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Technical Note: Field-Scale Surface Soil Moisture Patterns and Their Relationship to Topographic Indices

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Abstract

Understanding variability patterns in soil moisture is critical for determining an optimal sampling scheme both in space and in time, as well as for determining optimal management zones for agricultural applications that involve moisture status. In this study, distributed near-surface gravimetric soil moisture samples were collected across a 3.3 ha field in central Illinois for ten dates in the summer of 2002, along with dense elevation data. Temporal stability and consistency of the moisture patterns were analyzed in order to determine a suitable grid size for mapping and management, as well as to investigate relationships between moisture patterns and topographic and soil property influences. Variogram analysis of surface moisture data revealed that the geospatial characteristics of the soil moisture patterns are similar from one date to another, which may allow for a single, rather than temporally variable, variogram to describe the spatial structure. For this field, a maximum cell size of 10 m was found to be appropriate for soil moisture studies on most of the sampling occasions. This could indicate an appropriate scale for precision farming operations or for intensive ground sampling. While some areas had consistent behavior with respect to field mean moisture content, no conclusive relationships between the overall patterns in the moisture data and the topographic and soil indices were identified. There were, however, some small but significant correlations between these two sets of data, particularly plan and tangential curvature, and also slopes. In areas of convergent flow, moisture content exhibited a slight tendency to be wetter than average. There also seemed to be a small influence of scale on the relationship between moisture patterns and topographic curvatures.

Keywords

Geostatistics, Mapping, Precision agriculture

Disciplines

Agriculture | Bioresource and Agricultural Engineering

Comments

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FIELD-SCALE SURFACE SOIL MOISTURE PATTERNS AND THEIR RELATIONSHIP TO TOPOGRAPHIC INDICES

A. L. Kaleita, M. C. Hirschi, L. F. Tian

ABSTRACT. *Understanding variability patterns in soil moisture is critical for determining an optimal sampling scheme both in space and in time, as well as for determining optimal management zones for agricultural applications that involve moisture status. In this study, distributed near-surface gravimetric soil moisture samples were collected across a 3.3 ha field in central Illinois for ten dates in the summer of 2002, along with dense elevation data. Temporal stability and consistency of the moisture patterns were analyzed in order to determine a suitable grid size for mapping and management, as well as to investigate relationships between moisture patterns and topographic and soil property influences. Variogram analysis of surface moisture data revealed that the geospatial characteristics of the soil moisture patterns are similar from one date to another, which may allow for a single, rather than temporally variable, variogram to describe the spatial structure. For this field, a maximum cell size of 10 m was found to be appropriate for soil moisture studies on most of the sampling occasions. This could indicate an appropriate scale for precision farming operations or for intensive ground sampling. While some areas had consistent behavior with respect to field mean moisture content, no conclusive relationships between the overall patterns in the moisture data and the topographic and soil indices were identified. There were, however, some small but significant correlations between these two sets of data, particularly plan and tangential curvature, and also slopes. In areas of convergent flow, moisture content exhibited a slight tendency to be wetter than average. There also seemed to be a small influence of scale on the relationship between moisture patterns and topographic curvatures.*

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Soil moisture is a critical component of many systems, including agriculture, microclimate, and field-scale hydrology. However, use of soil moisture data in simulations and decision support systems in these areas is hampered by the fact that soil moisture varies in both space and time. Understanding the variation of soil moisture across a field can provide useful management information, and can aid in sampling system design. For example, assessment of soil moisture patterns is important for determining optimal management zones for agricultural applications that depend on moisture status (Delin and Berglund, 2005), such as precision irrigation (Starr, 2005). Understanding soil moisture patterns across a field is also important for interpreting other management information, such as penetrometer data (Hummel et al., 2004, Mouazen and Ramon, 2006,) soil electrical conductivity measurements (Allred et al., 2005), and patterns of disease outbreaks (Chong et al.,

2005). In addition, in some regions, near-surface soil moisture at or near the time of planting has an influence on crop yield (Jackson et al., 1987).

Numerous researchers have noted that moisture patterns within or across a given area exhibit some degree of temporal stability; that is, patterns of soil moisture persist in time even when the precise moisture levels change. Vachaud et al. (1985) found that certain locations within their roughly 0.2 ha study area were consistently wetter than the field average, while others were consistently drier, and still other locations were consistently at or near the average soil water storage. They also noted that there was a significant correlation between the soil water storage values from one sampling occasion to another. Jaynes and Hunsaker (1989) also noted a persistence of soil moisture patterns from one sampling occasion to another (before and after irrigation applications). Goovaerts and Chiang (1993), however, found a lower correlation when comparing 20 cm soil water contents between two dates, one in April and one in October. Pires da Silva et al. (2001) found a high degree of temporal stability in 20 cm moisture patterns from one day to the next, when looking at wetting and drying events separately. Martínez-Fernández and Ceballos (2003) found that in their study catchment, 5 cm soil moisture exhibited more temporal stability under dry conditions than wet conditions. Grayson and Western (1998), on the other hand, found that the overall moisture pattern was not stable in the four areas they monitored. Gómez-Plaza et al. (2000) found that 15 cm moisture patterns were stable at the transect scale, with differences apparent between dry and wet months.

