A Robust-Resistant Approach to Interpret Spatial Behavior of Saturated Hydraulic Conductivity of a Glacial Till Soil Under No-Tillage System

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Abstract
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Disciplines

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A Robust-Resistant Approach to Interpret Spatial Behavior of Saturated Hydraulic Conductivity of a Glacial Till Soil Under No-Tillage System

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A central Iowa glacial till soil under no-tillage condition was studied for its spatial behavior of saturated hydraulic conductivity (K) at the surface soil layers. Hydraulic conductivity measurements both in situ and in the laboratory were made at two depths of 15 and 30 cm at regular intervals of 4.6 m on two perpendicular transects crossing each other at the center of the field. Simplified split-window median polishing in conjunction with a robust semivariogram estimator were used to examine the spatial structure of the glacial till material. Results of this study indicated a nested structure of K at 30 cm depth. Soil clustering at the experimental site at intervals of 20 m, in addition to the soil microheterogeneity, contributed to variation in K, with an overall range of spatial dependence of K up to 60 m. Medians of split windows of 23 m width were found to be the "solo representatives" or "summary points" of the soil clusters contributing to spatial structure. In situ and laboratory measurements for K showed consistency in their trends even though some parametric variations were observed. K values observed near the soil surface at a depth of 15 cm were dominated by white noise and directional trends.

INTRODUCTION

Glacial deposits have often been regarded as one of the most variable and complex geological materials [Terzaghi and Peck, 1967; Dreimanis, 1976] and Lutenegger et al. [1983] concluded that the influence of genesis on various properties of till and diamiction materials occurs primarily as a result of gross differences in depositional environment and that supraglacial deposits are highly variable compared with basal till. These researchers determined that the postdepositional changes in glacial deposits can produce a complex set of effects on the behavior of the till soil. Moreover, recent studies indicate that preferential flow paths and spatial variability in hydraulic conductivity (K) of the soil have significant influence on chemical transport from agricultural fields to shallow groundwater [Kanwar et al., 1988, 1990a, b; Sharma et al. [1987] demonstrated that subsurface flow can be increased with increased spatial dependence in the hydraulic properties of the soil. Therefore more accurate characterization and quantification of K variability are needed to make reasonable estimates of water and chemical recharge rates to groundwater systems from glacial till agricultural watersheds.

Field experiments were conducted to study the spatial structure of K in a glacial till material in central Iowa, employing exploratory techniques and (robust) geostatistics. After appropriate scale transformations of measured K data were calculated using constant head and Guelph permeameters [Klute, 1965; Reynolds and Elrick, 1986], robust semivariograms were computed for two soil depths. A resistant approach of "split-window median polish" across transects was used to examine the appropriateness of the semivariograms. The main objective of this study was to examine the variability and the dependence of K on sampling distance, that is, minimum (optimum) number of representative samples to be analyzed to characterize K on a field scale. The second objective was to estimate and interpret semivariograms as a measure of continuity or autocorrelation of K for the glacial till material. The third objective was to observe the effect of soil depth on K variability. In addition to these objectives, consistency in semivariograms using two measuring techniques was also compared.

PREVIOUS APPLICATION

The geostatistical approach of using semivariograms [David, 1977; Journel and Huijbregts, 1978; Clark, 1979] to evaluate the spatial structure of soil properties has become increasingly popular. Several scientists in the last decade have devoted their attention to the spatial distribution of physical, chemical, and hydrogeological properties of soils. Gajam et al. [1981], Russo and Bresler [1982], Vaucelin et al. [1982], Yost et al. [1982], Russo [1984], Oliver and Webster [1986] and others used geostatistical estimators to determine the spatial structure of different soil properties. Webster [1985] summarized the various geostatistical tools available in the area of soil science. Onofio [1988] studied spatial and temporal variability of some tillage-induced soil physical properties of a Nigerian paleustult and found significant differences in soil macroporosity and K values due to tillage and date of sampling. Although most of these researchers used the basic assumptions needed for geostatistical analysis, they usually failed to examine whether the data measured in the field satisfied these assumptions [Horowitz and Hillel, 1983; Hamlett et al., 1986; Cressie and Horton, 1987]. Various studies by Cressie [1984, 1986], Cressie and Hawkins [1980], Cressie and Glonek [1984], Hamlett et al. [1986], and Cressie and Horton [1987] have introduced resistant and exploratory data analysis techniques such as effects of drift,
robust variogram estimation, and robust kriging to geostatistical analysis.

