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GEOINFORMATICS | RESEARCH ARTICLE

Geospatial approach to study the spatial distribution of major soil nutrients in the Northern region of Ghana

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Abstract: Spatial distribution of soil nutrients is not normally considered for smallholder farms in Ghana resulting in blanket fertilizer application which leads to low efficiencies of some applied nutrients. This study focuses on applying geospatial analyses to map 120 maize farms in 16 districts of the Northern region of Ghana to identify nutrient distribution. Soil samples were taken from these 120 locations and analysed for contents of nitrogen (N), phosphorus (P) and potassium (K). Spatial models of the contents were generated through geostatistical analysis to map the status of N, P and K nutrients across the locations. Study results indicated that proportion of area deficient in N is 97%, P is 72% and K is 12%. Distribution pattern for N and K nutrients were clusters of low or high contents at specific locations; and that of P was random. Outcome of this study could enhance site-specific nutrient recommendation in Ghana.

Subjects: Agriculture; Soil Sciences; Statistics; Technology

Keywords: smallholder farmers; geospatial analysis; spatial distribution; major soil nutrients; soil fertility

1. Introduction

Agriculture is the main economic activity in the Northern region of Ghana. According to statistics provided by FAO (AQUASTAT, 2005), majority of the population in the region are smallholder farmers

ABOUT THE AUTHORS

The author's key research activities are focused on the use of Geographical Information Systems to study the spatial pattern within natural resources. These activities include modelling and mapping underlying spatial features and factors that contribute to the continuous degradation of these natural resources in order to make decisions that could control and monitor the resources. The author's research interest in the presented paper, therefore, falls in line with these activities and presents the models and maps of major soil nutrients that will aid appropriate fertilizer application at different locations according to their initial contents. The paper relates to the broader call on research to improve soil fertility and control the continuous soil degradation in Ghana and Sub-Saharan Africa due to the inappropriate fertilizer application by smallholder farmers resulting in low crop yields which also contributes to food insecurity in the region.

PUBLIC INTEREST STATEMENT

The article describes the pattern of distribution of soil nitrogen (N), phosphorus (P) and potassium (K) nutrients contents in 16 districts of the Northern region of Ghana. Although the region is noted for producing most of the major food crops in Ghana, this study showed that the soils in most of the districts have low levels of N, P and K nutrients. The article, therefore, provides maps of distribution of these major soil nutrients contents at different locations after assessing the extent of their levels in the study districts. The generated maps showed locations where the nutrients levels are very low, low or adequate to support the production of maize crops in the study area. This study is to aid decision-making during application of N, P and K fertilizers to the soil so that high efficiencies of applied fertilizers would be attained to give desired crop yields.

and about 80% of the land area is used for cropping. The soils, however, in these land areas of Sub-Saharan Africa are poor, especially in nutrient levels (Wairegi, 2011). Improper fertilizer rates application (Martey et al., 2014) and poor land management (Nkonya, 2004) contribute to the low contents of nutrients in these soils. This had resulted to persistently low crop yields. To increase the productivity of these soils for enhanced crop yields and increase the income of smallholder farmers, spatial distribution of the major soil nutrients needs to be mapped and based on the results of the distribution, appropriate fertilizer needs could be recommended for localised intervention. Since soil is not a renewable resource (Haghdar, Malakouti, Bybordi, & Ali, 2012), the concept of soil nutrient content assessment becomes very important for higher agricultural productivity and the economic development of every country.

In addition, adoption and implementation of soil fertility management concepts may vary, it is, therefore, necessary to assess the soil nutrient levels within locations where smallholder farmers are cropping. The mapped results of the soil nutrient assessment could then be used for effective monitoring of changes that might occur between cropping systems' and seasons' overtime. Monitoring of the nutrient levels will enable stakeholders to assess soil fertility improvement or otherwise in such localities. The tedious and costly conventional methods needed to obtain soil nutrient information will also be reduced when nutrient levels are mapped because those conventional methods are no more affordable (Behrens & Scholten, 2006). Accordingly, mapping of the nutrient levels will provide spatial soil nutrients information that can be used as a decision support tool. Hence, developing spatial distribution maps of soil nutrients is important in the "breadbasket" regions of which Northern region of Ghana is one (Adesina, 2009), since it will help refine agricultural management practices, improve sustainable resource use as well as provide a base against which future soil nutrients can be recommended at site-specific locations (Fairhurst, 2012; Reetz & Rund, 2004). Mapping of soil nutrient levels, especially nitrogen (N), phosphorus (P) and potassium (K) would also facilitate proper monitoring and review of recommended farming technologies at locations from time to time. This might also help in the evaluation of the impact of a particular technology at a particular time (e.g. every 10 years) in a particular location depending on assessment of the soil quality (Wang & Gong, 1998). In addition, due to the growing knowledge in precision agriculture (Buick, 1997; Ping, Wang, & Jin, 2009), researchers and decision-makers in soil science would be in a better position to implement location-based technologies, if approximate levels of soil nutrients in specific locations in the region are mapped. This approach will improve soil fertility management results and increase the interest of smallholder farmers to invest more in the agricultural sector.

