Temporal and spatial scales of observed soil moisture variations in the extratropics

Jared K. Entin
Department of Meteorology, University of Maryland, College Park

Alan Robock
Department of Environmental Sciences, Rutgers – the State University of New Jersey, New Brunswick

Konstantin Y. Vinnikov
Department of Meteorology, University of Maryland, College Park

Steven E. Hollinger
Illinois State Water Survey, Champaign

Suxia Liu
Department of Hydrology, Institute of Geography, Chinese Academy of Sciences, Beijing

A. Namkhai
Environmental Consulting and Assessment Company, Ulaanbaatar, Mongolia

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Corresponding Author:

Professor Alan Robock
Department of Environmental Sciences
Rutgers - The State University of New Jersey
14 College Farm Road
New Brunswick, NJ 08901-8551
Phone: 732-932-9478
Fax: 732-932-8644
E-mail: robock@envsci.rutgers.edu

Abstract

Scales of soil moisture variations are important for understanding patterns of climate change, for developing and evaluating land surface models, for designing surface soil moisture observation networks, and for determining the appropriate resolution for satellite-based remote sensing instruments for soil moisture. Here we take advantage of a new archive of actual in situ soil moisture observations from Illinois and Iowa in the United States, and from Russia, Mongolia, and China, to evaluate the observed temporal and spatial scales of soil moisture variations. We separate the variance into two components, the very small scale of interest to hydrologists, determined by soils, topography, vegetation, and root structure, and the large scale, which is forced by the atmosphere. This larger scale, determined by precipitation and evaporation patterns, is of interest for global climate modeling, and we characterize the small scale as white noise for our analysis, keeping in mind that it is an important component of soil moisture variations for other problems. We find that the atmospheric spatial scale for all regions is about 500 km, and the atmospheric temporal scale is about 2 months for the top 1-m soil layer. The temporal scale for the top 10-cm layer is slightly less than 2 months. The white noise component of the variance for temporal variations ranges from 50% for the top 10 cm to 20-40% for the top 1 m. For spatial variations, the white noise component is the same for all depths, but varies with region from 30% for Illinois to 70% for Mongolia. Nevertheless, the red noise (atmospheric component) can be seen in all regions. These results are for Northern Hemisphere midlatitudes, and would not necessarily apply to other latitudes. Also, the results are based on observations taken from grassland or agricultural areas, and may not be similar to those of areas with other vegetation types. In China, a region with substantial latitudinal variation, the temporal scale for the top 1 m varies from 1 month in the south to 2.5 months in the north, demonstrating the

control of potential evaporation on the scales. Seasonal analysis of the scales of soil moisture for Illinois shows that during the winter the temporal scales are long, though the spatial scales are short. Both appear to be attributable to the seasonal cycle of potential evaporation.

1. Introduction

Soil moisture controls interactions between the land surface and the atmosphere, as changes in soil moisture affect both the energy and water cycles. Soil moisture plays an important role in determining the amount of runoff that occurs, and thus the likelihood of droughts and floods that may affect an area. Recently, our soil moisture observations have been used to help evaluate land-surface models [*Robock et al.*, 1995, 1998; *Douville et al*., 1995; *Yang et al.*, 1997; *Schlosser et al.*, 1997; *Slater et al.*, 1998a,b; *Mocko and Sud*, 1998]. For correct interpretation of results of such model-observation comparisons, it is critical to know the statistical structure of the soil moisture field.

Studying the scales of soil moisture is very important for understanding many aspects of weather and mesoscale phenomena, and for climate change. For climate modeling, understanding the scales of soil moisture helps determine the size of spatial grids and time steps. Analysis of scales can also explain how much soil moisture variation is due to small scale, short term influences and how much is due to large scale, long term influences. This knowledge is critical for understanding how well a land surface model can be expected to perform when attempting to reproduce soil moisture observations. Scales also relate how soil moisture changes at a point represent the area surrounding it. *Kagan* [1979] developed a procedure for statistically optimal averaging of multiple observations in space, to produce one value representative of the area. This technique requires knowledge of the spatial scale. Already his technique has been used in our work to compare soil moisture observations to land-surface model soil moisture calculations [*Entin et al.*, 1999], for averaging soil moisture for use in satellite remote sensing [*Vinnikov et al.*, 1999a], and for establishing a theory for spacing of soil moisture observation stations [*Vinnikov et al.*, 1999b].

Remotely-sensed satellite observations are only able to measure soil moisture within 1-2 cm of the surface, but can retrieve information that well represents the top 10 cm layer [*Vinnikov et al.*, 1999a]. Roots of plants penetrate deeper than this, and extract moisture from much thicker layers. Therefore, it is important to know how the temporal and spatial scales of this upper layer compare with those of the lower layers.

Hasselmann [1976] introduced the concept that a part of the climate system with high frequency variations could induce another part of the climate system to exhibit low frequency variations. *Frankignoul and Hasselmann* [1977] gave an example of this theory by showing that long-term sea surface temperature anomalies are a response of the oceanic surface layer to short time scale atmospheric forcing. *Hasselmann* [1976] also explained that the long-term climate variations could be explained using a statistical model of a first order Markov process. *Delworth and Manabe* [1988] used the concepts of Hasselmann to theorize that soil moisture might be a variable whose long-term anomaly patterns are responses of the land surface layer to the random forcing of precipitation.

Delworth and Manabe [1988] analyzed results from the Geophysical Fluid Dynamics Laboratory (GFDL) general circulation model (GCM) and developed the theory that soil moisture variations in time correspond to a first-order Markov process. They determined that the autocorrelation function $r(t)$ is exponential:

$$r(t) = e^{\frac{-t}{T}} \tag{1}$$

where t is the time lag and T is the scale of temporal autocorrelation, i.e., the e-folding time of soil moisture. They also determined that a good approximation of the time scale is

$$T \approx \frac{W_f}{E_P} \tag{2}$$

where W_f is the field capacity and E_p is the potential evaporation. This theory proved effective for thirty stations from the former Soviet Union [*Vinnikov and Yeserkepova*, 1991]. Although W_f can be defined for different layers, E_p is not layer specific. This makes it difficult to determine the relationship between temporal scale and soil layer depth.

Hasselmann [1976] suggested that there might be two dominant yet drastically different time scales for a particular climate system. Such drastically different estimates of the time scales of soil moisture variability may be found in many publications. *Ghan et al.* [1997] summarized the processes that affect surface hydrology as soil characteristics, vegetation, and meteorology. *Beven and Kirby* [1979] had also shown that topography has a significant impact on the spatial variation of soil moisture. Grouping soil characteristics, vegetation, and topography into a land surface category and equating meteorology to atmospheric forcing, a separation of scales can be seen between those processes that affect soil moisture. The land surface type affects immediate infiltration of water into and through the soil, as well as how much water can be held by the soil. The atmospheric component is responsible for the amount of water available to the soil, through rain or snowmelt, as well as the rate at which it is removed, through evapotranspiration (controlled by temperature, downward radiation, humidity, and wind speed).

Temporally, gravitational drainage implies a timescale around 1 day for the land surface, yet *Delworth and Manabe* [1988], in conjunction with *Vinnikov and Yeserkepova* [1991], and *Georgakakos et al.* [1995], have shown a temporal scale on the order of months. Spatially, *Nielsen et al.* [1973], *Vieira et al.* [1981], and *Vachaud et al.* [1985] have indicated that the spatial scale of autocorrelation of soil moisture is on the order of 10 m. In comparison, *Meshcherskaya et al.* [1982] and *Kontorschikov* [1979] have shown spatial scales in Russia and the Ukraine to be on the order of 100s of km. In addition, *Cayan and Georgakakos* [1995] suggested that spatial coherence of soil moisture in the United States is on the order of 100s of km. These differences can be reconciled by considering that the small scales (one day or 10 m) are related to the hydrological scale, in many cases due to the similarity of scale with related soil properties [*Nielsen et al.*, 1973; *Peck et al.*, 1977; *Simmons et al.*, 1979]. The large scale is related to the atmospheric forcing as shown by the connection between scales of precipitation and soil moisture by *Meshcherskaya et al.* [1982], and by *Cayan and Georgakakos* [1995] who connect large scale coherence of soil moisture with both precipitation and potential evaporation. A schematic diagram of how the hydrological scale and the atmospheric scale relate to the autocorrelation function of soil moisture may be seen in Figure 1.

In this paper, we examine the scales of temporal and spatial variation of soil moisture using an extensive observed soil moisture data set. In the next section, we describe the soil moisture data we used for our analysis. Then we present an overview of the procedure used for calculating the scales of soil moisture. Next, we discuss results from the various areas for which we have soil moisture observations. The final section presents discussion and conclusions.

2. Data

We used data from multiple observation networks across the Northern Hemisphere midlatitudes, all of which are available from the Global Soil Moisture Data Bank (http://www.envsci.rutgers.edu/~robock). There are 3 data sets from Asia: Russia, China, and Mongolia (Figure 2). In this paper, usage of the terms “Russia,” “China,” and “Mongolia” will specifically refer to the areas of these countries for which we have soil moisture data and not to the entire country. The Russian set is comprised of 50 stations from the former Soviet Union and is described by *Vinnikov and Yeserkepova* [1991]. The 78 stations from China are described by *Entin et al*. [1999] and the 40 stations from Mongolia are described by *Erdenentsetseg* [1996] and *Robock et al*. [1999]. All three networks used the gravimetric method to determine soil moisture, with observations taken every 10 days for 10-cm layers in the top 1 m of soil. In Russia, the observations are taken at grass plots at observing stations, even though the predominant vegetation in the region may be different. In Mongolia, there are 23 stations at pasture areas, 15 at wheat fields, and 2 stations with observations from both. The vegetation for the Chinese stations is a variety of crops, including potatoes, wheat, maize, sorghum, and peanut. For Mongolia, we only have data for the growing season (April-October) and some stations in Northern China and Russia have reduced or no observations during the winter.

We used two data sets from the United States. The first is an 18-station network in Illinois [*Hollinger and Isard*, 1994]. Data were taken from grassland plots at all 18 stations for the top 10 centimeters and then at 20 centimeter increments down to a depth of two meters. The data were observed by neutron probe, which was calibrated by gravimetric measurements. The soil moisture data were not observed systematically, so there was not a set number of days between each observation. Different stations had observations on different days. For purposes of this study, it was necessary to bin the data in time so that a standard time step could be assumed to evaluate the autocorrelation. The 36 dates used for soil moisture observation in the other countries were used to set up bins into which the data could be fitted. If there was an observation within four days of the bin center (i.e., the 8th, 18th, or 28th of each month) the observation was placed into that bin. If there were multiple observations taken during the time period of an individual bin, then the following procedure was applied. If the observations were all taken either before or after the bin-center date, then the observation that was taken closest to the bin center was used. If there were observations both before and after then only the two closest to the center were considered. These two values were weighted by the time from the bin center. If there were no observations taken in the range of the bin then that bin was set to an undefined value. This method obviously uses linear interpolation to estimate the data point, even though the thrust of this research is to prove an exponential distribution of values, so this could add some error variance to the calculations. However interpolation was required infrequently and because this interpolation was over a few days rather than on the order of months, it should not have had a large effect on the analysis.

