

Fine-scale spatial variability of physical and biological soil properties in Kingston, Rhode Island

José A. Amador^{a,b,*}, Yong Wang^b, Mary C. Savin^{a,b},
Josef H. Görres^{a,b}

^a *Laboratory of Soil Ecology and Microbiology, University of Rhode Island,
Kingston, RI 02881, USA*

^b *Department of Natural Resources Science, University of Rhode Island,
9 East Alumni Avenue Suite 5, Kingston, RI 02881, USA*

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Abstract

We evaluated the fine-scale (cm) variability of bulk density (ρ_B), organic matter content (%OM), volumetric water content (θ_V), and carbon mineralization rate (C_{min}) at specific values of water potential in an old field soil. We measured these variables in soil samples obtained using paired abutting, 5-cm diameter, 10-cm deep cores. To compare abutting core properties, abutting cores were randomly assigned to one of two groups, A or B, using permutation procedures in order to account for the possibility of chance effects. Comparisons were made using either 10 (θ_V and C_{min}) or 40 (% OM and ρ_B) pairs of samples in May, August, and November of 1997 and March of 1998. No differences were observed in the distribution of values among groups of cores for all the variables measured. Furthermore, there were no seasonal differences in coefficient of variation for any of the variables. Values of coefficient of variation followed the order: $C_{min} > \theta_V > \% OM > \rho_B$. The difference between paired cores relative to population means (RD) was highest for C_{min} (29.7%), followed by %OM (12.3%), θ_V (9.1%) and ρ_B (5.9%). Our results indicate that variability in soil properties (RD) at the centimeter scale is lowest for physical properties (θ_V and ρ_B) and highest for biological properties (%OM and C_{min}). The assumption of identity among adjacent cores does not appear to be justified for the soil properties evaluated in our study. © 2000 Elsevier Science B.V. All rights reserved.

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* Corresponding author. Fax: +1-401-874-4561.

E-mail address: jam7740u@postoffice.uri.edu (J.A. Amador).

1. Introduction

Soil properties and processes vary spatially at different scales. In many instances spatial variation is not random but tends to follow a pattern in which variability decreases as distance diminishes between points in space (Youden and Mehlich, 1937; Warrick and Nielsen, 1980). Spatial dependence has been observed for a wide range of soil physical, chemical, and biological properties and processes (e.g. Yost et al., 1982; Wollum and Cassel, 1984; Cahn et al., 1994; Cambardella et al., 1994; von Steiger et al., 1996; Amador et al., 1997; Lyons et al., 1998; Görres et al., 1998; Raun et al., 1998). Incorporation of functions that relate distance and variance among points (e.g. semivariograms) into spatial analysis of soils data results in more accurate estimates of soil properties and processes than those that consider only spatial independence between points (Warrick and Nielsen, 1980). Semivariograms for soil properties can also be used to reduce the need for expensive and intensive sampling, as in the case of precision agriculture (e.g. McBratney and Pringle, 1999).

The notion of spatial dependence of soil variability is incorporated in sampling schemes that rely on adjacent cores to compare soil properties (e.g. Banton et al., 1997) or processes (e.g. Raison et al., 1987; Sierra, 1996, 1997) or to obtain sufficient soil for specific determinations (e.g. bulking). Implied in these sampling schemes is the assumption of identity for adjacent samples, although this assumption is seldom tested (Sierra, 1996). The assumption of identity for adjacent soil samples is a practical one: sampling schemes that rely on abutting cores reduce the distance between sampling points to its practical minimum, and thus should minimize spatial variability.

Whether the assumption of identity among abutting cores holds true has important consequences for accurate measurement of a number of soil variables. In some instances, establishing a relationship between two soil variables requires destructive sampling that precludes measurement of both variables on the same sample. To overcome this difficulty, it is generally assumed that the value of the variable not measured is identical for both cores when adjacent cores are used. For example, some studies have attempted to use the spatial variability of electrical resistivity of soils as a proxy for spatial variability of soil physical properties (e.g. Banton et al., 1997). The nature of some soil physical properties, such as bulk density and porosity, requires that they are determined using undisturbed samples, precluding measurement of resistivity — which requires some disturbance — on the same sample. In other instances, it is necessary to repeat the same measurement at two different points in time on the same soil sample. This presents a practical problem when such determinations require destructive sampling. The use of adjacent cores may be recommended in these cases based on the expectation of identity of initial conditions. This is the case for field measurements of net nitrogen mineralization rates, which require that the inorganic nitrogen content of the soil be measured at two different times

(Sierra, 1996, 1997). The validity of the assumption of identity among adjacent cores can thus be critical to evaluate a number of soil properties and processes accurately.