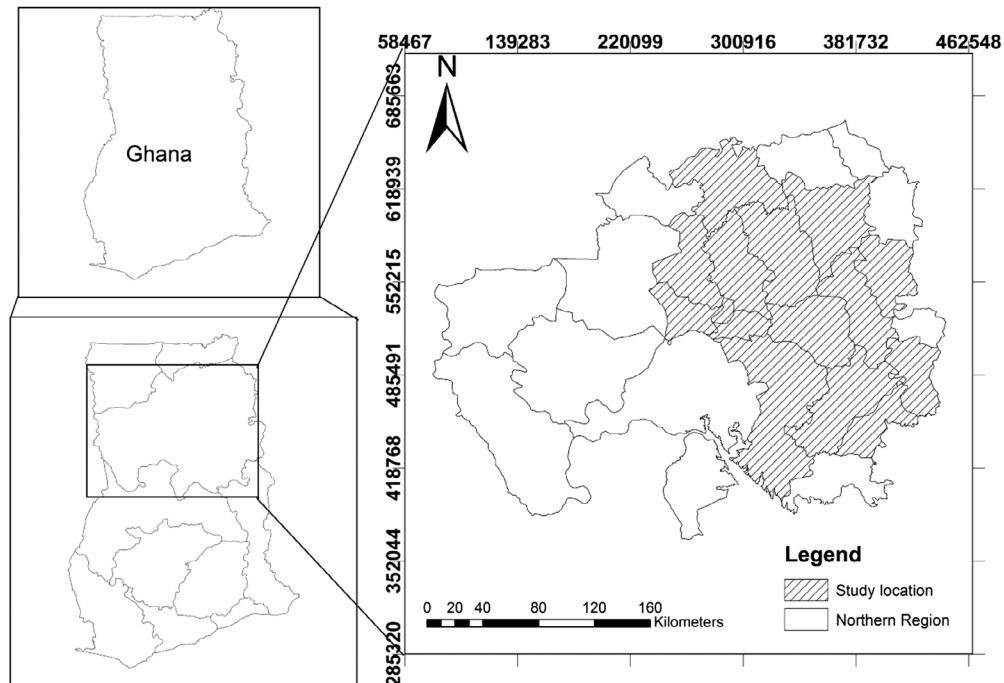
The aims of this study were therefore (i) to generate appropriate nutrient models and parameters in order to produce a spatial distribution map of major soil nutrient contents across the Northern region of Ghana and (ii) to evaluate their pattern of distribution through spatial modelling of the N, P and K contents. The results of the study would, therefore, reveal the spatial variation and pattern of distribution of N, P and K nutrient contents across the study area and their evaluation would help to make appropriate site-specific nutrient analysis.

2. Materials and methods

2.1. Study area

The study was carried out in 16 out of 22 districts in the Northern region of Ghana (Figure 1), which is one of the regions classified as the "breadbasket" area of Ghana (Adesina, 2009). This is because most of the major food crops in the country are cultivated in this region and they include maize, rice, cowpea and yam. The region covers an area of about 70,384 km² and is the largest of the 10 regions in Ghana. The study districts, however, covered an area of approximately 40,000 km². It lies in a geographical location of latitudes N9° 30' and N10° 00' and longitudes W0° 51' and W1° 00' with a mean elevation of 149 m above sea level (Getamap, 2006). The mean annual rainfall of the area ranges from 750 to 1,050 mm and the mean temperature is 28°C which can fall as low as 14°C in the night of December/January and rise as high as 40°C during the day in February/March. The region is located in the Guinea savanna agro-ecological zone. Some of the major soils found in the region

Figure 1. Map of study area.



include Lixisols, Luvisols, Acrisols and Gleysols (Dedzoe, Senayah, & Asiamah, 2001). The study, however, considered maize-cultivated fields since maize crop is one of the most cultivated cereals in the region and is regarded as one of the fundamental crops in the “food security equation” (Sauer, Hardwick, & Wobst, 2006).

2.2. Methods

The fields of eight maize smallholder farmers were chosen from each district that has data on particulars of farmers regarding their farming activities that have been recorded in the database provided by Savanna Agricultural Research Institute (SARI), as well as farmers who do not have their particulars included in the database. Each field was selected from different communities within a district to ensure uniformity of dispersion in the distribution of selected fields. Locations of selected maize fields, based on the objective of this study and for mapping purposes, were obtained with the Garmin GPS. Fifteen districts were found to have complete smallholder farmers’ data on maize production from 2012 to 2014 cropping seasons in the database provided by SARI and these districts were selected to be used in this study. A total of 120 locations were therefore obtained. A map showing the locations of the farms within the districts was produced (Figure 2).

