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Optimal spatial sampling schemes for mapping soil strength on a Southeastern US soil.

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Abstract. *Site-specific tillage has potential in reducing fuel consumption to ameliorate subsoil compaction problem in many Southeastern US soils. Its success depends on accurate soil compaction sensing and determination of spatial variability for mapping the compacted layer (hardpans) attributes (magnitude and depth) and prescription tillage. In the cone index sampling for hardpan characterization, questions exist on how to design the sampling scheme (grid spacing, sampling intensity) and sampling an area of field without substantial changes in soil properties that influence the cone index readings. Optimization of sampling schemes was investigated using kriging variance analysis for four sampling grid spacing (10 m x 10 m, 20 m x 20 m, 30 m x 30 m and 40 m x 40 m). Geo-referenced cone index measurements that were taken on an area of 2 ha at wet and dry soil moisture sampling periods were used for the study. The results showed that the mean kriging variance values for the grid spacing of 10 m x10 m and 20 m x 20 m were smaller than the sample mean variances of the peak cone index and depth to the peak cone index both at the wet and dry soil* *moisture conditions. The square grid sampling of 20 m x 20 m (sampling intensity of 24 per ha) appeared to be more efficient sampling scheme on Pacolet sandy loam soil providing an optimal kriging interpolation error and less time costly than the original10 m x 10 m.*

Keywords. Precision tillage, kriging variance, optimal sampling scheme, soil compaction.

Introduction

Soils in the Southeastern US have highly compacted root-restricting layers (hardpan) that adversely affect the crop production and the environment (Camp and Lund, 1968; Campbell et al., 1974; Busscher et al., 2006). The compacted layers are mechanically disrupted on annual or biannual basis using a sub-soiling operation to provide optimal rooting environment (Raper et al., 2004). Precision tillage that accounts for the spatial variability of soil hardpan has a potential in reducing tillage fuel consumption (Fulton et al., 1996; Gorucu et al., 2002; Raper et al. 2004).

Precision (site-specific) tillage is a management strategy whereby deep tillage could be applied at variable depths according to the soil compaction needs in the field. The success of precision tillage depends on the availability of accurate soil compaction sensing, field positioning, quantifying the field variability, and controlling the application of real-time or prescribed tillage. A measure of soil compaction can be obtained by a cone penetrometer which is a standardized device that measures the penetration force required to vertically insert a cylindrical rode with a steel cone down into the soil (ASAE 1999a, b). The data are reported as cone index (penetration force / cone base area) that empirically determines soil compaction. Being a point measurement, the sampling designs and interpolations of point cone penetrometer measurements for field or landscape level requires an understanding of the spatial continuity of soil strength or cone penetration resistance. Due to the influences of soil forming factors (climate, vegetation, geologic parent materials, topography and time) and management practices, soil properties exhibit inherent spatial variability within fields, across landscapes and on a regional scale (Mulla and McBratney, 1999). Soil strength also exhibits spatial variability across field and within a field (Clark, 1999; Raper et al., 2005; Tekeste et al., 2005). Among other factors, sampling issues is important for accurate representation of soil spatial variability in precision agriculture (Rains et al., 2001)

Geo-statistical techniques appropriately describe spatial variability and interpolation for un-sampled locations better than classical statistical methods that assume random distribution of residuals and spatial independence of variables (Isaaks and Srivastava, 1989). In the geo-spatial solutions using kriging interpolation method, a sampling scheme can be defined depending on the grid configuration, the search radius for interpolation, the number of points to be used for interpolation and the grid spacing (McBratney et al., 1981; Olea, 1984). A geo-referenced based cone index sampling design is a key procedure in precision tillage management for quantifying the soil hardpan variables and creating soil compaction map for prescribing deep tillage. Prior to cone index sampling, some important sampling issues that need to be considered are: 1) the sampling configuration; and 2) the number of sampling points or sampling intervals that would capture the spatial continuity and achieve the desired interpolation accuracy. Sampling should also be carried out within a time period that the soil moisture should not vary much to cause undesired effects on cone index readings. Square grid configuration is often employed for its simplicity in field operations for sampling of soil physical properties (Fulton et al., 1996; Raper et al, 2005; Veronese et al., 2005). Intensive sampling may provide detailed information on spatial continuity of a regionalized variable but it may be expensive and time consuming. Sparse sampling, on the other hand, could be cheap but it may miss important information for describing the spatial continuity of a regionalized variable.

