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Geostatistical investigation and GIS-based spatial distribution of some micronutrients in Wukari soils, Taraba State, Nigeria

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ABSTRACT

Mapping soil fertility is important for site-specific nutrient management; it gives an insight into soil nutrient content, which is crucial for land use planning, fertilizer recommendations, and sustainable management of soil resources. Micronutrient deficiency in the soil is a serious limitation for crop production. Evaluation and mapping the soil micronutrients of a particular area can be a possible solution to mitigating its deficiencies, as they will serve as a guide for nutrient management. A study was conducted in Wukari to quantify and visualize the distribution of pH, manganese, iron, and zinc within the study area. Soil samples were collected from 98 locations. The samples were analyzed for soil reaction (pH), manganese (Mn), iron (Fe), and zinc (Zn). A spatial map for pH, Mn, Fe, and Zn was developed through geostatistical analysis using an ordinary Kriging interpolator. The soil pH is slightly acidic to slightly alkaline (5.3 to 7.6), available manganese (0.01 to 13.97 mg/kg) with mean value of (3.00 mg/kg), available iron (0.43 to 21.20 mg/kg), with a mean value of 11.15 mg/kg, and available zinc content (0.04 to 15.27 mg kg1) has an average of 1.96 mg/kg. Based on the soil test results, the spatial variation of pH, Mn, Fe, and Zn was prepared. The spatial correlations (ranges) of soil properties varied from 8933.50 m for zinc to 16349.81 m for iron. The nugget/sill ratio of the semi-variogram model showed moderate spatial dependence for pH, manganese, and zinc (0.51, 0.59, 0.47), and weak spatial dependence for iron (0.85).

1.0 Introduction

Conventional soil management methods consider the entire field as one soil group and calculate the quantity of fertilizer needed for the entire land. Describing the spatial variation of soils in the field is a major problem when using modern, advanced technologies such as the Global Positioning System (GPS). The use of geographic information system (GIS) and GPS makes it easy to describe the spatial variation of soil fertility for a larger land area. For the collection, storage, retrieval, transformation, and display of data, geographic information systems (GIS) are powerful software tools (Burrough et al., 2015). The use of technologies such as GPS and GIS allows accurate mapping of fields and helps understand the spatial relationships between soil fertility factors (Burrough, 1998). Farmers can use site-specific soil fertility to ascertain the need for various nutrients on their farms.

Micronutrients are required in small quantities but are important for plant growth; their deficiencies in the soil can lead to severe crop failure, and excesses can be dangerous. Therefore, it is very important to examine their status on agricultural land for proper land management. Taking into account the spatial variation of soil fertility variables enables effective management of soil and allows for best fertilization based on the crop's specific needs (Khadka et al. 2019), thereby reducing the improper use of fertilizers. Despite Wukari's significance to Taraba State's agriculture sector, information on soil nutrients is still not available; consequently, the aim of this study is to create a spatial distribution map of micronutrients for Wukari local government area.

2.0. Materials and Methods

2.1. Study site

This study was conducted in Wukari local government area, in the southern part of Taraba State (Figure 1). Wukari is located between longitude 9^{o} 08′ and 10^{o} 23′ East (392487.77E, 81642288.39N) of the Greenwich Meridian and latitude 7° 35′ and 8° 15′ North (500000.00E, 90539916.70N) of the Equator. It is in the Guinean Savannah area in the Middle Belt region of Nigeria. The soil in the study area is light to medium, with some parts of the study area having heavy texture (Waizah and Onwu, 2024). Prior to sampling, a base map of the study area was created using ArcGIS 10.5. The entire study area was divided into a 5,000 x 5,000 m grid (Figure 2). The location of each auger sample collection point was geo-referenced. The grid map was used to identify boundaries and determine preliminary sampling points.

2.2. Soil sampling and laboratory analysis

Ninety-eight soil samples were collected using a coordinated soil sampling plan. At each sampling point, soil samples were collected at the depth of 0 – 30 cm around the geodetic control point using a soil auger to obtain composite sample, covering the entire study area. The samples were transported to the laboratory, air-dried, ground with a wooden pestle and mortar, sieved to remove pebbles, stones, and roots, and prepared for analysis. The Soil pH was determined potentiometrically using pH meter in the supernatant suspensions of a 1:2.5 soil to water ratio as described by Jaiswal (2003). The micronutrients (Fe, Mn, and Zn) was determined using the DTPA extraction method. The extractant 0.005*M* DTPA (diethylenetriaminepentaacetic acid), 0.1*M* triethanolamine, and 0.01*M* $CaCl_2$, with a pH of 7.3. 10 g of air-dry soil with 20 ml of extractant for 2 hours. The leachate is filtered, and Fe, Mn, and Zn, are measured in the filtrate by atomic absorption spectrophotometry. (Lindsay and Norwell, 1978).