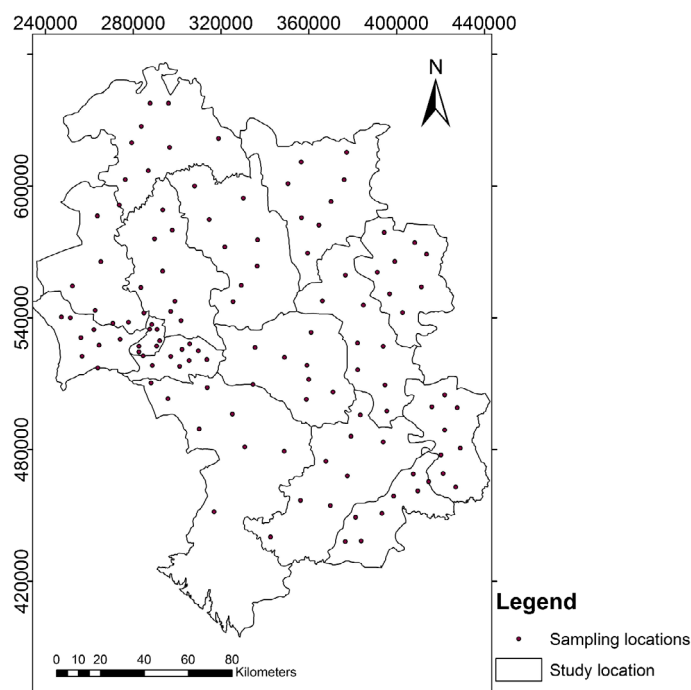
2.2.1. Soil sampling and analysis

Soil samples were taken from each of these 120 locations previously cropped to maize, between May 2013 and March 2014 with the soil auger. Twenty cores of 0–20 cm depth of soil were taken and hand-mixed thoroughly in a bucket to homogenise the sample. A composite sample was then taken from the bulk to represent that location as shown in Figure 2. The soils were analysed for total N, available P and exchangeable K contents; total N was determined by Kjeldahl’s method, available P by Bray I method and exchangeable K by ammonium acetate extraction (Matula, 2009).

2.2.2. Statistical and geostatistical analysis of nutrient contents

The soil nutrient contents obtained through the laboratory analysis were subjected to Genstat (twelfth edition) statistical descriptive analysis. Some statistical parameters that were observed for the purpose of this study were the mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis of the data distribution (Table 1).

Figure 2. Map of soil sampling locations.



Geostatistical analysis that employs the use of simple point kriging and simulations (ESRI, 2010) was used to model the total N, available P and exchangeable K contents to produce the spatial distribution maps. The simple kriging model is expressed as follows:

$$Z(s) = \mu + \varepsilon(s) \tag{1}$$

where $Z(s)$ = the predicted value at the prediction location

μ = a known constant

$\varepsilon(s)$ = estimated error

Simple kriging assumes normality within the data before modelling. However, in this study, data exploration of the soil nutrient contents revealed that the levels were not normally distributed as shown by the elements of test of normality, skewness and kurtosis values generated by the data statistics (Table 1).

Table 1. Statistical parameters of major soil nutrient contents (n = 120)

Variable	Total N (%)	P (mg kg ⁻¹)	K (cmol _c kg ⁻¹)
S.D.	0.02	3.61	0.11
C.V. (%)	29.85	70.56	67.30
Mean	0.07	5.12	0.16
Minimum	0.03	1.24	0.06
Maximum	0.13	15.57	0.73
Skewness	0.11	0.99	2.53
Kurtosis	2.43	2.96	7.71

A data transformation was therefore applied to the original nutrient levels to render the contents normalised before modelling. A logarithmic transformation was applied to the total N and exchangeable K contents and a normal score transformation (ESRI, 2010; Harter, 1961; Royston, 1982) was applied to the available P contents.

The normalised soil nutrient contents were then analysed geostatistically by fitting different semi-variogram models iteratively, to measure the spatial variation within the soil nutrient contents (Liu et al., 2006; Matheron, 1963). In addition, the semi-variogram provided the necessary input parameters for spatial interpolation of kriging (Krige, 1951). ESRI (2010) ArcGIS defines the semi-variogram as follows:

$$\gamma(s_i, s_j) = 1/2 \text{var}(Z(s_i) - Z(s_j)) \tag{2}$$

where var is the variance, s_i and s_j are two different locations and; Z is the difference in their values.

