DIVISION S-8—NUTRIENT MANAGEMENT & SOIL & PLANT ANALYSIS

Spatial Analysis of Soil Fertility for Site-Specific Crop Management

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ABSTRACT

Spatial patterns of soil properties and nutrient concentrations need to be characterized to develop site-specific farming practices that match agricultural inputs with regional crop needs. The spatial variation of soil organic C (SOC), soil water content (SWC), NO_3–N, PO_4–P, and K were evaluated in the 0- to 15-cm layer of a 3.3-ha field (Typic Haplaquoll and Argiaquic Argialboll) cropped with maize (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.]. The range of spatial correlation was determined from semivariance analyses of the data and was found to vary among and within fertility parameters. Nitrate had the shortest correlation range (<5 m) and SOC had the longest (>180 m), whereas SWC, PO_4–P, and K had intermediate spatial correlation ranges. In addition, SOC was found to have small-scale spatial variation nested within large-scale spatial variation. The spatial pattern of NO_3–N changed with time. Frequency distributions of SOC and SWC were close to normal, whereas the distributions of NO_3–N, K, and PO_4–P data were skewed. Median polishing detrending and trimming of outlying data were useful methods to remove the effects of nonstationarity and non-normality from the semivariance analysis. The results suggest that reducing sampling intervals from 50 to 1 m would reduce the variance of SWC, SOC, NO_3–N, PO_4–P, and K estimates by 74, 95, 25, 64, and 58%, respectively. A useful sampling pattern for characterizing the spatial variation of several soil properties-nutrients and scales should be random with sample spacing as close as 1 m and as far apart as the longest dimension of the field.

Soil properties and soil nutrients often vary across a field such that uniform fertilizer applications may result in over- and underfertilized areas. Runoff and leachate from overfertilized areas may contaminate water supplies, while crop yield may be restricted in underfertilized areas. To reduce this source of application error, maps of soil productivity and variable rate applicators, interfaced with navigational and computer control systems, are used to match agricultural inputs with site-specific crop needs. In addition to equipment innovations, statistical methods that can accurately summarize spatial patterns of soil data are needed to determine site-specific application rates.

Geostatistics, originally used in the mining industry (Matheron, 1963), has proven useful to soil science for characterizing and mapping spatial variation of soil properties. Geostatistics consists of variography and kriging. Variography uses semivariograms to characterize and model the spatial variance of data, whereas kriging uses (Burgess and Webster, 1980) the modeled variance to estimate values between samples. Details about variography and kriging are well documented (Burgess and Webster, 1980; Matheron, 1963), and specifics about using kriged values to develop maps for site-specific farming can also be found in the literature (Mulla, 1991; Mulla, 1989). However, few works have focused on using variography for estimating parameters important to site-specific farming, such as the optimum dimensions of application zones and distance between soil samples, and even fewer works have discussed using variography for predicting the agronomic benefits of site-specific applications.

The semivariogram illustrates the relationship between the sample variance and the lateral distance, known as the *lag*, separating samples (Fig. 1). From this relationship, a lateral distance between samples can be chosen that optimizes sample variance and number of samples. The lag distance where the variance approaches an asymptotic maximum, known as a *sill* (Fig. 1), is the range across which data are spatially correlated (Clark, 1979). As the lag distance approaches zero, the variance usually approaches a finite value, called the *nugget variance* (Burgess and Webster, 1980). The nugget represents residual variation, not removed by close sampling. Han et al. (1994) presented a mathematical procedure that uses the variance–distance relationship, summarized by the range, nugget, and sill, to optimize the dimensions of the application zone.

The agronomic benefits of using site-specific crop management practices are presumably related to the spatial patterns of soil properties and soil nutrient concentrations. Variography has been used to compare spatial variation of soil properties, scales, and times. For example, semivariograms of soil properties have shown that the range of spatial correlation for PO_4–P and K to be >100 m (Mulla, 1989; Webster and McBratney, 1987; Yost et al., 1982), in contrast to the 1- to 30-m range reported for NO_3–N (Dahiya et al., 1985; Van Meirvenne and Hofman, 1989; White et al., 1987). Variography also has been used to measure the range of spatial correlation of small- and large-scale variation (Gajem et al., 1981; Van Meirvenne and Hofman, 1989). Finally, Van Meirvenne and Hofman (1989) used variography to show that the range of spatial correlation for NO_3–N increased as mean NO_3^- levels decreased during fall and winter. Given the present limitations on accuracy of navigation systems and applicators and cost of sample analysis, the benefits of spatial applications may be highest for

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Abbreviations: SOC, soil organic C, SWC, soil water content.

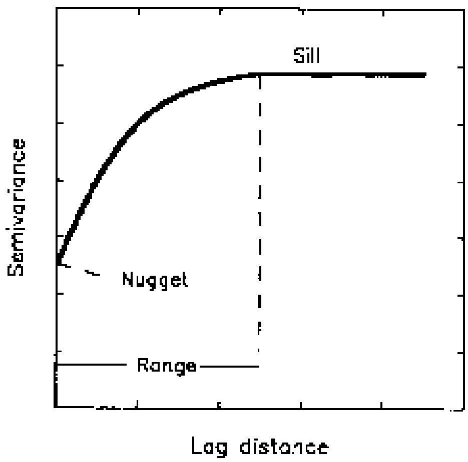

Fig. 1. Semivariogram, showing the range, nugget, and sill.

nutrients exhibiting long ranges of spatial correlation, large-scale variation, and spatial patterns that are temporally correlated.

