GEO-SPATIAL VARIABILITY OF SOIL ORGANIC CARBON IN A CASSAVA FIELD AT EKHA AGRO FARMS, LANLATE, OYO STATE, NIGERIA

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Abstract

Soil Organic Carbon (SOC) is one of the most important parameters affecting the chemical, physical and hydraulic characteristics of natural soils. Knowledge of spatial variability in soil fertility is important for site specific nutrient management. The study was conducted on a 467 hectare commercial cassava farm located at Lanlate (7º 36'N and 3º 27'E), Oyo State, southwestern Nigeria. Soil samples were collected from eighty–eight (88) sites on a grid system at 0-30 cm and 30-60 cm depths. Coordinates (latitude and longitude) of the locations of the sampling sites were obtained with the aid of a hand held Global Positioning System (GPS) (Garmin eTrex Ventura®) receiver,. The Walkley and Black (1934) wet digestion method was used to determine soil organic carbon content. Spatial analysis of the classified SOC was done in a GIS environment. A GIS software package ArcGIS 10.2 and ArcGIS Geo-statistical Analyst Extension were used. Various interpolation techniques, ordinary kriging, Simple Normal Score, Universal kriging, Empirical Bayesian Kriging and Ordinary co-kriging were used to produce the spatial distribution of the SOC. Ordinary co-Kriging with Nitrogen as a covariate gave the best model predictions for both surface and sub-surface depth. The best fit semivariogram models for SOC were "K-Bessel" and "J-Bessel" for surface and subsurface depths respectively. The nugget-to-sill ratio(Co/Co + C) for soil organic carbon at the surface depth was 0.103 and 0.062 for sub surface soil, these indicated a strong spatial dependence for both top soil and subsoil. The spatial distribution of soil organic carbon at Ekha farm is dominated by the constitutive factors and the random factors together. Based on the spatial interpolation, two management zones were delineated for SOC at the surface and subsurface depths.

Keywords: Precision Farming, Soil Organic Carbon, Semi -variogram, Spatial pattern, Kriging and Modeling.

INTRODUCTION

Soil organic carbon (SOC) is a complex and varied mixture of materials and makes up a small but vital part of all soils (CSIRO, 2011). Soil carbon improves the physical properties of soil. It increases the cation exchange capacity (CEC) and water-holding capacity of sandy soil and it contributes to the structural stability of clay soils by helping to bind particles into aggregates. (Leeper and Uren, 1993). Soil organic matter, of which carbon is a major part, holds a great proportion of nutrients, cations and trace elements that are of importance to plant growth. It prevents nutrient leaching and is integral to the organic acids that make minerals available to plants. It also buffers soil from strong changes in pH (Leu, 2007). It is widely accepted that the carbon content of soil is a major factor in its overall health. SOC is the largest carbon (C) reservoir in many terrestrial ecosystems including grasslands, savannas, boreal forests, tundra, some temperate forests, and cultivated systems, comprising as much as 98% of ecosystem C stocks in some systems (Schlesinger, 1977). Globally, the amount of C stored in soil is equal to the amount stored in vegetation and in the atmosphere combined (Schimel, 1995). Natural variations in SOC occur as a result of climate, organisms, parent material, time and relief (Young and Young, 2001). The greatest contemporary influence has been that of humans (CSIRO, 2011).

The traditional approach to soil fertility management has been to treat fields as homogenous areas and to calculate fertilizer requirements on a whole field basis. However, it has been reported for at least 70 years that fields are not homogeneous and sampling techniques to describe field variability have been recommended (Flower *et al*., 2005, Santra *et al.,* 2008). Describing the spatial variability across a field has been difficult until new technologies such as Global Positioning Systems (GPS) and Geographic Information Systems (GIS) were introduced. GIS is a powerful set of tools for collecting, storing, retrieving, transforming and displaying spatial data (Burrough, and McDonnell, 1998). GIS can be used in producing soil fertility map of an area that helps to understand the status of soil fertility spatially and temporally, which will help in formulating site-specific balanced fertilizer recommendation. These technologies allow fields to be mapped accurately and also allow complex spatial relationships between soil fertility factors to be computed (Patil *et al*., 2011).

