Evolution of physical controls for soil moisture in humid and subhumid watersheds

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Received 4 April 2012; revised 17 December 2012; accepted 19 December 2012.

[1] The covariability of soil moisture with soil, vegetation, topography, and precipitation is linked by physical relationships. The influence of each of these interdependent physical controls on soil moisture spatial distribution depends on the nature of heterogeneity present in the domain and evolves with time and scale. This paper investigates the effect of three physical controls, i.e., topography (slope), vegetation (type), and soil (texture), on soil moisture spatial distribution in the Little Washita and Walnut Creek watersheds in Oklahoma and Iowa, respectively, at two support scales. Point-support-scale data collected from four soil moisture campaigns (SMEX02, SMEX03, SMEX05, and CLASIC07) and airborne-scale data from three soil moisture campaigns (SGP97, SGP99, and SMEX02) were used in this analysis. The effect of different physical controls on the spatial mean and variability of soil moisture was assessed using Kruskal-Wallis and Shannon entropy respectively. It was found that at both (point and airborne) support scales, nonuniform precipitation (forcing) across the domain can mask the effect of the dominant physical controls on the soil moisture distribution. In order to isolate land-surface controls from the impact of forcing, the effect of precipitation variability was removed. After removing the effect of precipitation variability, it was found that for most soil moisture conditions, soil texture as opposed to vegetation and topography is the dominant physical control at both the point and airborne scales in Iowa and Oklahoma. During a very wet year (2007), however, the effect of topography on the soil moisture spatial variability overrides the effect of soil texture at the point support scale. These findings are valuable for developing any physically based scaling algorithms to upscale or downscale soil moisture between the point and watershed scales in the studied watersheds in humid and subhumid regions of the Great Plains of USA. These results may also be used in designing effective soil moisture field campaigns.

Citation: Gaur, N., and B. P. Mohanty (2013), Evolution of physical controls for soil moisture in humid and subhumid watersheds, *Water Resour. Res.*, *49*, doi:10.1002/wrcr.20069.

1. Introduction

[2] Soil moisture is a dynamic state variable. This dynamic behavior may manifest itself in long-term changes in mean soil moisture of an area on a yearly basis which are of interest to climate modelers or very short daily time scales wherein a change in soil moisture may cause convective storms [*Taylor et al.*, 2012]. Thus, in order to address the effects of soil moisture variability in hydrological and meteorological processes, it is very important to identify and understand the spatial and temporal variability of soil moisture and quantify it.

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0043-1397/13/10.1002/wrcr.20069

[3] The temporal and spatial patterns of soil moisture are dependent on a set of physical controls. These physical controls have been identified primarily as precipitation, soil, vegetation, and topography [*Famiglietti et al.*, 1999; *Entin et al.*, 2000; *Mohanty and Skaggs*, 2001; *Albertson and Montaldo*, 2003; *Teuling and Troch*, 2005; *Joshi and Mohanty*, 2010]. The physical controls interact to create certain spatial and temporal patterns of soil moisture. Due to the interdependent nature of these physical controls, it is often impossible to isolate their individual effects on the soil moisture distribution. Numerous studies have been undertaken to understand the controls that these factors assert over soil moisture spatial distribution [*Famiglietti et al.*, 1999; *Mohanty et al.*, 2000a, 2000b; *Joshi and Mohanty*, 2010] and their temporal persistence [*Mohanty and Skaggs*, 2001; *Jacobs et al.*, 2004; *Joshi et al.*, 2011]. The use of geostatistical analysis has been a popular choice for investigating the dominance of physical controls. Using geostatistical techniques in Tarrawarra catchment in Australia, *Western and Grayson* [1998] showed that the degree of wetness of top 30 cm of soil moisture affects the spatial distribution of the soil moisture. In a mixed vegetation

pixel with relatively homogeneous topography and soil type, *Mohanty et al*. [2000a] showed that variable land cover, land management, and microheterogeneity affect the soil moisture distribution. Yet in another study pixel with uniform vegetation, *Mohanty et al*. [2000b] showed the influence of topography in spatiotemporal arrangement of surface soil moisture. Using airborne remote sensing data, *Cosh and Brutsaert* [1999] showed that soil type strongly affects the soil moisture variability. *Ryu and Famiglietti* [2006] observed that within regional scale the soil texture and vegetation control the smaller-scale correlation, whereas the larger-scale correlations are controlled by precipitation.

[4] The other popular technique that has been used to study the dominant controls for soil moisture is the empirical orthogonal functions (EOFs) [*Preisendorfer and Mobley*, 1988; *Kim and Barros*, 2002; *Jawson and Niemann*, 2007; *Joshi and Mohanty*, 2010]. *Kim and Barros* [2002] used the EOF technique to explore the relationship between physical controls and the soil moisture spatial structure over a 40 km × 250 km region across the Southern Great Plains. They observed that topography dominated the spatial distribution of soil moisture during and after a rainfall event. Soil hydraulic properties controlled the spatial variability above the field capacity, while vegetation controlled the soil moisture distribution during drydown. In another study for the same region, *Jawson and Niemann* [2007] showed that soil texture, topography, and land use describe the spatial soil moisture patterns with the soil texture influencing the spatial and temporal distributions by the maximum amount. In an agricultural watershed in Iowa, *Joshi and Mohanty* [2010] showed that topography, rainfall, and soil texture have mixed effects on the soil moisture distribution at the watershed and regional scales, whereas vegetation parameters, namely, vegetation water content, have very limited influence at both scales.

1.1. Heterogeneity, Scale, and Soil Moisture Measurements

[5] All past studies suggest that the presence of spatial heterogeneity in any kind of physical control induces a variation in the observed soil moisture spatial distribution even under the same precipitation input. Also, studies showed that, under different wetness conditions, various physical controls interact differently [*Joshi and Mohanty*, 2010]. The effect and dominance of physical controls may also vary with different hydroclimates since vegetation type, topographic features, and soil morphology intricately depend on the hydroclimate of a region. Thus, along with investigating the spatial distribution of soil moisture across a domain, it is also equally essential to explore the nature of heterogeneity of its different physical controls. The importance of effectively representing land-surface heterogeneity for a broader understanding of the effect of scale on the soil moisture has also been emphasized by *Western et al*. [2002]. A brief description of how heterogeneity and soil moisture distribution are related to the scaling triplet [*Blöschl and Sivapalan*, 1995], i.e., support, extent, and spacing, is described below.

1.1.1. Support Scale

1.1.1.1. Point Scale

[6] At the point scale, soil moisture is measured using gravimetric method, time domain reflectometry (TDR), etc. These measurement techniques have the support size of a few square centimeters. At the centimeter scale, the measurements made are very sensitive to the pore sizes in the soil. Soil moisture measurements taken a few centimeters apart may differ greatly if a macropore in the soil is encountered as opposed to the soil matrix. Thus, the heterogeneity which may affect the soil moisture distribution that is obtained from the point observation scale is the soil structure. Soil structure is often a difficult quantity to quantify. However, since the formation of soil structure is itself controlled by the soil texture, and the nature of roots and organic life-forms (earthworms, etc.) present in the soil system, it can be quantified to some extent using these other measurable ancillary parameters.

1.1.1.2. Airborne Scale

[7] The usual airborne scale in the past field experiments (e.g., Southern Great Plain Hydrology Experiment (SGP) 1997 and Soil Moisture Experiment (SMEX) in 2002 and 2003) has been of the order of 800 m × 800 m. Airborne remote sensing of soil moisture attributes one soil moisture value to a large heterogeneous pixel (800 m × 800 m). At this large support scale, the heterogeneity in terms of soil pore sizes may no longer influence the measurements since the effect gets averaged out. However, each pixel has an intrinsic characteristic heterogeneity comprised of soil, vegetation, and topography, which is different from its adjoining pixel and is interacting to create a soil moisture distribution within the pixel. Thus, in order to understand the underlying dynamics of the soil moisture distribution at the remote sensing footprint scale, it is important to characterize the heterogeneity observed at this support scale. Pixels may differ in vegetation type, relief, and soil texture that may be characterized using topographic indices (e.g., slope and aspect), soil properties (e.g., soil texture and bulk density), and vegetation attributes (e.g., vegetation type, leaf area index (LAI), and normalized difference vegetation index (NDVI)).

1.1.2. Extent Scale

[8] When delineating a physical control as dominant, it is also important to mention the extent scale of the measurements. The rainfall, which according to past studies has the major influence on soil moisture, observed over a larger extent may be more variable. The rainfall heterogeneity observed at a watershed scale may be different from the heterogeneity observed at the regional and continental scales. Past studies have demonstrated that the influence of different physical attributes changes at different wetness conditions [*Joshi and Mohanty*, 2010]. Thus, increasing the extent scale in a scaling study can change the wetness conditions observed in the domain. This can influence the apparent dominant physical controls of soil moisture for the domains of different sizes. On the other hand, if the extent scale is limited, there is a loss of large-scale features [*Western et al*., 2002].

1.1.3. Spacing Scale

[9] The spacing at which observations are taken determines the heterogeneity captured. If the spacing is too large, it may not capture the soil moisture dynamics for a given extent at a particular observation scale. Thus, in order to describe the soil moisture dynamics of an area adequately, the spacing of observations should be such that it describes the heterogeneity of the entire extent. *Western*

et al. [2002] also pointed out a loss of detail in the small-scale features if a higher spacing is used. Measurement spacing along with the support scale may thus be considered to be a control of the level of detail of the soil moisture dynamics that can be resolved at a particular scale.

