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Authors

Famiglietti, James S
Ryu, Dongryeol
Berg, Aaron A
[et al.](#)

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Field observations of soil moisture variability across scales

James S. Famiglietti,¹ Dongryeol Ryu,² Aaron A. Berg,³ Matthew Rodell,⁴
and Thomas J. Jackson²

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[1] In this study, over 36,000 ground-based soil moisture measurements collected during the SGP97, SGP99, SMEX02, and SMEX03 field campaigns were analyzed to characterize the behavior of soil moisture variability across scales. The field campaigns were conducted in Oklahoma and Iowa in the central USA. The Oklahoma study region is sub-humid with moderately rolling topography, while the Iowa study region is humid with low-relief topography. The relationship of soil moisture standard deviation, skewness and the coefficient of variation versus mean moisture content was explored at six distinct extent scales, ranging from 2.5 m to 50 km. Results showed that variability generally increases with extent scale. The standard deviation increased from $0.036 \text{ cm}^3/\text{cm}^3$ at the 2.5-m scale to $0.071 \text{ cm}^3/\text{cm}^3$ at the 50-km scale. The log standard deviation of soil moisture increased linearly with the log extent scale, from 16 m to 1.6 km, indicative of fractal scaling. The soil moisture standard deviation versus mean moisture content exhibited a convex upward relationship at the 800-m and 50-km scales, with maximum values at mean moisture contents of roughly $0.17 \text{ cm}^3/\text{cm}^3$ and $0.19 \text{ cm}^3/\text{cm}^3$, respectively. An empirical model derived from the observed behavior of soil moisture variability was used to estimate uncertainty in the mean moisture content for a fixed number of samples at the 800-m and 50-km scales, as well as the number of ground-truth samples needed to achieve $0.05 \text{ cm}^3/\text{cm}^3$ and $0.03 \text{ cm}^3/\text{cm}^3$ accuracies. The empirical relationships can also be used to parameterize surface soil moisture variations in land surface and hydrological models across a range of scales. To our knowledge, this is the first study to document the behavior of soil moisture variability over this range of extent scales using ground-based measurements. Our results will contribute not only to efficient and reliable satellite validation, but also to better utilization of remotely sensed soil moisture products for enhanced modeling and prediction.

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1. Introduction

[2] Numerous studies have suggested that the realistic representation of spatial variability of surface soil moisture content can improve the predictive skill of hydrologic, weather prediction, and general circulation models, including processes such as evapotranspiration and runoff [Famiglietti and Wood, 1994], precipitation [Koster et al., 2000], and atmospheric variability [Delworth and Manabe, 1993]. A growing need for regional- to global-scale observations of the spatial distribution of soil moisture has motivated the development of airborne and satellite microwave sensors. The National Aeronautics and Space Administration (NASA) Advanced Microwave Scanning Radiometer (AMSR-E) is

currently providing moisture content estimates for near-surface soils (0–2 cm) at approximately a 43-km by 75-km footprint scale [Njoku et al., 2003]; and the European Space Agency (ESA) Soil Moisture Ocean Salinity (SMOS) mission will map 0–5 cm surface soil moisture at the 50-km footprint scale across the globe after its launch in 2008 [Famiglietti, 2004; Kerr et al., 2001].

[3] A number of error sources can degrade the accuracy of remotely sensed soil moisture content, so that it is critical to calibrate retrieval algorithms and to validate derived products using ground-truth data. The error sources include radio-frequency interference (RFI) [Njoku et al., 2005], vegetation water content [Crosson et al., 2005; Njoku et al., 2003], surface roughness [Crosson et al., 2005], and land surface heterogeneity [Crow et al., 2005b].

[4] Whereas remotely sensed soil moisture represents an average value within a footprint, ground-based measurements are often considered point measurements because the spatial scale of each usually represents a 4–5 cm diameter. The footprint scale ranges from a few hundred meters for an airborne radiometer, to about 60-km for a spaceborne radiometer. For this reason, a large number of distributed ground-based samples is needed to accurately estimate the mean soil moisture content within a remotely sensed foot-

¹Department of Earth System Science, University of California, Irvine, California, USA.

²USDA ARS Hydrology and Remote Sensing Laboratory, Beltsville, Maryland, USA.

³Department of Geography, University of Guelph, Ontario, Canada.

⁴Hydrological Sciences Branch, NASA Goddard Space Flight Center, Greenbelt, Maryland, USA.

print. The number of samples required to estimate the footprint-scale mean with a specified uncertainty is determined by the spatial variability of soil moisture within the sampling site [Famiglietti *et al.*, 1999; Ryu and Famiglietti, 2005].

[5] Soil moisture variability also plays an important role in the simulation of land surface processes, which are nonlinearly related to soil moisture [Giorgi and Avissar, 1997]. Ignoring subgrid-scale heterogeneity of soil moisture often produces a substantial bias in simulated surface water and energy fluxes [Crow and Wood, 2002; Famiglietti and Wood, 1995], infiltration and surface runoff, and the emission of mineral dust aerosol [Fécan *et al.*, 1999]. In order to reduce this error, subgrid-scale heterogeneity of soil moisture is often parameterized using the soil moisture variance and assuming a certain type of probability density function (PDF) such as Gaussian [Li and Avissar, 1994; Crow and Wood, 2002], gamma [Entekhabi and Eagleson, 1989; Famiglietti and Wood, 1994], or beta distribution [Famiglietti *et al.*, 1999], or a Gaussian mixture model [Ryu and Famiglietti, 2005]. Therefore information on sub-footprint-scale soil moisture variations will contribute not only to efficient and reliable satellite validation, but also to better utilization of remotely sensed soil moisture products for enhanced modeling and prediction capabilities.

[6] Variability of soil moisture is known to increase with the size of the spatial domain within which soil moisture measurements are taken, which is referred to as the “extent” scale [Western and Blöschl, 1999]. This implies that the number of soil moisture measurements should increase with the extent scale of a sampling site in order to achieve a specified accuracy. However, it has been practically difficult to examine the relationship between extent scale and soil moisture variability because it requires intensive field sampling, carried out in a short period of time, and over several scales simultaneously. Another factor complicating the study of soil moisture variability is that variations at a given scale may change with the mean wetness of a field. Accordingly, the affects of mean soil moisture content and the extent scale of a study domain need to be considered jointly in order to fully characterize the behavior of soil moisture variability.

[7] During the Southern Great Plains (SGP) Hydrology Experiments of 1997 and 1999, and the Soil Moisture Experiments (SMEX) of 2002 and 2003, intensive sampling was conducted at both field- and regional-scales for the purpose of validating airborne and spaceborne remotely sensed soil moisture products. During SGP97, Famiglietti *et al.* [1999] studied soil moisture variations within several 1.6 km aircraft remote sensing footprints. During the SGP99 experiment, we conducted nested-scale sampling at extent scales ranging from 2.5 m to 1.6 km. The SMEX02 and SMEX03 experiments provided our first opportunities for regional sampling at scales as large as satellite footprints. The large number of multiscale soil moisture measurements accumulated during these field campaigns provides a unique opportunity to examine the behavior of soil moisture variability across scales.

[8] In this study we characterize soil moisture variability with respect to both spatial scale and field-mean moisture content. More than 36,000 ground-based measurements of soil moisture collected in SGP97, SGP99, SMEX02, and SMEX03 were combined and analyzed to infer the statisti-

cal behavior of soil moisture variations at six distinct spatial scales and across a range of wetness conditions. Soil moisture standard deviation, coefficient of variation (CV), and skewness versus the mean moisture content are described at each scale. On the basis of these analyses we derive empirical relationships between soil moisture variability and the field-mean moisture content. Implications of this study for satellite validation and subgrid-scale parameterization of surface soil moisture are discussed in the final section. To our knowledge, this is the first study to document the behavior of soil moisture variability over this range of extent scales using ground-based measurements.

2. Background

[9] In this section we review previous studies of soil moisture spatial variability, and in particular, those dealing with variability in relation to mean moisture content and spatial scale. Additionally, our focus is primarily on studies of surface soil moisture variations. Wilson *et al.* [2003] and Choi *et al.* [2006] discuss the relationship between surface and deeper soil moisture variations.

[10] A number of prior works have addressed changes in surface soil moisture variance with increasing or decreasing field-mean moisture content. Bell *et al.* [1980], Famiglietti *et al.* [1998], Hawley *et al.* [1983], Hills and Reynolds [1969], and Reynolds [1970] reported that variance decreases with drying, while Famiglietti *et al.* [1999] and Hupet and Vanclooster [2002] observed an increasing standard deviation of soil moisture with decreasing mean moisture content. Crow and Wood [1999] suggested that soil moisture variability increases with drying within small areas (<1 km), but that it decreases with drying within large-scale fields (>10 km). Owe *et al.* [1982] observed maximum soil moisture variance in the mid-range of mean soil moisture, which resulted in the change of soil moisture variability along a convex-upward curve with increasing mean soil moisture. Peters-Lidard and Pan [2002] attributed this convex-upward relationship to the heterogeneity of soil texture, suggesting that soil moisture variance increases with drying if the mean soil moisture content is between saturation (i.e., volumetric soil moisture content is equivalent to porosity of the soil) and field capacity of the soil, but that it decreases with drying if mean soil moisture is lower than field capacity of the soil. We use the term field capacity in the traditional sense to represent the moisture content of a soil after it drains from saturation to the point where equilibrium is reached between the surface tension forces retaining the remaining water and the gravitational forces responsible for drainage [Shuttleworth, 1993]. Hydraulic conductivity of a soil medium is greatly affected by its texture, and the difference in the drainage rate among different soil textures is largest when the soil moisture content is between saturation and field capacity. Albertson and Montaldo [2003] showed that heterogeneous atmospheric forcing over the land surface can also result in a variance-mean moisture content relationship that peaks in the mid-range.

