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Temporal dynamics of PSR-based soil moisture across spatial scales in an agricultural landscape during SMEX02: A wavelet approach

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Abstract

In this study, we examined the characteristics of soil moisture dynamics of wet and dry fields across hierarchical spatial scales within the region of Soil Moisture Experiment 2002 (SMEX02) hydrology campaign in Iowa. The Polarimetric Scanning Radiometer (PSR)-based remotely sensed surface (~ 0–5 cm) soil moisture at 800 m × 800 m resolution was used in this study. Wavelet-based multiresolution technique decomposed the soil moisture into large-scale mean soil moisture fields and fluctuations in horizontal, diagonal, and vertical directions at hierarchical spatial resolutions. Results suggested linearity in the log–log dependency of the variance of soil moisture up to a resolution of 6400 m × 6400 m on PSR sampling dates during SMEX02. The wet fields (with high soil moisture) show almost similar variance for all the resolutions signifying the strong spatial correlation. Analysis of the dry fields (with low soil moisture) indicated a log–log linearity of moments with various scales, and the slopes of these relationships exhibit a concave functional form with the order of moments, typically representing a multiscaling process. The scaling exponent of soil moisture during dry-down suggests a transition from simple scaling (in wet fields) to multiscaling (in dry fields) behavior. The fluctuation components of multiresolution analysis in the horizontal, diagonal, and vertical directions for dry and wet fields exhibited self-similarity. Another important finding of this study is the increase of subpixel soil moisture variability with increasing resolution, especially for the wet fields. These findings will help develop appropriate up-and down-scaling schemes of remotely sensed soil moisture data for various hydrologic and environmental modeling applications.

Keywords: Remote sensing; PSR; Spatial scaling; Soil moisture; Passive microwave remote sensing; Agricultural landscape

1. Introduction

Soil moisture in shallow subsurface is a key state variable that affects hydrological, ecological, and meteorological processes ranging from local land–atmosphere interaction to global water cycle. Soil moisture is highly variable across space scales of few meters to kilometers and time scales of minutes to months. Significant amount of *in situ* and remote sensing research have been conducted to observe and characterize soil moisture at various spatio-temporal scales (Charpentier & Groffman, 1992; Cosh & Brutsaert, 1999; Famiglietti et al., 1999; Hu et al., 1997; Mohanty & Skaggs, 2001; Oldak et al., 2002). Soil moisture pattern (distribution) at a particular spatio-temporal scale evolves from interactions among different geophysical parameters, i.e., soil, topography, rainfall, and vegetation (Dubayah et al., 1997; Western et al., 2002). Despite the fact that soil moisture always exhibits spatio-temporal variability due to overlapping (governing) geophysical parameters, our knowledge of scaling characteristics of soil moisture variation is rather limited. In literature, a number of contradictions appear about the influence of these geophysical parameters on soil moisture variability.

With respect to soil and its properties, it always exhibits significant spatial variability that characterizes soil moisture transport processes. Soil was conceptualized as a hierarchical heterogeneous medium with discrete spatial scale by Cushman (1990), and Roth et al. (1999). They argued natural pattern of soil variability may exhibit embedded, organizational structures that lead to non-stationary soil properties and processes. With an increase of spatial scale, soil properties typically become non-

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stationary. The soil properties may change from deterministic at smaller scale to random at larger scale, with the small scale variation filtered out by larger scale processes (Kavvas, 1999). Rodriguez-Iturbe et al. (1995) also suggested that the spatial organization of soil moisture is a consequence of soil properties. Tomer et al. (2006) found significant correlation between soil properties and soil moisture at watershed scale. Temporal stability in soil moisture patterns can be associated with the arrangement soil types and textures on the landscape scale (da Silva et al., 2001). Also, soil texture is related to topographical attributes such as surface curvature, slope, and elevation. These attributes define the functional organization of soil hydrological processes, and in turn soil moisture variability.

Studies (Famiglietti et al., 1998; Hawley et al., 1983) have shown topographical characteristics have control on spatial variation of soil moisture. Topographic attributes reflecting lateral flows and accumulations at the landscape scale have been statistically related to soil moisture (Tomer and Anderson, 1995) and water retention characteristics (Pachepsky et al., 2001). Western and Blöschl (1999) found the proportion of variation in soil moisture accounted by terrain indices varied from 22 to 61%, depending on average soil moisture. However, Charpentier and Groffman (1992), Niemann and Edgell (1993), and Western et al. (2003) reported no systematic relationship between topography and soil moisture. Chang and Islam (2003) demonstrated that soil physical properties and topography control spatial variations of soil moisture over large areas. They have shown, topographical control will dictate soil moisture distribution under wet conditions, and soil physical properties control variations of soil moisture under relatively dry conditions. Numerous studies (e.g., Henninger et al., 1976; Nyberg, 1996; Robinson & Dean, 1993) have reported negative correlations between soil moisture and topographical attributes i.e., elevation and slope.. This correlation is smaller for finer texture soil and larger for coarser texture soil. The spatio-temporal controls of soil properties and topography on variability of soil moisture are induced by precipitation event and its characteristics (i.e., amount, rate, and spatial variability). Because of the extreme complexity in the inherent relationships among precipitation, soil moisture, and land–atmosphere feedback, relations of soil moisture to subsequent precipitation events are also significant.

The state and evolution of soil moisture are primarily forced by precipitation which is the major source of space and time variability in the hydrologic cycle. Past studies (Gupta & Waymire, 1990; Kumar & Foufoula-Georgiou, 1993a,b; Waymire et al., 1984) investigated the space–time rainfall characteristics at the ground level and have suggested multiscaling properties. It is conceivable that this attribute of precipitation in conjunction with other geophysical variables may introduce complicated scaling properties in soil moisture depending on spatial scales. At spatial scales of 100 m to kilometers, soil moisture variability could be found due to spatial variability in precipitation events. Sellers et al. (1995) presented spatial heterogeneity introduced by rainfall and removed through dry-down dynamics. At much larger scales, generally variations in precipitation leads to substantial changes in soil moisture conditions between climate regions.

Vegetation also influences soil moisture spatio-temporal variability. Among others, Mohanty et al. (2000) and Qui et al. (2001) have shown that soil moisture responds to variation in vegetation. The primary effect of vegetation is evapotranspiration from the soil profile. During transpiration, vegetation root water uptake is largely controlled by soil moisture status and its spatial (horizontal–vertical) variability. Root and soil interaction tends to homogenize soil water content in the root zone. Infiltration properties of soil are influenced by vegetation at the plant scale (Seyfried & Wilcox, 1995). With the increase in spatial scale, soil moisture variability is affected by variation in vegetation shifts from plant to patch to the community scale.

All these geophysical variables (soil, topography, rainfall, and vegetation) typically interact in a complex fashion to make soil moisture highly variable and introduce nonlinearity in soil moisture dependent processes. Thus, scaling of soil moisture is poorly understood and is difficult to measure and model in a comprehensive manner (Dubayah et al., 1997).

