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Spatial Variability of Selected Soil Chemical
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Application of Geostatistical Tools to Quantify Spatial Variability of Selected Soil Chemical Properties from a Cultivated Tropical Peat

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Abstract: Quantification of spatial variability is a vital prerequisite for precision agriculture. This study was aimed at quantifying the spatial variability of selected chemical properties in a tropical peat cultivated with pineapple. A 1-ha study plot was established in a commercial pineapple plantation in Simpang Rengam, Johor. Georeferenced topsoil samples ($n = 60$) were obtained systematically from 8×18 m spacings in the x and y direction, respectively. These samples were tested for total C, extractable P, K, Cu, Zn and B. Soil data were first explored using univariate statistics, including normality check, non-spatial outlier detection and data transformation. This was followed by variography and kriging analyses to quantify the spatial variability of chemical properties. Results revealed a high degree of spatial variability in the majority of chemical properties, which exhibited non-normal distributions with CVs ranging from 12 to 54%. All properties exhibited a definable spatial structure, which were described by either spherical or exponential models. Carbon, P and B showed strong spatial dependence. The majority of properties had a short effective range. Surface maps of chemical properties clearly showed spatial clustering of test values. Excepting K, all other properties showed acceptable accuracy of interpolated values. These combined data suggest the need for a site-specific approach in managing tropical peat cultivated with pineapple, particularly with regard to nutrient management.

Key words: Precision agriculture, spatial variability, tropical peat, pineapple

INTRODUCTION

Geostatistics are based on the concepts of regionalized variables, random functions and stationarity (Trangmar *et al.*, 1985) and include two fundamental components (Isaaks and Srivastava, 1989): (i) spatial continuity analysis and (ii) interpolation. Spatial continuity analysis is most commonly performed using variography while interpolation is often carried out using kriging. Variography uses semivariograms to characterize and model the spatial variance of data, while kriging uses the modeled variance to estimate values between samples.

The semivariogram, which basically measures the reduction in variance between sample points as separation distance decreases, can be estimated by the following formula (Burgess and Webster, 1980):

$$\gamma(h) = 0.5n(h) \sum_{i=1}^{n(h)} [z_i - z_{i+h}]^2 \quad (1)$$

Where:

- h = The separation distance between location x_i or x_{i+h}
- z_i or z_{i+h} = The measured values for the regionalized variable at location x_i or x_{i+h}
- $n(h)$ = The number of pairs at any separation distance h

In practice, the semivariogram is modeled using several authorized models (Oliver, 1987; Isaaks and Srivastava, 1989) such as Gaussian, spherical and exponential. These models are then fitted to the semivariogram data. Key features of a semivariogram model are described by three parameters, namely nugget, sill and range. Nugget is a measure of the amount of variance imposed by errors in sampling, measurement and other unexplained source(s) of variance. Sill refers to the total vertical scale of the variogram whereby the semivariance becomes constant as distance between sample location increases. Range is the separation

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distance that reflects a cutoff between spatial dependence and spatial independence. This implies that at separation distances greater than the range, sampled points cease to be spatially correlated (i.e., random).

A sequel to variography is interpolation, a technique aimed at estimating regionalized variables at unsampled locations using the structural properties of the semivariogram and the initial data set (Trangmar *et al.*, 1985). Several studies have compared kriging and alternative methods of interpolation such as inverse distance weighting and cubic splines. Use of inverse distance weighting is advocated for data exhibiting short-range variability (Cooke *et al.*, 1993) whereas spline-based interpolation is recommended for data sets that show an abrupt change in values across a short distance (Voltz and Webster, 1990). Whelan *et al.* (1996) found that inverse distance weighting is more effective than kriging when interpolating based on a small number of observations collected at moderate intensity.

Geostatistical analyses provide quantitative information about spatial variability, which is a principal requirement for Site Specific Crop Management (SSCM). SSCM is a fundamental component of Precision Agriculture (PA), which embodies a holistic farm management strategy where farm operators can adjust input use and cultivation methods, including seed, fertilizer, pesticide and water application, variety selection, planting, tillage and harvesting, to match varying soil, crop and other field attributes (Robert, 1999). PA contrasts with conventional agriculture that is based on uniform treatment(s) across a field.