We conducted an experiment to evaluate the variability among adjacent cores as part of a larger study of controls on seasonal dynamics and spatial patterns of soil fauna and nutrient mineralization in an old field. Adjacent cores were compared in terms of (i) bulk density (ρ_B), (ii) organic matter content (%OM), (iii) volumetric water content at specific values of water potential (θ_v), and (iv) carbon mineralization rate at specific water potentials (C_{min}). These variables represent commonly measured physical, chemical and biological soil properties and processes. The number of sample pairs ranged from 10 to 40, depending on the variable being evaluated. Samples were obtained in May, August, and November of 1997 and March of 1998. This allowed us to evaluate whether the variability among paired cores for different variables exhibited a seasonal component. In order to account for the possibility of chance effects, permutation procedures were used (Manly, 1997). Comparisons were made in terms of population means and variance, relative difference (RD), and scatter plots.

2. Materials and methods

2.1. Study area

The study was conducted in an old field within the Peckham Farm Research Area of the University of Rhode Island in Kingston, RI (41°30'N, 71°45'W). The soil at this site has been classified as a Hinckley sandy loam (sandy-skeletal, mixed, mesic Typic Udorthent) and had not been cultivated for at least 9 years prior to sampling. The dominant vegetation in the old field includes timothy (*Phleum pratense*), brome grass (*Bromus inermis*), orchard grass (*Dactylis glomerata*), Kentucky bluegrass (*Poa pratensis*), rose (*Rosa multiflora*), cinquefoil (*Potentilla erecta*), brambles (*Rubus* spp.) and goldenrod (*Solidago* spp.).

2.2. Sampling

The study area (40 × 20 m²) was divided into 50, 4 × 4-m² plots. At each sampling date, 40 plots were selected at random for sampling. The location of each sampling point within a plot was determined prior to sampling by generating x and y coordinate values randomly. At each sampling point two abutting, cylindrical aluminum cores (5-cm diameter, 10-cm deep) were pounded into the ground, dug out, and transported to the laboratory within 2 h of collection. The sample support used was found to be optimal for determination

of these properties by Starr et al. (1995). Sampling occurred on 13 May, 12 August, and 11 November of 1997 and 2 March of 1998. The soil temperature at a depth of 5 cm was 14°C, 22°C, 6°C, and 6°C in May, August, November, and March, respectively.

2.3. *Water potential equilibration*

A nylon cloth (30- μ m-mesh) was placed at the bottom of each core and secured with a rubber O-ring. All of the cores were saturated with water by placing them on the surface of a saturated sand (–3 and –10 kPa) or kaolin (–20 and –50 kPa) table (Eijkelkamp Agriresearch Equipment, Giesbeek, The Netherlands), covered to prevent evaporation, and allowed to equilibrate. The sand and kaolin tables were placed in a dark environmental chamber set at the field soil temperature. Each core was weighed daily until equilibrium was reached. Equilibrium was defined as the point at which the weight of the core was constant (within 1.0% of whole core weight) for two consecutive weight determinations. Once saturated, the 40 pairs of cores were randomly divided into groups of 10. For each group of 10 pairs, the tension in the sand table was adjusted to the desired final value and the cores were allowed to equilibrate. Each core was weighed repeatedly until equilibrium was reached.

2.4. *Carbon mineralization*

Carbon mineralization was measured only for the May and August sampling times. Equilibrated cores were placed in 1-l glass jars and the jars sealed with a metal screw cap fitted with rubber gasket and a rubber septum. The jars containing the cores were incubated in the dark at field soil temperature. A 20-ml sample of headspace gases was removed from the jar every 2–3 days using a gas-tight syringe and injected into a previously evacuated, 20-ml glass vial. A 1.0-ml sample of the gases in the glass vial was removed by displacement using an automated headspace sampler (model 7000, Tekmar). The concentration of CO₂ in the sample was measured with a gas chromatograph (model 14A, Shimadzu) fitted with a Porapak Q column (80/100 mesh, 305 cm). Carbon dioxide was converted to CH₄ using a heated (400°C) Ni catalyst and an H₂ gas stream, and the resulting CH₄ measured with a flame ionization detector. Injector, column and detector temperatures were 150°C, 60°C, and 300°C, respectively. Peak areas for CO₂ were determined by electronic integration. Conversion of peak areas to mass of CO₂ was made by comparison with vials containing a known concentration of CO₂. Following sampling, the lid was removed from the jars, the jars flushed with compressed air, and sealed again with a metal screw cap. Incubation was carried out for a total of 21 days.