Several studies were conducted to understand the spatio-temporal scale dynamics of soil moisture. Rodriguez-Iturbe et al. (1995) studied and characterized the spatial pattern of soil moisture, and concluded that the variance of soil moisture follows a power law decay, typical of scaling processes, as a function of area over which soil moisture is observed. It results in a linear relation between variance and observation scale, when plotted on a log scale. Hu et al. (1998) used multi-resolution analysis to investigate the scale variation of soil moisture by decomposing soil moisture images into average large-scale and detailed small-scale fluctuation components. They found that average large-scale soil moisture was non-stationary at the scale studied (30 m to 10 km) and the small-scale fluctuations exhibited simple scaling process, while the overall soil moisture variability exhibited multiscaling properties. Kumar (1999) used estimation techniques based on multi-resolution tree to characterize the subgrid variability of soil moisture at multiple scales by combining information, such as soil moisture measurements and soil hydrologic properties available at different scales. Western and Blöschl (1999) examined the effect on the apparent spatial statistical properties of soil moisture (variance and correlation length) with changing measurement scale in terms of spacing (distance between samples), extent (overall coverage), and support (integration area). They found the effect of spatial extent on the correlation length is most important among the three (extent, support, and spacing). The apparent variance increases with increasing extent, decreases with increasing support, and does not change with spacing. Cosh and Brutsaert (1999) showed that grouping soil by textural class was useful to characterize the soil moisture field and their dynamics into groups with different statistical properties. Famiglietti et al. (1999) used ground-based point-scale soil moisture measurements during SGP97 campaign within six selected Electronically Scanned Thinned Array Radiometer (ESTAR) footprints to investigate within-pixel variability of soil moisture data. They found significant variability in soil moisture because of different combinations of soil type, vegetation cover, management practice, and rainfall gradient. Mohanty and Skaggs (2001) also used ground-based datasets of SGP97 to show the characteristic differences in the space-time dynamics of soil moisture within several remote sensing footprints with various combinations of soil texture, slope and vegetation type. They found that flat topography with split wheat/grassland produced the greatest spatio-temporal variability and also showed that ESTAR footprint average matches well with ground-based soil moisture in sandy loam soil with rolling topography and pasture cover.

Another investigation of the spatial structure of soil moisture for Washita'92 and Washita'94 was presented by Peters-Lidard et al. (2001). They conducted scaling analysis of both measured and modeled soil moisture pattern and found multiscaling properties. Nykanen and Foufoula-Georgiou (2001) studied scaling properties of soil moisture and reported that their results disagreed with the results of Rodriguez-Iturbe et al. (1995) and Hu et al. (1997) who reported log–log linear relationships of the variance of soil moisture with scale. Recently, Oldak et al. (2002) studied the statistical properties of remotely sensed soil moisture field of Washita '92 and SGP97 experiment. They showed that the shape of scaling dependencies remains the same during drydowns, consequently reducing the volume of observations needed to predict scaling of surface soil moisture. Brunsell and Gillies (2003) conducted multiresolution analysis on radiometric temperature data of AVHRR (Advanced Very High Resolution Radiometer) and reported that at very large scales, statistical self-similarity was observed through all levels of aggregation. Studies at larger scales (50–1000 km) (Entin et al., 2000; Vinnikov & Robock, 1996) from agricultural sites in the former Soviet Union, Mongolia, China, and the USA have reported the soil moisture variation could be represented as a stationary field with a correlation length of 400–800 km.

To study spatial scaling of surface soil moisture, remote sensing offers products over large spatial extent. For soil moisture spatial scaling, high resolution data is preferable to capture the soil moisture dynamics with increasing scale. Air-borne passive microwave remote sensing offers techniques to estimate soil moisture in top 5 cm of the soil surface over a large area with good spatial resolution (Jackson 1993). The operational constraint of airborne passive microwave remote sensing is non-availability of large spatial soil moisture fields on regular basis. Lately space-borne sensors have the capability to map soil moisture in large areas at regular intervals. In the foreseeable future, no space-borne passive microwave remote sensing platform will have ground spatial resolution finer than 40 km (Crow et al., 2005). Within such a coarse resolution (>40 km), great degree of soil moisture variability is observed over a large range of spatial scales encompassing various soil types, topographic features, vegetation and meteorological conditions. Air-borne remote sensing campaigns such as Southern Great Plains 1997 (SGP97) hydrology experiment (Jackson et al., 1999), Soil Moisture Experiment 2002, SMEX02 (Bindlish et al., 2005), SMEX03 (Jackson et al., 2005), SMEX04, and SMEX05, provide opportunity to study the spatial scaling of soil moisture in variety of hydro-climatic conditions, within the coarse footprint resolution of space-borne passive microwave remote sensing as Advanced Microwave Scanning Radiometer (AMSR-E) sensor on the AQUA satellite.

In the continental United States of America, most of the soil moisture scaling studies at field/regional scale were conducted in the Oklahoma region (Washita'92, Washita'94, and SGP97) of the Southern Great Plain. The conclusions from these studies were based on evolution of soil moisture in a sub-humid climate having rolling topography with land cover dominated by rangeland, pasture and winter wheat. So, there is a definite gap in our understanding of soil moisture scale dynamics for different hydroclimatic conditions/regions. In this study, we mainly focused on the landscape of Iowa with row crop (corn and soybean) agriculture. Our primary objective is to investigate soil moisture scaling characteristics within wet and dry fields of a large agricultural landscape. The investigation will provide a basis for up-/down-scaling of soil moisture fields using high/low resolution data from wet and dry agricultural landscapes of Iowa and similar hydroclimatic regions for hydrologic and environmental modeling applications. Air-borne Polarimetric Scanning Radiometer (PSR)-based remotely sensed surface soil moisture fields during SMEX02 hydrology campaign in Iowa was used for the study.

Previous studies (e.g., Hu et al., 1998) have shown natural pattern of soil moisture field leads to nonstationary spatial fields. This nonstationary trend of natural variability present in

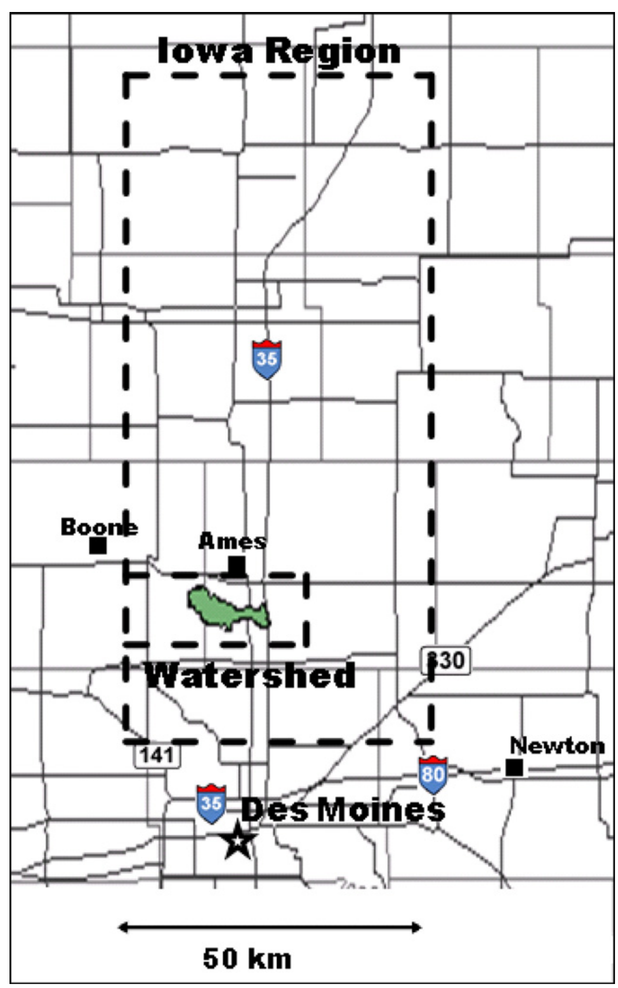

Fig. 1. Location of SMEX02 experiment and IOWA regional study area (Bindlish et al., 2005).

PSR-based remotely sensed surface soil moisture may be determined from geostatistical analysis, and by wavelet analysis. Scale-dependent nonstationary processes exhibit statistical properties that are different than what is usually assumed in geostatistical analysis. On the other hand in wavelet analysis the property need not meet any statistical assumptions other than that of finite variance. For this study, we selected wavelet analysis over geostatistical techniques, due to its distinct advantage and capability to process remotely sensed two-dimensional scale-dependent nonstationary spatial dataset. Wavelet based multiresolution analysis, described below, was used to relate soil moisture variability at the scale of the PSR footprint (800 m × 800 m) to larger scale average soil moisture field variability. We also investigated the scaling characteristics of fluctuation fields among various resolutions.