Researchers have studied spatial variability of penetration resistance (cone index) for mapping soil compaction using grid sampling procedure of 30 m x 30 m (Fulton et al., 1996) on 7.06 ha field of Maury silt-loam soil; 30 m x 11 m (Raper et al., 2005) on silt loam upland soils of Southeastern US on 2-3 ha field size; and 10 m x 10 m (Veronese et al., 2005) on 6.5 ha field size of Ferralsol clay soil. The sampling scheme employed by many of the researchers depended on experiences with soils, topography, costs and resource availability. Their sampling schemes were not designed based on quantitative methods prior to actual sampling. Efforts that use a statistical method (ASAE 1999b) have been defined to determine minimum sample size; however, such method could not be applied for spatial dependent variables. Quantitative method of optimization of sampling design is proposed in this study for mapping of soil compaction. The method is based on the ordinary kriging variance analysis from point samples of cone index collected on 10 m x 10 m grid system. A sampling design that has acceptable kriging estimated errors was considered as an optimal scheme with reduced sampling costs and enables to achieve the desired accuracy of soil compaction mapping for precision tillage applications. The objectives of the study were: 1) to determine kriging variance for four grid spacing systems; and 2) to develop a method for sampling optimization scheme using kriging variance analysis.

Materials and Methods

Ordinary Kriging Analysis

Analysis and modeling of spatial variability involves estimation of semivariances, fitting theoretical variogram models and kriging for spatial interpolations (Isaaks and Srivastava, 1989; Mulla and McBratney, 1999; Donald and Ole, 2003). Estimation of the semivariances were obtained using equation 1 (Isaaks and Srivastava, 1989).

$$\gamma(h) = \frac{1}{2N(h)}\left\{\sum_{i=1}^{N(h)}\left[Z(x_i + h) - Z(x_i)\right]^2\right\} \tag{1}$$

Where $\gamma(h)$ is the semivariance for interval class h, N(h) is the number of pairs separated by lag distance, $Z(x_i)$ is a measured variable at spatial location x_i, $Z(x_i + h)$ is a measured variable at spatial location of $x_i + h$. The semivariogram models are used to define the distribution of semivariances. The spatial structure ($\gamma(h) = C_o + C$) of a semivariogram comprises three basic parameters: *nugget effect* (C_o), *sill* ($C_o + C$), and *range*. The *nugget effect* is the variation due to sampling errors, micro-scale variability, or measurement errors that occurs at a scale smaller than the sampling interval. The *sill* is the asymptote of the semivariogram model. The *range* is a separation distance at which the semivariogram levels off at the sill and it indicates the distance over which the pairs of values of the variable exhibit spatially dependent. The theoretical semivariogram models that best fits the estimated semivariances distribution can be determined using non-linear fitting techniques. Theoretical models of the spherical, exponential, Gaussian, linear, or power forms could be considered in model fitting.

The kriging technique uses the optimal theoretical semivariogram model to predict values of the variable at the un-sampled locations. Ordinary kriging is the most widely used interpolation method in geo-statistical analysis of a regionalized variable (Van Groenigen, 2000).