The semi-variogram model that fitted the soil nutrients phenomena more accurately and provided the least root mean square error (RMSE) compared to others was selected for each of the nutrient levels. The RMSE was evaluated using the formula by Chai and Draxler (2014) as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x}_i)^2} \tag{3}$$

where N is the sample size, x_i is the observed value and \bar{x}_i is the mean value for the observed sample values.

The parameters that were obtained from the semi-variogram were the sill, *nugget* and *range*. The sill represented the amount of variation defined by the spatial correlation structure and it is the value of the semi-variogram at which the model first levels out (given as partial sill plus the nugget). The range is the lag distance from where the model levels off and the nugget is the variability error (measurement error) obtained at shorter distances than the typical sampling interval (Bohling, 2005). The nugget-to-sill ratio was then used to classify the spatial dependence within the nutrient contents.

The prediction model for the soil nutrients was finally validated to measure the accuracy of the prediction map generated showing the distribution of the nutrients. The prediction model that gave the minimum average standard error (i.e. which fits the distribution more accurately) and the least RMSE was considered to be simulated as a measure of uncertainty within the predictions.

The simple kriged maps of the major soil nutrients across the study area were then simulated (generated from 10 realisations from different statistical parameters, i.e. mean, median, SD, upper value, lower value, first and second quartiles, minimum and maximum values and the percentile) to generate stochastic models of the surfaces since simple kriged maps produced smooth surfaces.

Spatial autocorrelation, using the Moran's index (Moran, 1948) was then calculated to assess the significance of the pattern of distribution within the nutrient contents. The calculation was done as follows:

$$I_{\text{Nu}} = \frac{n_{(\text{loc})}}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n (\text{Nu}_{(\text{content})i} - \overline{\text{Nu}}_{(\text{content})}) \times \text{loc}_{ij} \times (\text{Nu}_{(\text{content})j} - \overline{\text{Nu}}_{(\text{content})})}{\sum_{i=1}^n (\text{Nu}_{(\text{content})i} - \overline{\text{Nu}}_{(\text{content})})^2} \tag{4}$$

where $n_{(\text{loc})}$ is the number of farm locations where soil samples were taken, loc_{ij} is the element in the spatial weights matrix corresponding to the pairs of locations i, j and $\text{Nu}_{(\text{content})i}$ and $\text{Nu}_{(\text{content})j}$ are nutrient contents in location i, j , respectively; and $\overline{\text{Nu}}_{(\text{content})}$ are the mean nutrient content values.

The spatial weight matrix was generated for each of the nutrient contents and denoted by

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n loc_{ij} \tag{5}$$

where loc_{ij} collectively defined the neighbourhood structure over the entire study location.

The z-score value for each of the nutrient contents and the Moran's index, I obtained from the spatial autocorrelation analysis were then used to specify the pattern of distribution that existed within the soil N, P and K contents. The probability value obtained was then used to assess the significance of the distribution, whether dispersed, clustered or of a random nature.