2. Materials and methods

2.1. Site description

The regional study area of SMEX02 in Iowa is shown in Fig. 1 (Bindlish et al., 2005). The details of the SMEX02 experimental plan can be found at URL http://hydroloab.arsusda.gov/SMEX02. The duration of the study was from June 6th to July 12th, 2002. Nearly 95% of the regional study area is used for row crop agriculture. Corn and soybean are grown on approximately 90% of the row crop acreage (nearly 60% of the crop is corn and 40% is soybean). The climate of SMEX02 regional site is humid, with an average rainfall of 835 mm. The regional site is considered as the pothole region of Iowa because of its undulating terrain. The PSR (Polarimetric Scanning Radiometer) observations were conducted from June 25th to July 12th, 2002. The PSR is an airborne microwave imaging radiometer operated by NOAA Environmental Technology Laboratory (Piepmeier & Gasiewski, 2001). The complete functional operation (flight lines and mapping specifications) of PSR is given in Bindlish et al. (2005). The PSR during SMEX02 used various frequencies (6 GHz, 6.5 GHz, 6.92 GHz, 7.32 GHz, 10.64 GHz, 10.69 GHz, 10.70 GHz, 10.75 GHz, and Thermal) for passive microwave remote sensing. Bindlish et al. (2005) closely examined the effects of RFI (Radio Frequency Interference) and reported that the 7.32 GHz and 10.7 GHz bands were far superior to the other frequencies. So the soil moisture fields of SMEX02 regions were created using these two PSR/CX band channels (7.32 GHz and 10.7 GHz). PSR-based soil moisture estimates (resolution: 800 m × 800 m, size: 153 × 74 pixels) observed for 10 days over the regional area during SMEX02 is illustrated in Fig. 2. They also concluded that despite the peak crop conditions (biomass ~8 kg/m^2) encountered during the SMEX02 experiment, good results were obtained using the full soil moisture retrieval algorithm. As illustrated in Fig. 2, there are some null values at the bottom portion of the soil moisture fields. For this study the null values were dropped from the study region by trimming the daily PSR-based soil moisture fields resulting in a net area of 125 × 74 pixels (59.2×10^8 m^2) for multiresolution analysis.

Extensive ground based soil moisture sampling were also conducted within selected (approximately 800 m × 800 m) fields of Walnut Creek watershed. Several fields (WC11, WC12, WC13, WC15, WC17, and WC24) of Walnut Creek watershed in the SMEX02 region were selected randomly to assess uncertainty within the PSR-based remote sensing pixels. During the SMEX02 experiment, 42 theta probe measurements at 14 different locations and 4 gravimetric soil moisture samples coinciding with 4 theta probe sampling locations were taken daily in every field. The theta probe observations with a measuring depth of 0–6 cm were calibrated using the gravimetric observations. The average of the calibrated theta probe measurements were used as the field average soil moisture values.

2.2. Multiresolution analysis of PSR estimated soil moisture fields

In remote sensing, spatial scale (resolution) is defined as the size of the smallest distinguishable part (pixel) of a spatial

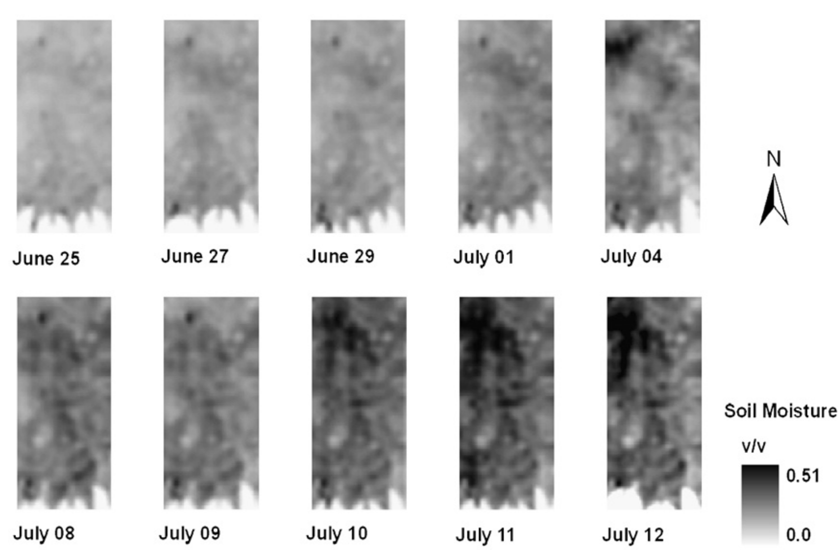

Fig. 2. PSR (C-band single channel) based soil moisture estimates over the regional area during SMEX02.

dataset (Lam & Quattrochi, 1992). Spatial dataset at different scales may carry different information. Each level of spatial scales has its own unique properties that are not the simple summation of the disaggregated part (Golley, 1989). Wavelet analysis, a relatively new tool in geophysics (Kumar & Foufoula-Georgiou, 1997) has the capability to decompose the nonstationary spatial dataset of high resolution into nonstationary fields of increasing spatial scales. Wavelet (and corresponding scaling function) is the basic function to decompose a spatial data into directional vectors/components described by wavelet coefficients. In this study, PSR-based soil moisture field is decomposed into wavelet coefficients, and these coefficients are specific to spatial scales and locations. The wavelet coefficient D derived from the decomposition corresponds to a wavelet function ψ of scale m and a particular position of the PSR dataset. Analysis of these coefficients can therefore give insight into scale specific variability of soil moisture. Reconstituting data from subsets of wavelet coefficients specific to different spatial scales allows us to generate representations of soil moisture fields at different spatial resolution, and so called multiresolution analysis (Mallat, 1989). In this study a discrete wavelet transform (DWT) was used to decompose the PSR-based soil moisture fields of SMEX02 into an equally large set of scaling and wavelet coefficients. A brief description of DWT follows.

For the sake of brevity and clarity the theory is presented in one dimension (x). Let the PSR data be defined as a function of location in space $f(x)$. A mother wavelet is also defined as a function of location $\psi(x)$. The mother wavelet function should meet three properties: the mean is zero, i.e., $\int_{-\infty}^{\infty}\psi(x)\mathrm{d}x=0$, the squared norm is 1, i.e., $\int|\psi(x)|^2\mathrm{d}x=1$, and it has a compact support. The third condition means that the wavelet only takes non-zero value over a narrow interval. This attribute makes the wavelet dampen rapidly, hence, operate very locally and consequently giving a localized description of $f(x)$ variability. In order to analyze, it is essential to shift (translate) the wavelet in space. The scale at which a wavelet coefficient describes $f(x)$ may be changed by dilating (shrinking/expanding) the wavelet function, $\psi(x)$. For a basic wavelet function, $\psi(u)$, a dilated and translated version $\psi_{\lambda,x}(u)$ may be obtained with the following equation:

$$\psi_{\lambda,x}(u)=\frac{1}{\sqrt{\lambda}}\psi\left\langle\frac{u\mp x}{\lambda}\right\rangle,\ \lambda>0, x\in R \tag{1}$$

where λ is the scale parameter of the wavelet which adjusts the dilation, R denotes the set of real number. The parameter x determines the location of the wavelet. The wavelet transform is an integral transform, i.e., a wavelet coefficient $Wf(\lambda,u)$ is obtained by integrating the product of a wavelet, $\psi(u)$, with the data, $f(x)$.

$$Wf(\lambda,u)=\int_{-\infty}^{\infty}f(x)\psi_{\lambda,x}(u)\mathrm{d}x \tag{2}$$

where, u is the location parameter.