The ordinary kriging system is an unbiased linear estimator that uses a weighted linear combination of the measured values (eq. 2) to predict the values at the un-sampled locations (Donald and Ole, 2003). The ordinary kriging system (eq. 3) is determined by minimizing the mean square estimate error, $E\left(\hat{z}_o - z(x_o)\right)^2$, and applying the constraint condition for the sum of kriging weight coefficients, $\sum_i^n \lambda_i = 1$.

$$\hat{z}_o = \sum_i^n \lambda_i z(x_i) \qquad (2)$$

Using the Lagrange multiplier optimization method (Kitanidis, 1997), the expression of minimum mean square estimation error and the constrain expression are solved to produce kriging system.

$$\sum_{j=1}^n \lambda_j \gamma\left(z(x_i) - z(x_j)\right) + v = \gamma\left(z(x_i) - z(x_o)\right) \qquad (3)$$

where υ is a Lagrange multiplier; λ is weighing coefficients; $\gamma\left(z(x_i) - z(x_o)\right)$ is the semivariogram model and **x** is location vector (Kitanidis, 1997). The kriging variance ($\sigma^2{}_k$) which is a measure of the estimation error is defined as;

$$\sigma_k^2 = v + \sum_{j=1}^n \lambda_j \gamma\left(z(x_i) - z(x_j)\right) \qquad (4)$$

The kriging system (eq. 3) and the kriging variance (eq. 4) equations comprise the semivariogram model, the number of observations and the location of the prediction points. Having a predetermined optimal semivariogram model, the kriging estimates and the kriging variance are, therefore, uniquely related to the spacing of the sampled points provided the sampling configuration and location of the prediction points are same.

The kriging system of equations indicated that once the semivariogram model and the sampling configuration is predefined, the kriging estimates and the kriging variance will be uniquely related the spacing of point samples. The kriging variance (eq. 4) obtained for different grid spacing systems can provide a comparative assessment of the kriging performance. The main focus in this study was how would the kriging prediction affected for sampling spacing grid systems that are related to optimal sampling scheme associated with sampling time, cost and the desired accuracy of soil compaction mapping.

Experimental Site Description

The data for the kriging analysis was obtained from an experiment conducted on an area of 2 ha at the experimental station of Auburn University in Auburn, AL on Pacolet sandy loam (*Fine, kaolinitic, thermic Typic Kanhapludults*) soil. The soil physical and chemical properties of the site are shown in Table 1.

Cone index measurements were collected in two replicates on each of a 10 m x 10 m grid cell covering an area of 2 ha using a tractor mounted Multiple Probe Soil Cone Penetrometer (MPSCP) equipped with GPS for field positioning (fig.1) (ASAE, 1999 a, b; Raper et al., 1999). The cone index data was acquired at 25 Hz to a depth of 60 cm. A dual-frequency RTK, *Ag*GPS® 214, GPS receiver was also used to obtain elevation data across the field. The measurements were obtained on June 29, 2004 and August 25, 2004 representing ‘wet’ and ‘dry’ sampling periods with soil moisture contents (0 - 35 cm) of 11.25% (d.b.) and 9.83% (d.b.), respectively. Sampling of the cone index data in two replicates on 200 grid points (400 sets of cone index data) took a full working day (8hrs). Within each sampling date there were no rainfall events that would cause undesired variations in cone index data due to soil moisture variations.

The hardpan parameters, the magnitude of the peak cone index and the depth to the peak cone index, were determined by analyzing the fluctuation of cone index in the layered soil profile (Tekeste et al., 2005). Exponential and spherical theoretical semivariogram models fitted to the semivariances distributions of the hardpan parameters on the wet and dry sampling periods were used for the kriging variance analysis. Geo-referenced sampling points on the10 m x 10 m grid systems were used for computing the semivariances and theoretical semivariogram models (Tekeste et al., 2005). New sets of hardpan parameters values that were collected at geo-referenced sampling points on 20 m x 20 m; 30 m x 30 m; and 40 m x 40 m grid spacing systems were selected from the data on the original grid spacing system (10 m x 10 m). The kriging procedures and statistical comparisons of the kriging variances for the four grid systems (10 m x 10 m; 20 m x 20 m; 30 m x 30 m; and 40 m x 40 m) were performed using the SAS procedures PROC KRIGD2D and PROC GLM (SAS. Release 8.02 SAS Institute Inc., Cary, NC, 2001). Means were compared using the Fisher's protected LSD at an alpha (α) level of 0.05.