The second U.S. data set is from two catchments in southwestern Iowa (41.2°N, 95.6°W). Each catchment contains records from three different observation areas. Corn was planted in each catchment, although two different techniques were used to prepare the plots for the planting of the vegetation. The data were observed for 13 consecutive layers; the top four were 7.8 cm thick, the next four were 15.2 cm thick, and the next five were 30.5 cm thick. For the first catchment, the data from the top four layers were taken using gravimetric measurements and the deeper measurements were made using neutron probes. For the second catchment, gravimetric techniques were used for the upper five layers and neutron probes were used for the deeper layers. For the most part, soil moisture was observed between April and October, on average twice a month. Although the observations were not taken at a standard time throughout the year, if observations were taken, they were performed on the same day at all six sites.

Following *Vinnikov et al.* [1996], we compare the spatial autocorrelation functions of soil moisture with those estimated for monthly precipitation. Monthly precipitation data, from 1951 to 1982 for 180 stations in China are from a data set described by *Shen* [1991]. Precipitation data for the United States are from the National Climatic Data Center's summary of the day data set

[*Hughes et al.*, 1992].

3. Analysis

Theory. Our analysis centers on the idea that there are two different scales that determine the variations of soil moisture in time or space [*Robock et al.*, 1995, *Vinnikov et al.*, 1996; *Vinnikov et al.*, 1999b]. The small scale, which we refer to as the land-surface related, or hydrological scale, produces differences in soil moisture because of different local soils, topography, root structure and vegetation. For our purposes, related to studying the global climate system, we consider this portion of the variance to be interfering with our attempts to evaluate the portion related to larger-scale structure, and so also refer to it as white noise. For other purposes, particularly related to studying the hydrology of a catchment or basin, this "white noise" is actually the signal of interest. As in equation 2, temporally the soil acts as a reservoir (W_f) and the atmospheric signal corresponds to the flux (E_p). Spatially, the analogy is slightly different. The larger scale, which we refer to as the atmospheric scale, demonstrates similarity of soil moisture over larger distances because of the similarity of the atmospheric forcing upon soil moisture, through similarities in precipitation and large-scale evapotranspiration patterns. As stated in section 1, the smaller scales are on the order of a few days, temporally, and tens of meters, spatially. Based on previous modeling [e.g., *Delworth and Manabe*, 1988] and limited observational [*Vinnikov and Yeserkepova*, 1991; *Vinnikov et al.*, 1996] results, the larger scales are on the order of months and 100s of kilometers. It is these large-scale values we seek to determine using our more extensive observational data.

Estimates of the temporal autocorrelation of soil moisture may be expressed as

$$r(\tau) = \sigma_s^2 \exp(-\tau/T_s) + \sigma_a^2 \exp(-\tau/T_a), \qquad (3)$$

where $r(\tau)$ is the covariance function and τ is the time lag [*Vinnikov et al.*, 1999a]. The variance

σ_s^2 and scale of temporal autocorrelation T_s are parameters of land surface-related variability, and the variance σ_a^2 and scale T_a are parameters of the atmosphere-related variability. T_a should be equivalent to T in equation (2). Because $T_s \ll T_a$, the first term in the right side of (3) may be interpreted as the white noise component of the process. The total estimated variance σ_o^2 is

$$\sigma_o^2 = \sigma_s^2 + \sigma_a^2, \tag{4}$$

and the part of the variance related to white noise processes η is

$$\eta = \sigma_s^2 / \sigma_o^2. \tag{5}$$

Similarly, estimates of the spatial autocorrelation of a soil moisture field may be expressed as

$$r(d) = \sigma_s^2 \exp(-d/L_s) + \sigma_a^2 \exp(-d/L_a), \tag{6}$$

where $r(d)$ is the covariance function, d is the distance, L_s is the scale of spatial autocorrelation of the land surface-related variability and L_a is the scale of the atmosphere-related variability. Because $L_s \ll L_a$, the first term on the right side of (6) may be interpreted as the white noise component of the process. Using the terminology of *Delworth and Manabe* [1988], we will also refer to the atmosphere-related variability as a red noise signal because it is related to persistence, in time or space, of soil moisture.

Procedure. For every station the seasonal cycle of soil moisture was determined and these values were subtracted from the observed values to create anomalies. These anomaly values were used to estimate the autocorrelation functions, to prevent correlating observations with the seasonal cycle. We performed the temporal analysis for the top 10-cm layer for Mongolia, China, Iowa, and Illinois, and for the top 100-cm layer for these four regions and for Russia. For temporal autocorrelation, the smallest lag used was 10 days, and the lag was increased in 10-day increments thereafter, up to a value of approximately four months. To determine the temporal scale, the natural log of the estimates of the autocorrelation coefficients were plotted against the lag. At times it was necessary to truncate the curve as the estimates began to approach zero. A line was fit through these values and the negative inverse of the slope of this line was equated to the time scale related to atmospheric forcing (e.g., Figure 3). The exponential of the y-intercept was equated with the amount of variance that was explained by the red noise signal. To determine the temporal scale of a region, the correlation coefficients were averaged together, at each lag value, and plotted along with a 95% confidence interval bracket. An exception was that no confidence intervals were plotted for the Iowa coefficients because only 6 stations were used. The procedure used to fit the line attempted to intersect as many of the actual average points as possible, while still staying within all of the confidence intervals.

The averaging done within data sets was to increase statistical significance, because many of the stations do not have the very long records that are preferable for this type of statistical analysis [*Vinnikov et al.*, 1996]. The level of homogeneity over the averaging regions can compromise this technique, and further discussion and analysis addresses some of the more important points concerning the lack of homogeneity.

The spatial scale was determined in a similar fashion. The autocorrelation was performed for each pair of stations (within a single data set) and the correlation coefficient was plotted against the distance between the stations. The stations were then grouped into different distance groups and the mean correlation coefficient value was computed for each distance grouping, along with a 95% confidence interval. This mean value and confidence interval were then converted into natural log values and plotted against the mean distance for the each bin (e.g., Figure 4). A line was fit through all the confidence intervals with an attempt to intersect as many mean points as possible. The negative inverse of the slope of the fit line determines the spatial scale in the soil moisture field related to atmospheric forcing, and the y-intercept represents the amount of variance that is explained by the red noise signal. When more than one line could be reasonable fit using the plotted points and intervals, two were plotted that, while still giving reasonable fits, would have the smallest and largest slopes. These were then used to give a range of possible values for the scales.

Due to the analysis technique, any non-atmospheric related variance was lumped into the land-surface related variability category. In this way the white noise signal generated by sampling error or errors made in taking the soil moisture observations are relegated to the land-surface variability.

4. Results

4.1 Temporal Scale

Results for Illinois temporal correlations are presented in Figure 3. Similar analyses for China, Mongolia, and Iowa are presented in Figures 5-7. Table 1 provides a summary of the empirical estimates of the temporal scale for these regions. There appears to be relative agreement for each layer between the different locations.

Analyses for Mongolia and Iowa do not include any winter observations, excluding the influence of months with lower potential evaporation on the scale estimate. Following equation (2), this emphasis on months with higher potential evaporation will cause the presented estimates of the temporal scale to be underestimates. The amount of underestimation is presented later in this section.

The temporal scale estimates increase slightly with depth, though this increase is too small to be statistically significant. With depth there is a corresponding increase in the amount of the variance that is explained by the red noise signal.

Given the theory that the time scale is dependent upon the potential evaporation [*Delworth and Manabe*, 1988] it is important to consider the range latitudes of the stations for each region. The theory also shows a dependence upon the field capacity. Although not all the stations have field capacity data, there is sufficient evidence that there is no systematic pattern of field capacity (e.g., Fig. 6 [*Robock et al.*, 1998]) and that, in general, there are similar values for all the stations within a region, with values randomly positioned.

Both Illinois and Mongolia are in a relatively tight range of latitudes, and thus in both, the total area represented likely experiences similar potential evaporation. The same cannot be said for China. Because of this we divided China into three regions: Northeast (Manchuria), Central, and South. The stations that comprise each of these areas are shown in Figure 1. The results are shown in Figure 8a and summarized in Table 2. For the entire top 1 m the temporal scale decreases in the direction of the Equator. To get a better representation of the difference between the scales of these three regions it was necessary to do a second estimate of the temporal scale, using only data from March through November (Figure 8b, Table 2). This helps alleviate the bias that results from fewer winter time observations in the analysis for stations in the Northeast, and to a lesser extent, in the Central region. From this second analysis we see an even stronger distinction between the three regions.

Using these results we estimate that excluding the winter months for scale values around two months lowers the estimate of the temporal scale anywhere between 0.2 and 0.6 months. This would cause the Iowa temporal scale estimates to match the Illinois estimates. The Mongolian estimates would also be closer to the values estimated for Russia and Northern China.

To further investigate the vertical dependence of the time scale, we analyzed data for the layers deeper than 1 m for Illinois and Iowa. In the deeper layers, 1-2 m, the temporal scale becomes even larger. For both Illinois and Iowa the values appear to be in the range of 5-7 months. The amount of variance explained by the red noise signal is above 90%, although the source of the signal may not be exclusively from the atmospheric influences. In addition, the amount of variance of soil moisture in the layer between 1 m and 2 m depth is much smaller (about 75% less) than in the top 1 m layer.

This finding of longer time scales, though still on the order of months, will help evaluate some land-surface models that incorporate a deep layer, or recharge zone, that is beneath the model's rooting depth (e.g., SSiB [*Xue et al.*, 1991] For the most part these models have gone untested as to their simulation of deep layer soil moisture. In models and in nature it is this layer that is sometimes responsible for providing the upper layers with moisture in times of water stress. When performing long-term climate modeling it is important that this layer acts correctly in terms of how quickly it can provide moisture.

4.2 Spatial Scale

The analysis of the spatial autocorrelations for Illinois is presented in Figure 4. Similar analyses for Russia, China and Mongolia are presented in Figures 9-11. A summary of the empirical estimates of the spatial scales of soil moisture variations for the different regions is given in Table 3. The results indicate that the spatial scale does not appear to change significantly with depth. However, as this is an initial study, our emphasis is on finding the most likely range of the spatial scale, as opposed to one specific number. With further study and a greater amount of data, in the future it may be possible that a discernable difference in scale is found for different layers.

Our results indicate that over the entire state of Illinois the soil moisture changes in a similar fashion. This is understandable, as on a single day the weather over one area of Illinois is probably roughly equivalent to any other spot in Illinois. This explanation is substantiated when we compare the difference between the aggregate of 10 days of weather between two different locations in Illinois. The variance in placement of convective activity is probably lessened because a portion of the precipitation related to convective activity is directed into runoff. Looking over a 10-day period may also smooth out the spatial distribution of where convective activity occurs. One of the limitations of the spatial analysis of Illinois is that the spatial scale is as great as the maximum distance between any of the two observing stations used in the analysis. This precludes detecting a non-exponential relationship at greater distances.

The observation network for the 50 stations in Russia spans more than 1500 km, mainly in a longitudinal direction. The spatial scale for the top 1 m falls into the range of 500-750 km, which agrees with *Meshcherskaya et al.* [1982], who presented results for May, June, September and October. In our case, however, data from the entire year (when available for the winter) have been used. Again, considering the weather patterns that affect Russia helps to explain the spatial scale. Weather systems tend to move from west to east over Russia, so different parts of Russia will see similar weather, albeit on different days.

The station network for China spans a great distance (> 1,000 km), but much of the extent is in a latitudinal direction. One might expect the spatial scales to be smaller, but the results show a similar spatial scale for China as for the other regions. We attribute this to the similarity of precipitation and temperature in the meridional direction [*Domrös and Peng*, 1988], for the regions in which the soil moisture data was observed.

