEX03 period. This study's characterization of each data source's errors may provide improved recognition of data errors, identify the AMSR-E retrieval algorithm's limitations, and facilitate data use in assimilation systems.

Table 3-1. Geographic locations, field characteristics, and average and standard deviation of forcing data for the entire year of 2003 (from 01/01/2003 to 12/31/2003) obtained from NLDAS (Note: values in parenthesis are the standard deviations) for Grids A, B, C, and D (Note: values in parenthesis are the standard deviations)

	Grid A	Grid B	Grid C	Grid D
Latitude and longitude of the Grid's NE corner	31.88°N, -83.69°W	31.88°N, -83.43°W	31.65°N, -83.69°W	31.65°N, -83.43°W
Major IGBP land use category (%)				
Cropland and pasture	68.7	58.1	65.2	71.8
Evergreen forest	23.6	35.8	26.6	18.0
Wetland	4.3	4.8	7.4	8.0
Reservoir	1.3	-	0.1	0.2
Mixed forest	1.0	0.5	-	-
Deciduous forest	0.6	0.2	-	-
Residential/Urban	0.5	0.6	0.7	2.0
Surface soil texture				
Sand (%)	78	79	78	78
Clay (%)	6	6	6	6
No. of in-situ sampling points				
Network	7	3	1	6
SMEX03	9	7	8	13
Forcing data				
Downward solar radiation [W/m^2]	244.8 (327.4)	244.5 (327.0)	245.7 (328.2)	246.2 (328.7)
Downward long wave radiation [W/m^2]	348.1 (62.1)	348.4 (62.2)	348.7 (61.6)	349.7 (61.6)
Air temperature [K]	291.7 (8.7)	291.8 (8.7)	292.1 (8.5)	292.5 (8.5)
U wind component [m/s]	0.3 (2.7)	0.4 (2.7)	0.3 (2.8)	0.3 (2.9)
V wind component [m/s]	0.3 (2.5)	0.3 (2.4)	0.3 (2.6)	0.3 (2.5)
Surface pressure [kPa]	100.6 (0.5)	100.7 (0.5)	100.6 (0.5)	100.9 (0.5)
Specific humidity [kg/kg]	0.011 (0.005)	0.011 (0.005)	0.011 (0.005)	0.011 (0.005)
Total precipitation [m]	1.41	1.31	1.49	1.38

Table 3-2. Temporal statistical moments, mean, standard deviation, and skewness of different soil moisture products (cm^3/cm^3) by grid (Note: Moments were calculated using single daily measurements from SMEX03 and AMSR-E at time for the network and CLM)

SMEX03 period	Grid A (06/23/2003 – 07/02/2003)				Grid B (06/23/2003 – 07/02/2003)				Grid C (06/23/2003 – 07/02/2003)				Grid D (06/23/2003 – 07/02/2003)			
	Network	SMEX03	AMSR-E	CLM	Network	SMEX03	AMSR-E	CLM	Network	SMEX03	AMSR-E	CLM	Network	SMEX03	AMSR-E	CLM
Mean	0.124	0.141	0.136	0.151	0.099	0.115	0.131	0.146	0.105	0.123	0.133	0.147	0.113	0.092	0.128	0.148
STDEV	0.035	0.037	0.014	0.038	0.044	0.041	0.013	0.044	0.051	0.048	0.013	0.040	0.036	0.042	0.012	0.050
Skewness	0.543	0.998	0.740	0.575	0.535	0.664	1.117	0.731	0.892	1.178	-0.328	0.662	0.179	1.809	1.162	1.064

2003 period	Grid A (01/01/2003 – 12/31/2003)			Grid B (01/01/2003 – 12/31/2003)			Grid C (05/29/2003 – 07/13/2003)			Grid D (01/01/2003 – 12/31/2003)		
	Network	AMSR-E	CLM	Network	AMSR-E	CLM	Network	AMSR-E	CLM	Network	AMSR-E	CLM
Mean	0.138	0.142	0.145	0.123	0.138	0.140	0.122	0.139	0.167	0.135	0.138	0.141
STDEV	0.039	0.014	0.053	0.053	0.015	0.052	0.053	0.013	0.046	0.045	0.014	0.053
Skewness	-0.011	0.727	0.440	0.722	0.834	0.468	1.239	0.306	-0.058	0.122	1.050	0.515

Table 3-3. Error estimation among four soil moisture products (cm^3/cm^3) for the SMEX03 study period

Statistical Measures	Grid A (06/23/2003 – 07/02/2003)					Grid B (06/23/2003 – 07/02/2003)				
	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E
Bias	0.027	0.013	0.015	-0.009	0.021	0.046	0.033	0.028	0.003	0.030
Mean Absolute Error (MAE)	0.028	0.018	0.029	0.022	0.036	0.047	0.033	0.035	0.024	0.035
Root Mean Squared Error (RMSE)	0.035	0.023	0.036	0.028	0.043	0.049	0.037	0.042	0.030	0.046
Correlation Coefficient (R^2)	0.658	0.791	0.425	0.761	0.419	0.857	0.837	0.796	0.636	0.424

Statistical Measures	Grid C (06/23/2003 – 07/02/2003)					Grid D (06/23/2003 – 07/02/2003)				
	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E	CLM Network	CLM SMEX03	AMSR-E Network	AMSR-E SMEX03	CLM AMSR-E
Bias	0.041	0.023	0.031	0.004	0.016	0.035	0.054	0.017	0.026	0.031
Mean Absolute Error (MAE)	0.042	0.033	0.046	0.039	0.033	0.035	0.054	0.029	0.040	0.036
Root Mean Squared Error (RMSE)	0.047	0.039	0.052	0.041	0.039	0.051	0.059	0.036	0.043	0.046
Correlation Coefficient (R^2)	0.824	0.530	0.473	0.638	0.333	0.462	0.714	0.500	0.745	0.443

Table 3-4. Error estimation among three soil moisture products (cm^3/cm^3) for the entire year of 2003, except Grid C from 05/29/2003 to 07/13/2003