Geostatistics (e.g., Goovaerts, 1997; Webster and Oliver, 2001; Nielsen and Wendroth, 2003) has been extensively used for quantifying the spatial pattern of environmental variables. Kriging has been used for many decades as synonym for geostatistical interpolation and has been proved as sufficiently robust for estimating values at unsampled locations based on the sampled data. In recent years soil scientists focused on using geostatistics and different kriging methods to predict soil properties at unsampled locations and to better understand their spatial variability pattern over small large spatial scale. (Yost *et al*., 1982; Trangmar *et al*., 1987; Miller *et al*., 1988; Voltz and Webster, 1990; Chien *et al*., 1997; Lark, 2002).

The purpose of this present study was, thus, to investigate the spatial variability of the soil organic carbon at two different soil layers in a cassava field.

MATERIALS AND METHODS

Description of the study area

The study was conducted on a 467 hectare commercial cassava farm located at Lanlate (7º 36'N and 3º 27'E), Oyo State, southwestern Nigeria (Fig 1). The climate of Lanlate area is hot subhumid and lies within the derived savanna zone, with annual rainfall of between 1200 and 1500 mm. The relative humidity is over 70% in the morning and falls to between 50 and 70% in the afternoon. The mean annual temperature is 27°C and the annual temperature range is 8°C. Some of the dominant vegetal species include *Panicum maximum, Imperata cylindrical, Andropogon gayanus, Chromolaena odorata, Eupatorium odoratum, Tithonia diversifofolia, Parkia biglobosa, Vitellaria paradoxa,* and *Piliostigma reticulata*l. The soils in the study area are Ferric Luvisols (Sonelveld, 2005). The study area was planted to cassava at different stages of growth (Figure 2). Soil samples were collected from eighty–eight (88) sites on a grid system using Global Positioning System (GPS), at 0-30 cm and 30-60 cm depths. The samples were air dried, crushed and passed through 2 mm sieve prior to analysis. The Walkley and Black (1934) wet digestion method was used to determine soil organic carbon content.

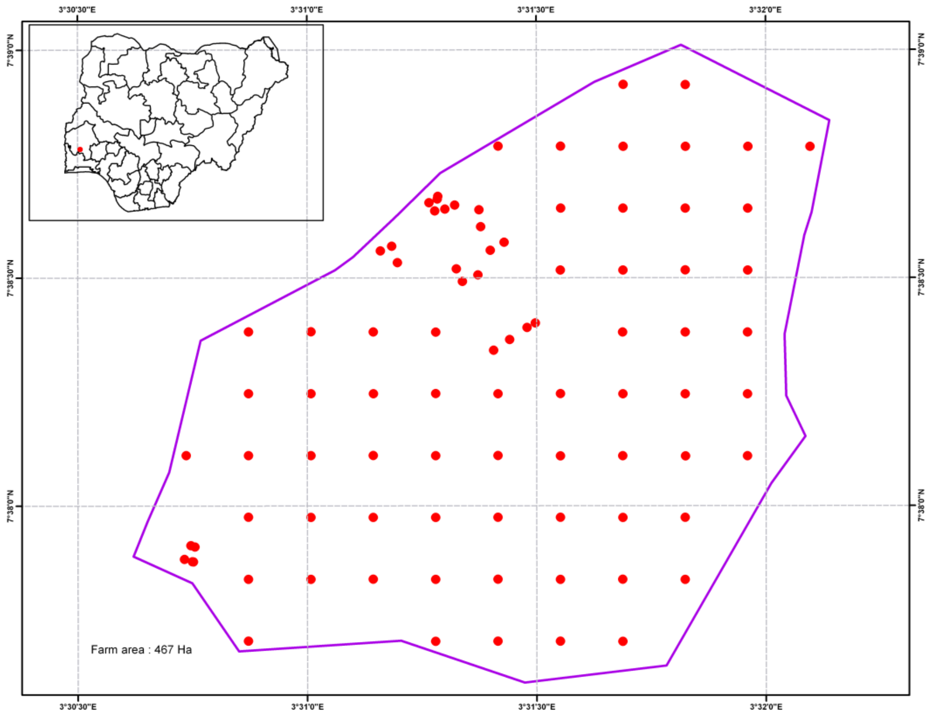


Figure 1: Map of the study area showing soil sampling locations (n=88)

Figure 2: View of the study area planted to cassava at different stages of growth.