The semivariogram must be correctly estimated to be useful. Variography is based on the theory of regionalized variables, developed from the assumptions that the semivariance statistic is normally distributed and that data are stationary (Webster, 1985). Simply stated, data are stationary when the semivariance for any lag is the same in all regions of the study area. When a trend or large-scale variation exists in a field, data may not be stationary and the variance–distance relationship may depend on direction. In addition, outlying values of a skewed frequency distribution may influence the variance–distance relationship (Henley, 1981).

Several authors described exploratory techniques that can remove the effects of skewed distributions and nonstationarity on the shape of the semivariogram and that can aid in understanding the structure of spatial variation (Hamlett et al., 1986; Tevis et al., 1991). Van Meirvenne and Hofman (1989), using polynomial detrending, separated small-scale variation from large-scale variation in soil NO_3–N data, while Hamlett et al. (1986), using median polishing detrending, accomplished the same objective for soil–water pressure potential data. Tevis et al. (1991) illustrated the use of mathematical transformations and elimination of outlying values to reduce the effect of a skewed frequency distribution. Although these techniques may improve spatial analyses of soil data, they have not been extensively evaluated.

The purpose of this study was to compare spatial variation among different soil properties, scales, and times in a central Illinois field. Using geostatistical, detrending, and data trimming methods, we compared semivariograms for SOC, SWC, NO_3–N, PO_4–P, and K and discussed the relevance of the results to site-specific crop management strategies.

MATERIALS AND METHODS

Experimental Site

The experimental site was a 3.3-ha field in a maize–soybean rotation, located in central Illinois on Drummer silty clay loam (fine-silty, mixed, Mesic Typic Haplaquoll) and Thorp silt loam (fine-silty, mixed, Mesic Argiaquic Argialboll). The site received dairy cow manure in 1989 and 1990 by combined broadcast and injection applications (76-cm rows). Manure was incorporated to a 15-cm depth. No fertilizer amendments were applied after 1990. The field was planted with soybean on 13 May 1991 and with maize on 6 May 1992.

Sample Collection and Chemical Analyses

Samples of the 0- to 15-cm horizon were collected to compare the spatial variation of soil nutrients (SOC, SWC, NO_3–N, PO_4–P, and K) at two scales (0.25 and 3.3 ha). Samples were collected using Dutch augers on a 50-m grid (n = 25) and from 200 randomly chosen locations within one 0.25-ha grid cell (Fig. 2) on 15 June 1991. A portion of each sample was placed into preweighed cans, and approximately 10 g of soil were added to preweighed bottles containing 50 mL of 2 M KCl.

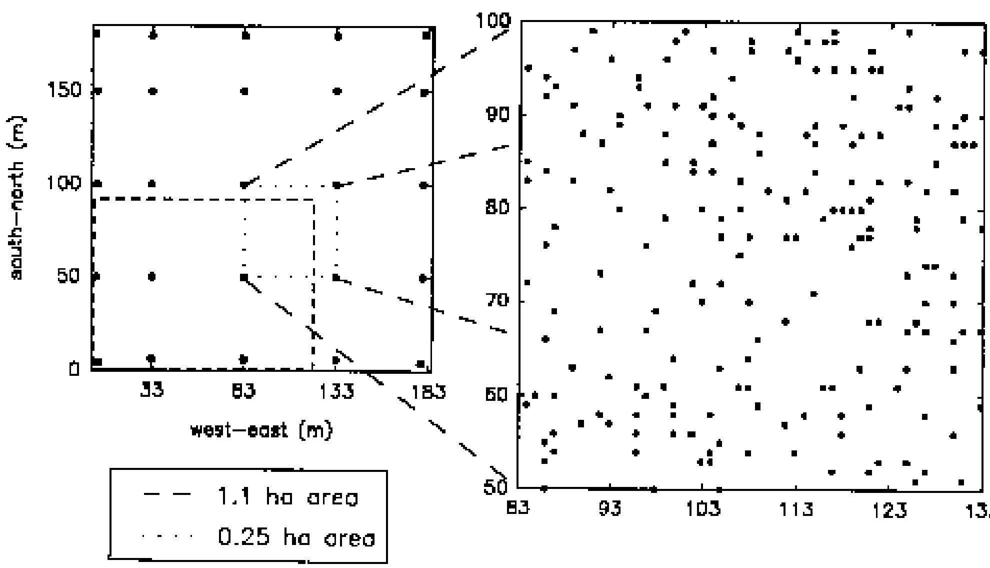

Fig. 2. Sampling patterns in the 0.25- and 3.3-ha areas and boundaries of the 0.25-ha and 1.1-ha areas.

The remainder of the sample was air dried for determinations of SOC, PO_4-P, and K. Soil in cans was oven dried 48 h at 105°C for gravimetric determination of SWC. Soil organic C was measured by dry combustion in an induction furnace. Samples were extracted with Bray No. 1 (0.025 *M* HCl and 0.03 NH_4F) at a 10:1 solution/soil ratio. The extracts were analyzed for K by flame emission using an atomic spectrophotometer and analyzed for PO_4-P by a Mo blue-ascorbic acid colorimetric method using a flow injection system (Lachat Quik Chem AE, Lachat Instruments, Milwaukee, WI). Potassium chloride extracts were analyzed for NO_3-N using the copperized Cd reduction method described by Keeney and Nelson (1982) and the Lachat flow injection system. Calculations of soil nutrient concentrations were adjusted for the initial water content of the soil.

Spatial patterns of soil NO_3-N in early and late spring of 1992 were also compared. Because the results of the 1991 samples indicated that soil NO_3-N data were noisy, the sampling pattern was changed. Samples of the 0- to 15-cm horizon were collected using a hand probe from 120, 6 by 15 m cells (1.1-ha area) 13 May and 15 June 1992 (Fig. 2). Composites of six subsamples from the central 3 by 11 m of each cell were added to preweighed cans for gravimetric determination of SWC, and approximately 20 g were added to bottles containing 100 mL of 2 *M* KCl. Soil extracts were analyzed colorimetrically for NO_3-N as described above.

