

Assessing soil physical properties variability and their impact on vegetation using geospatial tools in Kebbi State, Nigeria

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Abstract. Geospatial distribution of soil physical properties using Geographic Information System (GIS) is essential and efficient to site-specific farming and environmental management processes. This study attempts to evaluate the spatial distribution of soil physical properties and their impact on vegetation status in Kebbi State, Nigeria using the geospatial technique. A total of one hundred and fifty-six (156) soil samples were collected and analysed for soil organic matter (SOM), porosity, texture, Bulk Density (BD) and pH. The data were analyzed both statistically and geospatially to describe the spatial distribution of soil physical properties in the area. The Normalized Difference Vegetation Index (NDVI) was examined on Sentinel 2 satellite imagery. Results show the normal distribution for all parameters, except for soil texture and SOM indicating a positively skewed distribution. The spatial distribution of soil parameters results revealed the existence of low to moderate spatial distribution. In comparison to the NDVI, soil properties significantly correlate with vegetation status of the area, except soil porosity which shows an inverse correlation. The study revealed that the use of geospatial technique accurately generates the spatial distribution maps of soil properties in the area and therefore, present a recommendable tool for sustainable land management and environmental management.

1. Introduction

Understanding the variability of soil properties is vital for soil survey, land assessment, environmental management and most especially agricultural production [1]. Usually, researchers use descriptive and inferential statistics to describe the distribution and variation in soil properties and the relationship that exists between them [2]. Though, still viable methods, however, the results are sometimes qualitatively ambiguous [3], due to lack of spatial interpretation of the phenomenon. For an efficient and realistic appraisal of the variability of soil properties in a given area, nowadays, many researchers [4,5,6,7,8] adopts the use of geospatial technique using field dataset and geospatial tools to illustrate the pattern of spatial variability of the soil properties. Spatial interpolation tool uses points with known values and spatial reference to estimate values and spatial reference at another point [9]. The basic premise behind



interpolation is the determination of the unknown point, with the closest points having much more influence than those away from it.

Spectral vegetation indices (SVIs) are used as effective measures of vegetation status and are considered as useful means to evaluate vegetation characteristics as well as the assessment of its spatial variability. NDVI is the most often used SVIs because of its high connection with the Net Primary Productivity (NPP) of the land and as an accurate method for phenology/vegetation studies using remotely sensed data [10]. Soil properties are the most central elements for vegetation status as well as many land related activities; therefore, information on their spatial variability in a given land is crucial. This research aimed at (i) assessing the spatial distribution of soil physical properties (ii) to examine the relationship between the soil properties and NDVI as an indicator of vegetation status in selected areas of Kebbi State, Nigeria

2. Materials and Method

2.1 The study area

Kebbi State (13 local government areas) lies between Lat. $13^{\circ}54'58.925''\text{N}$ - $11^{\circ}7'27.002''\text{N}$ and Long. $3^{\circ}32'57.995''\text{E}$ - $4^{\circ}53'19.708''\text{E}$, it covers an area of about $18,591\text{Km}^2$, supporting the population of around 2,757,544 million people [11], located in the extreme north-western part of Nigeria (Figure 1). The temperature ranges between $35\text{-}40^{\circ}\text{C}$, annual rainfall is about 850mm and the relative humidity ranges between $10\text{-}25\%$ and $51\text{-}79\%$ during rainy and dry seasons respectively [12]. The vegetation is sudan savannah type and the land is a semi-arid typed, characterized by frequent weathering and leaching due to poor soil structure and low organic matter content [13]. The main economic activity is agriculture with over (70%) of the people practising one form of agriculture or the other.