Stable spatial patterns of soil water content are thought to be linked with properties that change little over time such as

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topography, soil particle size class, and drainage patterns, yet there is disagreement among researchers regarding which factors are the most influential. Vachaud et al. (1985) suggested soil particle size, particularly clay content, might play a role in explaining soil water temporal stability. Famiglietti et al. (1998) found that variability in surface (0-5 cm) soil water content along a downslope transect was related to porosity and hydraulic conductivity during wet conditions, whereas dry patterns were related to elevation, aspect, and clay content. Conversely, Green and Erskine (2004) found spatial water content to be more closely related to topography during the wettest conditions. Pachepsky et al. (2001) found that a regression model using slope, profile curvature, and tangential curvature explained over 60% of the variation in soil water content in the upper soil layers (4-10 cm). Qiu et al. (2001) noted that temporal dynamics of soil moisture were related to elevation, slope, and aspect in their study catchment. Because of variations and interactions between soil types, landscape management, and climate variables, it is likely that different factors are more influential in different regions and under different circumstances.

Understanding the important soil moisture patterns within a given area and their temporal stability can aid in identification of what some researchers have called average soil moisture monitoring sites (Grayson and Western, 1998). These sites are defined as locations within an area that are observed to have consistent behavior over time with respect to the average for that area (Vachaud et al., 1985). Such information could be useful for identifying the most advantageous sampling locations for a field in which intense monitoring is impractical, as well as for providing ground truth information for large-scale remote sensing imagery. Grayson and Western (1998) noted that methodologies were needed for determining catchment monitoring sites from topographic and soil characteristics. Their results suggested that areas of little convergence or divergence of flow (that is, where curvature was zero) and with aspect values close to catchment average, where radiative exposure is close to the average that the catchment receives, are likely candidates for being average moisture monitoring sites. Jacobs et al. (2004) found that these sites within fields tended to be located in areas of mild slope and moderate to moderately high clay content. Van Pelt and Wierenga (2001) noted that while relationships existed between soil texture and average moisture locations, more research is needed into the processes governing temporal stability of soil moisture before this concept can be widely used in production agriculture. In a precision agriculture setting, topographic data can be generated using the global positioning system of the tractor; thus, it is likely that high-density topographic data have been or can be obtained for fields managed in a site-specific system. High-density soil texture information, however, is more difficult, expensive, and time-consuming to obtain. Thus, of particular interest for typical precision agriculture settings is the influence of topographic data.

Moisture patterns in the field can be used for crop management purposes, but this requires determination of appropriate sampling and management zone size. Han et al. (1994) used geostatistical analysis to determine an optimal cell size for site-specific crop management. For field applications that are based on soil moisture, they used a single day's set of moisture data to determine a maximum cell size of 52 m from a

variogram analysis. However, since the variability in soil moisture can change over time, one sampling of data may not be sufficient to adequately determine an overall optimal cell size. Rahman et al. (2003) used a similar approach to recommend an optimal pixel size of 6 m or less for hyperspectral remote sensing images of chaparral and grassland in southern California to be used for vegetation indices, one of which was a plant water index.

Furthermore, one promising source of measurements of soil moisture is remote sensing, which offers the potential to generate repeatable spatial measurements (Kaleita et al., 2005). However, before this technology can be fully developed for agricultural purposes, an understanding of appropriate resolution and of the underlying variability in soil moisture is needed. The most promising type of this data is in the microwave region of the electromagnetic spectrum; in this region, the remotely sensed signal is responsive to soil water in approximately the top 6 cm (Jackson and Schmugge, 1989). Other research has shown potential for visible and near-infrared reflectance to be responsive to soil moisture to a similar depth under bare soil conditions (Kaleita et al., 2005). For this reason, the spatiotemporal variability at this depth has been of particular interest to researchers (Cosh et al., 2004; Mohanty and Skaggs, 2001; Jacobs et al., 2004; Famiglietti et al., 1998).

The objectives of this study were to investigate the spatial variability and temporal stability of near-surface soil moisture patterns for a central Illinois field in order to identify recommended management grid sizes and representative sampling locations, and to determine the relationship between the moisture patterns and topography to determine the extent to which soil moisture patterns can be predicted from invariant and readily available data.