Mongolia also appears to have similar spatial scales (200-400 km), but there is less certainty in this estimate because of the range of altitudes in the station network. Unlike for the other networks, in Mongolia there is a greater chance for a mountain to be between two stations. This works to decrease the correlation between two stations as mountains alter air mass properties and precipitation patterns. A large range of altitudes will perturb the potential evaporation field due to the atmosphere's decreasing ability to hold moisture with increasing altitude. The mountainous terrain also explains the low strength of the red noise signal found in the estimates. This implies the potential for small spatial scales for other mountainous regions around the globe.

4.3. Seasonality

In addition to knowing the scales of variation it is important to know how these scales vary during the year. The seasonal variation might also help explain other factors that affect the overall scales that might be missed in the annual computations. For example, the effect of potential evaporation on the temporal scales in China was more pronounced when the winter months were excluded.

The Illinois data set is the most appropriate for further analysis of seasonal scale variations due to the homogeneity of the network. Using a 5-point binomial smoothing on the correlation values for each month, we used these values in the following equation to determine the time scale for each month. For this analysis, the correlation value for a given month is the correlation between the last observation of the prior month and the last observation of that month (i.e. r for March, lag one, correlates the value on Feb. 28 and March 28. r for March, lag two, correlates the value on Feb. 28 and April 28.). Using the correlation for one month-and two-month lags, we were able to estimate the scale for each month of the year, T_m:

$$T_m = \frac{\ln\left(r_{m,2}\right)}{\ln\left(r_{m,1}\right)} \tag{7}$$

where m is the month for which the time scale is being calculated, $r_{m,1}$ is the correlation value between month m and month m+1, and $r_{m,2}$ is the correlation value between month m and month *m*+2. Figure 12 shows the seasonality of the temporal scale for both the top 1 m and top 10 cm soil layers. During the winter months the scales are largest due to the drop in potential evaporation that results from the drop in incident solar radiation.

The surprising feature is the increase in time scale for the top 1 m that occurs from spring to the summer months. The link between soil moisture and local precipitation could explain this increase. *Findell and Eltahir* [1997] found that for June, July, and August, rainfall is better correlated with prior soil moisture than with prior rainfall. As rainfall is a source of moisture for the ground, the soil moisture could be helping its own anomalies persist longer. Another possibility is that the time scale's dependence upon potential evaporation might decrease during severe dry conditions.

Figure 13 shows the spatial correlation for the four seasons, summarized in Table 4. Station pairs were bined by distance in a similar fashion as for the previous spatial scale analysis. The regression lines in Figure 13 are least-squares best-fit lines. Also in Table 4 is the summary of a similar analysis of the spatial scale of monthly precipitation. The smaller soil moisture spatial scale in the winter and larger in the summer implies a stronger dependence on the potential evaporation than on the precipitation, which exhibits almost the opposite cycle. Further study is needed to determine if the deviation of the soil moisture scale from the precipitation scale is due to the magnitude of the potential evaporation, the scale of the potential evaporation, or another aspect of the system.

5. Discussion and Conclusions

The major conclusions of this paper are:

- The temporal autocorrelation functions of soil moisture were studied using in situ soil moisture for different climatic regions and different soil layers. For all the regions studied, the shape of the autocorrelation function may be approximated by an exponential statistical model and may be partitioned into two components. One of them, the red noise component of variability, is related to atmospheric forcing and has a time scale of roughly two to three months for all locations studied. The other component is related to short term processes such as infiltration, cloud coverage, precipitation, and drainage. These estimates of the temporal scale for the upper 1 m are in good agreement with theoretical estimates of *Delworth and Manabe* [1988], which are directly related to field capacity and potential evaporation. The difference between the scales of the upper 10 cm and 1 m layers are not significantly different. For soil layers beneath 1 m, in Illinois and Iowa, the scales of temporal autocorrelation are much longer and may reach or exceed 6 months.

- In China, the only region with substantial latitudinal variations, the temporal scale for the top 1 m varies from 1 month in the south to 2.5 months in the north, demonstrating the control of potential evaporation on the scales.
- Spatial autocorrelation functions of soil moisture were studied using in situ soil moisture for different climatic regions and different soil layers. The scales of spatial autocorrelation for both the upper 10 cm and upper 1 m are on the order of several hundred km for all locations. There is good agreement between the soil moisture scales and scales of monthly precipitation, which may be the main factor of atmospheric forcing.
- The temporal scales have seasonal variation and maximum values in the winter.
- The limited volume of data does not allow extensive study of seasonal spatial scales, though as precipitation scales and potential evaporation change with season it is expected that soil moisture spatial scales exhibit similar behavior. However, we are unclear of the magnitude of the influence of these forces on the spatial scale and how they will change with season.

- Previously there was a dearth of long term soil moisture data to be used to study the nature of soil moisture variation, land surface modeling, and remote sensing techniques. This research has introduced several new observed soil moisture data sets for scientific use. Here the data have been used to address an issue that had been difficult to study because of a lack of sufficient useable data. These data will continue to be useful in other studies as well.

Previous work, by *Nielsen et al.* [1973], *Vieira et al.* [1981], and *Vachaud et al.* [1985] have suggested that there is a spatial scale of soil moisture, on the order of 10 m. Their work implied that beyond this distance there was too much variability in the soil properties to maintain a correlation of soil moisture. Strictly looking at single points in time, *Dubayah et al.* [1997] have shown that there is log-log linearity of the moments of soil moisture. Their work implies the maximum amount of variability caused by different land-surface types could be reached at distances on the order of a few km, for relatively homogeneous regions. However, *Kontorschikov* [1979], *Meshcherskaya et al.* [1982] and *Cayan and Georgakakos* [1995] have shown a second factor is able to impose large-scale coherence of soil moisture variations. *Meshcherskaya et al.* [1982] and *Cayan and Georgakakos* [1995] have related this coherence to both large-scale precipitation patterns and potential evaporation. In this work, we have interpreted this to mean that there is a similar theory for spatial autocorrelation of soil moisture as for the temporal autocorrelations. There exist two separate scales of variation, one smaller scale, dominated by land-surface variations, and a second larger scale influenced by meteorological processes. Using the soil moisture observation data has shown that this larger scale exists, and empirical estimates of the scale of spatial autocorrelations agree with the findings of *Kontorschikov* [1979] and *Meshcherskaya et al.* [1982]. The data sets described here are not of a high enough resolution to study the small hydrological scale variations of soil moisture.

Although new data sets have been introduced there are still few data sets of both high spatial and temporal resolution, that exist for several years, and which are adequate to study soil moisture variations at multiple scales. This leads us to consider using alternative forms of soil moisture data. One such "data set" comes from the European Centre for Medium-Range Weather Forecasting reanalysis (ERA) project [*Gibson et al.*, 1997]. Although these are model-derived estimates of soil moisture, the reanalysis procedure is able to incorporate some observations into the estimates and still allow the land-surface to come into equilibrium with the local atmosphere. We are in the process of studying the soil moisture generated by ERA. If the temporal and spatial scales estimates derived from the ERA soil moisture data match those seen in observations, then perhaps the completeness of this manufactured data set can be used for further investigation. One such investigation would be into the relationship between potential evaporation and soil moisture scales. In addition, further investigation into the seasonality of scales could be performed. Using the data from ERA might also allow first-guess type estimates of scales in regions for which we have no soil moisture observations.

Our results leave unresolved the question of whether it is necessary to resolve the sub-grid scale variability of soil moisture in global climate simulations. It is not necessary simply to capture the monthly-average effects of atmospheric forcing on soil moisture. However, especially for heterogeneous vegetation, soil and topography on the mesoscale intermediate between the hydrological and atmospheric scales we found, there may be non-linear interactions with mesoscale atmospheric circulations that feed back on the soil moisture. For short-term weather forecasts, higher resolution treatment of soil moisture clearly is important.

Our spatial scale results used all the long-term (> 10 years) records of soil moisture observations that we are aware of. All come from Northern Hemisphere midlatitudes, and all are for rather short vegetation. We look forward to evaluating records from other climates, especially the tropics, and from forested regions, when they become available, to see how representative these results are. For the temporal scale, we have long-term observations from a few forested regions at water balance stations in Russia, which we are currently evaluating, but we expect that interactions between the canopy and the soil in the tropics might be rather different.

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Table 1. Scales of temporal correlation for the atmospheric portion of the variance (T_a) for the top 10-cm and top 1-m soil layers for the different regions. Also shown are the standard deviation (σ_o; see equation 4) and the portion of the variance that can be attributed to white noise random variations (η; see equation 5).

	0-10 cm soil layer			0-100 cm soil layer		
	σ_o [cm]	η [%]	T_a [Month]	σ_o [cm]	η [%]	T_a [Month]
Illinois, U.S.	0.85	40-60	1.5-1.8	4.0	10-20	1.8-2.1
China	0.57	40-65	1.1-2.4	3.8	20-40	1.6-2.4
Mongolia	0.51	50-60	1.5-1.7	4.7	35-50	1.6-1.8
Iowa, U.S.	0.65	60-70	1.1-1.5	4.5	10-25	1.3-1.8

Table 2. Temporal scale (months) for China for the top 1 m for the 3 regions shown in Figure 5, both for the full year and for only March through November (No Winter), to account for sampling problems with fewer observations in the Northern region in the winter. The overall scale for the full year for all regions considered together is 1.6-2.4 months.

	Full Year	No Winter
Northern	2.8	2.5
Central	1.9	1.5
Southern	1.6	1.0

Table 3. Scales of spatial correlation for the atmospheric portion of the variance (L_a) for the top 10-cm and top 1-m soil layers for the different regions. Also shown are the standard deviation (σ_o; see equation 4) and the portion of the variance that can be attributed to white noise random variations (η; see equation 5).

	0-10 cm soil layer			0-100 cm soil layer		
	σ_o [cm]	η [%]	L_a [km]	σ_o [cm]	η [%]	L_a [km]
Illinois, U.S.	0.85	30-35	380-490	4.0	30-35	510-670
China	0.57	45-50	500-550	3.8	55-65	475-575
Mongolia	0.51	60-80	200-400	4.7	60-80	200-400
Russia	-	-	-	3.1	55-65	500-750

Table 4. Estimates of the seasonal values of the scales of spatial correlation for the atmospheric portion of the spatial correlation for Illinois top 1 m soil moisture. The portion of the signal attributable to white noise is also shown for soil moisture. The spatial scale for monthly precipitation is also shown.