[11] The coefficient of variation versus mean soil moisture relationship is useful for characterizing moisture content variations because it exhibits a fairly predictable exponential pattern, even when only a limited number of samples are collected. Bell *et al.* [1980], Owe *et al.* [1982],

Table 1. Summary of Previous Studies of Soil Moisture Variability Using Ground-Based Measurements

Study	Location	Extent	Sampling Depth
<i>Hills and Reynolds</i> , 1969	Chew Stoke, UK	2.4-m ² to 6-km ² fields	0–8 cm
<i>Reynolds</i> , 1970	Somerset, UK	715 5.9-m ² plots	0–8 cm
<i>Bell et al.</i> , 1980	Arizona, Kansas, and South Dakota, USA	62 160,000-m ² fields	0–15 cm
<i>Owe et al.</i> , 1982	South Dakota, USA	160,000-m ² to 2.6-km ² fields	0–10 cm
<i>Hawley et al.</i> , 1983	Oklahoma, USA	8 51,000-m ² to 179,000-m ² watersheds	0–15 cm
<i>Charpentier and Groffman</i> , 1992	Kansas, USA	2 4356-m ² plots	0–5 cm
<i>Famiglietti et al.</i> , 1998	Texas, USA	200-m transect	0–5 cm
<i>Famiglietti et al.</i> , 1999	Oklahoma, USA	6 640,000-m ² fields	0–6 cm
<i>Hupet and Vanclooster</i> , 2002	Louvain-la-Neuve, Belgium	63,000-m ² field	0–125-cm profile
<i>Albertson and Montaldo</i> , 2003	Virginia, USA	36-m transect	0–30 cm
<i>Jacobs et al.</i> , 2004	Iowa, USA	4 320,000 m ² to 1-km ² fields	0–6 cm

and *Charpentier and Groffman* [1992] reported that the CV decreases with increasing soil moisture. *Jacobs et al.* [2004] fit the CV versus mean moisture content of 800-m scale soil moisture data and applied the results to calculate the number of samples required to achieve a specified error when estimating the field mean. However, *Famiglietti et al.* [1999] noted that the decreasing pattern of the CV was largely controlled by increasing mean soil moisture. That is, the exponential decreases of the CV with increasing mean soil moisture is due in large part to the difference in magnitude between mean soil moisture and the standard deviation. Regarding skewness, because the range of soil moisture content is always bounded by the residual water content and porosity of the soil, soil moisture distributions become skewed and less variable as the mean approaches each end-member state, i.e., either the residual water content or the saturated water content [*Famiglietti et al.*, 1999; *Western et al.*, 2002]. The residual water content (or irreducible water content) is defined as soil water content at which any addition of suction head would not yield water from the soil [*Guymon*, 1994]. *Famiglietti et al.* [1999] and *Ryu and Famiglietti* [2005] observed systematic changes of the soil moisture probability density function (PDF) from positively to negatively skewed distributions at the 800-m and 50-km scales.

[12] The growing need to combine multiple soil moisture data sets of various resolutions and from diverse sources has heightened interest in the scaling characteristics of soil moisture distributions. *Blöschl and Sivapalan* [1995] and *Western and Blöschl* [1999] suggested that a “scale triplet,” composed of spacing, support, and extent, should be considered in studies of soil moisture scaling. Spacing refers to the distance between measurements, support refers to the effective area or volume that each measurement represents, and extent is the total area of the spatial domain. They reported that, in the case of spatially correlated soil moisture fields, soil moisture variability decreased with increasing support, but it increased with extent scale. Spacing between measurements did not affect the soil moisture variability. *Rodriguez-Iturbe et al.* [1995] analyzed soil moisture data from the Washita’92 experiment and showed that log variance decreased linearly with log support scale, indicating a power law decay of soil moisture variability within the observed range of support scales (30 m–1 km). *Hu et al.* [1997] showed that spatial correlation within soil moisture fields was an important factor which governed this relationship. *Ryu and Famiglietti* [2006] analyzed remotely sensed soil moisture data from SGP97 and found that soil moisture

variability was spatially correlated with a multiscale nested structure, which caused changes in the linear decay pattern of log soil moisture variance with log support scale.

[13] While several of the studies listed above have addressed soil moisture variations within limited domains (see Table 1), to our knowledge, there has been no systematic attempt to characterize the scaling behavior of soil moisture variability across extent scales varying from a few meters to the satellite footprint-scale. This work described below addresses this important research area.

3. Data and Methods

[14] The ground-based measurements of surface moisture content used in this study were obtained during the SGP97, SGP99, SMEX02 and SMEX03 campaigns. During these field experiments, both volumetric and gravimetric measurements were made using impedance probe and soil sampling tools respectively. Although gravimetric soil moisture sampling provides reliable moisture content measurements, the volumetric measurements were used for the analyses in this study because the number of gravimetric measurements was relatively small (i.e., too small to characterize soil moisture variability within the fields studied here). The experiments and soil moisture measurements used in this study are described below and summarized in Table 2.

[15] Impedance probe measurements represent the volumetric moisture content contained within the top 6-cm of soil. There are a number of ways to calibrate the probes. One is a field-specific calibration method [*Cosh et al.*, 2005], which compares impedance probe measurements with adjacent soil moisture measurements. While field-specific calibration is ideal for smaller-scale studies, it is impractical for the large-scale nature of the work described here. Instead we use the generalized calibration method [*Gaskin and Miller*, 1996], which was applied to the entire data set. Accuracy of the general calibration is $\pm 0.03 \text{ cm}^3/\text{cm}^3$ for measurements taken in mineral soils.

3.1. The Southern Great Plains 1997 Hydrology Experiment (SGP97)

[16] SGP97 was conducted from 18 June to 17 July 1997 in a 50-km by 250-km region of central Oklahoma. The major objective of the experiment was to demonstrate the mapping capabilities of the Electronically Scanned Thinned Array Radiometer (ESTAR), which was flown on a NASA P3B aircraft over the study region. The performance of the soil moisture retrieval algorithm, which was previously

Table 2. Field Sites, Number of Samples and Sampling Dates

Experiment	Scale	Site Names	Sampling Dates	Number of Daily Samples per Site	Total Number of Samples Collected
SGP97	800 × 800 m ²	LW03, LW13, LW21, ER05, ER13, CF04	19 June–16 July	27 at ER13 49 at others	5686
SGP99	2.5 × 2.5 m ² ~1.6 × 1.6 km ²	LW21, LW21S, LW22, LW22S	8–9, 11–13, 15–19 July	49 at all scales	4390
SMEX02 ^a	50 × 100 km ²	IA	25–27, 29–30 June; 1–2, 4–6, 7–12 July	23 at northern region 24 at southern region	2256
SMEX03 ^a	800 × 800 m ²	WC01, WC03–06, WC08–33	25–27 June, 1, 5–8, 9, 11–12 July	14 at all sites	14652
	50 × 100 km ²	ON	2–8, 10–15, 17 July	20 at northern region 16 at southern region	1512
	50 × 100 km ²	OS	2–8, 10, 12–14 July	26 at northern region 25 at southern region	1683
	800 × 800 m ²	LW02–04, LW11–13, LW20–22, LW27–29, LW31–33	2–8, 10, 12–14 July	14 at all sites	7029

^aDuring SMEX02 and SMEX03, three samples were taken at each sampling location. Therefore, for example, at the field scale (800 × 800 m²) sites, the total number of daily samples is 42.

developed for small-scale fields, was tested at larger scales during the experiment [Jackson *et al.*, 1999]. In order to validate aircraft footprint-scale soil moisture estimates from ESTAR, gravimetric soil moisture samples were collected at 49 sites, which were located in three major places: the Little Washita watershed (LW, 23 sites); the U.S. Department of Agriculture Agricultural Research Service Grazinglands Research Laboratory in El Reno (ER, 16 sites); and the Department of Energy Atmospheric Radiation Measurement Program cloud and radiation test bed (ARM CART) Central Facility (CF, 10 sites) (see Figure 1).

[17] In a separate study of soil moisture variability conducted during SGP97 [Famiglietti *et al.*, 1999], intensive ground sampling of soil moisture content was performed at six field-scale (800 × 800 m²) sites using impedance probes. Three of these sites were in the Little Washita watershed (LW03, LW13, and LW21), two sites at El Reno (ER05 and ER13), and one at the ARM CART Central Facility (CF04). LW03 and LW13 were located in gently rolling rangeland with loamy sand and loam soil, respectively. LW21, ER13, and CF04 were in a flat area with silty loam soil and winter wheat land cover. ER05 was located in gently rolling rangeland with silty loam soil. Within each 800-m scale site, 49 soil moisture measurements were taken nearly every day on a 7 by 7 100-m grid using the impedance probe, except at ER13 where only 27 measurements were taken. These impedance probe data were included in the data set analyzed in the present study.

3.2. The Southern Great Plains 1999 Hydrology Experiment (SGP99)

[18] SGP99 was conducted from 7 July to 22 July 1999 in the same region of central Oklahoma as the SGP97 experiment. The main goals of the experiment were to develop and verify a retrieval algorithm for a C-band radiometer, the Polarimetric Scanning Radiometer (PSR/C), as well as to evaluate its soil moisture mapping capability [Jackson *et al.*, 2003]. The goal of the PSR/C studies was to assess the utility of soil moisture products from satellite C-band radiometers such as AMSR-E, which launched shortly after SGP99.

[19] In addition to the gravimetric soil moisture sampling for validating remotely sensed soil moisture estimates, we conducted a multiscale nested-grid study of the scaling behavior of surface soil moisture variations. Multiscale sampling was carried out on ten days between 8 July and 19 July 1999 (see Table 1) in a 1.6-km site in the Little Washita watershed. The sampling site (LW21 and LW22) was a winter wheat field with silty loam soil and flat topography. Sampling was conducted at 5 distinct extent scales as shown in Figure 2 (1.6 km, 800 m, 100 m, 16 m, and 2.5 m). Forty-nine measurements of volumetric moisture content were made within each region on a 7 by 7 equally spaced grid, except in the 2.5-m plots, where 49 measurements were made in random locations. Field LW22 was plowed during the sampling period, which resulted in extreme soil drying. As a result, a number of soil moisture observations dropped below the detection limit of the impedance probes after plowing (i.e., the measured impedance yielded a negative value of moisture content). Therefore 191 soil moisture measurements taken on July 15 ~ 19

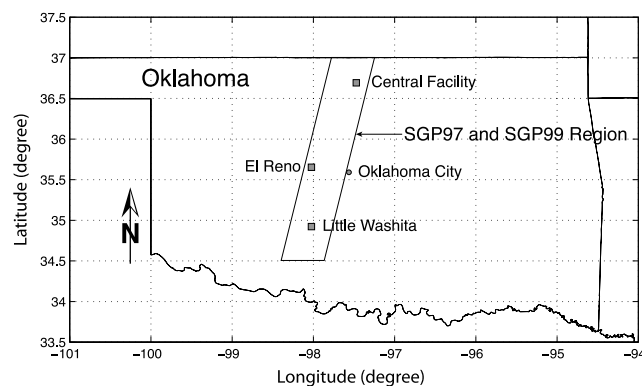


Figure 1. Location of the Southern Great Plains 1997 (SGP97) and 1999 (SGP99) Hydrology Experiments in Oklahoma. Aircraft soil moisture mapping was conducted within the 50-km by 250-km area, which is shown as a box in the figure. Soil moisture sampling was conducted in the three regions shown as gray boxes.

