Use of Similar Media Scaling to Characterize Spatial Dependence of Near-Saturated Hydraulic Conductivity

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ABSTRACT

Near-saturated hydraulic conductivity \( K_s \) reflects the presence of structural macro pores and mesopores that, in turn, determine the pathways of water infiltration and solute fluxes in soil. Little is known about the spatial dependence of structural pore space in soil, although such information will be required by stochastic models of solute transport that account for preferential flow in dual or multiple pore domains. Thus, the aim of this study was to investigate the spatial dependence of \( K_s \), Steady state infiltration rates were measured at supply pressure heads ranging from \(-9.1 \) to \(-0.4 \) cm using tension infiltrometers. Twenty five measurement locations were sited on a regular 10 \( \times \) 10-m grid with a 2-m spacing. An additional 12 measurement locations were placed in the center of the plot with the shortest lag being 0.5 m. Variability was expressed by a single parameter, the scale factor, strictly following the Miller and Miller similar media theory, and with the reference function defined by the Mualem–van Genuchten model. Hydraulic conductivity increased about three orders of magnitude across the pressure head range from \(-9.1 \) to \(-0.4 \) cm, confirming the strong influence of soil macropores on conductivity near saturation. However, the spatial variability of \( K_s \) did not depend on the soil water pressure head across the range measured. The scale factors were approximately lognormally distributed, with a coefficient of variation (CV) of 53%. Variogram analysis showed a clear spatial dependence of the scale factors within distances of at least 8 to 10 m and an uncorrelated variance (nugget) of \( \approx 13\% \) of the total variability. It was concluded that the macropores and mesopores, responsible for preferential water flow and solute transport near saturation, were not randomly distributed across the plot but showed a well defined spatial structure.

Straightforward application of soil physics theory to predict water flow and solute transport in field soils is confounded by the often large spatial variability of soil hydraulic properties (Warrick and Nielsen, 1980; Jury et al., 1991). Two main approaches have been developed to define and quantify this variability. Similar media theory (Miller and Miller, 1956) is based on the laws of viscous flow in porous material, together with the assumption that the structure of void spaces, on which soil hydraulic properties depend, is geometrically similar among different locations. In contrast, applications of geostatistical methods such as variogram analysis and kriging are not usually based on any fundamental physical theory and, therefore, do not provide any explanation of observed phenomena, but simply describe the spatial pattern of a variable within the maximum distance for which it is autocorrelated (Webster, 1985). Spatial variations are regarded as a deterministic function of separation distance, so that local predictions and interpolations are possible.

Even the simplest of closed-form models of the soil hydraulic functions require five parameters, each of which may vary spatially and show intercorrelation (e.g., Vauclin et al., 1994). Thus, provided the assumption of geometric similarity is valid in an operational sense, Miller and Miller scaling offers significant advantages for stochastic modeling purposes, because it expresses the spatial variability of soil hydraulic properties using only one parameter, the scale factor (Simmons et al., 1979; Russo and Bresler, 1980). Previous studies have used the probability density function of scale factors to express random spatial variability in stochastic models of soil hydrology (Peck et al., 1977; Boulier and Vauclin, 1986; Vachaud et al., 1988; Hopmans and Stricker, 1989; Braud et al., 1995; Ducco, 1997). However, few studies (e.g., Jury et al., 1987) have considered scaling factors as a realization of a three-dimensional, isotropic, stochastic function or have analyzed their spatial dependence with a geostatistical approach.

To date, most studies of the spatial variability of soil hydraulic properties have either concentrated on soil water retention properties in the dry range and/or on saturated hydraulic conductivity \( K_s \) (e.g., Nielsen et al., 1973; Burden and Selim, 1989; Ünlü et al., 1990; Mohanty et al., 1991; Vauclin et al., 1994; Istok et al., 1994; Reynolds and Zebchuk, 1996; Mallants et al., 1996, 1997). However, water flow and solute transport under dry conditions is negligible, while variability in \( K_s \) may also exert little significant control on leaching in the unsaturated zone, since applied fluxes at the surface are usually much smaller than \( K_s \) (Boesten, 1991; Hutson and Wagenet, 1991). So, in recent years, attention has increasingly focused on investigations of spatial variability in near-saturated conductivity \( K_{ns} \) (Wilson and Luxembourg, 1988; Mohanty et al., 1994; Logsdon and Jaynes, 1996), measured in undisturbed field soil using tension infiltrometers (White et al., 1992). Although no exact definition of \( K_{ns} \) is possible, operationally it can be de-