Statistical Analysis

Normality of the data was examined by kurtosis and skewness tests (Table 1). See Snedecor and Cochran (1980) for detailed descriptions of kurtosis and skewness tests. In cases where distributions showed significant kurtosis and skewness ($P < 0.01$), data greater than four standard deviations from the mean (highest 1-1.5% of the data) were discarded.

Isotropic (direction independent) semivariance of data was calculated using GS+ geostatistical software (Gamma Design Software, 1993). Semivariance is defined in the following equation:

$$\gamma(h) = \frac{1}{[2m(h)]} \sum_{i=1}^{m(h)} [Z_{(x_i)} - Z_{(x_i+h)}]^2 \qquad [1]$$

where γ is the semivariance for *m* data pairs separated by a distance of *h*, known as a lag, and *Z* is the value at positions x_i and $x_i + h$ (Matheron, 1963; Webster, 1985).

Lag widths and maximum lag distances were selected so that the minimum number of data pairs per lag class was 52, 112, and 38 for the 0.25-, 1.1-, and 3.3-ha areas, respectively. Many data and lags were used in the analysis so that the range of spatial correlation (distance to the sill) could be visually estimated from the semivariogram. The ranges of spatial correlation are summarized in Table 2.

The relationship between the sample variance and the distance between samples was summarized by comparing the variances of the minimum and maximum lags:

$$\Delta\gamma = \frac{(\gamma_{max} - \gamma_{min})}{\gamma_{max}} \times 100 \qquad [2]$$

where γ_{min} is the semivariance of the minimum lag distance, γ_{max} is the semivariance of the maximum lag distance, and $\Delta\gamma$ expresses the percentage reduction in the semivariance when the interval between samples is reduced from the maximum lag to the minimum lag distance (Table 2). The semivariance directly relates to the sample variance. In fact, Webster (1985) demonstrated that the semivariance is derived from the sample variance S^2:

$$S^2 = \frac{\sum_{i=1}^{n} [Z_i - \overline{Z}]^2}{n - 1} \qquad [3]$$

where $\overline{Z}$ is the mean of *n* data. For a pair of data ($n = 2$) separated by a distance *h*:

$$S^2 = [Z(x) - \overline{Z}]^2 + [Z(x + h) - \overline{Z}]^2 \qquad [4]$$

$$S^2 = \frac{1}{2}[Z(x) - Z(x + h)]^2 \qquad [5]$$

The term on the right side of Eq. [5] equals Eq. [1] where the number of data pairs, $m_i = 1$. Raw data from the 0.25- and 1.1-ha areas were detrended using median polishing software of Han (1993). See Tukey (1977), Hamlett et al. (1986), and Cressie et al. (1990) for detailed descriptions of median polishing. The procedure blocked the 0.25-ha area into a grid of 100 25-m^2 cells and the 1.1-ha area into a grid of 60 183-m^2 cells. Median polishing removed the median row and column values from the raw data through successive iterations until convergence was attained. The median polishing algorithm modeled the trend effects as:

Table 1. Statistical summary of soil data from the 0.25-, 1.1-, and 3.3-ha areas in central Illinois.

Variable	*n*	Average	SD	Max.	Min.	Kurtosis†	Skewness‡
				0.25-ha and 3.3-ha areas§			
				$g\ kg^{-1}$			
SWC¶	225	194.3	29.0	291.1	141.8	3.1	0.62
SOC¶	225	17.2	2.8	24.6	8.7	2.9	0.01
				$mg\ kg^{-1}$			
NO_3-N	225	6.2	3.7	29.2	0.9	10.5	2.02
PO_4-P	225	74.0	26.8	226.3	24.9	7.0	1.24
K	225	268.2	114.9	905.8	112.9	11.0	2.23
				1.1-ha areas			
NO_3-N May	120	8.3	2.3	25.4	0.8	25.4	3.28
NO_3-N June	120	1.6	0.82	4.3	0.4	3.3	0.83

† Data showed significant kurtosis ($P < 0.01$) if values were >3.98 or <2.37 for the 0.25- and 3.3-ha areas and >4.24 or <2.24 for the 1.1-ha area (Snedecor and Cochran, 1980, p. 492).

‡ Data showed significant skewness ($P < 0.01$) if values were >0.382 for the 0.25- and 3.3-ha areas and 0.508 for the 1.1-ha area (Snedecor and Cochran, 1980, p. 492).

§ Data from the 0.25- and 3.3-ha areas were pooled.

¶ SWC = soil water content; SOC = soil organic C.

Table 2. Semivariance statistics of soil data from 0.25-, 1.1-, and 3.3-ha areas in central Illinois.