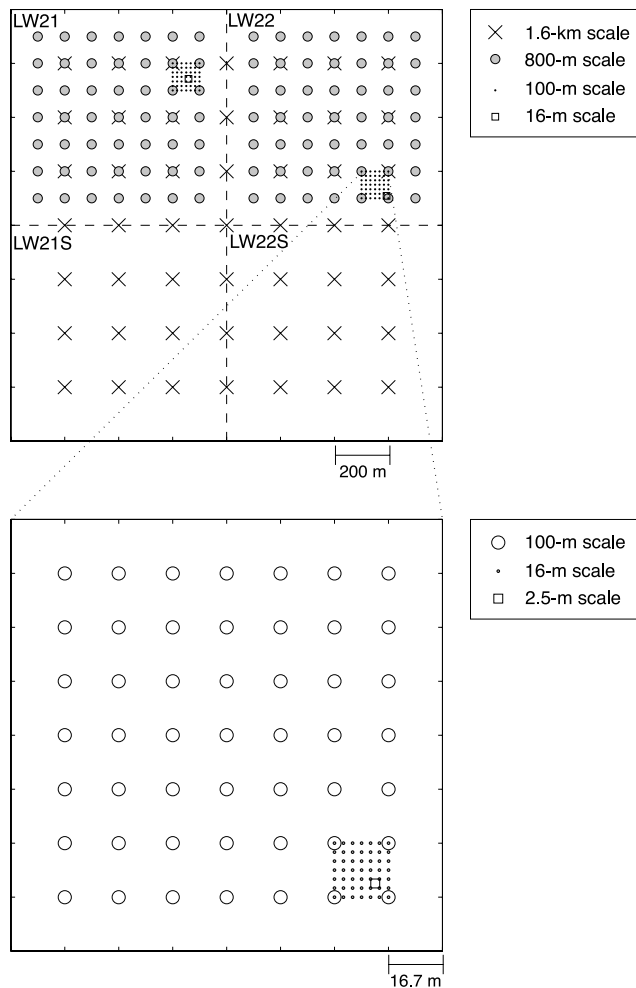


Figure 2. Nested sampling grids of SGP99. Volumetric soil moisture content was measured at five nested extent scales: 2.5 m, 16 m, 100 m, 800 m, and 1.6 km. The northwest corner of the LW21 was (565,247 m, 3,863,463 m) in universal transverse Mercator coordinates (UTM).

at LW22 were removed from the data set. The remaining multiscale impedance probe measurements of volumetric soil moisture were included in our data set for analysis.

3.3. Soil Moisture Experiment in 2002 (SMEX02)

[20] As a continuing effort to validate satellite remotely sensed soil moisture products and evaluate new approaches, SMEX02 was conducted from 25 June to 12 July 2002 in central Iowa (see Figure 3a). The main elements of SMEX02 included the evaluation of the performance of soil moisture retrieval algorithms over agricultural fields and to validate AMSR-E brightness temperature and soil moisture products. Because of the large footprint-scale of AMSR-E ($\sim 43 \text{ km} \times 75 \text{ km}$), intensive ground-based sampling, which was designed to provide mean soil moisture estimates within roughly one AMSR-E footprint, was performed within a regional-scale ($\sim 50 \text{ km} \times 100 \text{ km}$) field (see Figure 3c). The regional-scale region was named IA. Field-scale ($800 \text{ m} \times 800 \text{ m}$) samples were also taken in 31 watershed sites, which were named WC sites, in the Walnut Creek watershed area (see Figure 3b). Corn and

soybean dominated both the regional- and field-scale study area.

[21] A total of 47 sampling locations were distributed on a near-regular grid in the regional-scale study area (see Figure 3c). Both gravimetric and volumetric soil moisture contents were measured on 16 days between 25 June and 12 July 2002 (see Table 2). The use of row planting throughout the study area created a regular micro-topography, which was composed of ridges along the crop rows and furrows between them. In order to reduce the possible impact of soil moisture heterogeneity across the crop rows, three measurements were taken at each sampling location: one on the ridge, another in the furrow, and the third between the ridge and furrow. All of the impedance probe data from the IA regional site and the 800-m fields were used in the present study. However, when dealing with field- or regional-scale variability of soil moisture, averaging the three measurements at each sampling location can reduce the total variability in the field. Thus one of the three measurements at each sampling location was chosen randomly for the calculation of field- and regional-scale soil moisture variability. More detailed discussion of the data handling is described in the section 3.5.

3.4. Soil Moisture Experiments in 2003 (SMEX03)

[22] In SMEX03, the experimental domain was expanded to four regions (Oklahoma, Georgia, Alabama, and Brazil) in order to cover a broader range of vegetation conditions. The expanded regions included cotton fields and forests, in addition to the winter wheat and rangeland fields of Oklahoma. Only the impedance probe volumetric soil moisture measurements from regional- and field-scale sites in Oklahoma were used in this study. Regional-scale sampling was conducted in two $\sim 50 \text{ km} \times 100 \text{ km}$ sites in Oklahoma (see Figure 4). The northern region was named ON (Figure 4b) and southern region OS (Figure 4c).

[23] In the ON region, volumetric soil moisture contents were measured on 14 days at 36 sampling locations (see Table 2). In the OS study region, soil moisture contents were measured on 11 days at 51 sampling locations (see Table 2). The sampling period was shorter in the OS region because extremely dry conditions persisted in the southern part of Oklahoma during SMEX03, resulting in minimal changes in measured soil moisture content. Field-scale samples were taken at fifteen sites within the Little Washita watershed (Figure 4d). Volumetric soil moisture contents were measured at 14 locations in each of the 15 field-scale sites on 11 days, which were the same as the OS sampling dates. The sampling scheme was same as that used in SMEX02. Three volumetric soil moisture measurements were made at each sampling location. However, because row planting was not a common practice in the study region, the three measurement locations were chosen randomly at each sampling site.

3.5. Method of Analysis

[24] The main goal of this study is to examine soil moisture variations across multiple extent scales and wetness conditions. The more than 36,000 ground-based measurements collected during SGP97, SGP99, SMEX02, and SMEX03 were regrouped into six extent scales: 2.5 m, 16 m, 100 m, 800 m, 1.6 km, and 50 km. The soil moisture standard deviation, CV, and skewness were calculated using

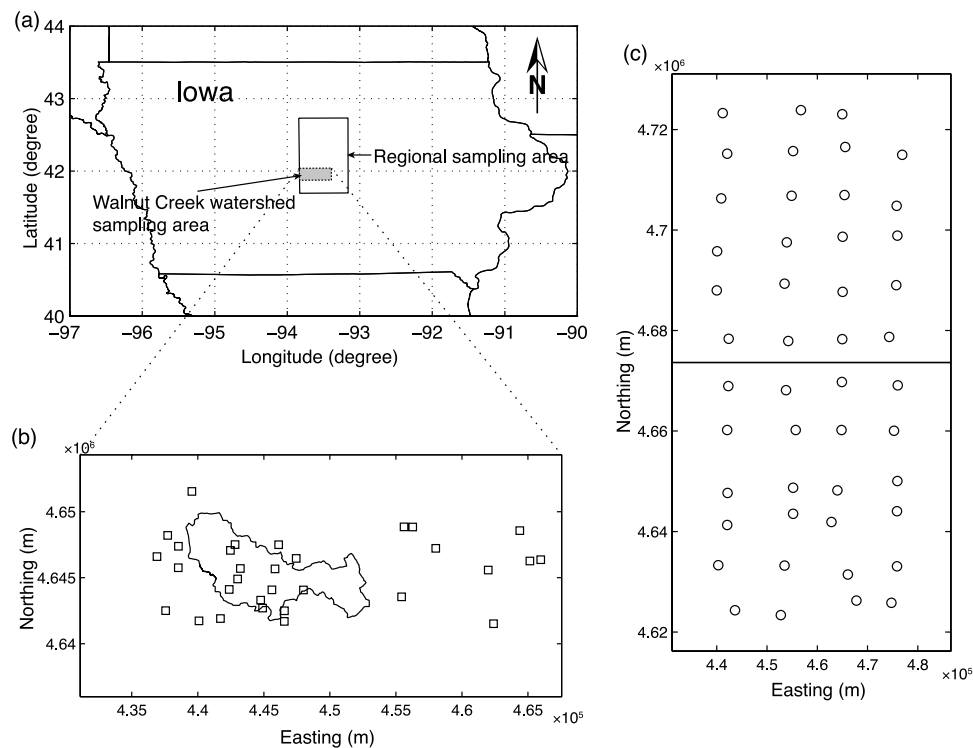


Figure 3. (a) Location of the Soil Moisture Experiments in 2002 (SMEX02) study area in Iowa. Regional-scale sampling was conducted at 31 800-m by 800-m scale sites located in the Walnut Creek watershed area, colored in gray. (b) Boundary of the Walnut Creek watershed and the locations of 31 field-scale sites. (c) 47 sampling locations within the regional-scale study area. The entire region was divided into two 50-km scale sub-regions by the horizontal line in the middle of the region.

a set of ground measurements collected each day, within the time span of 1–3 h, separately in each field. Soil moisture measurements from different fields or different sampling dates were not mixed to calculate the variability. In order to calculate the 50-km scale soil moisture statistics, each of the three regional-scale fields (approximately $50 \text{ km} \times 100 \text{ km}$) of SMEX02 (IA) and SMEX03 (ON and OS) were divided into two parts, i.e., northern and southern sub-regions. In the SMEX02 data set, the northern sub-region of the IA study area contained 23 sampling locations and the southern part contained 24 locations (see Figure 3c). For SMEX03, there were 20 sampling locations in the northern part and 16 sampling locations in the southern part of the ON region. In the OS study region, 26 sampling locations were in the northern part and 25 sampling locations were in the southern part.