Statistical Measures	Grid A (01/01/2003 – 12/31/2003)			Grid B (01/01/2003 – 12/31/2003)			Grid C (05/29/2003 – 07/13/2003)			Grid D (01/01/2003 – 12/31/2003)		
	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E	CLM Network	AMSR-E Network	CLM AMSR-E
Bias	0.007	0.003	0.003	0.017	0.015	0.001	0.045	0.023	0.029	0.006	0.004	0.002
Mean Absolute Error (MAE)	0.029	0.029	0.040	0.038	0.040	0.039	0.047	0.039	0.046	0.032	0.027	0.038
Root Mean Squared Error (RMSE)	0.039	0.037	0.050	0.047	0.049	0.047	0.055	0.046	0.058	0.039	0.038	0.045
Correlation Coefficient (R^2)	0.471	0.195	0.132	0.416	0.263	0.138	0.654	0.298	0.027	0.495	0.288	0.213

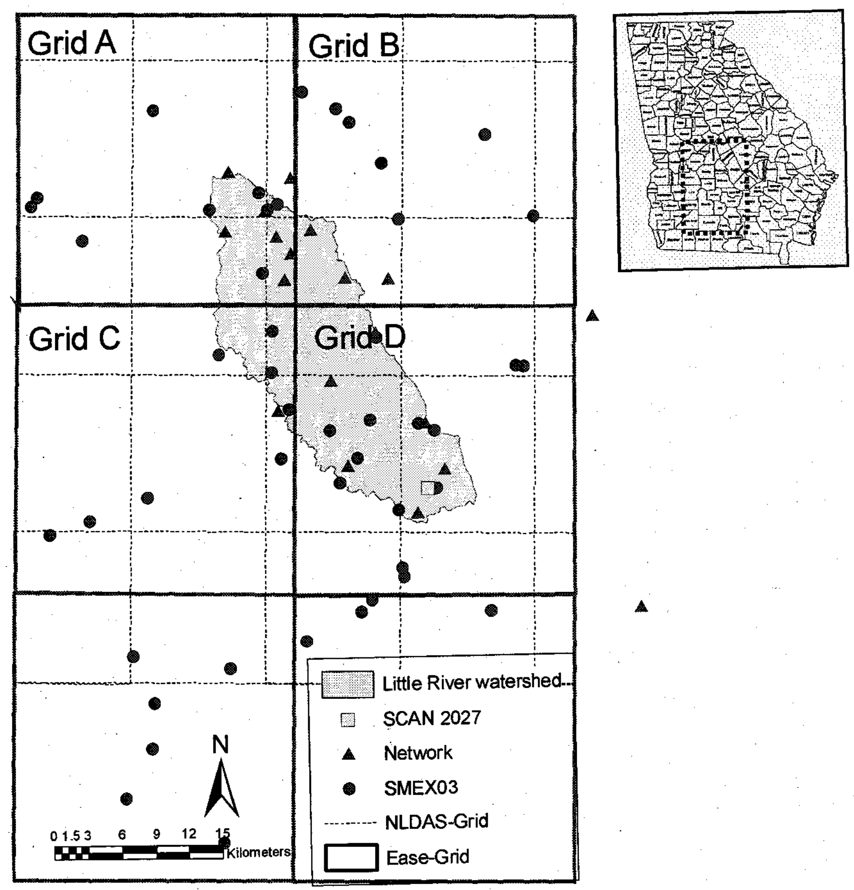

Figure 3-1. Little River watershed, SMEX03 GA regional sampling sites, network sites, NLDAS-Grids, and EASE-Grids