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**Abbreviations:** ME, mean of the reduced error vector; MRE, mean square reduced error; MSE, mean square error; RE, reduced error vector; RMSE, root mean square error.
fined as the hydraulic conductivity at pressure heads larger than about −10 cm, approximately equivalent to the measurement range of tension infiltrometers. Hydraulic conductivities measured in this pressure head interval reflect the presence of structural macropores and mesopores (Clothier, 1990; Messing, 1993; Jarvis et al., 1999) and are also in the range of normal rainfall rates in most climates (>0.01 cm h⁻¹). Thus, the near-saturated hydraulic conductivity function at and close to the soil surface largely determines the extent of preferential water flow and solute transport and therefore exerts a major influence on the risk of groundwater pollution (Jarvis, 1998).

Jarvis and Messing (1995) used similar media theory as a physically based averaging method to characterize differences in near-saturated hydraulic conductivity functions that were measured in six soils of contrasting texture. However, the number of replicates was much too small to assess the usefulness of this approach to describe spatial variability at any one site. In this study, we show how measurements of near-saturated hydraulic conductivity made by tension infiltrometers in a cultivated silt loam soil can be efficiently scaled using similar media theory. The spatial dependence of the derived scale factors is analyzed using a geostatistical approach.

MATERIALS AND METHODS

Site Details

Near-saturated hydraulic conductivity was measured in a 10 × 10-m plot on a silt loam soil (Typic haplaquept in the USDA-NRCS classification system) at Säby, in east central Sweden (59°49'N 17°39'E). The following are the main soil physical characteristics: organic material, 5.5%; sand (63–2000 μm), 29.0%; silt (2–63 μm), 53.8%; clay (<2 μm), 17.2%. Säby is located on a flat plain, 20 m above sea level, where the soil has developed in lake deposits during a steady rise of the land surface from the release of ice overburden since the last glaciation. The plot had been cropped with spring-sown cereals and rape during the last 10 yr. In May 1997, white clover was undersown as a cover crop in a main crop of spring barley. The measurements were made between 11 and 22 September 1997, soon after the harvest of the barley when the clover was being established.

Measurements

Six infiltrometers of a simple mariotte-bottle design (White et al., 1992) were used with 14.8-cm diam. bottom plates. Each infiltrometer was calibrated in the laboratory to account for the individual differences between nominal and actual tensions applied at the bottom plate. For the calibration, a flexible tube was connected to the water reservoir, and the tension was measured as a difference in water height from the bottom plate during infiltration, with a porous cloth acting as a surrogate for the soil. A dynamic calibration also indicates the degree of variation of tension to be expected during infiltration in the field, which would be caused by the formation and release of bubbles in the control tube (in our case, ±0.3 cm).

Measurements were made on a regular square grid of 2 by 2 m, with an additional set of locations nested in the center of the plot, and the closest spacing equal to 0.5 m (Fig. 1). The nested grid was not intended as a hierarchical cluster, but only as a way to better define the semivariance at close lags.

Fig. 1. Diagram of the 37 measurement locations.

The total number of locations was 37. This sampling intensity and scale was chosen mainly for practical reasons, representing a compromise between conflicting requirements to make the measurements as quickly as possible, thereby minimizing the risk of temporal changes in soil structure that affect near-saturated conductivity (Messing and Jarvis, 1993; Murphy et al., 1998), and the need to sample both short- and long-distance lags.