LOCATION AND METHODS

A University of Illinois research farm field in southeast Urbana, Illinois (40° 3' 25" N, 88° 24' 11" W) was used in this study, with data collected during the 2002 growing season. The Grein field is a 3.3 ha corn field with moderate topographic variation; average slope is 1.2%, with a 4.6 m elevation difference across the field. Grein has two soil types: Dana and Drummer. Dana is a moderately well-drained silt loam with clay content between 18% and 27% in the upper 28 cm and between 27% and 35% below, while Drummer is a poorly drained, moderately permeable silty clay loam with clay content between 27% and 35% in the upper 36 cm (USDA-NRCS, 1998). No subsurface drainage systems are installed in this field. The field was tilled after harvest the previous fall, and cultivated in the spring just prior to planting. The field was planted so that there were alternating strips of corn (16 rows at 76.2 cm spacing) and bare soil (6.1 m wide), as several soil surface and vegetation canopy studies were being done in this field simultaneously (Kaleita et al., 2005; Yao et al., 2003).

On ten occasions from June through September of 2002, surface soil moisture measurements were collected using gravimetric sampling at 44 locations in a grid pattern across the field (fig. 1). The soil moisture data were collected from within the bare swaths, which reduced a potentially influential source of temporal and spatial variability in these data:

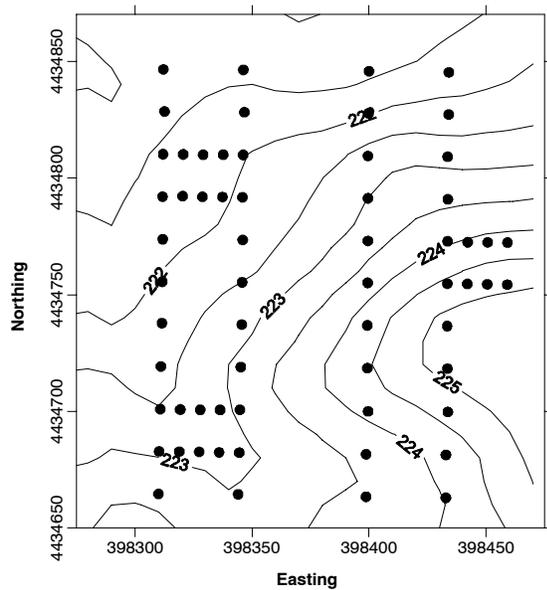


Figure 1. Sampling locations and Grein field topography. The contour lines represent elevation in meters. Easting and northing are given in UTM.

the impact of plant consumption of water and the vegetation's influence on infiltration and interception. Six transects of samples were also taken on nine of the ten occasions; these transect data were used only for establishing semivariograms. Sampling dates are shown with daily rainfall, obtained from a National Weather Service station in Urbana approximately 6.0 km from the field site, in figure 2. Sampling occasions were timed to capture a wide range of soil moisture conditions, from wet to dry. These grid dimensions, and the number of samples, were selected so that sampling of the entire field could be completed within a 2 h time period, minimizing the drying period from start to finish of the sampling.

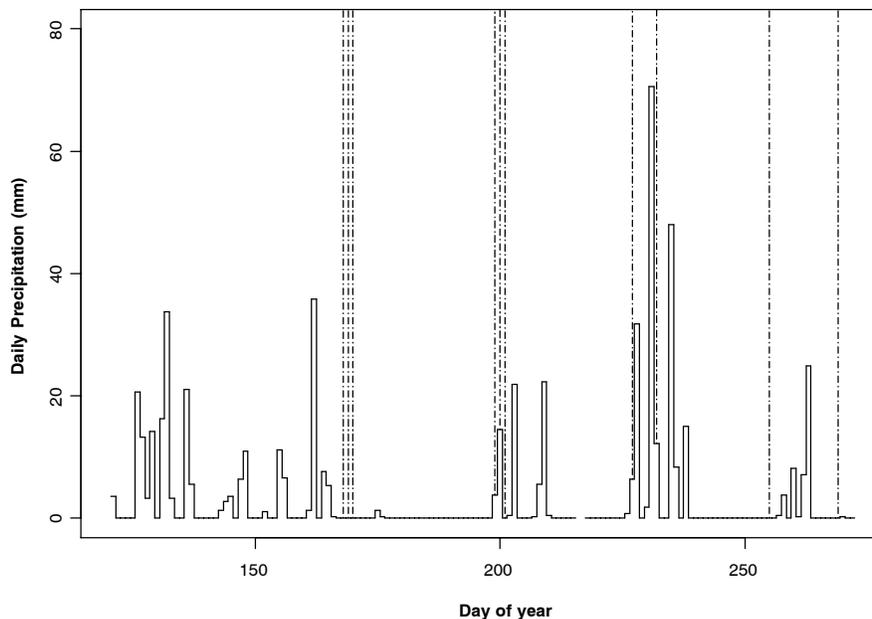


Figure 2. National Weather Service precipitation data for 1 June through 30 September 2002. Dates on which moisture data collection was done are marked with dotted lines. Those dates are: 17 June, 18 June, 19 June, 20 July, 21 July, 15 August, 20 August, 12 September, and 26 September.