Carbon mineralization rates were determined using data from the last 9–10 days of the incubation period, in order to ensure that CO₂ evolution rates were constant. Rates were determined from the slope of a line fitted to the data using

least-squares linear regression. At least four time points were used to estimate each rate.

2.5. Volumetric water content, bulk density and organic matter determination

To determine volumetric water content, the contents of the core were placed in a sealable plastic bag, mixed thoroughly by hand, and a known mass of wet soil (about 10 g) placed in a ceramic crucible. The soil was dried to constant weight at 105°C. The mass water content of the soil was determined from the difference in mass between wet and oven-dry soil. The bulk density of the soil was determined from the mass of oven-dry soil and the volume of the core. The organic matter content of the soil was determined by loss-on-ignition at 550°C for 4 h using a 10-g sample size.

2.6. Statistical analysis

The two abutting cores from each sampling point were randomly assigned to two groups (A or B) and values for mean (\bar{x}), standard deviation (SD), and

Table 1

Mean, standard deviation, coefficient of variation and confidence intervals of θ_v as a function of Ψ for randomly paired cores at different sampling dates

Ψ (–kPa)	Sampling date	θ_v								
		Mean			Standard deviation			Coefficient of variation		
		Avg	LCI	HCI	Avg	LCI	HCI	Avg	LCI	HCI
3	May	0.30	0.29	0.31	0.04	0.03	0.05	0.131	0.100	0.159
	August	0.35	0.33	0.36	0.05	0.03	0.07	0.153	0.095	0.206
	November	0.34	0.31	0.37	0.06	0.02	0.08	0.167	0.071	0.246
	March	0.31	0.30	0.32	0.03	0.02	0.04	0.088	0.049	0.121
10	May	0.22	0.22	0.23	0.03	0.02	0.03	0.113	0.079	0.142
	August	0.19	0.19	0.20	0.02	0.02	0.03	0.117	0.077	0.151
	November	0.23	0.23	0.24	0.04	0.03	0.04	0.159	0.146	0.171
	March	0.21	0.20	0.22	0.03	0.01	0.04	0.121	0.062	0.163
20	May	0.19	0.18	0.20	0.03	0.02	0.03	0.141	0.117	0.165
	August	0.17	0.17	0.18	0.02	0.02	0.02	0.115	0.093	0.133
	November	0.21	0.20	0.21	0.02	0.02	0.03	0.108	0.076	0.132
	March	0.22	0.21	0.23	0.03	0.03	0.04	0.155	0.124	0.180
50	May	0.18	0.17	0.18	0.02	0.02	0.03	0.128	0.094	0.159
	August	0.13	0.12	0.13	0.02	0.02	0.02	0.168	0.141	0.192
	November	0.16	0.16	0.17	0.02	0.02	0.03	0.143	0.096	0.183
	March	0.18	0.17	0.18	0.03	0.02	0.04	0.163	0.120	0.200

Values from one group are shown. Confidence intervals (95%) were estimated from 2.5 (LCI) and 97.5 (HCI) percentiles of the values resulting from 2000 permutations.

Table 2

Mean, standard deviation, coefficient of variation and confidence interval for % OM in randomly paired cores at different sampling dates

Sampling date	% OM								
	Mean			Standard deviation			Coefficient of variation		
	Avg	LCI	HCI	Avg	LCI	HCI	Avg	LCI	HCI
May	5.41	5.27	5.55	1.25	1.09	1.39	0.230	0.204	0.257
August	5.74	5.62	5.86	1.22	1.14	1.29	0.213	0.198	0.227
November	5.52	5.40	5.64	1.18	1.07	1.29	0.214	0.194	0.232
March	5.20	5.06	5.32	1.24	1.12	1.35	0.239	0.215	0.261

Values from one group are shown. Confidence intervals (95%) were estimated from 2.5 (LCI) and 97.5 (HCI) percentiles of the values resulting from 2000 permutations.

coefficient of variation (CV) were calculated for each group. This random permutation process was repeated 2000 times, yielding averages of \bar{x} , SD, and CV for each group. Individual groups of abutting cores remained paired through the permutation process, only assignment to either group A or B changed as a result of permutation. Confidence intervals (95%) were estimated from 2.5 and 97.5 percentiles of the values resulting from 2000 repetitions of the permutation process.