At each location, the steady state infiltration rate was measured manually at three different supply pressure heads, h, using tension infiltrometers. The supply pressure heads were slightly different for each location, but in all cases, the measurements started at the smallest value and ended with the largest (i.e., closest to saturation) in order to avoid hysteresis. The supply pressure heads ranged from −9.1 to −0.4 cm. After carefully clearing the surface of loose material, a layer of commercial, narrow-graded, fine sand =0.5 cm thick was applied to the soil surface between the rows of stubble, with an area equal to that of the infiltrometer in order to smooth out slight surface unevenness and to improve the contact between the infiltrometer and the soil. The variations in surface elevation were estimated to be of the order of ±0.3 cm, so that the sand layer normally varied between 0.2 and 0.8 cm in thickness. Since the site is flat with little microtopography and the infiltrometer of relatively small diameter, no problems were encountered in ensuring a level contact surface. The contact sand (mean particle diameter of 150 μm, 95% of particles with diameters between 63 and 250 μm) has a saturated hydraulic conductivity between 12 and 27 cm h⁻¹ (Stähli et al., 1998) and an air-entry pressure <−30 cm. Thus, the hydraulic conductivity of the sand is maintained across the range of supply potentials used (saturation to −9 cm), ensuring that it exerts a negligible hydraulic resistance. The sand was applied in a moist state to prevent it from falling into surface macropores and creating wicks (Jarvis and Messing, 1995).

Data Analysis

Near-saturated hydraulic conductivity Kₙₕ was calculated from the measured steady state infiltration rates, q, following the method outlined by Ankeny et al. (1991) and Messing and Jarvis (1993) that is based on a piecewise application of Wooding's (1968) equation for three-dimensional infiltration from a circular source, in which the slope of the relationship
between \( \ln q \) and \( \ln K_m \) and applied pressure head (Gardner, 1958) is assumed constant between adjacent supply pressure heads but not across the entire measured range. For stochastic modeling purposes, the paired \( K_m \) and \( h \) values must be scaled to a reference model function. Jarvis and Messing (1995) previously compared three models of terms of suitability for the purpose of describing \( K_m \) measured by tension infiltrometer. The Gardner (1958) exponential model, although simple and logically consistent with the approach used to derive \( K_m \) (i.e., Wooding’s equation), failed to give an adequate description across the range of measured pressure heads (Jarvis and Messing, 1995). A modified two-line exponential model (Keng and Lin, 1982) gave somewhat smaller residuals after scaling than the Mualem–van Genuchten model (Mualem, 1976; van Genuchten, 1980), but at the cost of one extra parameter. For these reasons, and also to match the requirements of some existing dual-porosity models (e.g., Gerke and van Genuchten, 1993; Nieber and Misra, 1995), we chose in this study to scale the paired \( K_m \) and \( h \) values derived at each location using the Mualem–van Genuchten model in its restricted form:

\[
K_m = K_v \left[ 1 - \frac{|a| h^{n-1} \left( 1 + |a| h^{k-1} \right)^{1-n} \right]^{n-1/2N} \tag{1}
\]

where \( K_v \) is the saturated hydraulic conductivity and \( a \) and \( N \) are fitting parameters that reflect the mean pore size and pore size distribution, respectively.

In this study, we compare two different scaling procedures. First, we assumed that the scale factor is the ratio of a local characteristic length and a mean reference length, according to Miller and Miller (1956) similar media theory. Thus, if the geometric nature of the scale factor is a strict assumption, then both \( K_m \) and \( h \) should be scaled with the same scale factor:

\[
h_{\text{ref}} = h_i \lambda_i \quad \text{and} \quad K_{m(\text{ref})} = K_{m(i)}/\lambda^2 \tag{2}
\]

where \( (\text{ref}) \) indicates the reference curve, \( i \) refers to each location, and \( \lambda \) is the scale factor. Secondly, we tested functional scaling (Tillotson and Nielsen, 1984), relaxing the assumption of geometric similarity, such that \( \lambda_{ai} = \lambda_{bi} \) where the subscripts \( k \) and \( h \) indicate the different scale factors for hydraulic conductivity and pressure head derived from Eq. 2.

The parameters \( N, \alpha \) and \( \lambda \) in Eq. [1] and the scale factors for each of the 37 locations were determined simultaneously by a least squares fitting procedure (generalized reduced gradient method), minimizing the sum of the squared differences between the measured and fitted values of \( \log K_m \). In the fitting procedure, the geometric mean value of \( \lambda \) was fixed at unity, as a normalization condition. The geometric mean was chosen instead of the arithmetic mean used by several other authors (e.g., Hopmans, 1987; Vachaud et al., 1988), since the scale factors were expected to be lognormally distributed (Simmons et al., 1979).