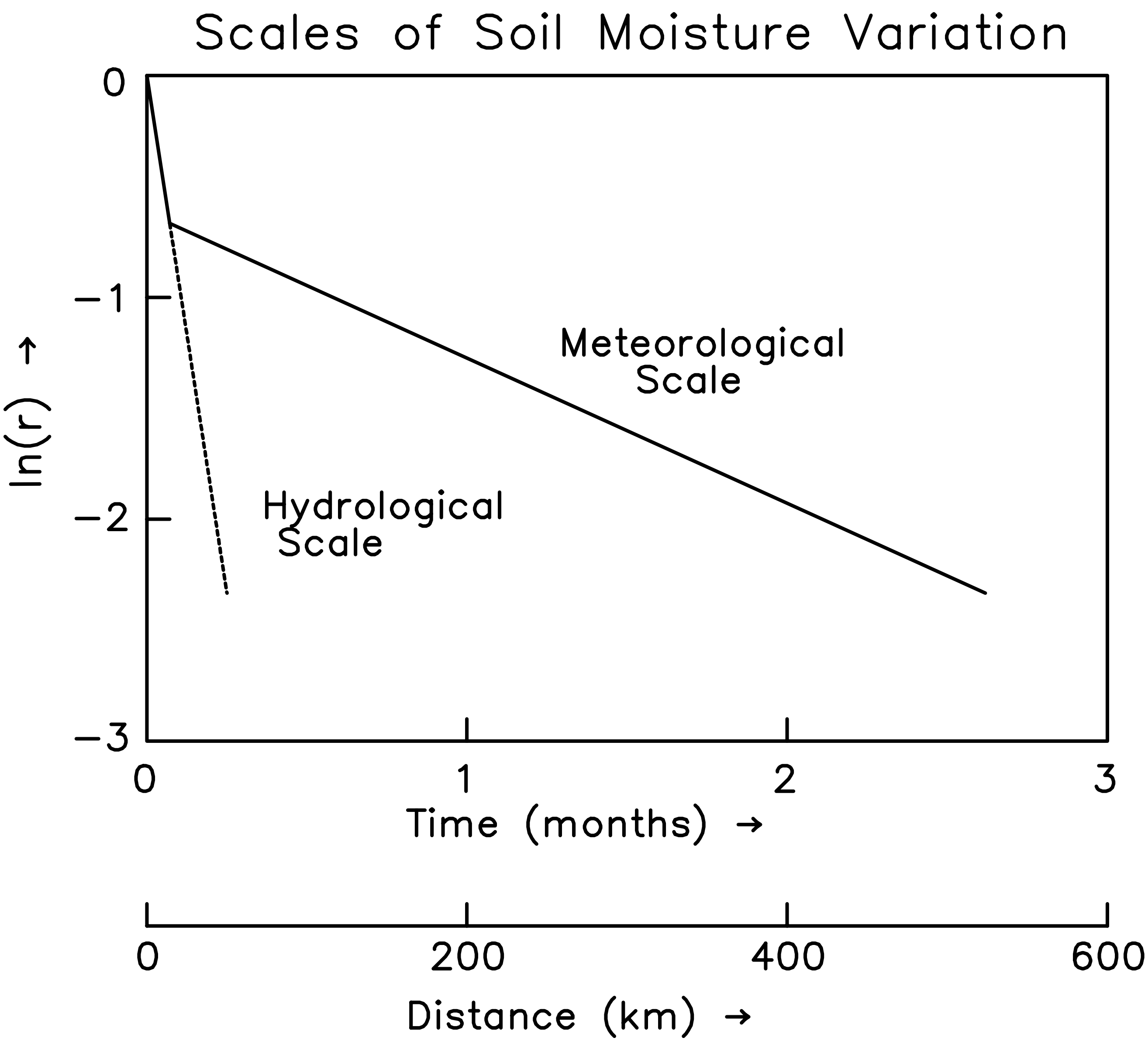
		L_a [km]	
Season	η [%]	Soil Moisture	Precipitation
Winter (DJF)	35-40	300-350	550-600
Spring (MAM)	15-20	400-450	350-400
Summer (JJA)	25-30	575-650	300-350
Autumn (SON)	25-30	525-575	450-500

List of Figures

11. Same as Figure 4 except using 42 stations from Mongolia.

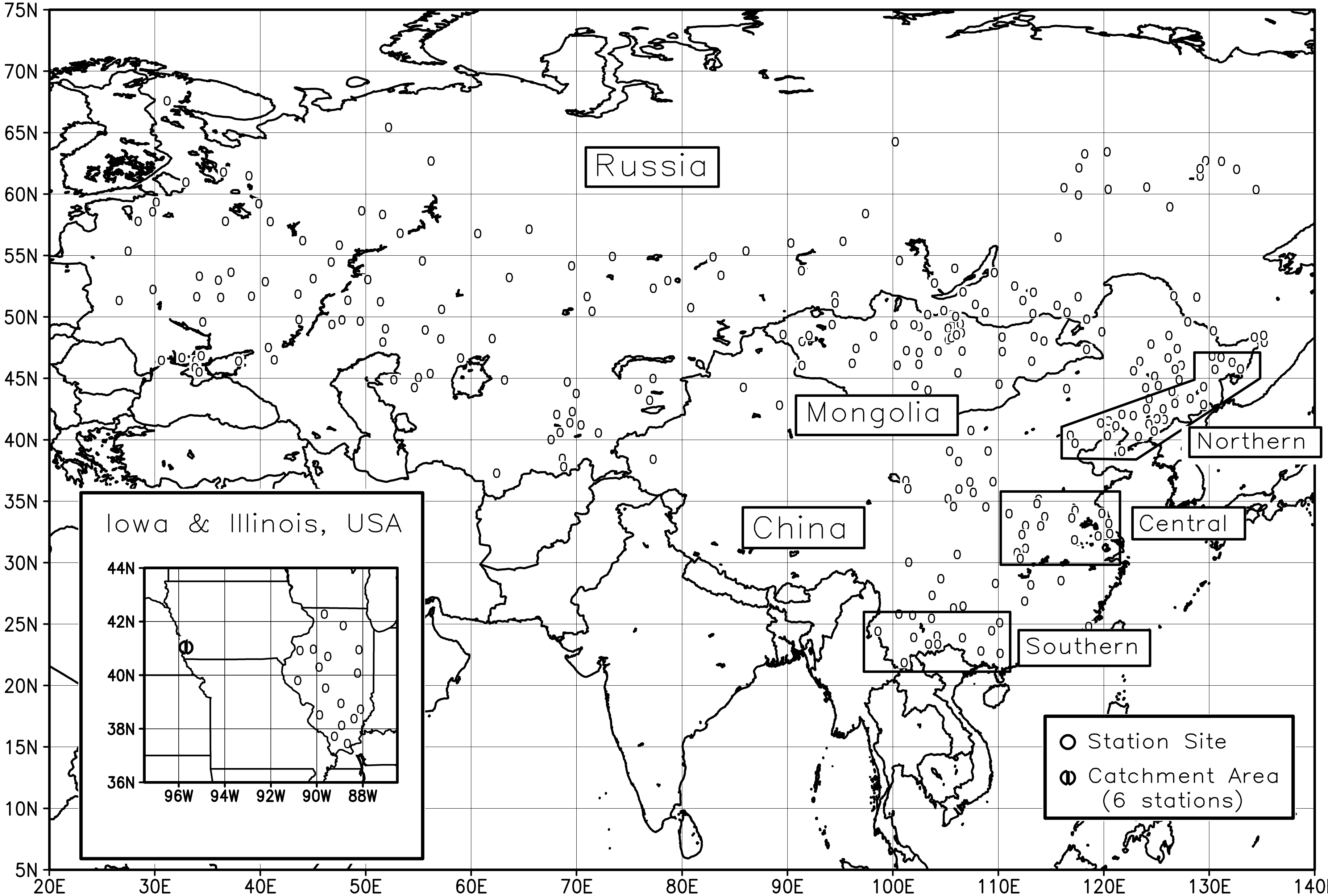
12. Seasonal temporal scale for Illinois. See text for explanation of how the scales were calculated.

13. Same as Figure 4, except each line represents data only from those months corresponding to the designated season. Analysis shown is only for the top 1 m. Regression lines were determined using the least-squares method.



Scales of Soil Moisture Variation
0
−1
−2
−3
ln(r) →
Meteorological Scale
Hydrological Scale
0
1
2
3
Time (months) →
0
200
400
600
Distance (km) →

Fig. 1



Russia
Mongolia
China
Northern
Central
Southern
Iowa & Illinois, USA
Station Site
Catchment Area
(6 stations)
75N
70N
65N
60N
55N
50N
45N
40N
35N
30N
25N
20N
15N
10N
5N
20E
30E
40E
50E
60E
70E
80E
90E
100E
110E
120E
130E
140E
44N
42N
40N
38N
36N
96W
94W
92W
90W
88W

Fig. 2

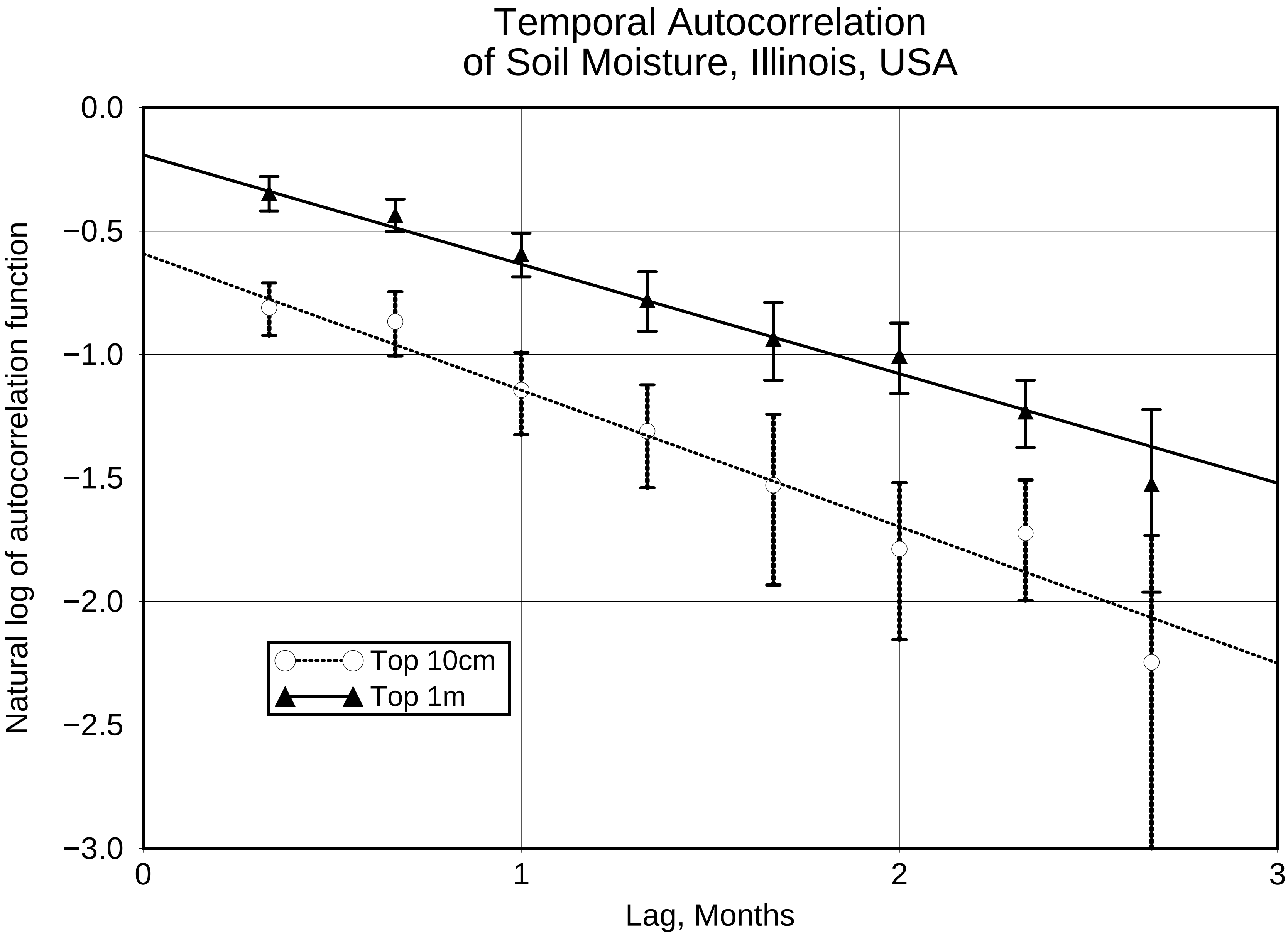

Temporal Autocorrelation
of Soil Moisture, Illinois, USA
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
Natural log of autocorrelation function
0
1
2
3
Lag, Months
Top 10cm
Top 1m