Variable	0.25-ha area				3.3-ha area			
	γ_{1m}†	γ_{50m}‡	$\Delta\gamma$§	Range¶	γ_{45m}†	γ_{180m}‡	$\Delta\gamma$	Range
	$g^2\ kg^{-2}$		%	m	$g^2\ kg^{-2}$		%	m
SWC#	430.00	1682.00	74.44	≥ 50	4.10	8.71	52.93	135
SOC#	0.86	18.00	94.44	≥ 50	0.22	1.08	79.63	≥ 180
	$mg^2\ kg^{-2}$				$mg^2\ kg^{-2}$			
NO_3–N	7.24	9.44	23.31	5	5.25	6.48	18.98	≤ 45
PO_4–P	404.57	1129.00	64.17	≥ 50	393.47	383.14	− 2.70	– ††
K	5265.80	12610.0	58.24	30–50	4206.60	4646.80	9.47	≤ 45
	1.1-ha area May				1.1-ha area June			
	γ_{8m}†	γ_{95m}‡	$\Delta\gamma$	Range	γ_{8m}†	$2\gamma_{95m}$‡	$\Delta\gamma$	Range
	$mg^2\ kg^{-2}$		%	m	$mg^2\ kg^{-2}$		%	m
NO_3–N	2.38	2.90	18.10	35	0.67	0.84	20.24	–

† Semivariance of the minimum lag distance.
‡ Semivariance of the maximum lag distance.
§ Comparison of semivariances of minimum and maximum lags: $\Delta\gamma = [(\gamma_{max} - \gamma_{min})/\gamma_{max}] \times 100$.
¶ Range of spatial correlation, determined from the semivariograms in Fig. 4 and 6.
# SWC = soil water content; SOC = soil organic C.
†† Range of spatial correlation could not be determined from the semivariograms in Fig. 4 and 6.

$$Z_{kl} = a + r_k + c_l + E_{kl}$$
$$k = 1, \ldots p$$
$$l = 1, \ldots q \quad [6]$$

where for p rows and q columns, Z is the value of cell k, l, a is the general effect, r is the effect of row k, c is the effect of column l, and E is the residual error.

Residual data were calculated by subtracting the trend value of each cell (the sum of a, r, and c) from the raw data. Sums of squares of raw and residual data were calculated to estimate the portion of variance represented by the trend (Table 3). Isotropic semivariances of the residuals were calculated to detect small-scale spatial variation.

RESULTS

Exploratory Analysis

Nitrate, K, and PO_4–P data sets were highly skewed due to several outlying values that greatly exceeded the mean, whereas SOC and SWC data followed nearly symmetric, normal distributions (Table 1). These high values may represent sites of high microbial activity or localized accumulations of nutrients. The shape of the semivariogram was found biased by values greater than four standard deviations from the mean. The semivariograms of the NO_3–N and K data from the 0.25-ha area (Fig. 3) exhibited a quadratic shape, indicating that data were most correlated at small and large lag distances. These variograms appeared to depart from the classical nugget–sill model presented in Fig. 1. Removal of data that were four standard deviations greater than the mean (highest 1.5% of the data) eliminated the quadratic shape of the NO_3–N and K semivariograms (Fig. 4). Additional trimming of the data (removal of highest 3% of the data) did not significantly change the shape of the semivario-

Table 3. Sum of squares statistics of soil data from 0.25- and 1.1-ha areas in central Illinois.

Source	n	Sum of squares: Total	Trend	Residual	Percentage of sum of squares represented by trend
		0.25-ha area			
SWC†	200	169804.6	90885.2	78919.4	53.5
SOC†	200	1312.9	992.3	320.6	75.6
NO_3–N	197‡	2015.8	− 37.9	2053.7	− 1.9
PO_4–P	198‡	119366.4	46809.9	72556.5	39.2
K	197‡	1861382.3	690448.3	1170934.0	37.1
		1.1-ha area			
NO_3–N May	119‡	366.5	36.8	329.7	10.0
NO_3–N June	120	79.7	18.1	61.6	22.7

† SWC = soil water content; SOC = soil organic C.
‡ Outlying data were discarded.

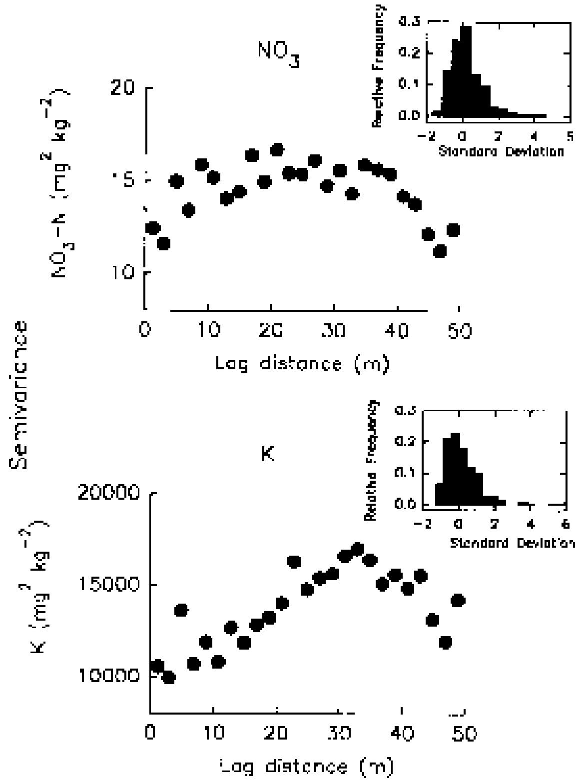

Fig. 3. Semivariograms and frequency distributions of NO_3-N and K data from the 0- to 15-cm horizon of the 0.25-ha area before trimming outlying data.

