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Spatial variability and its scale dependency of observed and modeled soil moisture under different climate conditions

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Abstract

Past studies on soil moisture spatial variability have been mainly conducted in catchment scales where soil moisture is often sampled over a short time period. Because of limited climate and weather conditions, the observed soil moisture often exhibited smaller dynamic ranges which prevented the complete revelation of soil moisture spatial variability as a function of mean soil moisture. In this study, spatial statistics (mean, spatial variability and skewness) of in situ soil moisture measurements (from a continuously monitored network across the US), modeled and satellite retrieved soil moisture obtained in a warm season (198 days) were examined at large extent scales (> 100 km) over three different climate regions. The investigation on in situ measurements revealed that their spatial moments strongly depend on climates, with distinct mean, spatial variability and skewness observed in each climate zone. In addition, an upward convex shape, which was revealed in several smaller scale studies, was observed for the relationship between spatial variability of in situ soil moisture and its spatial mean across dry, intermediate, and wet climates. These climate specific features were vaguely or partially observable in modeled and satellite retrieved soil moisture estimates, which is attributed to the fact that these two data sets do not have climate specific and seasonal sensitive mean soil moisture values, in addition to lack of dynamic ranges. From the point measurements to satellite retrievals, soil moisture spatial variability decreased in each climate region. The three data sources all followed the power law in the scale dependency of spatial variability, with coarser resolution data showing stronger scale dependency than finer ones. The main findings from this study are: (1) the statistical distribution of soil moisture depends on spatial mean soil moisture values and thus need to be derived locally within any given area; (2) the boundedness of soil moisture plays a pivoting role in the dependency of soil moisture spatial variability/skewness on its mean (and thus climate conditions); (3) the scale dependency of soil moisture spatial variability changes with climate conditions.

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1 Introduction

Spatial variability of soil moisture plays an important role in the estimation of land surface fluxes (evapo-transpiration – ET – and runoff), due to the non-linear relationship between soil moisture and the associated physical processes. The need for characterizing soil moisture spatial variability has grown stronger as more satellite derived soil moisture products have become available. In validating these satellite retrievals, knowledge of soil moisture spatial variability is needed in order to determine the number of soil samples that can represent the mean in each footprint (Brocca et al., 2012; Famiglietti et al., 2008; Wang et al., 2008). In addition, one of the key issues in utilizing satellite estimates is how to handle the apparent scale difference between the large footprint size represented by the satellite retrievals and the finer scale on which an application (for instance, a numerical model) is integrated, as soil moisture variability is known to be scale dependent.

One important feature of soil moisture spatial variability is its relationship with mean soil moisture. Various conclusions have been reached about their dependency (see reviews by Choi et al., 2007; Ryu and Famiglietti, 2005; Famiglietti et al., 1999, 2008): some studies have indicated that spatial variability increased as mean soil moisture became wetter while others have indicated just the opposite. Several hypotheses have been explored as to how the two opposite correlations could co-exist (Crow and Wood, 1999; Rodriguez-Iturbe et al., 1995). Famiglietti et al. (2008) and Brocca et al. (2012) showed an upward convex (or concave) relationship which consists of both negative and positive correlations between spatial variability and mean soil moisture. Although it has been indicated that this concave relationship is related to the boundedness of soil moisture which gives the mid-range soil moisture the maximum variability (e.g., Penna et al., 2009), convincing evidences are needed to prove this theory. A noticeable shortcoming of past studies is that they are based on data collected in a short time period and/or in specific climate regions (most with intermediate precipitation), which limited the dynamic range of soil moisture and prevented the full revelation of this relationship.

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The theoretical foundation for scaling spatial variability is the power law which states that the spatial variability at one scale is related to that at another scale by the power of a scaling factor (Crow and Wood, 2002; Hu et al., 1998). Studies using spatial aggregations have shown that the relationship between soil moisture variability and its spatial resolution generally follows the power law (Crow and Wood, 2002; Hu et al., 1998; Parada and Liang, 2003). Famiglietti et al. (2008) and Brocca et al. (2012) examined another aspect of the power law using field measurements, that is, the relationship between spatial variability and the extent scale (the maximum spatial range of measurements) and showed that the variability of soil moisture increased as the extent scale (< 50 km) increased. It is unknown if such scale-dependency still holds for even larger extents and, more importantly, if it can be linked to small scale variability using a single scaling factor.

In addition to in situ measurements, models provide spatially and temporally continuous soil moisture estimates with global coverage. Despite their wide applications in modeling land/air processes and for drought monitoring, it is not well understood to what degree model estimates can capture the spatial variability of true soil moisture fields. Although model estimates are expected to have reduced spatial variability due to large scale representations of static parameters and meteorological forcing fields, it is unknown how the uncertainty in input fields and model physics affects the spatial variability of modeled soil moisture. The same can be said about satellite derived soil moisture estimates which are influenced by a number of error sources such as vegetation water content (Jackson, 1993), in addition to their coarser spatial representations. Studying the spatial variability of these two data sources, which represent spatially averaged soil moisture values (in contrast to the point measurements of in situ data), along with in situ data not only provides additional insights into the nature of the soil moisture spatial variability and its scale dependency, but also helps identify the factors that influence the accurate representation of spatial variability in model and satellite derived soil moisture.