Fig. 3

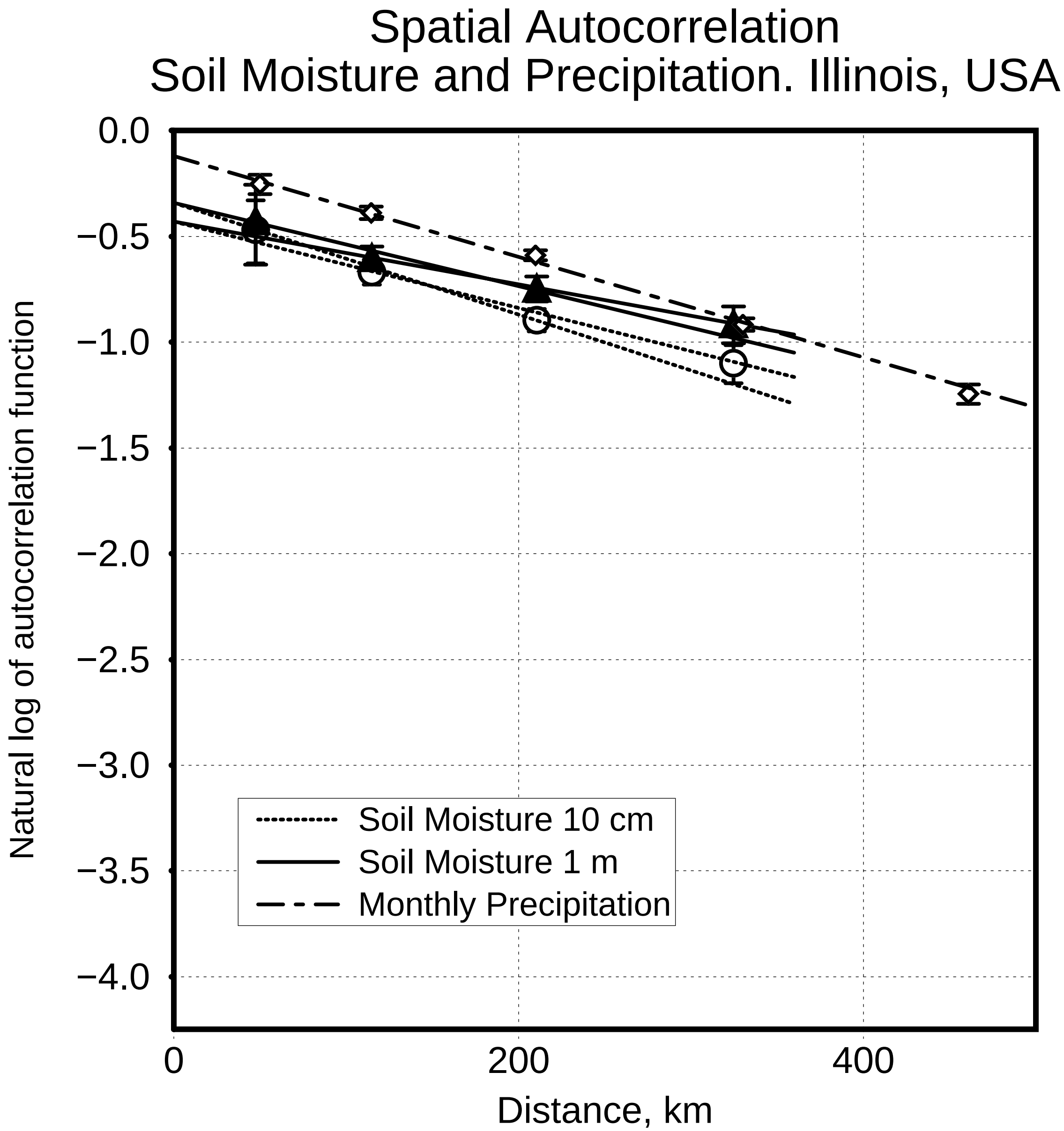
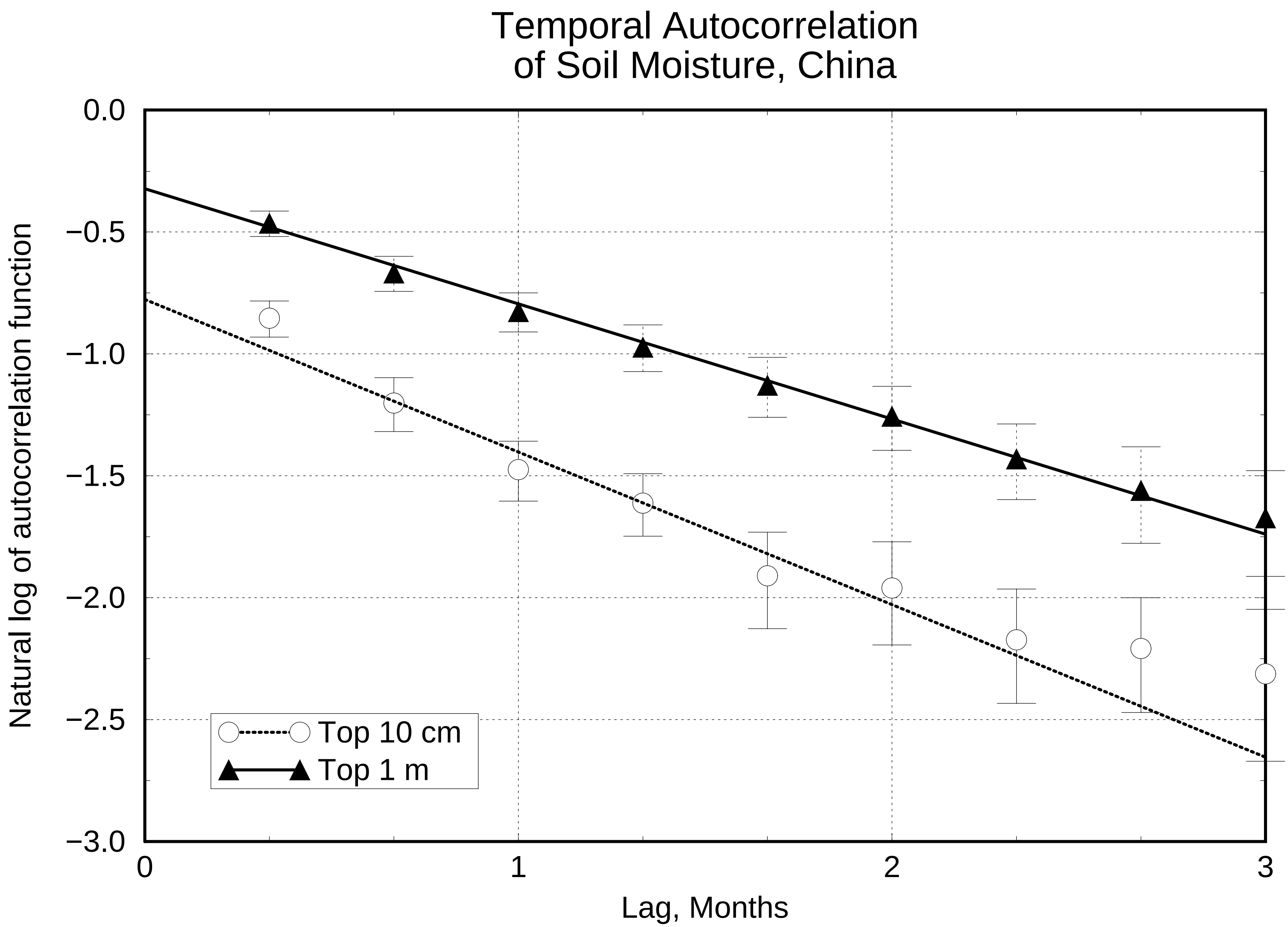

Spatial Autocorrelation
Soil Moisture and Precipitation. Illinois, USA
Natural log of autocorrelation function
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
0
200
400
Distance, km
Soil Moisture 10 cm
Soil Moisture 1 m
Monthly Precipitation

Figure 4



Temporal Autocorrelation
of Soil Moisture, China
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
Natural log of autocorrelation function
0
1
2
3
Lag, Months
Top 10 cm
Top 1 m

Figure 5

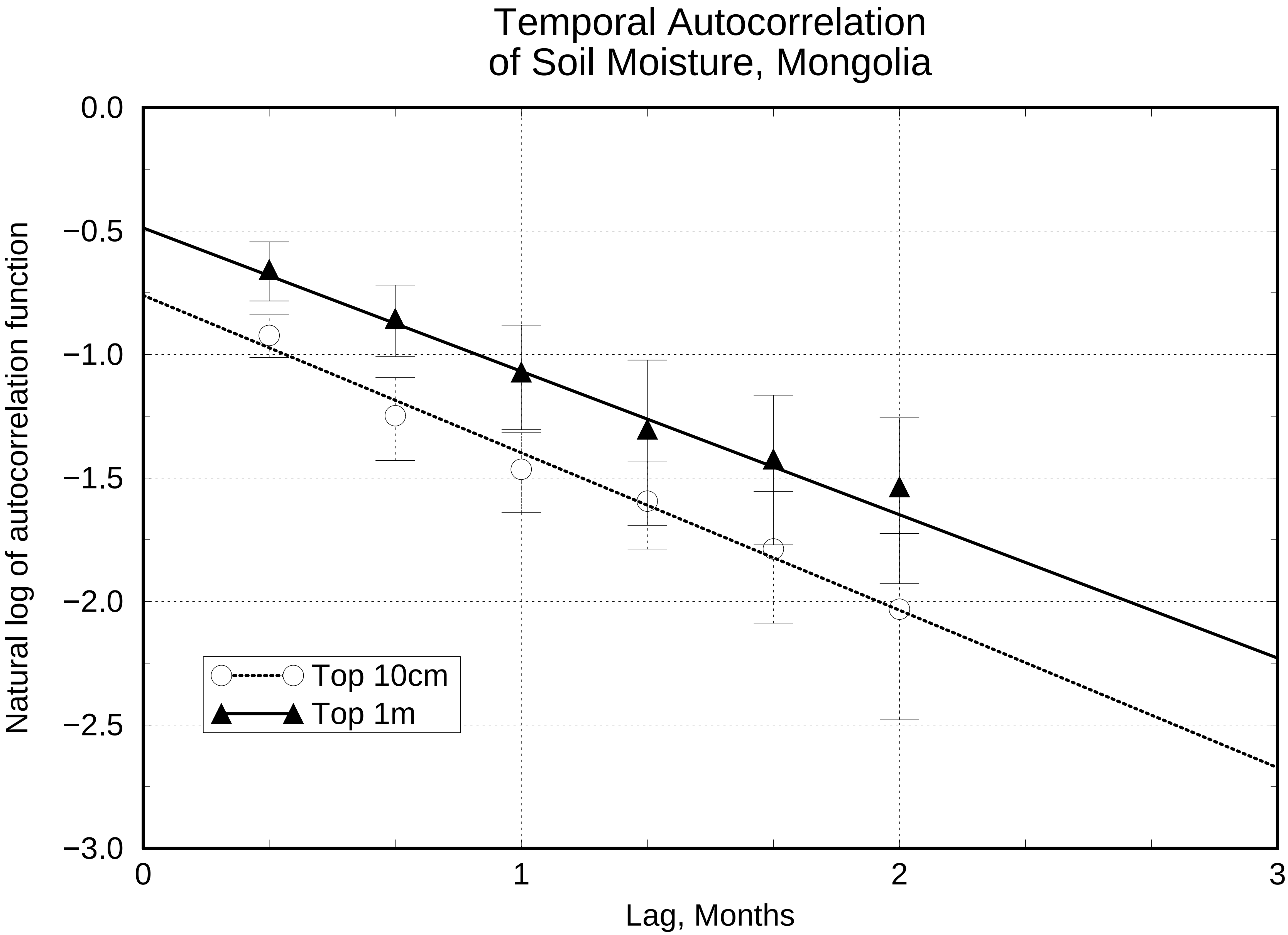

Temporal Autocorrelation
of Soil Moisture, Mongolia
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
Natural log of autocorrelation function
0
1
2
3
Lag, Months
Top 10cm
Top 1m

