SPATIAL VARIABILITY AND DISTRIBUTION PATTERN OF SOIL ORGANIC MATTER CONTENT IN THIRTEEN LOCAL GOVERNMENT AREAS (LGAS) OF NASARAWA STATE, NORTH CENTRAL NIGERIA

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Abstract

A study was conducted in Nasarawa State with the aim of determining the spatial variability and distribution pattern of the soil organic matter in the thirteen local Government areas (LGAs) of the State. Soil samples were collected from one hundred and twenty (120) composite sites at 0-15cm and 15-30cm 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 wet digestion method was used to determine soil carbon content and percent SOM was obtained by multiplying percent soil Organic Carbon (OC) by a factor of 1.724 following the assumptions that SOM is composed of 58% carbon. Spatial analysis of the classified SOM was done in a GIS environment. A GIS software package ArcGIS 11.0 and ArcGIS Geo-statistical Analyst Extension were used. An interpolation technique called "Ordinary Kriging" was used to produce the spatial distribution of the SOM. Spatial analysis results showed that the best fit semivariogram models for SOM were "Rational Quadratic" and "J-Bessel" for surface and subsurface depths respectively. The nugget-to-sill ratio(Co/Co + C) for SOM at the surface depth was 0.837 and 0.545 for sub surface soil, these indicated a weak and moderate spatial dependence for top soil and subsoil respectively. The spatial distribution maps of SOM at the top and subsoil showed that the soils were generally low in SOM content. Need to develop pro-farmer technologies that would support the supply and conservation soil organic matter was emphasized.

Keywords: Precision Farming, Tillage, Soil fertility, Relative Nugget Effect and Kriging

INTRODUCTION

Enhancement and maintenance of soil productivity is one of the essential aspects for sustained agricultural production in sub-Saharan Africa (Bunting, 1992). This is an important aspect, especially when the aim is to achieve one of the most important objectives of our time, overcoming hunger and poverty amongst the smallholder farmers who are the majority among the stakeholders in agricultural production systems (Micheni, 1996). Soil organic matter serves as an indispensable source of plant nutrients and enhances soil biological, chemical and physical properties. Organic matter (OM) also contributes to cation exchange capacity (CEC), soil water-holding capacity, aggregate stability, permeability and other desirable soil properties (Agbede, 2009). 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. The amount of SOM in the soil is dependent on the annual inputs of organic materials and the rate of decomposition, the later being the highest in hot, humid climatic regions (De Ridder and Van Keulen, 1990; Rowell, 1994). (Rowell, 1994).

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; 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).This study sought to determine the spatial variability and distribution pattern of the soil organic matter in the thirteen local Government areas (LGAs) of Nasarawa State, North Central Nigeria.

Materials and Methods

The study was conducted in Nasarawa State, North central Nigeria with a total land area of 27,137 sq. Km, and a population of 1,863,275 according to 2006 census. The state lies between latitude 7^{o} 45^{1} and 9^{o} 25^{1} N of the equator and between longitude 7^{o} and 9^{o} 37^{1} E of the Greenwich (Fig 1). Soil samples were collected from the depths of 0-15 and 15-30 cm each in a radial sampling scheme using an auger. During collection of samples; dead plants, old manures, wet spots, areas near trees and compost pits were excluded. This was done to minimize differences, which may arise because of the dilution of soil OM due to mixing through cultivation and other factors. One composite soil sample was then prepared from the 5-6 sub samples for each soil depth. The soil samples collected from representative fields' with 3-5 replications per LGA. A total of 100 composite samples were collected per depth from the thirteen LGAs in Nasarawa State. The samples were then air-dried, mixed well and passed through a 2 mm sieve for the analysis. An hand held Global Positioning System (GPS) (Garmin eTrex Ventura®) receiver was used to identify the geographical locations and elevation of the sampling sites. The Walkley and Black (1934) wet digestion method was used to determine soil carbon content and percent soil OM was obtained by multiplying percent soil OC by a factor of 1.724 following the assumptions that OM is composed of 58% carbon.

