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Scaling characteristics of spatial patterns of soil moisture from distributed modelling

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Abstract

Characterizing the spatial dynamics of soil moisture fields is a key issue in hydrology, offering an avenue to improve our understanding of complex land surface–atmosphere interactions. In this paper, the statistical structure of soil moisture patterns is examined using modelled soil moisture obtained from the North American Land Data Assimilation System (NLDAS) at 0.125° resolution. The study focuses on the vertically averaged soil moisture in the top 10 cm and 100 cm layers. The two variables display a weak dependence for lower values of surface soil moisture, with the strength of the relationship increasing with the water content of the top layer. In both cases, the variance of the soil moisture follows a power law decay as a function of the averaging area. The superficial layer shows a lower degree of spatial organization and higher temporal variability, which is reflected in rapid changes in time of the slope of the scaling functions of the soil moisture variance. Conversely, the soil moisture in the top 100 cm has lower variability in time and larger spatial correlation. The scaling of these patterns was found to be controlled by the changes in the soil water content. Results have implications for the downscaling of soil moisture to prevent model bias.

Keywords: Soil moisture fields; Spatial patterns; Scaling; Hydrological modelling

1. Introduction

The land surface component of the hydrological cycle is fundamental to atmospheric and climate processes (e.g., [25,9,23]). Spatial and temporal variability of rainfall and available energy, combined with land surface heterogeneity, induce complex variations in soil moisture dynamics and processes related to surface hydrology (e.g., [32,1,26]). The characterization of soil water spatial organization is critical to improve our understanding of land surface–atmosphere interaction. A deeper knowledge is needed about the relationship between soil moisture at the surface, measurable by remote sensing images, and in the root zone which affects evapotranspiration fluxes, runoff and deep percolation. Recent advances in remote sensing technologies highlight the possibility of frequent and spatially comprehensive maps of soil moisture in the first few centimeters of the soil matrix (e.g., [11,18]).

Soil moisture retrievals need to be used in conjunction with other information to interpret soil moisture values over deeper soil depths. In recent literature, the relationship between soil moisture at different depths has been investigated using field measurements over three pasture sites in New Zealand [33] and also adopting a detailed simulation model by Puma et al. [24]. In the first case, the authors were unable to find a clear relationship between the soil moisture measurements over depths of 30 cm and 6 cm. Puma et al. [24] found the existence of a dynamic

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relationship between the two variables, which is detectable when the soil moisture measurements refer to temporal intervals of less than five days.

An element of particular interest is the spatial variability of soil moisture for downscaling/aggregation of small scale processes to larger scales in order to prevent systematic biases in modelled water and energy fluxes (e.g., [4,5]). A promising approach towards this task may lie in examining the scaling behavior of soil moisture fields. Several studies have attempted to characterize the spatial structure of soil moisture using remotely sensed imagery (e.g., [27,10,12]), point measurements (e.g., [16,31]) and grid maps obtained via hydrological simulations (e.g., [8,7,22]). In particular, Rodríguez-Iturbe et al. [27] recognized that the spatial variance of the soil moisture fields follows a power law decay as a function of area. Such spatial structure could be influenced by the scaling of soil properties or controlled by the soil moisture state (wet or dry) as evidenced by changes in the scaling slopes.

The soil moisture state has been shown to have a controlling influence on the spatial variance of soil moisture patterns obtained during field campaigns (e.g., Washita '92, SGP '97, '99, SMEX '02 and '04). Among others, Ryu and Famiglietti [28], using data from SGP '97, observed that soil moisture variability peaks in the mid-range of soil moisture values and decreases towards wet and dry conditions. This behavior is consistent with recent developments of Albertson and Montaldo [1] who demonstrated how the infiltration process (after localized ponding) reduces the spatial variance of soil moisture in a way similar to the transpiration process when vegetation is under stressed conditions.

In this paper, spatial characteristics of simulated soil moisture have been examined for a square region (Fig. 1) centered over the state of Oklahoma (USA), where soil moisture outputs have been validated against point measurements see [17]. The relationship between deep layer soil moisture (100 cm) and the 10 cm surface layer is examined to identify the possibility of characterizing soil profile behavior from limited knowledge on the moisture state. Moreover, the dependence of scaling characteristics of the soil moisture variance on the soil moisture state are investigated using one year of simulations.