Within a 1 m square area at each location, two 3.8 cm diameter, 7.6 cm deep soil cores were taken and placed in a zip-seal plastic freezer bag and labeled. After sampling of the entire field was completed, the samples were taken back to the laboratory, where they were removed from the bags and weighed. The samples were then oven-dried at approximately 100 °C for 23 h, removed from the oven, and re-weighed. Several initial tests of an additional 6 h at this temperature indicated sufficiently minimal additional drying of these samples after 23 h. The dry-based gravimetric soil moisture was then calculated for each sample.

For the purposes of determining optimal management grid size, the spatial variability must be quantified. One way to do this is to compute the semivariogram of the spatially distributed data. The semivariogram estimate for a given dataset is described by the equation:

$$g(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(u_{\alpha}) - z(u_{\alpha+h})]^2 \quad (1)$$

where $g(h)$ is the sample semivariogram, $N(h)$ is the number of pairs of data locations that are separated by the lag h , and $z(u_{\alpha})$ is the data value at location u_{α} .

The semivariogram measures the average dissimilarity between data separated by a certain distance. Therefore, the semivariogram is a common function in analysis of spatial patterns. In many cases, at a certain distance or range, the semivariogram stops increasing and fluctuates around a sill value that is equivalent to the standard deviation of independent samples in the dataset. For sampling points closer together than this range, measurements can be expected to be correlated with one another. By definition, $g(0) = 0$, indicating two samples at the same location should be equivalent, but in practice the estimated semivariogram may not approach zero as h decreases. This is called a nugget effect, and is a function of measurement error and/or spatial variation at smaller than measured scales. A full discussion of the semivariogram can be found in Goovaerts (1997).

In order to analyze the spatial statistics of the moisture data, semivariograms were computed, and subsequently an exponential model with nugget was fitted to each date's results using a nonlinear least squares fitting routine. In general, two models were sufficient to describe all of the semivariograms: the exponential model, and the nugget. The exponential model with nugget is described by the equation:

$$g(h) = C \left[1 - \exp\left(\frac{-3h}{a}\right) \right] + C_0 \quad (2)$$

where C is the estimated semivariogram sill, a is the range, and C_0 is the nugget.

After Han et al. (1994), maximum cell size for management purposes is defined as the mean correlation distance (MCD):

$$\text{MCD} = \int_0^{h_{\max}} \rho(h) dh \quad (3)$$

where h_{\max} is the maximum distance between points in the field. The normalized complement function $\rho(h)$ is related to the semivariogram $g(h)$ through the equation:

$$\rho(h) = \frac{C_0 + C - g(h)}{C_0 + C} \quad (4)$$

For situations in which h_{\max} exceeds the semivariogram range a , equations 3 and 4 reduce to the following equation for an exponential semivariogram model with nugget:

$$\text{MCD} = \left(1 - e^{-3}\right) \frac{aC}{3(C + C_0)} \quad (5)$$

In order to compare patterns in soil moisture from one date to another, Spearman's rank correlation coefficients (r_s) were computed using equation 6:

$$r_s(j, j') = 1 - \frac{6 \times \sum_{i=1}^m (R_{i,j} - R_{i,j'})^2}{m(m^2 - 1)} \quad (6)$$

where $R_{i,j}$ is the rank of the soil moisture at the i th location on the j th sampling occasion, and m is the total number of sampling occasions (Vachaud et al., 1985). This coefficient is more appropriate for temporal pattern analysis than the Pearson correlation coefficient, as drying and wetting may occur at different rates in different locations.

The mean relative difference in moisture content ($\bar{\delta}_i$) for each location i was computed as:

$$\delta_{ij} = \frac{\theta_i - \bar{\theta}_j}{\bar{\theta}_j} \quad (7)$$

$$\bar{\delta}_i = \frac{1}{m} \sum_{j=1}^m \delta_{ij} \quad (8)$$

where θ_i is the moisture at the i th location, $\bar{\theta}_j$ is the field average of all θ_i on the j th sampling occasion, m is the total number of sampling occasions, and δ_{ij} represents the deviation in soil moisture of the i th location from the field average on the j th sampling occasion. This represents the average pat-

tern of moisture in this field for the occasions that were sampled. Locations with negative values of $\bar{\delta}_i$ were, on average, drier than the field mean; locations with positive values of $\bar{\delta}_i$ were on average wetter.

It is of interest to understand to what extent the behavior of a given location with respect to the mean is consistent in time. In order to quantify this consistency, the point-field variance at each location was calculated as:

$$\sigma_i^2 = \frac{1}{m-1} \sum_{j=1}^m (\delta_{ij} - \bar{\delta}_i)^2 \quad (9)$$

Low values of σ_i^2 indicate that the difference between volumetric moisture content at that location and the field average was consistent across sampling occasions. To quantify locations that are both consistent and near field average, the root mean square error (RMSE) was calculated:

$$\text{RMSE}_i = \sqrt{\bar{\delta}_i^2 + \sigma_i^2} \quad (10)$$

While it is valuable to know the locations of sites that are representative of the field average or are consistent over time, *a priori* identification of these sites would require an understanding of how invariant influences like topography affect these patterns. High-density topographic survey data (approx. 1 m resolution in the x - y direction, accurate to approx. 5 cm) were collected for this field. No soil textural data beyond that of the soil survey were available for the Grein field. With only two soil types in the field, use of average values from the soil survey is likely too coarse a resolution to explain patterns in the moisture data.