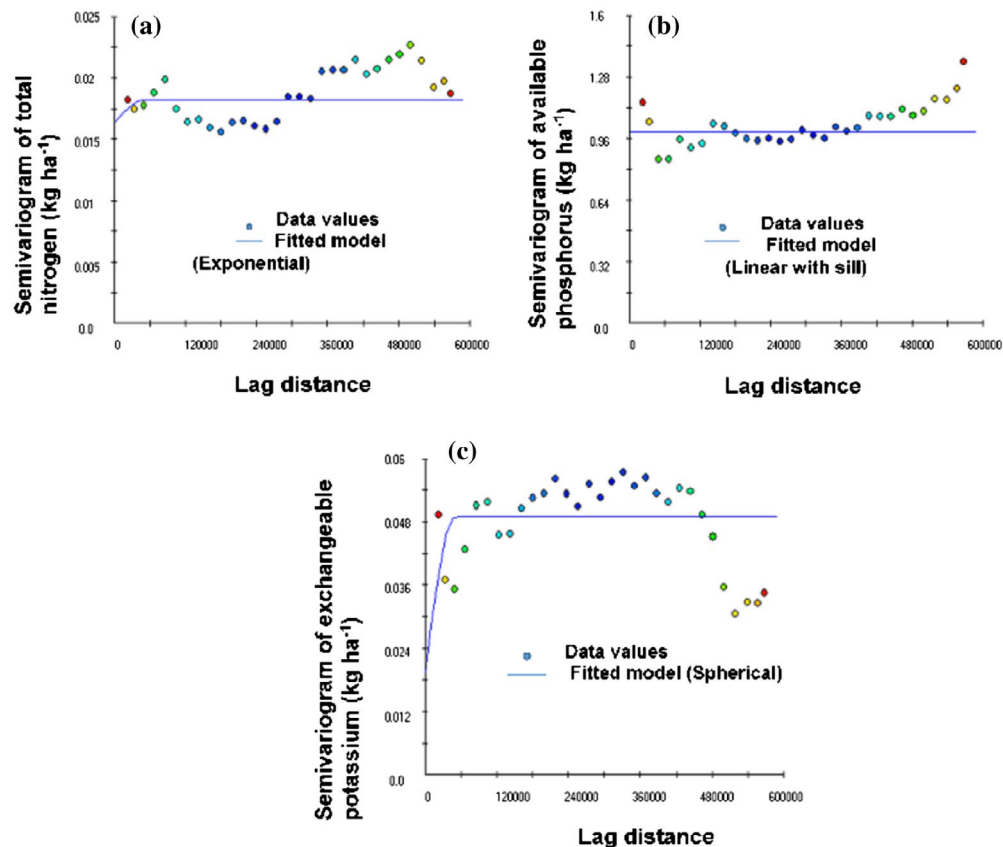
3. Results and discussion

3.1. Statistical description of major soil nutrient contents in the study area

Description of the untransformed N, P and K contents in the study area showed that their statistical distributions were all positively skewed (with skewness values of N = 0.11, P = 0.99 and K = 2.53; Figure 3). K contents had higher peak (Kurtosis = 7.71) with N and P contents showing near normal peaks (Kurtosis for N = 2.43; P = 2.96). For a standard normal distribution, skewness should be equal to zero and kurtosis equals to three as reported by Jondeau and Rockinger (2003). After data transformations, the N, P and K contents followed a near normal distribution which rendered the data values appropriate for modelling.

N and K contents followed log-normal distribution with positive skewness (see Table 1), an indication that large proportions of the study location have low to moderate concentrations (found within the range of 0.05–0.1% for N and 0.1 and 0.25 $cmol_c\ kg^{-1}$ for K; Table 1) whether clustered or random.

Figure 3. Fitted semi-variograms illustrating the strength of statistical correlation between major soil nutrients; (a) Nitrogen, (b) Phosphorus, and (c) Potassium in selected districts of the Northern region of Ghana.



Few locations recorded relatively high contents (i.e. N being more than 0.1% and K more than 0.25 cmol_c kg⁻¹) as reported by Wopereis, Defoer, Idinoba, Diack, and Dugué (2009) (see Table 2).

The CV determined for the nutrient concentrations showed that N contents had high variations within its distribution (CV value 29.85%; see Table 1), which signifies relatively low dispersion across the districts; those for P and K concentrations were of very high values (CV values of 70.56 and 67.30%, respectively) indicating more dispersion in their distributions. High CV value implies that the data distribution is more variable (dispersed) and, hence, less stable and less uniform (nCalculators, 2013). However, the contents normalised after applying the data transformations.

The near normal distribution of K after log-transformation might be due to the fact that the difference between the minimum and maximum contents were not so large (0.06 and 0.73 cmol_c kg⁻¹, respectively); as compared to that of P contents (Table 1). The fact that some locations recorded P contents as low as 1.24 mg kg⁻¹ and others, as high as 15.57 mg kg⁻¹ might account for the reason why P contents followed a normal score distribution.

The locations that recorded relatively high *p*-values were those locations where the smallholder farmers were incorporating about 3 t ha⁻¹ of only cattle manure or including NPK (15:15:15) fertilizers plus sulphate of ammonia to the soil (according to the data provided by SARI and interviews with farmers). According to Zhang, Johnson, and Fram (2002), available P builds up in soil when animal manure is applied at a high rate to meet nitrogen requirements and that could have contributed to the high P contents in those locations. The differences in the spatial distribution of the soil nutrient concentrations across the region may thus be attributed to differences in nutrient management practices (Tsirulev, 2010), differences in soil forming processes, inherent heterogeneity in parent material at the different locations, as well as land use pattern and amount of fertilizer used (Liu et al., 2006) by the smallholder farmers. The distribution of the major nutrients confirms the assertion that spatial variation of soil nutrients exist even in neighbouring fields as has been previously reported by Goovaerts (1998), van der Zaag (2010) and Voortman, Brouwer, and Albersen (2002).

When the nutrient contents in the study area were compared with the soil fertility status table (Table 4) produced by Wopereis et al. (2009), only 3% of the locations had N contents within average range for maize production leaving about 97% of the locations having N contents in the soil below recommended average. 28% of the locations studied had levels of P within average contents, whilst 72% had P contents below average. Twelve per cent of the located areas had good K concentrations, 61% were within average, whilst 27% had K contents below average. The low to moderate contents might have resulted from continuous cropping of maize on the same piece of farmland (as confirmed by the farmers to be their practice), low rates of nutrient fertilizers applied at such locations (Mwangi, 1996), soil nutrient loss through soil erosion (Barrows & Kilmer, 1963) and export of nutrients through harvested produce (including straw and stover collection) from the farm (Doran, Wilhelm, & Power, 1984).

