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A precision nutrient variability study of an experimental plot in Mukono Agricultural Research and Development Institute, Mukono, Uganda

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The spatial soil fertility status of a 2.5 ha experimental plot was generated by mapping the soil nutrient concentration and fertility status using GIS kriging technique. The research was conducted in Mukono Zonal Agricultural Research and Development Institute, Mukono, Uganda in October 2013. Soil samples across the experimental plot were randomly taken for laboratory analysis of nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg) and the organic matter content. The mean values of N, P, K, Ca, Mg and the organic matter content were 0.16%, 13.7 ppm, 0.44 cmol/kg, 5.35 cmol/kg, 4.83 cmol/kg and 2.78% respectively. The spatial concentration of each element and the organic matter was carried out by the interpolation technique using the 3D Analyst/Raster Interpolation/Kriging Tools while the overlay operations to generate the soil fertility map was carried out using the 3D Analyst/Raster Math Tools in ArcMap. The autocorrelation analysis was carried out using the Spatial Statistics/Spatial Autocorrelation Tools. The autocorrelation analysis indicated N, Ca, Mg and organic matter to be somewhat clustered each with the Moran's 1 Index of 0.37, P was clustered with Moran's 1 Index of 0.5 while potassium pattern was neither clustered nor dispersed. The spatial soil fertility pattern reflected the distribution of nutrient concentration.

Key words: Nutrient variability mapping, Kriging technique, fertility mapping.

INTRODUCTION

The mapping of nutrient distribution in soils had been reported in previous investigations (Jobbagy and

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Jackson, 2001; She and Shao, 2009; Craine and Dybzinski, 2013; Laiho et al., 2004; Salehi et al., 2013). The five major factors influencing soil formation and nutrient distribution were climate, organisms, relief, parent materials and time (Gebrelibanos and Assen, 2013). The effects of climate and organisms were explained in Jobbagy and Jackson (2000) on the distribution of soil organic carbon in the soil profile where it was observed that at a given climate, the percentage soil organic carbon in the soil was deepest in the shrublands, intermediate in grassland and shallowest in forests. The effects of parent rock and parent materials on soil chemical properties and nutrient distribution was discussed in the relationship among the six main rock types identified in south west Nigeria and the corresponding soil associations (Smyth and Montgomery, 1962; Periaswamy and Ashaye, 1982). In the report, the soils of Iwo soil association, were related to the coarse grained granite and gneisses, Ondo soil association related to the medium grained granites and gneisses, Egbeda soil association related to the fine grained biotite gneisses and schists, Itagunmodi soil association related to the amphibolites, Okemessi soil association related to quartz gneisses and schists, Mamu soil association related to sericite schists.

The spatial distribution pattern of soil nutrients and their relationships with topographic factors were reported in a research conducted by Song et al. (2011) in the Huangshui River drainage basin, China where slope curvature was observed to have significant effects on spatial distribution of nutrients and the generated digital mapping of the soil nutrients provided data support for the precise management of soil resources in the study area.

The use of remotely sensed imagery in assessing soil nutrient concentration was demonstrated by Chen et al. (2000) in the determination of soil organic carbon concentration using aerial photograph of a bare soil of a 115-ha field, located in Crisp County, Georgia. The use of geostatistical technique in mapping soil nutrient content was also demonstrated in the research by Ismail and Junusi (2009) in a Durian Orchard at Beudang, Malaysia using the Geostatistic Plus (GS++) tool to quantify the spatial nutrient content to predict nutrient values at unsampled location.

The spatial variability of soil nutrients could be conducted by either the grid-cell or grid point methods. The grid-cell method involved dividing fields into square cells and composting soil cores to give one sample per cell while the grid point method involved soil sampling at grid intersection points spaced on a square grid. Soil nutrient maps could then be generated by such methods as Delaunay triangulation, polynomial trend surface, inverse distance squared gridding, point kriging and block kriging (Wollenhaupt et al., 2013).

The spatial distribution of nutrient which employed interpolation methods were demonstrated in the spatial interpolation of soil pH across the Loess Plateau, China using the inverse distance weighted (IDW), splines, ordinary kriging and cokriging methods (Liu et al., 2013). The several other investigations conducted to assess spatial variability of nutrients had been previously reported (Sadeghi et al., 2006; Shah et al., 2013).

The objective of the research was to use the GIS kriging technique to produce precision soil nutrient concentration and fertility maps of a 2.5-ha experimental land in Mukono Agricultural Research and Development Institute Mukono, Uganda.