[25] During the SGP97 and SGP99 experiments, only one ground-based measurement was taken at each sampling location. Therefore soil moisture measurements from each site could be directly used to calculate the spatial variability of soil moisture. As described earlier, during SMEX02 and SMEX03, three samples were taken at each sampling location in order to reduce the uncertainty in the estimates of mean soil moisture for validation. Since averaging the three measurements at each sampling location can reduce the total variability of soil moisture in a field, one of the three measurements was chosen randomly for the calculation of field- and regional-scale soil moisture variability. Sampling once at each measurement location was per-

formed using uniform random number generation, which was repeated 1000 times at each field site. The resulting 1000 estimates of soil moisture variability were averaged to estimate the soil moisture variability for the field. The same sampling scheme was applied to calculate CV and skewness of field- and regional-scale fields in SMEX02 and SMEX03. Soil moisture standard deviation, CV, and skewness versus mean moisture content were plotted across scales as shown in section 4.

4. Results

[26] In this section, the statistics of soil moisture content variations across scales are presented. A brief description of the ranges of observed surface soil wetness during SGP97, SGP99, SMEX02, and SMEX03 is provided, followed by a discussion of soil moisture standard deviation, CV, and skewness versus mean moisture content. Functional relationships between soil moisture variability and mean moisture content, and between skewness and mean moisture content, are empirically derived. Last, soil moisture variability versus extent scale relationships are examined.

4.1. Mean Soil Moisture Content

[27] Figure 5 shows the distribution of mean soil moisture content for the field sites at different scales during the SGP and SMEX field experiments. The boxes in the plot display the interquartile ranges of mean soil moisture, and horizontal lines within the boxes indicate the median of mean moisture content. Whiskers extending outside of each box

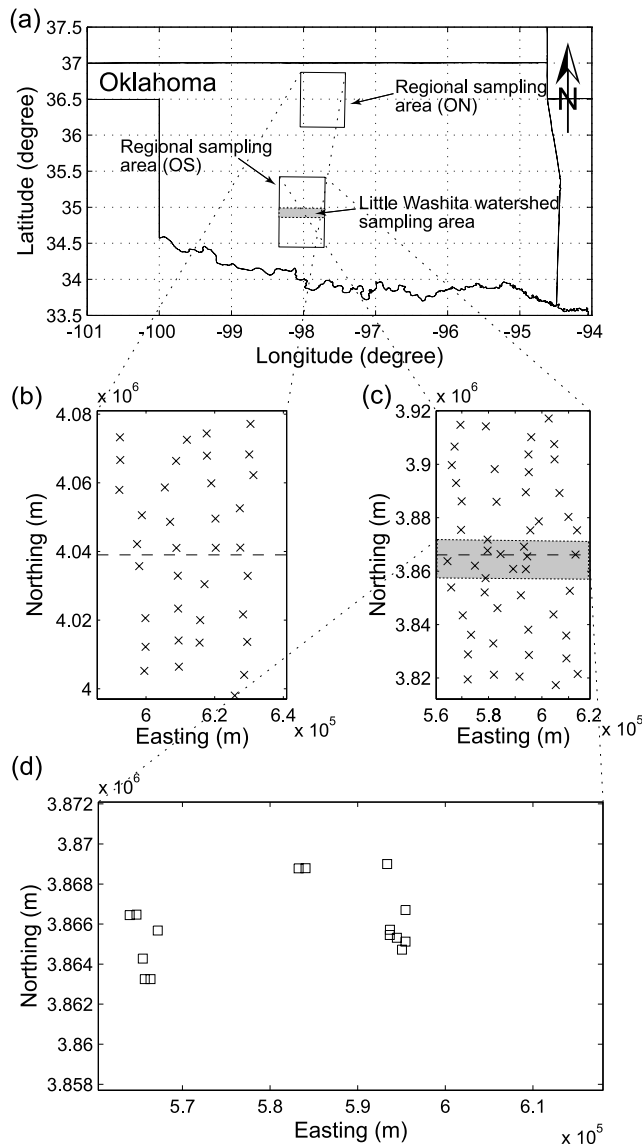


Figure 4. (a) Location of the Soil Moisture Experiments in 2003 (SMEX03) study area in Oklahoma. Two regional-scale study regions (ON and OS) are shown as boxes (b) 36 regional-scale sampling locations in ON. The dashed line in the middle divides the field into two 50-km scale sub-regions. (c) 51 regional-scale sampling locations in OS. The dashed line in the middle divides the region into two 50-km scale sub-regions. The shaded region in the middle is the Little Washita watershed sampling area. (d) 15 field-scale sampling sites in the Little Washita watershed study area.

show the range of the mean values: the maximum length of the whiskers in this plot is defined as 1.5 times the size of the interquartile ranges. Outliers are marked as crosses.

[28] Mean soil moisture contents show the widest ranges at for the 800-m scale sites during SGP97 and SMEX02. These SGP97 sites received large amounts of rainfall and also experienced long drying periods. Mean soil moisture contents of SGP99 vary within relatively narrow ranges, and the ranges at different scales are similar to each other. This behavior is attributed to the fact that all the multiscale sampling grids were within one 1.6-km scale site (see

Figure 2). The mean moisture content of a 50-km scale field is likely to have a narrower range than that of smaller scale fields because it is less likely for the larger area to become either uniformly wet or dry. The ranges of the 50-km scale fields of SMEX02 and SMEX03 in fact show a more limited range of mean soil moisture than the 800-m scale fields. During SMEX03, the ON and OS regional-scale sites experienced an unusually long dry period, resulting in narrow ranges of low mean soil moisture content. However, large-scale rainfall over almost the entire SMEX02 domain created very wet conditions for a few days during the experiment period. This provided a good opportunity to observe the behavior of soil moisture variability within a wide range of mean moisture contents at the 50-km scale.

4.2. Standard Deviation of Soil Moisture

[29] Figure 6 shows the soil moisture standard deviation versus mean moisture content at the six different extent scales. SGP99 data, 800-m scale data, and 50-km scale data were plotted separately due to the larger number of plots at the 800-m and 50-km scales. Although standard deviation data of SGP99 do not show a clear trend with increasing mean soil moisture, the standard deviation increases with extent scale as a whole. At the 800-m and 50-km scales, it is evident that the standard deviation increases until mean moisture content reaches around $0.2 \text{ cm}^3/\text{cm}^3$ and then decreases beyond that. It is also worth noting that, even though the standard deviation data were calculated using soil moisture measurements taken at many different sites, with varying land cover conditions, they are scattered within a fairly similar range at the 800-m and 50-km scales, respectively.

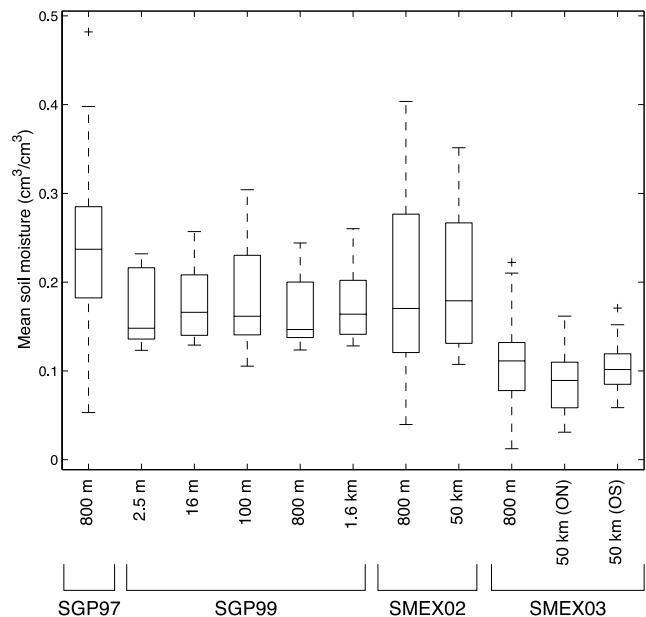


Figure 5. Box plots of mean soil moisture contents for the sampling sites of all scales. The box at each scale shows interquartile range (i.e., the range between the first and the third quartiles) of the mean soil moisture and the length of the whiskers is 1.5 times the vertical scale of the boxes. Mean soil moisture values outside of the whiskers are regarded as outliers and marked as crosses in the figure.

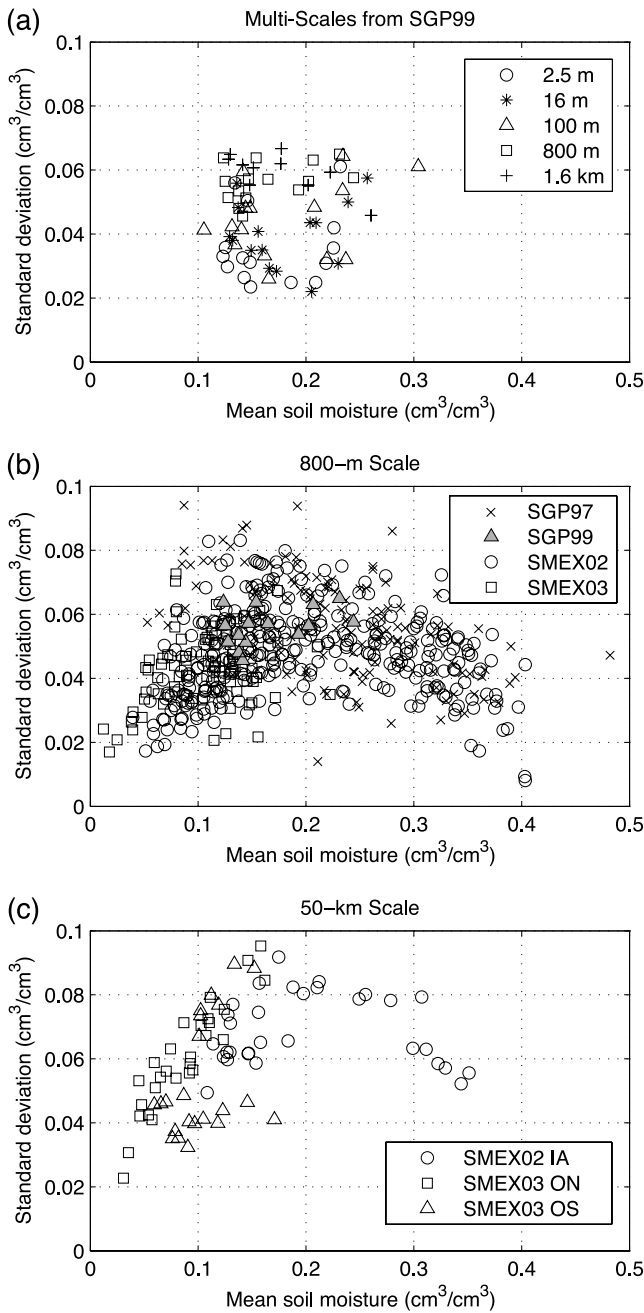


Figure 6. Soil moisture standard deviation versus mean moisture content (a) at five scales during SGP99, (b) at the 800-m scale during SGP97, SGP99, SMEX02, and SMEX03, and (c) at the 50-km scale during SMEX02 and SMEX03.