In this study the Haar wavelet (Haar, 1910) is used to conserve the amount of information within multiresolution analysis. The Haar wavelet was preferred over other wavelets because of its ability to detect rapid change in the data (Mahrt, 1991). The Haar wavelet $\psi(x)$ and scaling $\varphi(x)$ function is the simplest of all orthogonal (orthonormal) wavelets (Kumar & Foufoula-Georgiou, 1997) and is given as:

$$\psi_{\lambda,x}(x)=\left|\begin{array}{ll}1 & 0\le x<1/2\\ -1 & 1/2\le x<1\\ 0 & \text{otherwise}\end{array}\right. \tag{3}$$

$$\varphi_{\lambda,x}(x)=\left|\begin{array}{ll}1 & 0\le x<1\\ 0 & \text{otherwise}\end{array}\right. \tag{4}$$

In discrete wavelet transform (DWT), e.g., using Haar wavelet, the parameter λ can be varied discretely by setting λ to integer powers, m of basic dilation step λ_0, where $\lambda>1$. For Haar wavelet, $\lambda_0=2$, so the scale parameter increases in the dyadic series $\lambda_0^m=2,4,8,$. The location is incremented in steps which depend on the scale parameter so that $x=nx_0\lambda_0^m$, where n is an integer and x_0 is a basic step (commonly one interval between samples in PSR data). So a discretely scaled and translated wavelet is

$$\psi_{m,n}(x)=\frac{1}{\sqrt{2^m}}\psi(2^{-m}(x-n2^m) \tag{5}$$

The DWT coefficient is $D_{m,n}$, where:

$$D_{m,n}=\int f(x)\psi_{m,n}(x)\mathrm{d}x \tag{6}$$

The PSR data, $f(x)$, can be represented by a linear combination of the product of wavelets $\psi_{m,n}(x)$ and wavelet coefficient $D_{m,n}$, i.e.:

$$f(x)=\sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}D_{m,n}\psi_{m,n}(x) \tag{7}$$

The wavelet basic functions,$\psi_{m,n}(x)$, are orthogonal to their dilates and translates. So, when evaluating the sum of products of the wavelets and their coefficients over all locations but for just one value of the scale parameter, 2^k, we obtain an additive component of the discretely sampled data. This is called detail component for scale parameter 2^k, $Q_kf(x)$, where:

$$Q_kf(x)=\sum_{n=-\infty}^{\infty}D_{k,n}\psi_{k,n}(x) \tag{8}$$

When PSR data, $f(x)$, is subjected to extraction of detail component for a finite level of scales parameter 2^m, $m=0,1,..,k$. Beside the detail component, it also resulted in a smoothed representation of the PSR data for scale 2^k, denoted by $A_kf(x)$. The smoothed representation is described as:

$$A_kf(x)=\sum\langle f,\varphi_{k,n}\rangle\varphi_{k,n}(x) \tag{9}$$

where, $\varphi_{k,n}(x)$ is a scaled and translated basis function called the scaling function. The scaling function resembles a smoothing kernel of the corresponding wavelet function.

The derivation above elaborates how PSR-based soil moisture data could be partitioned into a set of detail directional components and a mean/smoothed representation using wavelet functions and its corresponding scaling functions. This decomposition is called a multiresolution analysis. So, the multiresolution analysis results in an approximate signal at scale k (smoothed field of coarsest resolution), and detail signals (components) at all other levels of decomposition. The additional advantage using Haar wavelet and scaling function within the multiresolution analysis is that the product at each scale level m is a smoothed resemblance of the original data. With the Haar wavelet and scaling function, the smoothed PSR-based soil moisture data for each scale level m would be the same as when the region is observed from the same type of sensor but at a resolution equal to scale level m. Therefore, the Haar wavelet is suitable to quantify the loss of information (detail components) within the dataset while decomposing to a coarser resolution. For two dimensional cases, based on work of Mallat (1989), the multiresolution analysis is given by:

$$A_{m-1}f(x,y) = A_m f(x,y) + Q^h_m f(x,y) + Q^d_m f(x,y) + Q^v_m f(x,y) \qquad (10)$$

where, h, d and v resembles horizontal, diagonal and vertical detail components of PSR data, respectively.

Applying the above algorithm of multiresolution analysis the PSR based soil moisture field of July 10th 2002 (SMEX02) at the original resolution (800 m×800 m) (Fig. 3a (level m=1)) was decomposed into four fields for the resolution of 1600 m×1600 m as illustrated in Fig. 3b. This includes the mean/smoothed field A_1 (top left quadrant) corresponding to the scale function and three fluctuation fields Q^h_1 (horizontal component: top right quadrant), Q^d_1 (diagonal component: bottom right quadrant), and Q^v_1 (vertical component: bottom left quadrant). Similarly the smoothed field A_1 presented in Fig. 3b could be decomposed further (level m=2) into four fields (A_2, Q^h_2, Q^d_2, and Q^v_2) of resolution 3200 m×3200 m. In this study, 10 PSR-based soil moisture fields for SMEX02 were decomposed till level m=5 (resolution: 25,600×25,600 m) using the multiresolution analysis. At each level of decomposition, the smoothed field (A) becomes more homogenous and the anisotropy is captured in the fluctuation components (Q). The horizontal, diagonal and vertical wavelet coefficients measure the intensity of the local variation within the pixel of the soil moisture field when decomposing for a particular scale. The value of the coefficient is zero when no variation (local signal is constant) is observed within the aggregated pixel for the scale under consideration. The value of the coefficient is large when the magnitude of the wavelet is near to the scale of heterogeneity in the soil moisture field. Thus, the variance of the wavelet coefficients gives information about subpixel variability for the spatial scales in remote sensing data (Percival, 1995). The variance is defined as:

$$\sigma^2_k = \frac{1}{N}\sum Q^2 \qquad (11)$$

where σ^2_k is the variance of the PSR dataset at scale k and N is total number of the wavelet coefficients Q in a particular direction (i.e., horizontal, diagonal, or vertical).

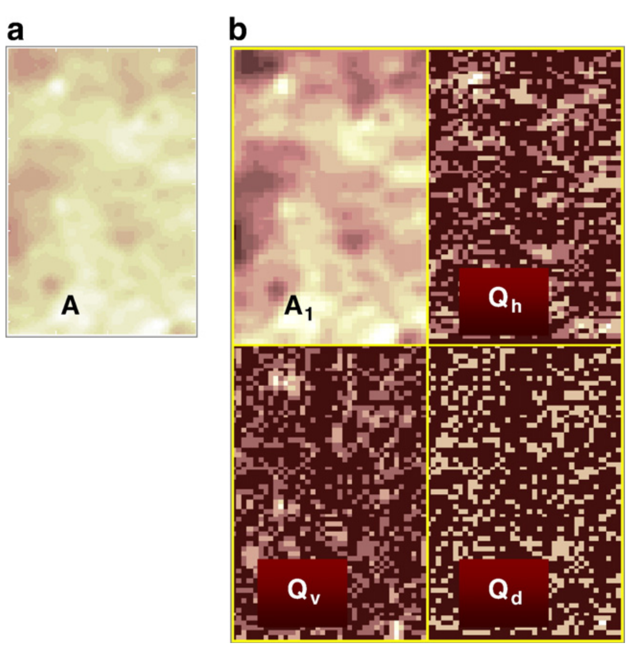

Fig. 3. Haar wavelet decomposition of a PSR based soil moisture field. (a) Represents original soil moisture field A (800 m×800 m) on June 25th 2002. (b) Average field A_1 (1600 m×1600 m) (top left quadrant) and three fluctuation fields Q^h_1 (1600 m×1600 m) (horizontal component: top right quadrant), Q^d_1 (1600 m×1600 m) (diagonal component: bottom right quadrant), and Q^v_1 (1600 m×1600 m) (vertical component: bottom left quadrant).