This study is part of an ongoing research program to diagnose site-specific strategies suitable for pineapple management on tropical peat. The objective of this study was to quantify the spatial variability of selected chemical properties in a tropical peat cultivated with pineapple.

MATERIALS AND METHODS

This study was conducted in a commercial pineapple plantation located in Simpang Rengam, Johor. Pineapple in this plantation is cultivated on a deep peat (classified as *Saprist*), which had an average pH of 3.1 and electrical conductivity of 454 $\mu\text{S cm}^{-1}$ and its cultivation is based on a 2-year cropping cycle that includes a 6-month fallow period.

A 1-ha study plot was demarcated based on crop variety (i.e., Gandul). The study plot comprised 95 planting beds with each bed measuring 0.6×100 m and spaced at 0.9 m between one and the other. The study plot had a plant spacing of 0.3 m and a net

stand density of 55,000 plants ha^{-1} . Topsoil samples (0-25 cm depth) were obtained systematically from 60 georeferenced points. Sampling points were spaced 8 m in the x direction (inter-bed) and 18 m in the y direction (intra-bed). Soil samples were tested for total C, extractable P, K, Cu, Zn and B using standard laboratory procedures.

Soil data were first subject to Exploratory Data Analysis (EDA) involving univariate statistics, including normality check and non-spatial outlier detection. Where necessary, non-normal data were transformed using the appropriate function. Following the EDA, soil data were analyzed using variography and kriging techniques. An isotropic semivariogram was constructed to determine the spatial structure and quantify spatial attributes such as nugget, sill and effective range. These attributes were used to perform point kriging. Variography and kriging were computed using GS+ Version 5.1.1 (Gamma Software Design, Plainwell, MI). Measured and kriged values were mapped using Surfer Version 7.0 (Golden Software Co., Golden, Co).

Kriged values were cross-validated based on the criteria proposed by Delhomme (1978) and Dowd (1984). Firstly, the interpolated Mean Error (ME) should be close to zero. The ME is calculated as follows:

$$ME = 1/n \sum_{i=1}^n [\bar{z}(x_i) - z(x_i)] \quad (2)$$

Where:

n = The number of sample points

$\bar{z}(x_i)$ = The predicted value of the variable at point x_i

$z(x_i)$ = The measured value of the variable at point x_i

Secondly, the Mean Squared Error (MSE) should be less than the sample variance. The MSE is given by:

$$MSE = 1/n \sum_{i=1}^n [\bar{z}(x_i) - z(x_i)]^2 \quad (3)$$

Thirdly, the ratio of theoretical and calculated variance, called the Standardized Mean Squared Error (SMSE), should be approximately close to one. The SMSE is given by:

$$SMSE = 1/n - 1 \sum_{i=1}^n [\bar{z}(x_i) - z(x_i)]^2 / \sigma^2 \quad (4)$$

Where:

σ^2 = The theoretical variance

RESULTS AND DISCUSSION

Univariate statistics: The majority of chemical properties, with the exception of P and Zn, exhibited non-normal distributions as determined by the Shapiro-Wilk statistic (Table 1). Among these properties, C and K were significantly skewed ($2 \times \text{SES} = 0.64$) while B was significantly kurtotic ($2 \times \text{SEK} = 1.26$). The coefficients of skewness and kurtosis describe the shape of the sample distribution. A positive skew indicates asymmetry in the distribution with the higher values tailing to the right and a negative skew represents lower values tailing left. Kurtosis describes the relative size of the distribution's tails. A positive kurtosis indicates that the distribution is peaked and a negative kurtosis indicates a relatively flat distribution. Both these coefficients depict the conformity of the data to a normal distribution. Transformation using \log_{10} was only performed on Cu, which initially showed a significant positive skew. After being log-transformed, Cu conformed to a normal distribution. The other non-normally distributed properties did not respond favorably to transformation, i.e., they remained non-normal after transformation.

The Coefficient of Variation (CV), which is the ratio of standard deviation to the mean, for the properties measured ranged from 12% for C to 54% for B (Table 1), indicating low to moderate variability in the data.

The skewed distribution of C is possibly due to the uneven burning of plant biomass prior to replanting while that of K can be attributed to leaching as a result of micro topographical variation. The relief within the study plot was <1 m.