The relative difference, RD, between adjacent cores was determined using the formula:

$$RD = \left| \left(\frac{X_A - X_B}{\bar{x}} \right) \right| * 100\% \quad (1)$$

where \bar{x} is the mean for the whole population (all cores), and X_A and X_B are values for individuals belonging to a paired set. Division of individual values by

Table 3

Mean, standard deviation, coefficient of variation and confidence intervals of C_{\min} as a function of Ψ for randomly paired cores at different sampling dates

Ψ (–kPa)	Sampling date	C_{\min}								
		Mean			Standard deviation			Coefficient of variation		
		Avg	LCI	HCI	Avg	LCI	HCI	Avg	LCI	HCI
3	May	1.73	1.42	2.05	0.16	0.15	0.18	0.091	0.076	0.116
	August	2.31	2.08	2.55	0.44	0.28	0.56	0.190	0.134	0.238
10	May	1.72	1.53	1.92	0.40	0.31	0.53	0.234	0.070	0.331
	August	1.74	1.52	1.95	0.45	0.35	0.53	0.258	0.179	0.316
20	May	1.57	1.43	1.72	0.55	0.42	0.66	0.349	0.254	0.437
	August	2.45	2.24	2.72	0.79	0.50	1.03	0.316	0.210	0.414
50	May	1.35	1.19	1.51	0.37	0.21	0.49	0.271	0.162	0.354
	August	1.94	1.76	2.11	0.41	0.27	0.54	0.214	0.139	0.274

Values from one group are shown. Confidence intervals (95%) were estimated from 2.5 (LCI) and 97.5 (HCI) percentiles of the values resulting from 2000 permutations.

Table 4

Mean, standard deviation, coefficient of variation and confidence interval for ρ_B in randomly paired cores at different sampling dates

Sampling date	ρ_B								
	Mean			Standard deviation			Coefficient of variation		
	Avg	LCI	HCI	Avg	LCI	HCI	Avg	LCI	HCI
May	1.05	1.04	1.07	0.09	0.08	0.10	0.09	0.07	0.10
August	1.02	1.00	1.03	0.09	0.08	0.11	0.09	0.08	0.11
November	1.01	1.00	1.01	0.09	0.08	0.11	0.09	0.08	0.11
March	1.02	1.02	1.03	0.09	0.08	0.10	0.09	0.09	0.10

Values from one group are shown. Confidence intervals (95%) were estimated from 2.5 (LCI) and 97.5 (HCI) percentiles of the values resulting from 2000 permutations.

\bar{x} standardizes the difference between two cores in a pair and allows for comparison of the magnitude of deviation between two cores of a pair among different soil variables.

We used Levene's test to examine equality of variance of the relative difference between a pair of cores in randomly assigned groups among soil variables. Because the variances are unequal and tend to increase with the means (Tables 1–4), a logarithmic (\log_{10}) transformation was performed on the average relative difference for each pair. We added 0.001 to values that were equal to 0 before transformation. ANOVA was then used to test the difference of RD among soil variables.

3. Results and discussion

Mean and standard deviation values for C_{\min} , OM, θ_v , and ρ_B calculated from permutation procedures (Tables 1–4) were well within the range of those reported by Görres et al. (1998) for an adjacent old field sampled at similar points during the course of a year. The coefficient of variation (all dates included) followed the order: $C_{\min} > \text{OM} > \theta_v > \rho_B$. Average values (all dates included) for CV ranged from 0.085 to 0.092 for ρ_B , 0.088 to 0.169 for θ_v , 0.213 to 0.240 for OM, and 0.091 to 0.647 for C_{\min} .