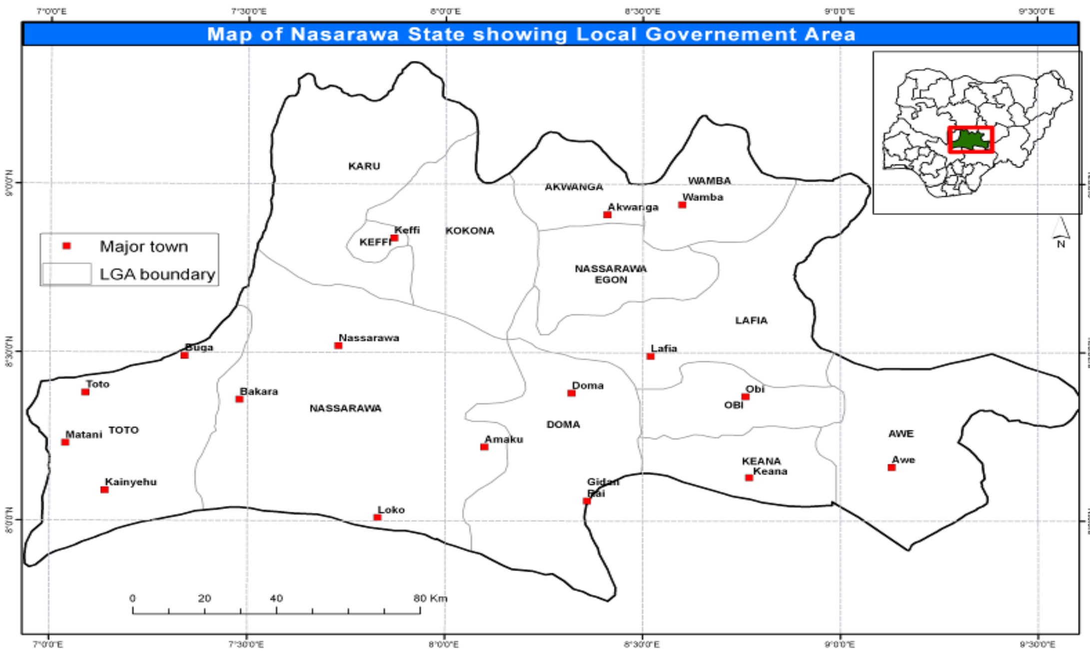

Fig. 3.1 The Thirteen local Government Areas in Nasarawa State

Statistical analysis

Exploratory data analysis was performed with SPSS (version 16) software. The data distributions were analyzed by classical statistics (mean maximum, minimum, standard deviation, skewness, kurtosis and coefficient of variation). Histograms with normal curve were plotted for both depths for possible outliers and extraneous values. Geostatistical methods required data with normal distribution. The data were checked for normality and transformed as appropriate. Spatial analysis of the classified organic matter content was performed in a GIS environment and experimental semi-variograms were calculated using equation (1)

(1)

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

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.

Other theoretical models (Rational, Quadratic, Hole effect, K-Bessel or Gaussian) were fitted to experimental semivariograms. Spatial analysis of the classified soil fertility properties (Table 1) were done in a GIS environment. A GIS software package ArcGIS 11.0 and ArcGIS Geo-statistical Analyst Extension were used. Models selections for semivariograms were done on the basis of goodness of model fit criterion. An interpolation technique called "Ordinary Kriging" was used to produce the spatial distribution of the soil parameters for the study area.

RESULTS AND DISCUSSION

Descriptive data analysis

Since statistically abnormal distribution of dataset can have an adverse impact on semivariogram and further interpolation, statistical knowledge of soil organic matter data is required before semivariogram analysis. The main descriptive statistics were used on the raw data, using software package SPSS v16.0. Basic statistic characteristics are presented in Table 1. The soil organic matter content of the study area at the top soil (0-15cm) ranged from 0.69 to 1.71%, while that of the subsoil range from 0.57 to 1.12% (Table 1).