3.1. Models of the spatial dependence of major soil nutrients

The semi-variogram models that were used to derive parameters needed to explain the spatial dependence of the soil nutrient contents are presented in Figure 3. These models were obtained based on the semi-variogram model that presented the least RMSE as a measure of uncertainty as shown in Table 3.

Table 2. Nutrient concentration levels indicating soil fertility status for maize production at a depth of 0–20 cm (Wopereis et al., 2009)

Nutrient level	N (%)	P (mg kg ⁻¹)	K (cmol _c kg ⁻¹)
Good	>0.1	>25	>0.25
Adequate	–	6–25	0.10–0.25
Low	0.05–0.1	3–6	0.05–0.10
Very low	<0.05	<3	<0.05

In general, variables of nutrient contents that have a nugget-to-sill ratio less than 0.25 are regarded to have strong spatial dependence within them (i.e. spatial relationship that exists in variable pattern) (Cambardella et al., 1994; Liu et al., 2006). The spatial dependence is considered moderate if the ratio is between 0.25 and 0.75 and weak if it more than 0.75. The nugget-to-sill ratio obtained from the semi-variogram model (Figure 3) for N, P and K contents in the study were 0.64, 0.39 and 0.62, respectively, an indication that their spatial dependencies were moderate. The moderate spatial dependencies within the nutrient contents imply that the degree of association between the variables at different locations may increase as the distances become close to each. This suggests that there could be a possible continuity of the N, P and K variables exhibiting similarities in their values at shorter distances (less than 50 km as shown by the range distance in this study; Table 3). Smallholder farmers located within shorter distances are likely to adopt similar fertilizer management strategies regardless of their soil nutrient variations, which might affect N, P and K contents in the soils in a similar pattern (Adler, Raff, & Lauenroth, 2001). As distances increase, fertilizer management strategies may differ and the dependencies could become weaker or stronger depending on impact of the management (Jonsson & Moen, 1998). Therefore, as previously reported by Luo, Ding, Mi, Yu, and Wu (2009), Pringle, Doak, Brody, Jocqué, and Palmer (2010) soil fertility management should be consistent within patterns of spatial distribution of nutrient contents in the soil in order to manage the considerable variation of the nutrient contents in the study area.

Nitrogen and K nutrient contents recorded in the study area showed a positive low nugget, an indication that sampling error, random and other inherent variations that existed in the variables (Bohling, 2005; Clark, 2010; Liu et al., 2006) were minimal. Phosphorus contents, however, showed a high nugget effect indicating random and inherent variations within the variables. The considerable range of variations within the N, P and K contents might be caused by effects of variable farm level soil fertility management (Tittonell, Vanlauwe, Leffelaar, Rowe, & Giller, 2005; Trangmar, Yost, & Uehara, 1985) across considerable distances from the locations.

The prediction uncertainty generated by the cross-validation of the model were 0.02 kg ha⁻¹ for N, 0.98 kg ha⁻¹ for P and 0.11 kg ha⁻¹ for K (Table 4). These values were less than 1 and hence considered appropriate for the model. The obtained root mean square standardised were also close to 1 for the N, P and K content variables suggesting that none of the variables were under-estimating or over-estimating the predictions as reported by (Hawkins & Sutton, 2011).

Table 3. Parameters for variogram model for major soil nutrients (NPK)

Major soil nutrient	Model	RMSE*	Nugget	Partial sill	Range (m)
Total N (kg ha ⁻¹)	Spherical	0.00213	– ^a	–	–
	Exponential	0.00211	0.0159	0.009	50000
	Gaussian	0.00212	–	–	–
	Linear with sill	0.00212	–	–	–
Available P (kg ha ⁻¹)	Spherical	0.1120	–	–	–
	Exponential	0.1186	–	–	–
	Gaussian	0.1179	–	–	–
	Linear with sill	0.1120	0.3666	0.582	50000
Exchangeable K (kg ha ⁻¹)	Spherical	0.0083	0.0316	0.019	50000
	Exponential	0.0084	–	–	–
	Gaussian	0.0084	–	–	–
	Linear with sill	0.0084	–	–	–

*RMSE (root mean square error).

^aValues that were not considered in the model.