Spatial structure and attributes: Semivariograms of the chemical properties are given in Fig. 1. The semivariograms were computed based on an active lag of 55 m and a lag class interval of 6 m.

All properties exhibited a definable spatial structure. Carbon, P and Cu were described by a spherical model, while K, Zn and B subscribed to an exponential model. The properties that exhibited strong spatial dependence were C, P and B with a nugget to sill ratio of 0.04, 7.41 and 2.13%, respectively. This physically means that the explainable proportion of the total variation in C, P and B is 99.96, 92.59 and 97.87%, respectively, while the remaining variation is attributable to random sources. The other properties showed a moderate spatial dependence.

The majority of properties had a short Effective Range (ER) i.e., <70 m. Both K and Zn, however, had moderate ER values. The practical significance of ER is that sampling points separated at distances greater than the ER will no longer exhibit spatial correlation. At this

Table 1: Univariate statistics for chemical properties

Variables	n ¹	CV			Skewness ²	Kurtosis ²	Normality ³
		Mean	Median (%)	(%)			
C (%)	60	43.00	45.50	11.77	-0.970	0.069	0.879**
P ($\mu\text{g g}^{-1}$)	58	33.15	33.20	27.34	0.629	1.026	0.945*
K ($\mu\text{g g}^{-1}$)	58	159.91	139.05	46.05	0.735	-0.079	0.937*
Cu ($\mu\text{g g}^{-1}$)	58	1.36	1.00	71.42	0.918	-0.362	0.960*
Zn ($\mu\text{g g}^{-1}$)	60	35.36	34.30	35.37	0.358	-0.547	0.976*
B ($\mu\text{g g}^{-1}$)	57	1.08	1.00	54.21	-0.107	-1.450	0.915*

¹: Counts < than 60 indicate that non-spatial outliers were removed from the data set. Non-spatial outliers were detected using the extreme studentized deviate (ESD) method, ²: Significant if the absolute value of skewness or kurtosis is ≥ 2 times its standard error. The standard error of skewness = $(6/n)^{0.5}$ while the standard error of kurtosis = $(24/n)^{0.5}$; ³: Estimated using the Shapiro-Wilk test. If the test statistic W is significant ($p < 0.05$) then the distribution is not normal. (For Cu, the W was computed after data transformation using \log_{10}); *: Significant at the 0.05 probability level; **: Significant at the 0.01 probability level, ns: non-significant

