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SPATIAL VARIABILITY STATUS OF SELECTED SOIL PROPERTIES IN NORTH-EAST AKWA IBOM STATE, NIGERIA

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ABSTRACT

Spatial variability status of selected soil properties in North-east Akwa Ibom State, Nigeria was assessed. The aim was to establish baseline information on the spatial variability status of selected soil properties in North-east Akwa Ibom State for site -specific and sustainable soil management. A terrain attribute (plan curvature) that is capable of capturing the short-scale spatial variability of soil properties in the field was used to guide field sampling. Plan curvature map was generated from digital elevation model (DEM) of the study area acquired from United State Geological Survey (USGS) at 30m resolution. The plan curvature map was classified into straight, convex and concave surfaces. Modified conditioned Latin hypercube sampling method was used in selecting observation points. Each observation point was purposefully selected to fall within the three classes of the plan curvature map to give a good coverage of both feature space (terrain attributes) and geographical space (study area). Soil samples were collected from each observation point at depths of 0-30 cm and 30-60 cm using soil auger. A total number of 152 soil samples were collected in the study area for laboratory analysis. Data generated were subjected to analysis of variance (ANOVA) and means were separated using least significant difference (LSD) at 5% level of significance. The depth interval of 0-30cm and 30-60 cm were integrated to form depth interval of 0-60 cm and data with skewed distribution were log transformed for semivariogram analysis. Soil properties were then subjected to semi-variogram analysis. The results showed that plan curvature was able to capture short scale spatial variation in some soil properties under study. Soil texture was sand in the surface and subsurface soils of both convex

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and concave slope while in straight slope, the soil texture was sand in the surface and loamy sand in the subsurface. Soil pH was strongly acidic in both straight and concave slope and slightly acidic in convex slope in both surface and subsurface soil. Organic carbon was high in concave and convex slope and very high in straight topography in both surface and subsurface soils. Total N was low in the convex and concave slope but moderately low in straight terrain. The available P of straight slope was higher than that of concave and convex slope.From the semi-variogram analysis, all the selected soil properties exhibited spatial dependence within some distances. The strength of the spatial dependence varied from moderate for sand, silt, soil pH, organic carbon, total N and available P to weak for clay and strong for exchangeable K. The best fitted models were Exponential for sand and silt; Gaussian for available P and Spherical for clay, pH, organic carbon, total N and exchangeable K.The range of autocorrelation was 136.2 m for sand, 76.4m for silt, 1.6 m for clay, 1.69 m for soil pH, 9.4 m for organic C, 7.1m for total N, 39.2 m for available P and 7.8 m for exchangeable K. This shows that beyond these ranges, the selected soil properties should be managed differently.

Keywords: Spatial variability, Autocorrelation, Semi-variogram, Sustainability, Spatial dependence

INTRODUCTION

Soil properties are generally known to exhibit high spatial heterogeneityeven within a short distance and time (McBratney *et al*., 2000), bothat a large scale (region) or small scale, even in the same type of soil. It has been reported by many scientists that spatial variations of soil properties across agricultural fields is a major source of variability in crop yields and quality (Gaston *et al.*, 2001, Silva-Cruz *et al.*, 2011). It poses a major constraint to sustainable crop production due to resultant non uniformity in output (Obi, 2015). Non-uniformity resulting from spatial differences in soil properties could be due to either variation in soil forming factors and processes (intrinsic factors) or management practices (extrinsic factors) such as fertilizer application, crop rotation and type of cultivation.Information on spatial nature of soils of an area is very vital as it encourages the use of inputs (such as fertilizers, pesticides etc) based on the right quantity, at the right time, and in the right place which increases agricultural productivity and reduces environmental degradation. This type of management is commonly known as "Site-Specific Management or Precision Agriculture. It is information and technology-based farm management system that identifies, analyses and manages spatial and temporal variability within fields for optimum productivity, profitability and sustainability (Goovaerts, 2000). Knowledge of the spatial distribution of soil properties is necessary to be able to identify areas that require intervention and the level at which those interventions are needed.

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Geostatistical techniques have proved useful for assessing spatial variability of soil properties and have increasingly been utilized by soil scientists and agricultural engineers in recent years (Webster and Oliver, 2001 and Iqbal *et al.*, 2005). It uses semivariogram analysis to identify and determine the structure and magnitude of spatial pattern of various measured soil properties and the degree of dependencies (autocorrelation) among neighboring observations provided the intrinsic stationarity assumption holds (Karl and Maurer, 2010). Semi-variogram analysis is used to model the spatial dependence of soil properties (regionalized variable), interpret spatial pattern and predict values of the variable (s) at unsampled locations, thereby providing valuable information for precision agriculture and environmental studies. Semivariogram models the variation of analyzed soil parameters by fitting them to one of the known semivariogram functions like Linear, Gaussian, Exponential or Spherical models.

Several studies on the spatial variability of soil pH, organic matter, electrical conductivity, phosphorus and potassium have been carried out (Bogunovic *et al*., 2014; Behera and Shukla, 2015, Wilson *et al*., 2016). Bungovic *et al.*, (2014) reported of moderate spatial variability of OM, AP and exch. K in soils of Croatia. He attributed the spatial variation to the different impacts of sea, river channels and/or groundwater on the soil. A good understanding of soil properties distribution will contribute to better soil management in agricultural areas (Brevik, *et al*., 2003). This is very important for farmers to make sustainable use of their lands. There is paucity of information on the spatial variability status of soil properties in Northeast Akwa Ibom State. Therefore, the objective of this study was to determine the spatial variability status of selected soil properties in Northeast Akwa Ibom State using geostatistical technique.

