SPATIAL VARIABILITY OF AVAILABLE NUTRIENTS AND SOIL CARBON UNDER ARABLE CROPPING IN CANTERBURY

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Abstract

Soil properties can vary spatially at a paddock to farm scale due to differences in topography, parent material, vegetation or land management. The objective of this study was to quantify the spatial variability of available nutrients and organic matter within a 10.4 ha paddock (predominantly Templeton silt loam; flat topography) at Lincoln that had a long-term history of arable cropping. Samples (0–7.5 cm depth) were collected in a grid pattern (30–35 m sampling intervals; total of 91 samples) for determination of mineral N, anaerobically mineralisable N (AMN), Olsen P, total C and total N. The data were evaluated using geostatistical as well as classical statistical methods, and a geographic information system (GIS) technique was used to produce nutrient and organic matter maps. Although the paddock had a relatively flat topography and had been managed uniformly for many years, nutrient levels exhibited substantial variability. For example, Olsen P ranged from 14 to 53 µg/g (mean 20 µg/g) and AMN ranged from 37 to 83 µg/g (mean 50 µg/g). Soil organic matter also showed significant spatial variability, with total C ranging from 19 to 31 g/kg (mean 27 g/kg). All measured variables except mineral N showed moderate to strong positional dependence. Semivariogram models showed that for Olsen P the autocorrelation distance was 700 m, compared with 184 m for AMN, and 300 m for total C. We examined the relationship between soil texture and organic matter using samples collected along two perpendicular transects within the paddock. Soil C showed a strong positive correlation ($R^2 = 0.79$; $n = 17$) with the amount of clay plus fine silt (<5 µm fraction) and a negative correlation ($R^2 = 0.81$) with sand content. These results suggest that textural variation was a major factor influencing within-paddock variability in soil organic matter at this study site.

Introduction

Soil properties can vary spatially due to a variety factors, including climate, parent material, topography, vegetation, and land management (Trangmar, 1986; West, 1989; Weijun, 2010). Soil characteristics and productivity can vary significantly over small spatial scales, e.g. within paddocks (Fulton et al., 1996; Wells et al., 2000; Gaston et al., 2001). Soil fertility assessments commonly rely on a random soil sampling protocol to obtain an average fertility value for a paddock. Thus, spatial variability is ignored and, consequently, some parts of the paddock may receive excessive fertiliser while other parts may suffer nutrient deficiency due to under-application.

Geostatistics coupled with geographic information system (GIS) technologies has substantial potential to discern spatial patterns within paddocks. In this study we used geostatistics and GIS to map and interpret the spatial variability of nutrients and soil organic matter at a paddock scale. A second objective was to identify factors contributing to within-paddock variability in the measured variables, especially soil organic matter.

Materials and Methods

Site description

The experimental site was a rectangular paddock (400 m long x 260 m wide; 10.4 ha) at Lincoln University that had a long-term history of arable cropping (wheat, peas, and seed crops). The site has a flat to gently sloping topography (Figure 1) and the predominant soil type is Templeton silt loam.

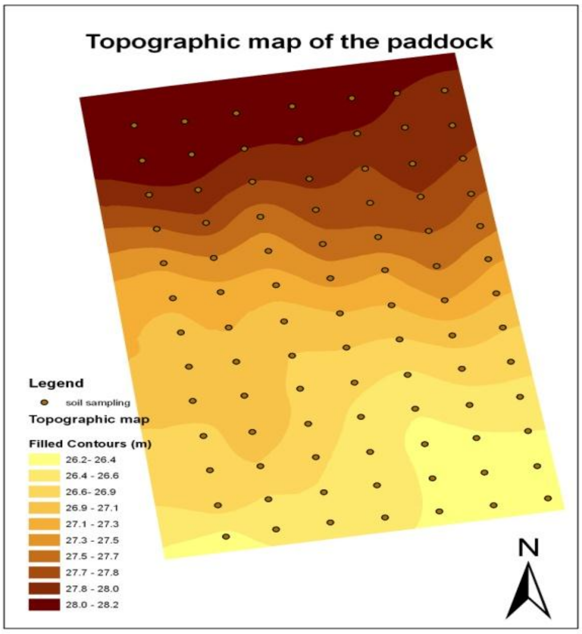

Figure 1: Elevation map of the paddock, showing sampling locations (elevation in units of meters above sea level).

