Profile Soil Moisture Across Spatial Scales Under Different Hydroclimatic Conditions

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Abstract: Soil moisture statistics across spatial scales have been considered critical to various Earth Science applications. Soil moisture measurements are available only at very fine scale (at *in situ* monitoring facilities) or at very coarse scale (by satellite retrieval) on a regular basis. These measurements have extremely contrasting features in terms of temporal and spatial scales. Although no immediate technological solution is available to bridge the gap in real measurements at the intermediate support scales that can be substantiated, an alternative scaled representation of soil moisture using a newly developed modeling approach is proposed here. In this article, we investigated the characteristic features of profile soil moisture (at 1-, 10-, and 50-cm depths) statistics at different spatial resolutions (i.e., ~8, ~25, and ~60 km) modeled from scaled geophysical parameters and atmospheric forcings. We used Aqua satellite–based Advanced Microwave Scanning Radiometer (AMSR-E)–estimated soil moisture and local scale soil parameters to derive upscaled soil parameters for soil moisture modeling at the desired spatial scale. The soil moisture statistics including probability density functions (PDF) for multiple spatial resolutions and depths across the soil profile are presented for three contrasting hydroclimatic regions across the United States. These results could provide region-specific conditions for land-atmosphere interaction models and root zone soil moisture assimilation for various hydrologic and environmental applications.

Key words: Soil moisture, scaling, hydroclimatic regions, MCMC, remote sensing, SVAT model.

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Better assessment of soil moisture at varying spatial scales can improve the modeling of land-atmosphere feedback mechanisms that strongly modulate variability in climate (Rodriguez-Iturbe et al., 1991) and hydrologic forecast models (Famiglietti and Wood, 1994). However, assessment of soil moisture at different spatial scales is a key challenge because of nonlinear dependence of soil moisture dynamics on geophysical parameters such as soil, vegetation, topography, and atmospheric forcings. At small scale (field or watershed), soil moisture variability is greatly influenced by soil, vegetation, and topography. Large-scale (regional) soil moisture fields are dominated by precipitation and radiative forcings. At even larger scale (i.e., subcontinental), climatic effects on soil moisture evolution caused by total precipitation depth and mean temperature are observed.

Soil moisture evolution is a typical spatiotemporal scaling problem (Beven 1995). Soil moisture scaling is also imperative and significant because the regular measurements are available at contrasting spatial scales, for example, *in situ* monitoring network (at point scale) and passive microwave remote sensing using polar orbiting satellite Aqua satellite of NASA (using AMSR-E instrument at ~60-km scale) and recently launched *Soil Moisture and Ocean Salinity* of European Space Agency. When transcending from small to large spatial scale or *visa versa*, the soil moisture characteristics at one scale are essential to define the soil moisture dynamics at another scale. The essence of scaling is to distill the key patterns from soil moisture observations at one scale and use these to make good predictions at another scale. Therefore, understanding the statistical distribution of soil moisture in varying space is important for a range of applications in hydrology, remote sensing, and land-atmosphere interactions. One approach to characterize statistical distribution of soil moisture is by developing probability density functions (PDF). Soil moisture PDF at different spatial scales can be used in representing nonlinear evolution and variability present within and beyond a specific scale. So far, most of the studies discussed soil moisture behavior at a particular scale. Prominent among them are the studies conducted at a field/watershed scale that have examined the PDF of soil moisture (e.g., Famiglietti et al., 1999; Mohanty et al., 2000b) using *in situ* measurements. Review of these studies reveals that the bounded nature of soil moisture (between wilting point and saturation) PDF could be explained adequately by normal distribution. For example, at a large scale, satellite-based passive microwave surface soil moisture measurement could provide relevant statistics. The behavioral features of satellite footprint-scale (~60 km) soil moisture PDF obtained by aggregating airborne Electronically Scanned Thinned Array Radiometer (ESTAR) approximately 800-m footprints in the Southern Great Plains region were examined by Ryu and Famiglietti (2005). They suggested that normal and β distributions are appropriate for soil moisture PDF during wet and dry fields, respectively. Moreover, satellite-based passive microwave remote sensing (e.g., AMSR-E) provides a spatially averaged soil moisture estimate over the 60-km region (Njoku et al., 2003), which masks the underlying within-footprint variability. Therefore, studies are required to investigate the relationship between soil moisture PDF of satellite footprints and at finer/subfootprint scales under different hydroclimatic conditions.