2.3. Scaling surface soil moisture

Scaling is a procedure to reduce a multi-dimensional parameter space into one-dimensional parameter space by taking advantage of the relationship between the parameter of interest and observable properties (e.g., characteristic length, area, volume, time). As defined by Blöschl and Sivapalan (1995) and Western et al. (2002), scaling assumes that the properties themselves change, while the dependence of parameter on observable properties is same over the range of scales. Soil moisture by virtue of its spatio-temporal variability due to dominant geophysical controls at different scales is subjected to certain characteristic scaling behavior. For soil moisture scaling study, wavelet analysis (described in the previous section) was used to decompose PSR-based high resolution soil moisture spatial datasets into nonstationary fields of increasing spatial scales to obtain soil moisture at different resolutions/scales.

Following (Gupta & Waymire, 1990), let $[Z(x)]$ represent an arbitrary stochastic soil moisture field of a spatial dataset indexed by vector $x \in R^d$, where R^d is d dimensional space. Then $[Z(x)]$ is statistically self-similar for any arbitrary set of points, $x_1, x_2, x_3, .., x_n$, the equality holds in the joint probability distribution of $[Z(x)]$:

$$P[Z(\alpha x_1) < z_1, \ldots, Z(\alpha x_n) < z_n] = P[\alpha^{h\theta} Z(x_1) < z_1, \ldots, \alpha^{h\theta} Z(x_n) < z_n] \qquad (12)$$

where α is the scale ratio and $h\theta$ is a real scaling exponent. In this study, for the soil moisture field the scale factor á$=A_i/A_0$, where A_i

is any pixel obtained from smoothing of the original (remote sensor) pixel and A_0 is the coarsest pixel size after multiresolution analysis. For simple scaling there is only one scaling exponent $h\theta$ and the process is said to be "fractal" or "mono-fractal". Here $[Z(x)]$, the stochastic soil moisture field of multi-dimensional space is represented with one-dimension through a scaling exponent $h\theta$. The expected moment of stochastic field can then be related to this single value as a function of scale:

$$E[Z^P(\alpha)] = \alpha^{ph\theta} E[Z^P(1)] \tag{13}$$

where p is the order of the moment, and taking the log of Eq. (13),

$$\log\, m_p(\alpha) = s(p) \log\, a + \log\, m_p(1) \tag{14}$$

where $m_p(\alpha)=E[Z^p(\alpha)]$ and $s(p)=ph\theta$. For a simple scaling process, the log–log linearity in log $m_p(\alpha)$ versus log α for each p and, linearity of the slope $s(p)$ change for each p must be satisfied. When the equality shown in Eq. (12) does not hold, then it is not possible to transform the stochastic soil moisture field $[Z(x)]$ from multi-dimensional space into a one-dimensional space through one scaling exponent $h\theta$. Consequently, we need to have different scaling exponents ($h\theta$) for different scales. In other words, $s(p)$ is a nonlinear function of p, and the soil moisture evolutionary process has multiscaling properties.

One more type of scaling typically found in soil moisture stochastic fields is the power law scaling of variance of soil moisture contents (Rodriguez-Iturbe et al., 1995). Power laws are among the most frequent scaling methods that describe the scale invariance found in soil moisture phenomena. The variance of soil moisture follows a power law decay as a function of the measurement support area where the spatial correlation remains unchanged with the scale of observation.

$$\mathrm{Var}_L = (\alpha)^h \mathrm{Var}_a \tag{15}$$

where Var_L is the variance at the smoothed level from multiresolution analysis, Var_a is the variance in the original soil moisture field, á is the scale-factor defined as before, and h is the slope. The exponent of the power law is found to be an index for the spatial correlation structure of the soil moisture field. An exponent of −1 refers to an iid (spatially independent identical distribution) process, while an exponent of 0 indicates a spatially (fully) correlated structure. Power laws can be seen as a straight line on a log–log graph since, taking logs of both sides, the above equation becomes

$$\log(\mathrm{Var}_L) = h\log(\alpha) + \log(\mathrm{Var}_a) \tag{16}$$

which has the same form as the equation for a line. The linear decay of soil moisture variance, $\log(\mathrm{Var}_L)$ with increasing support log(á) shows spatial correlation. Similar power law scaling was also found for soil properties in previous studies (Mattikalli et al., 1998; Rodriguez-Iturbe et al., 1995).

In this study, self-similarity analysis is used to evaluate the dependence of within-pixel variance on spatial resolution. The wavelet decomposition of PSR-based soil moisture fields resulted in within-pixel variance in the form of horizontal, vertical and diagonal wavelet coefficients. Self-similarity among wavelet coefficients is evaluated using scaling analysis mentioned in Eqs. (12)–(14).

3. Results and discussions

In this study soil moisture evolutionary process was observed at the base scale of 800 m × 800 m from the PSR instrument, and the subsequent coarse scale images were derived by wavlet decomposition technique. PSR-based soil moisture fields observed for 10 days during SMEX02 (Fig. 2)) were decomposed using multiresolution analysis up to $m=5$. With Haar wavelet decomposition ($\lambda_0=2$), the scale parameter increases in the dyadic series ($\lambda_0^m=2,4,8,..$.). With every level of decomposition the spatial extent increases by 4 times. Therefore, the decomposition resulted in 5 coarser resolution fields (1600 m × 1600 m, 3200 m × 3200 m, 6400 m × 6400 m, 12,800 m × 12,800 m, and 25,600 m × 25,600 m) of smoothed soil moisture fields from the base resolution of 800 m × 800 m. Further decomposition beyond level $m=5$ (i.e., resolution 25600 m × 25,600 m) was not carried out due to restriction imposed by the area of the SMEX02 experimental region. The decomposition also resulted in 3 fluctuation fields for detail components (horizontal, diagonal, and vertical) for each level of decomposition at 5 coarser resolutions. Five scale factors (log(á) = log(A_i / A_0): −5.3, −3.9, −2.6, −1.2, 0) corresponding to decomposed resolutions were calculated with A_0 as the coarsest resolution (25600 m × 25600 m).

3.1. Statistical characteristics of soil moisture during SMEX02

The volumetric soil moisture probability distribution function (pdf) is bounded between wilting point and porosity. Theoretically, this pdf cannot be normal, although normal distribution appears to be the best two-parameter distribution for bounded nature of spatial soil moisture (Western & Blöschl, 1999). Therefore, mean and variance were evaluated for the smoothed soil moisture fields at all scales of multiresolution analysis. The mean of soil moisture fields at various resolutions was plotted against log of scale factors in Fig. 4. Three groups are clearly visible in the plot (Fig. 4), the upper one is of wet fields (July 10th, July 11th, and July 12th during SMEX02), the intermediate one is of fields during drydown (July 1st, July 4th, July 8th, and July 9th during SMEX02) and the lower group is of dry fields (June 25th, June 27th and June 29th during SMEX02). The variance for soil moisture fields was plotted against scale factors on a log–log plot in Fig. 5. Like Fig. 4, similar three groups are clearly visible in the Fig. 5, with one exception of July 4th, 2002 which shows high soil moisture variance due to scattered precipitation in SMEX02 region. It is quite apparent from Figs. 4 and 5 that wet fields have high variability and dry fields have low variability. The variability at any given scale factor becomes smaller as the drydown progresses (Fig. 5). Minimal change in variability was observed for wet fields with increase in spatial resolution. However, in case of dry fields the variance drops off rapidly with increasing spatial resolution. The discussion of Sellers et al. (1995) about

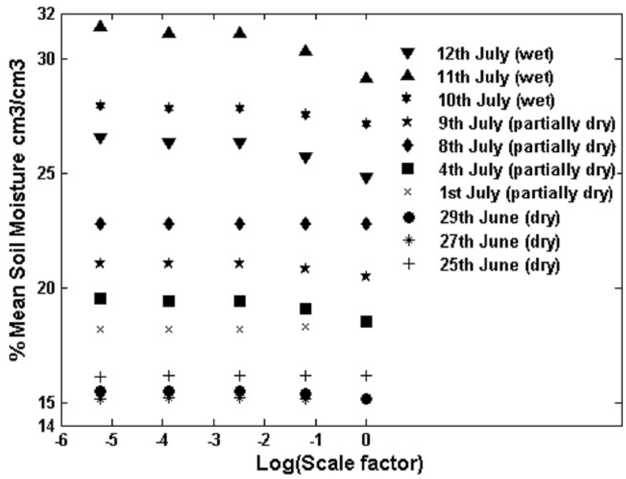

Fig. 4. Mean of soil moisture against log of scale-factors.

high spatial heterogeneity introduced by rainfall and removed through dry-down dynamics was also found applicable here at all scale factors. A noticeable feature in the study (Fig. 5) was a very low variance at scale factor 0 (25,600 m × 25,600 m) in the driest field (June 27th), which indicates an almost uniform soil moisture field. In Fig. 4, as the slope remains almost constant for the dry fields, the temporal decrease in variability is mostly related to the decrease in intercepts.