1.1.4. A New Dimension for the Scaling Triplet-Time

[10] Besides the spatial scales which control the representation of heterogeneity in an area, the time scale also holds utmost importance in assessing the dominance of physical controls of soil moisture. Heterogeneity on the land surface itself is dynamic and is governed by time. An agricultural watershed may be more dynamic than a natural terrain. It is highly likely that during different times in a plant's growth cycle or throughout the course of the year the hierarchy of dominance that physical controls exert over soil moisture spatial distribution may change with the changing heterogeneity. Thus, it is very important to specify and work with the time scale when discussing the spatial physical controls of soil moisture. The time scale may itself be split into support (time over which a given reading is averaged), spacing (time between two readings), and extent (time span of the experiment).

[11] In addition to the understanding of how scale may impact the heterogeneity and soil moisture distribution, it is equally essential to understand the physical processes that influence the soil moisture distribution at various scales. A brief discussion is given below:

[12] a. *Effect of Soil*: Soil texture is based on a range of composition of sand, silt, and clay. These quantities together are indicative (to some extent) of the soil structure and its hydraulic properties. Soil texture determines the pore sizes in the soil or alternatively the water holding capacity of the soil. The hydraulic properties of soil determine the downward hydraulic conductivity of a soil, the matric potentials that the soil may create to impede the flow of water through the soil, and also the plant available water content.

[13] b. *Effect of Vegetation*: Vegetation may impact the downward as well as upward vertical flow of water. Vegetation may reduce the impact of a precipitation event by interception. Different vegetation types lead to different amounts of interception, throughfall, and stemflow, thus affecting the input of water to the ground surface. Also, vegetation affects the upward flow of water through the process of transpiration. Different rooting structures will lead to different amounts of water uptake. The effect of vegetation on the soil moisture spatial distribution can be considered to be most dynamic.

[14] c. *Effect of Topography*: Topography usually affects the spatial redistribution of water under saturated conditions. Water tends to move from a higher potential to lower potential and thus flows along a path determined by the slope of the area. Topography also determines the aspect of an area, and based on the varying amount of sunlight available the evapotranspiration occurring on different aspects may vary. Thus, the water loss on different portions of topography might be different.

[15] The primary objective of this study is to assess the effect of spatially heterogeneous physical controls on soil moisture spatial distribution under different wetness conditions for two watersheds with different hydroclimates. The evolution of dominance of the soil moisture physical controls at the point and airborne scales for (1) the Walnut Creek (WC) agricultural watershed in Iowa and (2) the Little Washita (LW) watershed in Oklahoma has been investigated using Kruskal-Wallis analysis and the concept of entropy to individually assess the effect of physical controls on the mean and variance of soil moisture across a watershed.

2. Study Area and Data Description

2.1. Study Area

2.1.1. WC Watershed, Iowa

[16] The WC watershed is located in Boone and Story counties in Iowa. The region is characterized by humid climate with an average annual precipitation of 818 mm. The majority rainfall in this region occurs from April through September which is also the growing season in this agricultural watershed. The topography of the watershed is fairly flat. Owing to the comparatively young geologic development, the watershed is poorly drained and consists of low depressional areas or "potholes" which are hydrologically unconnected [*Hatfield et al*., 1999]. The main crops grown in the watershed are corn and soybean. The estimated evapotranspiration through the growing season varies approximately between 1 and 9 mm/d and 3 and 8 mm/d for corn and soybean, respectively [*Geli*, 2012].

2.1.2. LW Watershed, Oklahoma

[17] The LW watershed spreads over parts of Caddo, Canadian, and Grady counties in Oklahoma. The climate is subhumid with an average annual precipitation of 795 mm. It receives bulk of its rainfall in May, June, September, and October. The average potential evapotranspiration over these months is about 6.3 mm/d [*Mohseni et al*., 1998]. This watershed has a significantly rolling topography with an average elevation of 400 m and a maximum relief of 183 m. Surface runoff in the watershed is generally toward the east. The water-bearing aquifers underlying the watershed contribute to the LW river, and seepage has been observed along the portions of the channel in the central region [*Liew and Garbrecht*, 2003].

2.2. Data

[18] The soil moisture data set for the watersheds was obtained from the National Snow and Ice Data Center located at http://nsidc.org/data/amsr_validation/soil_moisture/index.html. The point-support-scale soil moisture measurements for the top 5 cm depth were taken using an impedance-based probe, namely, TDR (ML2 probes with HH2 data loggers of Delta-T Inc.; http://www.delta-t.co.uk), and were calibrated gravimetrically for the specific sites. Point-scale data for the LW watershed, Oklahoma (Figure 1), were obtained from the SMEX03 and Cloud and Land-Surface Interaction Campaign in 2007 (CLASIC07). Point-scale data for the WC watershed, Iowa, were obtained from the soil moisture sampling conducted during 2002 (SMEX02) and 2005 (SMEX05). Point-support-scale soil moisture measurements (100 m apart) were taken at 14 points in each of the fields chosen to monitor the hydrology of the watershed. At each of the 14 points in the WC agricultural watershed, three readings were taken: one on the furrow, one on the slope of the furrow, and the third one on the crop row. In the LW watershed for the pasture cover, three replicated samples were taken within a 1 m diameter sampling area at the 14

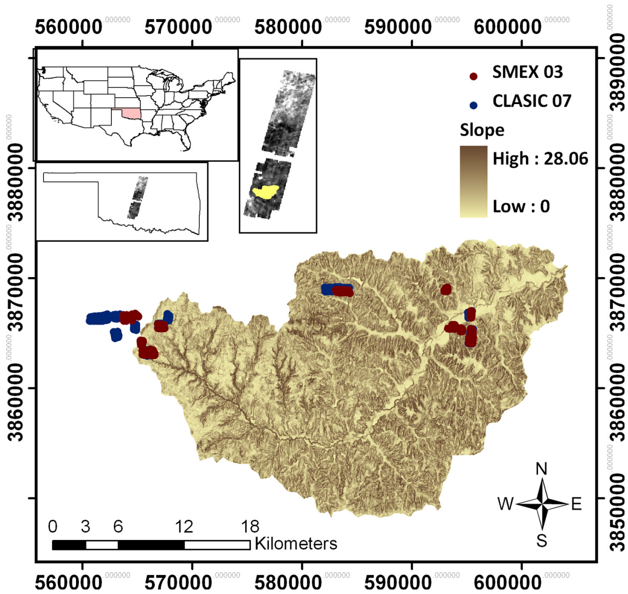

Figure 1. Slope and point-scale soil moisture data collected in Oklahoma.

sampling locations. In addition to the ground-based point sampling, soil moisture was retrieved from the airborne Electronically Scanned Thinned Array Radiometer (ESTAR) [*Jackson et al.*, 1999] during the SGP97 and SGP99 and Polarimetric Scanning Radiometer (PSR) [*Bindlish et al.*, 2006] during 2002. A brief description of the various soil moisture campaigns is given in Tables 1 and 2.

[19] Vegetation attributes for Iowa (Figure 2) were obtained during the field experiments, and digital elevation model (National Elevation Dataset, 30 m resolution) was used to create the slopes for the watersheds. The slope map at the 800 m resolution was constructed after aggregating the elevation data at 30 m to 800 m. The soil texture information has been obtained from Soil Survey Geographic Database (SSURGO) at 30 m resolution. Soil maps of the WC and LW watersheds in Iowa and Oklahoma are shown in Figures 3 and 4, respectively. The soil moisture variability observed over the two watersheds (at the airborne scale) is shown in Figures 5a and 5b.

3. Methodology

3.1. Kruskal-Wallis

[20] The first step in assessing the dominance of a particular physical control is to check whether its inherent heterogeneity leads to an effective separation of the mean soil moisture within a classification. This was done using the Kruskal-Wallis test on the mean soil moisture. This test is the nonparametric equivalent of the analysis of variance test and is used to distinguish between the difference in the means of two or more distributions. The null hypothesis for this test was H_N: there is no difference in the median soil moisture grouped by "a," where "a" represents the categories in a particular classification. This test was conducted to compare the separability between the mean soil moisture values of different categories within a classification.

3.2. Shannon Entropy

[21] The next step was to assess the variability in the data which was done using Shannon entropy. *Shannon* [1948] entropy has been a popular technique for investigating spatial variability in the field of hydrology [*Mishra et al.*, 2009; *Mogheir et al.*, 2004; *Phillips*, 2001]. However, to the best of the authors' knowledge, this is the first study to use the entropy technique to understand the dominance of the physical controls on the soil moisture spatiotemporal variability. The strength of this technique lies in its effective simplicity to incorporate the effect of the dependent or independent physical controls (categorical or numerical) on the soil moisture spatial distribution. It can be used on the data sets of a short or long length. However, in order to use this technique, it is essential to isolate the parameters (physical controls) whose effect we want to assess on the soil moisture spatial distribution.