Sampling method

Samples (0–7.5 cm) were collected in a grid pattern (Figure 1) with a sampling distance of 35 m across the paddock and 30 m along the paddock (total of 91 samples). The samples were air-dried and sieved (4 mm) prior to analysis.

Analysis methods

Mineral nitrogen (NH_4^+ and NO_3^-) was extracted in 2 *M* KCl and measured on a flow injection analyser (QuickChem 8000 FIA+, Lachat Instruments, Loveland, CO) using standard colourimetric techniques. Anaerobically mineralisable N (AMN) was determined as the amount of ammonium-N produced during a 7-day anaerobic incubation at 40°C (Keeney and Bremner, 1966). Total soil C and N were determined using a LECO CNS200 analyser. Available P was measured using the Olsen bicarbonate method (Olsen et al., 1954).

Data analysis

Classical statistical parameters (including mean, standard deviation, coefficient of variation [CV], Kolmogorov Smirmov normal distribution test, skewness and kurtosis) were obtained with SPSS (Statistical Product and Service Production). Geo-statistical analyses were conducted using GS$^+$7.0 software (Gamma Design Software, LLC., Plainwell, MI). Spatial analysis and soil nutrients mapping was completed by ArcGIS 9.2 (ESRI Inc).

Results and Discussion

Classical statistics

Although the paddock had an even topography and had been managed uniformly for many years, substantial variability was observed for Olsen P, mineral N and AMN (CV ranged from 16 to 33%; Table 1). Soil organic matter also exhibited significant variability, with total C ranging from 19 to 31 g/kg (Table 1). Variability was reduced somewhat by elimination of outliers identified using Q-Q plots. For example, exclusion of two outliers for mineral N reduced the CV from 33 to 26% and, when a single outlier for Olsen P was excluded, CV decreased from 26 to 21%.

Table1: Descriptive statistics of soil properties at the experimental site.

Soil properties	Min.	Max.	Mean	Std.Dev	CV %	Skewness	Kurtosis
Mineral N (µg /g)	15	93	33	11	33	1.159	1.771
AMN (µg /g)	37	83	50	8	16	0.659	0.754
Total C (g/kg)	19	31	27	2	8	-0.649	0.154
Total N (g/kg)	1.8	2.5	2.2	0.2	8	-0.850	0.657
Olsen P (µg /g)	14	53	20	5	26	0.804	0.118

Because of high skewness (Table 1) and the presence of outliers, it was necessary to normalize the data prior to the geostatistical analysis. Logarithmic and Box-Cox transformations were selected to normalize the dataset.

The Box-Cox transformation is given by: $f(x) = \begin{cases} \frac{x^{\lambda}-1}{\lambda}, & \lambda \neq 0 \\ \ln(x), & \lambda = 0 \end{cases}$

where f(x) is the transformed value and x is the value to be transformed. For a given data set (x_1, x_2,…..x_n), the parameter λ is estimated based on the assumption that the transformed values (y_1,y_2,…..y_n) are normally distributed. When λ=0, the transformed becomes the logarithmic transformation.

The logarithmic transformation resulted in smaller skewness and kurtosis for AMN and Olsen P and the transformed data passed the normality test. Box-Cox transformation data for total C and total N passed the normality test, but the transformed mineral N data did not pass the normality test (Table 2). Log-transformed data for AMN and Olsen P and Box-Cox transformed data for total C and total N were used in the spatial analysis.

Table 2: Skewness and kurtosis values for the original and transformed data.