Linearity in the log–log dependency of the variance on scale factors (Eq. (15)) can be observed in Fig. 5. Trends lines shown in Fig. 5 exhibit spatial correlation found during wet and dry days. Power law decay of the variance of soil moisture was observed as the spatial resolution degraded. More precisely, the linearity was observed up to a scale factor of −2.6 (6400 m × 6400 m) for all the PSR-based soil moisture fields considered during SMEX02. The linearity up to a scale factor of −2.6 shows spatial correlation irrespective of the wetness (i.e., wet or dry fields). There is a noticeable break in trend lines for dry days at a scale factor of −2.6 (6400 m × 6400 m). However,

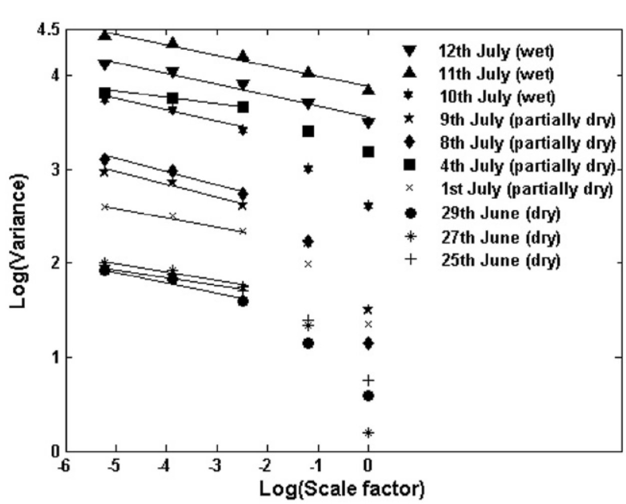

Fig. 5. Dependencies of the variance of soil moisture against scale-factors in a log–log plot. Trend lines are shown up to −2.6 scale-factors (6400 × 6400 m^2).

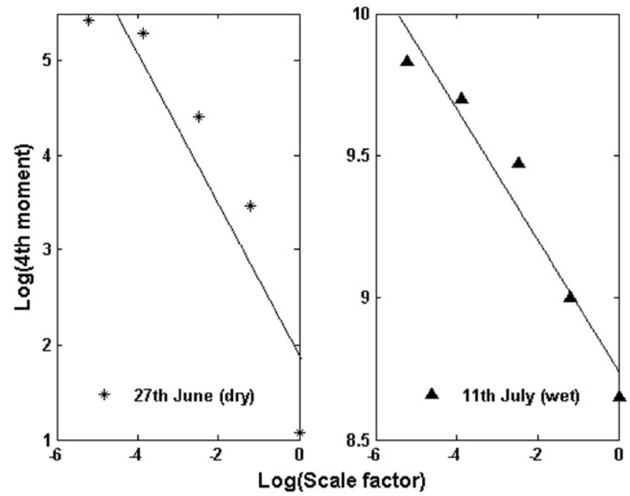

Fig. 6. Linear fit for moment of order four versus scale-factors on a log–log plot for average soil moisture fields of June 27th (slope $s(p) = -0.54$, and $R^2 = 0.85$) and July 11th 2002 (slope $s(p) = -0.17$, and $R^2 = 0.9$).

complete trend lines with small slope for wet days represent strong spatial correlation of soil moisture for all the scale factors. Rodriguez-Iturbe et al. (1995) reported similar type of scaling up to 1000 m × 1000 m for the Washita '92 experimental data. Hu et al. (1997) in their work found the linearity till 32,000 m × 32,000 m for the same dataset (Washita '92). Oldak et al. (2002) demonstrated that for ESTAR dataset during SGP97 the linearity was observed up to 7800 m × 7800 m. This result was different from the findings of Rodriguez-Iturbe et al. (1995) for Washita '92. They found that the slope decreases as drydown proceeds. However, for the same study region, Hu et al. (1997) found increase in slope as the soil moisture drydown continued. In our study, the slope remained almost constant, and the difference may be explained by the terrain and landuse in SMEX02 region.

3.2. Scaling analysis of soil moisture fields

Based on Eqs. (13) and (14), scaling analysis was conducted for all the PSR-based soil moisture fields of SMEX02. Moments were calculated until eighth order for each scale factor of all the soil moisture fields. Fig. 6 only illustrates log–log dependency of 4th moment of June 27th (dry field) and July 11th 2002 (wet field) plotted against scale factors. Similarly, 2nd to 8th moments were also plotted (not shown) against scale factors in a log–log plot for all the soil moisture fields. The slope in Eq. (14) was estimated by linear regression for moment order p (2nd to 8th moment) with high R^2. Linearity in $s(p)$ was observed up to scale factor of −2.6 (6400 m × 6400 m) for all sampling days of SMEX02, as for the variance (results not shown here). It was also observed that the slope $s(p)$ became smaller for higher order moments. In Fig. 7, slopes of June 27th (dry field) and July 11th (wet field) were plotted against moment order p. To exhibit simple scaling process during the wet days, linearity of the change in slope for each moment order p must be satisfied (Gupta & Waymire, 1990). The linearity of slope change shows no change in the soil moisture variability with increasing scale. A straight line was plotted based on slope of second and third orders of moments in Fig. 7. For June 27th (dry field) a non-constant rate of change of slope (non-linear, downward open concave function) with respect to moment order indicates that soil moisture does not obey a simple scaling law, therefore it represents a multiscaling process. The concavity of $s(p)$ is an indicator of increasing variability with decreasing scale. Multiscaling property was observed for all the dry fields (days) of SMEX02. Gupta and Waymire (1990) found the slope in the range of −5 to 0 for their rainfall analysis, which is much higher in absolute value than the slope we found in the present study. On the contrary, Wood (1994) found an upward concave functional relationship between the slope and the order of moment for the scaling properties of soil moisture fields simulated from the coupled water-energy model. Hu et al. (1998) and Oldak et al. (2002) demonstrated similar multiscaling behavior for the dry fields of Washita '92 and SGP97 Experiments, respectively. Another important finding of scaling characteristics of this study was simple scaling for all the wet fields during SMEX02. Thus, with simple scaling for the wet fields, if the slope is known, then given the observed pixel area and the moments at this resolution, the moments at any other resolution can be inferred. As illustrated in Fig. 7, the scaling exponent during drydown suggests a transition and evolution of soil moisture fields from simple scaling (during wet days) to multiscaling (during dry days) characteristics. This study supports the conclusion of Dubayah et al. (1997), Hu et al. (1998), and Oldak et al. (2002) who claimed that the multiscaling (mutifractal) is an appropriate statistical model for soil moisture spatial distribution during the drydown.