[22] *Shannon* [1948, 2001] entropy (I) is a statistical quantity representing a measure of the information that may be extracted from a system or analogously the uncertainty that the system comprises. Entropy for a system with a state random variable V is formulated as

$$\begin{aligned} &V : n \in N \\ &I_V(p_1, p_2, \ldots . p_n) = -\sum_{i=1}^{n} p_i \log_2 p_i \end{aligned} \tag{1}$$

where

$$\sum_{i=1}^{n} p_i = 1 \tag{2}$$

$p_1, p_2, \ldots, p_n$ are the probabilities of occurrence of the realizations of V, and I_V, the entropy of the system, is representative of the uncertainty of the random variable or the unresolved information in the random variable. However, instead of a unique value of uncertainty, all systems possess a range of uncertainty, which depends on the probability

Table 1. Overview of the Various Soil Moisture Campaigns[a]

Campaign	Location[b]	Duration	Support Scale	Measuring Instrument
SGP97	OK	18 June to 18 July 1997	Airborne (800 m × 800 m)	ESTAR
SGP99	OK	8 July to 20 July 1999	Airborne (555 m × 450 m)	ESTAR
SMEX02	IA	25 June to 12 July 2002	Point and airborne (800 m × 800 m)	TDR and PSR
SMEX03	OK	2 July to 17 July 2003	Point	TDR
SMEX05	IA	13 June to 4 July 2005	Point	TDR
CLASIC 07	OK	11 June to 6 July 2007	Point	TDR

[a]Data were not collected continuously for the duration mentioned. Sampling was not conducted on days with rain or when agricultural activity posed a threat to the data collectors. For SMEX03, data collected up to 6 July 2003 have been used because of insufficient data points on the other days.
[b]OK, Oklahoma; IA, Iowa.

Table 2. Details of Number of Data Points Used for the Analysis

Campaign	Classification	Minimum/Maximum Number of Points per Day Used in the Analysis	Number of Bins Used
Support: point			
SMEX03	Total	139–204	
	Based on soil type		
	Loam	10–13	3
	Silt loam	90–133	6
	Sandy loam	39–63	4
	Based on topographic position		
	Hilltop	55–91	3
	Slope	30–40	5
	Valley	54–78	4
CLASIC07	Total	101–112	
	Based on soil type		
	Loam	14–17	3
	Silt loam	44–54	5
	Sandy loam	34–43	5
	Based on topographic position		
	Hilltop	19–20	3
	Slope	49–56	4
	Valley	31–36	5
SMEX02	Total	244–278	
	Based on soil type		
	Loam	41–48	5
	Clay loam	195–230	9
	Based on vegetation		
	Corn	148–184	10
	Soybean	83–94	7
SMEX05	Total	286–321	
	Based on soil type		
	Loam	155–176	10
	Clay loam	125–145	8
	Based on vegetation		
	Corn	170–190	9
	Soybean	111–132	8
Support: airborne			
SGP97	Total	601	
	Based on soil type		
	Loam	68	5
	Silt loam	313	11
	Sandy loam	220	9
	Based on topographic position		
	Hilltop	119	6
	Slope	371	10
	Valley	111	6
SGP99	Total	473–532	
	Based on soil type		
	Loam	76–80	5
	Silt loam	214–268	10
	Sandy loam	183–184	8
	Based on topographic position		
	Hilltop	94–107	6
	Slope	298–334	10
	Valley	81–91	6
SMEX02	Total	64	
	Based on soil type		
	Loam	7	2
	Clay loam	57	5
	Based on vegetation		
	Corn	31	3
	Soybean	33	4

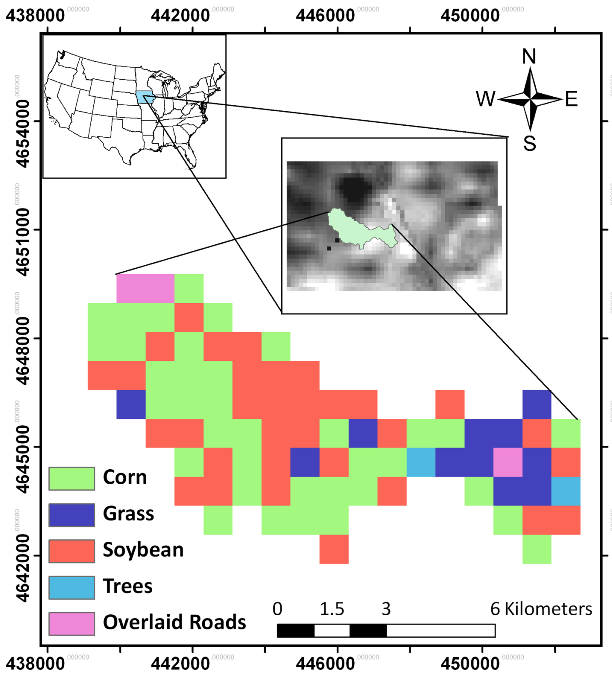

Figure 2. Land use land cover in the WC watershed, Iowa.

values associated with the set N chosen to represent the random variable. This range of uncertainty is quantified by a range of entropy values of the system. By addition of information to this system in terms of either constraints, like specifying the moments of the random variable, the range of uncertainty and correspondingly the range of entropy of the system reduce. In other words, with each addition of independent information to a system, the system goes from being stochastic (with a range of uncertainty) to being deterministic (i.e., possessing a unique probability distribution). The entropy of a completely determinate system is zero.

[23] Entropy is an extensive quantity and unlike energy does not follow the conservation laws. In order to express

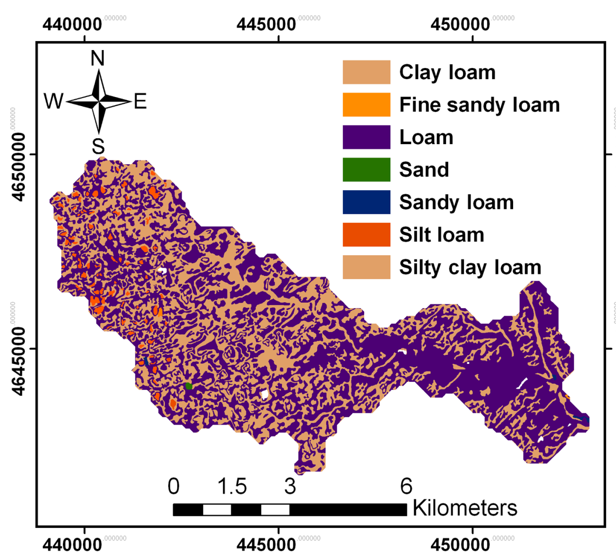

Figure 3. SSURGO-based classified soil map of the WC watershed, Iowa.

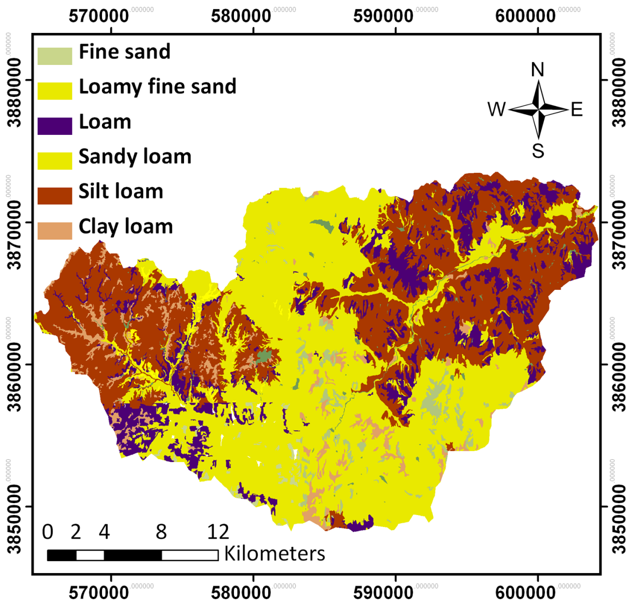

Figure 4. SSURGO-based classified soil map of the LW watershed, Oklahoma.

the combined uncertainty of two or more independent random variables, their respective entropy values may be added. However, if the random variables are dependent on each other, this dependence must be accounted for as "transinformation," $T(A,B)$, i.e., the amount of information common to both the sets of random variables. The joint information or entropy, $I(A,B)$, of this system of the random variables is calculated as shown in equation (3). For two independent random variables, "$T(A,B)$" is zero. This concept of transinformation can be extended to more than two variables as well.

$$I(A,B) = I(A) + I(B) - T(A,B). \quad (3)$$

3.2.1. Entropy as a Tool to Assess Physical Controls of Soil Moisture

[24] As discussed above, entropy of a system of random variables will decrease with the addition of information. The information which explains more uncertainty in the data will have a lower value of entropy of the random variable [*Pászto et al.*, 2009]. This property of entropy forms the basis of this study.

[25] In this study, the random variables under consideration are the point and airborne measurements of soil moisture. The addition of information to the random variable is done in the form of classification of the soil moisture data. These soil moisture values are classified under different categories based on the physical controls present at the location of the measurement. These categories are "soil type" and "vegetation type" for the agricultural watershed in Iowa and "soil type" and "topographical location" for the natural terrain in Oklahoma. The classification type which leads to a lower entropy explains the maximum uncertainty in the random variable. The factor on which the lowest entropy classification is based can be considered to be the most dominant physical control in terms of controlling the soil moisture variability.