Values of CV in the present study (Tables 1–4) are within the range of those reported for surface soils by others using sample support between 1.9 and 7.6 cm (core diameter) for ρ_B (Cambardella et al., 1994 ($n = 121$); Nielsen et al., 1973 ($n = 20$)) and θ_v at a specific water potential (Carvallo et al., 1976 ($n = 45$); Cameron, 1978 (n not reported); Nielsen et al., 1973 ($n = 20$)). The coefficient of variation for OM is also within the range of that observed by others (e.g. Cambardella et al., 1994 ($n = 121$); Raun et al., 1998 ($n = 490$))

using similar sample support. By contrast, the range of CV for C_{\min} observed by us (0.091–0.64) is considerably lower than that of 1.85 reported by Cambardella et al. (1994). Differences in sample support between our study and Cambardella et al. (1994) cannot account for the observed differences in coefficient of variation for C_{\min} . The cores used by Cambardella et al. (1994) were of the same diameter, but the volume of soil sampled was 50% greater than that in the present study. The lower variability in our measurements of C_{\min} is probably the result of the controlled moisture conditions used in our study. Soil moisture content has been shown to affect carbon mineralization markedly (e.g. Skopp et al., 1990; Amador and Jones, 1997).

Scatter plots (Fig. 1) show that values for paired cores increase proportionally for all properties measured. In addition, there is considerable scatter of values around the identity line. To quantify the relative variability between randomly paired cores and to allow us to compare variability among different soil

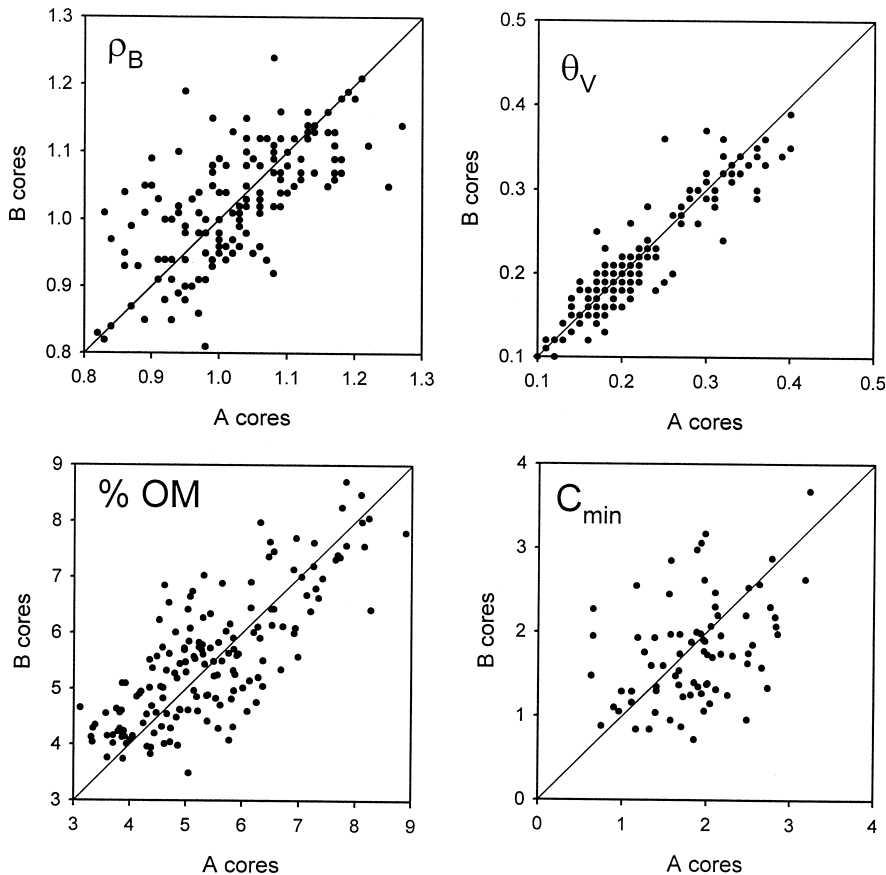


Fig. 1. Scatter plots of paired A and B core values for %OM, ρ_B , θ_V , and C_{\min} for the original group designations. Solid line represents identity between paired values.

properties, we calculated the value of relative difference (RD) using Eq. (1). There were marked differences among soil variables in RD calculated for paired cores (Table 5). ANOVA of log-transformed average values of RD for randomly assigned groups suggests that the mean RD values are different among the soil variables examined ($F = 25.07$; $d.f. = 3$ and 556 ; $P < 0.0001$). Tukey's post hoc multiple comparison tests indicate that the mean RD for C_{\min} and OM were higher than that for ρ_B and θ_V .

Levene's test suggests that the standard deviation of values of relative difference is not the same among soil variables ($F = 86.36$; $d.f. = 3$ and 556 ; $P < 0.0001$). When data for all seasons were combined, the variance was lowest for ρ_B and highest for C_{\min} , and was similar between OM and θ_V (Tukey's post hoc multiple comparison test).