	Original data		Logarithmic or Box-Cox transformed	
Soil properties	Skewness	Kurtosis	Skewness	Kurtosis
AMN	0.659	0.754	0.240	0.223
Olsen P	0.804	0.118	0.387	-0.280
Total C	-0.649	0.154	-0.070	-0.201
Total N	-0.850	0.657	-0.033	-0.175

Geostatistical analysis

Geostatistical analysis was conducted to determine the spatial structure of all soil properties. The theory of geostatistics, which was developed in 1960s (Matheron, 1963) for application in the mining industry (Journel and Huijbregts, 1978), has been widely used in spatial studies of soil characteristics (Trangmar et al., 1985). Semivariogram analysis is the key method to evaluate spatial variability. In this case study, empirical semivariogram values for soil properties were obtained using the equation [$Equation$ 1]:

$$\gamma(h)=\frac{\mathbf{1}}{\mathbf{2N(h)}}\sum_{\mathbf{i=1}}^{\mathbf{N(h)}}[\mathbf{Z(Xi)}-\mathbf{Z(Xi+h)}]^{\mathbf{2}} \qquad (1)$$

Where $\gamma(h)$ is the sample semivariance between all observations $Z(Xi)$, Z is the measured value at a particular location, *N(h)* presents the number of paired data at the distance *h*, and *(h)* is lag distance that separates the total numbers of data pairs. The semivariogram can be fitted with spherical, exponential, or Gaussian models (Eqs. 2–4), respectively:

$$\gamma(h) = \begin{cases} C_0 + C\left[\frac{3h}{2a} - \frac{h^3}{2a^3}\right], & h \le a \\ C_0 + C, & h > a \end{cases} \qquad (2)$$

$$\gamma(h) = C_0 + C\,[1 - \exp(-\frac{h}{a})] \qquad h \ge 0 \qquad (3)$$

$$\gamma(h) = C_0 + C\,\{1 - \exp(-\frac{h^2}{a^2})\} \qquad h \ge 0 \qquad (4)$$

Where C_0 is the nugget, C+ C_0 is sill, and a is the correlation length (Figure 2).

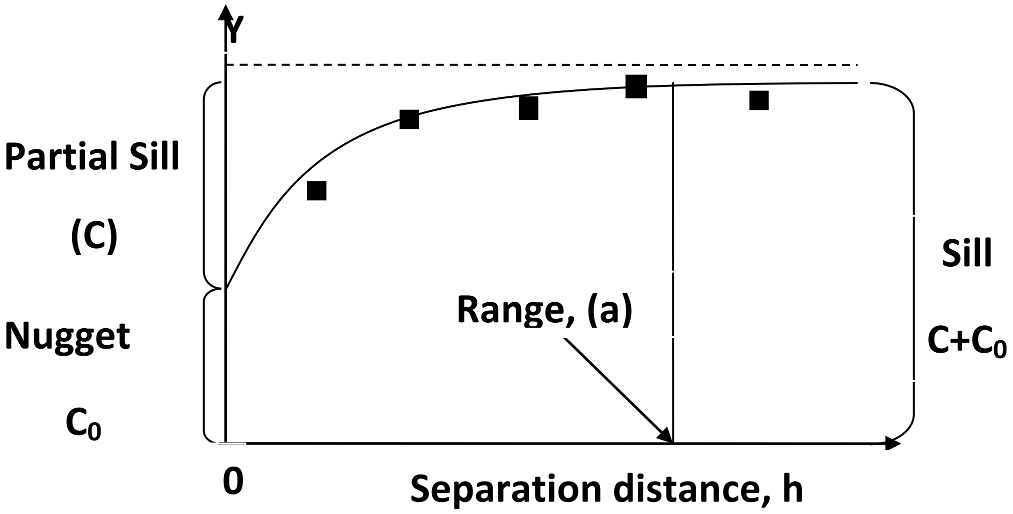

Figure 2: Example variogram illustrating the relationship between variogram parameters (nugget, partial sill, sill) and sample separation distance.

The semivariance generally increases with sample separation distance before reaching an asymptote at a distance a (the range value). Samples separated by distances greater than a are considered to be spatially independent whereas, within the range, samples show greater similarity when they are nearer to each other. Variance that exists at a scale shorter than the field sampling distance is found at zero lag distance and is known as the nugget variance (C_0). The nugget variance reflects the uncertainty caused by sampling errors or smaller-scale variability. The partial sill (C) is the variance caused by factors such parent material variability, and vegetation and topographic differences.