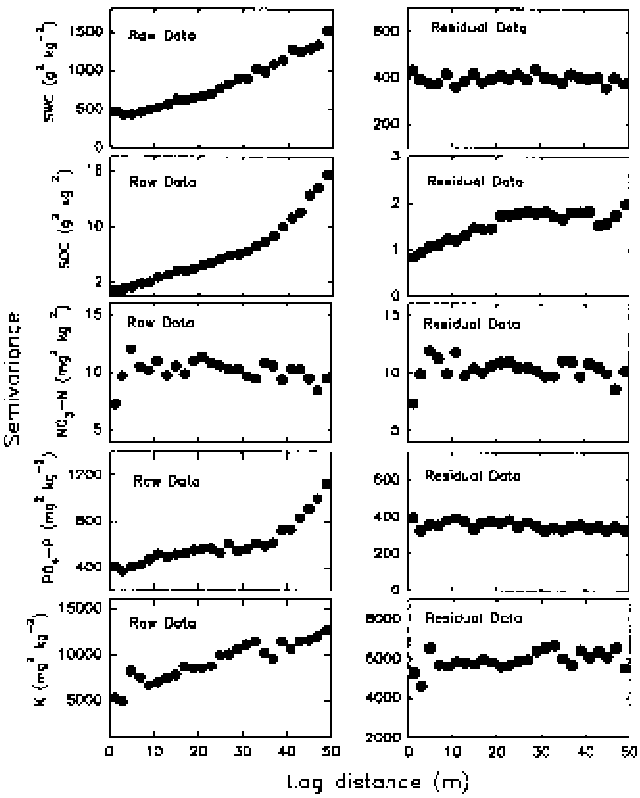

Fig. 4. Semivariograms of raw and residual SWC, SOC, NO_3–N, PO_4–P, and K data from the 0- to 15-cm horizon of the 0.25-ha area (residual data = raw data − trend data).

grams presented in Fig. 4 (data not presented), demonstrating that only the extreme values needed to be trimmed to ascertain the shape of the semivariogram. Hence, the highest 1.5% of NO_3–N and K data and highest 1% of PO_4–P data were not included in the following analyses.

Comparison of Soil Fertility Properties

Examination of the semivariograms of the raw data in Fig. 4 showed that the range of spatial correlation varied among soil properties. Within the intensely sampled 0.25-ha cell, K was spatially correlated to a distance >30 m. Nitrate had the shortest range of spatial correlation (<5 m). The semivariance for SWC increased with distance without reaching a sill in the 0.25-ha cell. Similar results were obtained for SOC and PO_4–P, suggesting that the range of spatial influence was >50 m for these soil properties.

In the 3.3-ha area, the semivariance of SWC reached a sill near 140 m (Fig. 5), whereas semivariance of SOC data increased without approaching an asymptotic value at the maximum lag distance (180 m). Semivariance of PO_4–P reached a maximum at 100 m and then decreased. Possibly a trend following a quadratic or second degree polynomial function would cause data of the shortest and the longest lag distances to be most correlated. Consistent with the variograms from the 0.25-ha areas, the semivariance for NO_3–N and K in the 3.3-ha field was constant with lag distance, indicating that data were not spatially correlated across distances >50 m.

The semivariograms also illustrate that sampling at

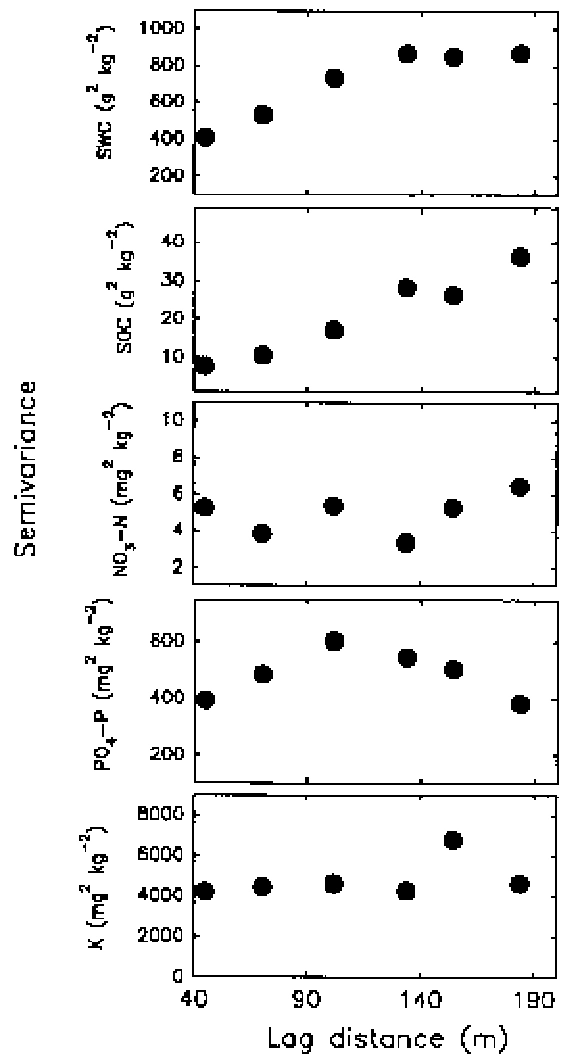

Fig. 5. Semivariograms of the raw SWC, SOC, NO_3–N, PO_4–P, and K data from the 0- to 15-cm horizon of the 3.3-ha area.

small intervals may improve the estimates of SOC and SWC more than estimates of other soil parameters. For example, sampling at 45-m intervals instead of 180-m intervals in the 3.3-ha area would reduce the variance of SWC and SOC estimates by 53 and 80%, respectively (Table 2, Fig. 5). Sampling at 1-m instead of 50-m intervals in the 0.25-ha area may further reduce the variance of SWC and SOC estimates (Table 2). In contrast, the variance of NO_3–N estimates would be reduced by <24% in the 0.25-ha area and 20% in the 3.3-ha area by sampling at the minimum lag distances (Table 2). The amount that the sample variance would decrease due to reducing the lateral distance between samples may depend on the shape of the semivariogram. Reducing the interval between samples from 50 to 35 m would reduce the variance of PO_4–P estimates by 47% but would not reduce the variance of NO_3–N estimates (Fig. 4).