MATERIALS AND METHODS

Soil sampling and laboratory analysis

Soil samples to a depth of 25 cm from randomly selected locations across the 2.5 hectare experimental area were taken for laboratory analysis. Soil samples were air-dried and sieved through a 2 mm sieve and analysed for N, P, K, Ca, Mg and organic matter content following the laboratory procedures described by Carter (1993). Organic carbon was determined by oxidising soil sample with dichromate solution and later titrated with ferrous sulphate solution. The total nitrogen was determined using micro-kjeldahl method and the available P determined by the Bray P-1 method. The exchangeable cations of K, Ca and Mg were extracted by leaching 5 g of soil with 100 ml ammonium acetate at pH 7 and the potassium in the leachate determined with a flame spectrophotometer while Ca and Mg were determined with atomic absorption spectrophotometer.

Interpolation technique for spatial distribution of nitrogen, phosphorus, potassium and the organic matter content and overlay operations for production of soil fertility map

The values of the nutrients input in Microsoft Excel and saved in coma delimited (csv) file format was added as a layer on the map in ArcMap in the Projected Coordinate Systems WGS 1984 UTM zone 31N. It was added as a layer and exported to Shape file through the Data/Export Data pathway. The spatial distribution of N, P, K, Ca, Mg concentration and the organic matter content was carried out separately for each element with the 3D Analyst/Raster Interpolation/Kriging Tools while the overlay operations to generate the soil fertility map was carried out using the 3D Analyst/Raster Math/Plus Tools in ArcMap. The autocorrelation analysis was carried out using the Spatial Statistics/Analyzing Patterns/Spatial Autocorrelation Tools.

RESULTS

Table 1 shows the coordinates of the perimeter and the

Table 1. Coordinates of the perimeter and the soil sampling locations.

Coordinates of the experimental land perimeter		Coordinates of the soil sampling locations	
Easting	**Northing**	**Easting**	**Northing**
470299	42304	470320	42292
470435	42326	470363	42301
470481	42242	470420	42312
470316	42214	470324	42267
470299	42304	470329	42228
		470354	42241
		470390	42238
		470381	42259
		470439	42252
		470431	42284
		470362	42271
		470339	42280
		470400	42285
		470410	42262

soil sampling locations of the 2.5 ha experimental plot while Figure 1 shows the spatial representation of soil sampling locations. The sampling locations were randomly selected across the experimental land with each representing an area within 10 m radius. On the map part of the administrative block and the major road from the main gate are shown.

Table 2 shows the values of nutrient elements with the mean values and the organic matter content as 0.16%, 13.7 ppm, 0.44 cmol/kg, 5.35 cmol/kg, 4.83 cmol/kg and 2.78%, respectively.

Figures 2, 3, 4, 5, 6 and 7 show the spatial concentration of nitrogen, phosphorus, potassium, calcium, magnesium and the organic matter content, respectively, while Figure 8 showed the soil fertility map. The autocorrelation analysis indicated N, Ca, Mg and organic matter to be somewhat clustered with the Moran's 1 Index of 0.37, phosphorus was clustered with Moran's 1 Index of 0.5 while potassium was neither clustered nor dispersed with Moran's 1Index of 0.28. The soil fertility classes I, II and III on the soil fertility map indicated low, medium and high fertility status respectively.

DISCUSSION

The attribute data which indicated the coordinates of the perimeter and soil sampling locations in Table 1 was used to generate the spatial data in Figure 1. This corroborated the previous study by Murray and Shyy (2000) on the integration of attribute and spatial data for identifying patterns in spatial information. The previous investigation by Andrienko and Andrienko (2001) also reported on the technique of analysis of numerical data associated with area geographical objects. The attribute data had been described to contain information about the features on a map that was linked to the map and the linkage achieved by specifying variables in the attribute data set and composite association in the spatial definition that had the same values (GISTUTOR, 2001).

The spatial concentration of each of N, P, K, Ca, Mg and the organic matter content in Figures 2 to 7 was generated through interpolation method of kriging. The interpolation technique enabled predicted values to be assigned to all other locations to create continuous surface representation of the nutrient concentration. This corroborated with the research findings of Oliver and Webster (1999) in the stochastic models of spatial variation in the mapping of soil salinity in the Jordan Valley of Israel and also the herbaceous cover in semi-arid Botswana. The geostatistical interpolation technique of kriging was also used to prepare the landslide susceptibility analysis map of Kota Kinabalu in Malaysia to locate areas prone to landslides (Roslee et al., 2012). The degree of accuracy of kriging technique in the prediction of soil properties was explained in the report of Omran (2012) in the descriptive tools of semivariograms to characterize the spatial patterns of continuous and categorical soil attributes. The application of kriging technique had been premised on the principle that soil properties closer together would tend to be more alike

