

Spatial Variation in Some Physical Properties of Vertisols of Kerau in Guyuk area of Adamawa State

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Abstract

This study assessed the spatial variation of some physical properties of vertisols of Kerau in Guyuk local government area of Adamawa State, Nigeria. The objective of this study was to examine the physical properties of vertisols and assess their micro-scale variation at the study site. Physical properties measured are %sand, silt and clay and available water capacity. Soil samples were collected at two depths of 0-15cm and 15-30cm with an auger. A total of 100 soil samples were collected and analyzed using standard analytical methods. Soil properties measured exhibited low coefficient of variability and strong spatial autocorrelations. The spherical and Gaussian models provided the best fit for soil properties of the study site at the scale of measurement. Kriged maps show no relations between surface depth distribution of properties and subsurface depths. Accordingly, Soil conservation measures that would improve soil structure are recommended for vertisols.

Keywords: vertisols, microscale, variation, semivariograms, kriging, kerau, range

1. Introduction

Soil physical properties play a very strategic role in defining the characteristics of vertisols of any area (Lin et al., 2005; Enger and Smith, 2004; Wilding and Drees, 1983). This, from the fertility point of view is hinged on the knowledge that they are products of the interplay of factors of soil formation and anthropogenic activities (Khan et al, 2007; Jung et. al., 2006; Ayoubi et al 2006; Lin et. al., 2005; Corwin, 2003; Warrick and Nielson, 1980). Vertisols physical properties are however known to be very variable and this variability at any given time is scale dependent more because of the mulching ability of the soil, the gilgai morphology and varying temporal moisture regimes of the soil (Kovda, et al, 2010; Garten Jr. et al, 2007; Wilding, et al., 2002; Yang et al 2002; Webster, 1997). This has most often been the major source of soil management problems to many a farmer especially in tropical Africa. Today, the focus is on precision farming for optimal crop production which requires knowledge of within-field variability comprising that over short distances of a few centimeters (short range variation) and that over longer distances of tens of meters (Garten Jr., et al, 2007; Lin et al, 2005; Oliver and Carrol, 2004).

Many studies have focused on studying variability at large and medium scales (Heuvelink and Webster, 2001). For instance, studies on soil texture by Adhikari et al, (nda), Warrick and Gardner, (1983) and Tanji, (1996) found that soil texture variability has a significant influence on the availability of nutrient, moisture and yield potential of any soil of any site. Similarly, Zhang et al (2010) assessed variability of surface soil moisture in karst regions using a 20m interval grid sampling technique and found that variability was explained by the exponential and Gaussian models with a weak to moderate spatial dependence and a mosaic pattern exhibited in the kriged maps. Wang et al (2001) observed that soil moisture exhibits changing spatial dependence with depth. Soil moisture is also known to exhibit moderate variability spatially at a field scale (She et al, 2010; Yang et al 2002). These studies are in tandem with the farming systems in the developed world. Information from such studies does not however relate with the small scale or small holder farming systems that exist in countries like Nigeria. Very little has also been done on variability in vertisols at micro-scales in the sudano-sahelian region of Nigeria where they present both structural and soil moisture problems to local farmers. It is based on the foregoing that this study investigated the variability in the physical properties of vertisols in Sudano-sahelian Nigeria at a micro-scale. This study assessed the spatial structure of physical properties of vertisols.

2. Methods

2.1 Study site

The study site is a 2.2ha *Sorghum bicolor* farm located on latitude 9^o38.613N - 9^o38.595N and longitude 11^o54.623E-11^o54.571E, with an elevation of approximately 200m above sea level and a near flat slope with a northeast to southwest trending of 0.02% in Kerau village of Guyuk local government area in Adamawa State. The area has a wet-dry savannah climate with mean annual rainfall of 978mm. The wet season spans between April and October with average temperatures as high as 35^oC in March and relative humidity that reaches 70% in

August, the peak of the rainy season (Adebayo, 1999). The local environment is almost arid, having been modified by human activities of sorts such that very few scattered trees and grasses now prevail. The vegetation can thus be described as Sudan savannah grassland. The study area within which the study site falls is drained by a network of seasonal streams radiating from the Lunguda plateau into the Benue River (Tukur, 1999). The soil of the study area can best be described as vertisols of the ustert suborder (Ray, 1999). The soils have a deep A-C horizon with gilgai morphology because of their ability to crack and mulch between dry and wet seasons (Sabine, 2008).

2.2 Field and Laboratory methods

Soil samples were collected with an auger at two sampling depths of 0-15cm (to represent the root zone) and 15-30cm (to represent zone of illuviation) in March 2012. Thus, a total of 50 soil samples were collected at the two depths using approximately 15m grid sampling design (fig. 2). A Garmin GPS was used to identify sampling locations.

Soil samples were air-dried, crushed and sieved through a 2mm mesh size sieve. Physical properties measured are Particle size distribution and plant available water capacity. Particle size analysis was carried out using the Bouyoucos hydrometer method (Bouyoucos, 1962). Plant available water capacity was determined by the Pressure Outflow Method (Klute, 1986).