Results and Discussions

The peak cone index and the depth to the peak cone index that characterize the hardpan of Pacolet sandy loam soil are shown in Table 2. The peak cone index was significantly higher (28% increase) under the dry soil condition than it was under the wet soil condition ($P < 0.0001$). The depth to the peak cone index appeared to be less affected by soil drying that the depth decreased only 5% (Table 2).

The sampled observation points for 10 m x10 m; 20 m x 20 m; 30 m x 30 m; and 40 m x 40 m grid systems are shown in figure 3. Kriging estimates and the kriging variances were computed for the 10 m x10 m; 20 m x 20 m; 30 m x 30 m; and 40 m x 40 m grid systems using the exponential and spherical semivariogram models (Table 3). Kriging estimates and the kriging variances computed for the wet and dry sampling periods are shown in Table 4 and Table 5. The kriging variances for the peak cone index and the depth to the peak cone index increased as the grid spacing increased (fig. 4). In all conditions of grid spacing, semivariogram model and the variable studied, the increase in the kriging variance (σ^2_k) with grid spacing appeared to level off from the 30 m x 30 m with the variance gets close to the sample variance

(σ^2_{sample}). In Figure 4A, for example, the sample variance for peak cone index on wet sampling period was σ^2_{sample} = 0.77. The change in kriging variances (σ^2_k) per the grid spacing increased linearly up to 30 m x 30 m grid spacing.

For the peak cone index on the wet sampling period, the kriging variance were significantly affected by the type of semivariogram model, the grid spacing and their interactions ($P < 0.0001$) with smaller variance when the exponential model was used. The effects of the type of semivariogram model, the grid spacing and their interactions on the kriging variance of the depth to the peak cone index were also statistically significant ($P < 0.0001$). The kriging variances for the depth to the peak cone index were higher than the peak cone index.

On the dry soil moisture conditions (fig. 5), the kriging variances for both the peak cone index and the depth to the peak cone index also increased as a function of grip spacing. The values at the dry soil conditions were higher than the wet soil conditions. Notice in all conditions, the kriging variances for both the peak cone index and the depth to the peak cone index for the 10 m x 10 m and 20 m x 20 m grid spacing were smaller than the sample variance.

The precision of kriging interpolation method when sampling of cone index at 20 m x 20 m instead of the 10 m x 10 m does not seem to be affected when compared to averaging the sampled values of peak cone index and the depth to the peak cone index. Sparse sampling at 30 m x 30 m and 40 m x 40 m grid spacing does not seem to provide precise kriging interpolation at the un-sampled points for soil compaction mapping.

Conclusion

The following conclusions can be drawn from this study.

(1). A method was developed to analyze the kriging variance for the hardpan variables under wet and dry soil moisture conditions for different grid spacing systems having a predetermined semivariogram models.

(2). Analysis of the kriging variance for the hardpan variables of the peak cone index and the depth to the peak cone index showed that cone index sampling at grid spacing of 20 m x 20 m on Pacolet sandy loam soil was an efficient sampling design providing an acceptable kriging precision.

(3). Future cone index sampling on 20 m x 20 m grid spacing has a potential in reducing the sampling time and cost as compared to the 10 m x 10 m grid spacing.