The objective of this research was to study the statistical characteristics and relationship of soil moisture PDF for the soil profile at various spatial scales from three contrasting hydroclimatic regions across the United States. To study the evolution of soil moisture within remote-sensing footprint with decreasing spatial scale, scale-dependent soil parameters are essential. A technique developed by (Das et al., 2008a) was used to derive scale dependent soil parameters from satellite-based soil moisture measurement and fine-scale soil parameters using a Bayesian approach. The soil moisture PDF at approximately 8-, 25-, and 60-km resolution for specific profile depths of 1, 10, and 50 cm are described for three different hydroclimatic regions of semiarid Arizona, semihumid Oklahoma, and humid Iowa.

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SCALING OF SOIL PARAMETERS

For upscaling of soil parameters, a Markov Chain Monte Carlo (MCMC) algorithm developed by Das et al. (2008a) is used. They hypothesized that the conditional probabilities represented by soil moisture evolution from a Soil Vegetation Atmosphere Transfer (SVAT) model using an ensemble of upscaled soil properties could help characterize soil moisture at AMSR-E footprint scale. The MCMC-based algorithm uses priors (PDF) from existing field-scale soil parameters (Sp) from the available Soil Survey Geographic (SSURGO) database at the Natural Resources Conservation Service (http://www.ncgc.nrcs.usda.gov/products/datasets/ssurgo), a scale parameter β having uniform distribution between 0 and 1, and likelihood from AMSR-E–based soil moisture time series data to generate a posterior of upscaled soil parameters with a scaling factor β_{60} at approximately 60-km resolution (Das et al., 2008a). The general relationship used in this study for upscaling of the soil parameters in MCMC algorithm (Eq. [1]) is represented as follows:

$$(Sp_{eff}) = (Sp)^{\beta_{60}} \quad (1)$$

where (Sp_{eff}) is the effective value of soil parameters from a probability distribution at approximately 60 km from MCMC realizations. The upscaling factor, β_{60}, relates the soil parameters at the field locations to the effective soil parameters at the ASMR-E footprint scale. For flat homogeneous bare soil, the value of β_{60} is 1 and the parameter values are independent of spatial scale. With increasing heterogeneity β_{60} is smaller than one. Das et al. (2008b) found that the upscaling factor β_{60} is smaller than one caused by heterogeneity introduced by soil types, topography, vegetation, and atmospheric forcings with increasing spatial scale. Essentially, all the nonlinearity encountered in the physical processes with increasing spatial scale is lumped in the scaling factor β_{60}. To obtain the scale factor (β_{int}) for intermediate spatial extent, we used an area ratio and coarsest scaling factor β_C, that is, β_{60}. The empirical equation that relates spatial extent to scaling factor at any intermediate scale to coarse scaling factor is expressed as follows:

$$\beta_{int} = (\beta_C)^{A_{int}/A_C} \quad (2)$$

where A_{int} and A_C are the support areas at intermediate and coarse resolution that correspond to β_{int} and β_C, respectively. The rationale of Eq. (2), following Das et al. (2008b), are that soil effective parameters for an intermediate spatial scale is located in the parameter space somewhere between the soil parameters at field (local) scale and soil effective parameters at coarse scale (i.e., ~60-km AMSR-E footprint in this study). A joint probability distribution $P_S(Sp, \beta|A)$ is introduced that is conditioned on the region of area A. The probability distribution $P_S(Sp, \beta|A) = Sp^{\beta}$, with Sp^{β} approaching Sp (field scale soil parameters) when $\beta = 1$, and Sp^{β} converging to Sp_{eff} at some value $0 < \beta \leq 1$. This enforces the condition that the intermediate-scale factor β_{int} must lie between $\beta = 1$ at field scale and $\beta_C \leq 1$ derived using MCMC algorithm at coarse (e.g., AMSR-E footprint) scale data. In other words, for specific region A_C, the inequality $1 \geq \beta_{int} \geq \beta_C$ inversely corresponds with increasing area ($A \sim 0 < A_{int} < A_C$). The formulation of Eq. (2) satisfies the inequality $1 \geq \beta_{int} \geq \beta_C$ that is, at field scale (A_{int}, ~0 km^2) the scaling factor β_{int} converges to 1, and at a coarse scale ($A_C \sim 60 \times 60$ km^2) β_{int} equals β_C. The area ratio in Eq. (2) leads to a nonlinear parametric adjustment of β_C to β_{int}. A caveat attached to such nonlinear parametric adjustment of scale factor is that the landscape characteristics (i.e., vegetation and topography) should not vary rapidly within A_C. This area-ratio based power law method was adopted as an alternative because remotely sensed soil moisture data at intermediate resolutions were not available to derive the effective soil parameters using the MCMC algorithm. Future satellite missions such as the Soil Moisture Active Passive mission of NASA will provide soil moisture measurements at much finer spatial resolution (~10 km) and will help establish a much thorough understanding related to gradation of scaling parameter β with respect to spatial scale. Based on the previous formulation of Eq. (2), Fig. 1 summarizes the characteristics of scale factor depending on the value of β_{60} with changing spatial extent, that is, area-ratio. For this study, we parametrically adjusted β_{60} to obtain β_{25} and β_8 for approximately 25- and 8-km spatial resolution, respectively. The SVAT model (described in next section) used the effective soil parameters (Fig. 1) at approximately 8-, 25-, and 60-km resolution for three different hydroclimatic regions to simulate the surface soil moisture for 2 years (2004–2005).