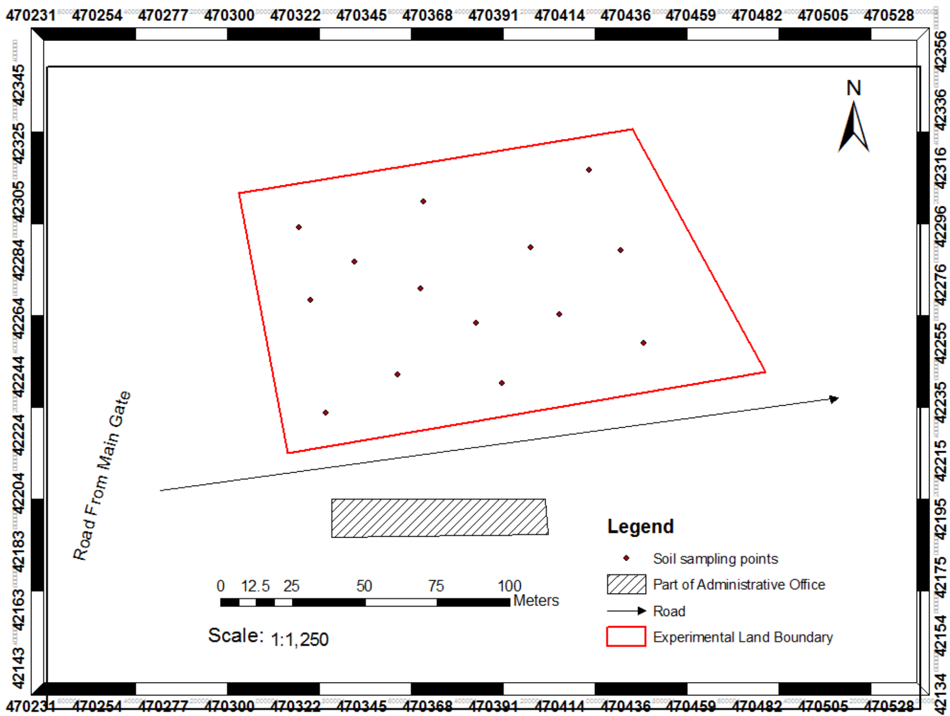

Figure 1. Experimental site with soil sampling locations.

Table 2. The values of N, P, K, Ca, Mg and the organic matter content at each sample location.

Easting	Northing	Nitrogen (%)	Phosphorus (ppm)	Potassium (cmol/kg)	Calcium (cmol/kg)	Magnesium (cmol/kg)	Organic matter (%)
470320	42292	0.16	13.4	0.36	4.48	4.88	2.78
470363	42301	0.12	11.8	0.28	3.68	4.22	2.12
470420	42312	0.14	11.2	0.21	3.24	3.86	2.12
470324	42267	0.19	15.7	0.70	8.17	5.56	3.60
470329	42228	0.18	14.8	0.65	7.49	5.48	3.46
470354	42241	0.19	15.6	0.54	6.56	5.42	3.24
470390	42238	0.18	14.9	0.71	6.52	5.52	3.42
470381	42259	0.14	13.9	0.43	5.52	4.86	2.86
470439	42252	0.13	13.2	0.34	3.86	4.14	2.26
470431	42284	0.14	11.6	0.24	4.42	4.64	2.88
470362	42271	0.15	13.8	0.42	5.58	5.24	2.88
470339	42280	0.17	14.1	0.51	6.51	5.38	2.86
470400	42285	0.15	13.6	0.32	4.40	4.12	2.14
470410	42262	0.14	13.6	0.41	4.42	4.32	2.24

than the distant points and the interpolation was a prediction made within the spatial extent of the measured locations.

The spatial concentration of the nutrient elements from the autocorrelation analysis which indicated N, Ca, Mg and organic matter to be somewhat clustered each with