[26] Despite the availability of various attributes to represent the various physical controls (e.g., hydraulic conductivity, percent sand, percent silt, and percent clay for soil; NDVI, LAI, and vegetation type for vegetation; and slope, aspect, and elevation for topography), broad classification categories, namely, soil type, vegetation type, and topographic location, were chosen. This was done in order to incorporate easily available categorical information and retain the individual identities of each physical control along with each classification being representative of the properties of the physical control. For example, "soil type" gives a fair idea about the range of hydraulic conductivity, infiltration, and evaporation behavior of a soil. Similarly, "vegetation type" is representative of the root zone and

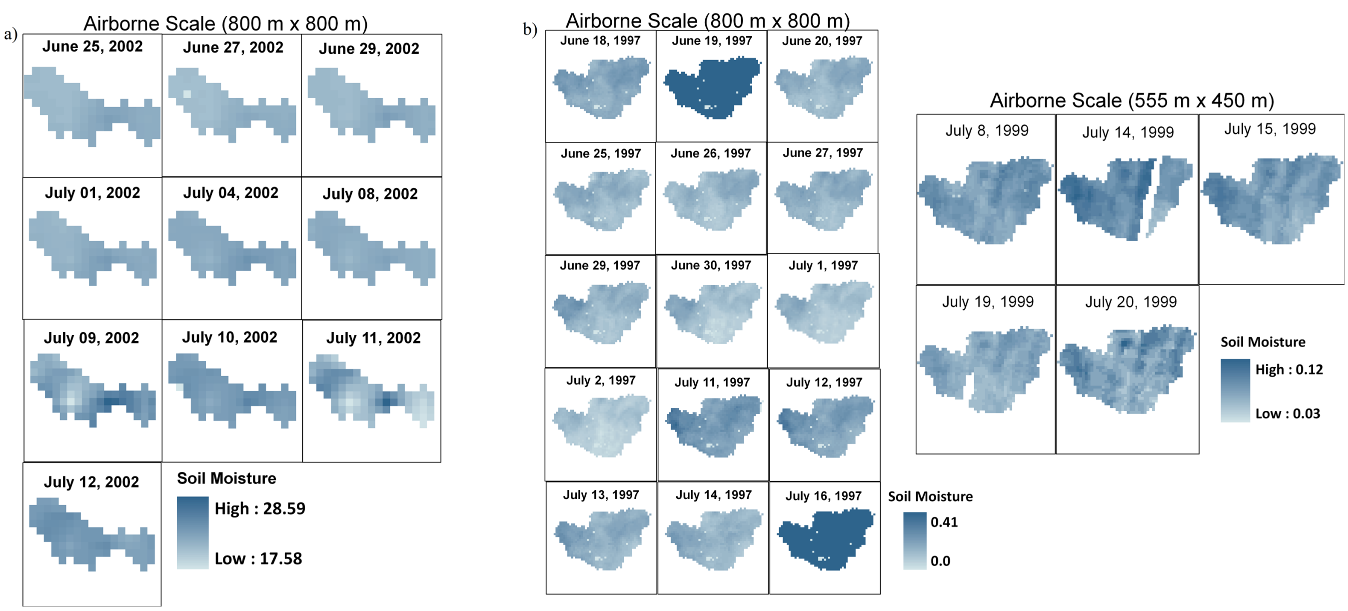

Figure 5. Airborne soil moisture maps for (a) the WC watershed, Iowa, and (b) the LW watershed (1997 and 1999), Oklahoma.

Table 3. Classification Categories for the WC Watershed, Iowa[a]

Classification Type	Categories
Soil type	Loam, clay loam
Vegetation type	Corn, soybean

[a]In a vegetation type classification scheme, if a particular soil moisture measurement in Iowa was taken in a location with corn as a vegetation type, it was placed under the classification, "corn." In soil-type-based classification scheme for the same data set, if the same soil moisture value was in loam soil, it was placed under the soil type "loam."

root water uptake, plant percentage cover on land, LAI, etc., for land use and land cover (LULC). There may be other factors like plant health which may not be represented in an adequate way under this classification scheme, but it was assumed that plant health at this extent scale may be excluded as a heterogeneous factor. "Topographical location" was determined based on the location of a sampling point on the slope. This classification scheme adequately represents most of the attributes of topography like elevation and slope. It does not however represent aspect which may be an important attribute for soil moisture variation. But considering the moderate relief of the area under consideration, aspect will not influence the soil moisture distribution significantly. The different classification categories used in this study are provided in Tables 3 and 4. The choice of these parameters for describing the heterogeneity was made based primarily on their suitability for representing the key landscape features and also on the ease of obtaining such categorical data.

3.2.2. Marginal Entropy Calculation for Soil Moisture

[27] We arranged the soil moisture values sm_k^d, where d represents the days (1, 2, . . . , d), and k represents the number of soil moisture values (1, 2, . . . , n_0) daywise to calculate entropy values for each day separately. Using the *Scott* [1979] algorithm of optimal binning, the frequency histograms for each day were calculated. According to this algorithm, the bin width (h) in the daily frequency histograms is defined as

$$h = 3.49 s n_0^{-1/3}, \qquad t = 1, 2, \ldots, d, \tag{4}$$

where h is the bin width, and s is the standard deviation of the daily soil moisture.

[28] The average value of "h" across the duration of the campaign was chosen as the representative bin width for a particular campaign.

[29] A probability p_i is assigned to each bin and calculated as

$$p_i = \frac{n_i}{n_0}, \qquad t = 1, 2, \ldots, d, \tag{5}$$

where n_i is the number of observations in the ith bin.

[30] Then, we substituted p_i in equation (1) to find out the daily marginal entropies.

3.2.3. Joint Entropy Calculation for Each Classification

[31] Soil moisture values were classified under different categories as mentioned in Table 3 and 4. A joint probability mass function (pmf) was constructed for the soil moisture values in different categories. The steps for constructing a joint pmf with two variables are given below. A joint pmf for three variables can be constructed along the same lines. It is important to note here that this method may become computationally intensive with the increasing number of categories in a classification scheme.

[32] The soil moisture values in one category (sm_j) under a classification were paired up with the soil moisture values in another category (sm_m) within the same classification to form unordered pairs on a daily basis (e.g., loam and sandy loam categories under soil classification).

$$(\mathrm{sm}_j, \mathrm{sm}_m), \ j = 1, 2, ..., J, m = 1, 2, ..., M.$$

[33] A contingency table representing the relative frequencies f_i was used to calculate the probabilities $p(sm_j, sm_m)$ as given in equation (6). The bin sizes for the two categories under the classification were decided based on equation (4).

$$f_i = p(\mathrm{sm}_j, \mathrm{sm}_m) = \frac{n_{jm}}{n_0}, \ j = 1, 2, ..., J, m = 1, 2, ..., M, \tag{6}$$

where n_{jm} is the number of observations in the jth (from category 1) and mth (from category 2) bins.

[34] Substituting $p(sm_j, sm_m)$ in equation (1) the joint entropies were obtained. This joint entropy of the data set corresponds to $I(A,B)$ in equation (3).

3.2.4. Bootstrapping

[35] In order to achieve statistically significant daily results, bootstrapping was employed to get multiple samples for each category in a classification. Bootstrapping enables the use of the sample data at hand as a population from which random samples may be drawn. Random sampling with replacement was done within each category. An equal number of data points were employed in each bootstrapping routine with 40 samples being created for each category. These results were used to compute the joint pmf and to identify the uncertainty range of the entropy values (represented by error bars).

3.2.5. Effect of Precipitation

[36] As mentioned above, if the extent scale is large enough and precipitation varies across the extent, the effect of precipitation may mask the actual effect of different physical land-surface controls on soil moisture. In order to remove the effect of precipitation, the entire computation was repeated for the soil moisture anomalies. In order to compute the soil moisture anomalies at the point support scale, the mean soil moisture values of every field in the entire study domain were computed. These means were subtracted from the soil moisture readings collected in each respective field. At the airborne scale, the soil moisture values were linearly detrended to obtain the anomalies. Linear

Table 4. Classification Categories for the LW Watershed, Oklahoma[a]

Classification type	Categories
Soil type	Loam, silt loam, sandy loam
Topography position	Hilltop, valley, slope
Slope: 0%–1.5%, flow accumulation: 0	Hilltop
Slope: 0%–1.5%, flow accumulation: >0	Valley
Slope: 1.5%–14%, flow accumulation: >0	Slope

[a]In soil-type-based classification scheme, if a particular soil moisture measurement in Iowa was taken in a location with loam as a soil type, it was placed under the soil type "loam."

Table 5. The *p* Values for Kruskal-Wallis test, WC Watershed, Iowa (Point Scale)[a]

DOY	Mean Volumetric Soil Moisture (%)	Soil	Vegetation
2002			
176	0.10	<0.0001[b]	0.0273[b]
177	0.10	0.0091[b]	0.0002[b]
178	0.09	0.0291[b]	0.0081[b]
182	0.07	0.0481[b]	0.0001[b]
186	*0.14*	*0.0068*[b]	*0.0006*[b]
187	*0.15*	*0.0921*	*0.2650*
188	*0.21*	*0.0874*	*0.2986*
189	0.18	0.0008[b]	0.8908
190	0.15	0.0086[b]	0.0807
192	*0.28*	*0.0013*[b]	*0.2168*
193	0.26	<0.0001[b]	0.9502
2005			
166	0.24	0.0011[b]	<0.0001[b]
167	0.21	0.0112[b]	<0.0001[b]
168	0.20	0.0082[b]	<0.0001[b]
169	0.18	0.3068	<0.0001[b]
170	0.17	0.0346[b]	0.1354
171	0.16	0.3759	0.0101[b]
172	*0.20*	*0.3992*	*0.0296*[b]
176	0.17	0.6679	0.2436
177	*0.32*	*0.0002*[b]	*<0.0001*[b]
178	0.27	0.0198[b]	<0.0001[b]
181	*0.32*	*<0.0001*[b]	*<0.0001*[b]
182	0.26	0.0351[b]	<0.0001[b]
183	0.23	0.0007[b]	<0.0001[b]
184	0.20	0.5525	<0.0001[b]

[a]The rows in italics represent that a rainfall event preceded the DOY.
[b]A significant difference in means with a significance level of 0.05.

detrending was done by linearly regressing a straight line through the soil moisture values plotted against its spatial location and then subtracting the regressed value from the actual soil moisture value. The entire coding for the analysis was done using MATLAB.