MATERIALS AND METHODS

The study area

The study was conducted in Northeast Akwa Ibom State (Fig. 1). It lies between latitudes 5^0 08´ to 5^0 31´ N and longitudes 7^0 37’ to 8^0 00´ E. It is bounded with Abia State in the North and Cross River State in the east. It comprises of Ini, Ibiono Ibom, Itu and Ikono Local Government Areas of Akwa Ibom State. The study area is underlain by coastal plain sands, shale, alluvial deposits and sandstone parent materials (Petters *et al*., 1989). Physiographically, the landscape comprises of a low-lying area, floodplain and ridge terrain. The floodplains are used for the cultivation of cassava during the dry season and other dry season crops (Petters *et al*., 1989). The climate is humid tropical, characterized by distinct rainy and dry seasons. Rainfall distribution is bimodal and of high intensity with annual range that varies between 2250 mm to about 2500 mm with 1-3 dry months in the year. Mean annual temperature varies between 26 - 28 ˚C with relative humidity of 75 - 80 %.

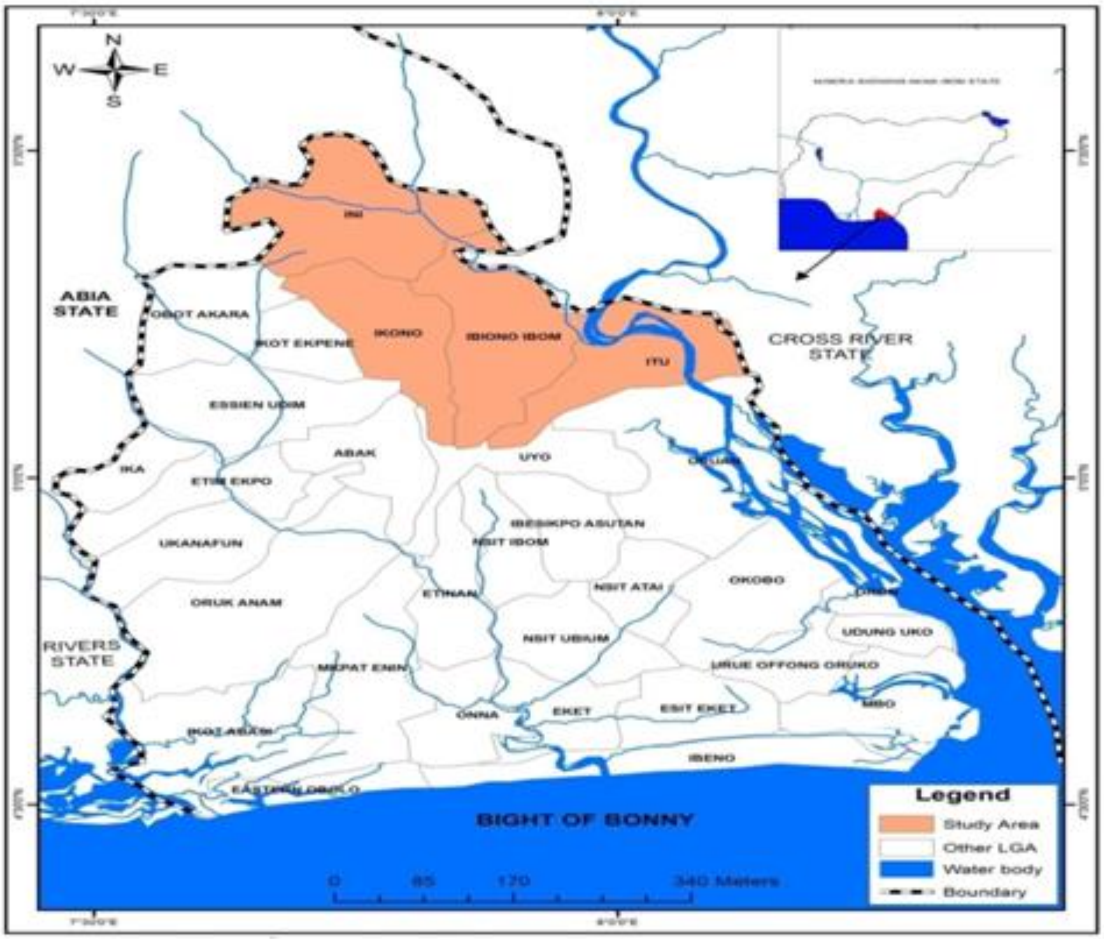

Fig. 1: Map of Akwa Ibom State showing the study area

Field sampling

A digital elevation model (DEM) was acquired from United State Geological Survey (USGS) at 30 m resolution. Using ArcMap 10.3 version, plan curvature map was generated from the digital elevation model of the study area to guide in field sampling (Fig.2).

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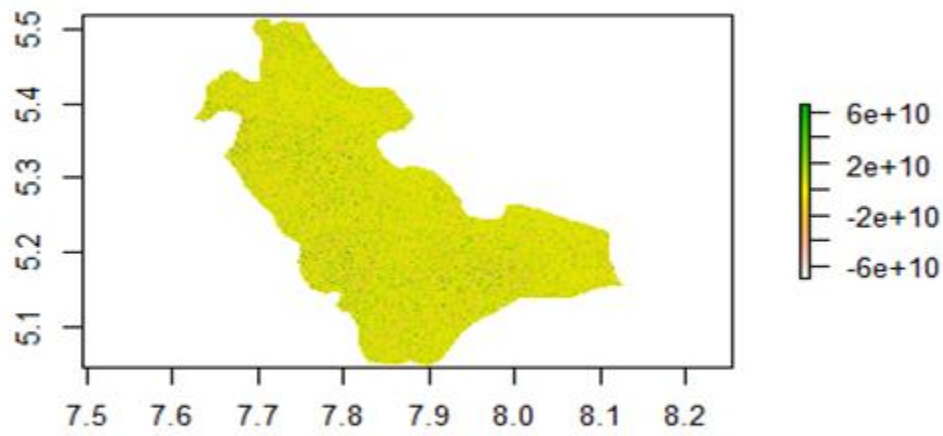