Nested Spatial Variation

Median polish detrending was useful for removing large-scale spatial variation from data of the 0.25-ha

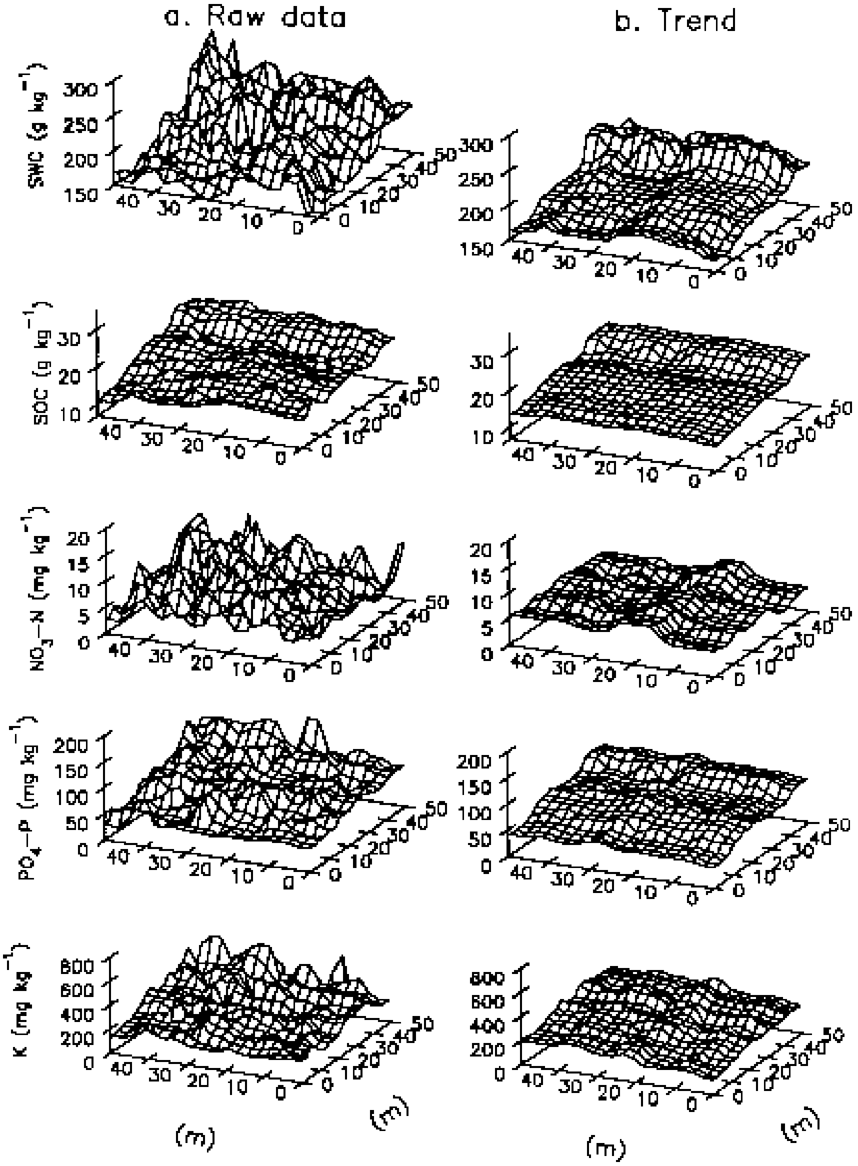

Fig. 6. Spatial distributions (a) and trends (b) of SWC, SOC, NO_3–N, PO_4–P, and K data from the 0- to 15-cm horizon of the 0.25-ha area.

cell so that the small-scale variation could be analyzed. Large-scale variation, or trends, tend to make the semivariance direction dependent (semivariance is greatest parallel to the trend and smallest perpendicular to the trend) and nonstationary (the semivariance is greater where the trend is steepest). As shown in Fig. 6, strong trends were present in the SWC, PO_4–P, and SOC data, whereas a slight trend was present in the K data and almost no trend was present in the NO_3–N data; the NO_3–N data therefore seemed most stationary. In a similar pattern, Table 3 quantitatively shows that the trends for SOC and SWC data were strongest, representing the highest percentage of the total sums of squares, and NO_3–N and K trends were weakest, representing the lowest percentage of the total sums of squares. A negative value was calculated for NO_3–N, presumably because the median polish method less efficiently estimated the trend than did the arithmetic average. Unlike least squares regression, median polishing does not minimize the sum of squares.

Semivariograms of residual data (raw data − trend data) were used to determine if data exhibited small-scale spatial variation (Fig. 4). The semivariograms for SWC and PO_4–P residual data showed almost no slope, indicating that the trend removed most of the variation represented by spatial correlation. Residual SOC data were found spatially correlated to a 25-m range in addition to the ≥180-m range reported above. These two ranges represent two scales of spatial variation, and both may have agronomic significance. Semivariograms of raw and residual NO_3–N data (Fig. 4) were similar, which might be expected because no variation was removed by detrending (Table 3). Significant variation was removed from the K data by detrending, and the semivariograms of the residual and raw data were different (Fig. 4). The semivariogram of the residual K data may indicate a range of spatial correlation of less 5 m, but the difference between the nugget and the sill values was too small to be conclusive.