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List of tables

Table 1

Descriptive statistics for the soil physical and chemical properties of a Pacolet sandy loam soil

Soil parameters	Depth -cm-	Mean	Median	Standard deviation	Coefficient of variation	Minimum	Maximum	95 % Confidence interval	Kurtosis	Skewness
Soil moisture (%)										
June 29,2004	0-35	11.25	11.01	2.30	20.40	8.54	17.52	10.42-12.08	2.57	1.59
	35-65	15.80	15.51	3.39	21.46	14.58	17.03	10.71-22.02	0.36	-0.72
August 25,2004	0-35	9.83	9.11	2.17	22.08	7.36	14.84	9.05-10.61	0.40	1.02
	35-65	17.82	17.09	4.43	24.88	16.22	19.42	11.13-23.23	-0.08	-1.58
Cone Index (Mpa)										
June 29,2004	0-35	2.61	2.63	0.54	20.56	1.75	4.00	2.42-2.81	0.74	1.11
	35-65	3.93	3.86	0.76	19.25	2.86	5.78	3.65-4.20	0.91	0.65
August 25,2004	0-35	2.87	2.83	0.72	25.15	1.62	4.56	2.61-3.13	0.50	0.38
	35-65	2.97	2.91	0.90	30.23	1.48	4.72	2.64-3.29	0.20	-0.40
Bulk density (Mg m^{-3})	0-35	1.39	1.41	0.04	3.11	1.29	1.48	1.38-1.41	-0.67	-0.03
	35-65	1.36	1.37	0.08	6.01	1.22	1.50	1.33-1.39	0.06	-1.07
Soil Organic Carbon (%)	0-35	0.70	0.72	0.13	19.01	0.42	0.90	0.65-0.75	-0.24	-1.21
	35-65	0.37	0.31	0.14	36.89	0.23	0.71	0.32-0.42	0.94	0.06
Clay (%)	0-35	8.63	6.79	5.36	62.11	2.14	26.07	6.70-10.56	1.20	1.90
	35-65	25.74	27.29	12.80	49.74	3.33	45.83	21.12-30.36	-0.30	-0.87
Silt (%)	0-35	14.76	14.73	2.01	13.62	10.18	18.21	14.03-15.48	-0.40	0.17
	35-65	13.08	12.92	3.86	29.49	5.00	18.96	11.67-14.47	-0.33	0.03
Sand (%)	0-35	76.61	77.86	5.92	7.73	59.11	84.11	74.48-78.75	-0.80	0.71
	35-65	61.18	59.27	12.96	21.19	42.71	91.67	56.51-65.85	1.00	0.97

Table 2

Descriptive statistics of the peak cone index and the depth to the peak cone index for the two measurement dates of June 29, 2004 and August 25, 2004

		Number of values	Mean	Median	Standard deviation	Coefficient of variation	Variance	Minimum	Maximum	95% Confidence interval	Kurtosis	Skewness
June 29, 2004	Peak cone index (MPa)	198	3.29	3.2	0.88	0.27	0.78	1.23	5.86	3.23-3.36	0.11	0.42
	Depth to the peak cone index (cm)	198	21.08	21	3.36	0.16	11.29	13.5	28	20.84-21.31	-0.7	0.14
August 25, 2004	Peak cone index (MPa)	200	4.12	3.99	1.36	0.33	1.84	1.68	8.69	4.03-4.23	0.81	0.78
	Depth to the peak cone index (cm)	200	20.08	20	3.56	0.18	12.65	10	28	19.83-20.33	-0.04	-0.06

Table 3

Descriptive semivariogram properties for the peak cone index and the depth to the peak cone index for the two measurement dates of June 29, 2004 ('Wet Sampling Period') and August 25, 2004 ('Dry Sampling Period').

Sampling Date	Variable	Model	Nugget -----MPa^2-----	Sill	Range ---m---	Regression coefficient	$\left(\frac{Sill - Nugget}{Sill}\right)$	WSS
29 Jun 04	Peak CI* (Mpa)	Spherical	0.26	0.40	43.70	0.98	0.36	322
		Exponential	0.29	0.43	150.48	0.98	0.32	300
	Depth to Peak CI (cm)	Spherical	0.81	5.83	16.67	0.99	0.86	248
		Exponential	0.00	5.73	15.75	0.99	1.00	259
25 Aug 04	Peak cone index (Mpa)	Spherical	0.15	0.93	26.09	0.97	0.84	505
		Exponential	0.59	1.07	168.91	0.98	0.44	411
	Depth to Peak CI (cm)	Spherical	5.45	6.72	95.09	0.98	0.19	283
		Exponential	5.26	6.86	125.02	0.98	0.23	290

*CI = Cone Index

Table 4. Kriging estimates and kriging variances for the peak cone index June 29, 2004 ('Wet Sampling Period') and August 25, 2004 ('Dry Sampling Period').