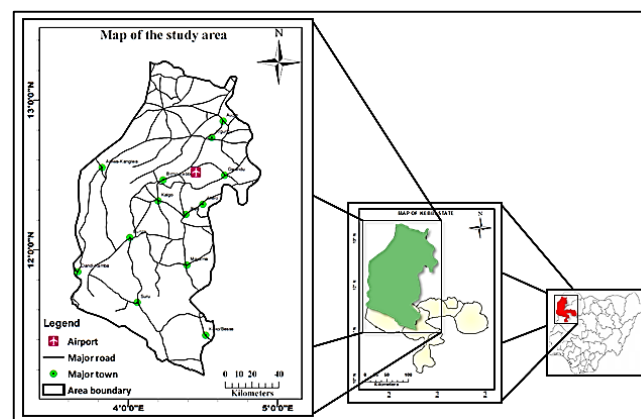


Figure 1. Map of the study area from Nigerian Map

2.2 Soil sampling and laboratory testing

A Multistage sampling technique was used to collect 12 soil samples randomly from each of the 13 local governments in the study area; this gives a total of one hundred and fifty-six (156) samples. However, in trying to reduce spatial redundancy, caution was taken to maintain the minimum distance in-between sampling points. Garmin GPS receiver was used to determine the location (coordinates) of the sampling points; other tools used for collecting soil samples include auger, hoe, hand trowel and polythene bags.

An average of 2-3kg of soil from a hole of 10-15cm was collected from each sampled point during January - March 2017. The samples were taken to the soil laboratory of Kebbi State University of Science and Technology, Aliero, for testing and analysis. Soil samples were oven-dried, ground and pass through a 2-mm sieve. Table 1 shows the methods used for testing each of the selected soil properties. The descriptive analysis of the data was conducted using SPSS software.

Table 1. Soil parameters, methods of testing and data sources

Parameter	Method of testing (Laboratory)	Data source
Soil Texture	Hydrometer	Field Survey and Lab. Experiment
Soil organic matter	Loss-On Ignition (Using muffle Furnace)	Field Survey and Lab. Experiment
Bulk density (BD)	Volume Displacement	Field Survey and Lab. Experiment
Soil Porosity	Volume Displacement	Field Survey and Lab. Experiment
Soil pH	Using a pH meter (Metrohm 827 pH Lab)	Field Survey and Lab. Experiment

Table 2. Detail of satellite data used for the study

Sensor	Image ID	Acquisition date	Spatial resolution (m)
Sentinel 2	L1C_T31PFP_A009414_20170411T101045	2017/04/11	10
	L1C_T31PFQ_A009414_20170411T101045		
	L1C_T31PEP_A009414_20170411T101045		
	L1C_T31PEN_A009414_20170411T101045		
	L1C_T31PFN_A009414_20170411T101045		

Source: USGS

2.3. Geospatial analysis

One of the outstanding features of GIS is its capability to incorporate many forms of dataset provided the dataset has a spatial reference (coordinates). The spatial reference (coordinates) of each of the acquired samples were converted into decimal degrees (CSV) format in Excel and transferred to ArcMap 10.3 software for further processing for the conversion of the soil properties into raster format. Subsequently, the spatial reference (coordinates) was transformed to Universal Transverse Mercator (UTM) zone 31, World Geodetic Survey 1984 (WGS84).

2.3.1 Spatial interpolation

Spatial interpolation in its simplest meaning refers to the process of using points with known values and spatial reference to estimate values and spatial reference at another point in the GIS environment [9]. Therefore, spatial interpolation serves as a tool for creating surface data from sample points for surface analysis. Many forms of interpolation methods do exist but for this study, the inverse distance weighted (IDW) (Equation 1) method was used. The basic premise in the IDW is that, for the determination of the unknown point, the closest points have much more influence than those away from it [14].

$$Z(S_0) = \frac{\sum_{i=1}^n \frac{z(S_i)}{d_i^p}}{\sum_{i=1}^n \frac{1}{d_i^p}} \quad (1)$$

where $Z(S_0)$ = interpolated value
 N = total number of sample data values
 S_i = i th data value
 d_i = distance between interpolated value and the sample data value
 p = weighting power

The spatial reference (x and y coordinates) of each of the acquired sampled point were used as the known sample point location to interpolate the unknown points. Therefore, the soil properties of the known point will stand as the Z-value for the determination of the unknown points.