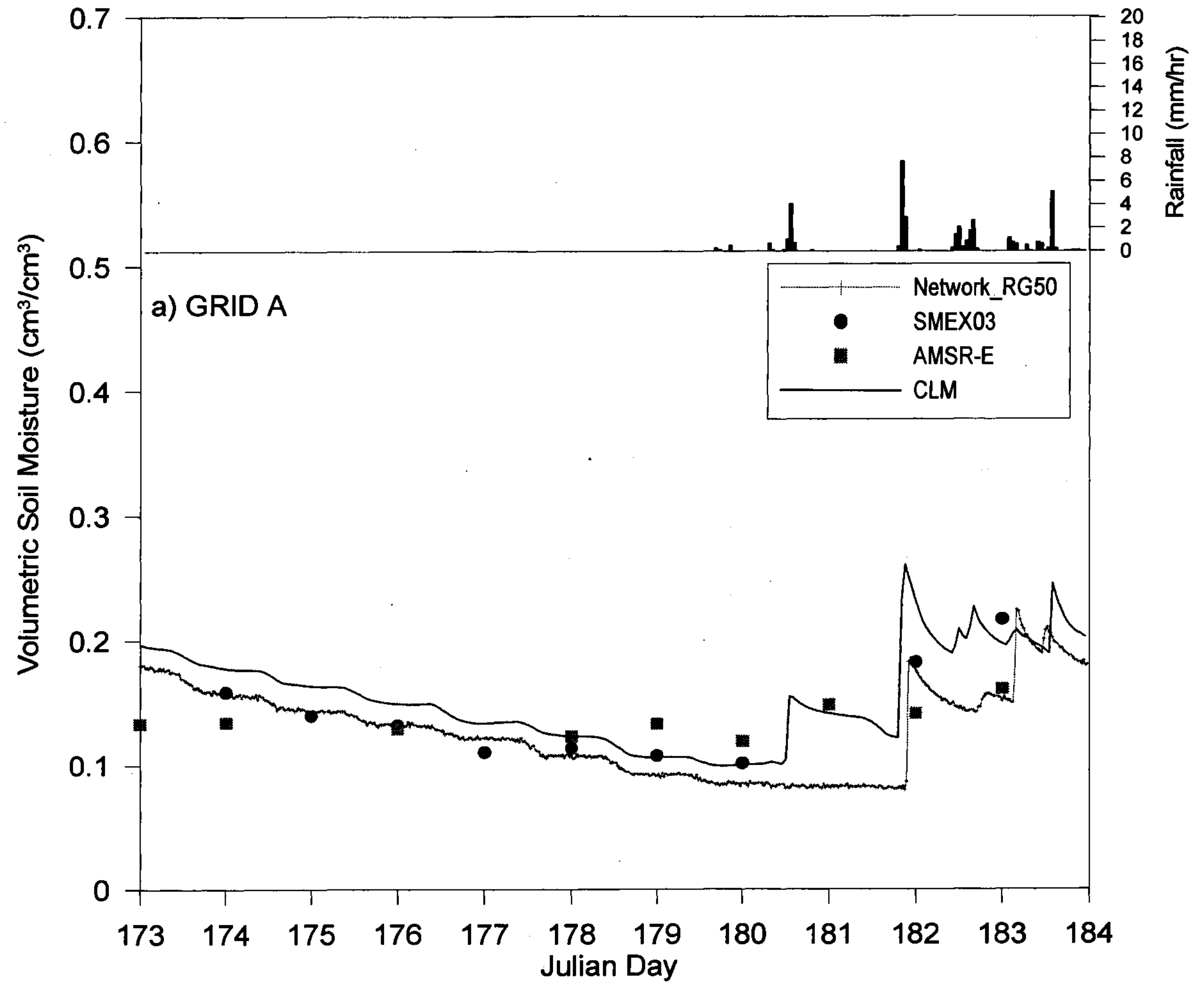

Figure 3-2. Time series of the four surface soil moisture products for the SMEX03 study period (06/23/2003 to 07/02/2003) by grid

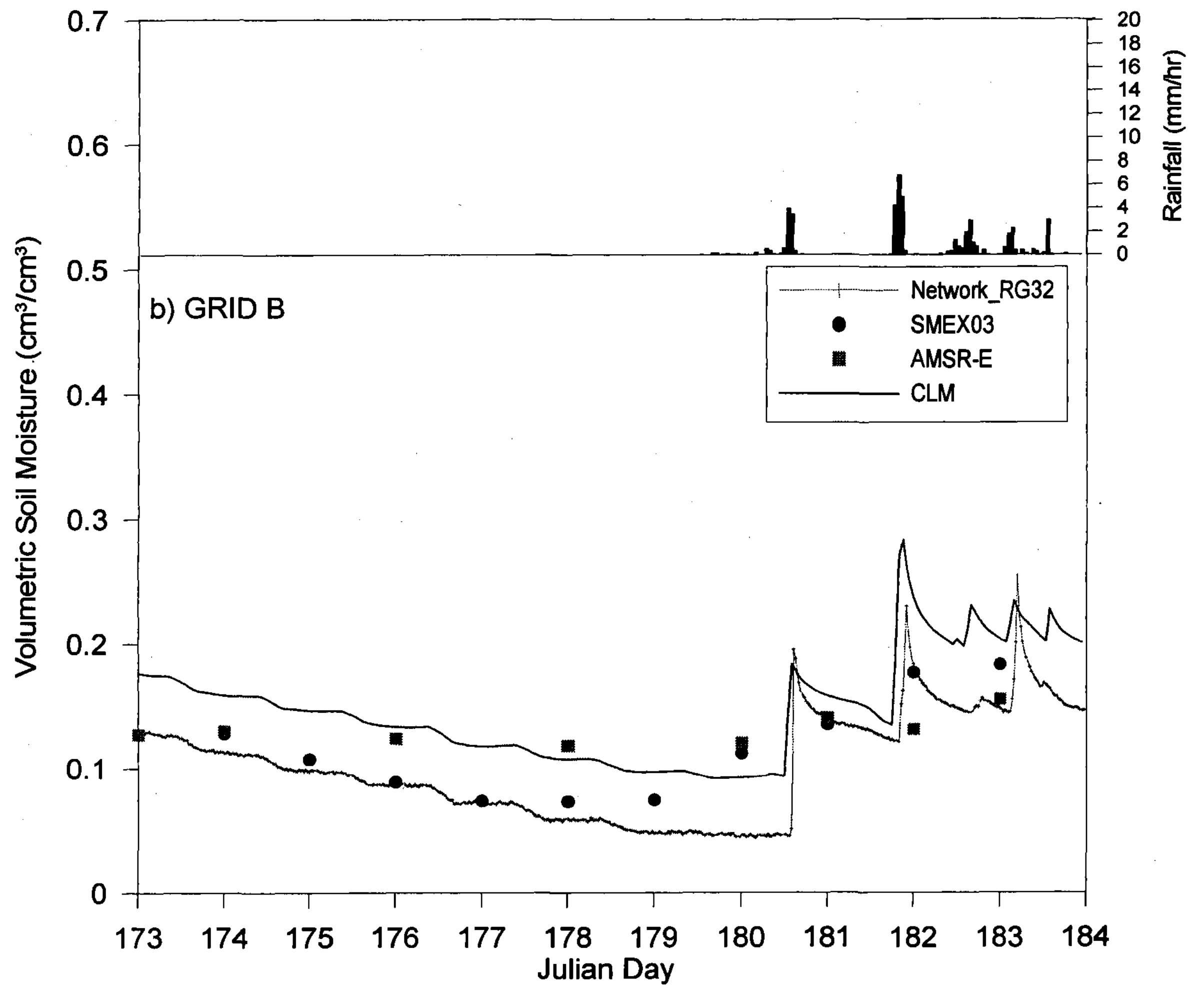

Figure 3-2. Time series of the four surface soil moisture products for the SMEX03 study period (06/23/2003 to 07/02/2003) by grid (Continued)