Table 1: Statistical parameters of soil organic matter content

Depth	0-15cm	15-30cm
N	120	120
Mean	1.2542	1.1738
Median	1.2575	1.1300
Std. Deviation	0.26055	0.26650
Variance	0.068	0.071
Skewness	-0.199	0.202
Std. Error of Skewness	0.221	0.221
Kurtosis	-0.766	-0.673
Std. Error of Kurtosis	0.438	0.438
Range	1.02	1.12
Minimum	0.69	0.57
Maximum	1.71	1.68

The frequency distributions and normal curves of the raw data for both depths are presented in Figure 2. However from a statistical view, the logarithmic transformation was applied on the two data sets to satisfy the requirements of normality for geostatistical analyses large coefficients and the results presented in Figure 3.

Semi-variogram models

The prediction of the spatial process at non-sampling 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 *et al*., 1985). In this study, the semivariogram models (Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole effect, K-Bessel, J-Bessel, Stable) were tested for each soil parameter data set.

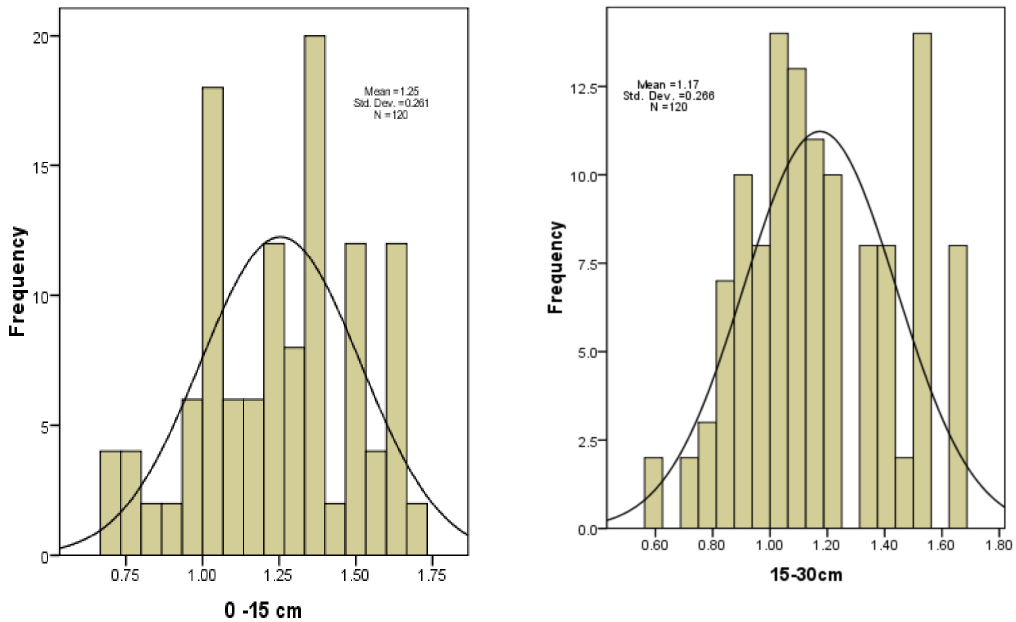

Figure 2 Histogram of Soil organic matter at 0-15 and 15-30cm Depths

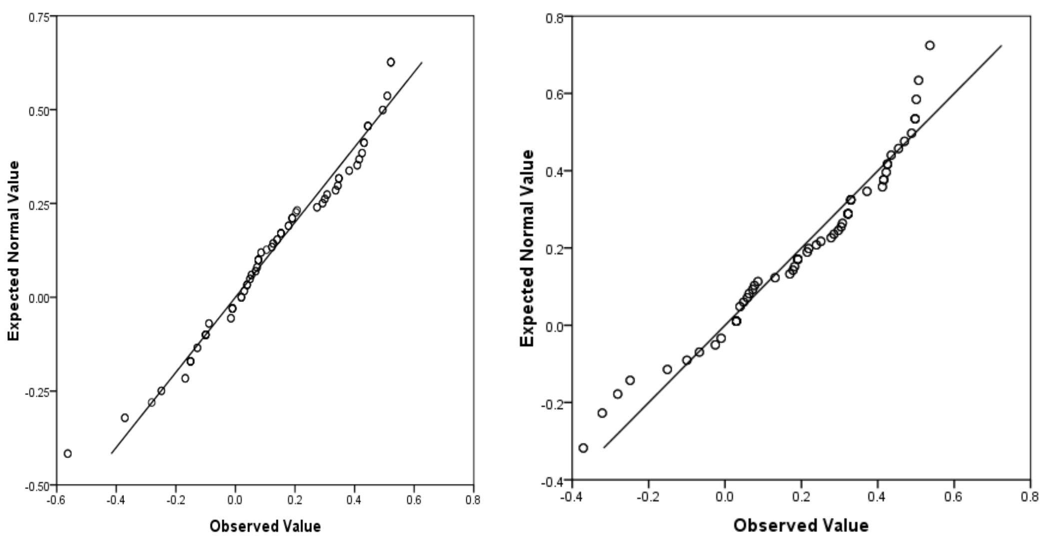

Figure 3 Normal probability distribution and Normal Q-Q Plot of Soil organic matter at 0-15 and 15-30cm

Spatial dependence of soil properties

The semivariance statistics of measured soil properties are shown in Table 2. Out of the several models fitted to the semivariograms, Rational Quadratic model was obtained as the best fit for top soil (0-15cm) while the best fit model for sub soil (15-30cm) was J-Bessel. Anisotropy was not evident in the directional semivariograms for both depths. Therefore, isotropic models were fitted. Both depths semivariogram models displayed positive nugget effect (0-15cm =0.045 and 15-30cm = 0.025) (Table 3) which may be as a result of sampling error, random, inherent variability or short range variability. Distinct classes of spatial dependence for the soil properties were obtained by the ratio of the nugget to sill. If the ratio was <25%, between 25 and 75% or >75%, the variable was considered strongly, moderately or weakly spatially dependent respectively (Cambardella, *et al*., 1994). 