2.3.2 Data quality assessment

All kinds of dataset possess one form of error or another, as such data quality assessment become crucial before embarking on to use the data for the particular application. The split-sample strategy [15], was

used for the purpose of data quality assessment. The dataset for each of the selected soil properties was randomly divided into three (3) categories. Two-thirds (2/3) of the dataset was used as training samples, designated as (A) and one-third (1/3) as testing samples designated as (B). The quality assessment or validation sample were extracted from the interpolation result by using spatial analyst tool, then convert to point in ArcMap 10.3 software. The values were exported to Excel for further analysis.

To evaluate the relationship that exists between samples (A) and (B) for each of the soil properties scatter plots were used and the correlation coefficient (R^2) was determined. The correlation coefficient value ranges from +1 to -1 representing a perfectly positive and perfectly negative relationship, respectively. Zero (0) represents absolutely no relationship between the variables and the value closer to +1 indicate highly positive relationship and the value closer to -1 indicate a highly negative relationship.

2.4 Vegetation analysis

Spectral Vegetation Indices (SVIs) are used as effective measures of vegetation characteristics and the NDVI technique is commonly considered as useful means to evaluate vegetation status and its spatial distribution [10]. Sentinel 2 satellite imagery with the 10m spatial resolution was first preprocessed (mosaicked and atmospherically corrected) and then analyse for the NDVI theme using image analysis tools in the ArcMap 10.3 software (Equation 2). The nominal NDVI value varies from '+1 to -1'. The values closer to '+1' indicate higher vegetation while values closer to '0' indicate lesser vegetation. '0' means no vegetation while '-1' indicate other land cover types. For this analysis, negative values, including zero were ignored.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (2)$$

where: *NIR* = Near-Infrared Band
Red = Red Band

2.5 Correlation analysis

Correlation analysis is commonly used for evaluating the relationship between two or more phenomenon. It describes how well sets of variables can predict a particular outcome; it helps to better understand the association that exists between the variables and reveals the relative contribution and the degree of influence among the variables [16,17]. Sample points were extracted from the thematic layer of each variable by using spatial analyst tool in ArcMap 10.3 software 'Extract by mask', these extracted rasters was converted to point using 'raster to point' tool. Finally, the point 'grid codes' was exported to excel software for further analysis. For each variable, one hundred and twenty (120) sample points were randomly extracted from the thematic map of both the input and output.

3. Results and discussion

The analysis of the collected data for soil physical properties (SOM, soil texture, soil porosity, BD and pH) was achieved using descriptive statistics. The spatial distribution of each soil parameter was evaluated using spatial analysis tools in ArcGIS 10.3 software and the thematic layers of each of the soil properties were generated using Inverse Distance Weighted (IDW) technique [9]. Statistically, the result indicates that the observations of soil properties (soil pH, porosity, bulk density) showed normal distribution, whereas, the soil texture and SOM distribution indicate positively skewed distribution (Table 3).

3.1 Spatial analysis

All vector dataset were converted to raster format based on their geospatial reference (coordinates), this is to allow for geospatial analysis. Henceforth, the dataset was subjected to spatial interpolation. Inverse distance weighted (IDW) technique was used to analyse the spatial distribution of the soil properties across the study area. Figure 2 (a-e), illustrate the thematic interpolated layers of the selected soil

properties (texture, porosity, SOM, BD and pH). The data quality analysis result indicates the relationships between samples A and B. The correlation coefficient for BD, soil porosity, SOM, soil pH and soil texture are 0.64, 0.53, 0.58, 0.53 and 0.54 respectively. This gives an overview of the relation that exists between the dataset.