4.3. Coefficient of Variation and Skewness of Soil Moisture

[30] Figures 7 and 8 show the CV and skewness versus mean soil moisture across scales. As in Figure 6, the SGP99 data, 800-m scale data, and 50-km scale data were plotted separately. At the 800-m and 50-km scales, the CV exhibits an exponentially decreasing pattern with increasing mean moisture content (Figures 7b and 7c). This pattern is not as clear in the limited ranges of mean moisture content observed in SGP99 data (Figure 7a). An increase in vari-

ability is noticeable across scales in Figure 7a. Figures 7b and 7c show more widely scattered values of the CV as mean soil moisture decreases, although the CVs from the 50-km fields (Figure 7c) lie in the upper range of those shown for the 800-km fields in Figure 7b. The scatter in Figure 7b is partly caused by the wide range of standard deviations within the range of mean soil moisture content between 0.05 and 0.2 cm³/cm³. Since the CV is calculated by dividing the standard deviation by the mean moisture content, the spread of the standard deviation is amplified as

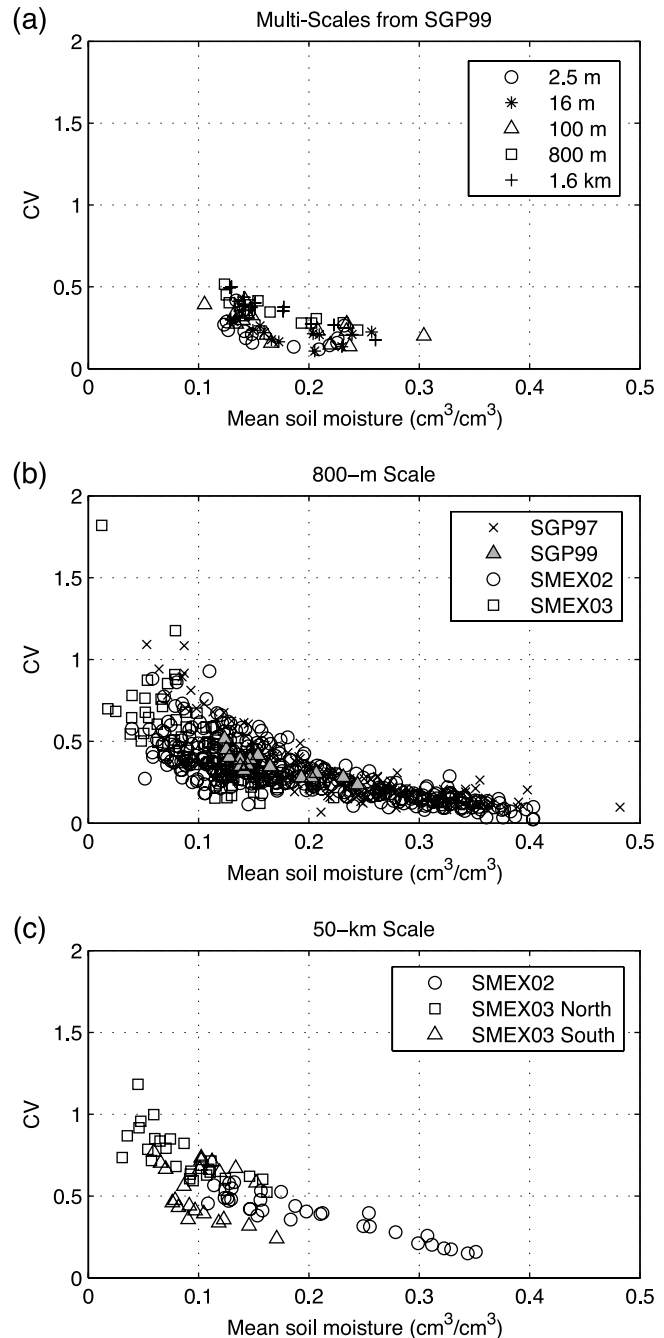


Figure 7. Coefficient of variation (CV) versus mean soil moisture plots (a) at five scales during SGP99, (b) at the 800-m scale during SGP97, SGP99, SMEX02, and SMEX03, and (c) at the 50-km scale during SMEX02 and SMEX03.

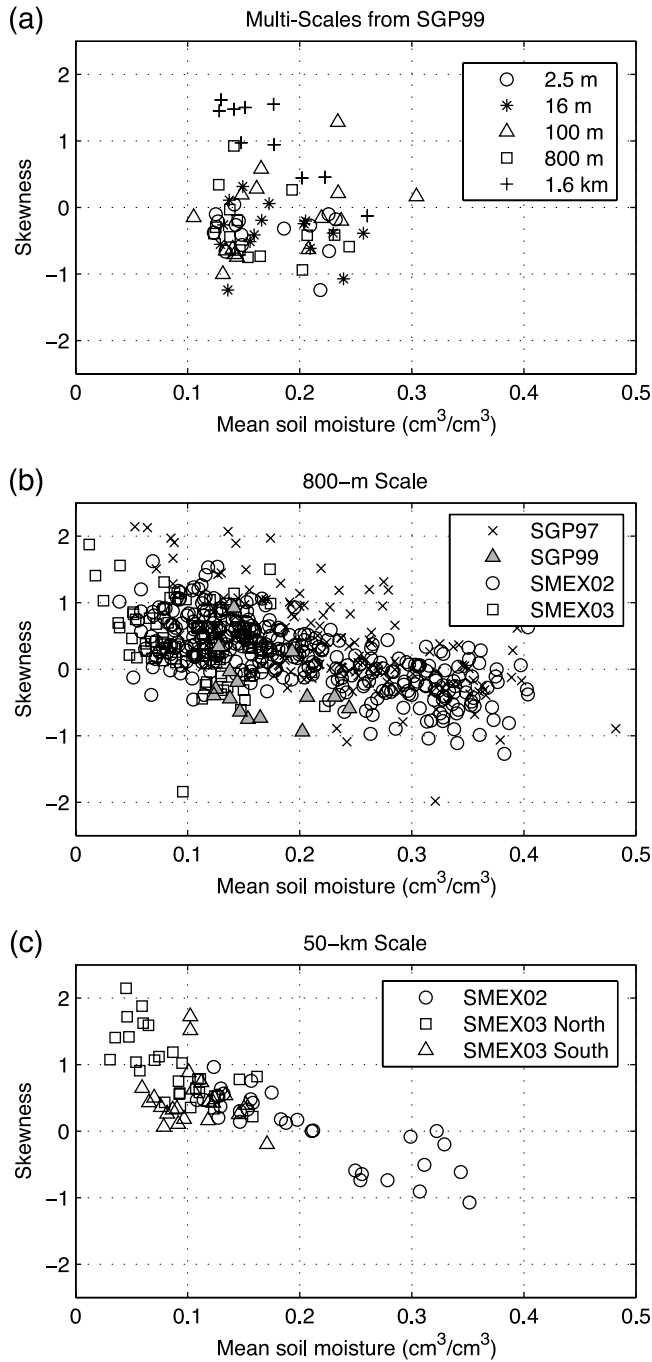


Figure 8. Skewness versus mean soil moisture plots (a) at five scales during SGP99, (b) at the 800-m scale during SGP97, SGP99, SMEX02, and SMEX03, and (c) at the 50-km scale during SMEX02 and SMEX03.

mean soil moisture decreases, resulting in more scattered CV values with drying.

[31] Figure 8 shows changes in skewness with mean soil moisture content. Our 2.5 m to 1.6 km data (Figure 8a) indicate that skewness generally decreases, from positive to negative values, with increasing mean moisture content, except at the 100-m scale where skewness increased with mean moisture content. In addition, Figure 8a shows an overall increase in skewness with scale, which implies that positive skewness of the soil moisture distribution under dry

surface conditions may be more pronounced at larger scales within a given range of scales. Skewness also decreases from positive to negative with increasing mean moisture content at the 800-m and 50-km scales. According to the skewness data shown in Figure 8, symmetric soil moisture distributions are most likely when the mean moisture content is between 0.2 and 0.3 cm^3/cm^3 at the 800-m, 1.6-km, and 50-km scales.

4.4. Variability Across Scales

[32] In order to compare the standard deviation, CV and skewness versus mean soil moisture across scales, the range of mean soil moisture from 0 to 0.5 cm^3/cm^3 was divided into ten bins of size 0.05 cm^3/cm^3 , and the variability data were averaged within each bin. Figure 9a compares the bin-averaged soil moisture standard deviation at the six extent scales. Convex upward trends are observed at the 1.6-km scale as well as at 800-m and 50-km scales. At 2.5-, 16-, and 100-m scales, however, the soil moisture standard deviation does not show a clear trend with mean soil moisture, which is likely caused by the limited number of reliable smaller-scale samples resulting from SGP99 (see section 3.2), and the associated narrow ranges of mean soil moisture contents. An increasing trend of the soil moisture standard deviation with extent scale is also obvious when the extent scale is larger than 100-m. At the 2.5-, 16-, and 100-m scales however, the standard deviation data were all in the similar range.

[33] Figure 9b shows a clear increase in the CV with increasing scale. The behavior of skewness with increasing scale is more complex however (Figure 9c), but for the fields with the largest number of measurements (800-m and 50-km), the increase in skewness described above in Figure 8 is apparent.