2.3 Statistical analysis

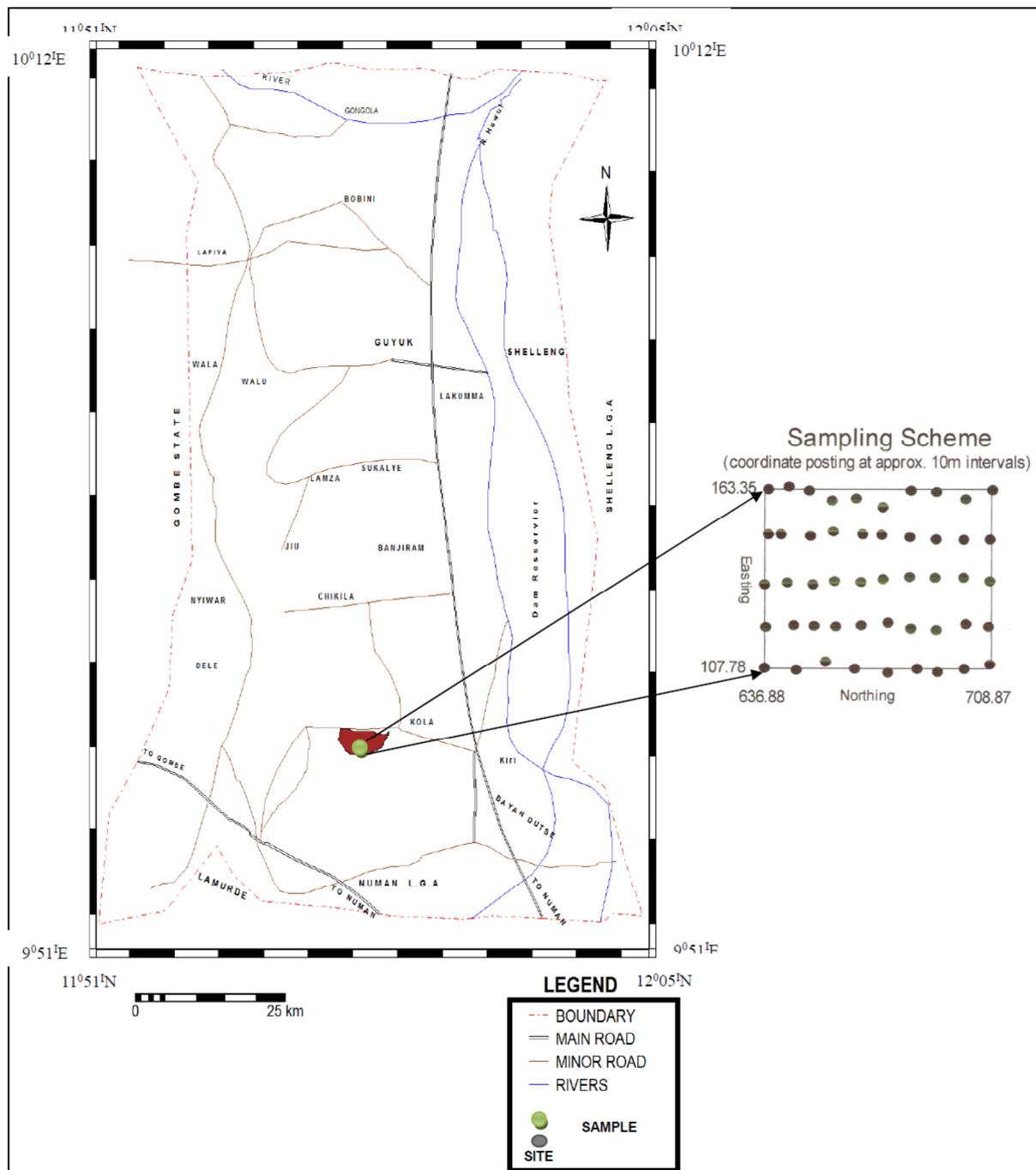
Statistical analysis was performed using the Gamma Environmental Design Software version 9.3 (Robertson, 2008). Other descriptive statistics such as the coefficient of variation was performed using the SPSS 15 for windows.

Descriptive statistics computed for this study included the mean, standard deviation, maximum and minimum values, skewness and kurtosis and the coefficient of variability.

Geostatistical analysis was performed to bring out the spatial structure of soil properties in the data set and the pattern of distribution at unsampled locations based on the semivariogram and kriging interpolations. The semivariogram, as given below was used to estimate the spatial structure of the variation of variables measured (Jung, et al, 2006; Isaaks and Srivastava, 1989).

Semivariogram $\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - Z(x_i + h)]^2$,
(where $\gamma(h)$ = semivariance; N = number of pairs; h = lag distance; x = data pair and i = location in space).

Accordingly, spatial structure is defined by three properties of the semivariogram – range (A), which is the spatial distance beyond which two observations are independent of each other; sill, ($C_0 + C$), which is the model asymptote that can never be less than the nugget; and nugget (C_0) a discontinuity at the origin arising from a combination of sampling and analytical errors (Robertson, 2008; Goovaerts, 1999, 1997).



3. Results and Discussion

3.1 Descriptive statistics of Soil Properties

Descriptive statistics for parameters describing texture (%sand, %silt and %clay distributions) and Plant Available Water Capacity (PAWC) at 0-15cm (surface depth) and 15-30cm (subsurface depth) are presented in table 1. All data were subjected to normality test. The clay fractions dominated the particle size distribution followed by sand and then silt. PAWC exhibited similar behavior laterally and vertically.

Table 1: Descriptive Statistics of Soil Physical Properties

Variable	Soil Depth	Mean	SD	SV	Min	Max	Skew	Kurt	CV (%)	Variability
pH	0-15cm	8.3	0.28	0.08	7.7	8.9	0.09	-0.74	3	Low
pH	15-30cm	8.6	0.51	0.26	7.6	9.8	0.37	-0.29	6	Low
%Sand	0-15cm	30.62	5.3	28.6	20	40	-0.05	-0.23	17	Moderate
%Sand	15-30cm	24.64	2.09	4.38	21	28	-0.24	-1.00	8	Low
%Silt	0-15cm	19.65	2.8	7.7	15	25	0.04	-1.03	14	Low
%Silt	15-30cm	19.62	2.99	8.93	16	26	0.34	-0.95	15	Low
%Clay	0-15cm	49.74	4.96	24.61	39	61	0.02	-0.41	10	Low
%Clay	15-30cm	55.74	3.8	14.3	47	63	-0.2	-0.87	7	Low
PAWC	0-15cm	59.85	7.86	61.82	40.8	70.7	-1.06	0.21	13	Low
PAWC	15-30cm	62.5	8.9	79.4	41.9	77.4	-0.53	-0.4	14	Low

Source: (Field Survey, 2012); SD: Standard Deviation; SV: Sample Variance; Min: Minimum; Max: Maximum; Kurt: Kurtosis; CV: Coefficient of Variability; %: Percentage. [Variability: $\leq 15\%$: low; 16-35%: moderate; $>35\%$: High variability]

The result in Table 1 shows that there is no significant inter-depth difference in the observed means of the soil pH and those of percentage sand and silt contents; however, that of Clay and PAWC are observed to be slightly lower in the surface depth than in the subsurface depth. The standard deviations between the surface and subsurface depths for Sand and Clay contents decreases with depth; while that of pH and PAWC increases with depth. There is thus, no significant difference in mean and SD values of Silt distribution in the study site. With the exception of Sand at the surface depth, all physical properties exhibited low spatial variability at both depths. This variation may be random and could thus be attributed to measurement anomaly. In general, soil physical properties exhibited low variability both across the field and with depth.