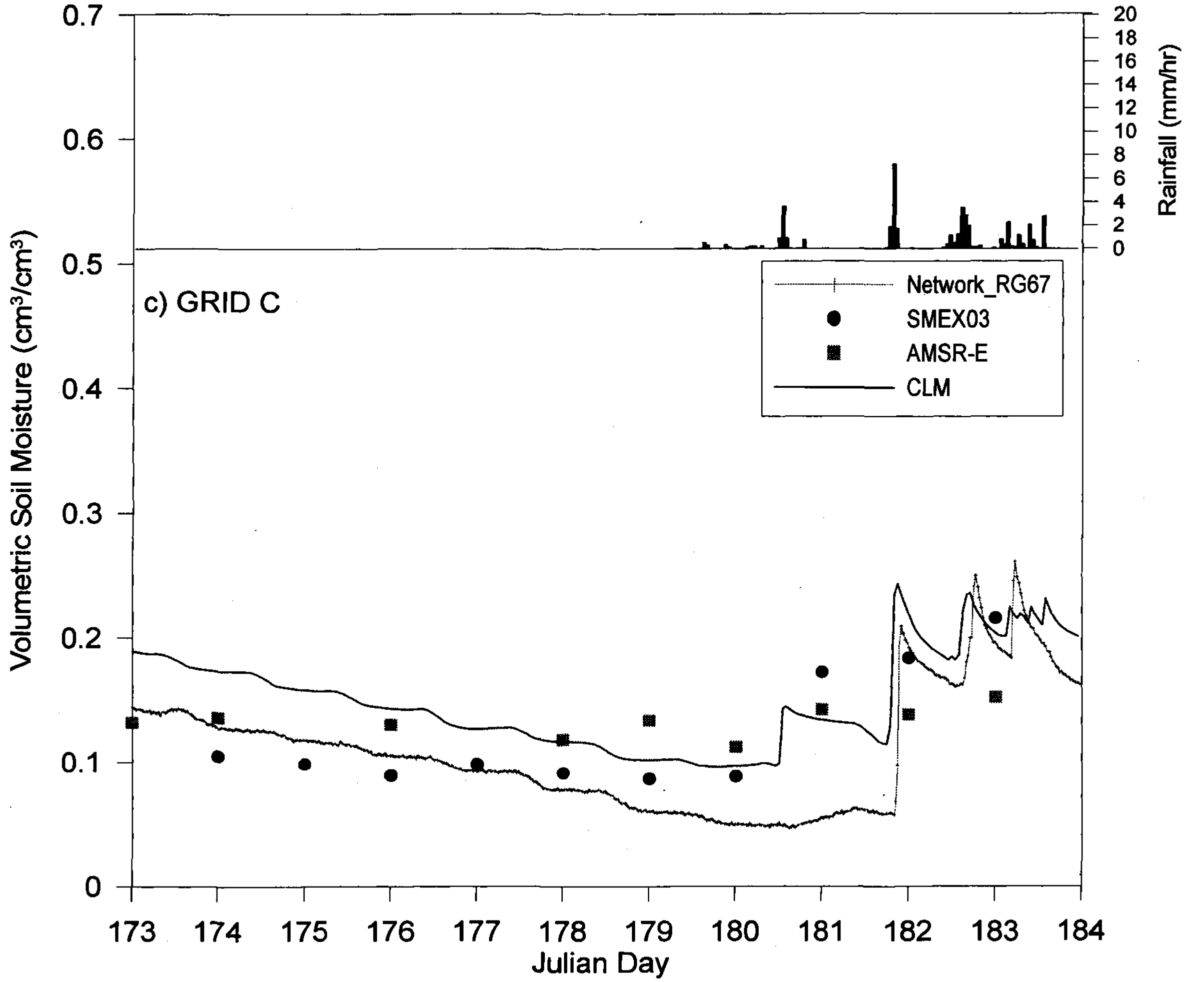

Figure 3-2. Time series of the four surface soil moisture products for the SMEX03 study period (06/23/2003 to 07/02/2003) by grid (Continued)