Table 4. Measure of uncertainties in the prediction estimates of N, P and K contents in 15 districts of the Northern region of Ghana

Transformed major soil nutrient	Average standard error	Root mean square standardised
Total nitrogen (kg ha ⁻¹)	0.02	0.97
Available phosphorus (kg ha ⁻¹)	0.98	0.97
Exchangeable potassium (kg ha ⁻¹)	0.11	0.99

3.2. Spatial distribution and autocorrelation of major soil nutrients

The simulated maps from the mean values of the nutrient contents (generated from 10 realisations from different statistical parameters) are presented in Figures 4a–4c. The means were presented because according to simulation concepts by ESRI (2010), the means do not change over the spatial domain of the data. In addition, the mean has a Gaussian distribution around the true value, as stated by the central limit theorem (Engblom, Ferm, Hellander, & Lötstedt, 2009) and will therefore provide a better representation of the distribution.

The nutrients contents ranged from very low to adequate levels for maize cultivation in the study area. The differences in the variation within the distribution might be attributed to factors such the differences in elevation topography of the study area (McKenzie, 2013), soil pH that might influence nutrient levels (Wang, Bai, Huang, Deng, & Xiao, 2011) as well as different fertilizer application strategies (Bationo, Waswa, Okeyo, Maina, & Kihara, 2011; Zingore, Murwira, Delve, & Giller, 2007) as practiced by smallholder farmers in the different districts.

The spatial autocorrelation test that was done to test the significance of the distribution of the soil major nutrient contents are presented in Table 5. The hypothesis for the pattern analysis was that the nutrients levels across the study area were randomly distributed. In the theory of random patterns described by ESRI (2010), when *p*-value is very small (in this study *p* < 0.05) and *z*-value is either

Figure 4a. Spatial distribution of total soil nitrogen contents in 16 districts within the Northern region of Ghana.

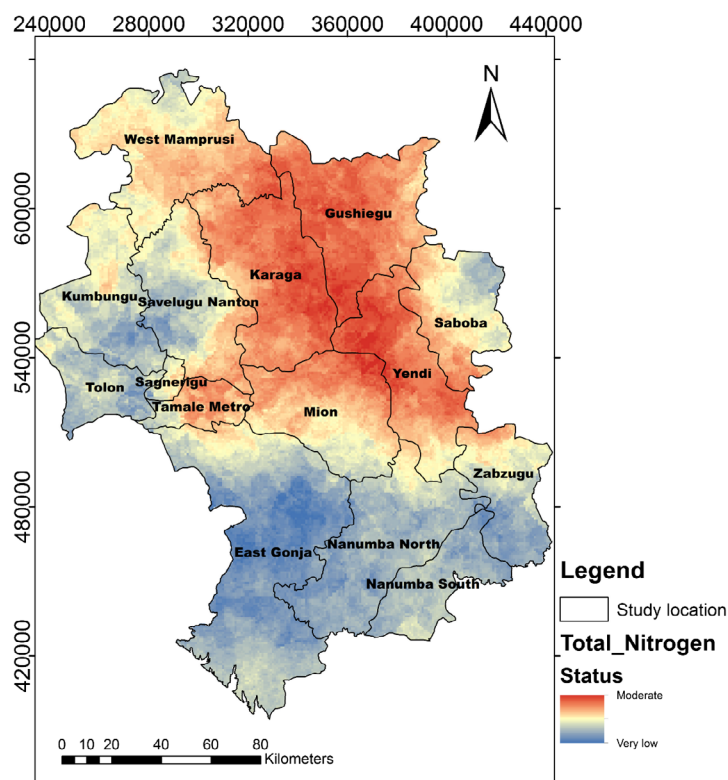


Figure 4b. Spatial distribution of available soil phosphorus contents in 16 districts within the Northern region of Ghana.