Grid Spacing (m^2)	Theoretical variogram	Kriging Variables	'Wet' Sampling Period					'Dry' sampling period				
			Mean	SD	95% LL	95% UL	Max	Mean	SD	95% LL	95% UL	Max
			--------------------cm----------------------					-----------------------cm--------------------				
10x10	Spherical	S E*	0.80	0.01	0.80	0.80	0.79	0.90	0.16	0.88	0.92	0.74
		Estimate	3.28	0.22	3.24	3.30	2.70	4.07	1.00	3.94	4.20	2.15
	Exponential	S E	0.09	0.04	0.09	0.10	0.05	1.15	0.02	1.14	1.15	1.14
		Estimate	3.35	0.71	3.25	3.44	1.54	4.10	0.49	4.03	4.16	2.73
20x20	Spherical	S E	0.85	0.02	0.85	0.85	0.82	1.16	0.17	1.14	1.18	0.76
		Estimate	3.24	0.28	3.21	3.28	2.59	4.03	0.66	3.94	4.11	2.16
	Exponential	S E	0.82	0.01	0.82	0.82	0.81	1.19	0.03	1.18	1.19	1.16
		Estimate	3.23	0.15	3.21	3.25	2.92	4.02	0.43	3.96	4.07	3.05
40x40	Spherical	S E	0.89	0.02	0.89	0.90	0.85	1.33	0.13	1.31	1.35	0.76
		Estimate	3.01	0.11	3.00	3.03	2.58	3.71	0.35	3.66	3.75	2.12
	Exponential	S E	0.85	0.01	0.85	0.85	0.83	1.24	0.03	1.23	1.24	1.20
		Estimate	3.01	0.10	3.00	3.03	2.78	3.72	0.32	3.67	3.76	3.14

*S E = Standard Error

Table 5. Kriging estimates and kriging variances for the depth to the peak cone index June 29, 2004 ('Wet Sampling Period') and August 25, 2004 ('Dry Sampling Period').

Grid Spacing (m^2)	Theoretical variogram	Kriging Variables	'Wet' Sampling Period					'Dry' sampling period				
			Mean	SD	95% LL	95% UL	Max	Mean	SD	95% LL	95% UL	Max
			--------------------cm----------------------					-----------------------cm--------------------				
10x10	Spherical	S E*	2.42	0.45	2.36	2.48	1.79	1.56	0.06	1.55	1.57	1.87
		Estimate	21.10	2.38	20.80	21.41	15.10	20.03	1.31	19.86	20.20	22.87
	Exponential	S E	1.60	0.62	1.52	1.68	0.43	1.17	0.05	1.17	1.18	1.44
		Estimate	21.18	2.74	20.83	21.54	14.19	20.02	1.34	19.85	20.19	23.04
20x20	Spherical	S E	3.13	0.49	3.07	3.19	1.82	1.68	0.10	1.68	1.70	2.08
		Estimate	21.43	1.33	21.26	21.60	15.92	19.37	1.05	19.23	19.50	22.25
	Exponential	S E	2.46	0.66	2.37	2.54	0.53	1.28	0.09	1.26	1.29	1.66
		Estimate	21.43	2.00	21.17	21.69	15.23	19.37	1.00	19.24	19.50	22.30
40x40	Spherical	S E	3.42	0.31	3.38	3.46	1.83	1.84	0.09	1.82	1.85	2.16
		Estimate	19.29	0.58	19.21	19.37	15.49	19.27	0.76	19.17	19.37	20.96
	Exponential	S E	3.04	0.49	2.97	3.10	0.53	1.39	0.09	1.37	1.40	1.73
		Estimate	19.21	1.07	19.07	19.35	14.78	19.33	0.83	19.22	19.44	21.26

*S E = Standard Error

List of figures

Figure 1. Multiple-probe soil cone penetrometer (MPSCP) with five probes and GPS system for cone index measurement at Pacolet sandy loam soil in Auburn, AL.