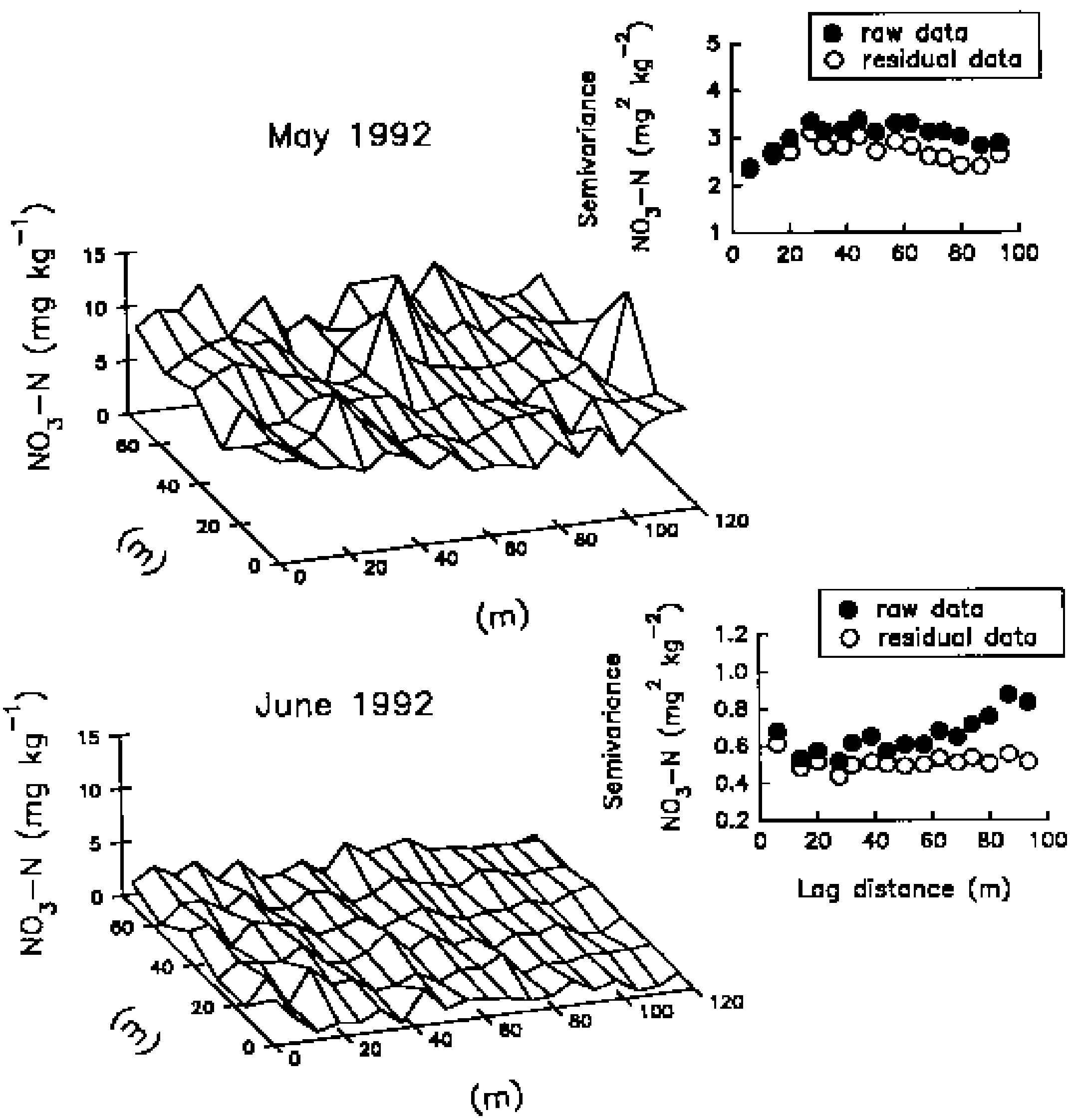

Fig. 7. Spatial distributions and semivariograms of raw and residual NO_3–N data (0–15 cm) from the 1.1-ha area in May and June 1992.

Time Effects on Spatial Variation of Soil Nitrate

Spatial variation of soil NO_3–N changed significantly during the spring of 1992. Soil concentrations of NO_3–N in the 0- to 15-cm depth decreased from an average of 8.3 to 1.6 mg kg^{-1} between 13 May and 15 June 1992 (Fig. 7, Table 1). A significant portion of the NO_3–N may have been leached to lower depths, denitrified, or absorbed by the maize crop before the June sampling. The NO_3–N levels of May and June were weakly correlated ($R = 0.24$). The shape of the semivariograms for NO_3–N (Fig. 7) also changed between May and June. The semivariogram for NO_3–N reached a sill at <30 m in May, whereas in June, the semivariance was constant with increasing lag distance until 60 m where the variance increased to a maximum value at 90 m. This increase in variance was presumably due to large-scale variation, because detrending produced a flat residual semivariogram, known as a pure nugget effect, (Fig. 7, Table 3), which indicates an absence of spatial correlation. In contrast, detrending of the May data removed little variation (Table 3) and did not significantly change the semivariogram shape (Fig. 7), suggesting that most of the spatial variation was small scale. These results indicate that timing of soil sampling could influence maps of soil NO_3–N, used to estimate site-specific application rates of N fertilizer.

DISCUSSION

Although the data are a limited representation of the spatial variation of soil fertility in central Illinois, they illustrate several points relevant to spatial analysis of soil data and site-specific crop management.

Proper estimation of the semivariogram is essential for characterizing the spatial patterns of soil nutrients. The semivariogram is based on the assumptions that the semivariances are normally distributed and that the data are stationary. Although the data of this study did not always satisfy these assumptions, the combination of median polish detrending and trimming of outlying values reduced nonstationarity and increased normality of the raw data. Logarithmic or 4th root transformation of the data may remove much of the effects of skewness and kurtosis (Cressie and Hawkins, 1980), but residual outliers would still bias the estimates of the mean semivariance calculated with Eq. [1]. Hamlett et al. (1986) noted that some researchers advocate detrending data with polynomials, but this method assumes that nonstationarity is deterministic when in fact, it may also have a stochastic component (Davidoff et al., 1986). Median polishing can remove both deterministic and stochastic components of nonstationarity, and therefore, may be more flexible than polynomials. However, median polishing is a nonparametric method without a statistical procedure for testing the significance of fitted trends.