Fig. 2: Plan curvature map generated from digital elevation model of the study area

The plan curvature map was classified into straight, convex and concave surfaces. The generated plan curvature map was cross-checked (ground- truthing) in the field with the aid of Global Positioning System (GPS). Modified conditioned Latin hypercube sampling method was used in selecting observation points. Each observation point was purposefully selected to fall within the classes of the slope gradient map and plan curvature map to give a good coverage of both feature space (terrain attributes) and geographical space (study area). Soil samples were collected from each observation point at depths of 0-30 cm and 30-60 cm using soil auger. A minimum of 50 soil samples were collected from each stratum of plan curvature and a total number of 152 soil samples were collected in the study area for laboratory analysis.

Laboratory analysis

The following analyses were carried out using standard procedures. Particle size analysis was carried out using the Bouyoucos hydrometer method as described by Udo *et al.* (2009). Soil pH was determined in water using a 1:2.5 soil to water suspension and read using a glass electrode. Organic carbon was determined by the dichromate wet-oxidation method as described by Nelson and Sommers (1996). Total nitrogen was determined by kjeldahl digestion and distillation method as described by Udo *et al*. (2009). Available phosphorus was determined using the Bray P1 extractant. The phosphorus in the extract was measured by the blue method of Murphy and Riley (1962). **Exchangeable K** was determined by flame photometer as described by Udo *et al*; (2009).

Statistical Analysis

Data generated were subjected to analysis of variance (ANOVA), means were separated using least significant difference (LSD) at 5% level of significance (Matheron, 1963). All

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computations were carried out using R statistical software (Venables and Ripley, 2002) and SAGA-GIS

Depth integration and log transformation of the target variables

The soil samples were collected at depth interval of 0-30 and 30-60 cm. The depths were integrated to form 0-60 cm. The data was subjected to normality test to ensure that the data were normally distributed. Log transformation was done on the target variables with skewed distribution (Venables and Ripley, 2002).

Geo-statistical analysis

Semi-variogram analysis

Semivariogram analysis was used to determine the spatial dependence (autocorrelation) of the target soil variables in the study area. The differences between the observation points which form the pairs points were calculated, squared, summed and divided by two and by the total number of sample pairs (N) with intermediate distance (h) as expressed by the equation:

$$\Upsilon(h) = \frac{1}{2 * N(h)} \sum_{i=1}^{N(h)} [y_i - y_{i+h}]^2$$ (Cambardella*et.al.*, 2004)

Where(h) is the estimated value of semivariogram for a distance h, N(h) is the number of observation pairs separated by a distance h and yi – yi+h represents the measured value of the target soil properties at two observation points.

The best fitted models for the target variables were exponential, gaussian and Spherical models. The model was selected based on the value of the least mean square error and goodness of fit. This yielded the variogram model parameters, including nugget variance (C0), variance (C1), sill (C0+C1), and range (k). The nugget/sill ratio, C0/(C0/C1), was used to quantify the strength of the spatial dependence with the following ratings: < 0.25 = strong spatial dependence; 0.25–0.75= moderate, and >0.75= weak spatial dependence (Cambardella *et al*., 2004).

RESULTS AND DISCUSSION

1. Physico-chemical properties of soils of the study area

The mean physicochemical properties of soils of the study area as influenced by slope curvature are shown in Table 1.

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Soil texture

The mean sand fraction of convex slope was 88.76 % in the surface soils (0-30 cm) and 83.25 % in the subsurface soils (30-60 cm). The silt fraction was 5.56 % and 5.42 % in the surface and subsurface soils respectively. The mean clay fraction was 5.68 % and 11.34 % in the surface and subsurface soils respectively. In the concave slope the mean sand fraction was 85.10 % in the surface soils and 81.97 % in the subsurface soils, the mean silt fraction was 6.71 % in the surface soils and 6.84 % in the subsurface soils while the mean clay fraction was 9.69 % in the surface soils and 11.02 % in the subsurface soils. In the straight slope, the mean sand fraction was 86.04 and 79.45 % in the surface and subsurface soils respectively, the mean silt fraction was 6.69 and 5.78 % in the surface and subsurface soils respectively, while mean clay fraction was 7.27 and 14.77 % in the surface and subsurface soils respectively. There was no significant difference ($p < 0.05$) in sand, silt and clay fractions between concave, convex and straight slope. But sand fraction was significantly higher ($p <0.05$) in the surface soil (0-30 cm) than subsurface soil (30-60 cm) while the reverse was the case for clay fraction. The high clay fraction in the subsurface soil compared to surface soil could be attributed to clay translocation or clay illuviation from the A- horizon to B- horizon (Ufot *et al.,* 2001). This observation is in agreement with Ufot *et al.*, (2001) who observed higher clay accumulation in subsurface horizons than the surface horizons in Abakiliki soils. Generally, the soil texture was sand in surface and subsurface soils of both convex and concave slope while in straight slope, the soil texture was sand in the surface and loamy sand in the subsurface.

Soil pH

Soil pH was 5.9 in both surface and subsurface soils. The mean soil pH of convex slope was significantly higher ($p < 0.05$) than that of concave and straight slope. There was no significant difference ($p < 0.05$) in soil pH between the surface (0-30 cm) and subsurface soil (30-60 cm) in the study area. The high pH values of convex slope or micro-hill compared to straight slope and concave or micro- depression could be attributed to parent material and slope shape. As the soil mantles within the micro-hills are eroded by running water, the parent rocks or underlying materials are exposed to weathering effects resulting in the release of bases that increase the soil pH (Abam and Orji 2019).