4. Results and Discussion

[37] This section is divided into two subsections. The first part discusses the Kruskal-Wallis results, and the second part discusses the entropy results. Each subsection is further divided into two parts: (1) the point scale and (2) the airborne scale. The two analyses comprehensively describe the effect of different physical controls of soil moisture on its spatiotemporal distribution. Kruskal-Wallis compares the mean soil moisture of different distributions, whereas the entropy-based analysis compares the variability observed in the distributions.

4.1. Comparison of Means: Kruskal-Wallis Based Analysis

4.1.1. Point Scale

[38] Year 2005 (SMEX05) was relatively wetter than 2002 (SMEX02) in Iowa. In Oklahoma, 2007 (CLASIC07) was very wet, whereas 2003 (SMEX03 campaign) was very dry. In addition, SGP97 in Oklahoma was an average year, whereas SGP99 again was very dry.

[39] Table 5 contains the *p* values of Kruskal-Wallis. From the *p* values calculated for 2002 (Iowa), we see that soil texture for the most part partitioned the mean soil moisture at a significance level of 0.05, whereas vegetation type was not as effective on the wetter days (day of year (DOY) 187 onward). Soil texture was consistently capable of separating the mean soil moisture from DOY 176 to 186. These days corresponded to low soil moisture values. On DOY 188, the mean soil moisture for the watershed increased from 0.15 to 0.21 (vol/vol) because of a precipitation event, and neither soil texture nor vegetation type induced an effective partition of the mean soil moisture. A failure for either of the two classifications inducing a mean difference in the soil moisture indicates an interaction of the soil and the vegetation or an extraneous factor besides the two, which is dominating under these conditions. However, during a similar increase from 0.15 to 0.28 (vol/vol) on DOY 192, the soil texture (but not vegetation) was capable of discerning a difference in the mean soil moisture. This can be attributed to the difference in the antecedent soil moisture conditions that prevailed in the watershed. Before the precipitation event on DOY 188 the antecedent soil moisture conditions were very low, whereas after the precipitation event on DOY 192 the antecedent moisture conditions were relatively higher. This indicates that when the crop is water stressed on account of limited soil moisture availability, the interaction between the vegetation and the soil increases, and jointly they control the soil moisture spatial distribution. Physically, this may refer to two competitive forces acting within the soil: (1) the matric potential of soil that tries to hold the water in the soil pores and (2) the suction potential of plant roots that tries to withdraw water from the soil pores. However, when the antecedent moisture conditions are high, the suction forces of the plant roots do not compete for the near-surface soil moisture since the deeper root zone is not water stressed. The density of the roots is higher in the slightly deeper root zone, and thus, observing the principle of minimum energy requirement, plants would preferentially take water from the deeper zone. Thus, we observe that after the second precipitation event the soil texture, which determines the water holding capacity of the soil pores, effectively partitions the mean surface soil moisture which could be due to more infiltration to the lower layers.

[40] In 2005, which was a relatively wetter year, we found that vegetation was slightly more capable of discerning a difference in the near-surface soil moisture. Corn and soybean have very different canopy structures. Corn has a very dense canopy and leads to greater interception as opposed to soybean that offers little to no interception. This holds true for the later half of the campaign when the canopies are fully developed. Also, it could be attributed to the difference in the infiltration properties of the soil under these (corn versus soybean) canopies, as the rooting structure and the organic content play an important role in the development of the infiltration properties of the soil [*Mohanty et al.*, 1994; *DasGupta et al.*, 2006]. On DOY 172, after a precipitation event, vegetation ($p < 0.05$) partitioned the mean soil moisture more than the soil texture ($p = 0.3992$). This is somewhat different from 2002. However, it is important to keep in mind that SMEX02 (DOY 176–193) and SMEX05 (DOY 164–185) captured different portions of the growth cycle of corn and soybean. DOY 172 in 2005 fell in the growing cycle of corn and soybean, and thus, the water requirements were considerably more

Table 6. The p Values for Kruskal-Wallis test, LW Watershed, Oklahoma (Point Scale)[a]

DOY	Mean Volumetric Soil Moisture (%)	Soil	Topography
2003			
183	0.129	<0.0001[b]	0.0608
184	0.117	<0.0001[b]	0.4389
185	0.108	<0.0001[b]	0.3529
186	0.096	<0.0001[b]	0.1101
187	*0.103*	*<0.0001*[b]	*0.2992*
2007			
160	0.271	<0.0001[b]	0.0810
161	0.247	<0.0001[b]	0.3963
162	*0.283*	*<0.0001*[b]	*0.1725*
163	0.259	<0.0001[b]	0.1166
164	0.242	<0.0001[b]	0.3791
168	*0.326*	*<0.0001*[b]	*0.3673*
169	0.304	<0.0001[b]	0.2835
170	0.291	<0.0001[b]	0.2835
174	*0.297*	*<0.0001*[b]	*0.1953*

[a]The rows in italics represent that a rainfall event preceded the DOY.
[b]A significant difference in means with a significance level of 0.05. Since there were three classifications, a Bonferroni correction was applied bringing the actual level of significance testing to 0.016 (0.05/3) for each individual comparison.

than in 2002, when we see more dominance of soil texture. This implies that in an agricultural watershed the effect of vegetation on the soil moisture dynamics is highly dependent on the crop growth stage. Another interesting observation is that if we compare the effect of soil texture and vegetation on the soil moisture means during the same stages of the crop growth cycle, we observe very different effects. In 2005, except for a brief exception of DOY 170 and 176, vegetation continued to exert an effect on the partitioning of the soil moisture means in contrast to what was observed in 2002. This can again be explained by referring to the antecedent soil moisture conditions. The year 2002 was a comparatively drier year with a larger range of soil moisture. The root zone vegetation dynamics (phenology) were probably very different in 2002 as compared with 2005. Thus, in addition to the crop growth stage, the antecedent wetness conditions in the study domain exert a large influence on the effect of different physical controls on the soil moisture spatial distribution. On DOY 176, neither vegetation nor soil texture displays a partitioning of the soil moisture mean. Hysteresis in the soil moisture variability, previously been reported at the field scale by *Teuling et al.* [2007] and *Ivanov et al.* [2010], may possibly be another contributor to this behavior.

[41] Table 6 contains the p values for the LW watershed, Oklahoma. Interestingly for Oklahoma, at the point scale, soil texture remained dominant throughout in the wet as well as dry years. There could be two possible explanations for this behavior. The first could be the soil texture is dominating and is the only factor responsible for deciding the separation of the mean soil moisture. The other possible explanation could be that such a small support scale is insufficient to represent a topographical position. But irrespective, this finding may prove to be highly useful for conducting future field campaigns.

4.1.2. Airborne Scale

[42] During SMEX02 campaign in Iowa, at the 800 m × 800 m scale, the p values of the vegetation-based Kruskal-Wallis test were on some occasions much lower than the p values of the soil-texture-based Kruskal-Wallis test (Table 7). On DOY 182, the soil moisture values rose up to 0.20 (vol/vol) and then consistently remain above it. During this period, vegetation showed lower p values on all days with the exception of DOY 190 and 191. The p value indicates the level of confidence that we have in the results that the two means are equal to each other or come from the same distribution. However, neither soil texture nor vegetation type partitions the mean soil moisture quite effectively with the exception of DOY 193 where vegetation emerges as the dominant factor. This could imply that soil-vegetation interaction effects are more important when observing the soil moisture at a coarser scale than their individual effects. A heterogeneity factor comprising both the soil and the vegetation together may be needed to effectively represent soil moisture heterogeneity in the WC agricultural watershed region. The analysis could also be indicative of a type II statistical error since the number of data points was relatively low.

[43] Contrary to the results from the agricultural watershed in Iowa, soil texture in the LW watershed, Oklahoma, partitioned the mean soil moisture effectively at the airborne scale (Table 8). Topography also displayed an effective partitioning of the mean soil moisture on most days. The interesting point to note here is that during SGP97, on DOY 178, there was a small precipitation event wherein the soil moisture value rose from 0.132 to 0.151 (vol/vol). Despite the precipitation event, topography failed to partition the mean soil moisture, even though soil continued to do so. On the other hand, on DOY 192, when the soil moisture value rose from 0.080 to 0.227 (vol/vol), topography was able to show an effective partitioning in the mean soil moisture. This was true even for DOY 197 wherein both the topography and the soil type showed an effective partitioning of the mean soil moisture. This result also shows that there exist certain precipitation amount thresholds wherein the influence of topography on the soil moisture means begins. During SGP99, which was a considerably drier year, soil texture partitioned the soil moisture mean more effectively than topography. Even though the airborne-scale and point-scale data were taken in separate years, soil texture dominance at both scales is noteworthy.