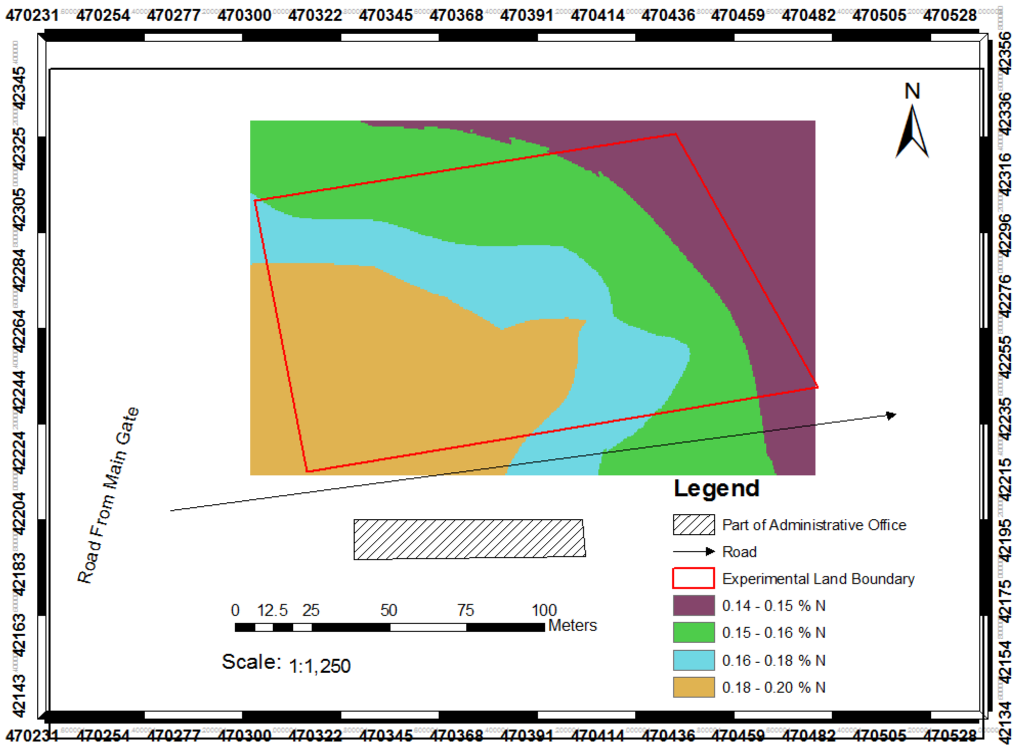

Figure 2. Nitrogen spatial concentration.

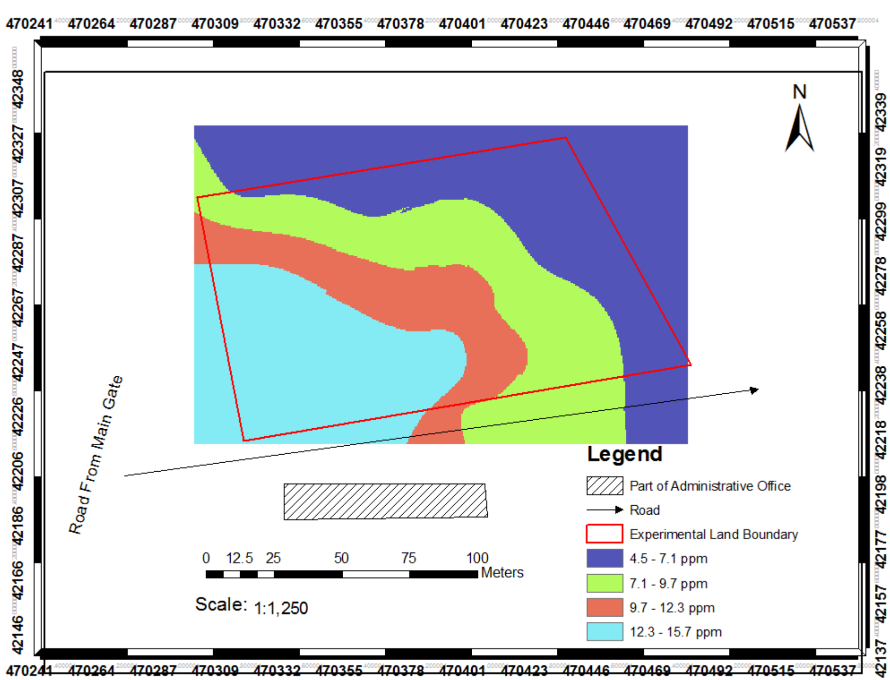

Figure 3. Phosphorus spatial concentration.