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Table 1: Means of selected Physical and chemical Properties of Soils of the Study Area as Influenced by plan curvature

Soil properties	Sand (%)			Silt (%)			Clay (%)			pH			Organic C (%)		
	Depth (cm)			Depth (cm)			Depth (cm)			Depth (cm)			Depth (cm)		
Strata	0-30	30-60	Mean	0-30	30-60	Mean	0-30	30-60	Mean	0-30	30-60	Mean	0-30	30-60	Mean
Concave	85.10	81.97	83.53	6.71	6.84	6.78	8.19	11.18	9.69	5.7	5.8	5.8	2.4	2.3	2.3
Convex	88.76	83.25	86.01	5.56	5.42	5.49	5.68	11.34	8.51	6.2	6.2	6.2	2.7	2.6	2.7
Straight	86.04	79.45	82.75	6.69	5.78	6.24	7.27	14.77	11.02	5.9	5.9	5.9	3.7	3.1	3.4
Mean	86.63	81.56		6.32	6.01		7.05	12.43		5.9	6.0		2.9	2.6	
LSD(0.05)	Curvature = 3.8			1.7			3.0			0.3			0.5		
	Depth (cm) = 3.1			1.4			2.4			0.2			0.4		
	Curvature x depth = 5.4			2.4			4.2			0.4			0.8		
	Total N (%)			Available P (mg/kg)			Exch. K (cmol/kg)								
Strata	0-30	30-60	Mean	0-30	30-60	Mean	0-30	30-60	Mean						
Concave	0.10	0.10	0.10	37.3	35.8	36.5	0.22	0.11	0.17						
Convex	0.12	0.17	0.14	31.6	31.3	31.5	0.14	0.11	0.12						
Straight	0.16	0.13	0.15	50.9	59.0	54.9	0.08	0.11	0.09						
Mean	0.13	0.13		39.9	42.0		0.15	0.11							
LSD(0.05)	Curvature = 0.05			3.8			0.07								
	Depth (cm) = 0.04			3.1			0.06								
	Curvature x depth = 0.07			5.3			0.10								

Organic carbon

The mean organic carbon of convex slope was 2.7 % in the surface soil and 2.6 % in the subsurface soils. In concave slope, the mean organic carbon was 2.4 % in the surface soil and 2.3 % in the subsurface soil. In the straight slope, the mean organic carbon was 3.7 % in the surface soil and 3.4 % in the subsurface soils. The mean organic carbon of straight slope was significantly higher ($p < 0.05$) than that of concave and convex slope. There was no significant difference ($p < 0.05$) in organic carbon content between the surface (0-30 cm) and subsurface soil (30-60 cm) in the study area. The high organic carbon values of straight slope compared to convex and concave slope could be attributed to slope shape, assoil loss is less in uniform slope thereby encouraging high biomass accumulation due to favourable physical, chemical and biological properties of the soil (Shary, 1991). This indicates variation in soil organic carbon content in the study area.

Total N

The mean total N of convex slope was 0.12 % in the surface soil and 0.17 % in the subsurface soils. In concave slope, the mean total N was 0.10 % in both the surface and subsurface soils. In the straight slope, the mean total N was 0.16 % in the surface soil and 0.13 % in the subsurface soils. There was no significant difference ($p < 0.05$) in total N between the concave, convex and straight slope as well as between the surface and subsurface soils.

Available P

The mean available P of convex slope was 31.6 mg/kg in the surface soil and 31.3 mg/kg in the subsurface soils. In concave slope, the mean available P was 37.3 mg/kg in the surface soil and 35.5 mg/kg in the subsurface soil. In the straight slope, the mean available P was 50.9 mg/kg in the surface soil and 59.0 mg/kg in the subsurface soils.The mean available P of straight slope was significantly higher ($p < 0.05$) than that of concave and convex slope which could be attributed to less soil loss by runoff and erosion, favourable soil moisture and temperature resulting in high biomass, mineralization of organic materials to release available P.

Exchangeable K

The mean exchangeable K of concave slope was significantly higher ($p < 0.05$) than that of straight slope but not different from that of convex slope. The high content of exchangeable K in concave slope compared to straight slope could be due to less eroded soil materials from concave slope compared to straight slope; and the deposition of soil materials eroded from convex slope thereby resulting in higher sediments with higher exchangeable K (Souza *et al.*, 2003).

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2. Normality Test of the Analytical Data

The data was subjected to normality test to ascertain its distribution; skewed data were made appropriate by logarithmic transformation as presented in Table 2.

Among the selected soil properties, the mean values of silt fraction, clay fraction, soil pH, available P and exchangeable K were greater than the median, indicating that the data distributions were right-skewed (positive skewness) with the majority of the data values greater than the mean. The mean values of soil organic carbon and total N were similar to the median values, indicating symmetry. The mean value of sand fraction was less than median value, indicating that the data distribution was left-skewed (negative skewness) with the majority of the data values less than the mean. After logarithmic transformation, skewness value of silt reduced from 0.57 to -0.91, clay reduced from 0.78 to -0.18, pH reduced from 0.81 to 0.47, available P reduced from 0.32 to 0.06 while exchangeable K reduced from 4.43 to -1.59. This shows that the skewness of logarithmic transformed data values were closer to 0 (symmetry) than the non-log transformed skewness data values. The skewness value of sand fraction increased from -0.45 to -0.68 after log transformation. Organic carbon and total N that were near 0 (symmetric), moved to -1.05 from 0.09 and from 0.26 to -0.72 after log transformation. Logarithmic transformation resulted in smaller skewness and kurtosis, causing the distribution to approach Gaussian (normal distribution).