Statistical analysis

Exploratory data analysis was performed by SPSS (version 16) software. The data distributions were analyzed by classical statistics (mean maximum, minimum, standard deviation, skewness, kurtosis and coefficient of variation). Histograms and Box-plots for organic carbon data were inspected for the possible outliers which affect the descriptive statistics and the characterization of spatial variation. Geostatistical methods require using data with normal distribution values, SOC data was also checked for normality and transformed as appropriate. Spatial analysis of the classified soil organic carbon was performed in a GIS environment. Experimental semi-variograms were calculated for the two depths using equation (1)

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{\alpha=1}^{N(\mathbf{h})}\left[z(\mathbf{x}_\alpha) - z(\mathbf{x}_\alpha + \mathbf{h})\right]^2$$

…………………….. (1)

Where:

$\gamma(h)$ is the semivariance for the lag distance h.

N (h) is the number of sample pairs separated by the lag distance h,

$z(\mathbf{x}\alpha)$ is the measured value at α^{th} sample location and $z(\mathbf{x}\alpha+h)$ is the measured value at point $\alpha+h^{th}$ sample location.

Theoretical models (Spherical, Rational Quadratic, Hole effect, Exponential, K-Bessel or Gaussian) were fitted to experimental semivariograms. A GIS software package ArcGIS 10.1 and ArcGIS Geo-statistical Analyst Extension were used. Model selection for semivariograms was done on the basis of goodness of model fit criterion. Various interpolation techniques, ordinary Kriging, Simple Normal Score, Universal Kriging, Empirical Bayesian Kriging and Ordinary co-Kriging were used to produce the spatial distribution of the SOC. The possible effect of covariates on the prediction of SOC was explored. Hence Cokriging was performed with Nitrogen, Calcium, Phosphorus, CEC, Magnesium, Potassium, Iron, Sodium, elevation, Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) as covariates with SOC. Long term average EVI and NDVI were obtained from AfSIS (2014).

Table 1 Organic Carbon Rating and Interpretations

Range (%)	Class
< 0.4	Very low
0.4 – 1.0	Low
1.0 – 1.5	Moderate
1.5 – 2.0	High
>2.0	Very high

RESULTS AND DISCUSSION

Statistical parameters of soil organic carbon

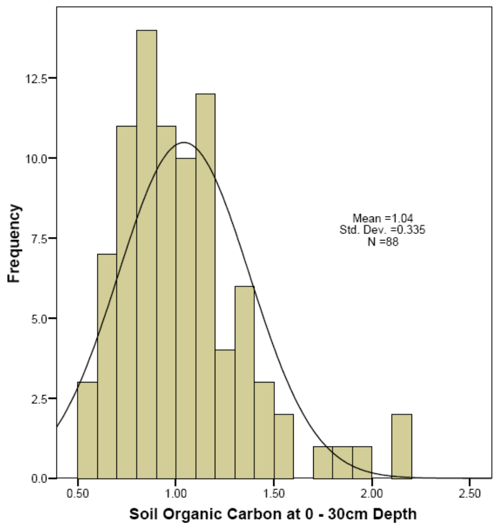
The summary statistical parameters of the soil organic carbon data set were listed in Table 2. To evaluate the data set, the mean, minimum values, maximum values, median values, standard deviation and variance were calculated. The organic carbon at the surface (0-30cm) depth ranged from 0.53 to 2.15 (mean = 1.0405), while that of the sub surface (30-60cm) soil ranged from 0.33 to 2.13. Kriging methods work best if the data is approximately normally distributed. In ArcGIS Geostatistical Analyst, the histogram and normal QQPlots were used to see what transformations, if any, are needed to make the data more normally distributed. Normal QQPlots provides an indication of univariate normality. Histogram and normal QQPlots analysis were applied for each soil organic carbon arameter and the results are presented in Figure 3. It was found that all the parameters required transformation for it to conform to the normality requirement of Kriging. For these parameters a log transformations were applied to make the distribution close to normal