3.2 Semivariogram Analysis of Physical Properties

The semivariograms for pH, sand, silt, clay and plant available water capacity (PAWC) at top soil and sub soil depths are presented in figure 1-5 and the summary of the semivariogram statistics presented in table 2.

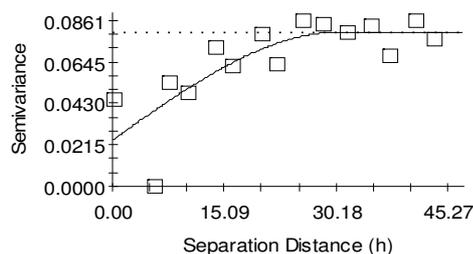
All the semivariogram statistics in Table 2 reveal a strong spatial autocorrelation in all the soil properties investigated at both the surface and subsurface depths. This is indicated in the sill to nugget value range of 0.01 to 7. Only surface pH reveals a medium spatial autocorrelation at the scale measured. The spherical and Gaussian models provided the best fit for physical properties measured. Range of spatial autocorrelation was between 6m for subsurface clay and 30m for surface pH. Thus, a maximum range of 30m should be considered as maximum sampling range in future sampling plans.

Table 2: Semivariogram statistics of physical properties

Variable	Soil Depth (cm)	Model	Range A (m)	r^2	RSS	C_0	C_0+C	$\frac{C}{C_0+C}$	$\frac{C_0}{C_0+C}$ (%) Nugget to Sill
pH	0-15	Spherical	30.8	0.62	0.003	0.024	0.08	0.70	30=M
pH	15-30	Spherical	18.2	0.81	0.021	0.012	0.29	0.96	4=S
Sand(%)	0-15	Spherical	27.42	0.69	0.00054	0.0022	0.032	0.93	7=S
Sand(%)	15-30	Gaussian	11.37	0.5	0.0003	0.00001	0.087	0.99	0.01=S
Silt(%)	0-15	Gaussian	10.17	0.97	1.42	0.01	8.52	0.99	0.12=S
Silt(%)	15-30	Gaussian	7.16	0.55	0.013	0.0001	0.17	0.99	0.06=S
Clay(%)	0-15	Gaussian	10.66	0.81	2.17E-03	0.0001	0.116	0.99	0.09=S
Clay(%)	15-30	Gaussian	6.84	0.56	1.915E-03	0.0001	0.076	0.99	0.13=S
PAWC	0-15	Gaussian	14.64	0.93	3.086E-05	0.0001	0.017	0.99	0.6=S
PAWC	15-30	Gaussian	19.57	0.83	7.384E-04	0.0001	0.071	0.99	0.14=S

Source: (Field Survey, 2012); $C/C_0+C=1$ (no nugget variance) or 0(pure nugget); Nugget/Sill ratio: S=Strong ($<25\%$); M=Moderate (>25 & $<75\%$); W=Weak ($>75\%$).

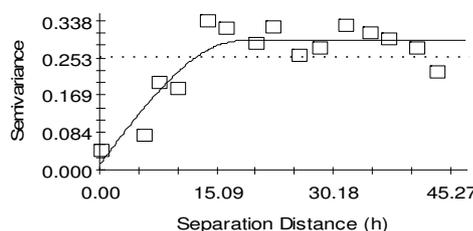
pH (0-15cm): Isotropic Variogram



Spherical model ($C_0 = 0.02400$; $C_0 + C = 0.08020$; $A_0 = 30.80$; $r^2 = 0.62$
 RSS = $2.756E-03$)

Fig. 1a: Topsoil pH Variogram

pH (15-30cm): Isotropic Variogram

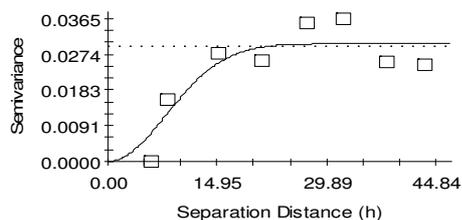


Spherical model ($C_0 = 0.01240$; $C_0 + C = 0.29180$; $A_0 = 18.15$; $r^2 = 0.81$
 RSS = 0.0209)

Fig. 1b: Subsoil pH Variogram

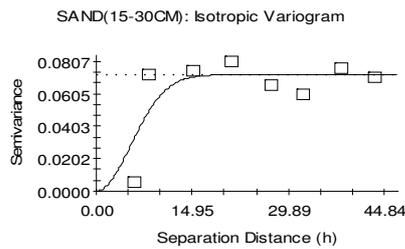
Figures 1(a) and (b) shows that the spherical model was the best fit for pH (with r^2 values at 0.62 and 0.81 and very small RSS) for the two depths. This suggests that there is a gradual decrease in spatial autocorrelation of pH at both depths within the observed range. The spatial dependence of soil pH with distance is thus limited to the 30.8m range laterally and 18m range vertically beyond which there is no spatial autocorrelation. This is an indication of high variability both laterally and with depth. Soil pH also exhibited a very negligible nugget effect both laterally and vertically; with smaller value vertically than laterally. This is an indication that the source of variability is structural. With a nugget to sill ratio between 30% laterally and 4.14% vertically, soil pH shows a strong spatial correlation structure in both directions (Table 2). Soil pH did not however, show any significant directional variation (anisotropic behavior) in vertisols of the study area.