Several topographic characteristics of the Grein field were computed on a 10 m grid from the elevation data: slope, aspect, plan curvature (the curvature along a contour line, perpendicular to the slope), profile curvature (the curvature in the direction of the slope), and tangential curvature (the curvature along a vertical plane tangential to a contour line). For the aspect data, which ranged from 0° to 360°, it was necessary to do a minor adjustment after computing this index. There is a discontinuity at 360°, and there were some data in this area. In order to eliminate the effect of the discontinuity, and because there were no data in the region from 100° to 200°, aspect values between 0 and 100 were increased by 360. For each sampling location, the grid box containing the respective UTM coordinates was used to match the data.

In addition to determining the topographic indices, several variants were also used for comparison. "Neutrality" for slope and aspect was calculated by taking the absolute value of the deviation of the index at each moisture sampling location from the field average of the index, so that neutrality is characterized by values close to zero. Absolute values of the curvature indices were also computed. Spearman rank correlation coefficients were then determined for comparison of topographic indices, as well as their variants, with the mean relative difference ($\bar{\delta}_i$), point-field variance (σ_i^2), and RMSE. Correlation with $\bar{\delta}_i$ would indicate that the index differentiates between areas that are typically wet and areas that are typically dry. An index well correlated with σ_i^2 would be useful for identifying locations with consistent behavior relative to the mean. An index correlated with RMSE could be used to identify locations that are consistently close to field average. Rank correlations, as opposed to Pearson correla-

tions, were used to account for monotonic but nonlinear relationships.

RESULTS AND DISCUSSION

For seven of the ten sampling occasions, spatial variability is well-described by a simple exponential variogram model, with or without a nugget (table 1, fig. 3). In the cases of 15 August, 12 September, and 26 September, no clear model is evident, and the variogram is best described by a pure nugget model. The ranges for the moisture data are fairly consistent; for all the models except those that are pure nugget, the range is between 32.8 and 68 m. The overall sills (including the nugget value) for the first seven dates are similar, between 2.27×10^{-4} m and 4.30×10^{-4} m, whereas they are below 1.65×10^{-4} for the last three dates. Maximum cell size for the sampling occasions varies from 8.2 to 21.5 m. For the dates that were modeled with a pure nugget semivariogram, computation of a maximum cell size is not possible. Theoretically, these dates have an infinitely small maximum cell size. A cell size of 10 m would be sufficient for six of the ten dates.

The difference between these results and those reported by Han et al. (1994), who found a maximum cell size of 52 m for a field on the University of Illinois Agricultural Engineering farm, which is within a mile of the Grein field, could be in part a function of sampling depth; the Han study used moisture measurements from the top 15 cm. The University of Illinois Agricultural Engineering farm fields are also essentially flat, eliminating the influence of topography on variability in soil moisture. Furthermore, MCD for soil moisture is temporally variable; thus, some of the difference may be in the unique characteristics of the sampling occasions.

Table 1. Exponential semivariogram model data and calculated maximum cell sizes for the Grein field by date. Because 15 August, 12 September, and 26 September were modeled by a pure nugget, computation of maximum cell size was not possible.

Date (2002)	Range (a) (m)	Sill (C)	Nugget (C ₀)	MCD (m)
17 June	67.8	3.00×10^{-4}	0	21.5
18 June	32.8	2.64×10^{-4}	0	10.3
19 June	62.5	2.35×10^{-4}	3.27×10^{-5}	17.4
19 July	67.3	1.65×10^{-4}	2.65×10^{-4}	8.2
20 July	47.8	3.27×10^{-4}	0	15.1
21 July	50.9	3.63×10^{-4}	0	16.1
15 Aug.	--	--	2.27×10^{-4}	--
20 Aug.	45.0	1.23×10^{-4}	0	14.3
12 Sept.	--	--	1.64×10^{-4}	--
26 Sept.	--	--	1.45×10^{-4}	--

When comparing moisture patterns from one date to the next (table 2), relatively low values of Spearman's rank correlation coefficients (maximum $r_s = 0.76$, average $r_s = 0.48$) indicate that a single day's sample is not sufficient to determine an overall moisture pattern for this field. Even on consecutive days where there was no rain (17 to 19 June), the moisture patterns are not tightly correlated; indeed, the highest correlation occurs on the two sampling dates that are the farthest apart in time (19 June and 26 Sept.). Nor do the patterns seem to be correlated on the basis of average moisture content (e.g., drier days do not exhibit more similarity to one another, on average, than they do to wetter days, and vice versa). Indeed, the driest day (21 July) and the wettest (15 Aug.) exhibit one of the highest rank correlations (0.69). Also given are the average moisture contents and the standard deviation in moisture for each date. No relationship was observed between average moisture content and standard deviation for this field.