4.5. Empirical Functions of Soil Moisture Variability and Skewness

[34] Here we use the CV and skewness versus mean moisture content data shown in Figures 7 and 8 to derive functional relationships that should be helpful for characterizing soil moisture variations in models or for validation purposes. An exponential function was used to fit the CV–mean moisture content relationship:

$$CV = k_1 \cdot \exp(-k_2\mu) \quad (1)$$

where k_1 and k_2 are model parameters, and μ is mean soil moisture content. The fitted functions are shown in the first column of Figure 10 and the parameters k_1 and k_2 of are listed in Table 3.

[35] Since the CV is calculated by σ/μ , where σ is standard deviation of soil moisture, equation 1 can be rearranged to give the standard deviation versus mean soil moisture relationship as follows:

$$\sigma = k_1 \cdot \mu \cdot \exp(-k_2\mu) \quad (2)$$

The functions derived using equation 2 are shown in the second column of Figure 10.

[36] A line was fit to the skewness versus mean moisture content data at each scale. Parameters of the linear fit and the RMSE of fit-curves are listed in Table 4.

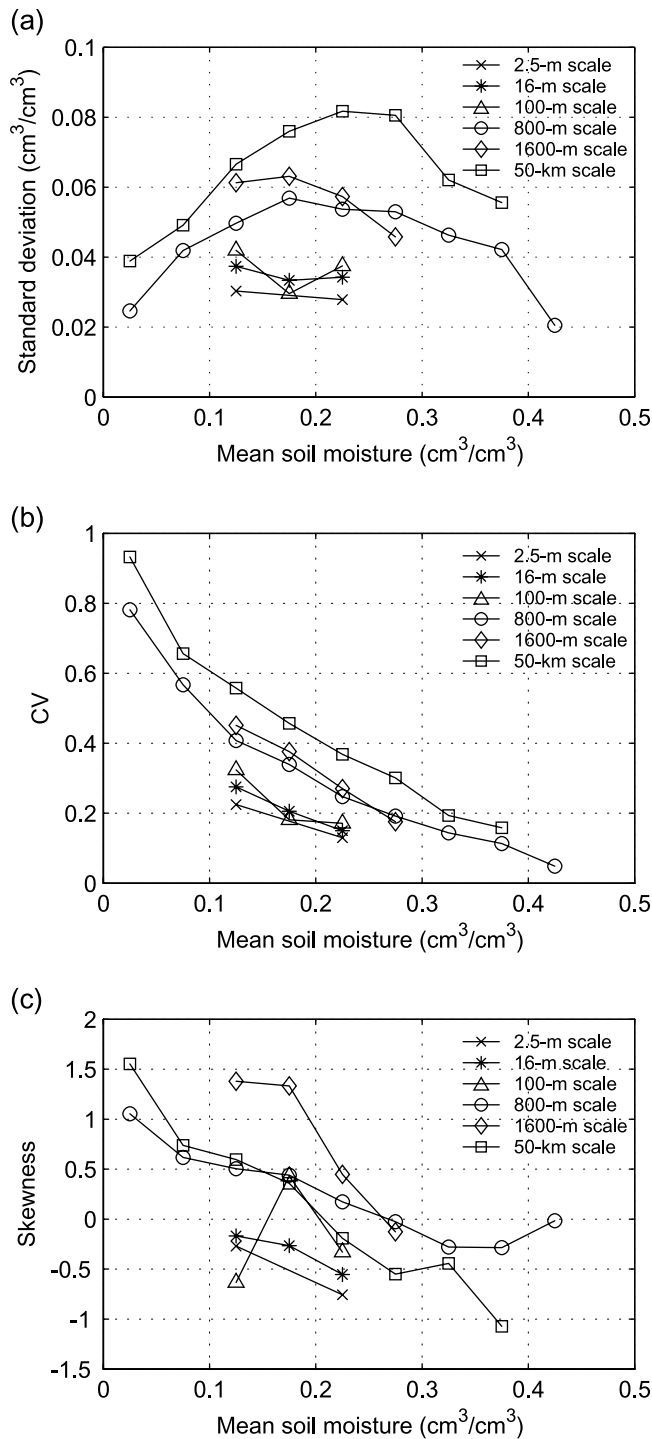


Figure 9. (a) Standard deviation of soil moisture at 2.5-m – 50-km scales averaged within 0.05 cm³/cm³-wide bins of mean soil moisture contents; (b) same as (a) but for CV; (c) same as (a) but for skewness.

[37] The second column of Figure 10 shows that the soil moisture standard deviation has a convex upward pattern with increasing mean moisture content. These functions mimic the observations and show an increasing standard deviation with increasing extent scale. Equation 2 implies a zero standard deviation at zero mean soil moisture, regard-

less of spatial scale. However, in theory, the soil moisture standard deviation at near-zero mean moisture content would be determined by spatial variations of the residual water content. All the standard deviation functions in Figure 10 exhibit a peak between 0.1 cm³/cm³ and 0.2 cm³/cm³ mean moisture content. The mean moisture content at which the standard deviation peaks can be analytically derived by differentiating equation 2 by μ , which results in $1/k_2$. Generally, the mean moisture content of peak soil moisture variability increases with extent scale (see Table 3).

[38] The fitted lines in the third column of Figure 10 show the observed variations of skewness with mean moisture content. Slopes of all the lines are negative except at the 100-m scale, where skewness increases slightly with mean moisture content. The slopes of the skewness lines generally increase with extent scale except at 1.6-km scale where the slope is much higher than other scales.

4.6. Scaling of Soil Moisture Variability

[39] Figure 11a shows the distribution of the soil moisture standard deviation at each of the six extent scales studied. Because of the limited ranges of mean moisture content at the 2.5-, 16-, and 100-m scales, only the standard deviation data with mean moisture contents between 0.1 cm³/cm³ and 0.3 cm³/cm³ at all scales were used to create the box plot (Figure 11a). It is important to use standard deviation data within the same range of mean moisture contents when comparing these data across scales. Owing to the convex upward nature of the standard deviation versus mean moisture content relationship, if the range of mean wetness varies across scales, the estimated standard deviation at a particular scale can be biased. The definitions of the box and whisker characteristics are the same as those in Figure 5. The circle in each box denotes the mean standard deviation at the corresponding scale. The greater range in standard deviation values at the 800-m and 50-km scales is likely a result of the larger sample size available for analysis. Figure 11a shows that the standard deviation increases from 0.036 cm³/cm³ at the 2.5-m scale to 0.071 cm³/cm³ at the 50-km scale. The mean standard deviations in Figure 11a were used to make the log standard deviation versus log extent scale plots shown in Figure 11b. The log of standard deviation increases linearly with log extent scale between 16-m and 1.6-km scales. However, the slope becomes noticeably smaller between the 2.5-m and 16-m scales, and between the 1.6-km and 50-km scales.

5. Discussion

[40] In this section we discuss the factors that may contribute to the observed behavior of soil moisture variability across scales. Implications for satellite validation and for enhancing land surface parameterizations are also presented.

5.1. Soil Moisture Variability Across Scales

[41] A number of factors affect spatial variability of surface soil moisture content, including precipitation, evapotranspiration, soil texture, topography, vegetation, land use, etc. Each factor exerts a degree of spatial organization on the soil moisture distribution by introducing or removing water into/from the soil, or by facilitating or hampering soil water redistribution. *Albertson and Montaldo*

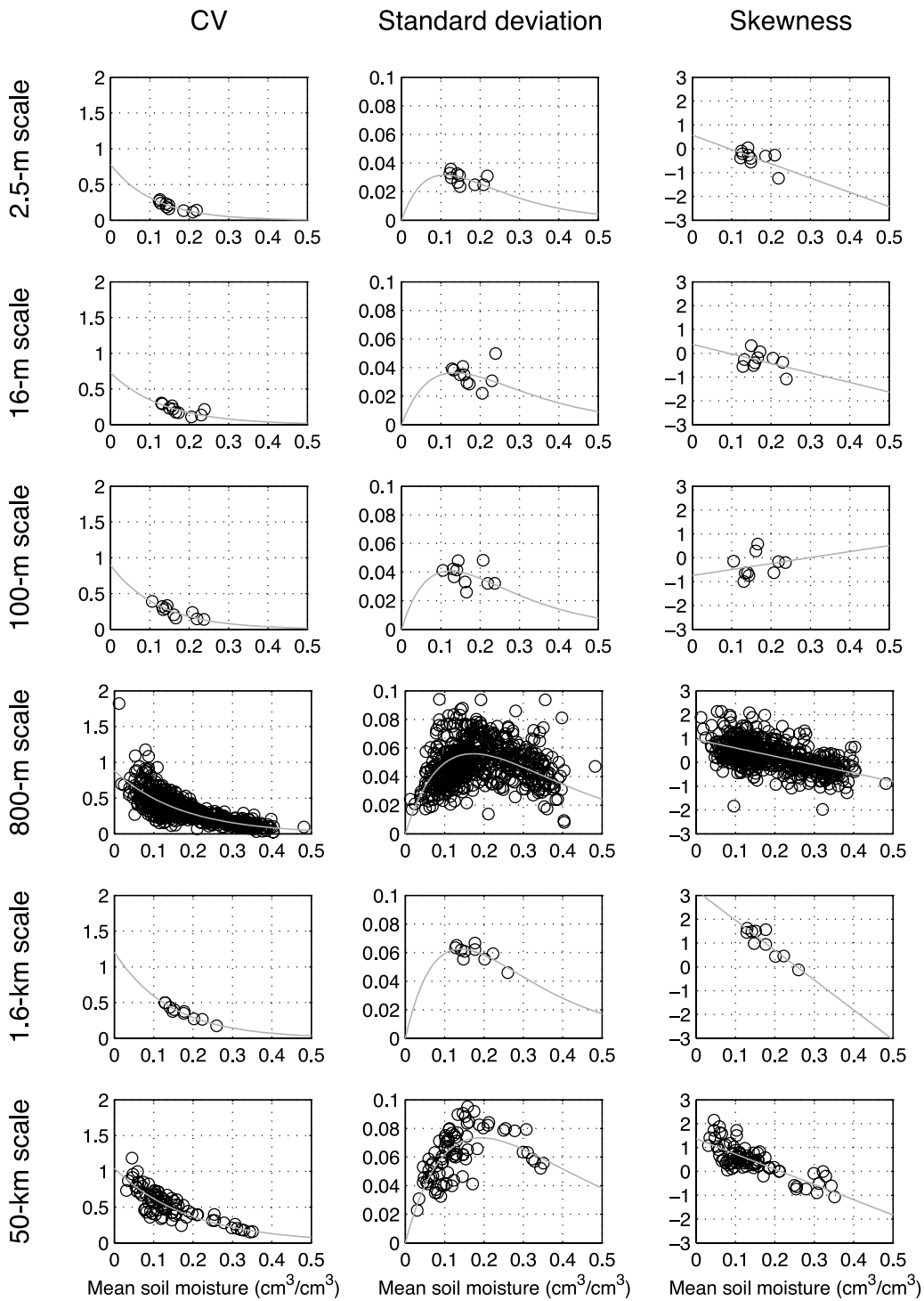


Figure 10. Empirically fit curves of CV, standard deviation, and skewness versus mean soil moisture across scales. Fitted curves of standard deviation versus mean soil moisture were constructed using the parameters by fitting curves to CV versus mean moisture content.