[44] This analysis also showed another important feature. WC watershed is an agricultural watershed with considerable

Table 7. The p Values for Kruskal-Wallis test, WC Watershed, Iowa (Airborne Footprint)[a]

DOY	Mean Volumetric Soil Moisture (%)	Soil	Vegetation
2002			
176	0.18	0.8213	0.8772
178	0.16	0.6437	0.9625
180	*0.18*	*0.8213*	*0.8561*
182	*0.20*	*0.7388*	*0.3041*
185	*0.23*	*0.7880*	*0.4319*
189	0.21	0.4451	0.2507
190	*0.23*	*0.6749*	*0.8351*
191	*0.27*	*0.5687*	*0.8984*
192	*0.35*	*0.6749*	*0.1525*
193	0.28	0.3720	0.0053[b]

[a]The rows in italics represent that a rainfall event preceded the DOY.
[b]A significant difference in means with a significance level of 0.05.

Table 8. The p Values for Kruskal-Wallis test, LW Watershed, Oklahoma (Airborne Footprint)[a]

DOY	Mean Volumetric Soil Moisture (%)	Soil	Topography
1997			
169	0.188	<0.0001[b]	0.0157[b]
170	0.173	<0.0001[b]	0.0639
171	0.147	<0.0001[b]	0.5906
176	0.138	<0.0001[b]	0.0868
177	0.132	<0.0001[b]	0.3856
178	*0.151*	*<0.0001*[b]	*0.501*
180	0.143	<0.0001[b]	0.0012[b]
181	0.106	<0.0001[b]	0.0002[b]
182	0.104	<0.0001[b]	0.0007[b]
183	0.080	<0.0001[b]	0.0054[b]
192	*0.227*	*<0.0001*[b]	*<0.0001*[b]
193	0.202	<0.0001[b]	<0.0001[b]
194	0.160	<0.0001[b]	<0.0001[b]
195	0.141	<0.0001[b]	<0.0001[b]
197	*0.170*	*0.9108*	*<0.0001*[b]
1999			
189	0.097	<0.0001[b]	0.036[b]
195	*0.118*	*<0.0001*[b]	*0.6542*
196	0.097	<0.0001[b]	0.0067[b]
200	0.075	<0.0001[b]	0.1364
201	0.076	<0.0001[b]	0.2705

[a]The rows in italics represent that a rainfall event preceded the DOY.
[b]A significant difference in means with a significance level of 0.05. Since there were three classifications, a Bonferroni correction was applied bringing the actual level of significance testing to 0.016 (0.05/3) for each individual comparison.

vegetation heterogeneity usually absent in a natural watershed like LW. The p values in the LW watershed for the Kruskal-Wallis tests based on the soil and the topography followed similar patterns for the most part across time as opposed to those in the WC watershed, where the soil and the vegetation dominated at different times. This may imply a stronger correlation between the soil type and the topography (slope) in comparison with the correlation between the vegetation type and the soil texture, which is more dynamic in nature. This could also suggest that for a similar spatial extent the absence of the (dynamic) vegetation-based heterogeneity leads to more predictable soil moisture dynamics as observed by *Albertson and Montaldo* [2003].

4.2. Evolution of Physical Control Dominance: Entropy-Based Analysis

[45] Entropy analysis using the raw soil moisture data from various field campaigns explains the control that the geophysical parameters exert over the soil moisture variability across a watershed. Watershed is a relatively large spatial extent, and different parts of the watershed may receive different amounts of rainfall. Since dominance of physical controls changes under different wetness conditions (as discussed in the previous section), it is possible that dominant physical controls across the watershed may not be the same. In order to remove the effect of variable precipitation from the analysis, the entropy computation was done on the soil moisture anomalies (computed as explained in section 3.2.5).

[46] The marginal entropy values using the daily soil moisture anomalies were plotted against the daily mean soil moisture in Figure 6. Marginal entropies refer to the entropies computed for all the soil moisture values grouped together (without any classification). For the point-scale entropy values in the WC agricultural watershed in Iowa, we observed that entropy (or variability) is maximum when the soil moisture was in the intermediate range (i.e., neither too high nor too low). In the LW natural watershed, Oklahoma, the entropy values were slightly higher during the dry year 2003 (SMEX03) as compared with the wet year 2007 (CLASIC07). At the airborne scale in the WC watershed, in line with the past research findings [*Rodriguez-Iturbe et al.*, 1995; *Western and Bloschl*, 1999], we observed that the entropy (and consequently the variability) was lower than at the point support scale. However, in the LW watershed, even though the airborne data from SGP97 showed slightly lower entropy than that observed at the point support scale, data from SGP99 showed otherwise.

[47] The joint entropy values calculated based on the soil moisture anomalies and the different classifications are provided in Figures 7a and 7b (point scale) and 7c and 7d

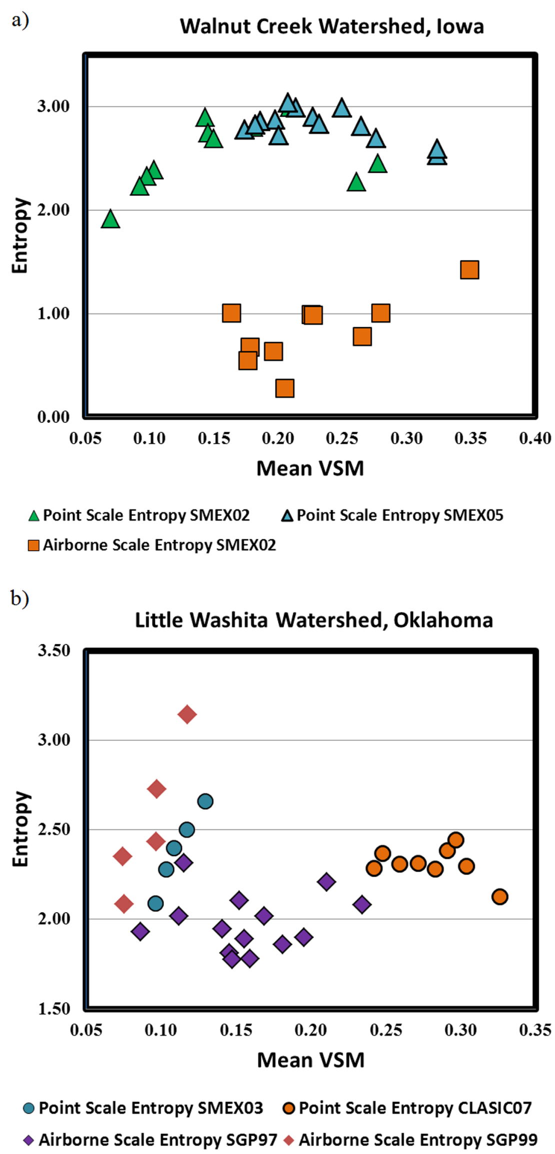

Figure 6. Mean volumetric soil moisture versus entropy: (a) the WC watershed, Iowa, and (b) the LW watershed, Oklahoma.