The aforementioned results of this study were observed without considering the subpixel variability and uncertainties (errors in sensor measurements) present within sensor footprints. The passive microwave remote sensing signature gives average value of the observed variable with unknown variance from a

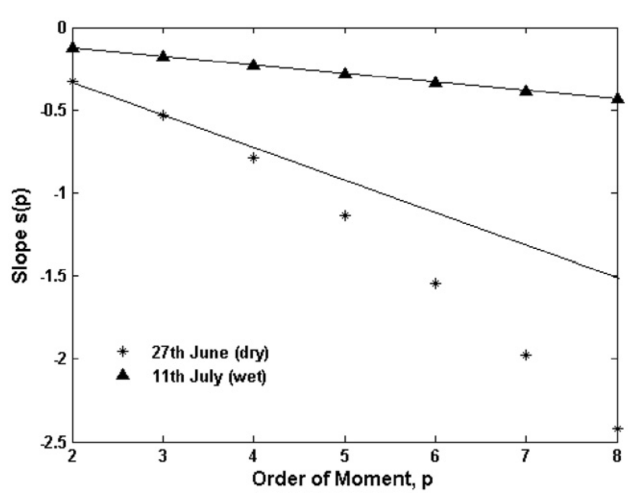

Fig. 7. Deviation and conformance to simple scaling in the change of slopes with respect to order of moments for soil moisture fields of June 27th and July 11th 2002 (SMEX02), respectively.

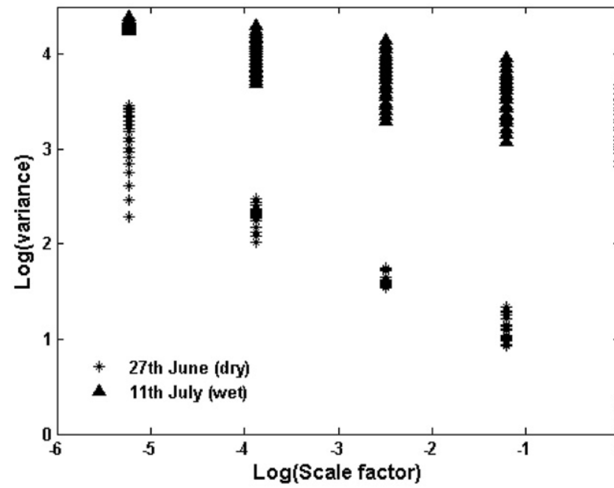

Fig. 8. Second moments of 20 realizations from soil moisture fields of June 27th, and July 11th 2002 (SMEX02).

heterogeneous volume within the footprint (Njoku & Entekhabi, 1996). The average value of the observed variable in passive microwave footprint is sensitive to three parameters i.e., soil moisture, soil temperature, and vegetation water content (Njoku et al., 2003). These three parameters are influenced by various geo-physical variables including soil properties, precipitation, DEM, radiation, and vegetation. At C-/X-band frequencies (i.e., 6.6 GHz or higher; PSR frequencies) the sensitivity to soil moisture becomes very low when vegetation water content exceeds about 1.5 kg/m^2. Furthermore, the C-/X-band also shares bandwidth with communication services and consequently get radio frequency interference (RFI) contamination.

To incorporate the sub-pixel variability and uncertainty in PSR-based remote sensing measurements, few fields (WC11, WC12, WC13, WC15, WC17, and WC24 of Walnut Creek watershed in SMEX02 region) were selected to assess variability present during dry and wet conditions. Based on ground-based point measurements, it was found that these fields exhibited a standard deviation of ±20% of volumetric soil moisture (VSM) and ±10% of VSM for dry and wet fields, respectively. The subgrid variability and uncertainty in the remote sensing footprints were accounted as Gaussian white noise in the study. An arbitrary cut-off point of 0.25 VSM was used to introduce white noise of ±20% for the footprints having soil moisture below 0.25 VSM, and ±10% for the footprints with soil moisture above 0.25 VSM. Twenty realizations were obtained from each PSR-based soil moisture estimate over the regional area during SMEX02. Similar scaling analyses were conducted on each realization.

Fig. 8 shows the scale-factor versus second moments on a log–log scale for each realization of June 27th (dry field) and July 11th 2002 (wet field). It is apparent that the range of second moments at particular scale factor for dry fields (June 27th) converges with increasing scale. This attribute was observed even after introducing greater uncertainty (±20% white noise) in dry fields. The study verifies that for dry fields, as support increases, the variability decreases due to the effects of averaging and disappearance of small scale features.

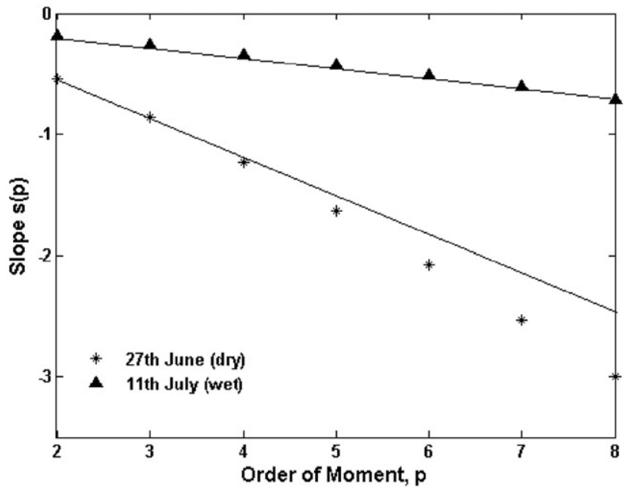

Fig. 9. Deviation and conformance to simple scaling in the change of slopes with respect to order of moments for soil moisture fields for 20 realizations of June 27th and July 11th 2002 (SMEX02), respectively.

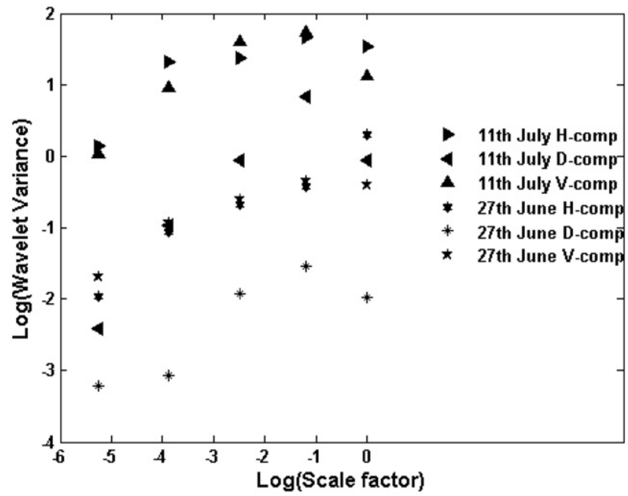

Fig. 10. Variance versus scale factor in log–log plot for fluctuation fields (horizontal direction) on June 27th and July 11th 2002 (SMEX02).

Multiscaling trends were also observed for all the dry fields, when 20 realizations were fitted (Fig. 9). The twenty realizations of wet fields exhibit contrasting features from dry fields. This analysis shows that the scaling properties of dry and wet soil moisture fields remain the same even after introduction of uncertainty.

Using satellite-based remote sensors, the surface soil moisture status of large regions can be monitored. They provide spatially continuous information that is typically limited to the upper centimeters of the soil. Most applications are found at the catchment and regional scale, with a specific emphasis on characterizing soil moisture variability (e.g., Famiglietti et al., 1999; Jackson & LeVine, 1996; Schmugge et al., 2002). For such application, the simple scaling and multiscaling results of wet and dry fields, respectively, from this study is effective for upscaling (aggregation) and downscaling (disaggregation) of soil moisture in agricultural landscapes of Iowa and similar hydro-climatic regions. The upscaled–downscaled soil moisture may help assess scale-appropriate soil water processes in hydrologic and environmental model applications.