Table 2: Summary statistics of selected soil properties

Soil property	Minimum	Maximum	Mean	Median	Skewness	Kurtosis	Distribution type
Sand (%)	63.86	94.64	84.43	84.54	-0.454	3.467	Leptokurtic
Log sand					-0.679	3.890	
Silt (%)	1.28	14.08	7.81	7.18	0.573	3.582	Leptokurtic
Log silt					-0.909	3.702	
Clay (%)	2.64	21.48	7.74	7.21	0.780	3.021	Mesokurtic
Log clay					-0.177	2.496	
pH	4.6	7.5	5.7	5.6	0.812	4.285	Leptokurtic
Log pH					0.467	3.675	
Org. C (%)	0.76	4.97	2.6	2.6	0.091	2.229	Platykurtic
Log org. C					-1.046	3.628	
Total N (%)	0.03	0.3	0.12	0.12	0.262	2.379	Platykurtic
Log total N					-0.716	2.932	
Av. P (mg/kg)	27.3	72.83	43.3	43.0	0.324	1.912	Leptokurtic

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Log Av.P					0.063	1.754	
Exch. K (cmol/kg)	0.002	0.61	0.14	0.09	4.428	27.903	Leptokurtic
Log exch. K					-1.586	7.989	

Leptokurtic shows sharp peak on the graph, platykurtic shows flat-top, mesokurtic shows bell curve. Normal distributions are mesokurtic distributions with coefficient of kurtosis equal to 3 or approximately close to 3. If the coefficient of skewness equal to 0 or approximately close to 0, the graph is symmetric and the distribution is normally distributed.

3. Semi-variogram parameters and models of selected soil properties

The semi-variogram parameters and models of the measured selected soil properties (sand, silt, clay, soil pH, OC, TN, Av. P and exch. K) are presented in Table 3 and the graphs are presented in Figures 3 to 10. The spatial structures of soil properties are revealed by the semi-variogram. the soil properties exhibited significant spatial dependence. Using visible interpretation and sum of square error (SSEr), exponential model was the best fitted model for sand and silt, gaussian model was used for available P and spherical model was the best fitted model for pH, organic carbon, total N, exchangeable K and clay fraction when compared to other models.

Nugget /sill ratio varied from moderate spatial dependence for sand (45.1 %), silt (43.1 %), soil pH (28.5 %), organic C (50.6 %), total N (50.0 %), available P (39.2 %) to strong spatial dependence for exchangeable K (11.1 %) and weak spatial dependence for clay fraction (83.1 %) (Cambardella *et al.*, 2004). Generally, strong spatial dependence of soil properties is related to structural intrinsic factors such as texture, parent material and mineralogy while moderate to weak spatial dependence of soil properties could be related to weak correlation of soil properties with auxiliary variables and random extrinsic factors such as plowing, fertilization and other soil management practices (Zheng *et al*., 2009).

The nugget, which represents random variation caused mainly by the undetectable experimental error and field variation within the minimum sampling space (Cerri *et al*., 2004; Askin and Kizikaya, 2006) was 25.9 for sand, 10.2 for silt, 5.93 for clay, 0.06 for soil pH, 0.60 % for organic C, 0.001 for total N, 33.4 for available P and 0.003 for exchangeable K. The implication is that the variations in soil organic C, total N and exchangeable K were well explained or captured by the sampling distance or sampling scale used in the study as their nugget values were closer to zero (Cerri *et al*., 2004). But the sampling scale or distance for sand, silt and available P could not adequately capture or explain the variation in these properties since their nugget values were far away from zero.

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The range, which is an indication of the distance beyond which measured selected soil properties are no longer spatially correlated (Tabi and Ogunkunle, 2007), was 136.2 m for sand, 76.4 m for silt, 1.6 m for clay, 1.69 m for soil pH, 9.4 m for organic C, 7.1 m for total N, 39.2 m for available P and 7.8 m for exchangeable K. This shows that the values of sand fraction were more alike within 136.2 m apart; values of silt were alike within 76.4 m apart, clay values were alike within 1.6 m apart, etc. The study revealed that the selected soil properties were not similar in distance of autocorrelation, which could be attributed to factors of soil formation and soil management practices (Hengl *et al*.,2007)

Table 3: Semi-variogram models and parameters of selected soil properties

Soil property	Nugget (Co)	Sill (Co +C)	Co/Co+C (%)	Range (m)	Model	SSErr	Spatial dependence
Sand	25.87	57.37	45.1	136.2	Exponential	8736.8	Moderately
Silt	10.20	23.79	43.3	76.4	Exponential	10216.9	Moderately
Clay	5.935	7.145	83.1	1.58	Spherical	218.421	Weakly
pH$_{(H2O)}$	0.059	0.207	28.5	1.69	Spherical	0.1550	Moderately
Organic C	0.598	1.181	50.6	9.42	Spherical	0.7742	Moderately
Total N	0.0010	0.002	50.0	7.09	Spherical	5.85e-06	Moderately
Av. P	33.35	85.05	39.2	9.23	Gaussian	4839.3	Moderately
Exch. K	0.003	0.027	11.1	7.83	Spherical	0.0017	Strongly

Classes of spatial dependence: ≤ 25% = strongly spatially dependent, 26-75% = moderately spatially dependent; > 75% = weakly spatially dependent (Cambardella *et al*., 1994).