SVAT MODEL AND STUDY AREA AND DATA

The implementation detail of the SVAT system (Van Dam et al., 1997) is given in Das et al. (2008b). Figure 2 illustrates large regional areas in semiarid Arizona (sparse vegetation), subhumid Oklahoma (grassland/pastures), and humid Iowa (agricultural) that were selected for the study, with areas of 26,250 km^2, 28,125 km^2, and 28,125 km^2, respectively. Time series data of AMSR-E–based soil moisture products for these regions were used in the MCMC algorithm mentioned earlier. Global Precipitation Climatology Project (http://precip.gsfc.nasa.gov/)–calibrated rainfall product at approximately 25-km resolution and spatially aggregated to approximately 60-km resolution was used as precipitation forcing in SVAT modeling at approximately 25- and 60-km resolution, respectively. For SVAT modeling at approximately 8-km resolution, NEXRAD (WSR-88D) data of approximately 4-km resolution aggregated to approximately 8 km was used. Eight-day composite LAI (based on MODIS platform on TERRA satellite) with 1-km spatial resolution was used for the study and was spatially averaged to approximately 8-, 25-, and 60-km resolution to match the scale-specific SVAT modeling. The atmospheric forcing data, which are considered spatially homogeneous at large scale such as relative humidity, air temperature, and so on, are from the North America Regional Reanalysis. The soil parameters were obtained from the Soil Survey Geographic (SSURGO) database.

RESULTS AND DISCUSSION

The characteristics of the soil moisture PDF at specific profile depths across different spatial scales for three diverse

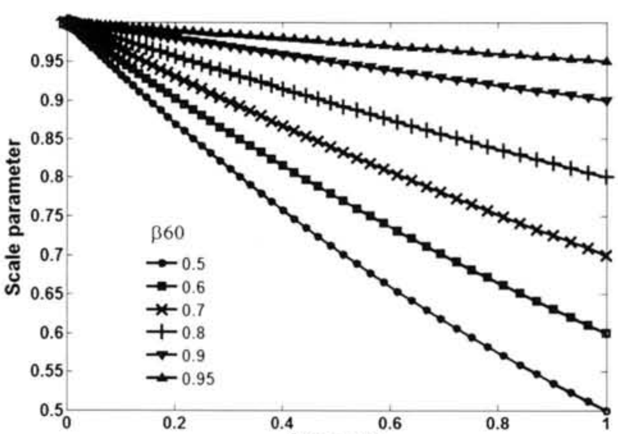

FIG. 1. The characteristics of scale factor based on value of β_{60} with changing spatial extent, that is, area ratio (A_x/A_{60}).