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The objective of this study is to examine the spatial variability of in situ, modeled and remotely sensed soil moisture in large extent scales (> 100 km) under different climate conditions and their scale dependency. The three types of data are: in situ soil moisture measurements from the Soil Climate Analysis Network (SCAN), North American Land Data Assimilation System (NLDAS) Noah model estimates, and Advanced Microwave Scanning Radiometer-EOS (AMSR-E) soil moisture retrievals. The SCAN network which has stations across the US provides diverse climate conditions to study the impact of climate on the spatial variability of soil moisture in a more complete soil moisture range than examined in previous studies. Model estimates and satellite retrievals provide the spatial continuity which is lacking from scattered SCAN measurements and an opportunity to study the impact of spatial resolutions on soil moisture statistical moments and its scale-dependency. The scale referred to in the rest of the paper is the extent scale, i.e., the maximum spatial dimension covering all sampling points, which is one aspect of the scale triplet (resolution, support and extent) as defined by Western and Blösch (1999) and the spatial resolution is the grid size or footprint at which modeled or satellite derived soil moisture are obtained.

2 Data and study design

Figure 1 shows the location of the SCAN sites within the continental US. To study the relationship between soil moisture variability and climate, the continental US was split into three regions along the −104° and −96° longitude lines: West, Mid-continent (MidCon) and East, which roughly represent dry (noting that no SCAN sites exist on the west coast), intermediate and wet conditions, respectively. In West and East, two sub-regions were further chosen to create a smaller scale for statistical analysis. The sub-region in West essentially encompasses the state of Utah (thereafter is referred to as Utah) and the sub-region in East is located in the Mississippi/Tennessee/Alabama area (thereafter refers to as Miss-Tenn). No sub-region was selected for MidCon due to lack of densely located SCAN stations in the region. The number of SCAN locations

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in each region is given in Table 1. The extent scale (maximum vertical or horizontal dimension) is about 500 to 700 km for the sub-regions and about 2000 to 3000 km for the three large climate regions. Figure 1 also shows three series of concentric squares, with side lengths ranging from 110 to 1500 km which were used to study the scale dependency of modeled and remotely sensed soil moisture in Sect. 4.3.

Most SCAN stations began measuring soil moisture in the early 1990s while new stations such as those in Utah have observations since 2007. To include as many stations as possible, 2008 was chosen as the study year, which was further limited to 1 May to 15 November (198 days) to eliminate the impact of freezing/thawing conditions on the analysis. SCAN soil moisture is recorded hourly at the 5, 10, 20, 50 and 100 cm depths using a dielectric constant measurement device which was calibrated using soil texture information retrieved at each station (Schaefer et al., 2007). As SCAN stations generally are located in agricultural areas, typical soil types are silt loam and fine sandy loam.

Modeled soil moisture fields were generated by the Noah land surface model embedded in NLDAS (Mitchell et al., 2004). Noah has been developed and maintained by NOAA's Environment Modeling Center for use in their coupled weather forecasting system. The soil moisture simulation of Noah is based on a vertical discretization of the Richards' equation into four soil layers with thicknesses of 10, 30, 60, and 100 cm. Noah was never calibrated against SCAN soil moisture and thus its estimates are independent of the in situ measurements. NLDAS precipitation is based on daily measurements from over 10 000 gauges located in the US which are then temporally disaggregated into hourly data using hourly Doppler radar images (Cosgrove et al., 2003). As given in Table 2, NLDAS precipitation (for the study period) generally agrees with SCAN, especially in terms of capturing climate differences in each region. For NLDAS, total precipitation averaged over all grid points in each region is also provided in Table 2, which shows some differences from that averaged at SCAN sites due to the scattered nature of the SCAN network. The 1-km STATSGO soil texture used by NLDAS/Noah was also found (not shown) in good agreements with field

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soil descriptions at SCAN sites. Hourly Noah soil moisture estimates, which are integrated on a 0.125-degree grid were extracted from archived NLDAS/Noah outputs (http://www.emc.ncep.noaa.gov/mmb/nldas/).

Advanced Microwave Scanning Radiometer for EOS (AMSR-E) soil moisture retrievals produced by the NOAA's National Environmental Satellite, Data and Information Service (Zhan et al., 2008) were used in this study. This AMSR-E product, derived from the X-band frequency brightness temperature using the Single Channel Retrieval algorithm (Jackson, 1993), has larger dynamic ranges than the official AMSR-E product (Njoku et al., 2003) with more realistic mean values in the wetter climate areas than the official product (not shown). The sensing depth of the AMSR instrument is believed to be about 1–2 cm from the surface (Njoku et al., 2003). AMSR-E retrievals, with a 25 by 25 km spatial resolution and 1 ∼ 2 retrievals per day, represent spatially and temporally the coarsest data set among the three data sources.

3 Statistical moments

To compare the three data sets, the first three statistical moments were calculated for daily soil moisture values in each climate region and sub-region. All statistics were calculated using NCL (http://www.ncl.ucar.edu/overview.shtml) build-in functions and their mathematical formulations are provided here. For N soil moisture values on day t in any given region, their spatial mean, M, is given by:

$$M_t = \frac{1}{N} \sum_{i=1}^{N} \theta_{i.t} \tag{1}$$

where $\theta_{i,t}$ is the soil moisture at location i on day t.