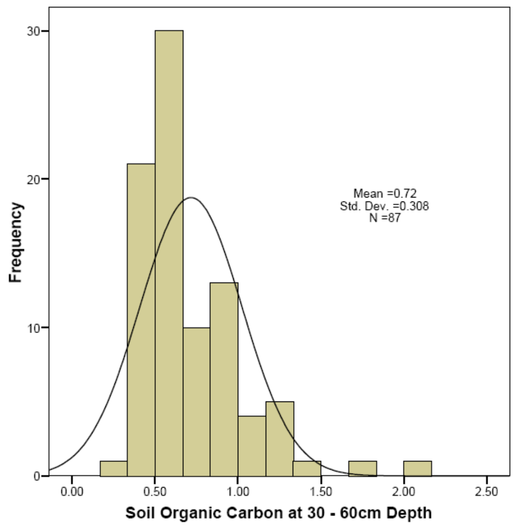
Table 2. Summary Statistical parameters of soil organic carbon at surface (0-30) and sub surface (30-60) depths

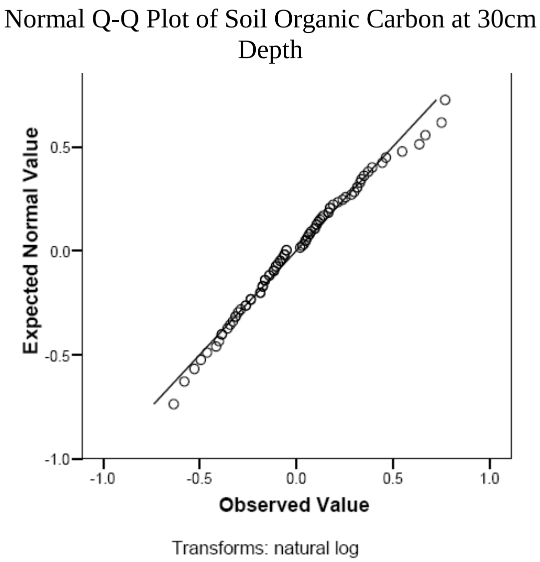
	Soil Organic Carbon	
	30cm	60cm
N	88	87
Mean	1.0405	0.7157
Std. Deviation	0.33469	0.30830
Variance	0.112	0.095
Skewness	1.268	1.834
Std. Error of Skewness	0.257	0.258
Kurtosis	1.903	4.935
Std. Error of Kurtosis	0.508	0.511
Range	1.63	1.80
Minimum	0.53	0.33
Maximum	2.16	2.13

Semivariogram models

The prediction of the spatial process at nonsampling sites using geostatistics requires a theoretical semivariogram. It is necessary to decide on a theoretical variogram based on the experimental variogram. It is vital to choose an appropriate model to estimate spatial statistics as each model yields different values for nugget variance and range which are essential for geostatistical analyses (Trangmar, 1985). In this study, the semivariogram models (Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole effect, K-Bessel, J-Bessel, Stable) were tested with optimized parameters. Prediction performances were assessed by cross validation. Cross Validation allows determination of which model provides the best predictions. For a model that provides accurate predictions, the standardized mean error (ME) should be close to 0, the root-mean-square error (RMS) and average standard error (AVS) should be as small as possible, and the root-mean square standardized error (RMSS) should be close to 1. When the average estimated prediction standard errors are close to the root-mean-square prediction errors from cross-validation, then you can be confident that the prediction standard errors are appropriate (ESRI, 2001). After applying different models for each soil parameter examined in this study, the error was calculated using cross validation and models giving best results were determined. Table 3 shows the most suitable models and their semivariogram associated parameter values, which are called the nugget, range, and partial sill for each soil organic carbon data set.







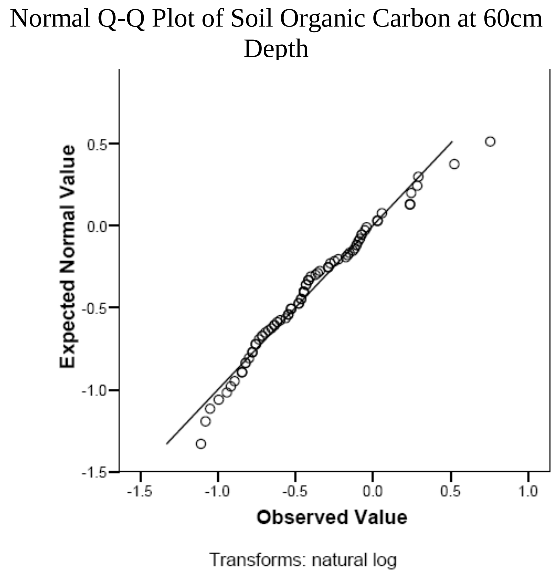


Figure 3: Histogram of Soil organic carbon at (a) 0-30cm & (b) 30 - 60cm showing a normal probability distribution and Normal Q-Q Plot of Soil Organic Carbon at (c) 0-30cm & (d) 30-60cm depths