Table 2: Cross validation statistics of kriged values for chemical properties

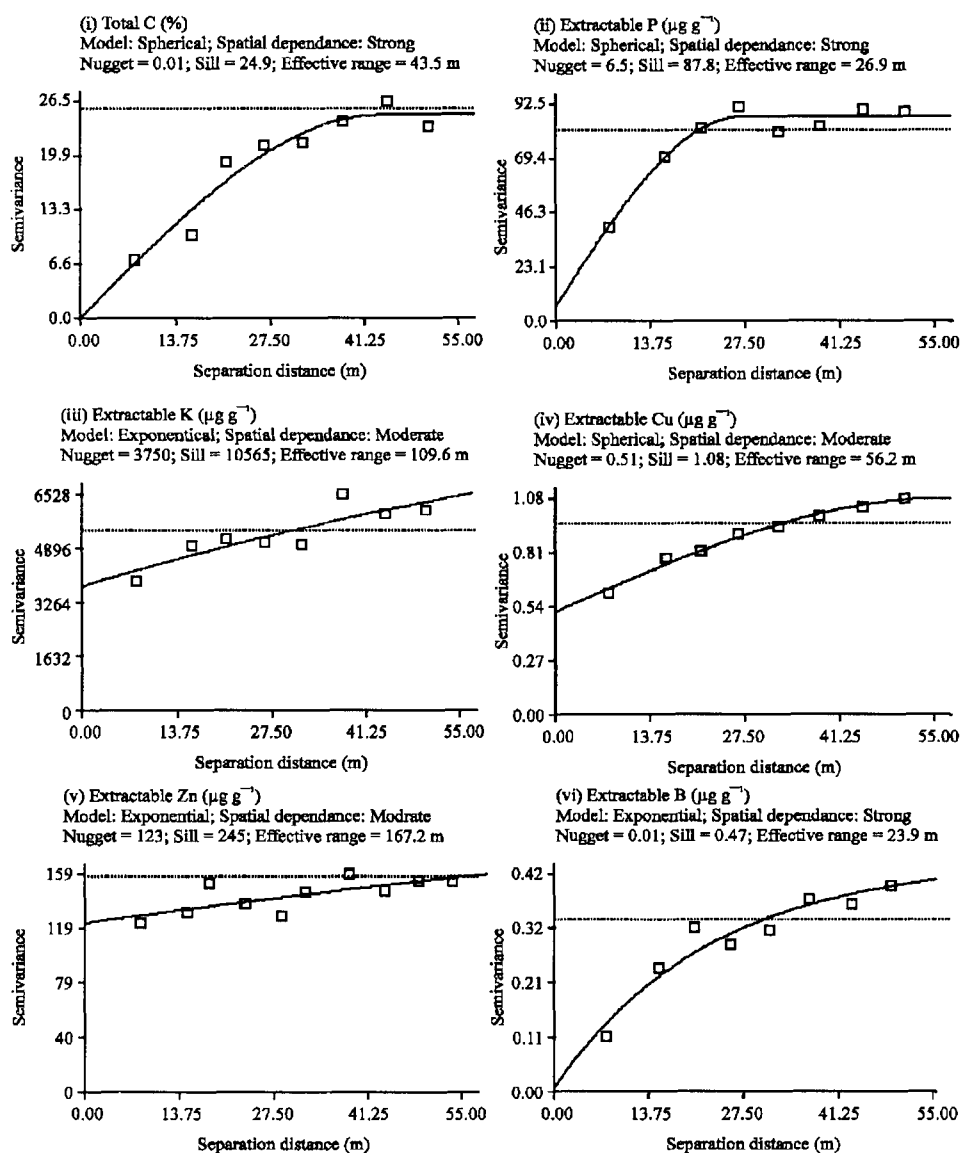
Variables	Sample			
	variance	ME	MSE	SMSE
C (%)	10.82	0.001	9.76	0.92
P ($\mu\text{g g}^{-1}$)	82.10	-0.290	71.11	0.88
K ($\mu\text{g g}^{-1}$)	5421.97	-0.660	4878.00	0.92
Cu ($\mu\text{g g}^{-1}$)	0.95	0.010	0.77	0.83
Zn ($\mu\text{g g}^{-1}$)	156.35	0.080	159.94	1.04
B ($\mu\text{g g}^{-1}$)	0.18	0.004	0.15	0.86

junction, it is worth noting that the semivariogram does not provide any information for distances shorter than the minimum spacing between samples. Sampling designs aimed at delineating spatial structures usually employ separation distances that are lesser than the ER. Flatman and Yfantis (1984) recommended that samples be spaced between 0.25 and 0.5 of the ER. Based on this, it is clear that sample spacing for C, P, Cu and B should be closer than that of K and Zn.

Spatial variability: The distribution and pattern of both measured and kriged values for each chemical property are represented as surface maps (Fig. 2).

Generally, all properties exhibited spatial clustering of test values across the study plot. The surface maps suggest a linear association between Cu and C, Cu and K and Cu and Zn. Based on measured values, significant correlations at the 5% probability level were registered for Cu and C ($r = 0.49$), Cu and K ($r = -0.35$) and Cu and Zn ($r = 0.40$). The interaction of Cu and C is expected because Cu is typically sorped onto C-rich organic surfaces (Foth, 1991).

Cross-validation statistics showed that all properties, with the exception of K, satisfied the interpolation accuracy criteria (Table 2). From a management perspective, accurately kriged values can provide a cheap and fast means of estimating a particular variable (in this case, chemical property), without having to perform field sampling and laboratory analyses.



Interpreted based on Cambardella *et al.* (1994), where:

	Inference
Nugget: Sill < 0.25	Strong spatial dependence
0.25 < Nugget: Sill < 0.75	Moderate spatial dependence
Nugget: Sill < 0.75	Weak spatial dependence

Fig. 1: Spatial structure and attributes of chemical properties

However, this is only practical for variables that are temporally stable, i.e., test values that do not change significantly over time.