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 spatial dependence varied from 26.89km for the top soil 26.48km for the subsoil. Soil organic matter content at both depths had a rather high range indicating low or no spatial correlation within a smaller distance of soil property. This implied that samples could be taken at comparatively longer distances. This result concurred with the general assertion that soils in Sub - Saharan Africa are generally, inherently and spatially low in soil organic matter content (Ojeniyi, 2012; Jayeoba, 2011; Agbede *et al*., 2011). Relative Nugget Effect (RNE) (ratio of the nugget to sill) of SOM at the top soil was 83.7% (Table 3) showing a weak spatial dependence while the sub soil had a RNE of 54.5% indicating a moderately spatial dependence (Cambardella *et al.*, 1994).

Table 3 Parameter values of model fittings of semivariogram of soil organic matter content

Properties	**Depth (cm)**	**Model**	**No of Lag**	**Lag size**	**Nugget (C_o)**	**Partial sill (C)**	**Range (h)/ m**	**Sill (C_o + C)**	**Ratio C_o/ (C_o + C)**	**RNE %**
Org. Matter	0-15	Rational Quadratic	15	1792.77	0.045	0.009	26891.57	0.053	0.837	83.7
Org. Matter	15 - 30	J – Bessel	18	2068.04	0.025	0.021	26482.04	0.046	0.545	54.5

Kriging Analysis and Spatial interpolation of soil properties

Kriging is a method for making optimal, unbiased estimates of regionalized variables at unsampled locations using the structural properties of the semivariogram and the initial set of measured data. A useful feature of kriging is that an error term expressing the estimation variance or uncertainty in estimation is calculated for each interpolated value. Kriging always produce an estimate equal to the measured value if it is interpolating at a location where a measurement is obtained (Burrough, 1997; Stein and Bouma 1993; Jayeoba *et al*., 2012). In order to identify the spatial distribution patterns of soil properties in the study area, it is necessary to present the data in the form of a map. Spatial distribution maps of soil organic matter content obtained by ordinary kriging based on Rational Quadratic and J-Bessel models for surface and sub surface depths in Nasarawa state is presented in Figure 4.