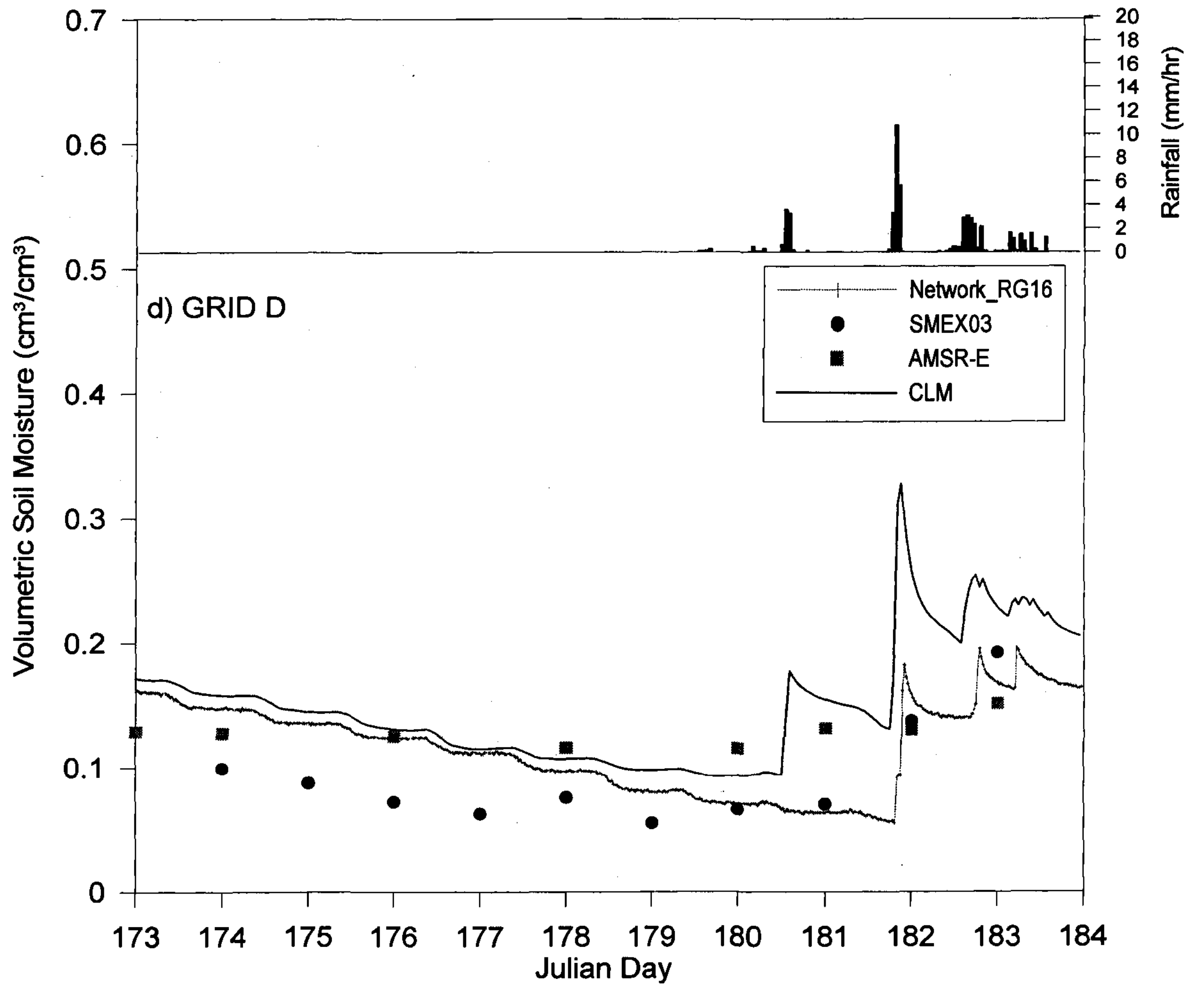

Figure 3-2. Time series of the four surface soil moisture products for the SMEX03 study period (06/23/2003 to 07/02/2003) by grid (Continued)

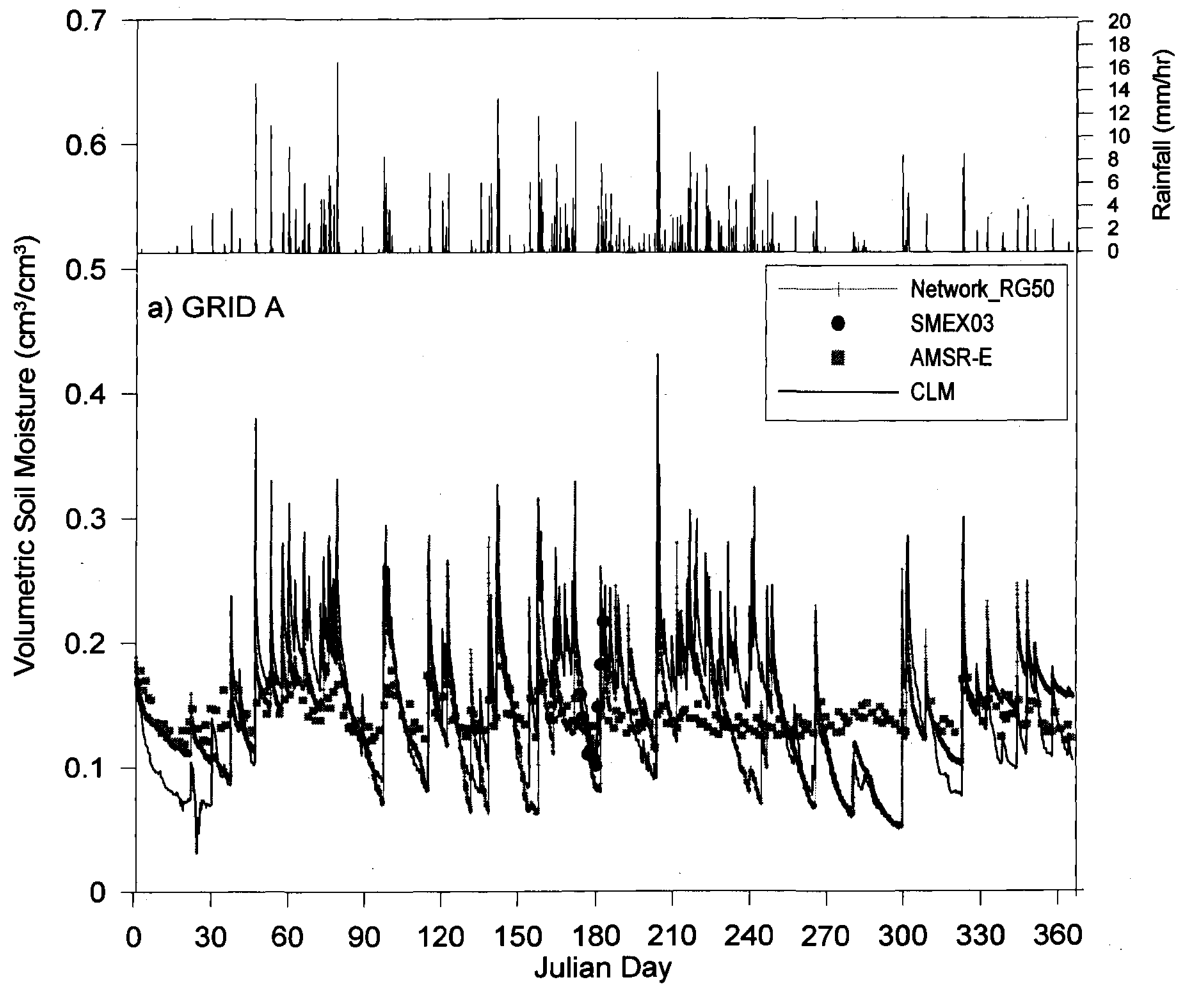

Figure 3-3. Time series of the four surface soil moisture products for 2003 (01/01/2003 to 12/31/2003) by grid