[2003] note that transpiration and infiltration-runoff processes can either increase or decrease the spatial variance of soil moisture depending upon the initial distribution of soil moisture and spatial heterogeneities of land surface parameters. This implies that each of the above listed factors can either enhance or reduce the spatial variability of soil moisture depending on how it is spatially distributed

and how it is combined with other factors. For example, relatively homogeneous land surface properties can act dissipatively to reduce soil moisture variability created by heterogeneous precipitation [Entekhabi and Rodriguez-Iturbe, 1994]. On the other hand, heterogeneous soil texture can increase soil moisture variability by redistributing soil water after homogeneous precipitation [Peters-Lidard and

Table 3. Parameters of CV Versus Mean Soil Moisture Relationship and RMSE

Scale	k_1	k_2	$1/k_2$	RMSE (CV)	RMSE (Stdev)
2.5 m	0.7803	9.0607	0.1104	2.424E-02	3.865E-03
16 m	0.7287	7.3796	0.1355	3.823E-02	8.043E-03
100 m	0.8941	8.0774	0.1238	3.992E-02	6.880E-03
800 m	0.8840	5.8070	0.1722	1.244E-01	1.341E-02
1.6 km	1.2070	7.1128	0.1406	2.197E-02	3.692E-03
50 km	1.0429	5.2212	0.1915	1.178E-01	1.265E-02

Pan, 2002]. Teuling and Troch [2005] presented another example of how the relative strengths of transpiration and soil water drainage, and their spatial variations, interact to either increase or decrease the spatial variability of soil moisture. According to their analysis, drainage of soil water destroys the variance of soil moisture created by spatially variable transpiration. However, when soil moisture for transpiration was limited by rapid drainage from coarse grained soil, transpiration resulted in a decrease of soil moisture variability. This means that heterogeneous transpiration in a field can either increase or decrease soil moisture variability depending on the relative strength of drainage. The hydraulic conductivity of soil and its spatial heterogeneity play a crucial role in determining the relative strength of soil water drainage. Our analysis reveals that the behavior of soil moisture variability with mean moisture content exhibits a fairly consistent relationship over a wide range of scales, in particular at the 800-m and 50-km scales in the study areas considered in this work. This implies that only a few of the factors that influence variability listed above play a dominant role in controlling the variations observed here depending on the relative strength of each factor. For example, convective rainfall events over the 50-km-scale fields in Oklahoma created large variability in soil moisture by fractionally wetting fields during SGP97, and the variability was further increased by the spatial heterogeneity of soil texture. However, the vegetation cover did not play an important role when the variability was dominated by the heterogeneities of rainfall and soil texture [Ryu and Famiglietti, 2005]. The largest regional-scale variability of soil moisture during SMEX02 was also observed when the study area was partially wetted by rainfall [Crow et al., 2005a].

[42] Kim and Barros [2002] and Oldak et al. [2002] analyzed spatial patterns of surface soil moisture from SGP97 and reported that variability was predominantly controlled by precipitation patterns under wet conditions and by soil texture and vegetation water content under dry conditions. The observed behavior of the soil moisture standard deviation in this work can be similarly understood. Precipitation is relatively homogeneous at the 800-m scale,

Table 4. Parameters of Skewness Versus Mean Soil Moisture Fits and RMSE

Scale	a_1	a_2	RMSE
2.5 m	0.5686	-5.9918	2.65E-01
16 m	0.3720	-3.9939	3.22E-01
100 m	-0.7425	2.5079	4.56E-01
800 m	0.9567	-3.5275	4.84E-01
1.6 km	3.2067	-12.5374	2.41E-01
50 km	1.3664	-6.3947	3.88E-01

so that after wetting by rainfall, variable redistribution by heterogeneous soil texture, vegetation and evapotranspiration would predominantly control the observed variability behavior. At the 50-km scale, the mesoscale structure of precipitation becomes a primary control on soil moisture variations under wet conditions, and results in an overall increase of soil moisture variability in addition to that attributed to increased heterogeneity of soil texture and vegetation. Ryu and Famiglietti [2005] noted that fractional rainfall over footprint-scale SGP97 sites creates high soil moisture variability in the mid-range of mean soil moisture, resulting bimodal probability density function.

[43] Results of this study also showed that the mean standard deviation (Figures 11a and 11b) increases with extent scale. Figure 11b showed log standard deviation with log extent scale. Log standard deviation was seen to increase linearly with log extent scale between 16 m and 1.6 km. In other words, soil moisture standard deviation (or variance) increases as a power of the extent scale at this range as follows:

$$\text{Var}(S) = C \cdot S^D \quad (3)$$

where C is a parameter, D is a fractal power, S is extent scale as area, $\text{Var}(S)$ is the variance at S . The fractal power

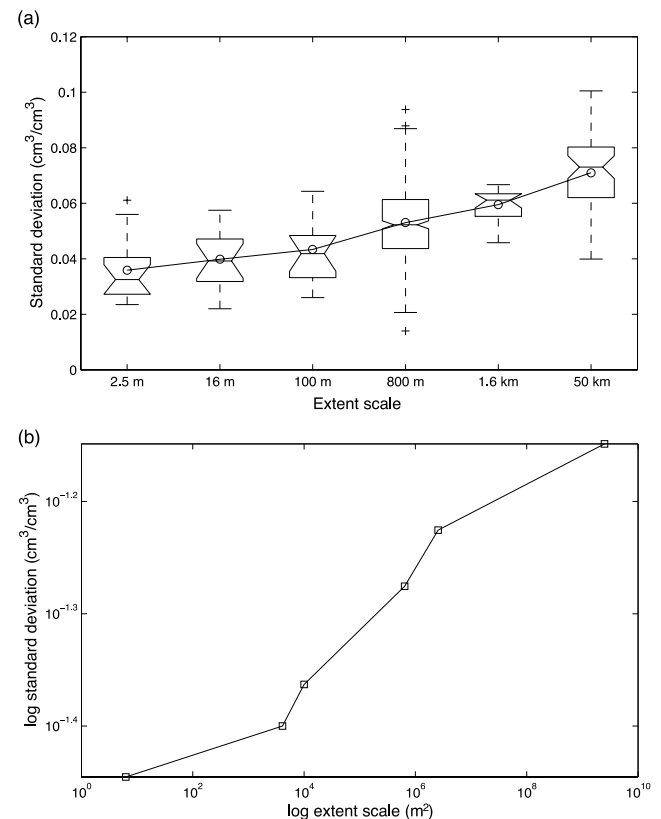


Figure 11. (a) Standard deviation versus extent scale of soil moisture. Circles in the boxes denote the mean standard deviation at the studied scales. The definitions of the boxes, whiskers, and outliers are same as in Figure 5. (b) Log standard deviation versus log extent scale. Mean standard deviation at each scale, marked as circles in Figure 11a, was used in this plot.

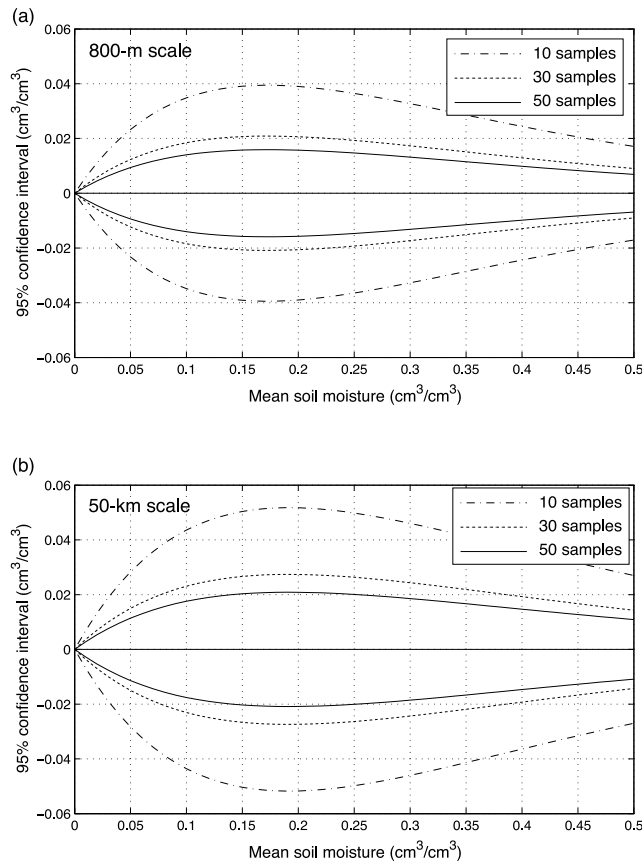


Figure 12. 95% confidence intervals of mean soil moisture content at the (a) 800-m scale and (b) 50-km scale given 10 (dotted and dashed lines), 30 (dashed lines), and 50 (solid lines) point measurements.

D was calculated as 0.086 by fitting a straight line to log variance versus log extent scale between 16 m and 1.6 km. Such a relationship can be used to estimate the average variance conditions at a particular scale.

[44] *Western and Blöschl* [1999] showed that the spatial correlation pattern represented by a semi-variogram played an important role in reproducing the trend of log variance versus log extent scale. Their analysis indicated that the existence of a nugget in the semi-variogram flattens the log variance versus log extent curve at smaller extent scales. The semi-variogram nugget represents measurement error, instrument error, or variance of data at very fine scales. Our analysis shows a mean standard deviation $0.036 \text{ cm}^3/\text{cm}^3$ at the 2.5-m scale, which may suggest a value very close to the nugget. This is close to the nugget values of 0.026 and $0.028 \text{ cm}^3/\text{cm}^3$ reported by *Anctil et al.* [2002]. This level of variability is also close to the instrument error, $0.03 \text{ cm}^3/\text{cm}^3$, of the impedance probes used in this study. Flattening of log standard deviation of a spatial variable with increasing log extent can be a good indicator of spatial correlation, because the log semivariogram of the variable quickly levels off when the spatial scale reaches the range of the semivariogram [Gelhar, 1993]. The reduced slope existing between 1.6 km and 50 km in Figure 11b may imply the existence of a variogram range between the two scales. Variogram

ranges between 10 km and 30 km were found during SGP97 [Ryu and Famiglietti, 2006].