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Following the same notation, the spatial variability of soil moisture is measured by the sample standard deviation:

$$\sigma_t = \left(\frac{1}{N-1} \sum_{i=1}^{N} (\theta_{i,t} - M_t)^2 \right)^{1/2} \quad (2)$$

and the skewness, which measures the asymmetry of the data distribution, is defined as:

$$S_t = \frac{\left(\sum_{i=1}^{N} (\theta_{i,t} - M_t)^3 \right) / N}{\left(\left[\sum_{i=1}^{N} (\theta_{i,t} - M_t)^2 \right] / N \right)^{3/2}} \quad (3)$$

For two soil moisture time series at any given location (i), their temporal correlation is given by the Pearson correlation coefficient:

$$r_i^{12} = \frac{1}{N_t \sigma_i^1 \sigma_i^2} \sum_{t=1}^{N_t} (\theta_{i,t}^1 - Y_i^1)(\theta_{i,t}^2 - Y_i^2) \quad (4)$$

where superscripts 1 and 2 represent the two time series; N_t is the number of data points in each time series which is 198 days for this study; Y_i and σ_i are the temporal mean and standard deviation at location i for each time series, respectively.

4 Results

4.1 Mean, spatial variability and skewness

Daily soil moisture values were first calculated at each SCAN station (or grid/pixel containing the SCAN site for Noah and AMSR-E retrievals) and then pooled together

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to calculate the daily spatial statistics- mean, variability and skewness – in each region (climate and sub-region). Because AMSR-E retrievals are surface observations only, the statistical analysis was limited to the top layer of SCAN measurements and Noah estimates. All soil moisture values used for statistical calculations and presented in the following graphs are in volumetric percentages (%).

Figure 2 is the box plot of the daily mean soil moisture for the three data types in each region. The lower, center and upper limits of each box represent the 25th, 50th and 75th percentiles of spatial means while the two whiskers represent the minimum and maximum value in each data set. All three data types show the sensitivity to climate conditions with median soil moisture increasing from west to east. Observed soil moisture (SCAN and AMSR-E) are more sensitive to changes in climate conditions than Noah whose median soil moisture increased less than the others as the climate becomes wetter.

Noah and AMSR-E estimates have smaller dynamic ranges in all regions, as the boxes are generally smaller than those of SCAN. In West and Utah, Noah estimates show positive bias with the median value near 0.2. AMSR-E retrievals, on the other hand, generally exhibit a drier bias against SCAN soil moisture in each region. Temporally averaged (over the 198 days) daily mean values given in Table 1 further confirm these biases. Uncertainty in forcing and parameter fields and deficiencies in model physics can lead to biased model estimates while factors such as no retrievals during rainfall and the shallow sensing depth of satellites may be responsible for the underestimation of AMSR-E data. Exploring the exact cause for such deviations is beyond the scope of this study; instead, the rest of the study focuses on how mean soil moisture as given by each data source influences the higher moments.

Figure 3 shows the standard deviation of daily soil moisture as a function of spatial means. For SCAN soil moisture, an upward convex was observed between the variability and mean soil moisture across different climate conditions. In West and Utah, soil moisture variability increases as soils become wetter while the opposite is observed in East and Miss-Tenn. The spatial variability peaks in MidCon where no obvious trend

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is observed. This upward convex was observed in some previous studies in smaller scales (e.g., Famiglietti et al., 2008; Brocca et al., 2007, 2012) but has not been observed at the continental scale. This revelation not only confirms the existence of such relationship between spatial variability and mean soil moisture, but also helps explain why and when this upward convex can occur. Comparing SCAN statistics in Figs. 2 and 3 reveals that the upward convex is directly linked to the overall soil wetness: when mean soil moisture is below about 0.2 (as in West and Utah), soil moisture variability increases with soil wetness; when mean soil moisture is above 0.2 (in East and Miss-Tenn), the variability decreases with increased wetness. In MidCon where mean soil moisture values are centered at 0.2, no trend is observed, and overall variability is the highest. Note that the trend in East is not as significant as in West which is due to its mean soil moisture not wet enough to expand the trend. When deeper SCAN soil moisture measurements (which are wetter than the surface soil moisture) were analyzed (not shown), the decreasing trend in east regions became much noticeable.

As indicated by Penna et al. (2009), the real reason for this upper convex is mathematical: spatial variability of soil moisture which is bounded by zero and saturation (about 0.45) is suppressed at its two bounds and thus, reaches the maximum in the middle range (near 0.2). Splitting the continent into wet, intermediate, and dry climatic regions created a full range of mean soil moisture values, which led to the revelation of this upper convex. Different conclusions were reached about this relationship in past studies because most of them did not contain a full range of soil moisture values.

Noah soil moisture only exhibits one half of the upper convex, with spatial variability in East and Mis-Tenn failing to form a decreasing trend due to the smaller dynamic ranges of soil moisture in these areas (see Fig. 2). AMSR-E soil moisture, on the other hand, shows significantly different patterns of spatial variability: spatial variability increases with mean soil moisture in all regions. This behavior is directly linked to the fact that the median value of AMSR-E retrievals is near or below 0.2 in regions (Fig. 2); as a result, spatial variability of soil moisture bears the signature of a dry climate. This result reaffirms the pivoting role of mean soil moisture in spatial variability and in the formation

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of the upper convex. Figure 3 also shows spatial variability generally decreases as the spatial resolution decreases from SCAN to AMSR-E, which is further confirmed by the temporally averaged standard deviations in Table 1.

To illustrate the temporal variation of spatial variability, Fig. 4 shows the time series of spatial mean soil moisture, soil moisture spatial variability (StD) and mean precipitation in the three climate regions. SCAN soil moisture shows strong seasonality with larger dynamic ranges. Noah soil moisture exhibits similar seasonality but with smaller dynamic ranges and noticeable wetter conditions in the summer. Both of them also show strong correlation with daily precipitation. The similar seasonality is not present in AMSR-E soil moisture which even shows the reversed seasonality in East. The insensitivity of X-band brightness temperatures to seasonal changes (Jackson, 1993) may be responsible for such larger deviations.