Spatial Structure of Soil Organic Carbon

The parameter values of different model fittings of semivariogram of soil organic carbon are summarized in Table 3. The semivariogram obtained from the experimental data often had a positive value of the intersection with the variogram axis expressed by the named nugget effect C_0. The existence of a positive nugget effect in the soil organic carbon data can be explained by sampling errors, shortage variability, and unexplained and inherent variability. C_0 can also indicate the irresolvable variance that characterizes the micro homogeneity at the sampling location. Some semivariograms are generally well structured with small nugget effect. It showed that the sampling is adequate to reveal the spatial structures (McGrath, 2004). It can be seen from Table 3 that the K-Bessel and J-Bessel nugget values were 0.0928 and 0.0114 for top and sub soil respectively. According to the nugget effect, the semivariogram increased until the variance of the data called Sill *C* was reached. Under this semivariogram value, the regionalized variables at the sampling locations are spatially correlated. The sill value represents total experimental errors (Ersoy, 2004). If the distance of two pairs increases, the variogram of those two pairs will also increase. Eventually, the increase of the distance cannot cause an increase in the variogram. The distance which causes the variogram to reach the plateau is called the range. In other words, the range is considered as the distance beyond which observations are not spatially dependent (Gallardo, 2003). The range of influences were 575.11 m for soil organic carbon at top soil (0-30) and 141.21m at the sub surface depth (30-60cm) in the study area.

Table 3 Parameter values of different model fittings of semivariogram of soil organic carbon by ordinary co-kriging.

Properties	Depth (cm)	Model	No of Lag	Lag size (m)	Nugget (Co)	Partial sill (C)	Range (h)/ m	Sill (Co + C)	Ratio Co/ (Co + C)
Soil Organic Carbon	0-30	K-Bessel	12	71.88	0.092807	0.81007	575.11	0.90287	0.103
Soil Organic Carbon	30 - 60	J-Bessel	12	192	0.0114	0.16576	141.214	0.17687	0.062

The nugget-to-sill ratio ($C_0/(C_0+C)$) defines the spatial property. The variable is considered as a strong spatial dependence when the value of $C_0/(C_0+C)$ is less than 0.25, a moderate spatial dependence when this value is between 0.25 and 0.75, and a weak spatial dependence when the value is more than 0.75 (Cambardella et al., 1993). The nugget-to-sill ratio for soil organic carbon at the surface depth was 0.103 and 0.062 for sub surface soil, these shows a strong spatial dependence for both top soil and subsoil. These reveal that the spatial distribution of soil organic carbon at Ekha farm is dominated by the constitutive factors and the random factors together. The background content, type of soil forming mineral and soil type are the main aspects of the constitutive factors and human activities such as tillage-cropping systems, management measures, wastewater irrigation, vegetation cover, manure, crop residue management and artificial pollution are the random factors. Because of the disruptions and influences by human activities, the spatial relationship of soil organic carbon in the study area was weakened. Table 4 presents cross validation prediction errors for both topsoil and subsoil. From this table the best model prediction is assessed by the smallness of Root Mean Square error (RMS), its closeness to Average Standard error (AVS) and nearness of RMSS to 1. At the topsoil based on these paramaters Empirical Bayesian Kriging (EBK) performed with an RMS 0.322 and RMSS of 1.017 among kriging methods without covariates. However, all the Cokriging methods with different covariates outperformed EBK except for those with EVI and NDVI as covariates. This result suggests that other soil variables such as Nitrogen, Calcium, Magnessium and Cation Exchange Capacity (CEC) when used as covariates with SOC improved the prediction errors parameters. The best Cokriging prediction of SOC was with Nitrogen as covariate followed by Calcium and CEC. A similar pattern can be seen with the results of the prediction errors at the subsoil (30-60cm) where the kriging methods with covariates performing better than those without covariates. Among those without covariates, however, EBK was outperformed by simple Normal Score Kriging method with a RMS of 0.291 against 0.305 by EBK. This is in contrast with the results obtained for the top soil. Nitrogen still gave the best prediction errors when used as covariates to predict SOC and this was still followed by Calcium, CEC and magnesium respectively. Other soil parameters such as Iron, Potassium do not improve SOC prediction errors.