Figure 6

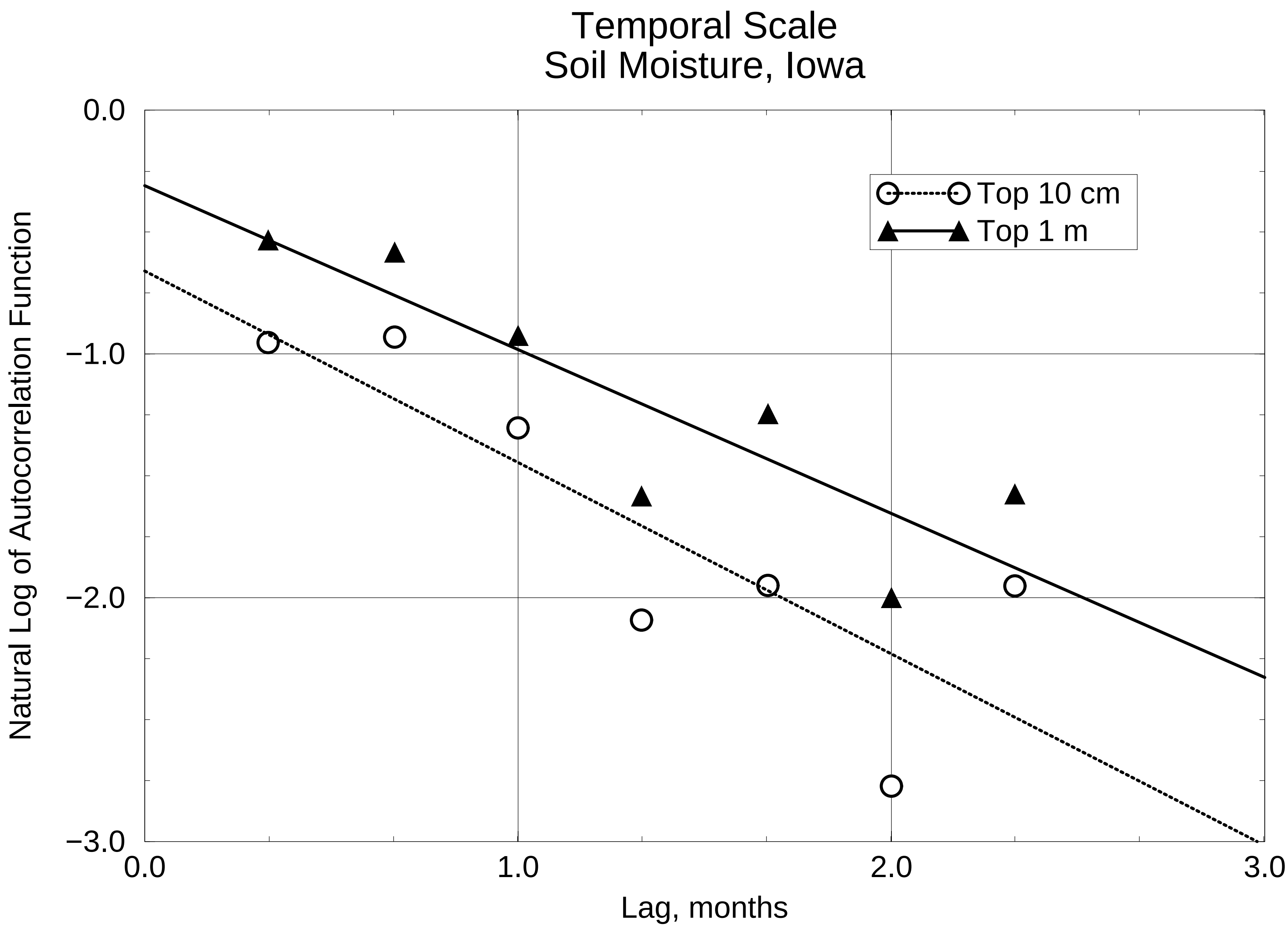
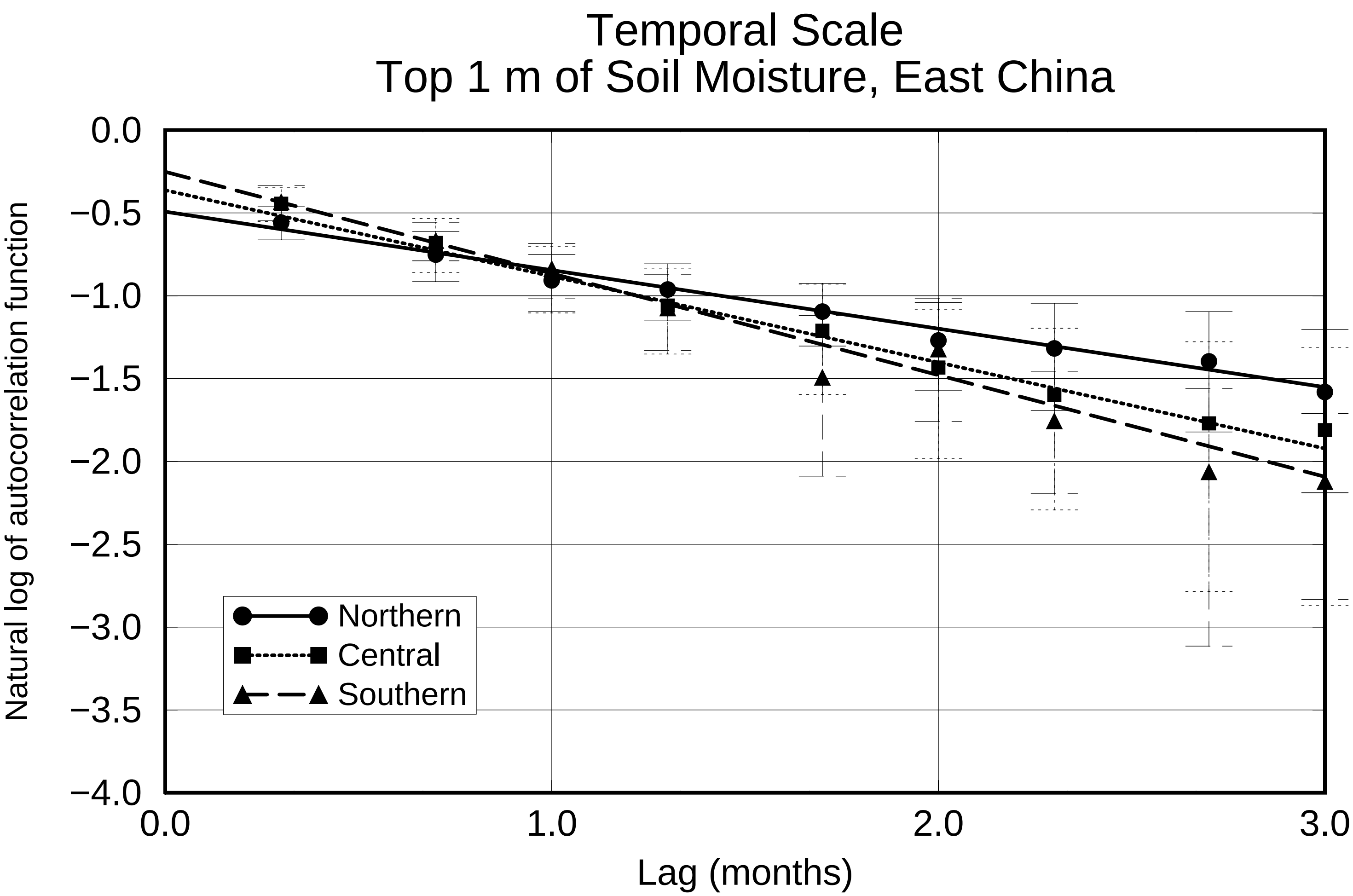
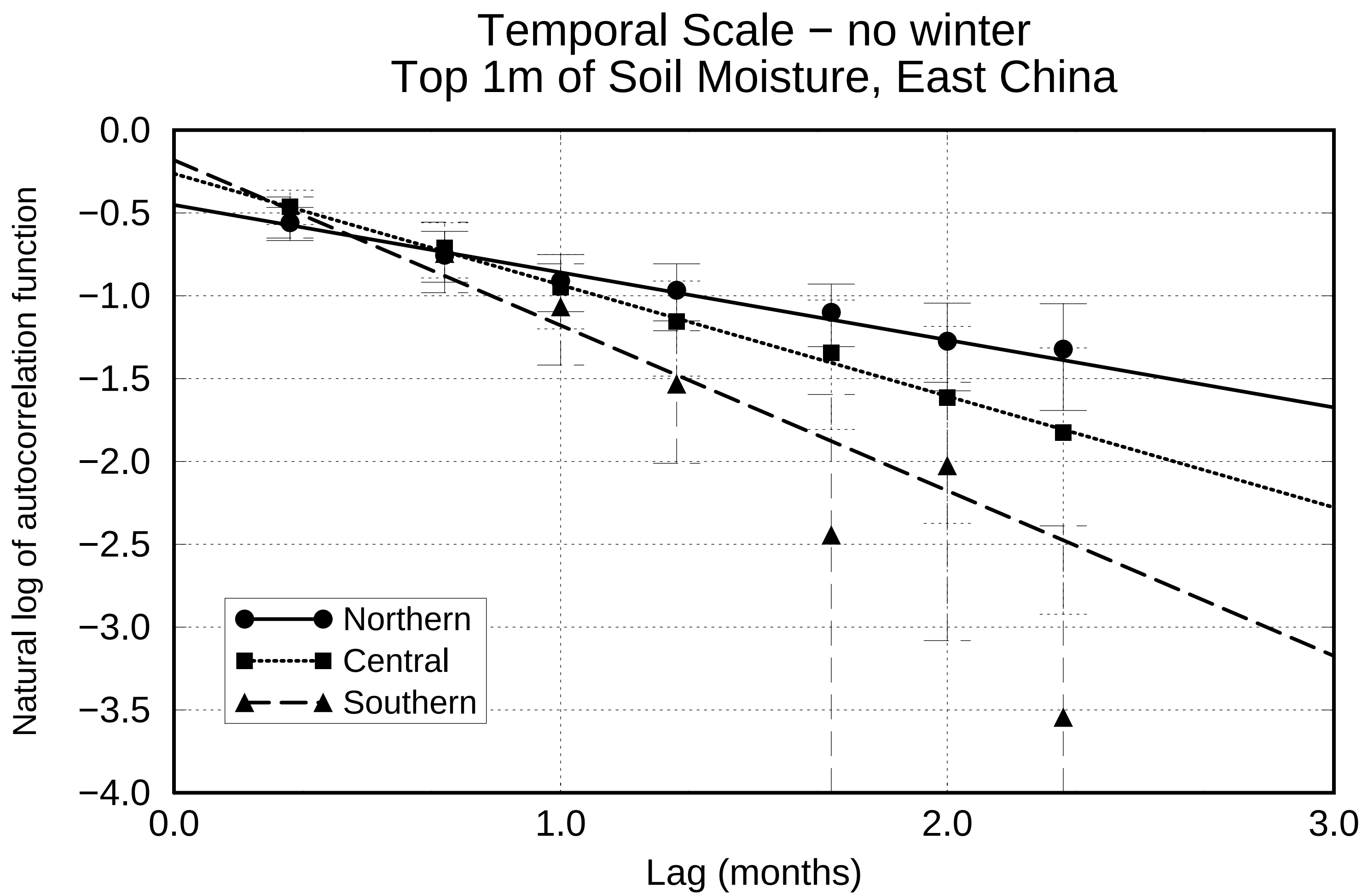