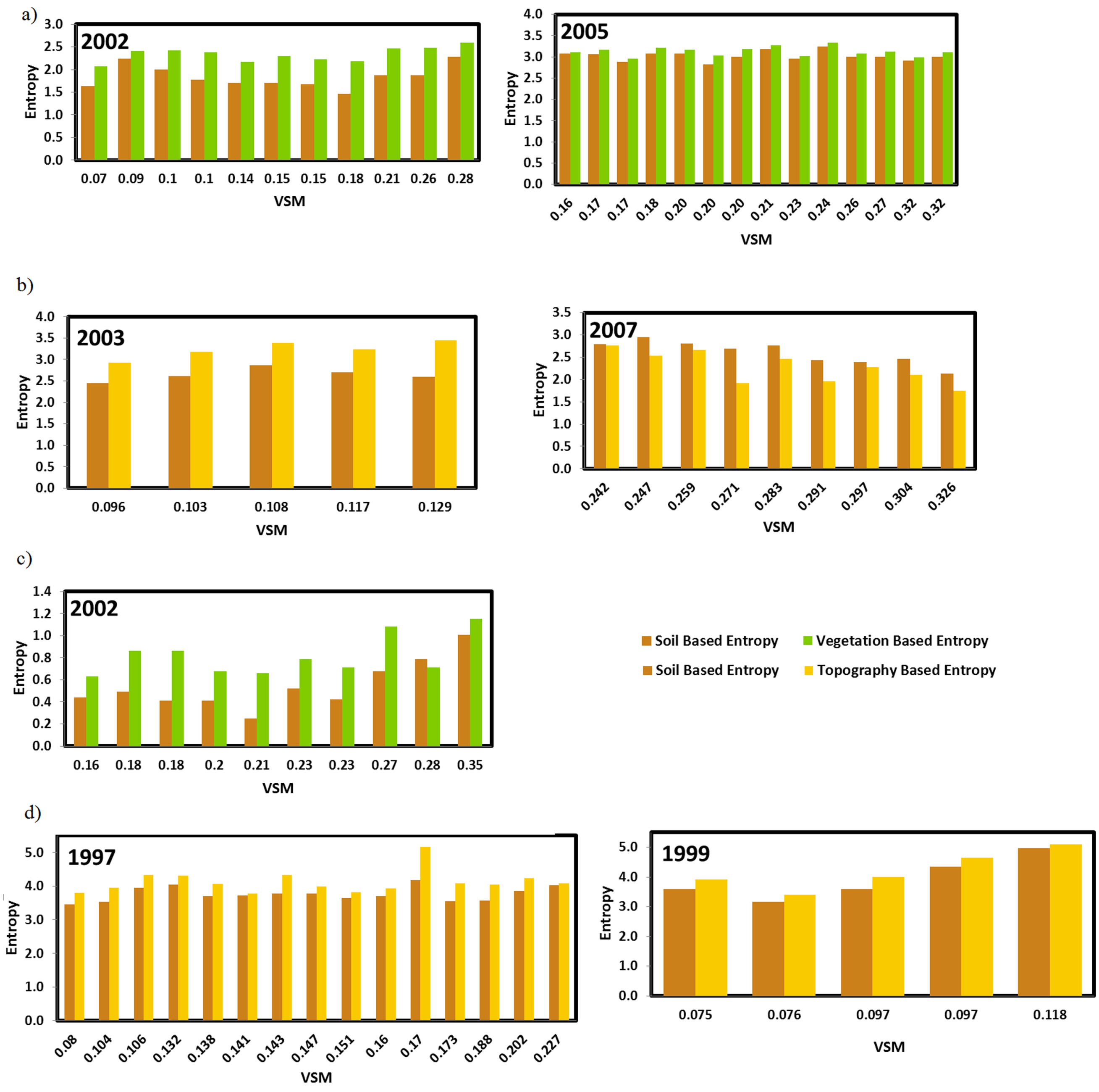

Figure 7. Joint entropy values based on different physical controls for (a and c) the WC watershed, Iowa, and (b and d) the LW watershed, Oklahoma.

(airborne scale). Joint entropies refer to the entropy values computed based on a particular classification scheme. These values represent the mean entropy values based on the bootstrapping result. In Iowa, a comparison of the mean soil moisture for the watershed between the 2 years reveals that 2005 was a wetter year as compared with 2002 (Figure 8). Correspondingly, we observed that even though the marginal entropy values were similar for the years 2002 and 2005 (Figure 6a), the joint entropy values based on the soil and vegetation classifications were higher for 2005 (Figure 7a). The same however cannot be said for the LW watershed, Oklahoma, where the dry (SMEX03) and wet (CLASIC07) years show a similar range of joint entropies based on the soil-based and topography-based classifications (Figure 7b). This analysis also shows that the inclusion of a vegetation-based heterogeneity leads to an increase in the variability of the soil moisture during wet conditions, which is also consistent with the findings of *Albertson and Montaldo* [2003].

[48] At the airborne scale, as compared with the point support scale, we see a lowering of the joint entropy values in Iowa (Figures 7c and 7d). This implies that at the airborne scale the soil texture and vegetation types (as a heterogeneity index) perform better than at the point scale. For Oklahoma, even though the marginal entropy values for the airborne scale followed a similar range (Figure 6b) when

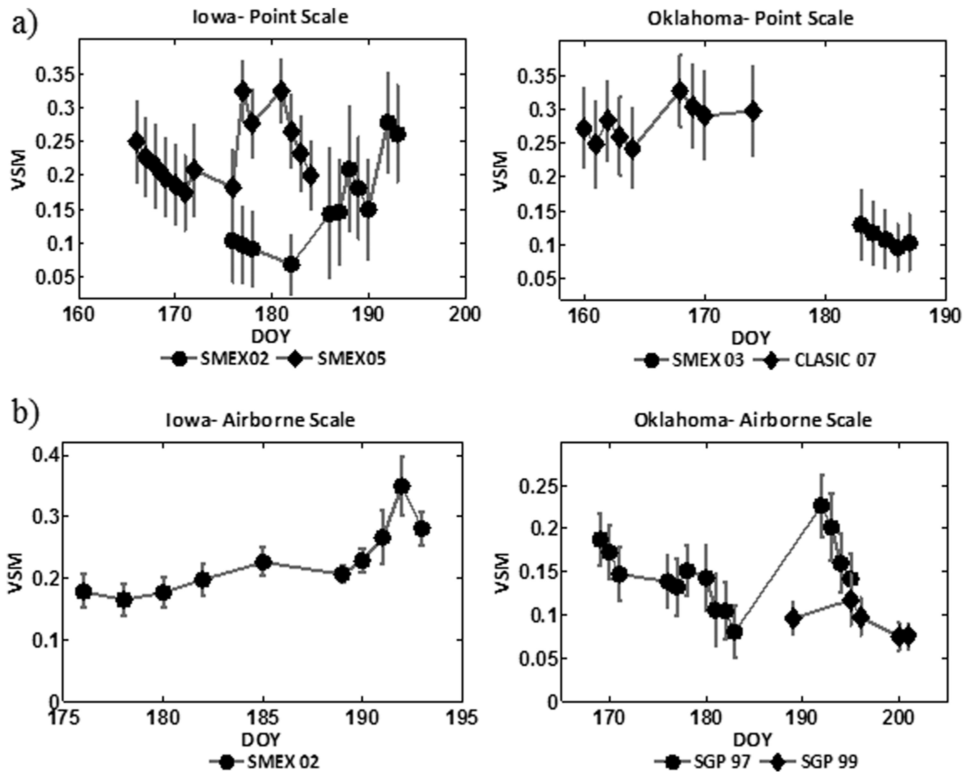

Figure 8. Time series of mean soil moisture: (a) point support scale and (b) airborne footprint scale. SMEX02 and SMEX05 (Iowa) and SGP97, SGP99, SMEX03, and CLASIC07 (Oklahoma).

compared with the point-scale values, the joint entropy values show a marked increase (Figures 7b and 7d). This means that the soil-based and topography-based classifications do not represent the soil moisture variability well at this scale.

[49] The differences between the joint entropy values based on the different classification schemes were computed, and the difference between the two (ΔEntropy) was evaluated (Figures 9 and 10). For Oklahoma, (ΔEntropy) represents the difference between the soil-based and topography-based entropies. For Iowa, (ΔEntropy) represents the difference between the soil-based and vegetation-based entropies. We would also like to point out that the transinformation between the entropies based on the different classifications has been excluded from the analysis. However, this does not take away the credibility of the analysis since we worked with the entropy difference and not the absolute entropy values to ascertain the dominant physical control.

4.2.1. Point Scale

[50] In Iowa, using the raw soil moisture data at the point support scale (Figure 10a), we observe that during the relatively wet SMEX05 year, vegetation appeared to dominate the soil moisture spatial distribution. However, during SMEX02 the controls shifted between soil and vegetation at the precipitation events (as marked by an increase in the soil moisture, Figure 8). This was also consistent with the mixed results obtained using the Kruskal-Wallis analysis where 2002 showed mixed effects. However, this could be a result of the different amounts of rainfall that occurred over different parts of the watershed. After removing the effect of rainfall (Figure 9), we observed that across both the years the soil texture was explaining more of the variability in the data. Though the difference between the soil-based and vegetation-based entropies evolved with time, soil texture gave us more information about the spatiotemporal distribution at the point support scale.

[51] The soil moisture conditions in Oklahoma represented two extremes of the wetness spectrum. The year 2003 was very dry, whereas 2007 was very wet. Using the raw soil moisture data, we observe that soil was the dominant physical control in 2003 as opposed to the dynamic evolution of the dominant physical controls evident in 2007. However, after removing the effect of precipitation from the analysis, we discovered that soil still dominated the spatiotemporal distribution of soil moisture in 2003, whereas only topography-based dominance was evident in 2007. This analysis reinforces the diagnosis that variable rainfall across the watershed can lead to misleading results. For the dry year 2003, excluding the effect of rainfall did not have any effect on the analysis. The dominant physical control was soil texture. However, in the wet year 2007, despite the fact that topography was unable to effectively partition the mean soil moisture (Kruskal-Wallis), it still explained more variability (entropy) in soil moisture spatial distribution than soil. A clear dominance of one factor is difficult to outline in this case.

4.2.2. Airborne Scale

[52] In Iowa (2002), soil texture is dominant. Even though the magnitude of ΔEntropy changed after removing the effect of precipitation, the analysis did not change