SAND(0-15CM): Isotropic Variogram



Gaussian model ($C_0 = 0.00001$; $C_0 + C = 0.03012$; $A_0 = 11.24$; $r^2 = 0.794$;
 RSS = $2.058E-04$)

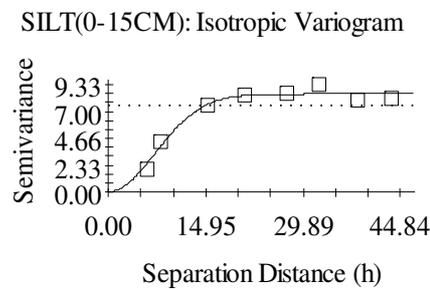
Fig. 2(a): Surface soil %Sand Variogram



Gaussian model ($C_0 = 0.00010$; $C_0 + C = 0.07240$; $A_0 = 7.59$; $r^2 = 0.646$;
 RSS = $1.605E-03$)

Fig. 2(b): Subsurface soil %Sand Variogram

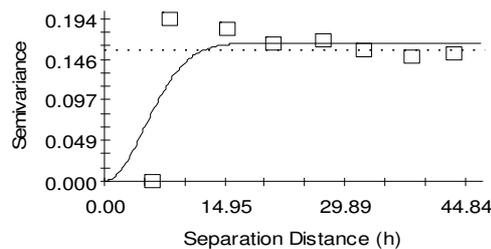
Figure 2(a) revealed that spatial dependence in the sand separate was explained by the spherical model at the surface depth. Particle sands are autocorrelated within the 27m range and exhibited little signs of unaccounted short scale variation. Sand separates at the subsurface depths are however described adequately by the linear model with a long range variation occurring beyond the 544m range.



Gaussian model ($C_0 = 0.01000$; $C_0 + C = 8.51600$; $A_0 = 10.17$; $r^2 = 0.969$;
 RSS = 1.42)

Fig. 3(a): Surface soil %Silt Variogram

SILT(15-30CM): Isotropic Variogram

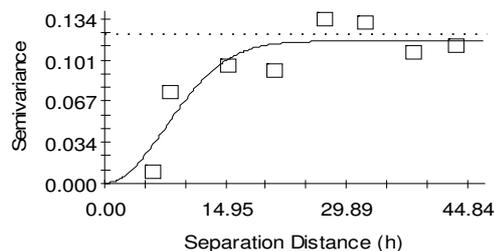


Gaussian model ($C_0 = 0.0001$; $C_0 + C = 0.1652$; $A_0 = 7.16$; $r^2 = 0.546$;
 RSS = 0.0131)

Fig. 3(b): Subsurface soil Silt Variogram

Fig. 3(a) shows that the spherical model adequately describes the spatial dependence of Silt distribution at the study site. Silt content was spatially autocorrelated within the 28m range. The high nugget value of 2.3 is an indication of unaccounted random variation in silt distribution. Similarly, the linear model provided the best fit for silt at the subsurface depth with a very small nugget (0.018). Silt at the subsurface depth is auto-correlated within the 43m range.

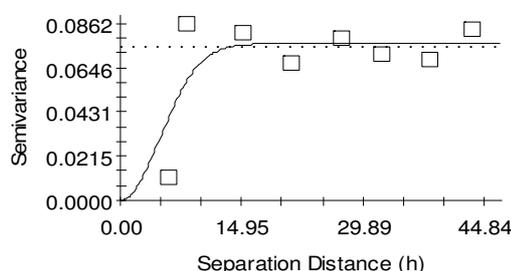
CLAY(0-15CM): Isotropic Variogram



Gaussian model ($C_0 = 0.0001$; $C_0 + C = 0.1162$; $A_0 = 10.66$; $r^2 = 0.806$;
 RSS = $2.167E-03$)

Fig. 4(a): Surface soil %Clay Variogram

CLAY(15-30CM): Isotropic Variogram

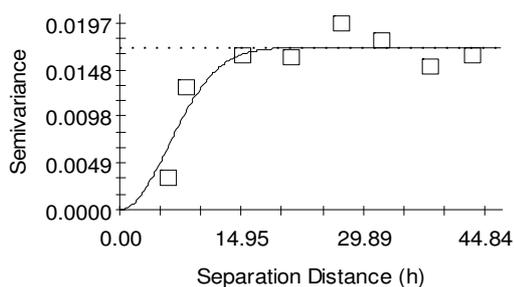


Gaussian model ($C_0 = 0.00010$; $C_0 + C = 0.07640$; $A_0 = 6.84$; $r^2 = 0.575$;
 RSS = $1.915E-03$)

Fig. 4(b): Subsurface soil %Clay Variogram

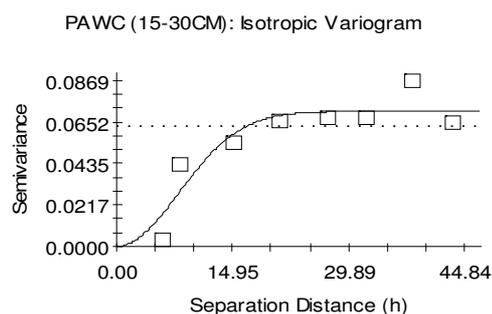
Fig. 4(a) and (b) shows that while exponential model was the best fit for surface clay content, the linear model provided the best fit for clay content at the subsurface depth. Spatial dependence occurs within the 73m range at the surface depth and 43.6m at the subsurface depth. There is however, a large nugget at the subsurface depth, which is an indication of random variation due perhaps to sampling errors.

PAWC (0-15CM): Isotropic Variogram



Gaussian model ($C_0 = 0.00001$; $C_0 + C = 0.01712$; $A_0 = 8.45$; $r^2 = 0.833$;
 RSS = $3.086E-05$)

Fig. 5a: Surface soil PAWC Variogram



Gaussian model ($C_0 = 0.00010$; $C_0 + C = 0.07090$; $A_0 = 11.30$; $r^2 = 0.830$;
 RSS = $7.384E-04$)

Fig. 5b: Subsurface soil PAWC Variogram

Fig. 5(a) and (b) reveals that gaussian model described the spatial distribution of PAWC at both the surface and subsurface depths; with spatial dependence occurring within the 301m range at the surface depth and 12.57m range at the subsurface depth. This suggests that there is long range variation across the field and short range variation with depth. Thus, crops with tap root system will do better throughout the farming season, while arable crops with fibrous root system may suffer moisture shortages during dry spell periods.

3.3 Kriged Maps of Soil Physical Properties

The results of semivariogram analysis were used in ordinary kriging interpolation to produce prediction maps of the spatial distribution of soil physical properties of the study site. The cross validation technique was used to validate the semivariogram models fitted. All the soil properties analysed shows that the experimental models fitted to standard variograms were satisfactory with 16 neighbours as the ideal neighbourhood size for the kriging estimation. The maps are shown in figs. 6-10.