Temporal Scale
Soil Moisture, Iowa
Natural Log of Autocorrelation Function
Lag, months
Top 10 cm
Top 1 m
0.0
−1.0
−2.0
−3.0
0.0
1.0
2.0
3.0

Fig. 7



Temporal Scale
Top 1 m of Soil Moisture, East China
Natural log of autocorrelation function
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
0.0
1.0
2.0
3.0
Lag (months)
Northern
Central
Southern

Fig. 8a



Temporal Scale − no winter
Top 1m of Soil Moisture, East China
Natural log of autocorrelation function
Lag (months)
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
0.0
1.0
2.0
3.0
Northern
Central
Southern

Fig. 8b

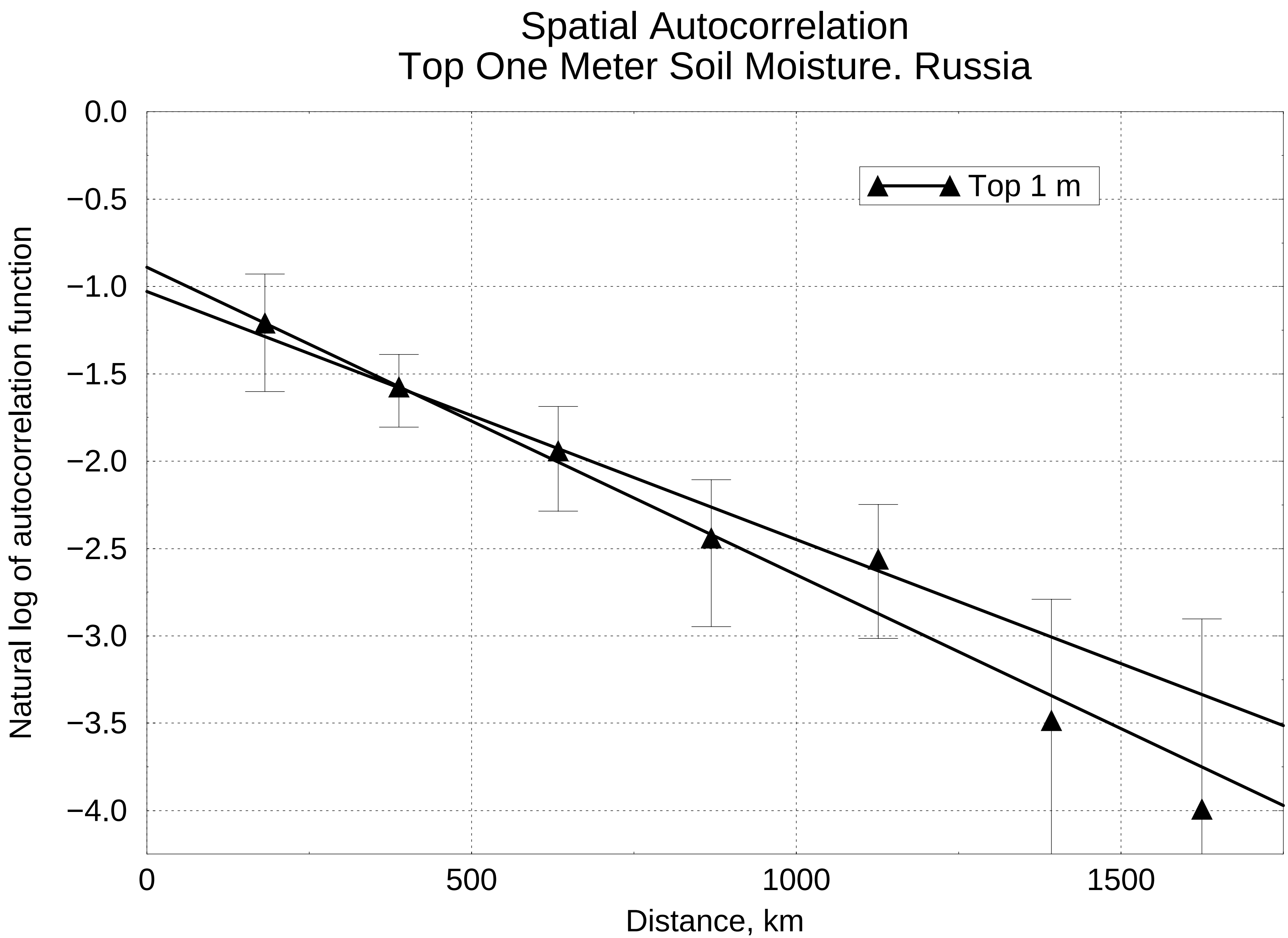

Spatial Autocorrelation
Top One Meter Soil Moisture. Russia
Top 1 m
Natural log of autocorrelation function
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
0
500
1000
1500
Distance, km

Figure 9

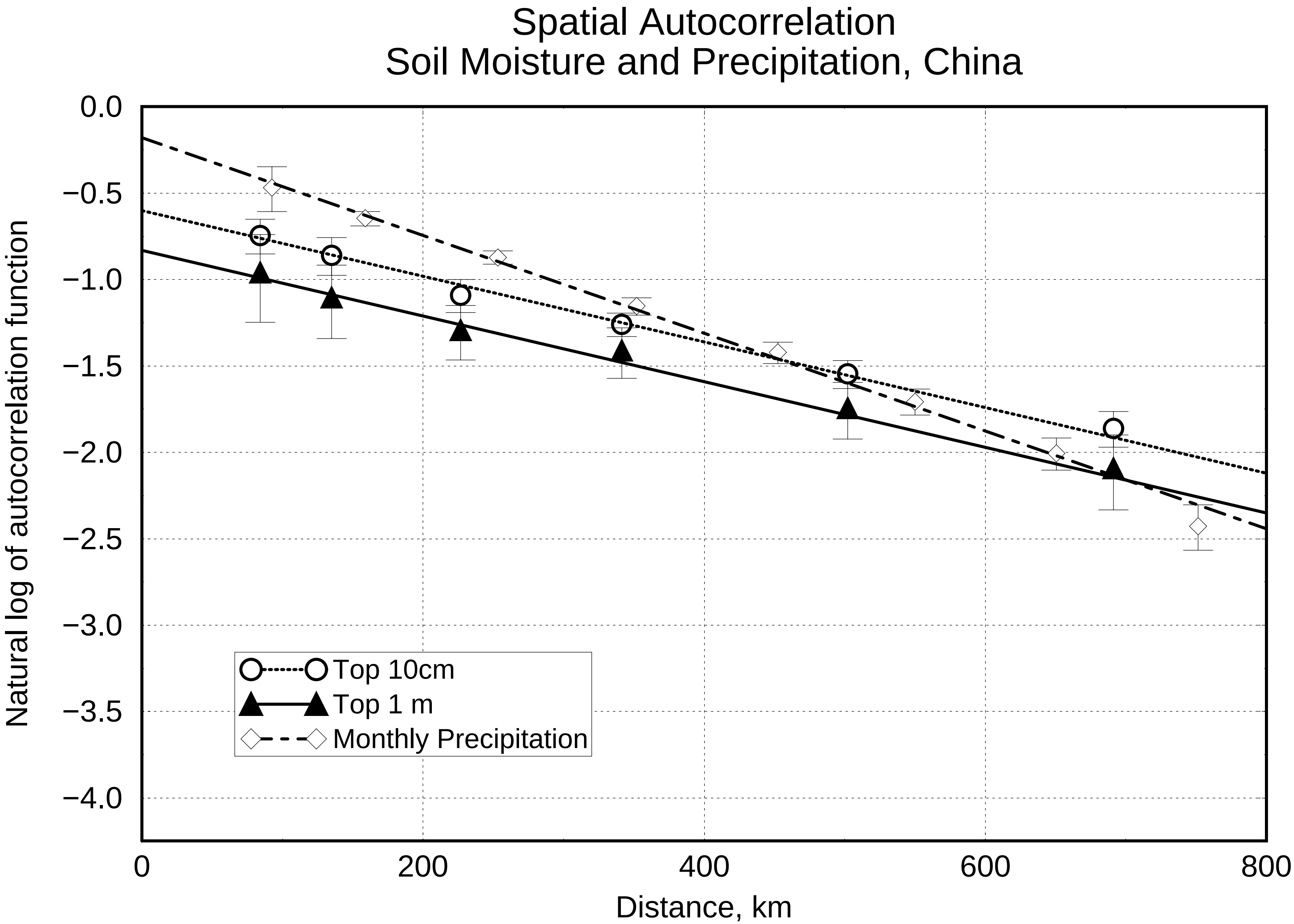

Spatial Autocorrelation
Soil Moisture and Precipitation, China
Natural log of autocorrelation function
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
0
200
400
600
800
Distance, km
Top 10cm
Top 1 m
Monthly Precipitation