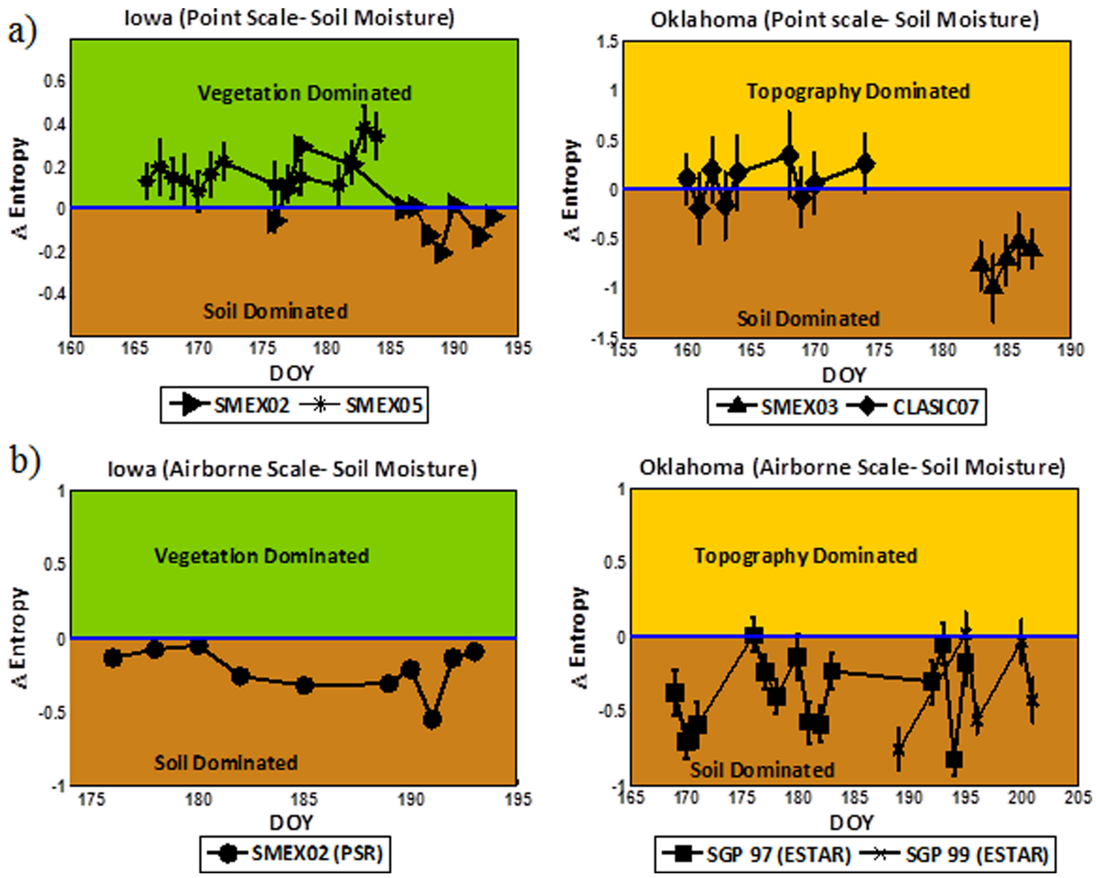

Figure 9. SMEX02 and SMEX05 (Iowa) and SGP97, SGP99, SMEX03, and CLASIC07 (Oklahoma). Time series of entropy difference (raw soil moisture): (a) point support scale and (b) airborne footprint scale.

much. The same was observed in Oklahoma in 1997 and 1999. Soil texture was the dominant physical control, and the analysis result did not change much after removing the effect of precipitation. These results were consistent with *Cosh and Brutsaert* [1999] who showed that soil plays the most dominant role in controlling the spatial variability of soil moisture. However, it cannot be said that soil texture would be the most dominant factor of the spatiotemporal distribution of soil moisture in Iowa since it did not partition the mean soil moisture effectively. In Oklahoma on the other hand, soil texture can be called the most dominant physical control of soil moisture. It should also be noted that retrieval algorithms utilize vegetation (land cover, single scattering albedo, and vegetation water content) and soil information (soil texture) when estimating soil moisture [*Bindlish et al*., 2006]. The effect of slope is not considered in the radiometer-based soil moisture retrievals. This result may be an artifact of the structure of the retrieval algorithm itself.

[53] From the above entropy-based analysis, we saw a change in the interaction between the physical controls before and after removing the effect of precipitation for the point support scale but not so much for the airborne scale. It can be deduced that the effect of variability of precipitation across the extent is more pronounced when the support scale is smaller.

5. Conclusions

[54] In this study we investigated the evolution of dominance of different physical controls on the spatial distribution of the soil moisture across time for the WC watershed, Iowa, and the LW watershed, Oklahoma. The two watersheds were located in different hydroclimates and had a distinctly different inherent heterogeneity. The WC watershed in Iowa is an agricultural watershed in a humid climate with heterogeneity in the form of vegetation and soil type. The LW watershed in Oklahoma is a more natural watershed in a subhumid environment with heterogeneity existing in the form of topography and soil type. The analysis was conducted at two levels. The Kruskal-Wallis-based analysis formed the primary step and assessed the applicability of the physical controls in causing a separation in the mean soil moisture due to the heterogeneity observed in the particular physical control. We found that in the WC watershed the broad classifications of the vegetation type and the soil type served to explain the differences in the soil moisture well. Soil texture performed slightly better in 2002, whereas vegetation performed better in 2005. However, at the airborne scale, neither soil nor vegetation served as good representatives of heterogeneity. In the LW watershed, on the other hand, soil and topography (slope) performed relatively well at both the point and airborne scales. Soil texture partitioned the mean soil moisture to a greater extent at both the scales.

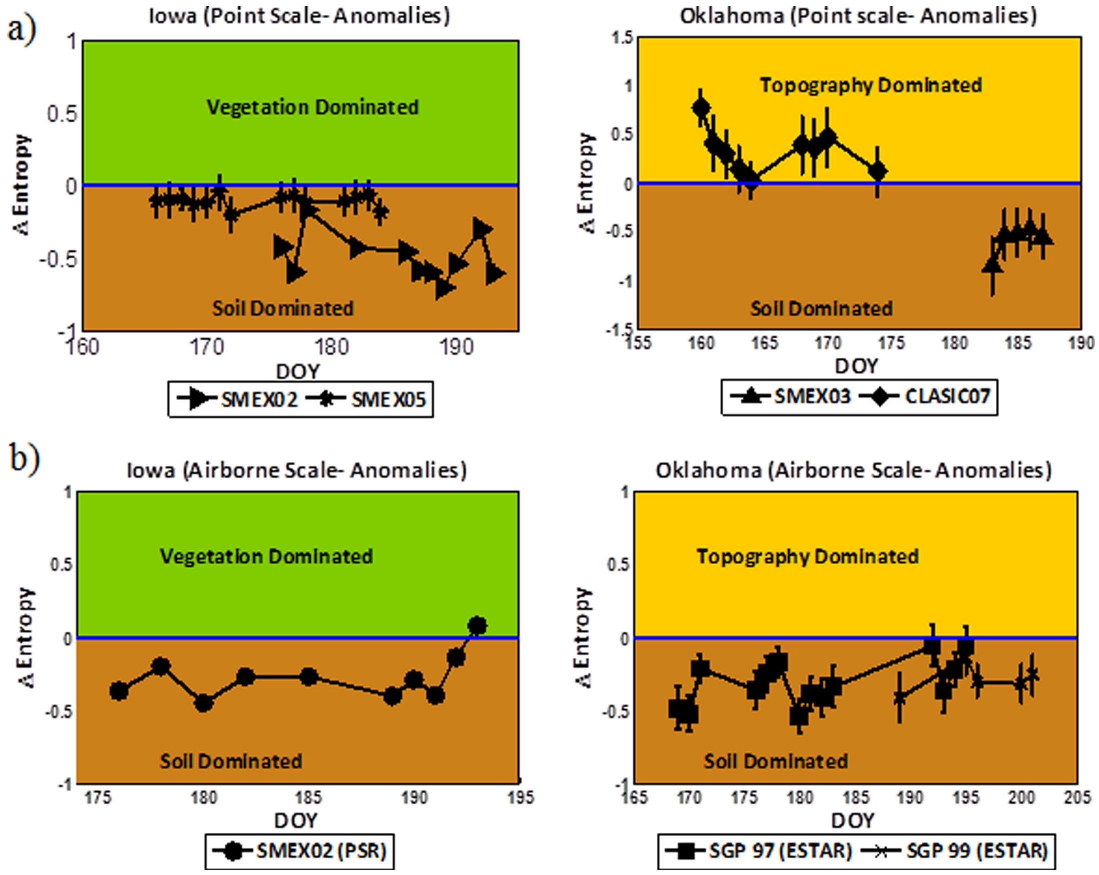

Figure 10. SMEX02 and SMEX05 (Iowa) and SGP97, SGP99, SMEX03, and CLASIC07 (Oklahoma). Time series of entropy difference (soil moisture anomalies): (a) point support scale and (b) airborne footprint scale.

[55] The second level of analysis comprised assessing the partitioning of the variability of soil moisture by the physical controls which was done by computing the entropy values. At the point scale, we found that in Iowa the soil texture partitioned the soil moisture variability across both the years. However, in the LW watershed, the 2 years showed different results. In the dry year, soil texture showed better partitioning of the soil moisture, whereas in the wet year the topography showed better partitioning. At the airborne scale, soil texture showed an effective partitioning of the soil moisture variability for both the watersheds. However, this may be an artifact of the structure of the soil moisture retrieval algorithm itself.

[56] We also found that given the same extent scale the variable precipitation is more liable of effecting the apparent interactions of the physical controls with the data observed at a smaller support scale. An important take home message from the study is that during a field campaign while collecting ground-based data, it is very important to collect representative samples from different vegetation and soil types in the agricultural watersheds since they jointly control the soil moisture spatial distribution. In the absence of the vegetation-based heterogeneity in the watershed the soil-texture-based heterogeneity seems to yield more control on the soil moisture spatial distribution as opposed to topography. However, since the nature of heterogeneity controls the spatial distribution of soil moisture, this result must be restricted to watersheds with similar heterogeneity.

[57] **Acknowledgments.** We acknowledge the partial support of the National Science Foundation (CMG/DMS grant C10-00021) and NASA THPs (grants NNX08AF55G and NNX09AK73G) and thank all the students, scientists, and volunteers who participated in the various soil moisture campaigns and collected valuable data. We would also like to thank Vijay P. Singh, Raghavendra Jana, Chao Li, and the reviewers of this manuscript for valuable discussions that enhanced the quality of this manuscript.

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