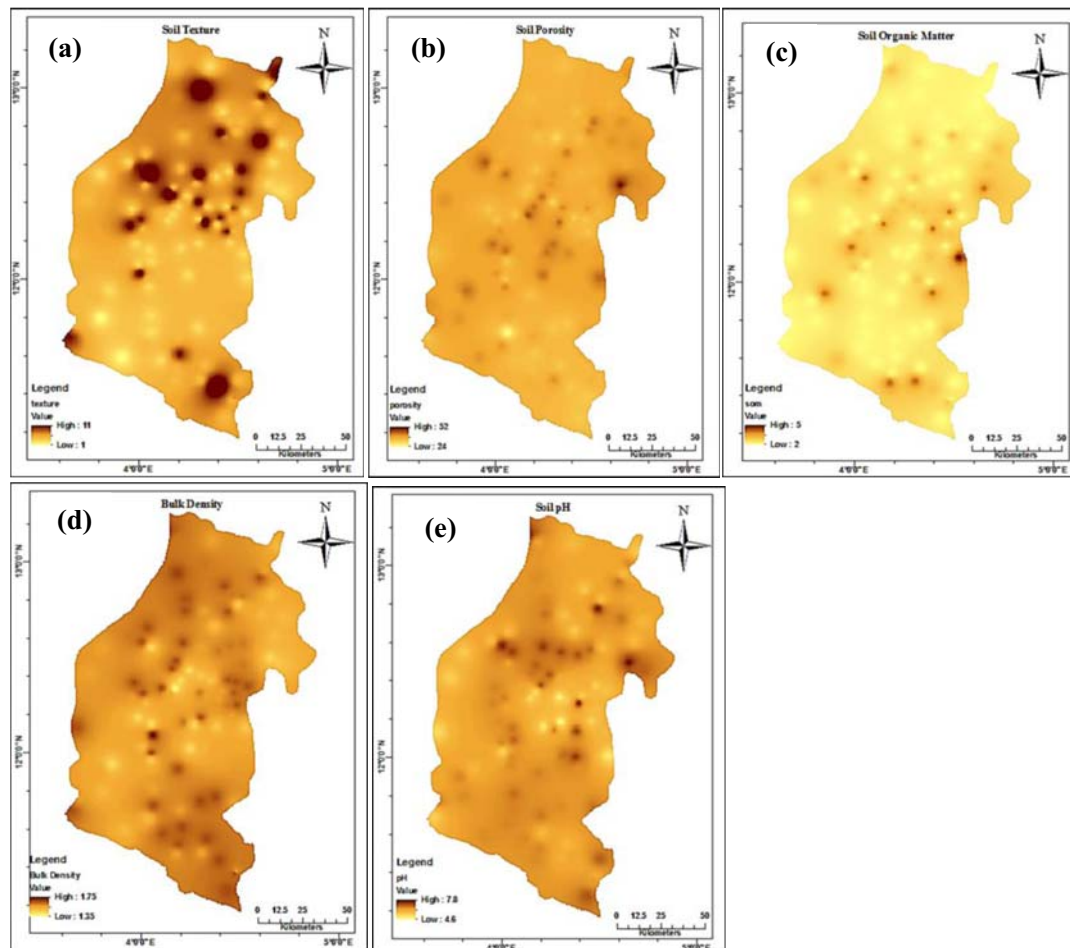


Figure 2. Soil thematic maps for (a) texture, (b) porosity, (c) SOM, (d) Bulk density and (e) pH

Table 3. Descriptive summary of the selected soil properties

	SOM (%)	Porosity (%)	BD (g/cm ³)	Texture	pH
Mean	1.56	37.83	1.57	3.94	6.31
Standard Error	0.06	0.31	0.01	0.21	0.05
Mode	1.00	40.00	1.56	2.00	6.55
Standard Deviation	0.80	3.92	0.08	2.64	0.68
Sample Variance	0.63	15.37	0.01	6.95	0.46
Kurtosis	1.12	1.16	-0.42	1.65	0.04
Skewness	1.34	0.21	-0.39	1.58	-0.12
Range	3.00	29.00	0.41	11.00	3.66
Minimum	1.00	24.00	1.35	1.00	4.68
Maximum	4.00	53.00	1.76	12.00	8.34
Count	156	156	156	156	156

SOM=Soil organic matter BD=Bulk density

For a more representative appraisal, the result obtained from interpolation was reclassified in descending order based on the degree of distribution as high, moderate and low categories (Table 4).