3.3. Study of self similarity of PSR-based soil moisture

The fluctuation fields or detail components (horizontal, diagonal and vertical wavelet coefficients) measure the intensity of the local variation of soil moisture within the scale factor (resolution). Variances (Eq. (11)) for horizontal, diagonal and vertical wavelet coefficients were calculated for each level of scale factor. Fig. 10 shows the variance of horizontal, diagonal, vertical component against the log of scale factor for June 27th (dry field) and July 11th (wet field) of SMEX02. Fig. 10 illustrates an interesting feature of subpixel variability present in wet and dry fields at various scale-factors. A steady increase in subpixel variability is observed up to the scale factor of −1.2 irrespective of wet or dry field. This characteristic may be attributed to the landuse topography, and soil type of SMEX02

Table 1
Results of regression: slope $s(p)$, coefficient of determination R^2 for order of moment versus scale-factors in horizontal, vertical and diagonal directions (stationary fluctuation components) for PSR based soil moisture estimates of SMEX02

SMEX02	Horizontal		Diagonal		Vertical	
June 27th 2002						
Order of Moment p	Slope $s(p)$	R^2	Slope $s(p)$	R^2	Slope $s(p)$	R^2
2	−0.51	0.99	−0.96	0.98	−0.66	0.91
3	−0.81	0.96	−1.44	0.95	−0.99	0.91
4	−1.13	0.92	−1.95	0.94	−1.35	0.90
5	−1.47	0.86	−2.46	0.94	−1.73	0.87
6	−1.82	0.81	−2.99	0.91	−2.13	0.85
July 11th 2002						
2	−0.36	0.96	−0.59	0.93	−0.41	0.92
3	−0.54	0.93	−0.90	0.93	−0.65	0.92
4	−0.73	0.89	−1.22	0.93	−0.91	0.86
5	−0.94	0.86	−1.54	0.93	−1.18	0.82
6	−1.16	0.83	−1.88	0.92	−1.48	0.79

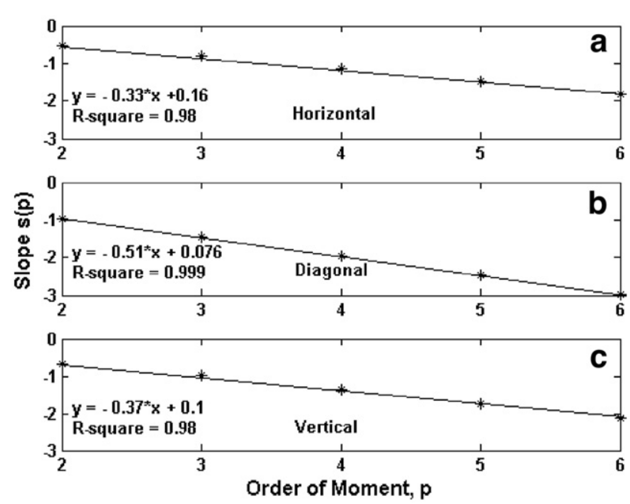

Fig. 11. Slope $s(p)$ versus order of moment p plots for fluctuations fields on June 27th 2005 (SMEX02): (a) horizontal, (b) diagonal and (c) vertical directions.

region. With increasing scale factor, more variability was introduced in the soil moisture fields due to different row/broadcast cropping patterns, rolling topography, and multiple soil types. Another noticeable property was high subpixel variability (high wavelet variance) for wet field when compared to dry field at all scale factors. This phenomenon shows the effect of local ridge/furrow features of row cropping and rolling topographic control in wet fields. Usually, soil moisture tends to accumulate in the depressions and dissipate at the ridges due to overland and lateral flow. With drydown the control shifts to soil type and vegetation type, making soil moisture field more uniform.

To examine self-similar nature of PSR-based soil moisture fields of SMEX02, the first six moments of wavelet coefficients of fluctuation fields (horizontal, diagonal and vertical components) for twenty realizations (from aforementioned uncertainty study) were calculated for each level of decomposition (multiresolution analysis). Table 1 presents the slope in (Eq. (14)) and R^2 for the order of moment versus scale factor in a log–log plot for all the fluctuation fields of June 27th (dry field) and July 11th (wet field) of SMEX02. Figs. 11 and 12 illustrate the rate of change of slope with respect to moment order p for three fluctuation components of dry and wet fields, respectively. The linearity with high R^2 suggests the presence of self similarity (stationarity). A constant rate of change from the 2nd order moment indicates simple scaling in all the three directions irrespective of dry or wet field. It is also interesting to note that the similar behavior was observed by Hu et al. (1998) in their study of fluctuation fields in Little Washita watershed using the ESTAR data collected during Washita ’92, and by Brunsell and Gillies (2003) in AVHRR data of July 2nd 1997 in the SGP97 region. This result is important when characterizing PSR-based remotely sensed soil moisture fields. Although dry fields show multiscaling attributes, when appropriately decomposed the subgrid scale characteristics of the soil moisture distribution may be described by simple scaling.

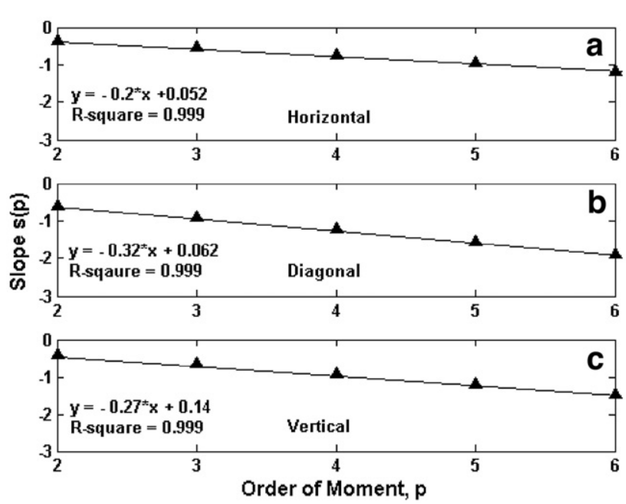

Fig. 12. Slope $s(p)$ versus order of moment p plots for fluctuations fields on July 11th 2005 (SMEX02): (a) horizontal, (b) diagonal and (c) vertical directions.

4. Conclusion

We have examined the spatial structure of PSR-based remotely sensed soil moisture of wet and dry fields during the SMEX02 field campaign in Iowa (with row crop agriculture of corn and soybean) using Haar wavelet multiresolution analysis. The multiresolution study was conducted on 5 distinct spatial resolutions (scale-factors). Our study shows that soil moisture follows power law scaling with increasing scale-factors attesting similar findings by other researchers in previous field campaigns at other locations using different remote sensing equipments. The scaling exponent during drydown suggest a transition from simple scaling (in wet fields) to multiscaling (in dry fields) behavior. The fluctuation fields (horizontal, diagonal and vertical wavelet coefficients) measuring the intensity of the local variation of soil moisture within a particular resolution showed simple scaling properties irrespective of wet or dry days. A caveat of this study is the use of Haar wavelets for decomposition aggregation with of soil moisture stochastic fields. With Haar wavelet decomposition the scale parameter increases in the dyadic series (2,4,8,..), resulting in increasing the spatial extent by almost 4 times. The implication of such decomposition may be crucial while determining the spatial correlation of soil moisture fields with increasing scale, especially in dry fields. Hence, there is a possibility of that the spatial correlation may exceed the suggested resolution of 6400 m × 6400 m.

The results contribute to the basic understanding of soil moisture variability and its spatial scaling features which may help develop scale-appropriate techniques to assess effective soil parameters and upscaled soil water processes and use them in ecological and climatological modeling in agricultural landscapes. Currently, satellite-based passive microwave remote sensing provides the most feasible way to measure soil moisture in large regions with footprint size ranging tens of kilometers. However, most of the hydrological/environmental models operate at field or watershed scale with model grid size ranging in meters. Therefore, the transition from simple scaling (in wet fields) to multiscaling (in dry fields) behavior will help guide the hydrology and land-surface modeling communities towards developing better downscaling schemes of the remotely sensed soil moisture, and parameterization of statistical distributions of surface soil moisture and related hydrologic processes at subpixel scale. The results of this work can help improve the simulations of subpixel-scale hydrologic processes and fluxes (e.g., infiltration, evapotranspiration, and surface runoff) that are nonlinearly related to soil moisture in agricultural landscapes of Iowa and similar other environments.

Acknowledgements

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