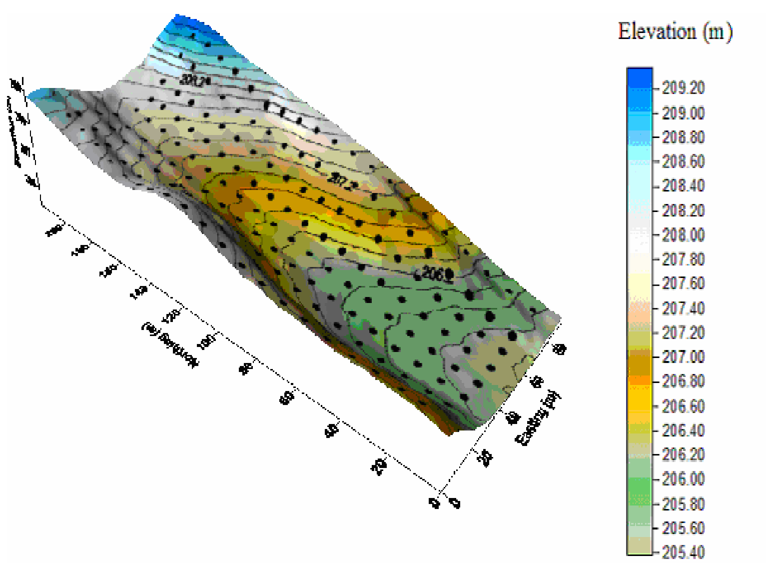

Figure 2. Elevation of the sampling field of Pacolet sandy loam soil. The marks indicate the sampling points for cone index measurement.

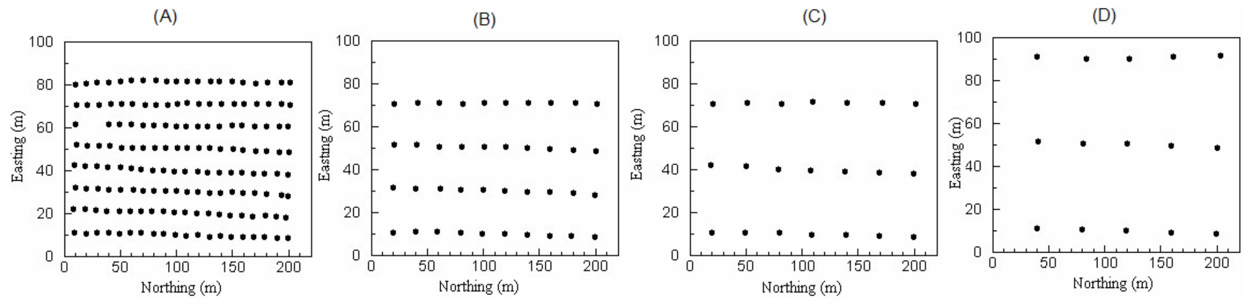

Figure 3. The sampling observation points in the field of Pacolet sandy loam soil for grid spacing of 10 m x 10 m (A); 20 m x 20 m (B); 30 m x 30 m (C); and 40 x 40 (D) m.