Techniques reported by Tukey [1977] for performing exploratory analyses could be adopted to characterize the spatial structure of soil properties. This paper demonstrates how the soil hydraulic conductivity data taken at spatial locations and arranged on a regular "cross" (i.e., two transects intersecting each other at the center of the field at an angle of 90°) can be analyzed with exploratory data analysis techniques when nonstationarity is the inherent property of most of the soils [Hamlett et al., 1986].

Theoretical Background for Spatial Analysis

Matheron [1963] proposed the technique of "Geostatistics" for spatial analysis of ore reserves from sampled data whose relative spatial locations were known. David [1977], Journel and Huijbregts [1978], and Clark [1979] have addressed this problem and presented case studies in the field of mining.

Experimental variograms are the main tools used to explore the spatial structure of soil properties in the field. Because these semivariograms can provide the basis for further geostatistical assessment of soil properties, accurate analysis of data is needed before developing semivariogram or kriging maps [Hamlett et al., 1986]. A brief theory of geostatistics is reviewed, with attention paid to crucial stationarity assumptions.

Assuming that $Z(x)$, a regionalized variable where $(x)$ denotes a location in the space domain $(I)$, is the random measurement of the case-specific soil property taken at location $(x)$, two types of stationarities are typically assumed that $Z(x)$ may satisfy. $Z(x)$ is said to be stationary of order 2 (i.e., second-order stationarity) if (1) $E(Z(x)) = m$, for any $x$, which states that the expected value of the random function in space exists and does not depend on location $x$, and (2) $E[(Z(x + h) - Z(x))^2] = C(h)$ for any $x$ and $h$, which states that for each pair of variables $(Z(x + h), Z(x))$ the covariance function $C(h)$ exists and does not depend on location but only on the separating vector $h$ [Journel and Huijbregts, 1978, p. 32]. The less demanding intrinsic hypothesis by Matheron [1963] makes the following stationarity assumptions, which are expressed entirely in terms of differences $(Z(x + h) - Z(x))$ of the regionalized variable: (1) $E[(Z(x + h) - Z(x))] = 0$, for any $x$ and $h$; in other words, one expects $Z(x)$ to be constant for any $x$ and $h$ in $I$, and (2) $2\gamma(h) = E[(Z(x + h) - Z(x))^2]$, for any $x$ and $h$, where $\gamma(h)$ is a semivariogram estimator which states that variance of the difference in soil property depends only on the separating vector $h$. Thus second-order stationarity implies the intrinsic hypothesis, but in the reverse is not true. Following Matheron [1963], Journel and Huijbregts [1978] and Burgess and Webster [1980] studied spatial variability using semivariograms and defined an average semivariogram $\bar{\gamma}(h)$ in a specific direction as

$$\bar{\gamma}(h, \alpha) = \left[1/2N(h, \alpha) \sum_{i=1}^{N} (Z(x_i + [h]) - Z(x_i))^2 \right].$$

where $\bar{\gamma}(h, \alpha)$ is a semivariogram estimator, $\alpha$ implies direction, $|h|$ is modulus of interval, $N$ is the number of pairs having a specified separating vector, and $Z(x_1), \ldots, Z(x_n)$ are soil property data taken at field locations $x_1, \ldots, x_n$. Journel and Huijbregts [1978, pp. 175 and 262] reported that semivariograms may be directionally dependent and that data can be checked for anisotropy by computing $\gamma(h, \alpha)$ for different $\alpha$. Note that for field data the separation vector $(|h|, \alpha)$ would present a range of values rather than a particular value.

Unfortunately, the field data of many soil properties generally contain some outliers that can obscure the whole $\gamma(h)$ estimation by increasing the variance. Among many others, Cressie and Hawkins [1980] proposed a modified estimator, known as a robust estimator, suitable to curtail the effect of these outliers by downweighting and defined as

$$\bar{\gamma}(h, \alpha) = \left[1/2N(h, \alpha) \sum_{i=1}^{N} (Z(x_i + [h]) - Z(x_i))^2 \right]^{1/2}.$$
EXPERIMENTAL METHODS

A 115 m x 183 m experimental plot was used for this study at the Agronomy and Agricultural Engineering Farm near Boone in central Iowa. Soil types in this plot were Nicollet loam and Clarion loam derived from glacial till. The plot had gentle slopes of less than 2% on the north and was on a slightly convex rise on the south with low relief [U.S. Department of Agriculture, 1984]. It has also been under no-tillage management for the last 6 years. A Guelph permeameter [Reynolds and Elrick, 1986] was used to measure the in situ values of K at sites located on two perpendicular transects crossing at the center of the field. The transects were oriented in NW-SE and NE-SW directions along the major and minor axes of the field and are shown in Figure 1. This type of sampling pattern is not commonly used to study the spatial dependence of soil hydraulic properties. The design was intended to limit the number of K measurements and to generate sufficient number of pairs at intermediate lag distances. The sampling pattern also provided an adequate number of pairs for directional geostatistical analysis and for exploratory data analysis in NW-SE and NE-SW directions.