Kriging Analysis and Spatial interpolation of soil organic carbon

In order to identify the spatial distribution patterns of soil organic carbon in the study area, it is necessary to present the data in the form of a map. For this purpose, SOC distribution map was obtained by the ordinary kriging based on the rational quadratic and K-Bessel models. Kring is based on the regionalized variable theory and is regarded as a powerful interpolation technique because it provides for the optimal interpolation estimate and has been used successfully to investigate the spatial variability of continuously varying environmental parameters and incorporate this information into mapping (Burrough, 1997; Stein and Bouma 1993). Spatial distribution maps of soil organic carbon for surface (0 – 30cm) and subsurface (30 – 60cm) of Ekha Agro farms, Lanlate are presented in Figure 4 and Figure 5 respectively.

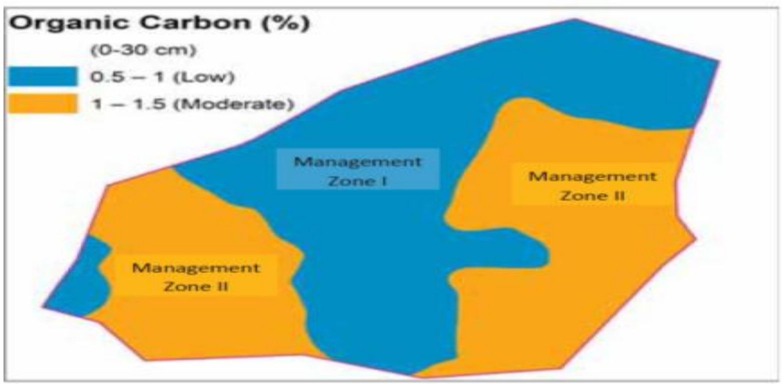


Figure 4: Spatial distribution map of soil organic carbon using ordinary Cokriging method for surface (0 – 30cm) of Ekha Agro farms, Lanlate, Nigeria.

Table 4: Cross validation prediction error parameters for different Kriging methods (covariates are in bracket for Cokriging methods)

0-30 cm depth

	Empirical Bayesian Kriging (EBK)	Ordinary Kriging	Universal Kriging	Simple Normal Score Kriging	Ordinary Cokriging (Nitrogen)	Simple Normal Cokriging (Nitrogen)	Simple Normal Cokriging (Calcium)	Simple Normal Cokriging (CEC)	Simple Normal Cokriging (Magnesium)	Ordinary Cokriging (NDVI)	Simple Normal Cokriging (EVI)
Mean error (ME)	-0.0114	-0.0004	-0.0004	-0.0043	-0.0053	-0.0034	-0.0058	-0.0057	-0.0051	-0.0010	-0.0045
Root Mean Square Error (RMS)	0.3221	0.3298	0.3298	0.3298	0.2383	0.2311	0.2640	0.2681	0.2877	0.3288	0.3287
Mean Standard Error (AVS)	0.3120	0.3227	0.3196	0.3100	0.2351	0.2069	0.2532	0.2573	0.2708	0.3230	0.3098
Root Mean Square Standardized (RMSS)	1.0170	1.0101	1.0321	1.0578	0.9989	1.0706	0.9795	0.9857	1.0220	1.0087	1.0479
Model Type		Hole Effect	Hole Effect	Hole Effect	K-Bessel	K-Bessel	Stable	Stable	Stable	Hole Effect	Hole Effect
30-60cm depth											
Mean error (ME)	0.0006	0.0001	-0.0014	0.0115	-0.0062	-0.0070	-0.0013	0.0017	0.0049	0.0026	0.0039
Root Mean Square Error (RMS)	0.3051	0.3201	0.3183	0.2912	0.2153	0.1999	0.2649	0.2744	0.2896	0.3026	0.3050
Mean Standard Error (AVS)	0.3041	0.2998	0.3128	0.2804	0.2580	0.1908	0.2482	0.2587	0.2623	0.2943	0.3005
Root Mean Square Standardized (RMSS)	0.9796	1.0660	1.0167	1.0067	0.9773	1.0912	1.0001	1.0080	1.0592	1.0021	1.0011
Model Type		J-Bessel	Hole Effect	J-Bessel	J-Bessel	Stable	K-Bessel	K-Bessel	Rational Quadratic	Hole Effect	Gaussian