Table 4. Soil parameters, class range and category

Parameter	Class Range	Category
Soil Texture	L,SCL,SL,LS&CL	High
	SC, SiL & SiCL	Moderate
	Si, C, SiC & S	Low
SOM (%)	>3	High
	2.3-3	Moderate
	<2.3	Low
Soil Porosity (%)	>40	High
	35-40	Moderate
	<35	Low
BD (g/cm ³)	>1.6	High
	1.55-1.6	Moderate
	<1.55	Low
Soil pH	<6	High
	6-7	Moderate
	>7	Low
NDVI (%)	>25	High
	10-25	Moderate
	<10	Low

where: S=Sandy, LS=Loamy sand, SL=Sandy loam, SiL=Silt Loam, Si=Silt, L=Loam, SCL=Sandy clay loam, SiCL=Silt clay loam, CL=Clay loam, SC=Sandy clay, SiC=Silt clay, C=Clay, SOM=Soil organic matter, BD=Bulk density, NDVI=Normalized difference vegetation index

3.1.1 Soil texture

The spatial interpolation of soil texture was conducted, the correlation between samples A and B was assessed, with the correlation coefficient, $R^2=0.57$. Table 5 reveals the spatial distribution of the soil texture classes with about 26%, 71% and 2% of the total area classified as high, moderate and low texture soil respectively. The soil in the study area generally, is more or less textually loamy and clay type while less than 10% of the accounted for sandy soil. An indication of moisture retention ability by the majority of the soil in the study area as well allows for optimal fluid permeability, this makes it more suitable for agricultural production. Figure 3(a) discloses explicitly the thematic distribution of the soil texture in the area.

3.1.2 Soil porosity

Soil porosity analysis shows that the result ranges from 24-52%. The relationship between samples A and B was assessed with a correlation coefficient, $R^2=0.53$. The percentage distribution of the soil porosity in the area, with 39%, 55% and 6% of the total land area belonging to high, moderate and low porosity classes respectively (Table 5). Impliedly means that a larger portion of the soil in the study area has less than 40% porosity while less than 6% has pore spaces greater than 40%. The result indicates that the area is considered moderately porous. This means that unlike high and low porous soil that allows for easy water passage and water ponding and logging respectively, moderately porous soils allow for a steady and gradual fluids movement. Spatially, the high porous soil is concentrated more in extreme north and south parts of the study area. The low porous soil is scattered in the area. The resultant spatial distribution is presented in Figure 3(b).

3.1.3 Soil organic matter (SOM)

The SOM content in the study area analysed shows the result to ranges from 2%-5%. The relationship between samples A and B gives a correlation coefficient, $R^2=0.53$. The percentage distribution of the

SOM shows the highest area covered by moderate SOM content accounting for about 42% of the total area. The high SOM class has 38%, while low SOM class has 19% (Table 5). Organic matter as an important component of the soil, it serves many purposes including nutrient storage and supply, erosion prevention and increases the water holding capacity of the soil. Accordingly, the result indicates that bulk of the soil found in the area has high to moderate organic matter content of more than 2.5%, while less than 20% has OM content of less than 2.3%. Spatially, low organic matter content is concentrated more in the northern part of the study area as shown in figure 3(c).