K measurements with the Guelph permeameter were made at 4.6-m intervals on both transects, at 15 and 30 cm depths. This resulted in 66 in situ measurements of K for each depth (as shown in Figure 1). All K measurements were made in the crop rows to avoid compaction due to wheel traffic, which would lower K values significantly by reducing total porosity and macroporosity [Onofik, 1988]. The Guelph permeameter method described by Reynolds and Elrick [1986] was adopted for measuring the steady rates of recharge at 5 and 10-cm heads, and K values were calculated using the relationship based on Richard's analysis for steady state discharge from a cylindrical well in an unsaturated soil.

In addition to the Guelph permeameter technique, six undisturbed soil cores were taken from each of the 66 sites, with three replicates from each depth. Undisturbed soil cores (76 mm in diameter and 76 mm long) were collected with an Uhland core sampler for K measurements in the laboratory, using the constant head permeameter method [Klute, 1965]. For the method, 198 (3 x 66) cores were collected from 66 sites for each depth. After discarding few bad samples, 185 samples for the 15 cm depth and 188 samples for the 30 cm depth were analyzed. Details on the method of collecting undisturbed soil cores for K determination in the lab are given by Kanwar et al. [1989].

EXPERIMENTAL RESULTS

Table 1 and Figure 2 give the summary of the experimental K values obtained using the in situ Guelph permeameter and the laboratory constant head permeameter methods. The K values shown in Figure 2 for the laboratory method are the

<table>
<thead>
<tr>
<th>Method Adopted</th>
<th>Lab* Depth</th>
<th>Field Depth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15 cm</td>
<td>30 cm</td>
</tr>
<tr>
<td>Number of observations</td>
<td>185</td>
<td>188</td>
</tr>
<tr>
<td>Average, cm/s</td>
<td>$6.293 \times 10^{-4}$</td>
<td>$8.737 \times 10^{-4}$</td>
</tr>
<tr>
<td>Maximum, cm/s</td>
<td>$2.662 \times 10^{-3}$</td>
<td>$2.163 \times 10^{-3}$</td>
</tr>
<tr>
<td>Minimum, cm/s</td>
<td>$5.240 \times 10^{-5}$</td>
<td>$3.037 \times 10^{-5}$</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>$5.664 \times 10^{-4}$</td>
<td>$6.296 \times 10^{-4}$</td>
</tr>
<tr>
<td>Variance</td>
<td>$3.208 \times 10^{-7}$</td>
<td>$3.965 \times 10^{-7}$</td>
</tr>
<tr>
<td>Coefficient of variation, %</td>
<td>90.00</td>
<td>72.07</td>
</tr>
</tbody>
</table>

*These statistical parameters are based on average K (i.e., of three replicates).
arithmetic averages of three replicates collected from each site. On the average the constant head laboratory method provided higher K values than the Guelph permeameter method. Moreover, the standard deviations and coefficient of variations for K were generally higher for the laboratory method in comparison with the Guelph permeameter method. These differences between lab and field data could have been caused by macroporosity effects, experimental method effects, and/or sample volume effects. A study by Lauren et al. [1988] showed a large variation in K values due to sample volume used when the soil contained macropores. They found more accurate K estimates with larger soil samples. Our study contained a large number of macropores (wormholes and root channels) oriented nearly vertically within the top 30 cm of the soil. The wormholes and root channels were different in size and density at 15 and 30 cm depths because of differential growth and density of plant roots at different depths [Singh et al., 1991].

In addition to the sample volume or macropore effects, the variation between the lab and Guelph permeameter methods might be compounded because of the inherent differences. The Guelph permeameter measures the composite of horizontal and vertical values for K under anisotropic conditions, whereas the lab method determines the vertical K values. Moreover, the K values measured by the Guelph permeameter are also affected because of smearing of the well wall, compaction, and air entrainment, which could also reduce the conductivity in comparison with the measured K values in the lab. For some soil cores we observed extremely high K values due to short-circuiting of water through the unexpectedly large number of continuous macropores (channels). Similar phenomena have been reported by Lauren et al. [1988] and Kanwar et al. [1989].