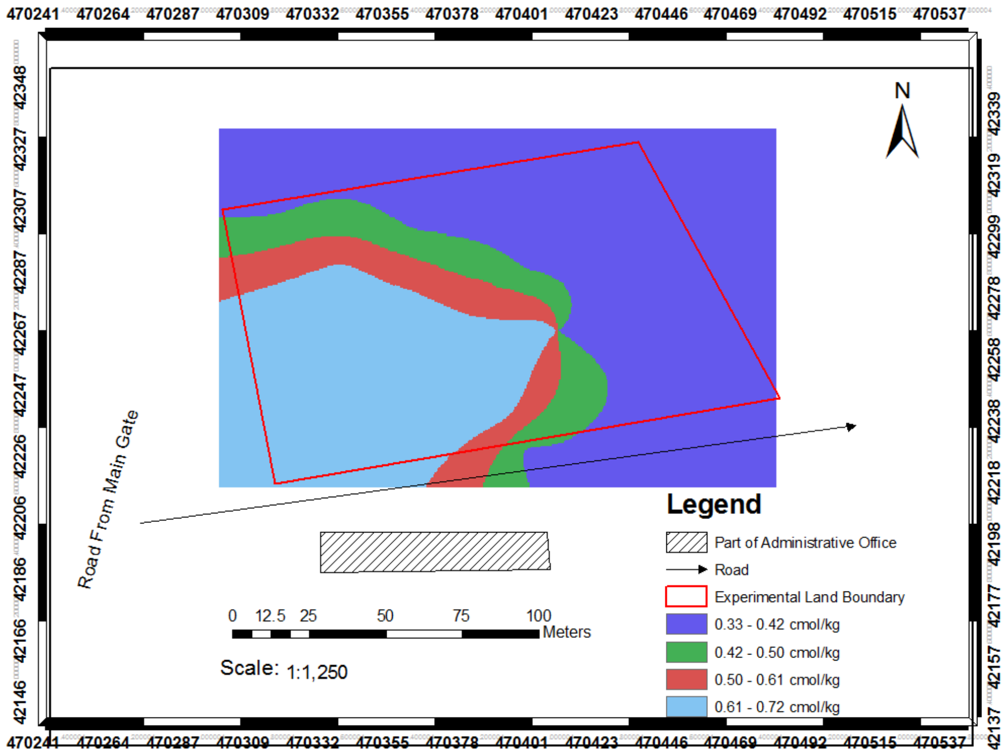

Figure 4. Potassium spatial concentration.

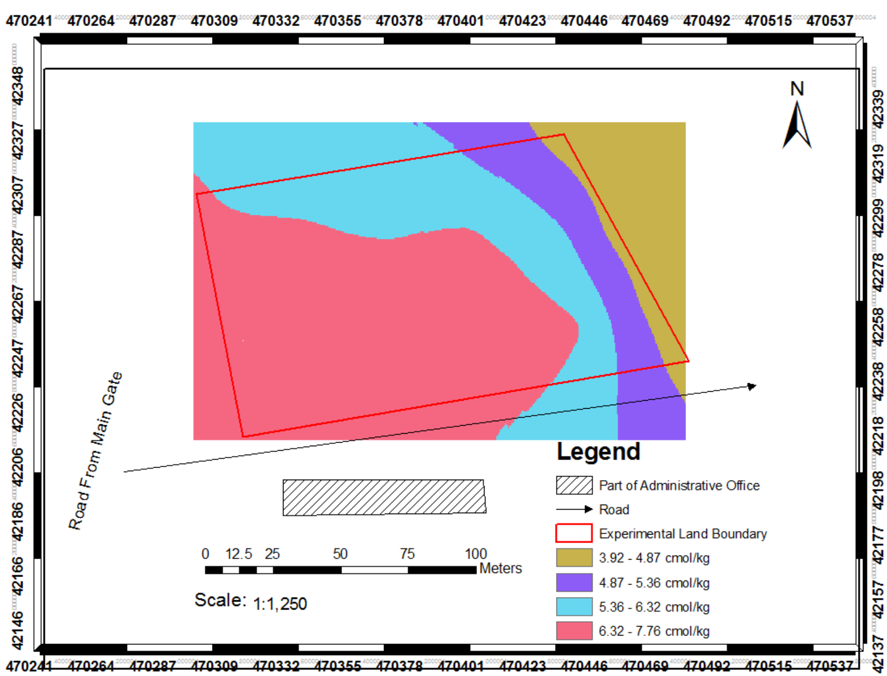

Figure 5. Calcium spatial concentration.