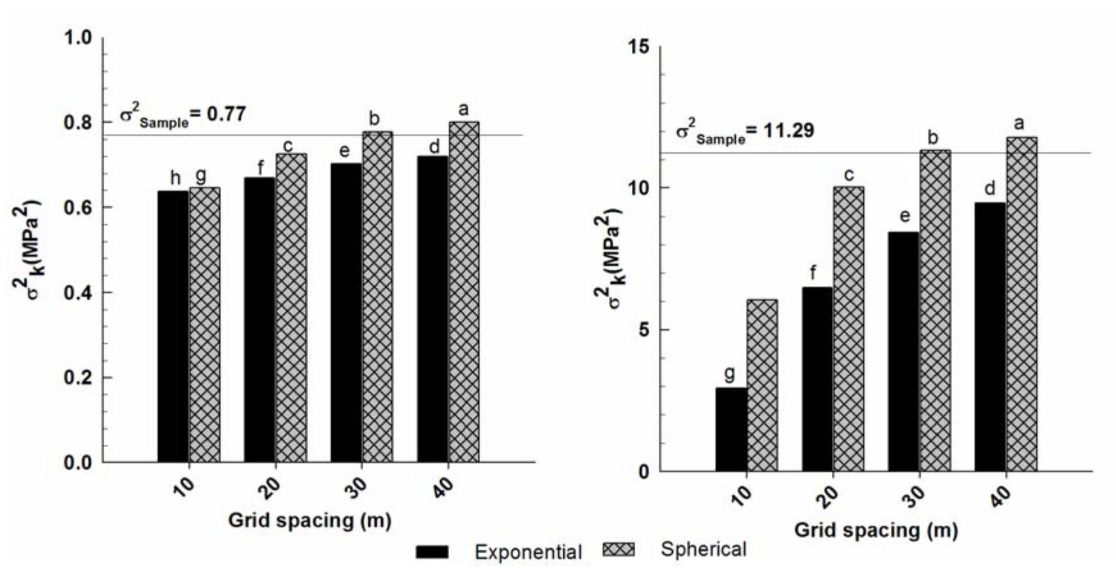

Figure 4. Mean Kriging variance ($\sigma_k^{\,2}$) of peak cone index (A) and the depth to peak cone index (B) as a function of grid spacing (m) for Wet Sampling Period (June 29, 2004) in the field of Pacolet sandy loam soil. Letters of the same type within each plot indicate no statistical differences (α=0.05).

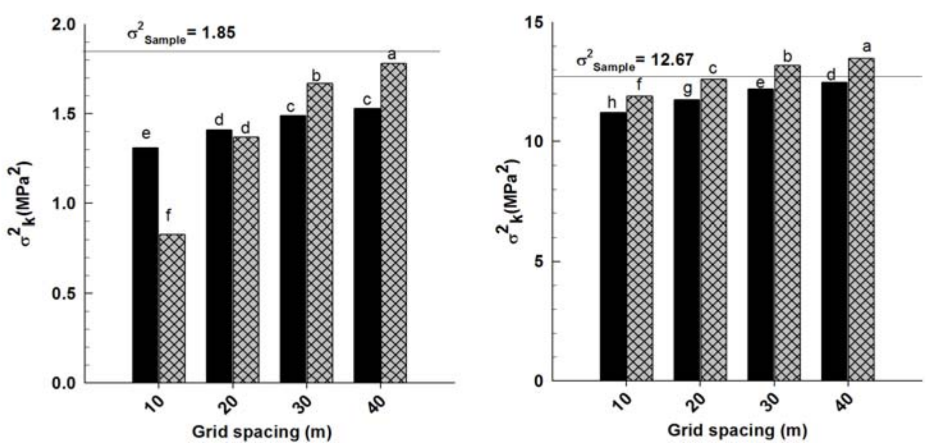

Figure 5. Mean Kriging variance ($\sigma_k^{\,2}$) of peak cone index (A) and the depth to peak cone index (B) as a function of grid spacing (m) for dry sampling period (August 25, 2004) in the field of Pacolet sandy loam soil. Letters of the same type within each plot indicate no statistical differences (α=0.05).