Spatial Analysis and Discussion

Robust-Resistant Approach for Semivariogram Development

Exploratory techniques [Tukey, 1977; Velleman and Hoaglin, 1981] are suitable for spatial analyses of soil properties using resistant (i.e., arithmetically stable) and robust (i.e., model stable) methods [Hamlett et al., 1986; Cressie and Horton, 1987]. Incorporating resistant measures and robust ideas, the basic objective of exploratory data analysis techniques is to overcome the nonstationarity within the experimental data, which is a common occurrence under field conditions. Downweighting by a robust estimator [Cressie and Hawkins, 1980] or removal by resistant measures [Tukey, 1977] of any outliers present in a data set helps to achieve the stationarity conditions for the semivariogram development.

For the K data collected in this study a resistant technique (little affected by data outliers) was used to examine the spatial structure of K values in conjunction with geostatistics. Normal probability plots and plots of median against interquartile range squared were also developed to examine the data distribution and variance stationarity. The running median smoother approach [Velleman and Hoaglin, 1981, pp. 163] is simplified to a split-window median polish technique for our spatial analysis and is discussed in the following sections. A major finding is that while serving as an efficient smoothing tool, the median behaves more as a "sole representative" or "summary point" for the data set of a particular window.

Figure 2 shows normal probability plots of raw K data for two soil depths using two methods (i.e., in situ Guelph permeameter and laboratory constant head permeameter). These plots show a highly skewed distribution of K data. For the resistant analysis, stationarity of the variances against medians was checked. Because we matched our sampling grid design and expected soil clustering in the glacial till material (due to differential and incremental deposition of soil material during the process of formation and afterward), both transects were divided into a number of regular windows each having an equal number of sampling sites. Figure 3 shows the median of the windows and their interquartile range squared to inspect the stationarity of variance. This figure shows that the variance (interquartile range squared) is correlated with the median value, indicating the presence of nonstationarity in the variance. To remove the nonstationarity and nonnormality in the data sets, different transformations and resistant-based remediation techniques were tried.

K data were transformed to produce a nearly normal distribution (i.e., approximately symmetric, bell-shaped stem-and-leaf plot), and homogeneous variances [Cressie, 1985] using the "universal transformation principle." Different transformations were invoked to squeeze or spread the data set to obtain a more bell-shaped or Gaussian curve. Square root, cube root, and other power transformations [Tukey, 1977; Cressie and Horton, 1987] and scaled transformations [e.g., Bresler et al., 1982] yielded good results in transforming the nonnormal data sets to nearly normal data sets. But the question arises about the stationarity of variance, which could not be assured by these transformations. Log transformation yielded fairly homogeneous variance (i.e., interquartile range squared) with respect to the median of windows across the transects (Figure 3) for K values at 15 cm depth (lab method) but did not show much improvement for K values at 30 cm depth. A comparison of Figure 2 illustrating raw K data with Figure 4 illustrating log-transformed K data and the χ² test (Table 2) clearly indicate that K values tend to be lognormally distributed. Although log transformation has nearly normalized the data set, the presence of local trends or regional clustering in the soil might be causing the nonstationarity. Therefore normalized data is assumed to follow the relation

\[ Z(x) = \mu(x) + \varepsilon(x), \]

where \( Z(x) \) denotes the log-transformed regionalized variable at location \( x \), \( \mu(x) \) is a measure of central tendency, that is, deterministic drift of the variable at location \( x \), and \( \varepsilon(x) \) is the random component at location \( x \) normally distributed with zero mean, which satisfies the second-order stationarity required for spatial analysis. All experimental K data were therefore log-transformed, and loge K values were used for further analysis. But at the same time it is known that additivity principles are valid only on the same scale [Cressie, 1985]. Therefore it was decided to carry out the entire analysis with the data on log scale and to transfer the results to the original scale whenever required.
Fig. 2. Steady state $K$ data: (a) 30 cm, field; (b) 30 cm, lab; (c) 15 cm, field; and (d) 15 cm, lab. Spatial distribution plots are on the left and normal probability plots are on the right.
Fig. 3. Median-interquartile range squared plots for $K$ data sets: raw data (left) and log-transformed data (right).

**Semivariograms at 30 cm Depth**

Experimental semivariograms based on $\log_e K$ values were developed and are presented in Figure 5. These two-dimensional mean isotropic semivariograms were based on all 66 log-transformed data (with wild outliers present). A robust estimator [Cressie and Hawkins, 1980], however, was used to curtail the effects of these outliers by downweighting. Strong positive spatial dependence was found for both in situ and lab methods at a depth of 30 cm under no-till conditions. Figures 5c and 5d show plots of $\hat{\gamma}(h)$ versus $h$. The dip in the lag range of 15 to 30 m may be an indication of some kind of short-scaled variation in $K$. It may be cyclic or clustered. Short-scale variation should not be confused with microheterogeneity of soil. Moreover, these semivariograms show an overall range much higher than these short-scale variational ranges. The lower "nugget effect" in comparison with the sill value in Figures 5c and 5d indicates that spatial structure dominates microheterogeneity in the soil. At the same time, moderately steeper slopes of these variograms signify the changes in $K$ values, indicating moderately irregular, erratic, or discontinuous surfaces.