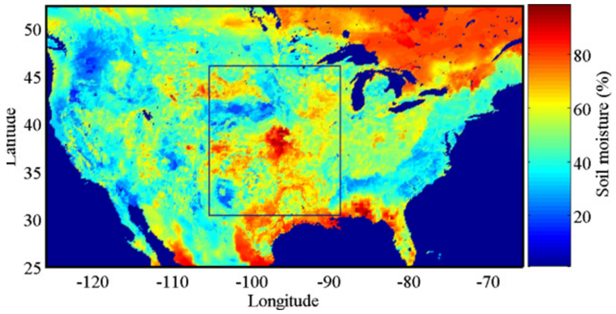

Fig. 1. Description of the NLDAS domain, showing the relative soil moisture in the 100 cm soil layer, at the first of October 1998. The square drawn in the middle describes the study area considered in the present paper, which is formed by 128 × 128 pixels.

2. Data and methodology

The North American Land Data Assimilation System (NLDAS) [20,29] provides estimates of soil moisture from four different models at sub-daily intervals across the United States. The NLDAS is a multi-institution partnership aimed at developing a real-time and retrospective data set, using available atmospheric and land surface meteorological observations to compute the land surface hydrological budget. Further information about the NLDAS project along with model outputs can be found at http://ldas.gsfc.nasa.gov/.

Although the NLDAS retrospective simulations extend back to 1996, the analysis presented here makes use of simulations from the variable infiltration capacity (VIC) model for the water year October 1998 to September 1999, reducing the influence of initial model conditions [3]. The VIC model [13–15,2,34] represents one of the four land surface models adopted within NLDAS to compute hourly surface energy flux and hydrological characteristics at 0.125° resolution (~14 km) across North America. It is a semi-distributed grid-based hydrological model in which subgrid variability in soil properties is represented by a spatially varying infiltration capacity. The current version of VIC uses a scheme based on three soil layers, with a top layer of 10 cm and the remaining two layers have depths that vary over different regions. Although the model resolution is coarse, it is worth nothing that it accounts for the subgrid heterogeneity by subdividing each cell in N classes according to vegetation type, variability in topography through the use of elevation bands, spatial variability in precipitation and in soil moisture storage capacity.

VIC outputs several hydrological variables of interest including: depth averaged soil moisture, surface runoff, evaporation, transpiration, etc. Here we focus on the relative soil moisture averaged at depths of 10 cm and 100 cm, as these soil layers represent different regimes in land surface and atmospheric processes and interactions.

3. Results and discussion

3.1. Characteristics of relative soil moisture in deep and shallow layers

Developing a relationship between the relative soil moisture at the surface to that in deeper layers of soil would be very useful for remote sensing applications. Unfortunately, their interaction is not always clear see [33]. Simulation results are used to compare the two variables for each pixel within the study region, with results shown in Fig. 2. The graph describes the deep layer relative soil moisture (S_{100}) statistics conditional on the relative soil moisture in the top 10 cm (S_{10}). Relative soil moisture is defined as the ratio between the volumetric soil moisture θ averaged over

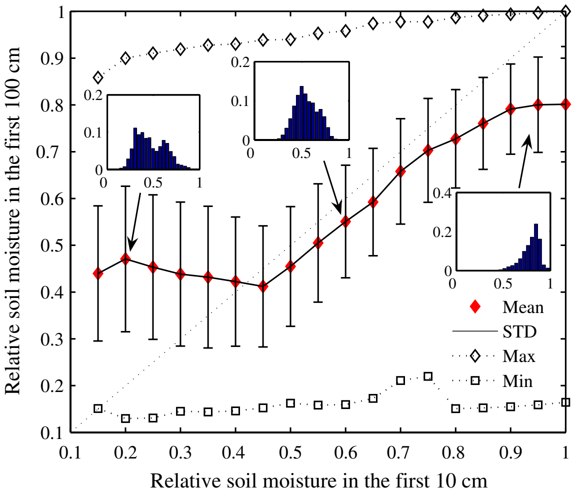

Fig. 2. Values of the mean relative soil moisture in the top 100 cm given the relative soil moisture in the first 10 cm. The error bar describes the standard deviation from the mean, while squares and diamonds define the minimum and the maximum values of S_{100}, respectively. The three insets describe the histograms of S_{100} conditional on the superficial soil moisture, S_{10}, at 0.20, 0.60 and 0.95.