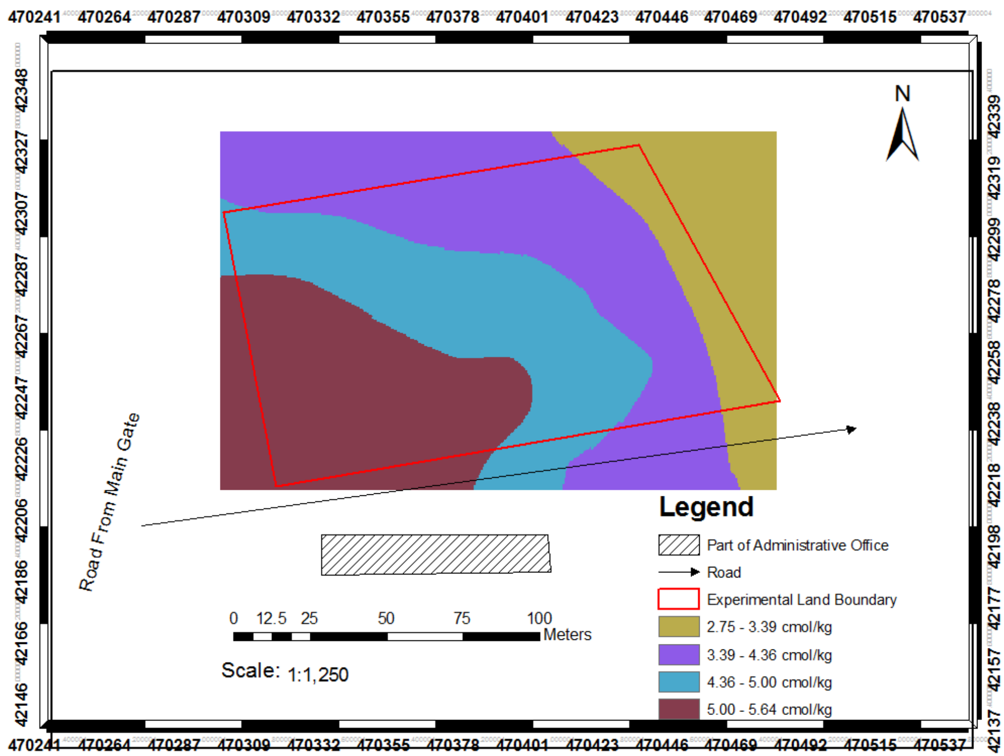

Figure 6. Magnessium spatial concentration.

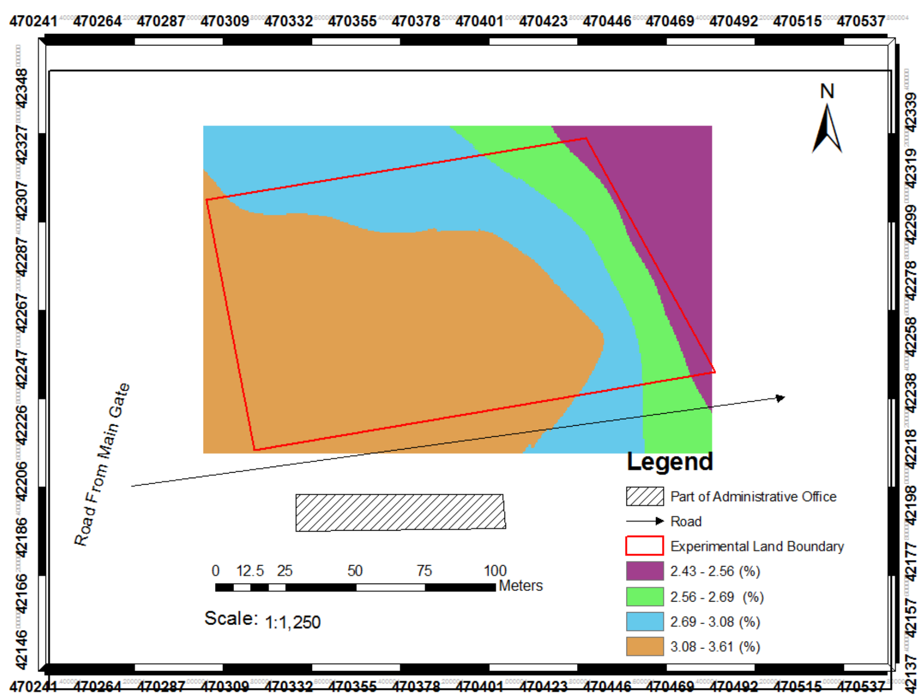

Figure 7. Organic matter spatial distribution.