Figure 10

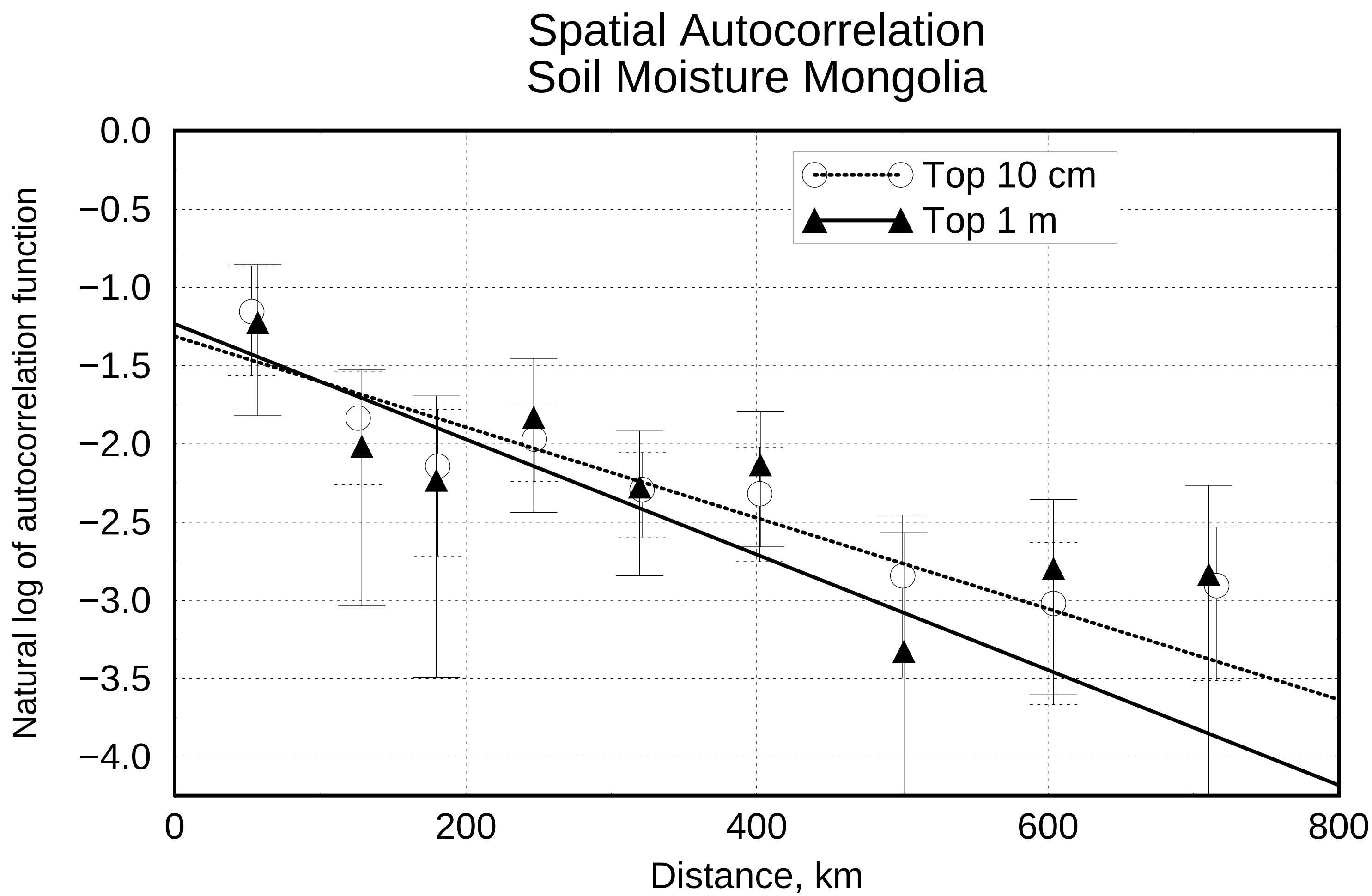

Spatial Autocorrelation
Soil Moisture Mongolia
Top 10 cm
Top 1 m
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
Natural log of autocorrelation function
0
200
400
600
800
Distance, km

Fig. 11

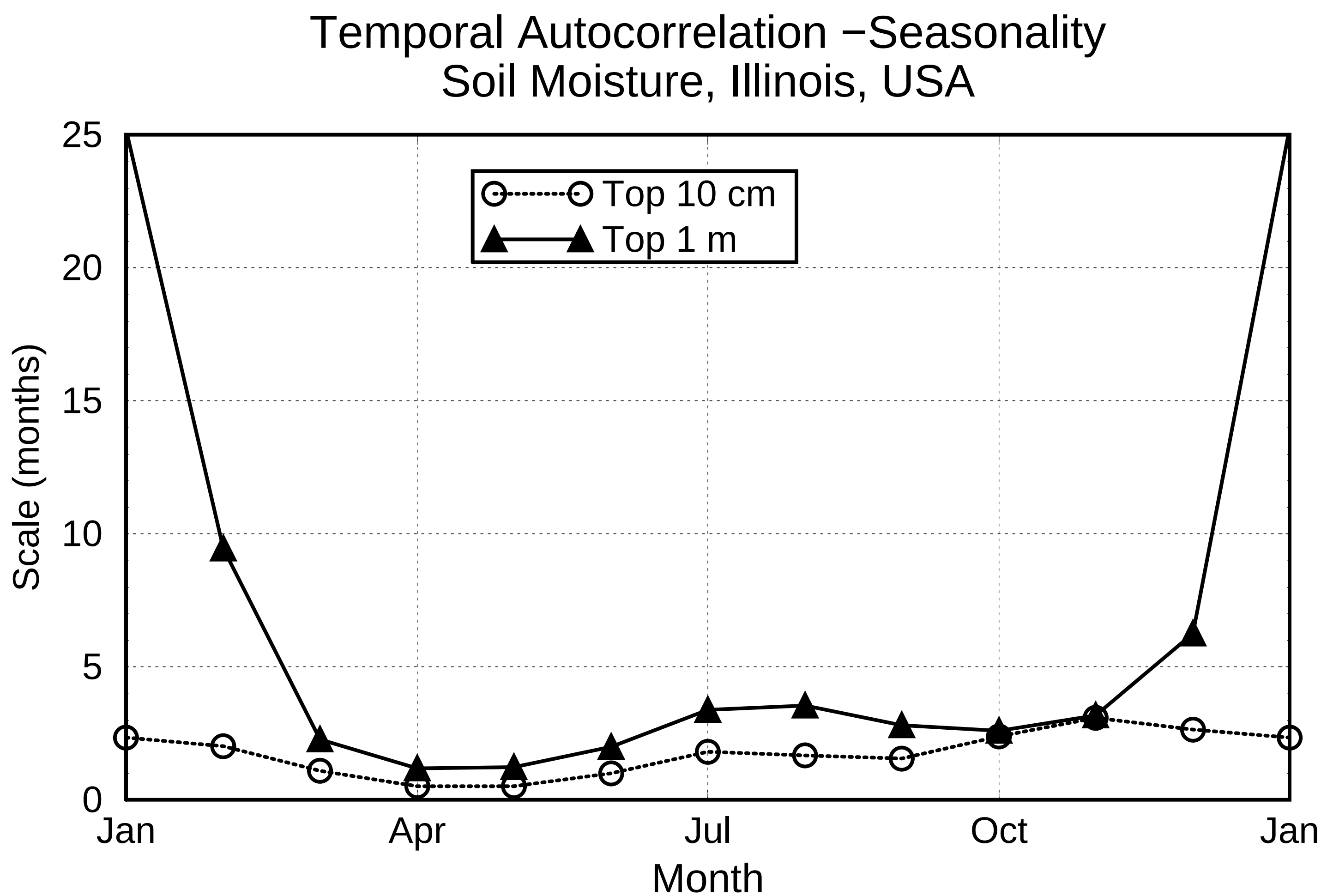
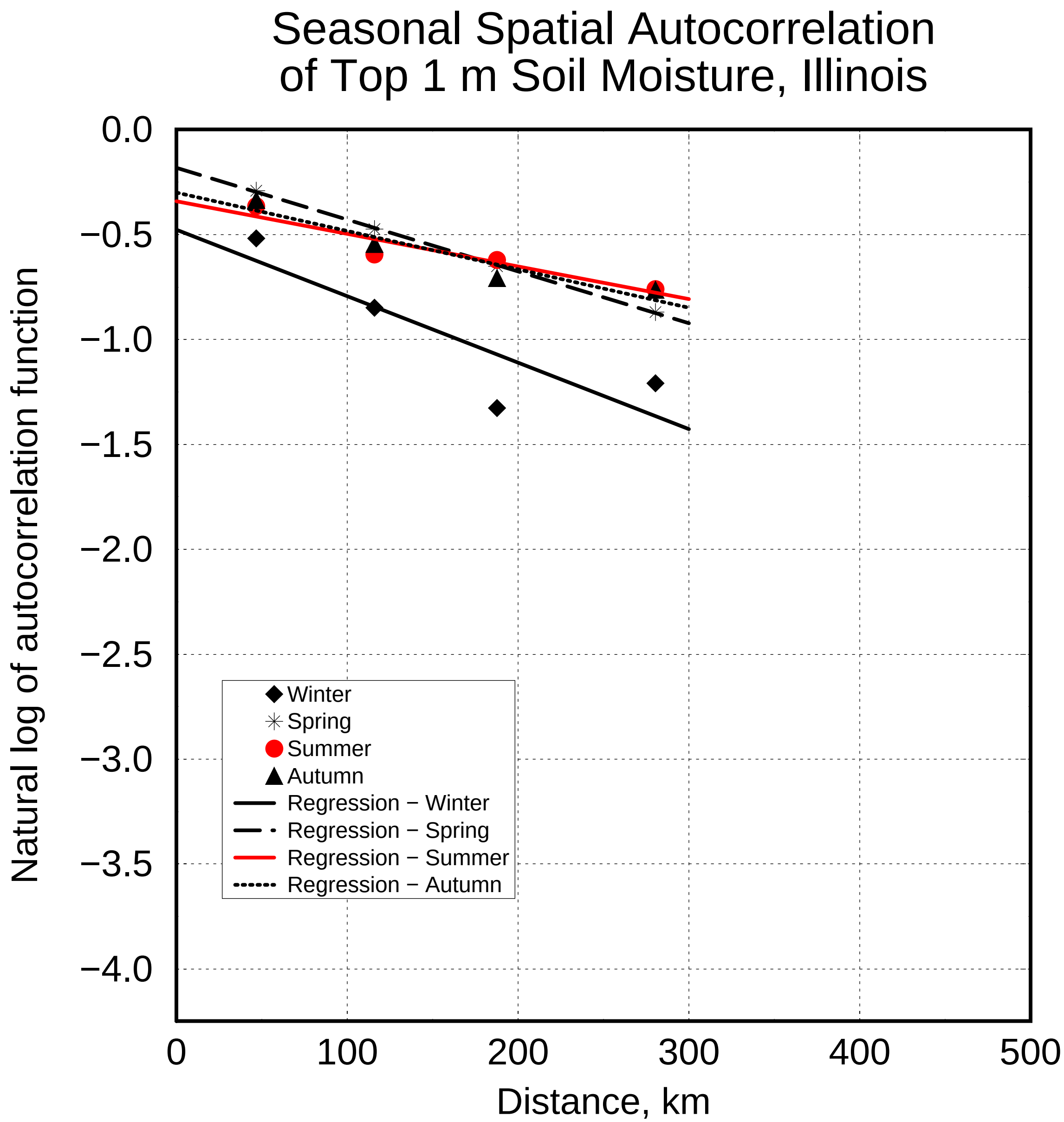

Temporal Autocorrelation −Seasonality
Soil Moisture, Illinois, USA
Top 10 cm
Top 1 m
Scale (months)
0
5
10
15
20
25
Jan
Apr
Jul
Oct
Jan
Month

Fig. 12



Seasonal Spatial Autocorrelation
of Top 1 m Soil Moisture, Illinois
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
−3.5
−4.0
Natural log of autocorrelation function
0
100
200
300
400
500
Distance, km
Winter
Spring
Summer
Autumn
Regression − Winter
Regression − Spring
Regression − Summer
Regression − Autumn

Fig. 13