Surface pH (0-15cm) of Kerau Vertisols

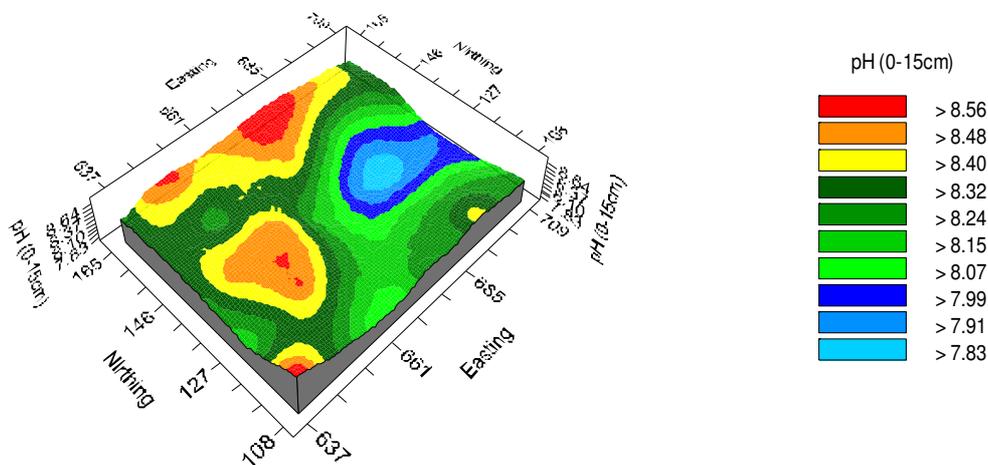


Fig. 6(a): Spatial Distribution of Surface pH

Figure 6(a) shows a patchy distribution of soil pH at the surface depth with higher values (8.4 to 8.5) occurring on the western tip and the lower south of the study site. Lower values of pH (<7) are observed at the northern part of the site. generally, fig. 6(a) shows a predominant pH range of 8 and 8.5 in the study site.

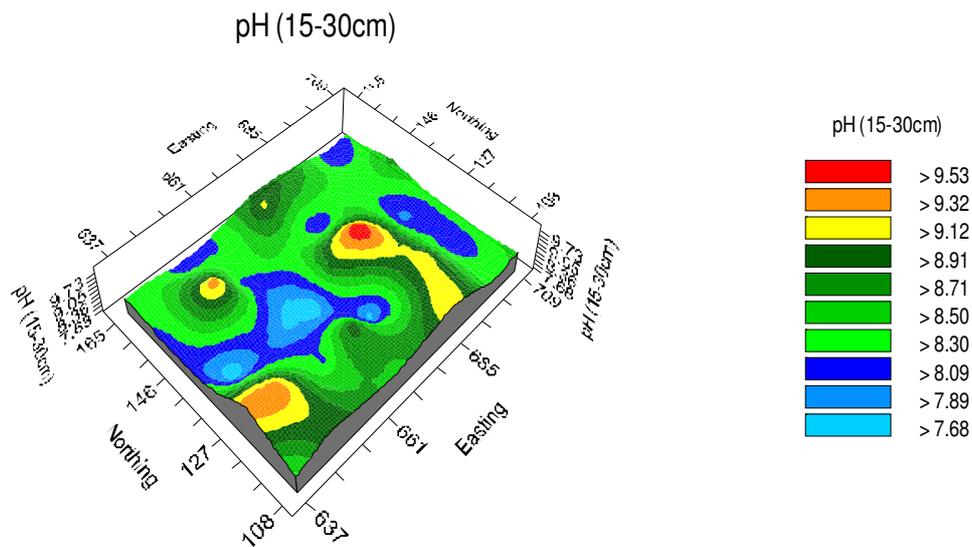


Fig. 6(b): Spatial Distribution of Subsurface pH

Fig. 6(b) also shows a patchy distribution of pH at the subsurface depth with a patchy strand of high pH (9 to 9.5) in the north and occurring as conical spots in the southern parts of the site interlaced with patches of lower pH surfaces. The occurrence of few localized areas of the site with high pH values (>9) may perhaps be due to localization of nutrients in micro-depressions in the site. In general, soil pH at the site is predominantly high between 8 and 9.

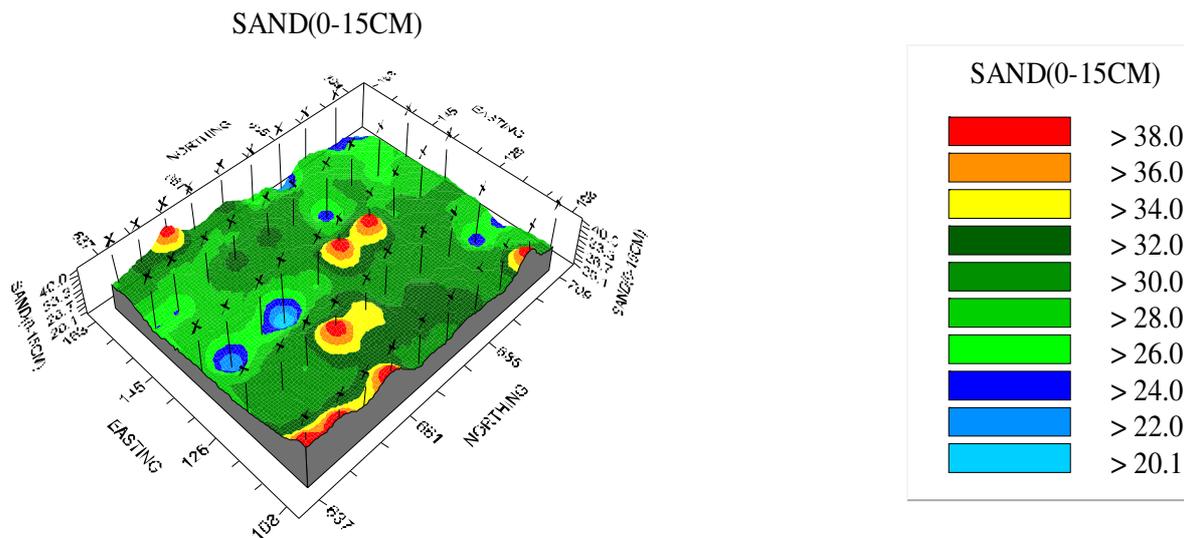


Fig. 7(a): Spatial Distribution of Surface Sand

Fig. 7(a) shows a generally low distribution values in sand content (26-32%) at the site. Isolated patches of sand content greater than 34% are seen to dot the site. Few patches of low sand content ($\leq 25\%$) are also observed in south, northwest and northeast tips of the site. This suggests that at the surface depth, sand content is generally low.