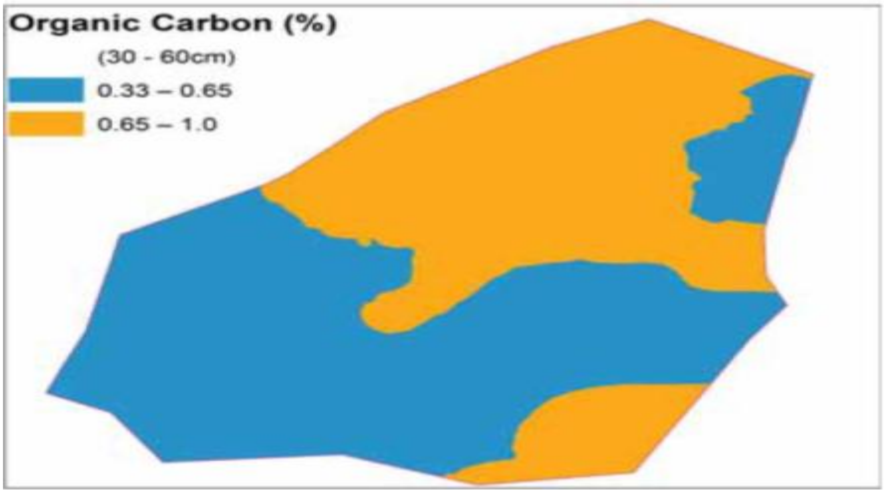


Figure 5: Spatial distribution map of soil organic carbon using ordinary Cokriging method for subsurface (30 – 60cm) of Ekha Agro farms, Lanlate, Nigeria

The spatial interpolation of surface (0-30cm) and subsurface (30-60cm) soil organic carbon for Ekha Agro farms, Lanlate as shown in Figure 4 and 5 above, revealed that the SOC of the farm ranged between low and high at the surface depth and low to moderate at the subsurface soil (Table 1). The spatial pattern of SOC at the top soil and subsoil are similar and can successfully be divided into two management zones based on the SOC contents of the farm. Management zone I has SOC in the range of Moderate to high while Management zone II has low SOC. Farm management strategies that will promote buildup of SOC in management zone II and maintenance of SOC stock in zone I should be encouraged. This can be achieved through leaving crop and cover crop residues in place or by applying manure amendments. Crop residues include inputs from roots, which are crucial to enhancing the slow and stable organic matter pools

Conclusion

Geostatistical characterization of the spatial variability through semivariograms or correlograms generally brings new insight into the way soil attributes are influenced by the environment such as geographical distribution of soil types or topography. In this study, kriging based on geostatistical techniques was applied to analyzing and interpreting soil organic carbon at the surface (0-30cm) and subsurface (30-60cm) depths in a commercial cassava farm at Lanlate, southwestern, Nigeria. The analysis of the spatial structure showed that SOC at both depths were spatially correlated. SOC was generally higher at the topsoil than at subsoil. Covariates such as Nitrogen, Calcium, CEC and Magnesium improved predictions errors thereby making for more reliable predictions. The spatial distribution of soil organic carbon at Ekha farm is dominated by the constitutive factors and the random factors together. The background content, type of soil forming mineral and soil type are the main aspects of the constitutive factors and human activities such as tillage-cropping systems, management measures, wastewater irrigation, vegetation cover, manure, crop residue management and artificial pollution are the random factors. Because of the disruptions and influences by human activities, the spatial relationship of soil organic carbon in the study area was weakened. However based on the spatial interpolation of the SOC, two management zones (I and II) were delineated for the surface and sub-surface depths. Farm management strategies that will promote buildup of SOC in management zone II and maintenance of SOC stock in zone I should be encouraged.

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