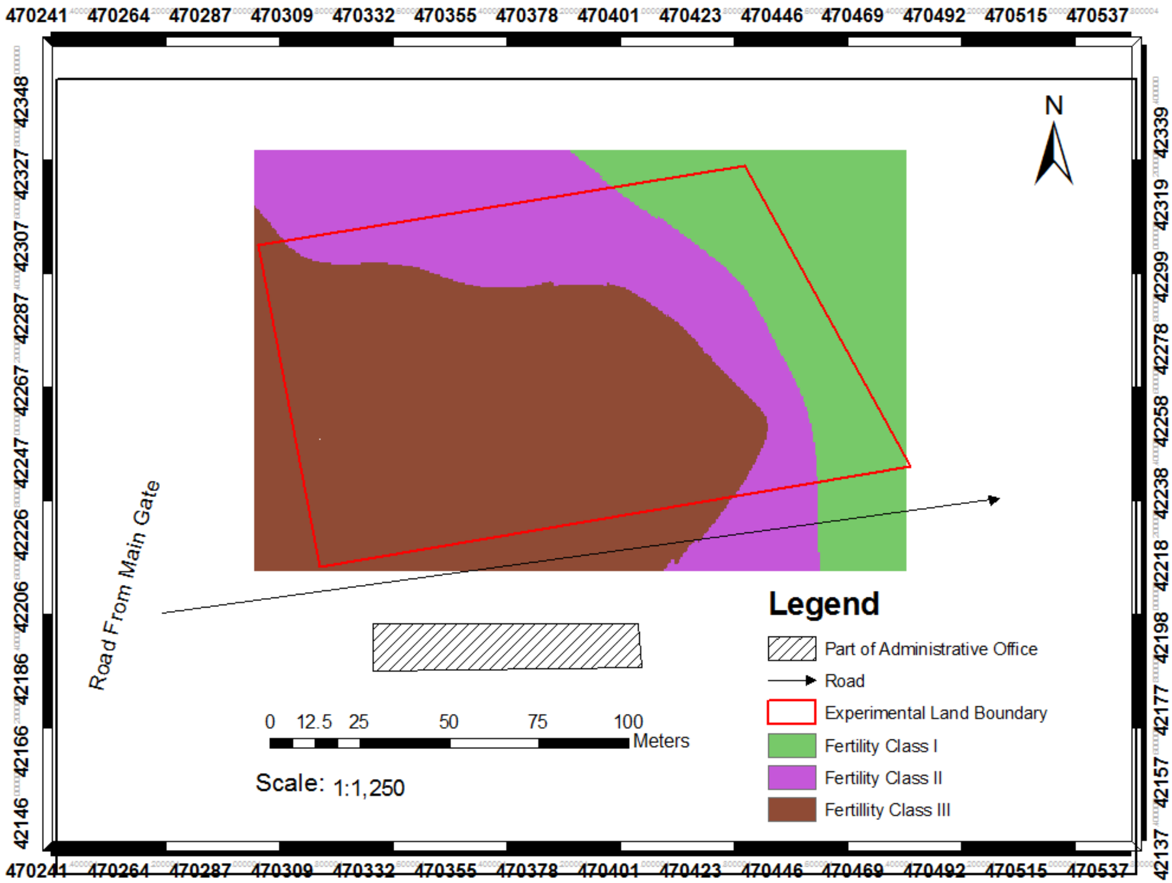

Figure 8. Soil fertility map.

the Moran's 1 Index of 0.37, P with clustered pattern with Moran's Index of 0.5 and K which was neither clustered nor dispersed with Moran's Index of 0.28 corroborated earlier observation of Huo et al. (2010, 2011) on the improvement of spatial interpolation accuracy of heavy metals concentration in soils and also in the autocorrelation analysis of soil pollution data on soils in Taiwan (Chu and Chang, 2011).

The spatial nutrient concentration maps integrated in an overlay operation to generate the soil fertility map corroborated the overlay procedure adopted by Onunkwo-Akunne et al. (2012) for the production of industrial, residential and waste disposal maps that were further superimposed to produce a composite land use map useful for regional and urban planning.

The spatial distribution of the soil fertility status of the experimental land as shown in Figure 8 reflected the spatial concentration of nutrients in Figures 2 to 7 which corroborated the previous observation of Salehi et al. (2013) on the determination of soil fertility status from the nutrient concentration.

Conclusion

The somewhat clustered nutrient concentration pattern observed could be adduced to past fertilizer application and cropping pattern on the experimental land. The high mean values of 0.44 and 5.35 cmol/kg for K and Ca, respectively could be attributed to past continuous application of CAN and NPK. A situation map of nutrient distribution was generated with the use of GIS Kriging technique.

Conflict of Interests

The author(s) have not declared any conflict of interests.

REFERENCES

Andrienko G, Andrienko N (2001). Exploring spatial data with dominant attribute map and parallel coordinates. Computers, Environment and Urban Systems, 25:5-15.

Carter MR (1993). Soil Sampling and Methods of Soil Analysis. Canadian Society of Soil Science. Lewis Publishers, London. 823pp.

Chen F, Kissel DE, West LT, Adkins W (2000). Field-Scale Mapping of Surface Soil Organic Carbon Using Remotely Sensed Imagery. Soil Sci. Soc. Am. J. 64(2):746-753.

Chu H, Lin Y, Chang T (2011). Spatial Autocorrelation Analysis of Soil Pollution Data in Central Taiwan. International Conference on Computational Science and its Applications held in Spain. pp. 219-222.