Temporal correlations and root mean square errors (RMSE) of the Noah and AMSR-E estimates with respect to SCAN soil moisture at each SCAN site were also calculated and their region-averaged values are given in Table 3. Noah shows better correlation and lower RMSE than AMSR-E in all regions, except in West where AMSR-E has lower RMSE. As can be seen from Fig. 4, the low correlation of AMSR-E with SCAN measurements mainly stem from its lack or inaccurate seasonality.

Figure 4 shows that the temporal variation of spatial variability for SCAN and Noah soil moisture obeys the climate dependency rules observed in the above analysis: spatial variability is positively correlated (i.e., one increases/decreases as the other increases/decreases) with mean soil moisture in West and negatively correlated in East. Both positive and negative correlations are seen in MidCon. Temporally, Noah soil moisture spatial variability varies less than that of SCAN, which is directly linked to the smaller dynamic range of Noah soil moisture estimates. As expected, AMSR-E retrievals generally show positive correlation (a dry climate feature) with mean soil moisture in all three regions. While the dynamic range of soil moisture for SCAN data remains more or less the same across all regions, the dynamic range of its spatial variability decreases from west to east. This is due to the fact that soil moisture in

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MidCon and East fluctuates around 0.2 and therefore any increasing or decreasing trend of spatial variability is frequently reversed. Similar behaviors are seen with Noah estimates, but not with AMSR-E retrievals which have the smallest dynamic range in spatial variability in West. These results further underscore the importance of accurately estimating climate specific mean soil moisture at any given time for accurately depicting soil moisture spatial variability.

Skewness measures the asymmetry of a probability distribution and is important for ensemble related data assimilation techniques which often assume normality. Figure 5 shows the skewness of soil moisture for the three data types. SCAN exhibits climate dependent skewness: soil moisture is positively skewed in West and Utah, negatively skewed in East and Miss-Tenn, and centered at zero-skewness in MidCon. Similar to spatial variability, this climate-specific skewness is caused by climate-dependent mean values in each region and the boundedness of soil moisture. For example, in the dry climate where median soil moisture value is below 0.2, the left tail (representing values below the median) of soil moisture distributions is suppressed by the zero bound which leads to positive skewness.

Noah estimates exhibit a somewhat similar behavior in skewness across different climate zones. Because their mean values do not reach very dry and wet end of the full soil moisture range, soil moisture in West and East is only slightly skewed. There are some strayed data points in Utah that have negative skewness even though the means are less than 0.2. This is associated with the relative uniform soil moisture conditions in June that made the statistics less representative. AMSR-E soil moisture, on the other hand, shows all positive skewness in each region due to its drier spatial means in all regions.

4.2 Impact of sampling density on spatial variability

Due to the limitation of the SCAN network, the above statistical analyses were based on scattered data points that may not represent the true averaged behavior of soil moisture in each region. To evaluate the impact of sampling sizes (number of sampling

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points within each region), daily mean and spatial variability of Noah estimates were calculated using all grid points (between 25° N and 49° N for all three regions and east of 121° W for West to exclude the coastal area) and compared with those using data at SCAN locations only. The scatter plot of Fig. 6 shows that daily means calculated using the two sampling schemes are nearly unbiased against each other in each region. This is further confirmed by their temporally averaged mean values in Table 1. Since Noah was never calibrated against SCAN soil moisture, this result suggests that spatial means derived using data at SCAN sites are representative of true means in each region.

Similarly, Fig. 7 shows that spatial variability of Noah soil moisture calculated from all grid points exhibits similar climate dependency as that in Fig. 3. One noticeable thing is that, with increased sample sizes, the impact of scale is more evident as the variability in West and East is noticeably larger than those in Utah and Mis-Tenn. The uneven distribution of SCAN locations may be responsible for the lack of impact of scales on spatial variability as shown in Fig. 3. Table 1 shows that, on average, the spatial variability of soil moisture did not change significantly with increased sampling density in most regions except in MidCon and West. The more noticeable increase of spatial variability in West is likely associated with increased precipitation (see Table 2) when all grid points were sampled. Increasing precipitation increased the wetness of soil moisture which led to increased spatial variability because of the positive correlation between spatial variability and mean soil moisture in West. In MidCon, mean soil moisture slightly increased even though precipitation decreased with increased sampling, suggesting that SCAN locations missed some low precipitation spots. This preferential sampling of the SCAN network may be the reason why spatial variability decreased with increased sampling in MidCon. Nevertheless, the climate dependency of spatial variability was captured by data from SCAN sites alone.

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4.3 Scale dependency

To further explore how the scale dependency of soil moisture spatial variability varies under different climates, a range of extent scales shown in Fig. 1 (dark and light green concentric squares) were used to calculate the spatial variability of Noah and AMSR-E soil moisture. Since SCAN soil moisture only has one extent scale in MidCon, spatial variability of soil moisture by Famiglietti et al. (2008) at the 2.5 m, 16 m, 100 m, 800 m, 1600 m and 50 000 m extent scales (values taken at the 0.2 mean soil moisture from their Fig. 9) were merged with SCAN data in MidCon. Most their measurements were obtained from the Great Plains, which has similar climate condition as MidCon. To obtain a unique spatial variability value for each scale, the daily spatial variability of SCAN, Noah and AMSR-E were averaged over the 198 days and plotted against extent scales in Fig. 8.