The value of the scale factor is a relative variable that depends on the reference curve and on the entire population of values. Nevertheless, we consider them as any other measurable, spatially dependent, soil characteristic, and we analyze the spatial distribution of the scale factors using traditional geostatistical methods. The semivariance is defined as

\[
\gamma(u) = \frac{1}{2n(u)} \sum_{i=1}^{n(u)} \left( Z(x_i) - Z(x_i + u) \right)^2 \tag{3}
\]

where \( \gamma(u) \) is the estimated semivariance for lag distance class \( u \), \( Z(x_i) \) and \( Z(x_i + u) \) are the measured sample values at point \( x_i \) and \( x_i + u \), respectively, and \( n(u) \) is the total number of sample pairs for the interval \( u \).

A model was fitted to the semivariogram and checked by cross-validation, testing for the absence of systematic errors and the consistency of the kriging variance and error. In particular, following Jury et al. (1987) and Russo and Jury (1987), we checked the following:

\[
\text{ME} = \frac{1}{n} \sum_{i=1}^{n} \frac{|Z(x_i) - Z(\hat{x}_i)|}{n} = 0 \tag{4}
\]

where

\[
\text{RE} = \frac{\sum_{i=1}^{n} (Z(x_i) - Z(\hat{x}_i))^2}{\sum_{i=1}^{n} \left( \text{var}[Z(x_i) - Z(\hat{x}_i)] \right)} \tag{5}
\]

and that

\[
\text{MRE} = \left[ \frac{1}{n} \sum_{i=1}^{n} \text{RE}(x_i)^2 \right]^{1/2} \approx 1 \tag{6}
\]

where ME is the mean of the reduced error vector RE, MRE is the mean square reduced error, \( n \) is the sample size, \( Z(x_i) \) and \( Z(\hat{x}_i) \) are the measured and predicted values at location \( i \), where \( i \) varies from 1 to \( n \). Finally, ordinary (point) kriging was used to interpolate the data and to create an isarithmic map of the scale factors.

RESULTS AND DISCUSSION

Unscaled Hydraulic Conductivity

Figure 2 shows the paired \( K_m-h \) data measured at the 37 locations. Parameter values for the Mualem–van Genuchten model derived by fitting to the unscaled data were 30.9 cm h\(^{-1}\) for \( K_v \), 0.51 cm\(^{-1}\) for \( \alpha \) and 1.513 for \( N \). The mean square error between the measured points and the unscaled curve (MSE) was 0.294 cm\(^2\) h\(^{-1}\) (root mean square error, RSME = 0.542 cm h\(^{-1}\)).

Table 1 reports the variability of hydraulic conductivity measured at the 37 locations, as a function of the applied soil water pressure head (divided into class intervals of 1 cm for \( h \)). It can be noted that the classes were not equally represented, so that the level of significance of the CV varies between classes, and that the sample sizes are generally small, particularly at the extreme values of supply pressure head where data are sparse. Table 1 shows that the CV ranged from 36 to 77\%, with no apparent trend of the variability of hydrau-
Table 1. Geometric mean and coefficient of variation (CV) of the measured hydraulic conductivity.

<table>
<thead>
<tr>
<th>Class‡</th>
<th>Average soil water pressure head, h</th>
<th>Number of pairs</th>
<th>Hydraulic conductivity, Kns</th>
<th>Geometric mean</th>
<th>CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>-cm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1</td>
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<td>0.20</td>
<td>76.7</td>
<td></td>
</tr>
<tr>
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<td>5.2</td>
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<td>0.09</td>
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<td></td>
</tr>
<tr>
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<tr>
<td>7</td>
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<tr>
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<td>67.1</td>
<td></td>
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<tr>
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<td>9.0</td>
<td>4</td>
<td>0.02</td>
<td>51.3</td>
<td></td>
</tr>
</tbody>
</table>

‡ The supply pressure heads were subdivided into classes of 1 cm.