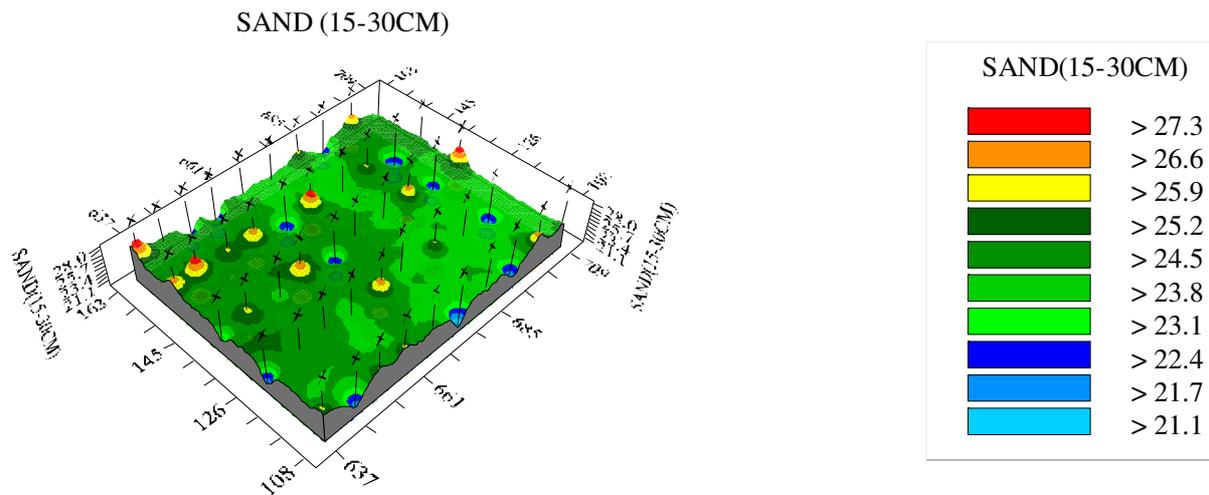


Fig. 7(b): Spatial Distribution of Subsurface Sand

Sand distribution at the subsurface depth is observed to be generally lower as shown in Fig. 7(b) compared with surface sand content of fig 7(a). The sand content ranges between 23% in the northern half of the site and 25% in the southern half in general. Few hotspots of high (>25%) and low (<22%) values dot the entire site. This suggests that there is a very insignificant variation in silt distribution laterally.

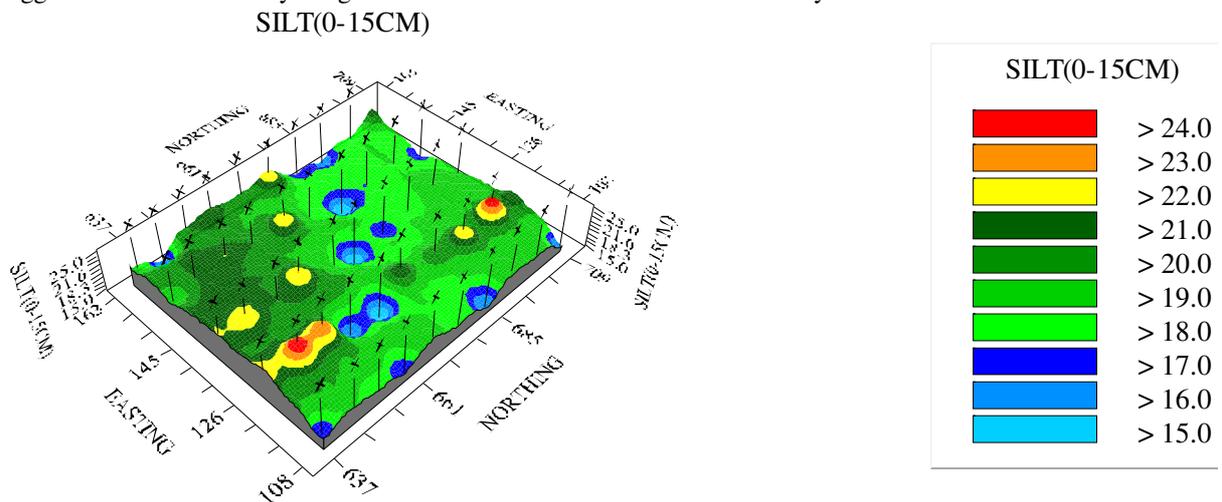


Fig. 8(a): Spatial Distribution of Surface Silt

The kriged map of surface silt above (fig. 8a) shows a general silt range distribution of between 18% and 21% at the site. While higher values of 20% and 21% occurs in the southern half of the site, lower values of 18% and 19% covers the northern half. This shows that there is no significant variation in silt distribution with depth.