Log-transformation was used in Fig. 8 because, based on the self-similarity theory, the spatial variability is related to scales in an exponential function (the so-called power law) which can be linearized through log-transformation (Hu et al., 1998) as:

$$\log(\sigma_\lambda) = H \log(\lambda) + C \quad (5)$$

where λ represents the scale (in this case the extent scale); σ_λ is the spatial variability (standard deviation) at scale λ; C is a constant; H is a scaling factor indicating the degree of dependency of spatial variability on scales. Following this relationship, linear relations were fitted for each data type (black lines in Fig. 8).

Figure 8 shows Noah and AMSR-E soil moisture estimates in all regions and the combined in situ soil moisture in MidCon exhibit strong linear relationship between the log-(standard deviation) and log-(extent scale), indicating the scalability of observed and modeled soil moisture. But the degree of scale dependency varies depending on data sources and climate regions. Table 4 provides the slope of the linear relationship (H in Eq. 5) for each data set in each region. Coarser resolution soil moisture estimates show stronger scale dependency than finer ones, meaning their spatial variability increases faster as extent scales increase. From the dry to wet climate, in situ

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measurements suggest a decreasing scale dependency, albeit the limitation of only two scales for SCAN in West and East. This behavior was not observed in AMSR-E retrievals and Noah estimates which exhibit the weakest scale-dependency in MidCon and the strongest scale-dependency in East.

To identify the source of such climate dependency for NLDAS soil moisture, the slope of NLDAS precipitation scale dependency is also provided in Table 4. The spatial variability of NLDAS precipitation exhibits the similar climate dependency as Noah soil moisture, hinting a strong influence of precipitation forcing on modeled soil moisture and its spatial variability. One explanation for the weak scale dependency of NLDAS precipitation in MidCon is that the climate condition does not change as much as in West and East when the extent scale increases. For instance, with increasing extent scale in West, the contrast between the wetter north and drier south becomes stronger and so the increased spatial variability in precipitation.

Figure 8 shows that the data obtained from Familglietti et al. (2008) and the SCAN data in MidCon generally fit into a linear function, suggesting that a single scaling relationship can potentially be used to scale spatial variability from very small scales to much larger scales. Brocca et al. (2012) reported a slope of 0.16, using data collected in a similar climate condition as MidCon, which is close to the 0.11 value for the combined in situ data in MidCon (Table 4). More studies on field soil moisture measurements are needed, especially in drier and wetter climates, to further confirm the transferability of fitted scale-dependency, i.e., Eq. (5), from one region to another if their climate conditions are similar.

5 Summary and discussions

We showed that spatial statistics of in situ soil moisture strongly depend on climate with distinct mean, spatial variability and skewness observed in each climate region. Further, the upward convex relationship between spatial variability and mean soil moisture were observed for data collected at much large scales across different climate zones.

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Although this relationship has been observed in small scale studies, the unique design of this study, i.e., grouping soil moisture measurements by climate conditions and using longer data records, provided affirmative evidence that the upward convex is caused by the boundness of soil moisture. In conjunction with the climate specific mean soil moisture, each portion of the upward convex is linked to a unique climate condition, making the relationship between spatial variability and mean soil moisture climate-dependent as well. These climate-specific statistical features may assist in qualitatively evaluating model estimates or satellite retrievals. For instance, the underestimation of AMSR-E retrievals in East was reflected not only in their mean (less than 0.2) but also in their positive skewness and the lack of negative correlation between spatial variability and soil wetness.

Noah modeled soil moisture exhibited much smaller spatial variability than in situ soil moisture due to the large scale representation of forcing and parameter fields as well as inadequacy in model physics. The small dynamic range of Noah estimates, especially lack of seasonal changes, limited the occurrence of extreme soil moisture values and made the upward convex relationship barely discernable and skewness nearly non-existant. The upward convex was not observed for AMSR-E soil moisture retrievals due to the incorrect mean soil moisture in the wet climate. These results underscore the importance of obtaining accurate mean values for model and satellite estimates.

Observed and simulated soil moisture all exhibited scalability as governed by the power law, but with different degree of scale-dependency: coarser resolution data sets showed stronger scale dependency than finer ones. The three data types also show distinguished scale dependency in different climate regions. With limited two extent scales in West and East, in situ soil moisture seems to suggest decreasing scale dependency as the climate condition becomes wetter. This result needs to be further explored in future studies when more in situ data become available. Noah and AMSR-E soil moisture estimates exhibited the strongest scale dependency in the wet climate and the weakest in the transitional zone. Environmental influences such as precipitation

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may have an impact on the scale dependency of modeled soil moisture, which also requires further investigation using long data records.

Regardless of data sources, a key conclusion from this study is that the statistical distribution of soil moisture values needs to be derived locally within a given area and time period because their statistical moments are controlled by the proximity of the mean to the upper (saturation) and lower (zero) bounds. For this reason, downscaling of remote sensing data through data assimilation is preferred because it constrains the assimilated soil moisture with the correct spatial mean (i.e., satellite retrievals) while maintaining the spatial and temporal resolution of the model (Li et al., 2012). Although the current AMSR-E product may be less satisfactory (especially in the Eastern US), future satellite missions should bring more accurate estimates.