[45] It is worth noting that, although soil moisture variability was characterized using soil moisture measurements taken at many different sites located in the central US with varying land cover conditions, they still share similar climatic, topographic, and land surface features. For example, the Iowa study region is one of low-relief topography. The topography of the Oklahoma study region is moderately rolling, but the maximum relief is still less than 200 m. The dominant soil texture in the Iowa region is a loam with localized inclusions of silty clay loam (<http://hydrolab.arsusda.gov/smex02>), and the Oklahoma region is dominated by a silt loam (38%) with several bands of loam and sandy loam (*Jackson et al.*, 1999). These land cover and topographic characteristics should be considered when contemplating the transferability of these results to other regions.

5.2. Uncertainty and Implications for Satellite Validation

[46] Validation of satellite soil moisture observations requires a large number of ground-based samples to accurately determine the footprint-scale mean moisture content. Time stability of soil moisture, which can result from the static influence of soil, vegetation, and topography [Cosh *et al.*, 2005; Grayson and Western, 1998; Mohanty and Skaggs, 2001], suggests the existence of a representative sampling location, where the local value of soil moisture content is most often close to a larger-area mean. While such a locations can help to reduce the uncertainty in mean soil moisture estimates from a limited number of ground-based observations, at the footprint-scale, the dynamic influence of precipitation variability reduces the likelihood of the existence of such a point. Another alternative is to use the spatial distribution of soil moisture produced by a distributed hydrologic model to help determine sampling strategies and reduce the uncertainty in ground-based mean estimates [Crow *et al.*, 2005a].

[47] Ground-based soil moisture measurements offer third alternative for direct and reliable estimation of the footprint-scale mean moisture content. The empirical relationships between the standard deviation and mean soil moisture content suggested in this work can be utilized to calculate the uncertainty of the large-area mean derived from a certain number of soil moisture samples, including its evolution with drying or wetting. Additionally, they can be used to determine the number of samples required to achieve a specified uncertainty. For example, using the standard deviation of soil moisture σ given by equation 2, the 95% confidence interval of the true mean soil moisture content μ from N ground-based measurements can be calculated by the Student's t distribution as follows:

$$\bar{X} + t_{0.025,N} \cdot \frac{\sigma}{\sqrt{N}} < \mu < \bar{X} + t_{0.975,N} \cdot \frac{\sigma}{\sqrt{N}}, \quad (4)$$

where $t_{m,n}$ is the inverse of the Student's t for a probability m with degrees of freedom n , and \bar{X} is the sample mean from N measurements. Figure 12 shows the evolution of the 95% confidence limits with varying surface wetness. The largest uncertainties increase with increasing standard deviation, uncertainty decreases with an increasing number of samples, and the same number of samples results in a

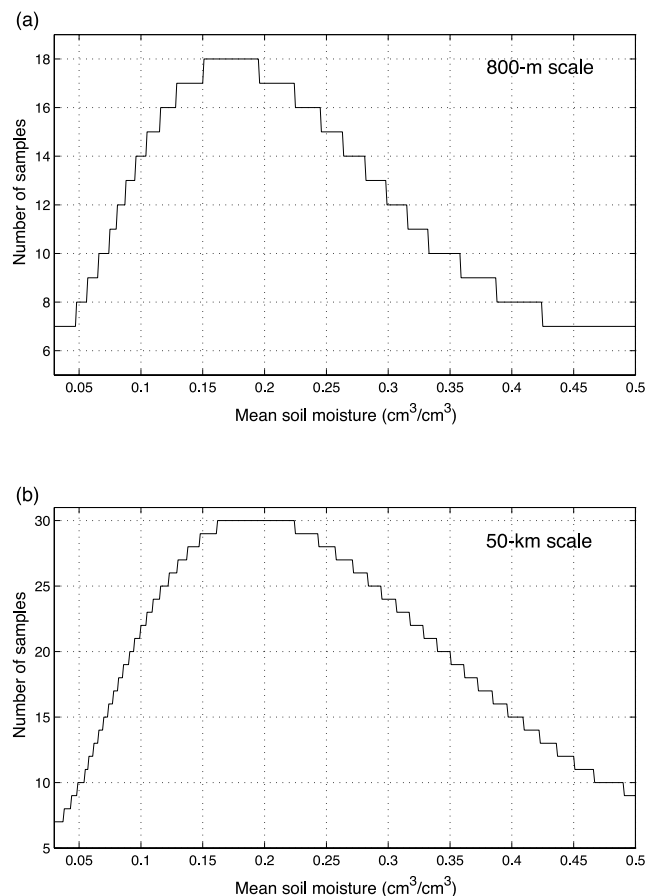


Figure 13. The number of point samples required to achieve $\pm 0.03 \text{ cm}^3/\text{cm}^3$ accuracy of mean estimates with 95% confidence.

larger uncertainty in the mean estimate as the extent scale increases from 800 m to 50 km.

[48] The number of samples required to achieve a specified accuracy at a specified scale can also be calculated using the empirical functions. For example, the number of samples required to achieve $\pm 0.03 \text{ cm}^3/\text{cm}^3$ accuracy with 95% confidence can be calculated by applying equation 4:

$$N = \left(t_{0.975, N} \cdot \frac{\sigma}{0.03} \right)^2 \quad (5)$$

Figure 13 shows that the number of samples changes peaks in the mid-range of mean moisture content, following the behavior of the standard deviation. Figure 13 suggests that a maximum of 18 samples is required to measure the 800-m mean to within 3%, while the 50 km mean would require a maximum of 30 samples.

[49] In this work, it was assumed that the data are independent and spatially uncorrelated. Assuming the independent and random nature of the variables, equations 4 and 5 yield a very conservative estimate of the number of required samples, as the Student's *t* yields a wider distribution than a Gaussian PDF given the limited number of samples. However, in the case of soil moisture sampling, these assumptions may not hold. In particular, the data are skewed, they

demonstrate kurtosis [Famiglietti *et al.*, 1999] and they exhibit spatial correlation [e.g., Ryu and Famiglietti, 2006]. In the presence of these conditions, the results shown in Figures 12 and 13 may represent rather underestimated number of samples necessary to achieve the 95% confidence interval and to estimate the mean soil moisture value at the scales shown.

5.3. Parameterization of Soil Moisture Variability in Land Surface Models

[50] Empirical functions of standard deviation and skewness versus mean soil moisture, as well as those of log variance versus log extent scale, can also aid the subgrid- or sub-footprint-scale parameterization of soil moisture variability in land surface models at a variety of spatial scales. Several land models require information on soil moisture variance, or assume a particular form for the soil moisture PDF, to capture subgrid variations in soil moisture. The empirical relationships derived here can be used to estimate soil moisture variance and skewness up to the 50-km scale.

[51] A picture of how soil moisture PDFs change with scale also emerges when the results of Famiglietti *et al.* [1999] and Ryu and Famiglietti [2005] are considered along with the findings of this work. Famiglietti *et al.* [1999] showed that at the 800-m scale during SGP97, soil moisture PDFs evolve from positively skewed exponential distributions under dry conditions, to normal distributions in the mid-range of mean moisture content, to negatively skewed exponential distributions under wet conditions. They suggested that the beta distribution is an appropriate choice to capture soil moisture variability at this scale. In this study we analyzed soil moisture PDFs from SGP99 (not shown), and found that bimodality appears quickly when the extent scale increases from 800 m to 1.6 km, owing primarily to increasing heterogeneity of land cover. The existence of vegetation, the distribution and density of roots, and the practice of cultivation can significantly affect the spatial variability of soil moisture [Mohanty *et al.*, 2000]. Ryu and Famiglietti [2005] showed that the exponential PDF form disappears as the extent scale increases from 800 m to 50 km and the likelihood of occurrence of extreme wet or dry conditions decreases. They also noted the occurrence of bimodal PDFs in the mid-range of mean soil moisture content, which as previously mentioned, was attributed to fractional rainfall cover. At this scale, they showed that a mixture of two Gaussian distributions can accurately represent the evolution of soil moisture variations across the full range of wetness conditions. The skewed normal distribution [Azzalini and Capitanio, 1999] can also be utilized to reproduce the variance and skewness observed at large scales, though a mixture model would be required to reproduce bimodality.

6. Summary

[52] Over 36,000 impedance probe moisture content measurements, taken during four different large-scale field campaigns (SGP97, SGP99, SMEX02, and SMEX03) were analyzed in order to characterize soil moisture variability with changing field mean moisture conditions and extent scales. Six distinct extent scales were explored, from that of a small field plot to the scale of a satellite remote sensing footprint (2.5-m, 16-m, 100-m, 800-m, 1.6-km and 50-km).

[53] Results indicate that soil moisture variations follow predictable patterns with respect to changing extent scales and field-mean moisture content. Soil moisture variations, quantified in terms of the standard deviation, CV and skewness, all show a general increase with increasing spatial scale. The standard deviation-mean moisture content relationship displays a convex-upward relationship, which was first suggested by Owe *et al.* [1982]. The CV decreases with increasing mean moisture content, while skewness changes from positively skewed to negatively skewed. Empirical relationships between soil moisture variations and mean moisture content were derived across scales. Such relationships can be used to estimate the uncertainty in field observations of mean moisture content. Moreover, the work described here can provide insight into improving the parameterization of surface soil moisture variations in land surface models. The results of this study may be applicable to regions with similar climatic, topographic, and land surface features to our study area in the central US. The transferability of these results to other regions will require further study.

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A. A. Berg, Department of Geography, University of Guelph, Ontario, Canada.

J. S. Famiglietti, Department of Earth System Science, University of California, Irvine, CA, USA. (grlonline@agu.org)

T. J. Jackson and D. Ryu, USDA ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA.

M. Rodell, Hydrological Sciences Branch, NASA Goddard Space Flight Center, Greenbelt, MD, USA.