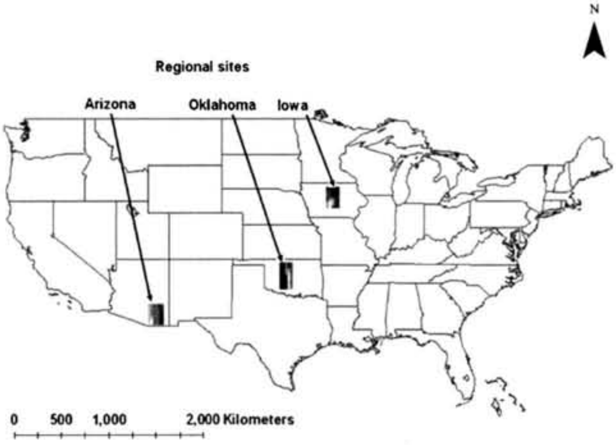

FIG. 2. Regional sites used for the study.

hydroclimatic regions were studied for two consecutive years (2004–2005). The characterization of soil moisture at specific spatial scale with mean, S.D., minimum, maximum, 5 percentile, and 95 percentile is summarized in Table 1. The results are also described with PDF (Fig. 3), having a Gaussian kernel density with a bandwidth of 0.005, which retains the most obvious modes. Region-specific notable behaviors and characteristics of the soil moisture PDF for the three hydroclimatic regions are discussed later.

Arizona Region

For this semiarid region, Table 1 reveals various spatial scaling effects of surface and root zone soil moisture. At all depths (1, 5, 10, and 50 cm), there was a decrease in mean and S.D. of soil moisture with increasing spatial scale. This verifies the phenomenon of spatial smoothing associated with soil moisture and is essentially associated with homogenization of geophysical parameters (soil physical properties, vegetation, topography, and rainfall) with increasing spatial scale. The minimum and maximum values of soil moisture evolution at 1-, 5-, and 10-cm depths for all the specified scales (~8, ~25, and ~60 km) were found very similar. However, the maximum soil moisture values at the 50-cm depth were much smaller than (<50%) the maximum values at the shallower depths. At the depths between 5 cm and 100 cm, plant roots play a major role in describing the status of soil moisture. In SWAP model simulations, the maximum rooting depth was prescribed to be 100 cm. Plant root water uptake is largely controlled by soil water energy status and spatial (horizontal-vertical) variability of soil moisture. Root-soil interaction tends to equalize soil water content in the root zone. The tendency of homogenization of soil moisture at these depths resulted in lesser range (maximum–minimum) and could be attributed to root water uptake dynamics of various vegetation types present in the region. The phenomenon of homogenizing soil moisture in the root zone also reduces soil water flux variability. Figure 3 illustrates the PDF of soil moisture at a spatial scale of approximately 8, 25, and 60 km for the depths of 1, 10, and 50 cm, respectively. For this region, the PDF at 1-cm depth have very low variabilities and are positively skewed for approximately 8-, 25-, and 60-km resolution, although the kurtosis of the PDF decreased with increasing resolution. The right-skewed PDF at the 1-cm depth were also representative of sandy texture soil with rock fraction having large infiltration capacity (high conductivity). In such semiarid conditions, the potential fluxes at soil-atmosphere interface are also high, and most of the time the actual fluxes are much smaller than potential fluxes (Das et al., 2008a). Another feature of PDF from the semiarid Arizona region is the high coefficient of variation of soil moisture in comparison with the case of Iowa and that of Oklahoma. This is a typical soil moisture behavior caused by a low mean value in a semiarid climate (low precipitation) with sandy soil texture (high infiltration potential). The right-skewed PDF (Fig. 3) of approximately 25- and 8-km resolution show signs of multimodality at all the depths, which could be attributed to within-pixel (~60 km) or subgrid variability in precipitation and soil types. The Arizona region receives convective thunderstorms during the summer months, which are

TABLE 1. Soil Moisture Statistics for Different Hydroclimatic Regions at Specific Resolutions