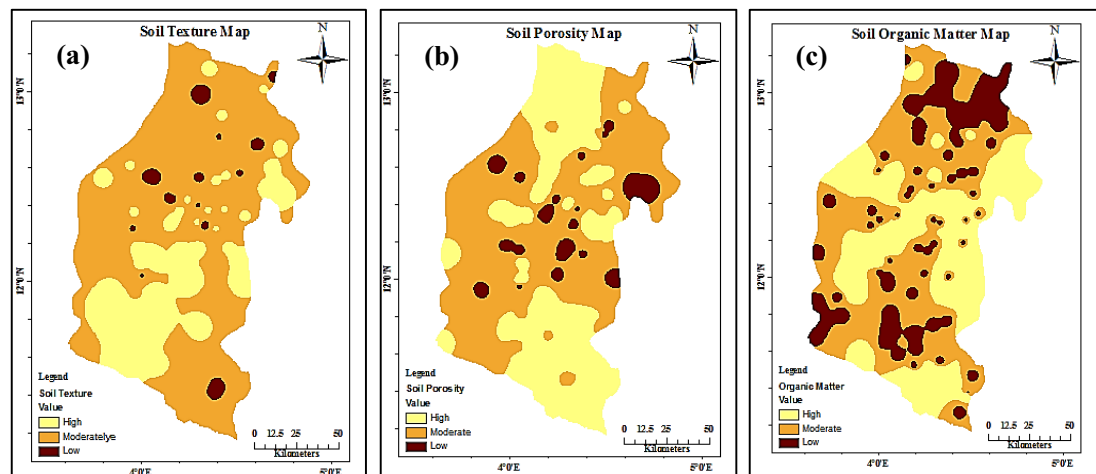


Figure 3. Map for (a) Soil texture, (b) Soil porosity and (c) SOM

Table 5. Distribution of the soil physical properties

Parameter	Texture		Porosity		Organic matter		Bulk density		pH	
	UU	LA (%)	LA (Km ²)	LA (%)	LA (Km ²)	LA (%)	LA (Km ²)	LA (%)	LA(Km ²)	LA (%)
Class										
High	4,848.5	26.1	7,2671	39.1	7,143.6	38.4	3,690.9	19.9	14,530	78.2
Moderate	13,259.3	71.3	10,268	55.2	7,923.9	42.6	9,462.5	50.9	1,979.2	10.6
Low	483	2.6	1,056	5.7	3,524	19.0	5,438	29.2	2,081.9	11.2
Total	18,591	100	18,591	100	18,591	100	18,591	100	18,591	100

LA=Land area

3.1.4 Bulk density (BD)

The BD result obtained from the analysis of soil samples in the study area falls within the range of 1.35-1.75g/cm³. The association between the samples A and B was assessed with a correlation coefficient $R^2=0.63$. The result shows that about 51% of the area is covered with soil having moderate BD, whereas, 20% and 29% are classified as high and low BD classes respectively (Table 5). A larger percentage of the soil in the study area has a grain size between 1.35-1.6g/cm³, while less than 30% of the soil has a grain size above 1.6g/cm³. This signpost that most soils in the study area have a grain size that is within the range that can allow for increased water holding capacity. Table 5 indicates the spatial distribution of the BD while Figure 4(a) displays the thematic map of the soil BD in the study area.

3.1.5 Soil pH

The soil pH result ranges from 4.6 -7.8 in the study area. The relation between sample A and B were evaluated and the correlation coefficient, $R^2=0.53$. The percentage distribution of soil pH (Table 5) in the area shows that 78% falls within the high pH class. The moderate and low pH class has about 11% each respectively. Soil pH measures the acidity and alkalinity in given soils and usually ranges from 0 to 14, with 7 being neutral, values below 7 are acidic and above 7 are alkaline. The optimal pH for most plant

growth ranges between 5.5 and 7.0. The result obtained shows that a larger portion of the soil in the area has a pH value of less than 6, indicating that the soil is moderately acidic. However, 20% of the soil in the study area has pH value greater than 6, implies that the area is more or less neutral in nature. Spatially, the distribution of the soil pH in the study area shows that less acidic soils are found more in the central part of the study area. Figure 4(b) shows the thematic layer of the spatial distribution of the soil pH in the study area.

3.1.6 The NDVI

The result derived from NDVI analysis using Sentinel 2 satellite data indicate that the vegetation cover of the study area ranges from -0.3-1. It is usually expressed as a percentage vegetation cover of an area. The result was further reclassified as, areas with more than 25% vegetation cover indicates the presence of woody vegetation classified as 'High', while areas with vegetation cover between 10-25% indicate the existence of shrubs and are classified as moderate whereas areas with less than 10% vegetation cover indicate open grassland, bare land or dead grasses and are classified as low. From the results, it clearly showed an increase in spatial vegetation cover southward of the study area as depicted in the NDVI theme and classified NDVI in Figure 4(c).