The supply pressure heads were subdivided into classes of 1 cm (Fig. 2), at which macropores of equivalent diameter >0.3 cm conduct water, and where larger variability may be expected. For example, Mohanty et al. (1994) reported similar CVs for $K_{ns}$ at supply pressure heads of -3, -6, and -15 cm in plant rows and no-track interrows in a corn field (68-80%), and somewhat larger CVs at saturation (91% and 125%, respectively). In contrast, in a forest soil, Wilson and Luxmoore (1988) found no clear difference in the variability of steady state infiltration measured at saturation compared to supply pressure heads of -2, -5, and -15 cm.

Scaling Near-Saturated Hydraulic Conductivity

Miller scaling was performed on the measured data, fitting the three parameters of the reference curve (Eq. [1]) together with the 37 scaling factors defined by Eq. [2]. Because of the large degree of freedom, the solver failed to find an absolute minimum of the sum of squares, leading to nonunique solutions strongly dependent on the initial values chosen for $\alpha$, $N$, and especially, $K_s$. We therefore decided to fix $K_s$ at the value found from least squares fitting to the unscaled data. This resulted in a stable (unique) solution to the scaling problem with parameter values for the scaled or reference curve of 30.9 cm h$^{-1}$ for $K_s$, 0.49 cm$^{-1}$ for $\alpha$, and 1.578 for $N$ (Fig. 3). The scale factors derived from the simultaneous scaling to the reference curve were compared with those obtained by separately transforming the measured data for each location onto the unscaled curve. The relationship between the two sets of scale factors was highly significant ($R^2 = 0.96$), so the simultaneously scaled and fitted solution was considered robust and accepted. Miller scaling reduced the MSE by 54%.

It was not possible to find a unique solution using functional scaling, despite fixing the value of $K_s$ to that found for the unscaled fitted curve. This is perhaps not surprising since the number of fitted parameters is nearly doubled when different scale factors for $K_{ns}$ and $h$ are assumed. To obtain a solution, we decided to use the parameter values found for the unscaled fitted curve as initial guesses, resulting in parameter values for the reference curve of 30.9 cm h$^{-1}$ for $K_s$, 0.47 cm$^{-1}$ for $\alpha$, and 1.545 for $N$. This functional scaling reduced the MSE by 86%. Thus, although the efficiency of the scaling is certainly improved compared to the case that assumes strict Miller similitude, the use of separate scale factors for $K_{ns}$ and $h$ is questionable, because it appears impossible to find a unique solution. Furthermore, two important advantages in using Miller scaling are lost: (i) the physical basis of the method is seriously weakened, reducing the procedure to a pure mathematical exercise; and (ii) two partially correlated scale factors are needed to describe variability, instead of only one. This raises questions as to whether the parameter correlation is only site-specific or whether it can be extrapolated to other locations.

Conventional Statistical Analysis of the Scale Factors

A conventional statistical analysis was performed on the Miller scale factors, assuming they are independent samples of a population. The $\lambda$ values ranged between 0.26 and 3.08 and their distribution was approximately lognormal (Fig. 4), as has been found by several authors.
for many other flow and transport properties (see review in Jury et al., 1991). This was confirmed by a Kolmogorov-Smirnov test, which rejected the null (normal) hypothesis for \( \lambda \) (\( P = 0.023 \)), but did not reject the hypothesis that \( \ln(\lambda) \) was normally distributed (\( P = 0.2 \)). The CV of the scale factors, calculated for a lognormal variable (Gilbert, 1987), was 53%.