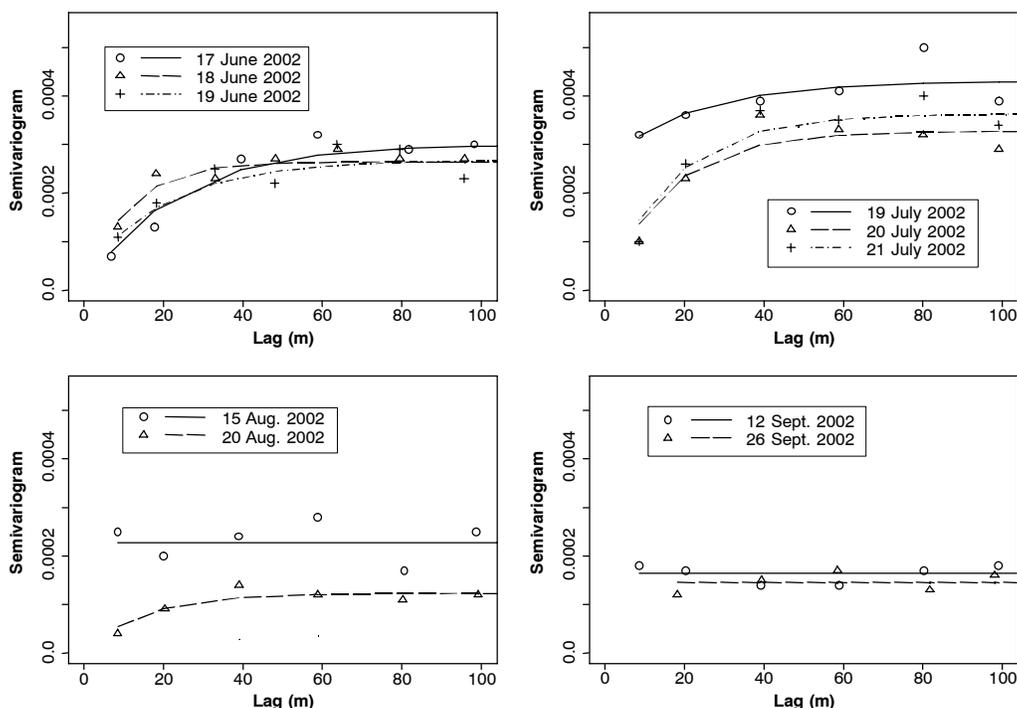


Figure 3. Estimated and modeled variograms for each sampling date. The computed variogram is represented by points, while the modeled variogram is represented by a line.

Table 2. Spearman's rank correlation coefficients for soil moisture patterns on ten dates during the summer of 2002, as well as mean and standard deviation of moisture content.

	17 June	18 June	19 June	19 July	20 July	21 July	15 Aug.	20 Aug.	12 Sept.	26 Sept.
Mean	0.18	0.17	0.17	0.12	0.25	0.22	0.18	0.24	0.13	0.15
Std. dev.	0.018	0.017	0.016	0.019	0.019	0.019	0.020	0.017	0.010	0.012
17 June	1									
18 June	0.57	1								
19 June	0.54	0.38	1							
19 July	0.61	0.42	0.26	1						
20 July	0.55	0.45	0.49	0.43	1					
21 July	0.53	0.42	0.46	0.32	0.72	1				
15 Aug.	0.61	0.31	0.59	0.47	0.71	0.69	1			
20 Aug.	0.50	0.31	0.31	0.33	0.36	0.53	0.55	1		
12 Sept.	0.54	0.48	0.48	0.31	0.46	0.43	0.40	0.31	1	
26 Sept.	0.76	0.58	0.58	0.37	0.55	0.50	0.65	0.42	0.56	1
$\bar{\delta}_i$	0.86	0.67	0.68	0.64	0.74	0.72	0.77	0.57	0.65	0.79

Some of this dissimilarity between dates could be an artifact of the sampling technique, since the destructive nature of the gravimetric sampling meant that samples could not be taken from precisely the same location on each occasion; rather, samples were located within a 1 m square area. It could also be that the 0-7.6 cm depth is too shallow and subject to enough temporal variation that the near-surface moisture pattern is not evidenced by comparing a single occasion's pattern to another single occasion's pattern.

Nonetheless, there are some similarities in the data, and there are areas in the field that generally tend to be wetter or drier than average. This pattern is shown in figure 4. One can note, for example, a typically drier area at the top of the hill. Overall, this mean relative difference pattern explains 52.2% of the variance in the original moisture data, when comparing all δ_{ij} values to $\bar{\delta}_i$. This implies that if the mean relative difference pattern for this field were known, then estimates of the mean moisture content at any time would enable one to capture a significant amount of the moisture pattern across the field at that time. These results are similar to those of Starr (2005), who used a pattern that accounted for 47% of the variability to develop a precision irrigation scheme for potatoes. However, because of the remaining variability, not all locations would be suitable for the purposes of determining estimates of the field average, nor for adjusting the temporally stable pattern for a given day's moisture condition.