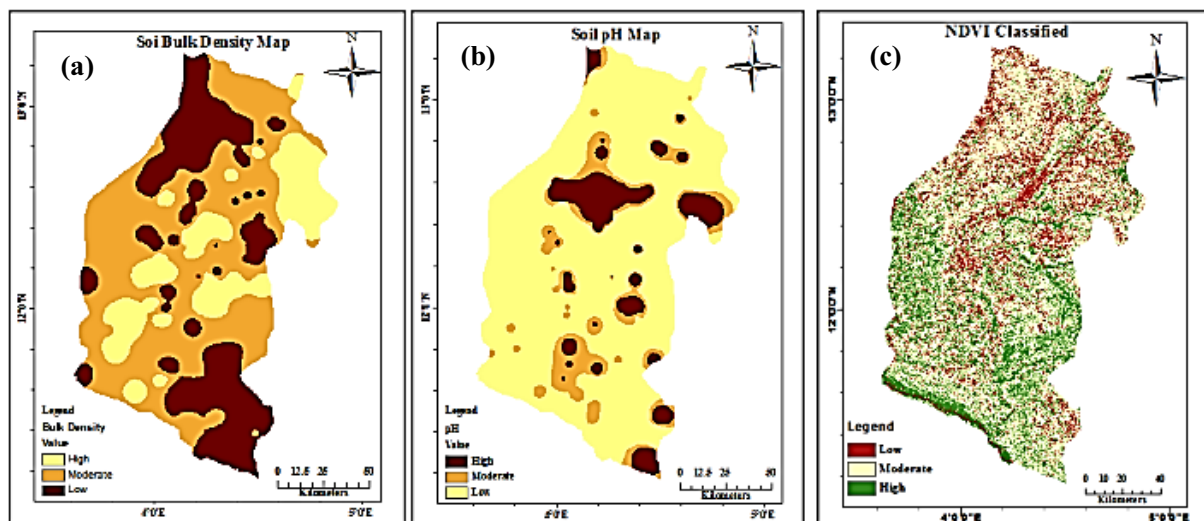


Figure 4. Map for (a) BD, (b) pH and (c) NDVI

3.2 Relationship between soil properties and the NDVI

The correlation between soil physical properties and the NDVI results were presented in Table 6. The indications here are that NDVI is correlated significantly with the SOM, BD as well as the soil texture with a correlation coefficient (r) of 0.47, 0.35 and 0.34 respectively. A very weak correlation was also observed between NDVI and soil pH (0.12) in the study area. However, it was observed that there is a negative correlation between NDVI and soil porosity with the coefficient (-0.06). The result corresponds with the findings of [4,18], that SOM and soil texture has a direct relationship with the NDVI. The result also disagrees with the finding of [19] in a related study, it was also observed that soil porosity and bulk density has a positive and negative correlation with NDVI respectively; however, the study was conducted in a hilly slope area.

Table 6. Correlation between soil properties and the NDVI

	NDVI (%)	Texture	Porosity (%)	BD (g/cm ³)	SOM (%)	pH
NDVI	1					
Texture	0.343	1				
Porosity	-0.062	-0.230	1			
BD	0.348	0.348	-0.012	1		
SOM	0.467	0.296	0.087	0.464	1	
pH	0.124	0.113	0.172	0.035	0.155	1

Significant ($p < 0.05$)

4. Conclusion

This study showed that the area has low to moderate of soil physical properties distribution. These properties exhibit a significant correlation with vegetation status in the area. An inverse correlation was also observed between vegetation status and soil porosity. Even though the assessment of the spatial distribution of soil physical properties was performed efficient using GIS, the geospatial techniques are also worthwhile to be used for sustainable land and environmental management. However, further study needs to be conducted on the soil chemical properties so as to furnish the land managers and agriculturist with synaptic information on the distribution of chemical components of the soil in the area. More interpolation methods (Kriging, spline and trend) need to be applied so as to identify the best method. It is recommended to conduct further studies using more sampling points for better and accurate result.

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