Table 3: Geostatistical parameters for soil nutrients and organic matter.

Soil nutrients	Semi var. model	Nugget C_0	Sill C_0+ C	Range a	Nugget/Sill (%)	Spatial dependence	R^2
AMN	Spherical	0.0017	0.0034	184	50	moderate	0.83
Olsen P	Gaussian	0.0056	0.03	700	14	strong	0.96
Total C	Gaussian	11.1	53.2	300	21	strong	0.98
Total N	Gaussian	10.4	29.0	268	36	moderate	0.97

Parameters of the variograms for soil nutrients and carbon are given in Table 3. The ratio of nugget variance to sill variance indicates the degree of spatial correlation, with ratios <25%, 25–75%, and >75%, showing strong, moderate and weak spatial correlation, respectively. For the measured variables, there was moderate (AMN, total N) to strong (Olsen P, total C) spatial correlation within the experimental site (Table 3). The range value (a), which indicates the distance beyond which sampling points are independent of each other, was as high as 700 m for Olsen P and ranged between 184 and 300 m for the other parameters.

Spatial distribution maps for soil nutrients and organic matter were obtained using ordinary kriging methods based on the observed semi-variogram parameters. Unlike the other variables, mineral N did not show a clear spatial structure (Figure 3). Olsen P was highest near the paddock gate (possibly due to fertiliser spillage) and along the southern paddock edge. Much of the centre area had Olsen P <20 µg/g (the value below which application of fertilizer P may be beneficial). The results suggest that P use efficiency could be improved at this site by implementing a variable rate fertiliser strategy.