The analyses conducted in this study were based on the full magnitude of soil moisture which contains the time-variant (anomalies) and time-invariant (mean) components. It is unknown if the spatial variability of anomalous soil moisture, which is a greater concern in some applications, exhibits similar climate dependency. Although Mittelbach and Seneviratne (2012) found that soil moisture only constituted a small percentage of soil moisture spatial variability, they also showed that the spatial variability in anomalies varied differently from that in the full magnitude of soil moisture when precipitation changed. Information on the spatial variability of soil moisture anomalies is also critical for validating terrestrial water storage (TWS) as provided by Gravity Recovery and Climate Experiment (GRACE, Swenson and Wahr, 2006) satellites. GRACE TWS, which are monthly anomalies, include soil moisture, groundwater, snow and surface water, with soil moisture as one of the major components (e.g., Rodell et al., 2007). Thus, a similar study on the spatial variability of anomalous soil moisture and its scale dependency under different climates is also needed and will be conducted in the future when longer in situ data records become available to obtain more reliable mean soil moisture states in each region.

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Table 1. The number of SCAN stations, temporally averaged (over 198 days) spatial mean and spatial variability (StD) of soil moisture (%) in each region. Statistics were calculated using data values at SCAN sites, except the numbers in parentheses which were computed using all grid points in each region.

Region	Number of SCAN sites (NLDAS grid points)	SCAN		NLDAS		AMSR-E	
		mean	StD	mean	StD	mean	StD
West	34 (25 152)	0.11	0.082	0.17 (0.18)	0.051 (0.069)	0.06	0.024
Utah	16 (1681)	0.09	0.072	0.17 (0.17)	0.042 (0.045)	0.06	0.020
MidCon	19 (15 168)	0.19	0.112	0.21 (0.22)	0.074 (0.060)	0.12	0.050
East	56 (35 520)	0.23	0.109	0.25 (0.24)	0.046 (0.050)	0.19	0.045
Mis-Tenn	32 (3185)	0.25	0.106	0.26 (0.25)	0.038 (0.037)	0.19	0.039

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Table 2. Total SCAN and NLDAS precipitation (mm) for the study period (1 May to 15 November).

region	SCAN	NLDAS (at SCAN sites)	NLDAS (at all grid points)
West	181	173	222
Utah	134	142	132
MidCon	486	554	483
East	580	702	670
Mis-Tenn	596	673	661

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Table 3. Temporal correlations (r) and root mean square errors (RMSE) of Noah and AMSR-E soil moisture with SCAN measurements. Values were calculated at each SCAN site and then averaged over all SCAN locations in each region.

region	Noah		AMSR-E	
	r	RMSE	r	RMSE
West	0.61	0.104	0.31	0.08
MidCon	0.66	0.087	0.42	0.11
East	0.64	0.090	0.19	0.11

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Table 4. Slopes of linear relationship between log-(spatial variability of soil moisture – % – and precipitation) and log-(extent scale) in each climate region. NLDAS precipitation (mm) was calculated using values at SCAN locations only..

	West	MidCon	East
In situ soil moisture	0.15	0.11	0.02
Noah soil moisture	0.28	0.16	0.52
AMSR-E soil moisture	0.38	0.35	0.60
NLDAS precipitation	0.55	0.29	0.63

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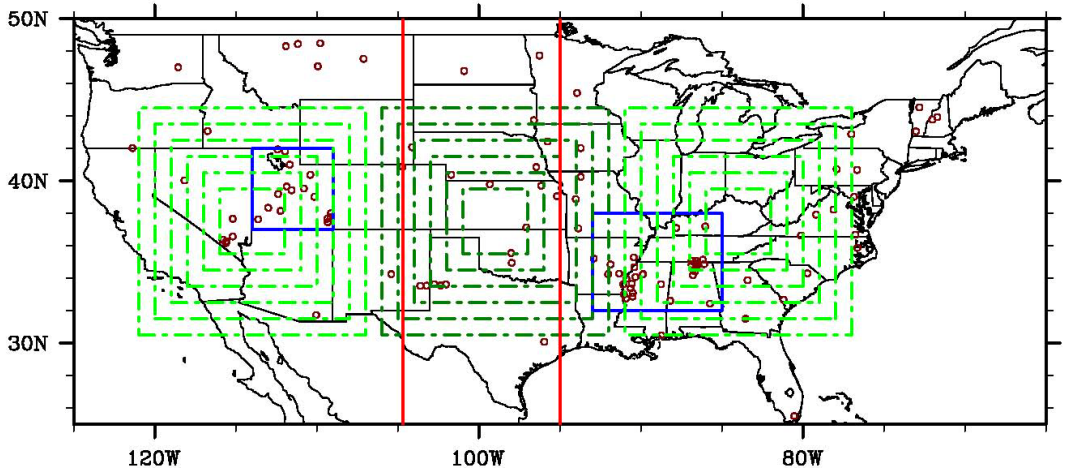

Fig. 1. SCAN site locations (in brown circles), climate regions (divided by red lines), sub-regions (in blue rectangles), and three series of concentric squares (in dark and light green) used in the scale-dependency study for Noah and AMSR-E soil moisture data.