Directional semivariograms ($\gamma_i$) as shown in Figures 5c
and 5d at 30 cm depth were developed along the transects (NW-SE and NE-SW) and along the diagonal directions (N-S and E-W), with a tolerance of ±22.5°. The average semivariogram \( \gamma^* \) using the weighted average \( \left( \frac{1}{ni} \Sigma_i \gamma_i \right) \) was developed. All-directional mean isotropic variograms \( \bar{\gamma} \) compared well with average variograms \( \gamma^* \). But the directional semivariograms show new interesting behaviors. In both instances (laboratory and in situ) the main feature of directional variation is easily observed. Sill is maximum for \( \gamma \) in the NW-SE direction and minimal in the E-W direction, although the range remains approximately the same for all directions. Looking at Figures 5c and 5d, it is difficult to differentiate whether the difference between these directional variograms are due to the proportional effect or to anisotropy indicating the underlying depositional process of glacial till. Looking at the semivariograms toward higher lag distances, one might assume that the phenomenon is proportional. By focusing the comparison near the origin, one might conclude that the phenomenon is indeed zonal anisotropy [Journel and Huijbregts, 1978, p. 181; David, 1977, p. 135], which may not be true because all measurements were made at the same depth (30 cm). Moreover, because the sampling scheme adopted was regular and on bisecting transects, the chances of clustered-sampling locations were eliminated, and such locations are the usual causes of "quasi-stationarity" producing a "proportional effect" in semivariogram estimates. Therefore it is difficult to determine the cause of the underlying process contributing to the spatial structure of \( K \). The proportional effect, however, seems to be effecting more than the anisotropy effects, considering the nonstationarity of the log-transformed data due to soil clustering described earlier. Therefore all-directional mean isotropic semivariograms estimated using the entire \( K \) data set for both transects

<table>
<thead>
<tr>
<th>Method</th>
<th>Depth, cm</th>
<th>( K )</th>
<th>( \chi^2 )</th>
<th>Degrees of Freedom</th>
<th>P.L.</th>
<th>( \ln K )</th>
<th>( \chi^2 )</th>
<th>Degrees of Freedom</th>
<th>P.L.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lab</td>
<td>15</td>
<td>33.36</td>
<td>4</td>
<td>&lt;0.005</td>
<td></td>
<td>3.17</td>
<td>3</td>
<td>0.366</td>
<td></td>
</tr>
<tr>
<td>Lab</td>
<td>30</td>
<td>13.45</td>
<td>4</td>
<td>0.0093</td>
<td></td>
<td>11.3</td>
<td>3</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td>Field</td>
<td>15</td>
<td>40.55</td>
<td>4</td>
<td>&lt;0.005</td>
<td></td>
<td>7.19</td>
<td>4</td>
<td>0.124</td>
<td></td>
</tr>
<tr>
<td>Field</td>
<td>30</td>
<td>19.67</td>
<td>3</td>
<td>&lt;0.005</td>
<td></td>
<td>6.94</td>
<td>3</td>
<td>0.072</td>
<td></td>
</tr>
</tbody>
</table>

P.L., level of significance.
represent the spatial structure of the till soil at 30 cm. The "short-scale variation," representing the clustering phenomenon, and the "large-scale variation," indicating soils of similar hydraulic properties, seem to have greater spatial correlation (i.e., smaller $\gamma$ values) along the NE-SW transect than along the NW-SE transect. The orientation of maximum and minimum continuity along these directions suggests incremental deposition causing layered and overlapping soils.

**Semivariograms at 15 cm Depth**

Semivariograms for 15 cm depth (Figures 5a and 5b) were of dissimilar characteristics and dominated by white noise and trends. Even though semivariograms $\gamma(h)$ for the Guelph permeameter and lab methods did not match very well, both revealed a typical concave trend, and the one for lab measurements was more prominent. In these variograms the higher nugget effect versus sill is caused by random variability of "microheterogeneity" in comparison with structural variation, indicating a weak spatial dependence. Possible reasons for this variation are farm traffic and freezing and thawing phenomena which break the soil structure unevenly at the surface of no-till soil. Hamlett et al. [1986] observed a similar phenomenon for their soil water tension study in no-till plots, which was due to variability in soil surface residue cover and soil pore continuity. From this evidence it can be concluded that the no-till plots lack good spatial structure at the surface soil layer of 0-15 cm.