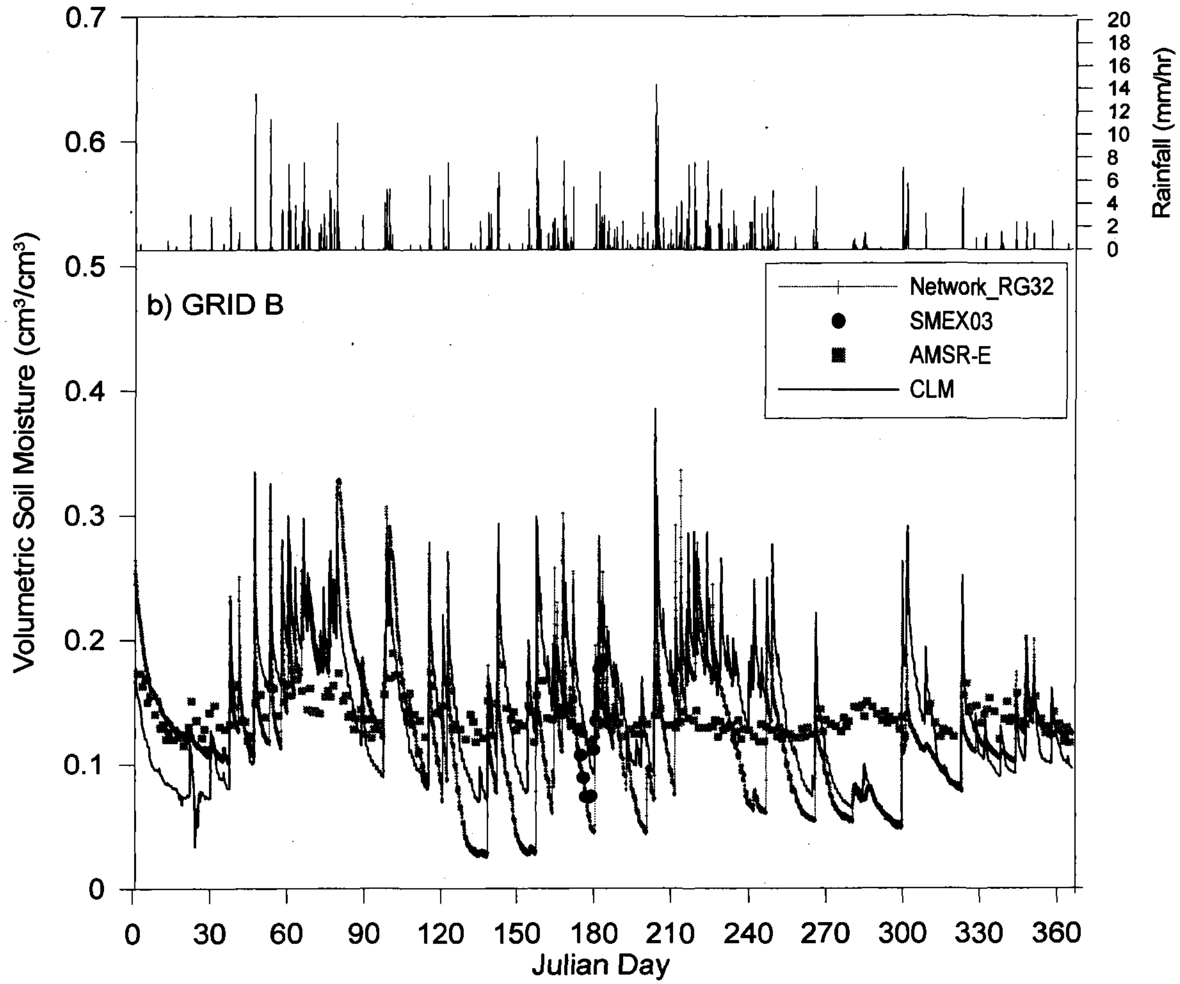

Figure 3-3. Time series of the four surface soil moisture products for 2003 (01/01/2003 to 12/31/2003) by grid (Continued)