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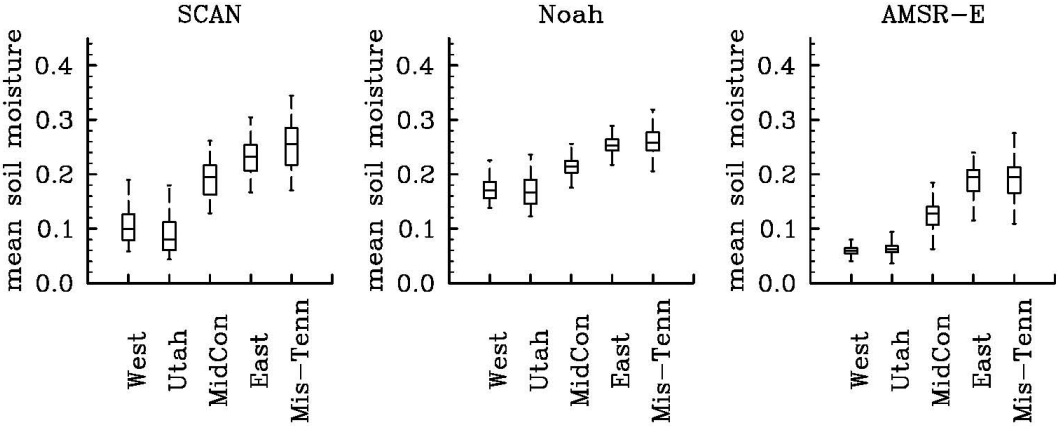

Fig. 2. Box plot of daily mean soil moisture (in volumetric percentage, %) in climate regions and sub-regions for the three data sources.

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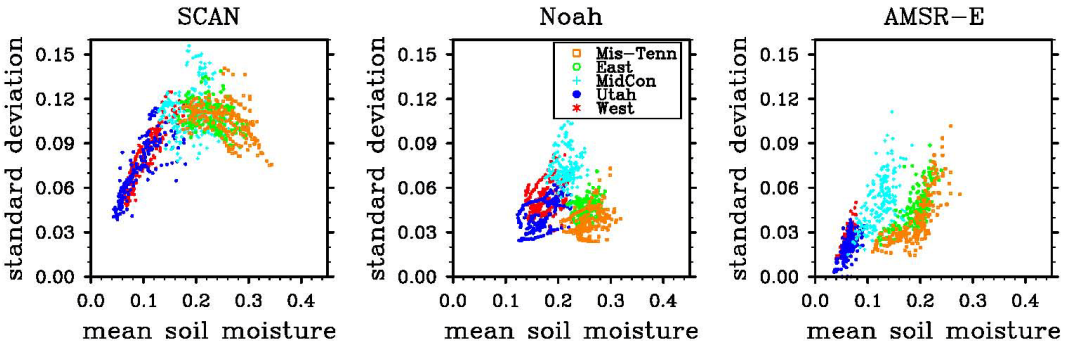

Fig. 3. Spatial variability (standard deviation) of soil moisture as a function of mean soil moisture (%) for the three data sources.

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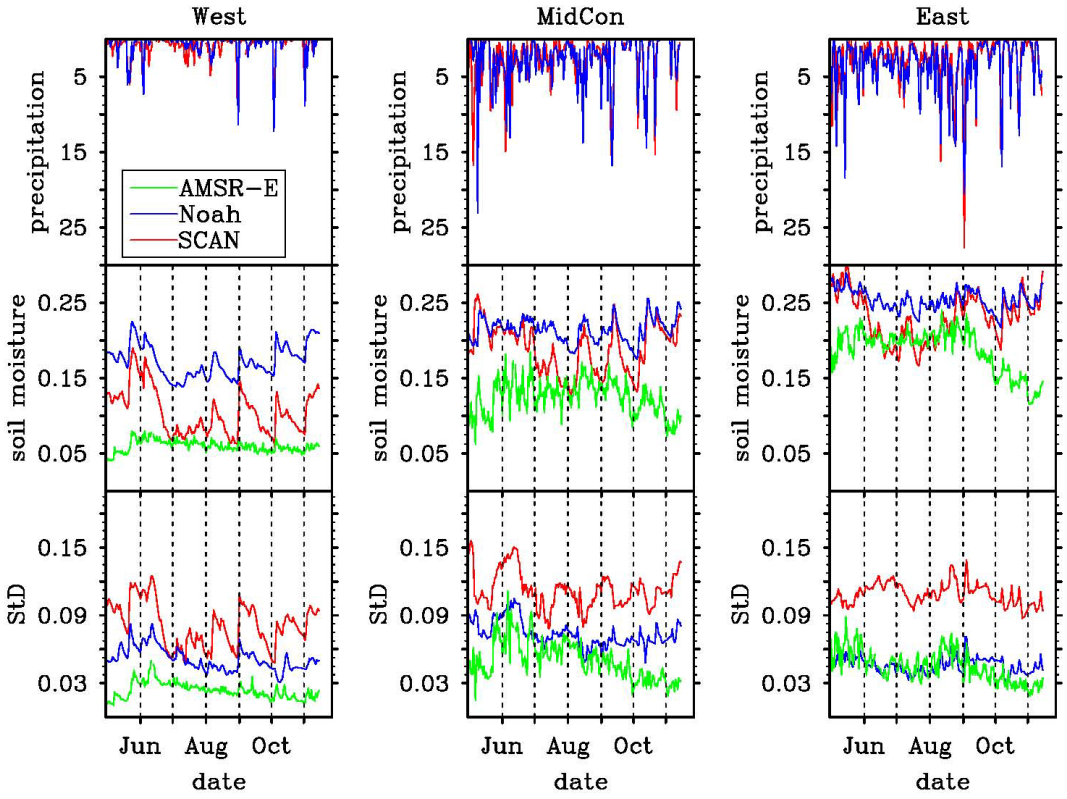

Fig. 4. Time series of daily (averaged over values at SCAN sites only) precipitation (mm), spatial mean soil moisture (%) and soil moisture standard deviation (StD) in climate regions.