Values of RD followed the same pattern observed for the coefficient of variation, with variables controlled by physical properties (ρ_B , θ_V) exhibiting less variability than those controlled by biological processes (OM, C_{\min}). This trend is not unexpected. For example, Starr et al. (1995) observed that physical variables (e.g. water content and bulk density) exhibited the least variability and were least sensitive to variations in sample support, whereas those variables involving biological processes (e.g. denitrification rate) exhibited the greatest variability and were most sensitive to sample support, requiring a larger sample support to average out small-scale variability. Microbial processes such as carbon mineralization exhibit greater small scale variability than physical processes because they require spatial coincidence of the appropriate size and type of microbial community and quality and quantity of substrate at the micrometer scale. These factors can be expected to vary considerably in space at the cm scale. For example, Parkin (1987) found that the rate of denitrification in soil varies considerably at the cm scale and is strongly dependent on the spatial distribution of microbially available carbon. It is likely that even the short (5 cm) distance between the centers of abutting cores is large enough to introduce variance.

What causes non-identity in paired soil samples? Our data allow us to dismiss a few explanations. For instance, non-identity is unlikely to be the result of

Table 5
Average (all dates included) and standard deviation values for relative difference (RD; Eq. (1)) between randomly paired cores for bulk density, volumetric water content, organic matter content, and carbon mineralization rate

Soil property	RD (%)	Std. dev. (%)
ρ_B	5.94	5.27
θ_V	9.11	9.07
OM	12.33	9.14
C_{\min}	29.68	24.28

sampling bias, given the absence of statistically significant differences among sets of paired cores (data not shown). Alternatively, differential effects of sampling time on particular variables could be responsible. For example, the organic matter content, moisture content, and bulk density were determined on two different groups 28 days apart. A significant degree of decomposition of organic matter could have occurred during incubation, especially if roots constitute an important part of the OM pool. This would have resulted in higher values of OM and lower values of bulk density for the A cores. However, the permutation process randomizes assignment of cores to either group, such that this mechanism could not account for lack of identity.

There are other sources of variability that undoubtedly contribute to non-identity. Random experimental error may differ in magnitude between measurements on adjacent cores, contributing to non-identity. In addition, the uncertainty of measurements resulting from random errors increases with the number of measurements needed to arrive at a derived quantity such as bulk density or carbon mineralization rate. This could explain some of the differences in values of RD for physical and biological properties: whereas the former require relatively few measurements to arrive at a value, the latter require a larger number of different types of measurements. The heterogeneous spatial distribution of soil components no doubt also contributes to non-identity. For example, plant roots are not distributed homogeneously in space at the scale at which we examined variance. The heterogeneity of root distribution may have contributed to non-identity of both the physical and biological properties, since root channels contribute to the porosity and pore size distribution, roots are mineralized by microorganisms, and root carbon contributes to soil organic matter.

Regardless of the mechanism responsible for non-ideal behavior, our results indicate that the assumption of identity among abutting soil cores for bulk density, volumetric water content, organic matter content, and carbon mineralization is not warranted at this field site. Although our data are limited to one ecosystem, it is reasonable to expect that for other ecosystems the relative degree of deviation from identity will likely follow the same patterns observed here. Thus, variables controlled by physical processes can be expected to be closer to identity than those controlled by biological processes, since controls on these variables are likely to be similar across ecosystems. Even for variables with behavior close to ideal — e.g. volumetric moisture content — caution must be taken when assuming identity. Scatter plots of volumetric moisture content show that there can be considerable dissimilarity among adjacent cores (Fig. 1). The assumption of identity may thus hold true only for the central tendency of sufficiently large data sets.

Our findings have consequences for the design of soil sampling schemes. They support the contention that it is erroneous to assume that different variables show the same form of spatial variation (e.g. Pettitt and McBratney, 1993) even at very small distances. In addition, our results provide a quantitative

estimate of the variance for these soil properties at the practical limit for distances between sampling points. This variance could be used as an estimate of an upper bound for the nugget variance. A priori knowledge of nugget variance can be a useful parameter in the design of sampling schemes to assess spatial variability (e.g. McBratney and Pringle, 1999; Pettitt and McBratney, 1993). However, the actual deviation of nugget estimate of adjacent paired cores based on the variances of several lag classes is not estimated in this study.

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