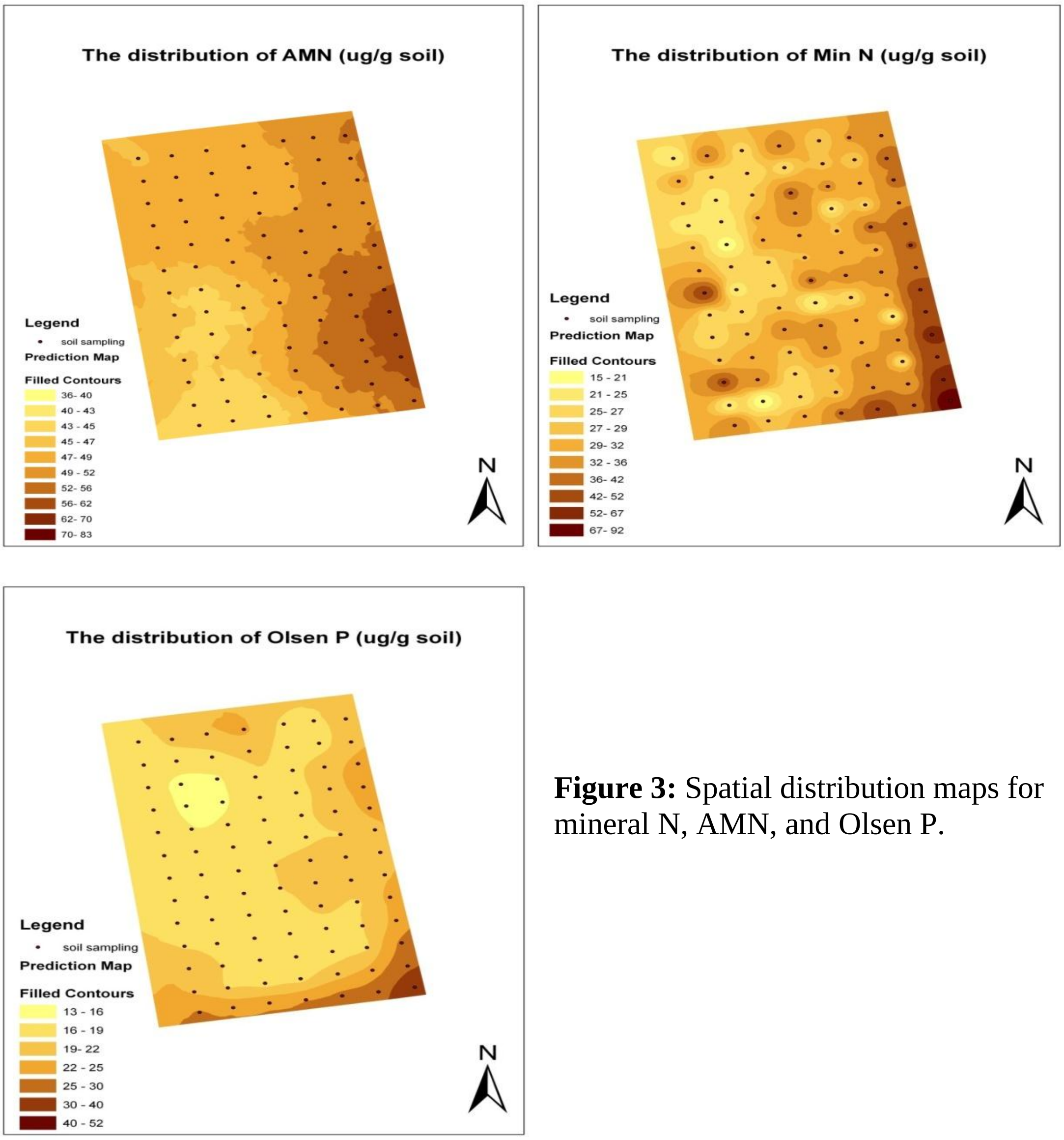

Figure 3: Spatial distribution maps for mineral N, AMN, and Olsen P.

Total N and C showed very distinct spatial patterns, i.e. values were low in the south-west and high in the northern and eastern sectors (Figure 4). As would be expected, the spatial patterns of total C and N showed strong similarities; however, there were some differences in the fine detail that may be associated with higher concentrations of mineral N, particularly in the south-east corner near the farm gate. Within-paddock variability in total soil C cannot be attributed to differences in management practices as the entire paddock had been managed in a uniform manner. To examine whether the spatial pattern was related to textural variation, we performed a textural analysis on samples collected along north-south and east-west transects through the paddock. These transects included samples with a wide range of total C and N values. The soils were separated into three fractions (>50, 5–50, and <5 µm) after sample dispersion using an ultrasonic vibrator. The results revealed that there was considerable textural variation within the paddock. For example, the sand content (>50 µm) ranged from 15% to 40% within the analysed samples. There was a very strong, positive relationship (R^2 = 0.79) between total C and the amount of fine (<5 µm) material and a negative relationship (R^2 = 0.81) between total C and sand content (Figure 5). Similar relationships with texture were observed for total N (not shown). The positive relationship between fine material and total C (and N) reflects the fact that organic matter tends to concentrate in the fine size fraction.