a given depth and the soil porosity *n*. The soil moisture in the deeper layer has a consistently larger variability when the top layer of soil is dry ($S_{10} \leqslant 0.45$) showing values of standard deviation around 0.15 and a constant mean. Thereafter the standard deviation becomes smaller and approaches 0.10, while the expected value of S_{100} increases with the surface soil moisture. The mean of S_{100} becomes significantly lower than the values in the first layer when $S_{10} \geqslant 0.70$, due to soil dynamics producing more frequent saturation in the upper layer.

While the soil moisture at the near surface may be obtained from remote sensing images, this information does not provide values that can be directly extended to deeper layers of the soil column, since the soil moisture is not uniformly distributed with depth. The analysis of the simulated soil moisture illustrates that the probability distribution of deep layer soil moisture given the soil state in the first layer, changes dramatically for different values of S_{10} (see insets in Fig. 2). In particular, the distribution of S_{100} becomes concentrated around the mean with an increase of the soil moisture at the surface, while for the smaller values of S_{10} the histogram shows increased dispersion of the data. This implies that prediction of soil moisture in the deep layer given the superficial soil moisture, has an uncertainty that increases with a reduced near surface estimate. One way to reduce such uncertainty is to use data assimilation models that explicitly account for the infiltration process into the deeper layer using measured climatic forcing (e.g., [21,30,19,6]).

3.2. Scaling of the soil moisture

The spatial structure of soil moisture values have been explored by studying the scaling properties of mean daily soil moisture maps throughout a year. Here we seek to examine these scaling properties, and search for possible dependence of such properties on the underlying dynamics.

Some examples of the variance of the relative soil moisture as a function of the averaging area are shown in Fig. 3 for the two depths considered in this work. Relative soil moisture maps were successively aggregated from the original 0.125° resolution up to a final resolution of 1.0°, representing the typical resolution of a global circulation model (GCM). Across the range of scales examined here, the variance of the soil moisture (σ^2) follows a simple power-law relationship

$$\sigma_\lambda^2 = \left(\frac{\lambda}{\lambda_0}\right)^\beta \sigma_{\lambda_0}^2, \tag{1}$$

where λ represents the scale factor and β is the slope of the scaling function that ranges between -0.12 and -0.05 for S_{100} and between -0.32 and -0.12 for S_{10}. It is worth nothing that Rodríguez-Iturbe et al. [27], using a limited number of soil moisture maps collected with a passive microwave sensor during the Washita ’92 Experiment, found values of β (between -0.21 and -0.28) close to those obtained in the case of S_{10}.

As a general remark, a decrease of the slope, β, of the scaling function of the variance corresponds to an increase in the spatial correlation of the field. In the ideal case (perfect spatial correlation), the slope of the scaling function should approach zero; while in the case of no correlation it is expected that the variance of the field decays with a slope of minus one. Here, the slope of the scaling functions generally becomes more negative with decreasing mean soil moisture.

The six examples provided in Fig. 3 (three for each depth) outline several differences in the spatial organization of the soil moisture patterns. In general, S_{100} is character-

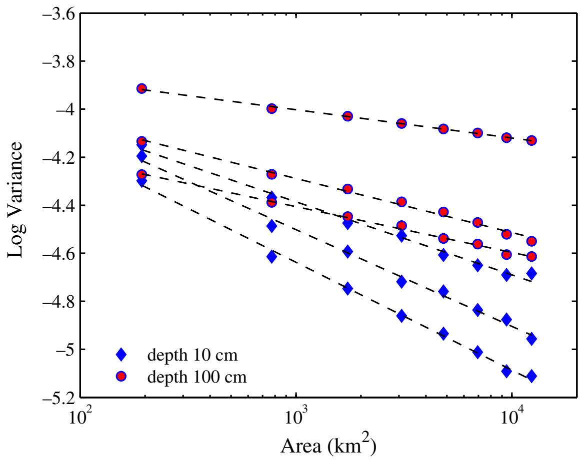

Fig. 3. Six examples of scaling functions describing the variance of the soil moisture at two different soil depths obtained by the VIC model as a function of the averaging area. Examples refer to the soil moisture maps of 31/01/99, 28/05/99 and 20/08/99.