### Spatial Analysis of the Scale Factors

The Miller scale factors were analyzed for their spatial dependence. As the distribution appeared lognormal, geostatistical analysis was performed on the log-transformed \( \lambda \) values. Exponential, spherical, and circular models fitted the experimental variograms equally well. We chose to report the results of the exponential model, because theoretically it has more widespread applicability and generality (McBratney and Webster, 1986). The choice of criteria to fit this model to the data was critical: eye-fitting, which is favored by most geostatisticians (Goovaerts, 1997), gave more importance to short-distance lags, with a zero nugget and 8 m as the effective range (defined here, by convention, as the distance at which 95% of the sill value is reached in the exponential model, equal to three times the radius parameter). Least squares fitting, giving the same weight to all the points (Fig. 5), gave a nugget value of 0.052, a sill of 0.401, and an effective range of 15 m. This estimate of the range must be considered tentative since it represents a slightly larger distance than the major lag explored in this study. However, regardless of the model chosen to represent the variogram, Fig. 5 shows that \( K_n \) is clearly spatially correlated within distances of at least 8 to 10 m. Earlier, Wilson and Luxmoore (1988) found ranges of \(<15 \) m for \( K_n \) in one forested watershed, but no spatial dependence at distances larger than the smallest explored lag (4 m) in another. Logsdon and Jaynes (1996) noted a range of 17 m for \( K_n \) measured at a pressure head of \(-15 \) cm in a corn field, providing the soil had not been disturbed by tillage in the previous weeks. A very short autocorrelation range was observed when measurements were made shortly after tillage. They also observed that \( K_v \) was autocorrelated only within a very short lag (<1 m), regardless of soil disturbance due to tillage. Ciollaro and Romano (1995) reported a range of 7 m for both \( K_v \) and hydraulic conductivity measured at a pressure head of \(-1 \) m in undisturbed subsoil at 45-cm depth under a peach orchard.

Figure 5 shows that for unweighted least squares fitting, the nugget effect, or spatially uncorrelated component of variance due to microvariance or measurement error, was 0.05 or 13% of the spatially dependent component of variation. This nugget value is small compared to that found by some other authors. For example, Mohanty et al. (1994) found that the uncorrelated component of \( K_v \) and \( K_n \) dominated or nearly dominated the total variability. Differences in the degree of spatial dependence may depend on differences in site management and also on the nature of the parent material and soil forming processes. Our measurements were made in inherently uniform soil that developed in post-glacial lake deposits, planted with narrow-spaced row crops such as barley, and repeatedly tilled. In contrast, Mohanty et al. (1994) worked in a heterogeneous glacial till soil under no-till corn with wide plant spacings, all of which may be expected to lead to a larger nugget component of the variability.

The variogram model was validated with a jack-knifing approach (Gambolati and Volpi, 1979; Russo and Jury 1987). The measured points were suppressed one at a time and the model, using the other points, predicted their values. The mean of the reduced errors (ME = 0.019) was not significantly different from zero (\( P = 0.907 \)), and the reduced errors were normally distributed. This means that there was only nonsystematic error in the predicted values. In addition, the mean reduced squared error (MRE = 0.987) was not significantly different from unity (\( P = 0.89 \)), that is, the kriging variance was consistent with the corresponding error.

Figure 6 shows the kriged map of the scale factors based on the exponential model fit shown in Fig. 5. The
spatial pattern observed is not related in any discernible way to soil management at the site (e.g., tillage) and so presumably reflects spatial patterns in basic soil properties, especially those related to the soil structure, although no complementary measurements were made to confirm this hypothesis. If the assumption of the geometric nature of the scale factors is valid, the pattern shown in Fig. 6 should be the same for any other soil property that is dependent on the larger voids.

CONCLUSIONS

Near-saturated hydraulic conductivity measured by tension infiltrometers in a silt loam soil under arable cropping could be successfully scaled in this study (MSE was reduced by 54%) by assuming geometric similarity among measurement locations. However, a unique solution could only be obtained by fixing saturated hydraulic conductivity to the value found from least squares fitting to the unscaled data. No unique solution could be found in the functional scaling approach, in which separate scale factors for hydraulic conductivity and pressure head are calculated by relaxing the strict assumption of geometric similarity.

The Miller scale factors were lognormally distributed with a CV of 53%. Although hydraulic conductivity varied approximately three orders of magnitude across the range of pressure head sampled, no apparent dependence of the degree of spatial variability of $K_n$ with soil-water pressure head was observed. The scale factors were clearly spatially dependent within distances of at least 8 to 10 m. An unweighted exponential model for the variogram gave the uncorrelated part of the variance (nugget) at ~13% of the spatially dependent component. This nugget variance could be due to measurement errors or to variability at distances of <0.5 m, which was the shortest lag used in this study.

We conclude that the distribution of macropores and mesopores, as reflected in the measured near-saturated hydraulic conductivity function, shows a clear spatial structure, and that stochastic models describing preferential flow and transport in structural pores should take this structure into account. Similar media theory appears to be an especially useful operational tool to express the variability of hydraulic conductivity close to saturation.

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