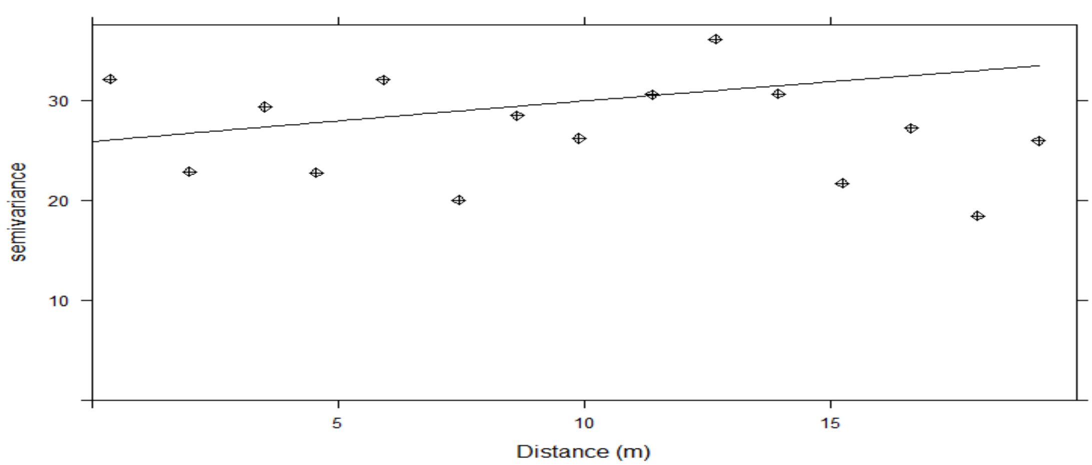

Fig. 3: Semi-variogram of sand fraction

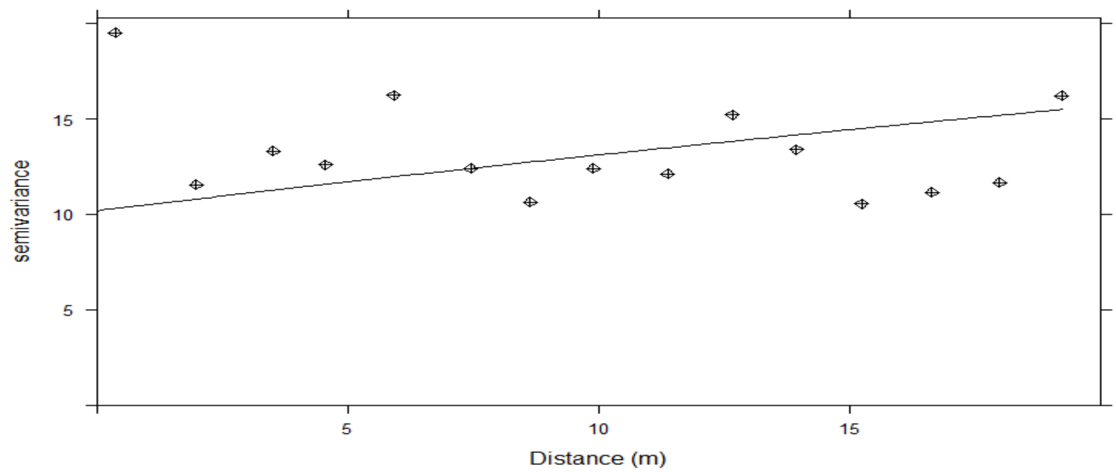

Fig. 4: Semi-variogram of silt fraction

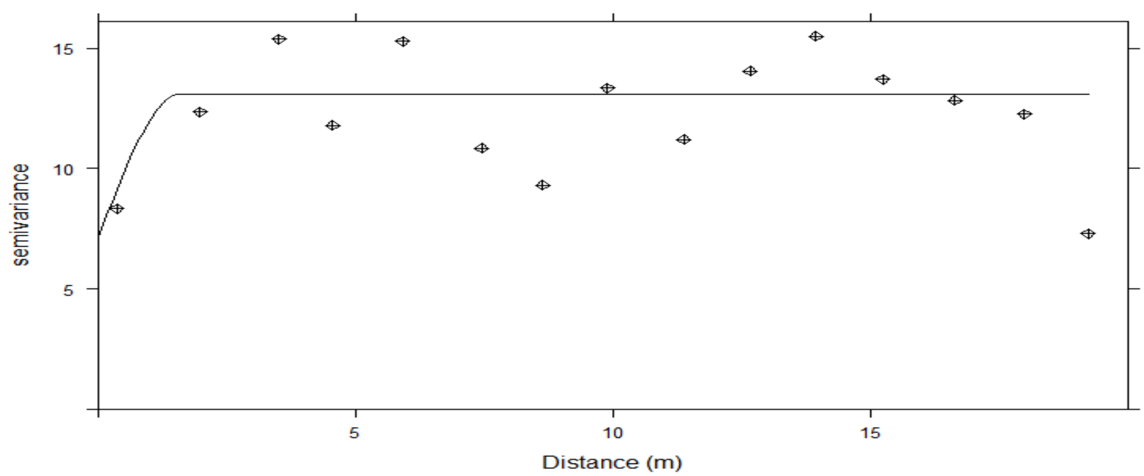

Fig. 5: Semi-variance of clay fraction

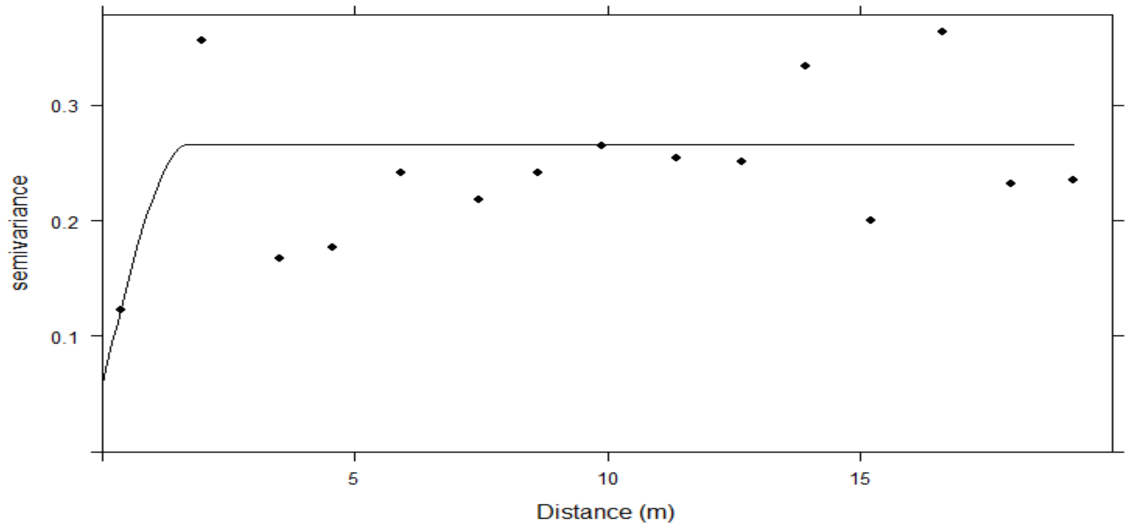

Fig. 6: Semi-variance of soil pH

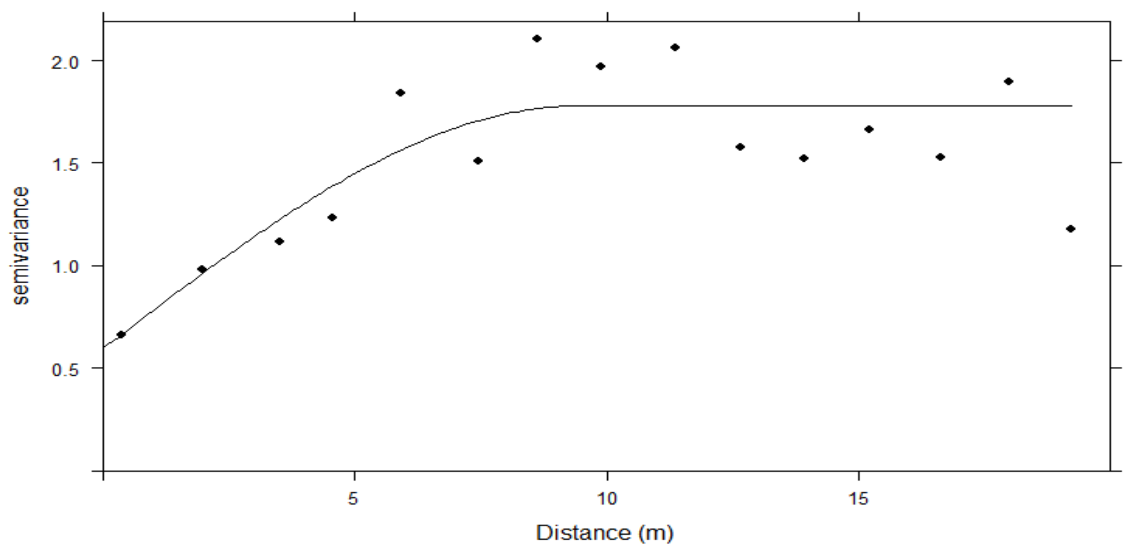

Fig. 7: Semi-variance of organic carbon

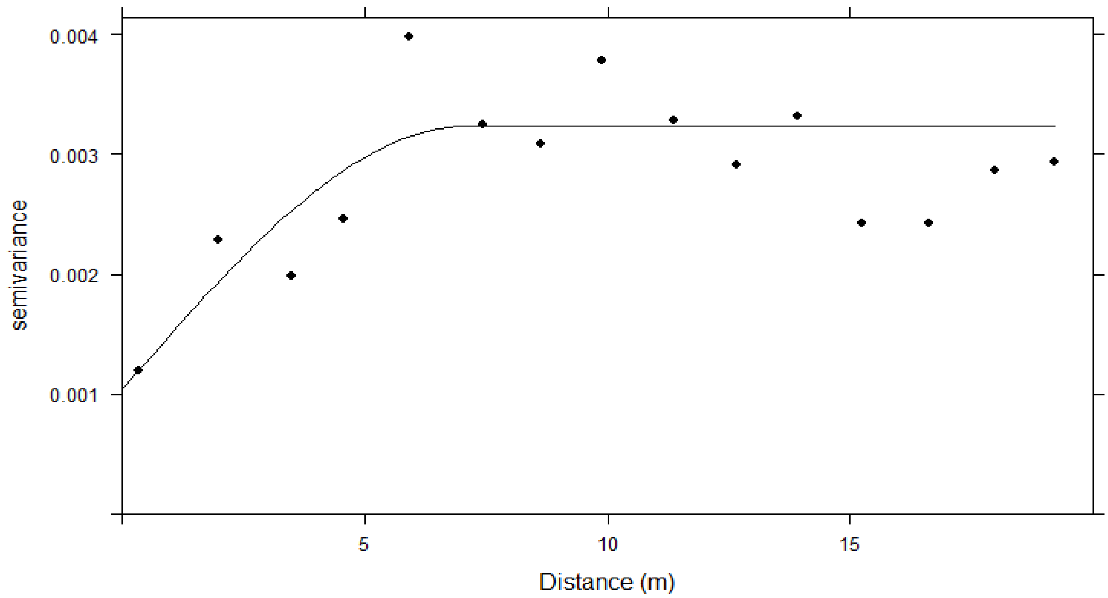

Fig. 8: Semi-variance of total N

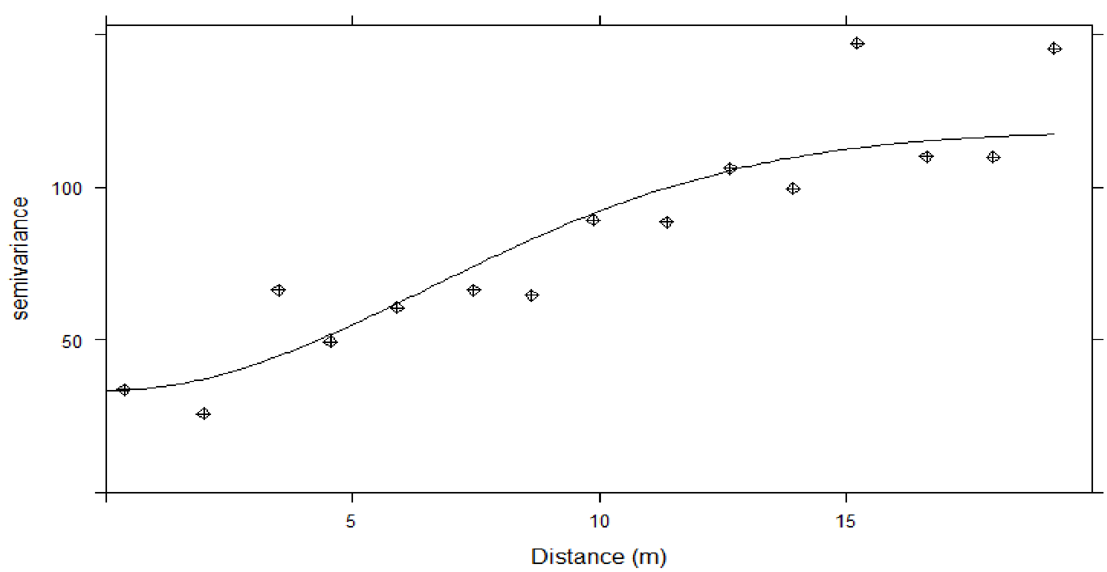

Fig. 9: Semi-variance of available P

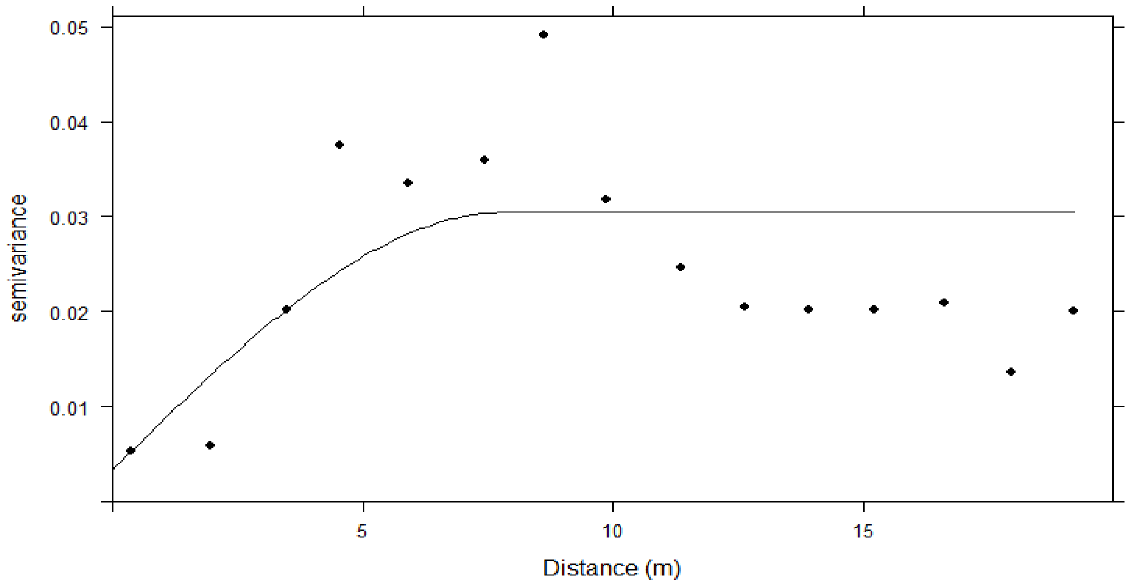

Fig. 10: Semi-variance of exch. K

CONCLUSION

The results showed that plan curvature was able to capture short scale spatial variation in selected soil attributes under consideration. Soil texture was sand in the surface and subsurface soils of both convex and concave slope while in