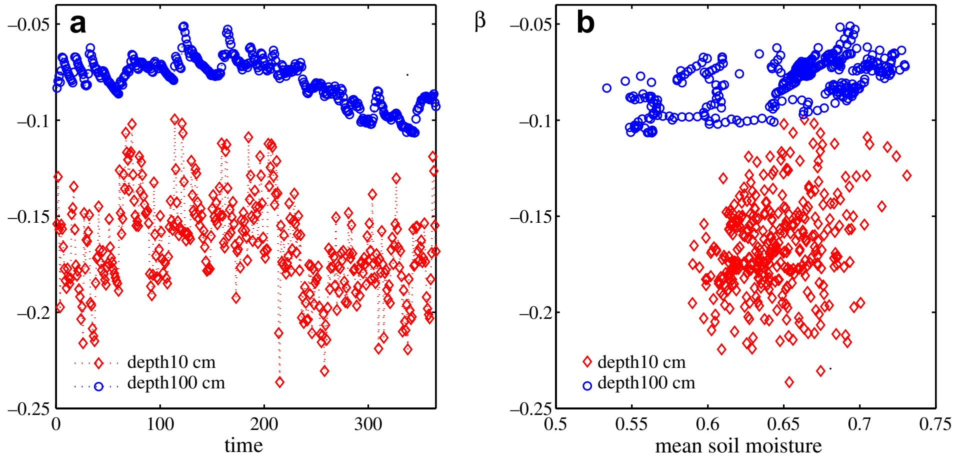

Fig. 4. Slope of the scaling functions of the variance of the soil moisture averaged over a depth of 100 cm (a) and 10 cm layer (b) as a function of the daily mean soil moisture state for one year of simulation.

ized by lower absolute values of the slope of the scaling function which change less significantly throughout time than those of S_{10} (see Fig. 4a). In all analysed cases, the data follows a power-law relationships over two logarithmic scales for both 10 and 100 cm depths with slopes in the range given above.

In order to further investigate the scaling behavior of the soil moisture, the slope of the scaling functions, β, is plotted against the mean soil moisture in Fig. 4b. The objective is to study whether changes in the slope of the scaling functions are controlled by soil moisture fluctuations, and moreover, if the magnitude of these changes are related to actual variations in the soil water content. It is observed that for a given mean daily soil moisture map, β values for S_{100} change in a much smaller range than for S_{10} and that there is considerable dispersion in the slope of the power laws particularly in the shallow surface layer (S_{10}). Moreover, the link between the slope of the scaling functions and the mean soil moisture illustrates a cyclic behavior due to a persistent pattern in the case of S_{100}. In the shallow surface layer, trends are detectable only over a relatively short time period due the higher variations in relative soil moisture induced by rainfall and soil losses.

Fig. 5a and b show the relative change in the slope of the scaling function against the changes in the mean daily soil moisture content of S_{100} and S_{10}, respectively. In general, one observes an increase in the slope of the scaling function (becoming more negative) during the drying process and a decrease of the slope during wetting. It is also seen that changes in the slope of the power law tend to be smaller during the drying than those observed during the wetting. The dynamics of soil moisture in the top layer can be observed in Fig. 5b, where there are rapid changes in β for S_{10} with fluctuations of the soil moisture content. The two regimes (drying and wetting) are in this case even more distinct and clearly defined.

The previous results illustrate that the changes in the spatial organization of daily soil moisture are controlled not only by the mean value of the process but also, very significantly, by the different dynamics of the wetting and drying cycles.