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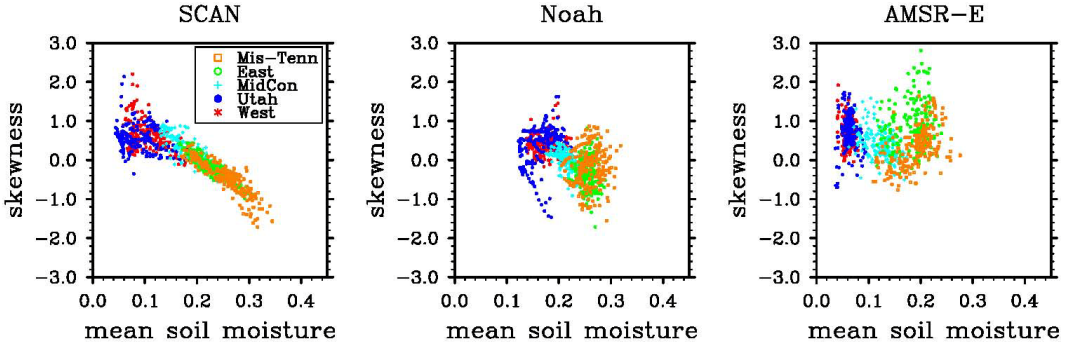

Fig. 5. Soil moisture skewness as a function of spatial mean soil moisture (%) for the three data sources.

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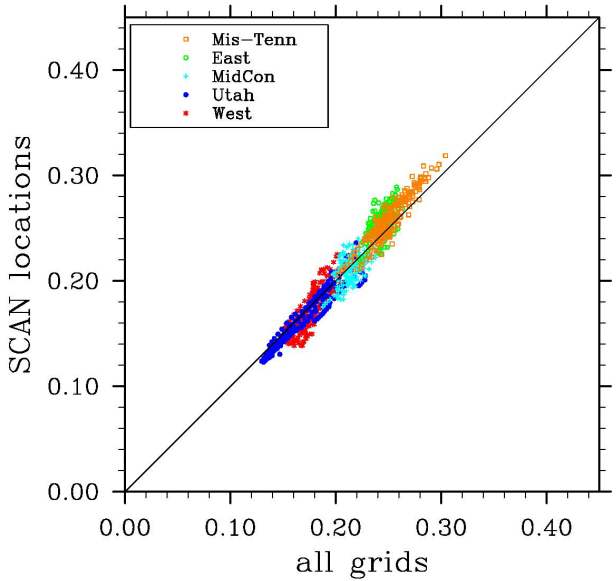

Fig. 6. Scatter plot of Noah daily mean soil moisture (%) averaged at SCAN locations versus that averaged over all grid points in each region.

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Spatial variability of observed and modeled soil moisture

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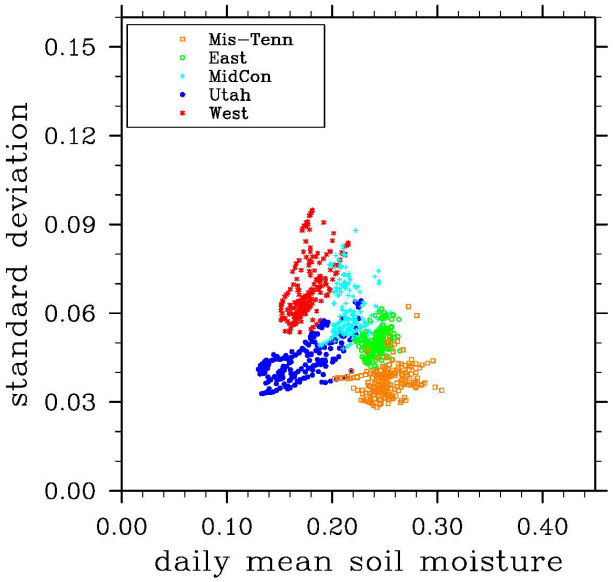

Fig. 7. Standard deviation of Noah soil moisture as a function of daily mean soil moisture (%). Statistics were calculated using all gridded data in each region.

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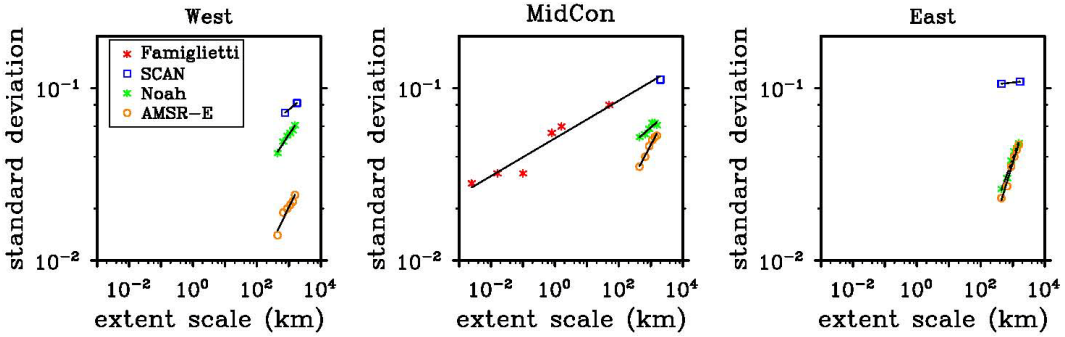

Fig. 8. log-(standard deviation of soil moisture) as a function of log-(extent scale) in climate regions. Standard deviations of SCAN, Noah and AMSR-E soil moisture were obtained by temporally averaging daily values in each region over the 198 days.

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