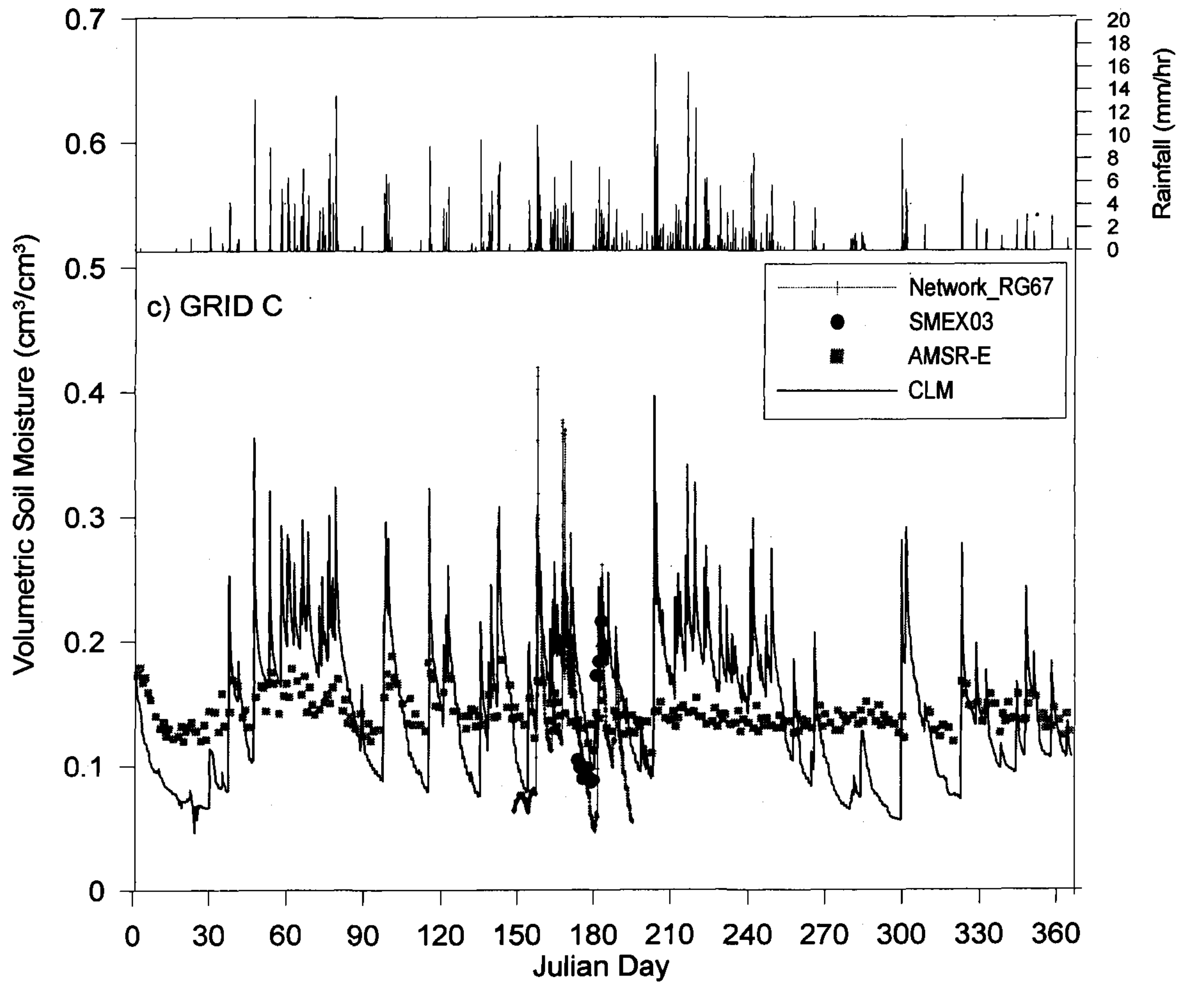

Figure 3-3. Time series of the four surface soil moisture products for 2003 (01/01/2003 to 12/31/2003) by grid (Continued)

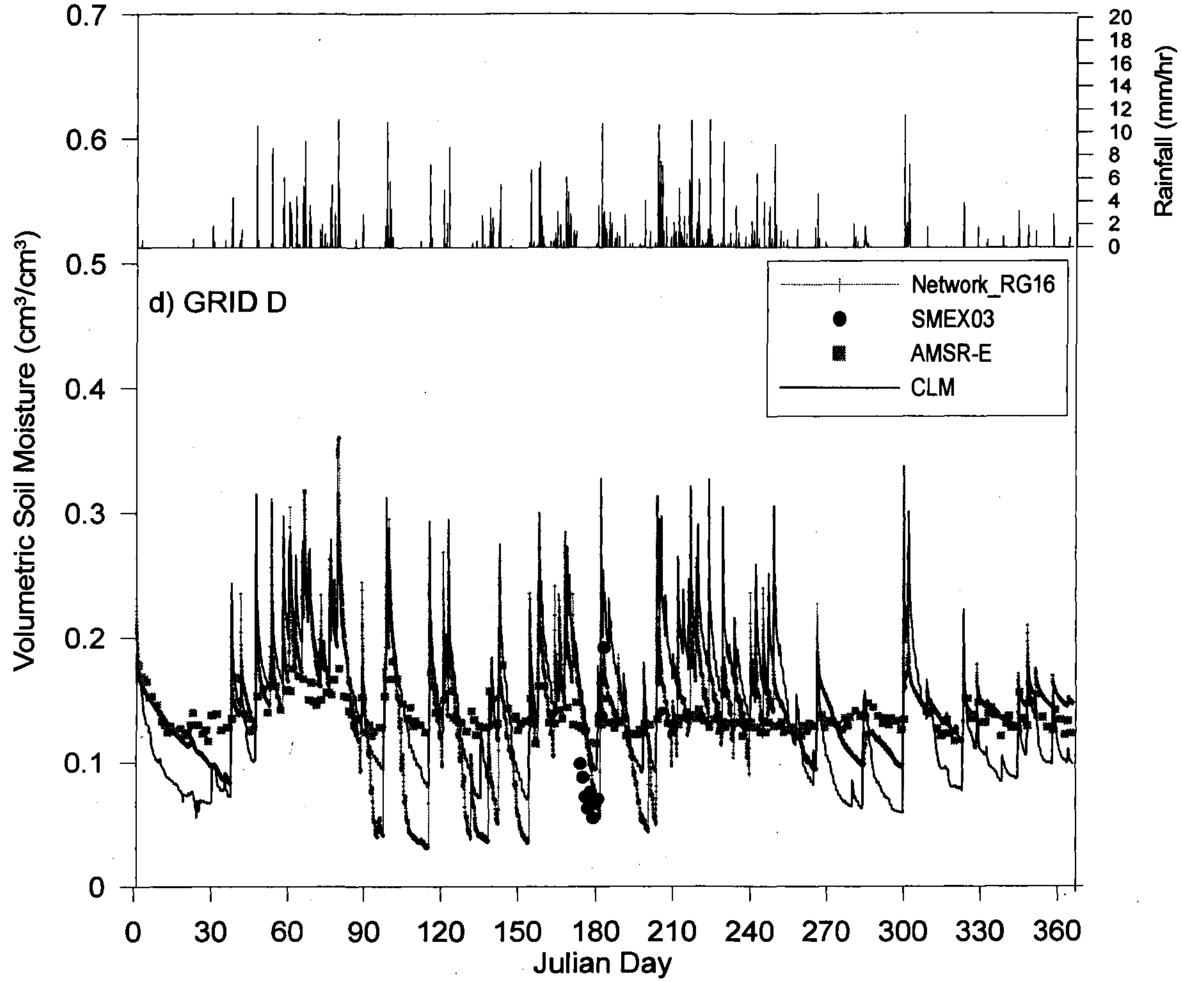

Figure 3-3. Time series of the four surface soil moisture products for 2003 (01/01/2003 to 12/31/2003) by grid (Continued)

CONCLUSION

In this study, soil moisture variability and time stability were considered across different soil depths and scales from a variety of field experiments. This chapter reviews the significant findings and sets a context for these findings within hydrological sciences. The major findings of this study are as follows:

1. The spatial variability patterns of surface and root zone soil moisture were well captured by negative exponential functions between mean and coefficient of variation of soil moisture. The surface depth showed the least negative relationship between the mean and the coefficient of variation of soil moisture. The soil moisture variability generally decreased as sampling extent scale increased. Additionally, its variability increased as soil depth increased.

2. The surface soil moisture was well described by a normal distribution, except during dry down phases when it was positively skewed. At deeper depths, the normal distribution generally captured the soil moisture variability.