**Theoretical Model Fitting**

Usually, the forecasting of variogram models facilitates follow-up spatial studies. Therefore an effort was made to generalize the structural trends by fitting experimental semi-
variograms with standard theoretical models. The fitted theoretical models were found useful in analyzing and interpreting our results of the split-window-based resistant approach.

Theoretical models were fitted for the experimental variograms at 30 cm depth by the trial and error approach and were validated using a simple point-kriging approach (see Figures 6a and 6b). The developed theoretical models for the observed $K$ data had a nested structure with three distinct components. A small "nugget effect" ($C_0$) indicates inherent "microheterogeneity" of soil samples. A spherical model with sill ($C_1$), which fabricates the structure of the soil within a lag distance of about 20 m, could be termed a "short-scale variation." The third component, modeled with another spherical model with sill ($C_2$), indicating "large-scale variations," had an overall range of spatial dependence for $K$ up to 60 m (in situ method). An exponential model with the same sill and range, however, showed equally good fit as the spherical one but showed the typical asymptotic behavior. Thus the spherical one was preferred over the exponential one. The overall nested structure of the models and their characteristic parameters are presented in Tables 3 and 4. Comparison of these models for two different $K$-measuring techniques showed excellent consistency in their trends even though some variations in their parametric values were observed. The three major cross-validation criteria (KAE, KRMSE, and KMSE) estimated are shown in Table 5. Values of KAE, KRMSE, and KMSE were close enough to their recommended optimum. Correlation coefficients ($R^2$) between the regionalized variable and the kriged estimate were reasonably good at 0.64 and 0.58 for lab and in situ methods, respectively, ensuring the nested model as a good fit (Figure 7).

Summarily, the semivariograms of log-transformed data $Z(x)$ for 30 cm depth show cyclic or clustering behavior at about 20 m lag distance, thereby indicating a nonrandom shift for both measuring techniques. At 15 cm depth for $K$ values measured with the Guelph permeameter the normal probability plot and the semivariogram estimators confirm the effect of random variability contributing toward the "nugget effect." The semivariogram estimators at 15 cm depth for lab measurements (Figure 5b) showed, however, a typical linear drift in the NW-SE direction. Handling this kind of cyclic or clustering pattern and/or directional trend and coming up with model parameters is not a trivial task [David, 1977, p. 266; Journel and Huijbregts, 1978, p. 313]. Webster and Burgess (1980), Yost et al. (1982), and other researchers have discussed methods of handling drift (or detrending the data) by modeling it and using up to second-degree polynomials. On the other hand, Hamlett et al. (1986) adopted the nonparametric median polish approach [Tukey, 1977] to remove the drift along all grid directions and found it a better and more economical approach than the former because the nature of data or residuals can be visualized after every operation. This approach could support the spatial analysis by judging the normality of data and stationarity of variance and of median and by revealing the presence or removal of drift or clusters, resulting in interpretable semivariogram estimators $\gamma(h)$.

**Split-Window Median Polish**

Following semivariogram development, an exploratory approach of "split-window median polish" was used to analyze and interpret the behavior of the log$_e$ $K$ data sets. This approach was found suitable for analyzing the cyclic or clustering behavior of the data sets. Both the NE-SW and NW-SE transects were split into a number of spans or windows of equal lengths (and equal numbers of sampling sites because of the regular sampling pattern). Medians of these windows were estimated. Window lengths having odd three (13.8 m), five (23 m), and seven (32.2 m) numbers of sampling points were chosen to calculate the medians of the windows of $K$ data. Windows of up to a maximum of seven sites (i.e., 32.2 m) were considered, because the previous estimated semivariograms for the log-transformed $K$ values at 30 cm depth showed a clustering behavior in the spatial structure at a lag distance of about 18 to 23 m. The first