Nonstationary and outlying data may also reduce the accuracy of maps of soil properties. Han et al. (1993) suggested that a good approach for mapping soil properties where data exhibit large-scale variation would be (i) detrend the data by median polishing, (ii) model the variance–distance relationship of the residual data, (iii) develop kriged estimates of the residual values at unsampled locations from the modeled variance, and (iv) add these estimated values back to the trend. In addition to this procedure, our results would suggest that removing outlying data may aid in modeling the variance–distance relationship. Other methods, such as universal kriging, also have been proposed to account for nonstationarity. Webster and Burgess (1980) discussed some limitations of using universal kriging for estimating soil properties.

These results showed that soil fertility parameters had different ranges of spatial correlation within the same field. The different ranges of spatial correlation for nutrients may be related to the mobilities of the ions. Nitrate, the most mobile of the three ions of this study, had the shortest range of spatial correlation, whereas PO_4–P, presumably the least mobile, was spatially correlated across the longest distance. In addition, spatial distribution of PO_4–P appeared to be correlated with SOC. Semivariograms of PO_4–P and SOC from the 0.25-ha cell were similar in shape (Fig. 4), the raw data exhibited similar trends (Fig. 6), and the PO_4–P and SOC data were correlated (r = 0.56).

The results also indicated that some soil parameters will be more difficult to use for site-specific soil management than others. Specifically, soil NO_3–N may have limited applications for site-specific crop management. First, because the spatial patterns of soil NO_3–N may not be correlated across long time intervals, the interval between sampling and application may need to be short. A short range of spatial correlation imposes additional application and sample limitations. With a 5-m range of spatial correlation (data from the 0.25-ha area), an applicator traveling at 8 km h^{-1} would need to modulate fertilizer rates every 2.25 s to match N fertilizer rates to soil NO_3–N levels. Also, sampling at this correlation range would require 400 samples ha^{-1} to develop an accurate soil NO_3–N map. Thus, modulating N fertilizer rates to match soil NO_3–N levels may not be economical without using an automated system for real-time measurement of soil NO_3–N. Several researchers are developing automated systems that can conduct real-time measurements of NO_3–N levels in the plow layer (Adsett and Zoerb, 1991; Birrell and Hummel, 1992). Even if these systems could reduce measurement intervals from 50 to 1 m, the results of this study show that the variance of soil NO_3–N data may not decrease by more than 25%.

In contrast, SWC, SOC, PO_4–P, and K showed promise as variables for site-specific crop management. Soil moisture information may be used for varying seed planting depth, SOC data for regulating soil-applied herbicide rates or estimating N mineralization potential, and PO_4–P and K tests for estimating P and K fertilizer rates. Currently, sensors are being developed for automated measurement of moisture (Christensen and Hummel, 1985; Price et al., 1990), SOC (Sudduth et al., 1991), and K (Cardwell et al., 1988; Tsukada et al., 1990) so that data collection might be economical at a small scale. These results indicate that reducing measurements from a 50- to a 1-m scale would reduce variation of SWC, SOC, PO_4–P, and K data by 74, 94, 64, and 58%, respectively. Even sampling intervals of larger distances, such as 10 m, would still reduce the variance associated with these variables. Timing soil sampling for analysis of SOC, PO_4–P, and K may not be as critical as for NO_3–N because these variables presumably change slower with time than does NO_3–N.

The correlation between soil parameters and the fertilizer requirements of a crop also needs to be considered when discussing the agronomic benefits of site-specific soil applications. Varying N fertilizer rates as a function of soil NO_3–N concentrations would be agronomically beneficial only if soil NO_3–N is an indicator of plant available N. Studies in several locations in the USA have shown that pre-sidedress levels of NO_3–N in the plow layer are correlated with maize grain yield (Blackmer et al., 1989; Binford et al., 1992; Brown et al., 1992; Meisinger et al., 1992). Very little information is available to compare variable rate and conventional technologies for applying fertilizers. Side-by-side comparisons have shown that less fertilizer could be applied with variable rate than with conventional applications without yield loss (Mulla et al., 1992), but these studies do not preclude the possibility that the fertilizer rates employed may have exceeded the needs of the crop. In such studies, fertilizer efficiency could also be increased by reducing conventional application rates.

Additionally, these results demonstrate that sampling patterns used for manual collection of soil samples need to accommodate the variety of ranges of spatial correlation associated with different soil properties. Perhaps the most flexible pattern would be random locations with samples as close as 1 m and as far apart as the longest dimension of the field. Grid patterns are easiest to set up but require more samples than do random patterns to measure variances of small lag distances. Alternatively, intensely sampling one or several grid cells to measure the variances of small lag distances, as was done in this study, biased results to particular regions of the field. With improved and less expensive geographical positioning systems becoming available, sampling on random patterns in large areas may become feasible.

CONCLUSIONS

The results of this study demonstrate that within the same field, spatial patterns may vary among several soil fertility parameters, scales, and times. Although this study characterized the spatial patterns of soil fertility at a single location in central Illinois, the results illustrate some useful concepts relevant to site-specific crop management: (i) Variography can be a useful tool for designing effective soil sampling strategies, for establishing the dimensions of application zones, and for screening soil fertility variables for use in site-specific applications. (ii) Median polish detrending and data trimming techniques, used together with variography and kriging, may improve characterizations of spatial variation and accuracy of soil productivity maps. (iii) Soil sampling patterns need to be flexible to accurately characterize the spatial patterns of several soil properties.

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