	Arizona						Iowa						Oklahoma					
	Mean	S.D.	Min	Max	5%	95%	Mean	S.D.	Min	Max	5%	95%	Mean	S.D.	Min	Max	5%	95%
1-cm depth																		
60 km	0.0392	0.011	0.024	0.347	0.029	0.051	0.1362	0.0262	0.019	0.411	0.083	0.167	0.1408	0.0249	0.033	0.396	0.089	0.169
25 km	0.0574	0.0206	0.026	0.4	0.035	0.087	0.1696	0.0395	0.02	0.4	0.104	0.238	0.1757	0.0391	0.029	0.416	0.112	0.25
8 km	0.0728	0.0421	0.028	0.432	0.04	0.172	0.1931	0.0473	0.025	0.474	0.134	0.294	0.1836	0.0455	0.025	0.458	0.119	0.274
5-cm depth																		
60 km	0.0489	0.0125	0.026	0.337	0.035	0.068	0.1402	0.0207	0.02	0.41	0.102	0.167	0.1446	0.0199	0.039	0.396	0.106	0.169
25 km	0.0727	0.0217	0.03	0.385	0.047	0.111	0.1734	0.0354	0.02	0.398	0.12	0.239	0.1792	0.0357	0.044	0.42	0.126	0.251
8 km	0.0961	0.0381	0.037	0.431	0.054	0.175	0.1952	0.0457	0.033	0.472	0.14	0.295	0.1865	0.0431	0.032	0.457	0.129	0.275
10-cm depth																		
60 km	0.052	0.0142	0.026	0.308	0.036	0.075	0.1427	0.0181	0.026	0.403	0.111	0.167	0.1474	0.0171	0.041	0.396	0.116	0.17
25 km	0.078	0.0231	0.03	0.385	0.049	0.122	0.1762	0.0335	0.021	0.396	0.127	0.239	0.1822	0.0338	0.049	0.415	0.135	0.252
8 km	0.1041	0.0371	0.037	0.43	0.058	0.176	0.1969	0.0445	0.036	0.47	0.145	0.296	0.1891	0.0413	0.05	0.454	0.137	0.276
50-cm depth																		
60 km	0.0569	0.0131	0.032	0.107	0.04	0.085	0.1549	0.0301	0.065	0.243	0.129	0.205	0.1607	0.019	0.075	0.235	0.144	0.215
25 km	0.0785	0.0251	0.038	0.164	0.044	0.129	0.1913	0.0306	0.132	0.306	0.157	0.2535	0.1985	0.0308	0.145	0.306	0.163	0.269
8 km	0.0823	0.032	0.038	0.206	0.048	0.157	0.202	0.041	0.14	0.362	0.161	0.2995	0.2018	0.0363	0.147	0.353	0.165	0.2885

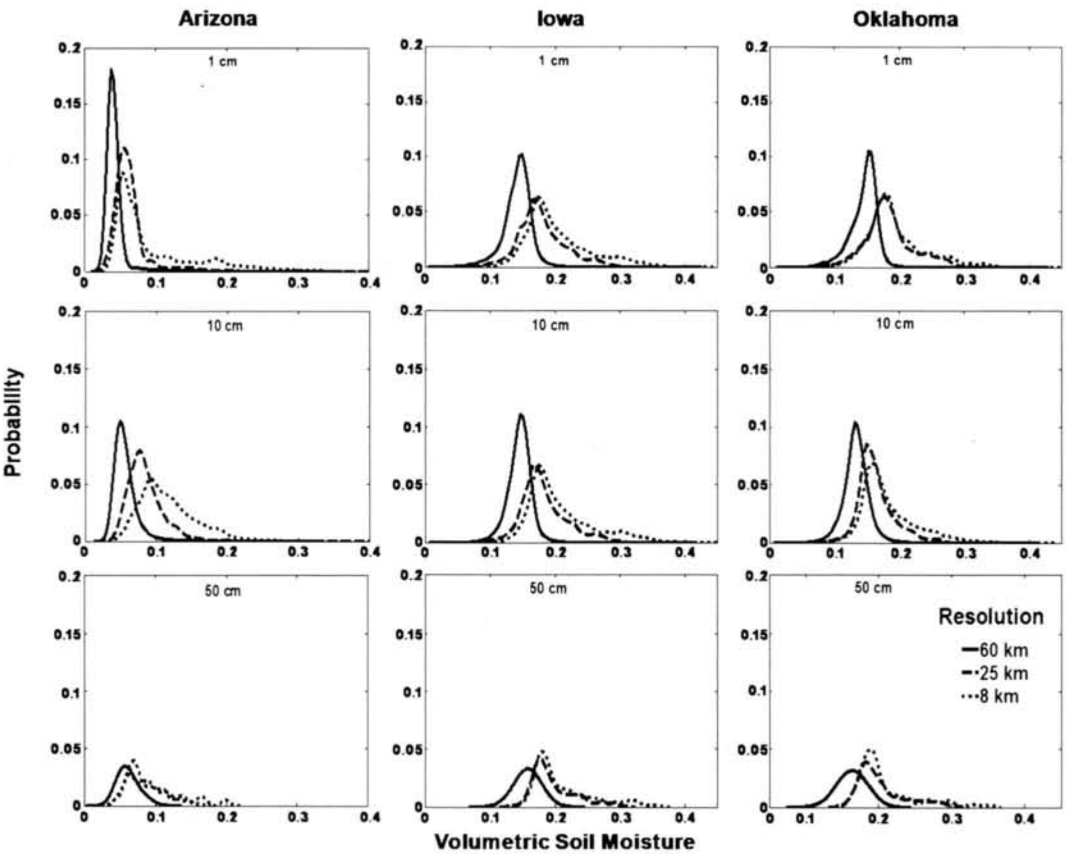

FIG. 3. Soil moisture PDF for the Arizona region, the Iowa region, and the Oklahoma region.