<table>
<thead>
<tr>
<th>Depth, cm</th>
<th>Method</th>
<th>Models</th>
<th>Applicable Range, m</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>lab</td>
<td>$\gamma(h) = 0.265 + 0.583(1.5h/18 - 0.5h^3/18^3) + 0.715(1.5h/46 - 0.5h^3/46^3)$</td>
<td>$h &lt; 18$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma(h) = 0.265 + 0.583 + 0.715(1.5h/46 - 0.5h^3/46^3)$</td>
<td>$18 \leq h &lt; 46$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma(h) = 0.265 + 0.583 + 0.715$</td>
<td>$h \geq 46$</td>
</tr>
<tr>
<td>15</td>
<td>field</td>
<td>$\gamma(h) = 0.663 + 0.742(1.5h/23 - 0.5h^3/23^3) + 0.954(1.5h/60 - 0.5h^3/60^3)$</td>
<td>$h &lt; 23$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma(h) = 0.663 + 0.742 + 0.954$</td>
<td>$23 \leq h &lt; 60$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma(h) = 0.663 + 0.742 + 0.954$</td>
<td>$h \geq 60$</td>
</tr>
</tbody>
</table>

**TABLE 4. Summary of Spatial-Dependent Parameters of ln K at 30 cm Depth for the Glacial Till Soil**

<table>
<thead>
<tr>
<th>Method Adopted</th>
<th>Depth, cm</th>
<th>Nugget Effect ($C_0$)</th>
<th>Structural Component</th>
<th>Range</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Sill $C_0/C_1&amp;C_2$</td>
</tr>
<tr>
<td>Lab</td>
<td>30</td>
<td>0.265</td>
<td>0.583*</td>
<td>0.715*</td>
<td>1.563</td>
</tr>
<tr>
<td>Field</td>
<td>30</td>
<td>0.663</td>
<td>0.742*</td>
<td>0.954*</td>
<td>2.359</td>
</tr>
</tbody>
</table>

*Spherical.*
TABLE 5. Values of Cross Validation Criteria for the Nested Models of ln K at 30 cm Depth

<table>
<thead>
<tr>
<th>Method</th>
<th>Depth, cm</th>
<th>KAE</th>
<th>KRMSE</th>
<th>KMSE/SD</th>
<th>Search Radius, m/Neighborhood Size</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lab</td>
<td>30</td>
<td>-0.0033</td>
<td>1.0556</td>
<td>0.8963/1.196</td>
<td>46/10</td>
<td>0.64</td>
</tr>
<tr>
<td>Field</td>
<td>30</td>
<td>-0.0173</td>
<td>1.0041</td>
<td>1.1127/1.368</td>
<td>60/13</td>
<td>0.58</td>
</tr>
</tbody>
</table>

The best sets of residuals were obtained with a window width of 23 m (of five sites) with nearly normal distribution. Stem-and-leaf plots and normal probability plots are shown in Figure 8 for 23-m windows. Moreover, the medians of these residuals for all the windows across the transects were zero irrespective of interquartile range squared, which satisfies the variance and median stationarity rule for semivariogram development.

Median-polished residual values were used for semivariogram estimation and are plotted in Figure 9. Instead of achieving better variograms with better structure, all appeared to exhibit the pure "nugget effect." However, when plots were examined of the window median across the transects (as shown in Figure 10 for NE-SW and NW-SE transects), some interesting features were discovered. The plots for 30 and 15 cm depth (Figures 10a and 10d) show that the spatial structure lies in the median of the windows, indicating structural variation (i.e., regular variation of the median from window to window and clustering of soil of similar hydraulic properties inside the window, with few exceptions. Comparing the plots of medians (Figure 10) with the semivariograms drawn for log-transformed K values before median polishing (Figure 5) could reconfirm our results in terms of range of "short-scale" and "large-scale" variations. Examining these figures, it can also be judged that the overall range (large-scale variation) of soils of predictable K at 30 cm depth is of about three window lengths of 69 m (measured in situ) and about two window lengths of 46 m (measured in the lab). That reconfirms the overall spatial range found from the semivariogram analysis. Moreover, each window of 23 m length would represent soil of similar K value, indicating short-scale variation. Therefore when medians were subtracted from the raw data, the structural components were removed from the data set, leaving behind the "nugget effect" in the residuals, which resulted in the structureless semivariograms, as shown in Figure 9. Therefore the open-ended question, Is stationarity of regionalized variable a critical criterion for semivariogram estimation in this type of clustered soil?, may be posed at this moment. Interestingly, at 30 cm depth, both in situ and lab semivariogram estimators, as well as the medians across the transects, showed consistency in their trends even though some differences were observed in their sills and overall range of influence, which may have been caused by the basic difference between the two techniques.