3. The maximum surface soil moisture relative variability was mostly affected by soil factors. The rainfall and topography were the most significant

factors to characterize how variability patterns change with mean surface soil moisture.

4. The time stability patterns were well maintained regardless of the soil depth. The surface time stability can provide valuable insight to root zone time stability patterns.

5. The simple physical model reasonably replicated observed soil moisture variability patterns. This model can be used to identify statistical relationships necessary to disaggregate physically based land surface model predictions.

Inter-comparisons of surface soil moisture from remotely sensed data (AMSR-E), land surface model (CLM), and ground data were conducted for SMEX03 study period and entire year of the 2003 at SMEX03 Little River region. The major findings of this study are as follows:

1. There was good agreement among the different soil moisture products, although each data source had its restrictions. The CLM simulated soil moisture values agreed well with ground based in-situ soil moisture for both the long and short periods.

2. The AMSR-E provided reasonable average soil moisture compared to the CLM and ground data, but it had almost no temporal variation during the

growing seasons, May to October. The error characteristics of the AMSR-E data are strongly influenced by vegetation density.

3. Both the CLM and AMSR-E had complementary benefits with relative low MAE and RMSE errors for the CLM and very low biases for the AMSR-E.

Based on the inter-comparison analysis, each data source was identified as a reasonable approach to obtain regional soil moisture. Ultimately, the AMSR-E error characteristics identified here should be used to guide enhancement of retrieval algorithms and improve satellite observations for hydrological sciences. As they stand, the AMSR-E data products might be a valuable input to simulate land surface-atmosphere interactions for regional weather prediction systems, especially at data limited regions. Furthermore, the AMSR-E data can provide relative surface moisture to augment runoff predictions of rainfall-runoff processes. This is one of the few direct ways to identify antecedent soil moisture conditions (AMC) because of highly non-linear characteristics of soil moisture. However, direct application of refined moisture values is not possible due to the limited range of AMSR-E values.

Hydrological variability across spatial scales is poorly understood. Even without a full range of moisture values, AMSR-E can provide valuable datasets for validation of land surface modeling to examine sub-grid variability of soil moisture at large extents as well as the structure of this variability.

In a broader context, the statistical soil moisture variability results of this study are essential to understand numerous water and energy balance processes. For instance, this information can be used to characterize evapotranspiration processes, one of the least understood physical processes in hydrology. The evapotranspiration processes have spatial and temporal heterogeneity characteristics that are poorly understood, yet are strongly influenced by soil moisture availability. Furthermore, these heterogeneous latent heat fluxes contribute water and energy and drive cloud creation and precipitation in regional climate systems.

The current results for soil moisture variability information can also improve rainfall-runoff process. The predictive runoff approaches that use mean antecedent soil moisture conditions (AMC) might be enhanced by soil moisture variability estimates derived from this study's exponential relationships. Similarly, groundwater recharge variability is also affected by spatial and temporal variability of soil moisture. Better characterization of the unsaturated zone's moisture variability and distribution can improve infiltration predictions.

The soil moisture variability knowledge also can provide a practical approach to estimate the heterogeneity effects of land surface processes in modeling systems over a range of scales. Typically, the variability information has been used in an explicit mode that analyzes the heterogeneity effects by distinction of each model element in modeling systems. This study's soil moisture variability patterns can be applied to both lumped and distributed modeling. First, the probability density function (PDF) of soil moisture at different depths can be used to represent variability that controls profile heterogeneity within a spatially lumped, but vertically stratified soil profile model such as TOP MODEL and VIC.

The most efficient PDFs to represent soil moisture variability were a log-normal distribution in the surface layer and a normal distribution in subsurface layers. This information can provide an effective way to determine how well current soil moisture dynamics schemes characterize soil moisture variability patterns by soil depth.

Second, distributed modeling that contains grid or sub-grid variability can be improved by using spatially distributed soil moisture variability information. There are typically two approaches to represent sub-grid heterogeneity in distributed modeling systems, discrete and statistical approaches. In the statistical approach, my results can be used to develop grid or sub-grid statistical PDF representations. Several previous studies have concluded that this approach provided improved simulations, but it was practically quite complex due to numerical computations at each element. In simplified PDF representations, only the most critical variables should be considered. Additionally, model spatial distribution increasingly changed as a function of observed area or based on the process modeled. Allowing statistical behavior to change by scale may be a critical factor to develop up-scaling or down-scaling schemes in physically-based land surface processes.

The above ideas reflect several potential science areas in land surface processes might be better understood and predicted using research on soil moisture variability. These thoughts provide insight for potential inquiry and testable hypotheses for future research.

FUTURE STUDY

Soil moisture variability patterns found in this study can provide better identification for the temporal and spatial behavior of hydrological processes. Physical modeling is essential to represent and predict hydrological processes because it is almost impossible to execute intensive field campaigns at large scales for long periods. Time stability analysis was recognized as a valuable tool to predict reasonable mean soil moisture without a significant sampling error. However, time stability and modeling in this study was conducted at a field scale for short duration. One of the most arguable issues in hydrology is how well variability patterns can be connected over a range of scales. Thus, future studies are needed that include larger scales, longer periods, and a variety of landscapes.

Several previous studies found that remotely sensed data had much less temporal variability compared to modeled and ground data. We also found consistent results with the previous studies as the remotely sensed data had less temporal variability than modeled and observed soil moisture. For future studies, bias reduction methods such as Cumulative Distribution Function (CDF) matching technique can be used to reduce the error of the remotely sensed data. The CDF matching technique has been widely used in diverse disciplines. CDF matching between the model and remotely sensed data can be conducted for annual and seasonal periods based on the relationship between the remotely sensed soil moisture and Leaf Area Index (LAI) products. Scale factors will be calibrated based on the difference between the model and remotely sensed data. The scaled remotely sensed data will be validated using model and ground-based measurements. This process can improve current utilization of remotely sensed products.

Through these future studies, the parameterization requirements of hydrologic systems considering soil moisture heterogeneous characteristics as a function of physical properties can be better satisfied.

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