Estimates of the mean moisture content could be determined by sampling at locations that are consistently representative of the field average (RMSE ≈ 0). Monitoring locations could also be located in places where the moisture content tends to be different from average, but consistently above or below the field average by the same amount ($\sigma_i^2 \approx 0$); observations at these locations could be used to scale the $\bar{\delta}_i$ pattern to simulate current conditions. The patterns calculated for the Grein field are shown in figure 5. As these figures illustrate, the region around (398445 E, 4434700 N) would be a poor place to sample the field if one were interested in capturing the field average, as this region does not have consistent behavior relative to the mean over time. Sampling in the area around (398400 E, 4434800 N), however, would provide an estimate of field-average soil moisture consistently.

In comparing these patterns to the aforementioned indices, while none of the rank correlations are high, there are significant ($p \leq 0.05$) relationships between $\bar{\delta}_i$ and plan

curvature ($r_s = 0.36$) and tangential curvature ($r_s = 0.40$), and between σ_i^2 and slope neutrality ($r_s = 0.30$) and absolute value of tangential curvature ($r_s = -0.36$). The relationship between $\bar{\delta}_i$ and plan curvature indicates a slight trend that, in general, areas of divergent flow are drier than areas of convergent flow. A similar relationship is true for tangential curvature. Relationships of topographic indices to σ_i^2 indicate that suitable locations for monitoring the field average have a slight tendency to be located in areas where flow is neither convergent nor divergent, and where slope is close to the field average. However, multiple linear regression models using several variables at a time to estimate the moisture patterns did not result in higher predictive value in any of the cases.

It is possible that one problem with this analysis is that of scale: the 10 m grid may not be the most appropriate resolution for examining the influence of topography on soil

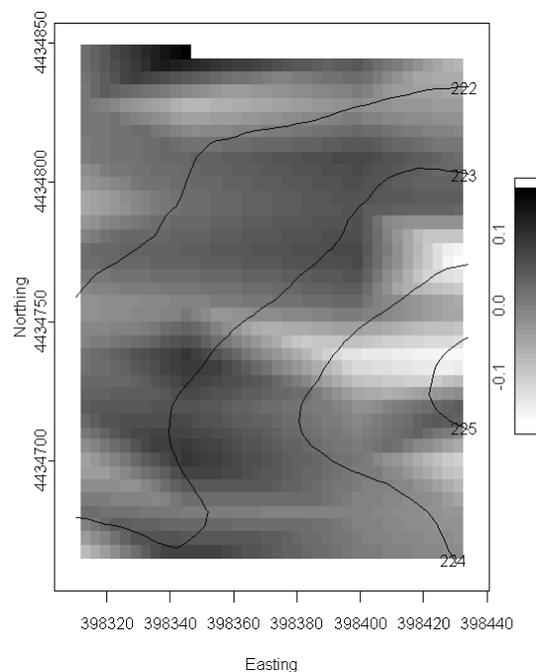


Figure 4. Interpolated spatial distribution of deviations from mean. Contours represent elevation in meters. Easting and northing are given in UTM. A triangulation interpolation method was used for the purpose of visualization.

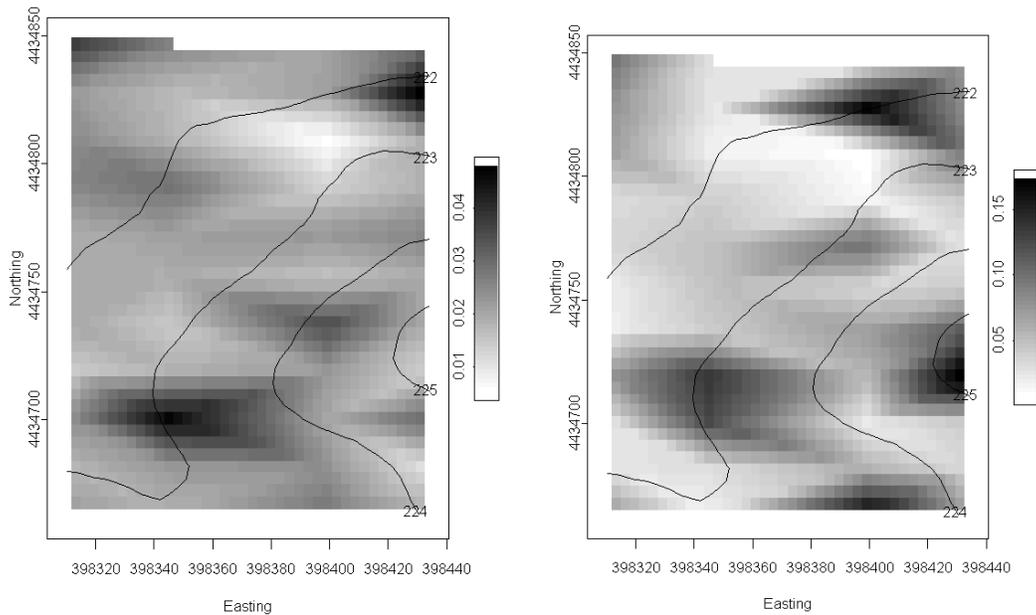


Figure 5. Interpolated spatial distribution of point-field variance (right) and RMSE (left). Contours represent elevation in meters. Easting and northing are given in UTM. A triangulation interpolation method was used for the purpose of visualization.