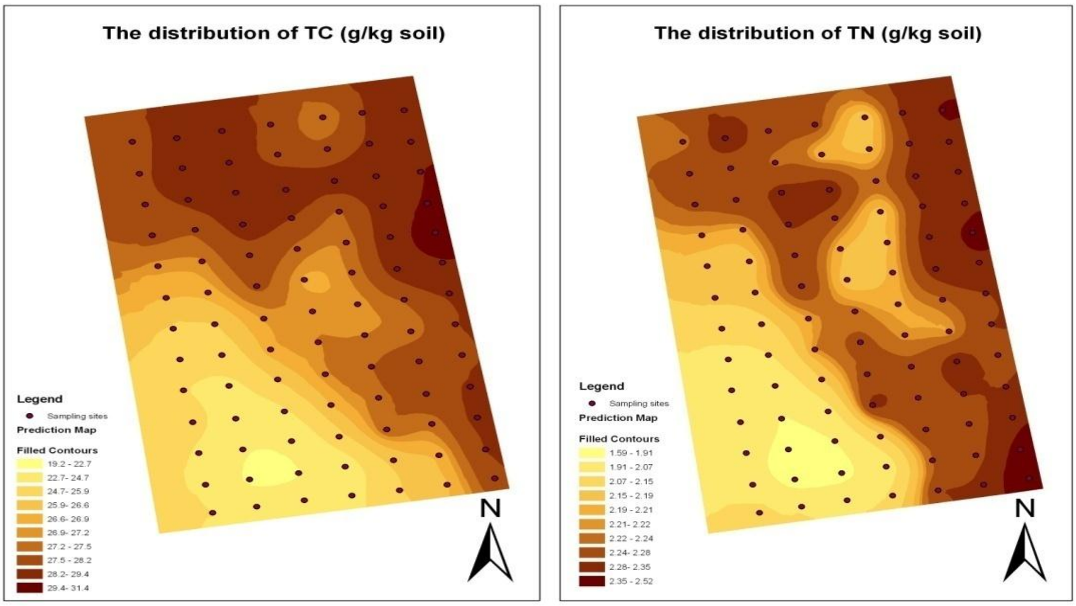

Figure 4: Spatial distribution maps of soil total N and C.

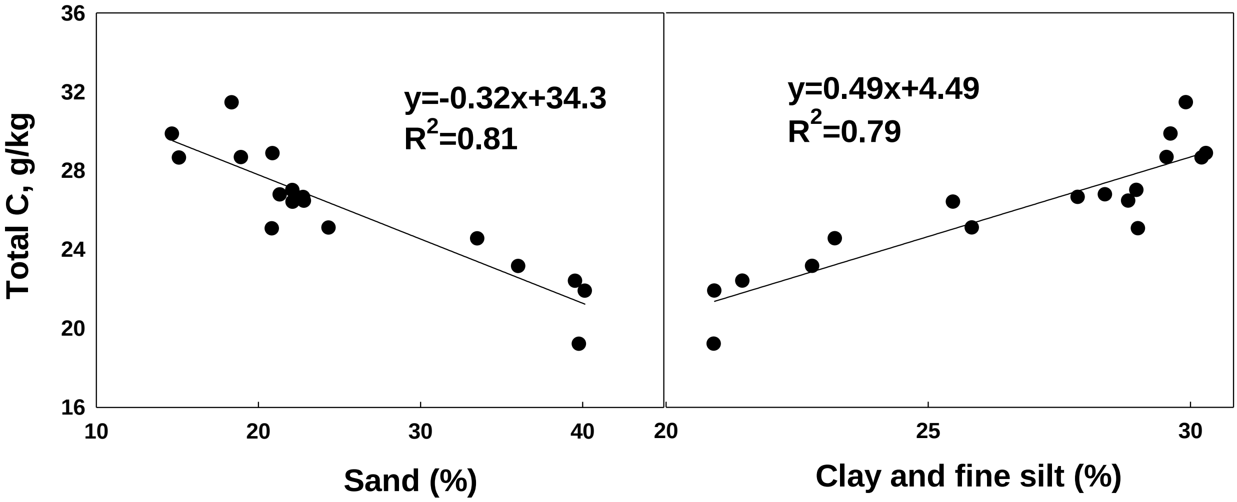

Figure 5: Relationship between soil texture and total C, based on samples collected along two perpendicular transects in the paddock.

Conclusions

There was substantial spatial variation in the measured soil properties within the paddock Anaerobically mineralisable N and Olsen P both showed moderate to strong autocorrelation, while soil organic matter (total C and N) had moderate spatial autocorrelation. Our results confirm that the combination of geostatistics and GIS provides a powerful tool to describe the spatial distribution of soil properties and to develop high resolution maps that may aid variable rate management (e.g. fertilization) at a paddock scale. Soil texture difference was a major contributor to spatial variability in soil organic matter at this study site. Consideration needs to be given to spatial variability when designing a sampling strategy to quantify soil C stocks.

Acknowledgements

Funding for this research was provided by the following Foundation for Research, Science and Technology programmes: Land Use Change and Intensification (LUCI, CO2X0812) and Sustainable Land Use Research Initiative (SLURI, CO2X0813). We thank Fran McCallum and Charles Wright for technical assistance.

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