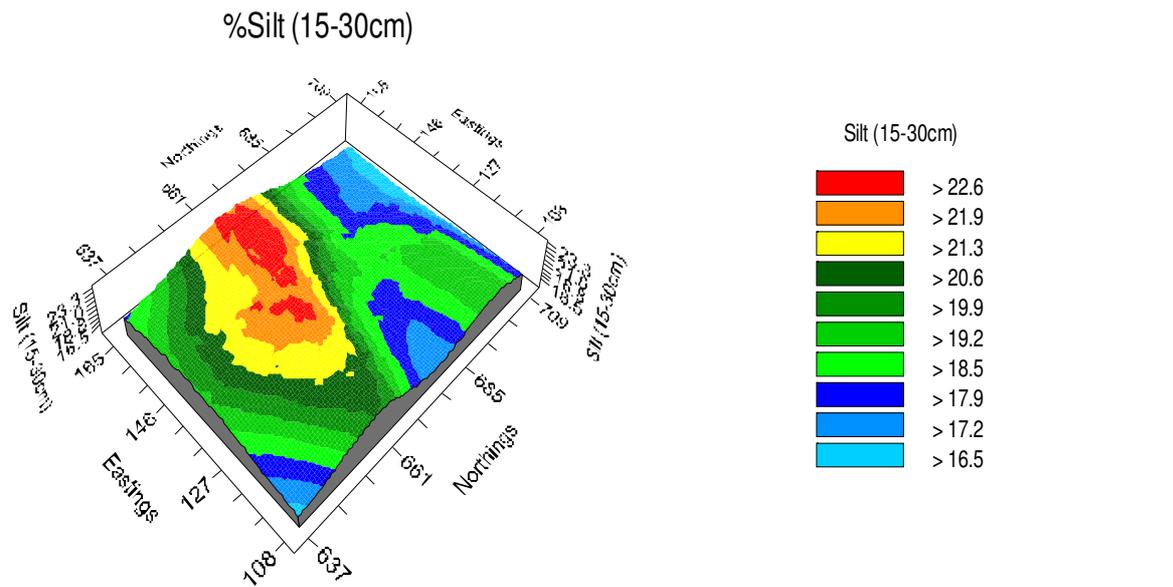


Fig. 8(b): Spatial Distribution of Subsurface Silt

Fig. 8(b) reveals a concentration of high silt content ($\geq 21\%$) in the west-central part of the site that gradually decreases northwards and southwards from the center. Values of silt below 17% are observed to occupy the north to northwest, east and southeast tips of the site.

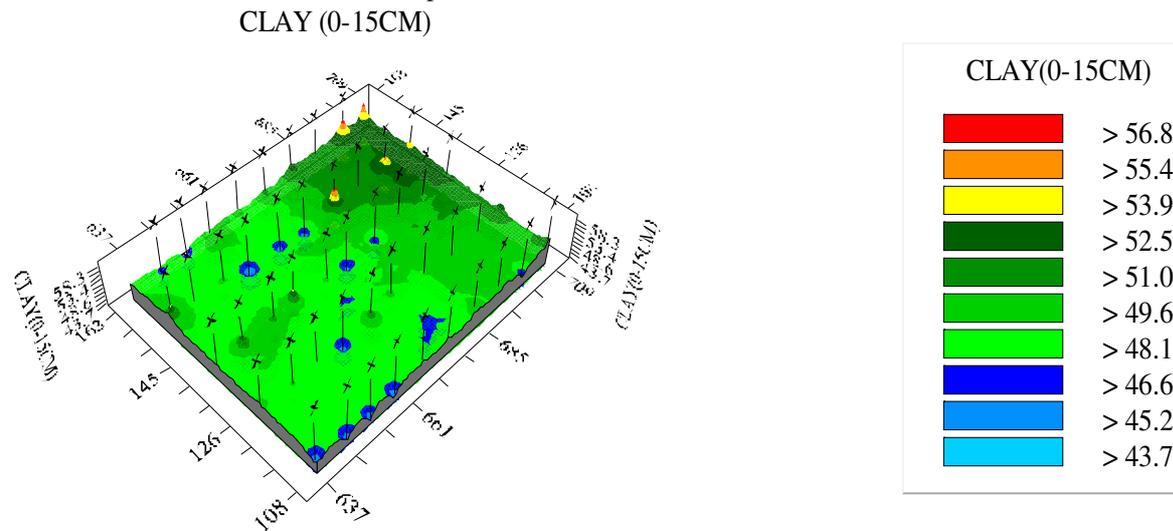


Fig. 9(a): Spatial Distribution of Surface Clay

Fig. 9(a) shows a general range of 48-52% clay distribution content on the site. Clay distribution is observed to dominate the PSD at the surface depth when compared with sand (27%) and Silt (20%). Increase in clay content is higher in the northern half of the study site.

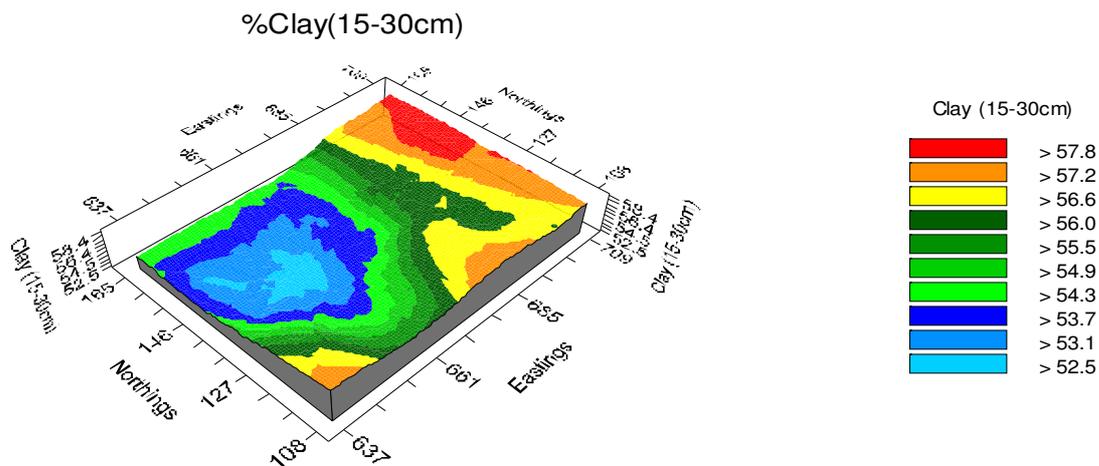


Fig. 9(b): Spatial Distribution of Subsurface Clay

Fig. 9(a) shows high values of between 56% and 57% occupying the north, northeast and southeastern corners of the site at the subsurface depth. Most of the southern half has lower clay content (below 53%). In general, subsurface clay distributions range between 52% -53% in the south and 56%-57% in the northern part of the site. This indicates a general increase in clay distribution with depth at the study site.