straight slope, the soil texture was sand in the surface and loamy sand in the subsurface. Soil pH was strongly acidic in both straight and concave slope and slightly acidic in convex slope in both surface and subsurface soil. Organic carbon was high in concave and convex slope and very high in straight topography in both surface and subsurface soils. Total N was low in the convex and concave slope but moderately low in straight terrain. The available P of straight slope was higher than that of concave and convex slope. From the semi-variogram analysis, all the selected soil properties exhibited spatial dependence within some distances. The strength of the spatial dependence varied from moderate for sand, silt, soil pH, organic carbon, total N and available P to weak for clay and strong for exchangeable K. The best fitted models were Exponential for sand and silt; Gaussian for available P and Spherical for clay, pH, organic carbon, total N and exchangeable K. The range of autocorrelation was 136.2 m for sand, 76.4 m for silt, 1.6 m for clay, 1.69 m for soil pH, 9.4 m for organic C, 7.1 m for total N, 39.2 m for available P and 7.8 m for exchangeable K. This shows that beyond these ranges, the selected soil properties should be managed differently. Therefore, in the management of these soils, uniform application of fertilizer for nutrient in-

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balance should be discouraged. Site-specific soil management should be promoted in the study area.

In conclusion, different predictors with higher correlation with soil properties as well as hybrid interpolation method (such as regression kriging) is highly recommended for spatial study in the study area.

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