moisture patterns. Thus, the above analysis was repeated for 6 m, 4 m, and 2 m grid resolutions. Smaller grid resolutions were not investigated, since the resolution of both the moisture sampling data and the topographic survey were approximately 1 m.

Elevation, slope, and aspect values at moisture sampling locations were very similar for the four grid sizes. Values for plan, profile, and tangential curvature, however, exhibited significant differences with scale. Because plan and tangential curvature values were linked with relative mean difference in moisture content at the 10 m topographic resolution, $\bar{\delta}_i$ was compared to curvature values for the 6 m and 4 m resolutions as well (fig. 6). In the case of plan and tangential curvature, rank correlation increased with finer resolution from 10 m to 4 m, but decreased for the 2 m resolution. Rank correlation for profile curvature was insignificant for all but the 4 m grid. This indicates that there is likely some optimal scale on which to compare the moisture pattern and topographic data.

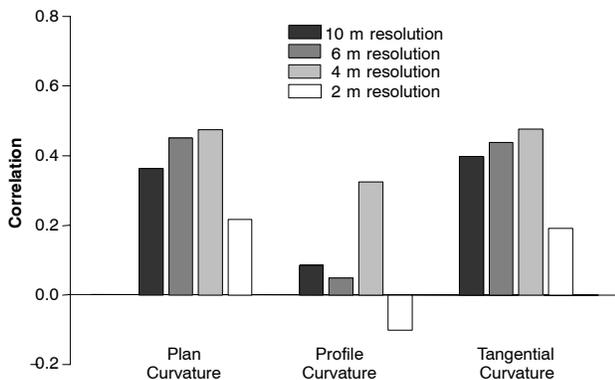


Figure 6. Correlation between relative mean difference in moisture content and curvatures for 10 m, 6 m, 4 m, and 2 m topographic grid resolutions.

CONCLUSIONS

Based on ten occasions of surface soil moisture observations across a 3.3 ha field, a maximum cell size of 10 m was found to be appropriate for moisture studies on most occasions. This could indicate an appropriate scale for precision farming operations such as site-specific irrigation, or for aggregating yield data to best capture potential site-specific variabilities. However, current technologies for in situ monitoring of soil moisture at this scale would be impractical, suggesting that precision irrigation technologies may be infeasible where the soil moisture is highly variable, without the aid of a method for estimation of distributed soil moisture data at a high resolution. At the same time, this scale could also indicate an optimal pixel size for remotely sensed studies of field moisture status. These data, in turn, could be used in a decision support system for precision agriculture management.

For the same field, a temporally stable pattern did not emerge by simply comparing the pattern on one day to the next and so forth. Repeated observations, however, did reveal a pattern in which certain areas were usually wetter or drier than the field average. Other locations were generally close to the field average over time. This pattern accounted for over half of the variability in the individual moisture patterns. While 48% of the spatial variability in soil moisture was thus not accounted for by this temporally stable pattern, there is nonetheless potential to use this pattern in a management scheme (Starr, 2005). This, however, should be done with an understanding that a significant amount of variability is not accounted for. Alternatively, this pattern can be useful in interpreting and responding to variability in crop yield. For example, should low crop yields occur in areas that tend to be dry, this would indicate that additional fertilization in these areas will likely be ineffective in raising yields. Multi-season work is necessary to determine how this pattern is affected by annual differences in weather patterns.

Some degree of temporal consistency is evident in this field, in that certain locations had repeatedly consistent be-

havior with respect to the field-average moisture content. These locations would be appropriate locations for long-term monitoring of field-average moisture content. This type of information is critical for validating remotely sensed estimates of soil moisture. These locations can also be used in large-scale irrigation scheduling using estimation of field-average moisture content, or in field-level modeling efforts of crop and hydrologic response.

The patterns in this field could not be well explained by topographic data. Lack of strong correlation to topographic indices could be due to the shallow nature of these measurements or to the relatively moderate topography in this field. Because topographic data alone are insufficient for generating temporally stable or consistent moisture patterns, extensive sampling would be necessary to establish these patterns. This extensive sampling could include repeated soil moisture measurement and/or soil texture information, which some research has shown to be influential (e.g., Vachaud et al., 1985; Famiglietti et al., 1998; Pires da Silva et al., 2001).

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