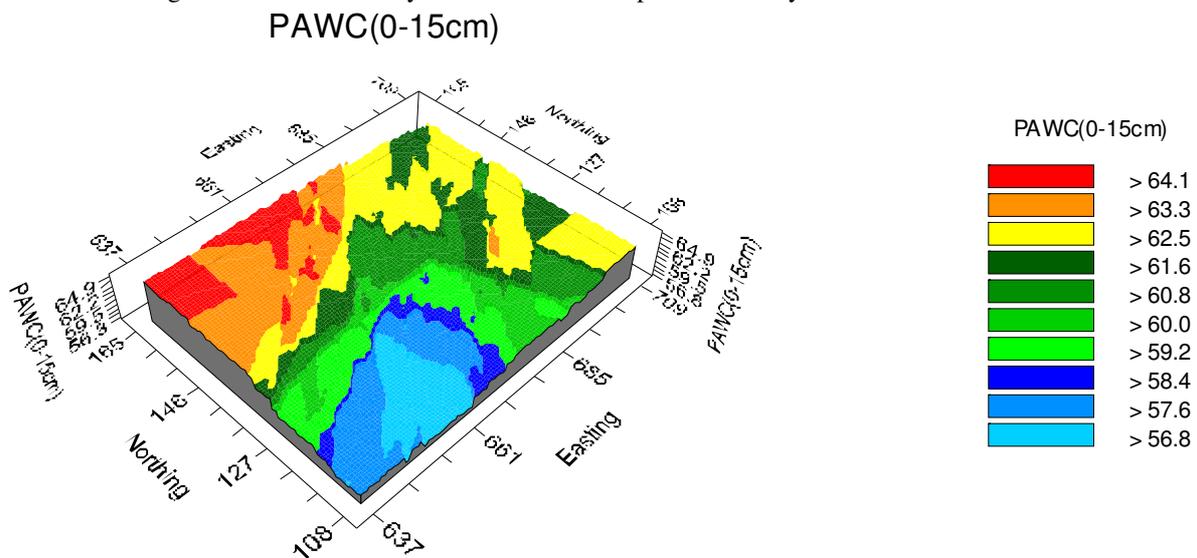


Fig. 10(a): Spatial Distribution of Surface PAWC

Fig. 10(a) shows a gradational increase in surface PAWC values in an east to west pattern, with low PAWC (56%-58%) found in the southeast corner and high PAWC (62%-64%) occurring in the southwest corner. The lower PAWC in the southeast corner of the site may be due to poor infiltration occasioned due to higher clay content of vertisols in that part of the site.

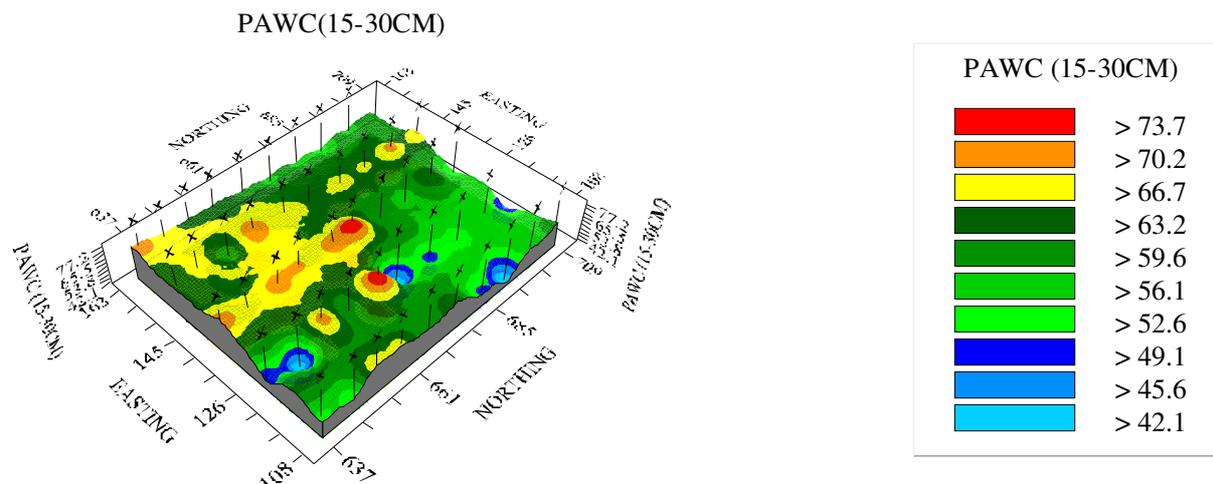


Fig. 10(b): Spatial Distribution of Subsurface PAWC

Fig. 10(b) however, reveals patchy distribution of PAWC at the subsurface depth with high PAWC values observed to predominate most of the south-western corner of the site. Other parts of the site are dominated by clay distribution range of 52% - 63% in general. The PAWC range at the subsurface depth is generally between 52% and 66% with half of the site to the east having higher values.

4.0 Discussion

This study shows that vertisol of the study site has a PSD mean range of 27% Sand to 20% Silt to 53% Clay. Low mean sand content is observed to decrease with depth in relation to clay, suggesting the downward migration of clay particles during the mulching process. This is perhaps the reason behind the gradual increase in plant available water content with depth especially in the southwest quadrant of the site (as revealed by kriged maps). The high PAWC observed may thus be attributed to the higher clay distribution of vertisols of the site. Strong spatial autocorrelation is observed in all physical properties analyzed at both depths. The spherical model that provided the best fit for pH at both depths and surface sand indicates a progressive decrease of spatial autocorrelation until 30m for surface pH, 18m for subsurface pH and 27m for surface sand, beyond which there is no autocorrelation. This suggests that pH and surface sand have higher level of short range variation. Similarly, the Gaussian model that provided the best fit for Silt, clay and PAWC at both depths suggests that these properties have smooth variation with distance and shorter ranges (11m on the average) than that represented by the spherical model (25m on the average). In general, the variation in soil properties seems to be more of a structural one than random.

5.0 Conclusion

The findings of this study shows that mean value of pH is 8.5, PAWC is 60%, Sand is 27%, Silt is 20% and Clay is 53%. All physical properties measured exhibited low variability at the scale and depth of measurement. The spherical model adequately describes the strong spatial dependence in sand distribution and surface silt distributions; while the Gaussian model adequately describes the strong spatial dependence of subsurface silt, clay and PAWC distribution in vertisols of the study site. Kriged maps show no relations between surface depth distribution of properties and subsurface depths; this is related to the mulching ability of vertisols. Considering the high clay content and short moisture range, any form of dry spell may adversely affect the development of crops at the study site. Thus, soil farm practices that would improve the soil structure (such as growing high residue crops, cover crops, reduce soil disturbing activities, and manage residue) should therefore be employed by farmers in the study area. Accordingly, conservation measures that promote infiltration, reduce evaporation, minimize disturbance, manage residue, and prevent mixing of salt-laden lower soil layers with surface layers are advised.

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