Craine JM, Dybzinski R (2013). Mechanisms of plant competition for nutrients, water and light. Functional Ecol. 27(4): 833-840.

Gebrelibanos T, Assen M (2013). Effects of slope aspect and vegetation types on selected soil properties in a dryland Hirmi watershed and adjacent agro-ecosystem, northern highlands of Ethiopia. Afr. J. Ecol. doi: 10.1111/aje.12118.

GISTUTOR (2001). GIS Data: the link between spatial and attribute data. http://www.gistutor.com/esri-arcgis/1-beginner-arcgis-tutorials/4-gis-data- the-link-between-spatial-and-attribute-data.html

Huo XN, Li H, Sun DF, Zhou LD, Li BG (2010). Multiscale spatial structure of heavy metals in agricultural soils in Beijing. Environmental Monitoring Assessment, 164:605-616.

Huo XN, Zhang WW, Sun DF, Li H, Zhou LD, Li BG (2011). Spatial pattern analysis of heavy metals in Beijing agricultural soils based on spatial autocorrelation statistics. Int. J. Environ. Res. Public Health 8:2074-2089.

Ismail MH, Junusi RM (2009). Determining and Mapping Soil Nutrient Content Using Geostatistical Technique in a Durian Orchard in Malaysia. J. Agric. Sci. 1(1):86-91.

Jobbagy EG, Jackson RB (2000). The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol. Applic. 10:423-436.

Jobbagy EG, Jackson RB (2001). The distribution of soil nutrients with depth: Global patterns and the imprint of plants. Biogeochemistry 53:51-77.

Laiho R, Penttila T, Laine J (2004). Variation in soil nutrient concentrations and bulk density within peatland forest sites. Silva Fennica, 38(1):29-41.

Liu Z P, Shao MA, Wang YQ (2013). Large-scale spatial interpolation of soil pH across the Loess Plateau, China. Environmental Earth Sciences, 69(8):2731-2741.

Murray AT, Shyy T (2000). Integrating attribute and space characteristics in choropleth display and spatial data mining. Int. J. Geog. Inform. Sci. 14(7):649-667.

Oliver MA, Webster R (1999). Kriging: A method of interpolation for geographical information systems. Int. J. Geog. Information Systems, 4(3):313-332.

Omran E (2012). Improving the Prediction Accuracy of Soil Mapping through Geostatistics. Int. J. Geosci. 3(3):574-590.

Onunkwo-Akunne C, Onyekuru SO, Nwankwu GI (2012). Land Capability Index Mapping for Waste Disposal Landuse Option Using Geographic Information System (GIS) in Enugu Area, South Eastern Nigeria. J. Geog. Information System, 4:444-461.

Periaswamy SP, Ashaye TI (1982). Updated Classification of some Southwestern Nigeria Soils. Ife J. Agric. 4(1&2):25-41.

Roslee R, Jamaluddin TA, Talip MA (2012). Integration of GIS Using GEOSTAtistical INterpolation Techniques (Kriging) (GEOSTAINT-K) in Deterministic Models for Landslide Susceptibility Analysis (LSA) at Kota Kinabalu, Sabah, Malaysia. J. Geog. Geology, 4(1):18-32.

Sadeghi A, Graff CD, Starr J, Mc Carty G, Codling E, Seffon K (2006). Spatial Variability of Soil Phosphorus Levels Before and After Poultry Litter Application. Soil Sci. 171(11):850-857.

Salehi A, Ghorbanzadeh N, Salehi M (2013). Soil nutrient status, nutrient return and retranslocation in poplar species and clones in Northern Iran. J. Biogeosci. Forestry 6:341-346.

Shah Z, Malik W, Bhatti A, Rahman H (2013). Spatial Variability of Nutrients in Wheat Plants in Semi-arid Regions of Northwestern Pakistan. Communications in Soil Sci. and Plant Analysis, 44(16):2472-2487.

She DL, Shao MA (2009). Spatial variability of soil organic C and total N in a small catchment of the Loess Plateau, China. Acta Agriculturae Scandinavica, Section B. Soil and Plant Sci. 59(6):514-524.

Smyth AJ, Montgomery RF (1962). Soils and Land use in Central Western Nigeria, Ibadan Government Printer, pp 265.

Song X, Kou C, Chen J (2011). Soil nutrient distribution and its relations with topography in Huangshui River drainage basin. Chinese J. Appl. Ecol. 22(12):3163-3168.

Wollenhaupt NC, Wolkowski RP, Clayton MK (2013). Mapping soil test phosphorus and potassium for variable-rate fertilizer application. J. Production Agric. 7(4):441-448.