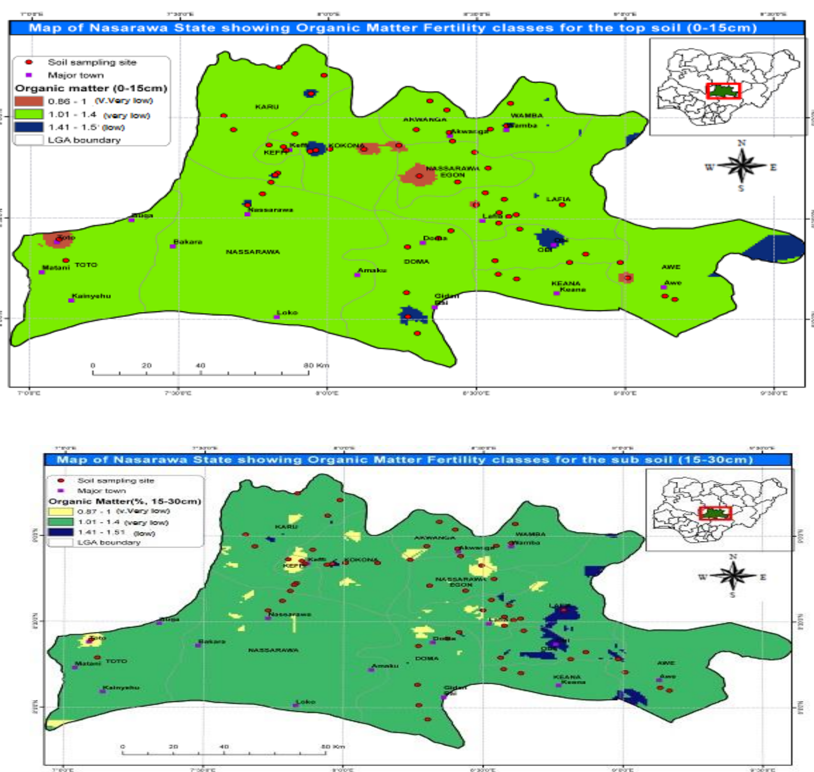

Figure 4 Spatial Distribution of Soil Organic Matter in Nasarawa State at the surface (0-15cm) and sub-surface (15-30cm) depths

	0-15cm		15-30cm	
Organic Matter	%	Area (sqkm)	%	Area (sqkm)
V. Very Low	1.3	330.7	2.3	609.0
Very Low	96.7	25442.8	95.9	25236.6
Low	2.0	538.2	1.8	466.1

Source: Jayeoba, 2013

The spatial interpolation of organic matter content at the top soil and sub-soil in Nasarawa state showed that the entire land area of the state has low (<2.0%) organic matter content. However most (96.7%) of the land area (25,442.8km^2) had organic matter content in the range of very low (1.0 – 1.4%) at the top soil. The sub soil, as observed for the top soil also had most (95.9%) of the land area (25, 236.6km^2) having an organic matter content in the range of very low (1.0 – 1.4%)(Figure 4). These results agree with the findings of Ojeniyi, 2012 that cultivated soils in the tropics have lower levels of organic matter compared with soils in the temperate regions due to direct effect of continuously high temperature.

CONCLUSION

Knowledge of spatial distribution pattern of organic matter is vital to its sustainable management. Arresting the decline of soil organic matter is the most potent weapon in fighting against unabated soil degradation and soil nutrient depletion in Nigeria. Improving SOM is therefore, crucial in the sustenance of soil quality and future agricultural productivity in Nasarawa State. Development of management options that support its maintenance or even increase SOM in the soil depend upon factors that regulate its destruction or conservation. Integration of conservation tillage and organic matter application as surface mulch is worth exploring. Therefore, there is a need to develop pro-farmer technologies that would support the supply and conservation soil organic matter.

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