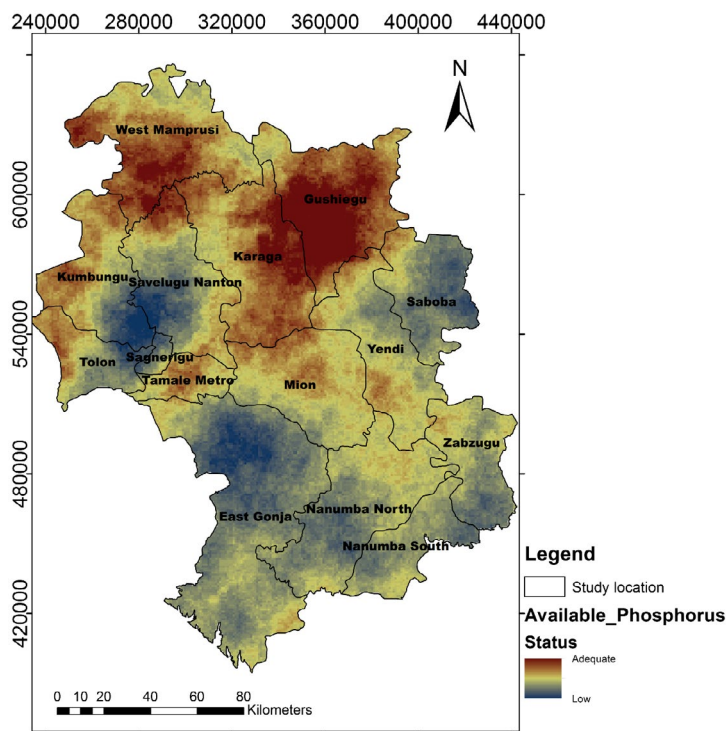


Figure 4c. Spatial distribution of exchangeable soil potassium contents in 16 districts within the Northern region of Ghana.

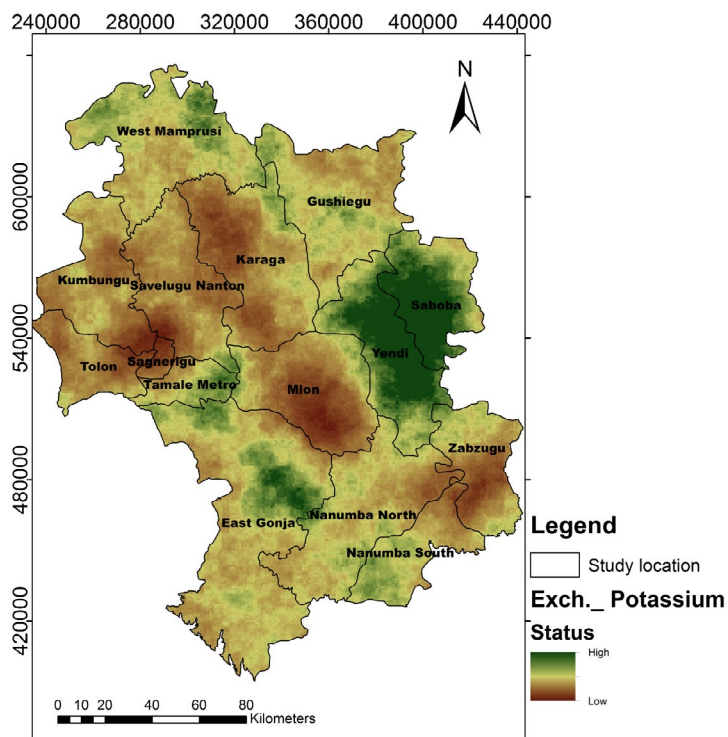


Table 5. Test of significance of pattern analysis for soil nutrient concentration; ($p < 0.05$) and ($1.96 < z < -1.96$)

	Nitrogen (N)	Phosphorus (P)	Potassium (K)
Moran's Index	0.28	0.04	0.27
Expected Index	-0.01	-0.01	-0.01
Variance	0.002	0.002	0.002
z-score	6.73	1.18	6.70
p-value	0.0003	0.24	0.0001

very high or very low ($1.96 < z < -1.96$), the spatial pattern is not likely to reflect a random form of distribution. In addition, a negative Moran's I index value indicates that the data are dispersed and a positive value indicates a tendency of clustering (clusters of high values only or low values only) at particular locations (Anselin, 1996). Test of significance for values returned by the analysis of the major soil nutrients indicated that N and K have clustered distributions in the study area (Table 5); with low levels clustered at one location and high levels at the other. On the other hand, the pattern of distribution of P did not appear to be significantly different from a random distribution.

Management strategies towards soil N, P and K nutrients enhancement could be implemented in the districts using the spatial distribution maps (Figures 4a–4c) as guide. Soil spatial distribution maps, therefore, provide a quick reference and reliable means by which variability within soil nutrients can be assessed to make decisions on fertilizer allocation at specific locations (Schnug, Panten, & Haneklaus, 1998).

4. Conclusion

Geospatial analysis of soil nutrient contents in the study area has proved to be essential in identifying locations in the Northern region of Ghana, where N, P and K levels are relatively low, moderate and high, respectively. Large proportions of the area recorded nutrient levels below average (N = 97%, P = 72% and K = 12%) which indicated that the study area has low nutrient levels. Models of the distribution maps suggest that N and K nutrients levels were clustered spatially and the distribution pattern of P in the study area was a random one. The soil nutrient information on low levels of N, P and K contents in the study area could be improved using the spatial distribution maps as a guide for fertilizer allocation and management taking into account the pattern within the distribution. The spatial distribution maps generated through this study therefore provided foreknowledge of the N, P and K nutrients status in the districts which could be used by research scientists as bases for fertilizer recommendations. When these considerations are made, proper site-specific nutrient recommendations could be promoted in order to increase soil nutrient fertility in the region.

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