mostly fractional (localized) in nature. In addition, the deep groundwater table present in this region induces a large downward vertical flux resulting in low soil moisture content within the soil profile.

Iowa Region

In contrast to the Arizona region, Iowa region has much higher mean and S.D. values of soil moisture (Table 1) across the soil profile at all spatial resolutions (~8, ~25, and ~60 km). The coefficient of variation is smaller because of a high mean soil moisture; however, the variability (S.D.) is also higher as compared with the Arizona region. The influence of soil texture and vegetation on soil moisture is quite apparent for this region. The dominant clayey loam texture soil found in the Iowa region retains high soil moisture. The humid climate of the region with an average rainfall of nearly 850 mm also contributes to high soil moisture content. Nearly 95% of the regional study area is under row crop agriculture. Corn and soybean are grown on approximately 90% of the row crop acreage (with 60% corn and 40% soybean) with a peak crop biomass of approximately 8 kg/m^2. The high organic content on the soil surface also contributes to high retention of soil moisture. Homogenization of soil moisture at greater depths of root zone (e.g., 50 cm) is observed because of transpiration. The shallow groundwater table of this region also retards the vertical downward soil water movement, consequently increasing the soil moisture content in the soil profile. It is also noteworthy that the PDF in Fig. 3 illustrate almost similar mean and variability in soil moisture at the resolution of approximately 8 and 25 km. Examination of geophysical parameters (soil properties, vegetation, and rainfall) that control soil moisture evolution displays very small differences between approximately 8- and 25-km resolutions. However, a large extent (3,600 km^2) at approximately 60-km resolution shows a clear effect of spatial smoothing on soil moisture evolution across the soil profile. During the winter months, this region experiences freezing of soil and subzero temperature with low solar radiations, resulting in small evaporative fluxes across the land-atmosphere boundary and ultimately high soil moisture content in the soil profile.

Oklahoma Region

The Oklahoma region soil moisture statistics (Table 1) shows a similarity with the Iowa region. This similarity could be attributed to high vegetation content, shallow groundwater table, and similar soil properties at a large spatial scale. Land use and land cover of the Oklahoma region is dominated by rangeland and pasture (63%) with significant area of winter wheat and corn that influences the soil moisture evolution. The loamy texture soil of this region with high vegetation throughout the year with an average rainfall of nearly 800 mm per year retains high mean soil moisture in the soil profile. The region also exhibits spatial smoothing similar to the Iowa region. At approximately 8-km and 25-km spatial resolution soil moisture shows similar PDF (Fig. 3), emphasizing spatial consistency and similarity in vegetation and precipitation in these scales. The region for all the specified spatial scales also displays a lower range (minimum–maximum) and S.D. of soil moisture at deeper depth (e.g., 50 cm) because of root transpiration.

CONCLUSIONS

Although no immediate technological solution is available to bridge the gap in real soil moisture measurements between *in situ* and remote sensing footprint support scales that can be substantiated, an alternative scaled representation of soil moisture using a newly developed modeling approach is proposed. The study presents soil moisture statistics and PDF for soil profile at three specific resolutions (~8, ~25, and ~60 km) from three different hydroclimatic regions (semiarid Arizona, humid Iowa, and semihumid Oklahoma) in the United States. The geophysical parameters including soil properties, vegetation, and precipitation were scaled appropriately to make them suitable for SVAT modeling of soil moisture at specific resolutions. The characteristics of the soil moisture PDF exhibited an influence of various dominant geophysical parameters and boundary conditions for different hydroclimatic conditions. The PDF also highlight the soil moisture evolution across spatial scale caused by smoothing effects of different geophysical parameters. The study shows the level of soil moisture variability bounds for the AMSR-E satellite footprint and its subgrid variabilities at various spatial resolutions as well as provides useful estimates for soil moisture data assimilation in various Earth Science applications.

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