In the plots for 15 cm depth, medians (Figures 10c and 10d) are dominated by white noise and a NW-SE drift matching the structureless semivariograms of the residuals (Figures 9a and 9b), indicating no apparent large-scale structure in the original data sets of K values for the surface layer (0-15 cm). Moreover, comparison of semivariograms at 15 cm depth (lab method), for log-transformed K data (Figure 5b with Figure 9b for median-polished residuals),
Fig. 8. Stem-and-leaf plots (left) and normal probability plots (right) of ln K residuals after split-window median polish: (a) 30 cm, field; (b) 30 cm, lab; (c) 15 cm, field; and (d) 15 cm, lab.
reconfirms the presence of a drift in the medians of the windows. Thus it attributes the median a "solo representative" or "summary point" of the window when the structure can be best described as a "single-window structure."

**Split-Window Median Polish Versus Universal Kriging**

Universal kriging [Matheron, 1971; Journel and Huijbregts, 1978; Webster and Burgess, 1980] was performed on lab 15-cm data to give a qualitative comparison with split-window median polish to remove the local drift. Least square fits (simple regression) of the log-transformed K values versus X-Y coordinates of the field indicated a reasonable correlation between the X axis (NW-SE) and the K values. As reported by previous researchers, drift of an order higher than quadratic is almost never needed in universal kriging. Linear and quadratic drifts were tested by trial and error in conjunction with different linear and nugget variograms to represent the residuals. From the cross-validation criteria in this instance we did not achieve anything significant for quadratic trend over the linear trend. Therefore in order to avoid needed detail, linear trend was considered to be the best approximation. The experimental variograms (up to eight lags) were almost falling on the best fit linear model for all directions. Universal kriging was therefore performed with a moving neighborhood (search radius) of eight lag distances. Semivariograms of the residuals after removing the linear drift showed a limited or absent spatial relation for the laboratory K data set (Figure 11). Such a behavior is often referred to as "nugget effect." These changes indicate that a higher rate of variability and smaller zone of influence resulted from detrending. As expected, however, detrending followed by residual semivariogram development decreased the estimate of bias (sum of residuals: original data minus kriged estimate) but not significantly. Furthermore, comparison of Figures 11 and 9b shows the close match of results obtained by both the methods. It assures that the split-window median polish is an equally suitable and much easier approach for the spatial analysis of clustered soils.

**SUMMARY AND CONCLUSIONS**

Spatial structure for saturated hydraulic conductivity (K) of a glacial till material under no-tillage condition was examined for two depths with two K measuring techniques. Evidence of nonstationarity in K data pose problems on the reliability of semivariogram estimators. Analysis of data before developing the semivariogram was discussed. Log transformation followed by an economical resistant data analysis using split-window median polishing technique was used to remove the median and variance nonstationarity from a data set generating valuable semivariogram estimators for the interpretation of the structural variability.

A robust estimator [Cressie and Hawkins, 1980] was used to accommodate the contaminating outliers. Semivariograms estimated for both methods of K measurements were found to have close similarity for 30 cm depth. Good spatial structure was observed (short-scale variability) within a lag distance of 20 m for determining K values of the glacial till soil. Beyond this range a more clustering effect in K was observed with an overall range (large-scale variability) of 60 m (in situ method). Spatial structure of K was modeled using the nested structure of three different components, namely, random variability due to soil "microheterogeneity",...
"short-scale variability", which may be due to clustering of till material by differential deposition, and "large-scale variability" due to the soil of the same type or origin. The nugget effect, and two spherical models, were used in the above in order to fabricate the overall structure of the till material. Further exploratory data analysis exposed an interesting fact indicating that spatial structure of the clustered soil lies in their medians, which may be called "solo representatives" or "summary points" of clusters. This clustering phenomenon is due to differential deposition of soil layers by glacial drifts during its formation or subsequent incremental deposition due to wind drifts.

Semivariogram estimators for in situ K values at 15 cm depth under the no-till condition did not exhibit any large-scale structure in addition to weak small-scale structure. Variability is dominated by the heterogeneity in the soil. Reasons for this behavior may be due to uneven breaking of soil structure due to freezing and thawing at this shallow layer. Moreover, a typical directional trend was found for both in situ and lab measurements of K. This trend became more prominent in the medians of the windows across the NW-SE transect. Split-window median polish was found to be a useful tool, for clustered soils, in performing a reliable spatial analysis, resulting in more realistic structural estimators for better interpretation of K data.
Acknowledgments. We are thankful to the Iowa Geological Survey of the Iowa Department of Natural Resources for funding this study. We also thank N.A.C. Cressie, Department of Statistics, Iowa State University, for his valuable suggestions and comments to improve the quality of this manuscript. Sincere appreciation is due to Zack Mosli for his help in field measurements. This paper is J-14156 of the Iowa Agriculture and Home Economics Experiment Station, Ames, Iowa, project 2792.

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(Received December 12, 1990; revised June 20, 1991; accepted June 25, 1991.)