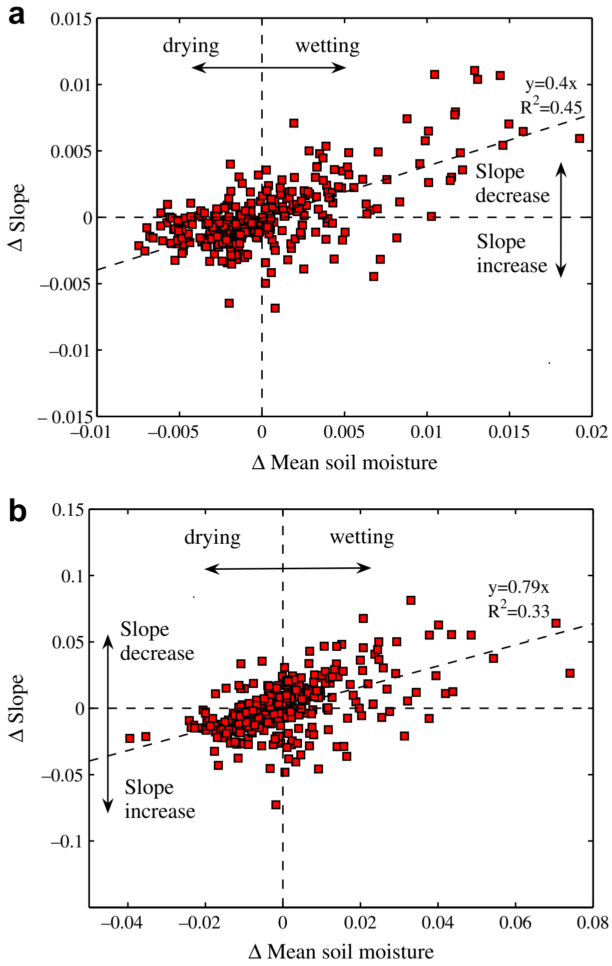

Fig. 5. Change of the slope of the scaling functions of the soil moisture variance as a function of the change in the mean soil moisture from day to day over a soil depth of 100 cm (a) and 10 cm (b). Variations have been computed as the difference between values at $t + 1$ minus values at time t. The two variable are related by a linear relationship with $R^2 \geqslant 0.33$.

4. Conclusions

The soil moisture products of the VIC model [13–15,2,34] have been used to investigate the scaling characteristics of daily soil moisture patterns.

The study also analysed the relationship between the two variables S_{10} and S_{100}, outlining high variability of S_{100} for lower values of S_{10}. In these cases, the prediction of S_{100} given S_{10} is very uncertain and likely requires additional information about vegetation, soil properties and climate to be considered.

Deep soils show a greater organization in their spatial patterns of water content, and displays a persistence which is maintained throughout the studied time period. On the other hand, the top layer of soil has higher temporal variability in its spatial scaling characteristics due to increased fluctuations resulting from infiltration (wetting) and evapotranspiration-leakage (drying) processes. The analyses reveal that the drying process tends to reduce the spatial correlation of the soil moisture. Conversely, the spatial correlation of soil moisture fields increases with positive changes in the soil moisture state. A possible explanation for the changes in the organization of the soil moisture can be found in the spatial fields of the physical controls on the process; namely vegetation, soil texture and rainfall. Rainfall in particular is certainly responsible for the increase of spatial correlation of soil moisture, while vegetation and soil texture heterogeneity are likely to introduce a higher degree of spatial variability at smaller scales in the soil moisture process throughout the drying process.

The comparison of the soil moisture over different depths highlighted major differences in the temporal dynamics of the process. With knowledge of the near surface soil moisture (i.e. using remote sensing) it would seem that characterizing the relative soil moisture in the deeper layer is very uncertain. Primarily, this is due to the strong differences existing both in the temporal and spatial dynamics of the processes controlling soil moisture at different depths. However, the presence of a large spatial correlation and time stability in the deeper soil represents an advantage in the use of point measurements, for instance. Some further work focusing on the correlation structure of fields influencing the soil moisture (topography, vegetation, soil properties and rainfall) is expected to increase our knowledge of the feedback mechanisms intrinsic in the scaling properties of soil moisture.

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