General discussion: This study demonstrated that selected chemical properties of tropical peat were

spatially variable. A previous investigation showed that pineapple yields were also spatially variable across the same study site (Balasundram *et al.*, 2005). As such, it appears that uniform agronomic management based on conventional strategies may not be suitable to optimize crop production. Instead, a site-specific approach such as

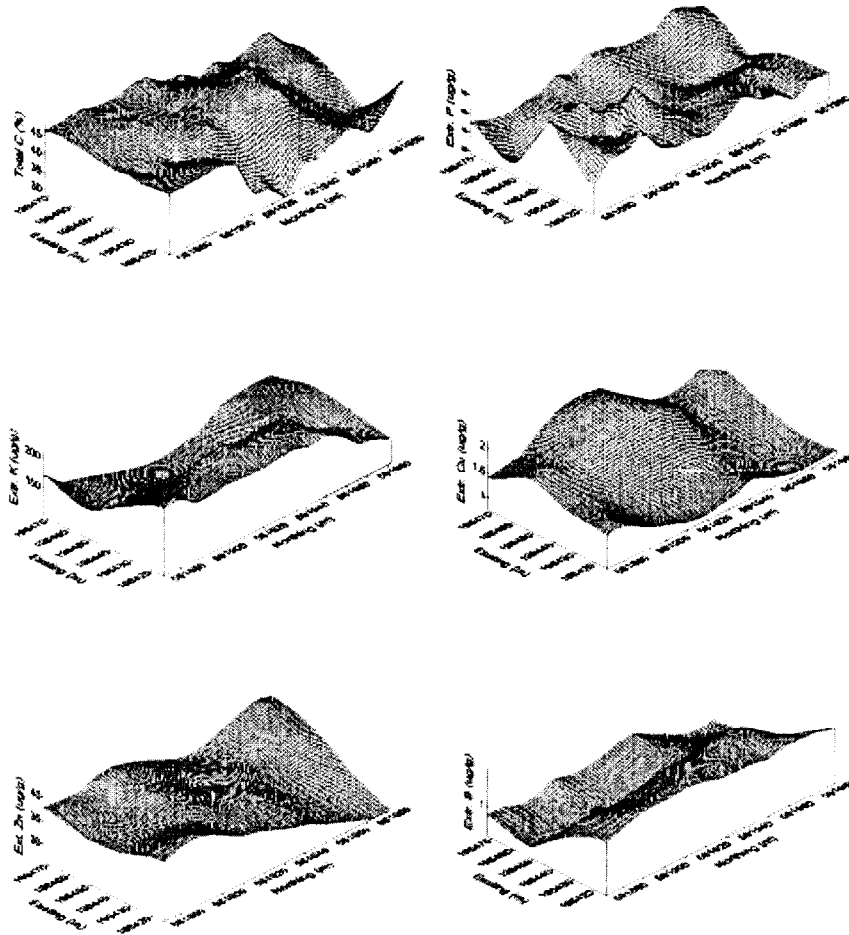


Fig. 2: Spatial variability of chemical properties (based on measured and kriged values)

Crop Management Zoning (CMZ) may offer a better outcome. CMZ refers to quantitative grouping of areas with similar production potential/limitation in order to facilitate optimum crop and soil management as a function of local variability. Crop management zones, if designed accurately and efficiently, can potentially lead to increased crop productivity and quality (Balasundram, 2003).

CONCLUSION

A high degree of spatial variability was observed in selected chemical properties from a 1 ha cultivated tropical peat. The majority of chemical properties exhibited non-normal distributions with CV ranging from 12 to 54%. All chemical properties exhibited a definable spatial structure,

which were described by either spherical or exponential models. Properties such as C, P and B showed strong spatial dependence. The majority of properties had a short effective range, which indicates the need to employ closer sample spacing in order to account for spatial correlation. Surface maps of the chemical properties, which comprised measured and kriged values, clearly showed spatial clustering of test values. With the exception of K, all other properties showed acceptable accuracy of interpolated values, which can be used to estimate elemental concentration in a cost-effective and time-saving manner. These combined data suggest the need for a site-specific approach in managing tropical peat cultivated with pineapple, particularly with regard to nutrient management.

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