2.3. Geospatial analysis

The coordinates and data of the soil analysis results were entered into an attribute table in MS-Excel and processed with ArcGIS 10.5 software. Ordinary Kriging (OK) interpolation was used to predict values at un-sampled locations (Cressie, 1992). Ordinary Kriging (OK) and semi-variograms were used to evaluate and analyze spatially dependent variables. OK allows the interpolation of values from un-sampled locations and the creation of a map showing the spatial distribution of the variable.

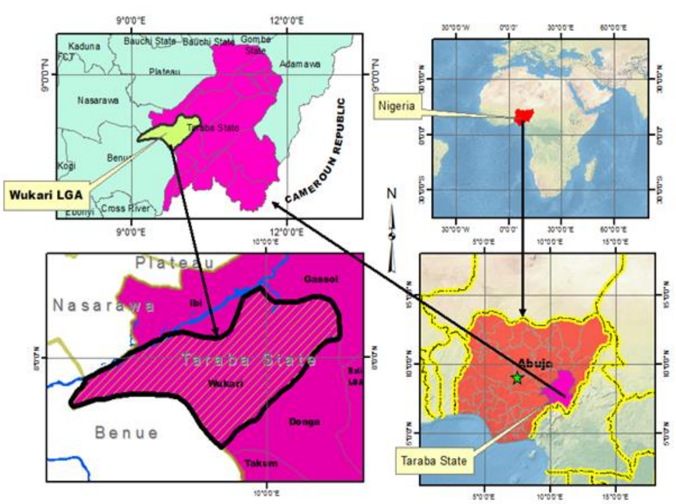


Fig. 1: study area (Source: Waizah *et, al* 2022)

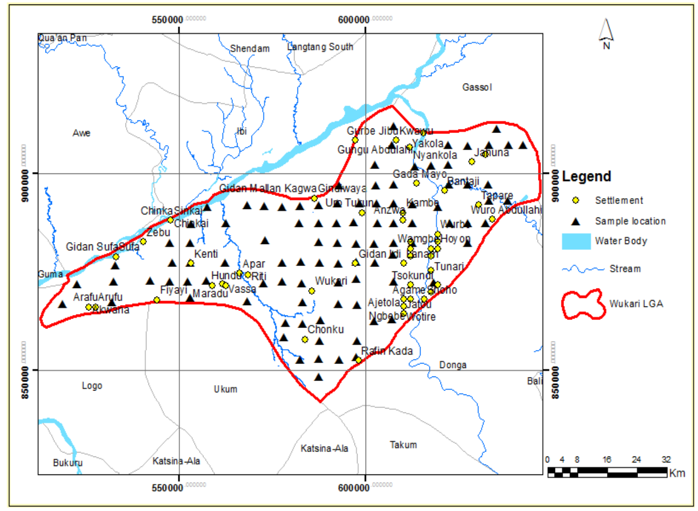


Fig. 2. Base Map of the Study Area (Source: Waizah et, al 2022)

2.4. Semi-variogram Modeling

ArcGIS 10.5 software was used to create spatial maps using ordinary kriging; a Gaussian model was fitted, and nugget, sill, and range were evaluated to determine the spatial distribution and spatial dependence of each of the soil micronutrients. The spatially dependent structure was investigated using semivariogram. The experimental semi-variogram was calculated using a geostatistical method as below.

$$y(h) = 1/2N(h)\ 1) \sum_{i=1}^{N(h)} [Z(xi) - Z(x+h)]^2$$

Where:

y (h) is experimental semi-variance, N (h) is the number of pairs of measured values Z(x), Z (xi + h) separated by a vector (h).

2.5. Cross validation

A cross-validation approach to evaluate the efficiency and error of soil property prediction maps was carried out. The root mean square error (RMSE) and mean error (ME) of the model were calculated. The smaller the RMSE and ME, the more accurate the map (Yaser *et al*., 2013).

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} \{Z(xi) - Z^*(xi)\}^2}$$

$$ME = 1/n \sum_{i=1}^{n} \{Z(xi) - Z^*(xi)\}$$

Where:
xi = prediction of variable X
n = number of records
Z(xi) = random variable at location xi

2.6. *Building the geostatistical model (spatial distribution map)*

The model shows spatial variance in micronutrient distribution across the study area. Geostatistical wizard ArcGIS 10.5 was used to create the model. The input dataset for Kriging modeling was the recorded soil sample properties defined by coordinates, and each micronutrient element was selected as a data field for interpolation. Once the model was created, the transformation and de-trending were displayed. The output surface was set as the "prediction surface" because the model predicts values at un-sampled locations.

Normal Quantile-Quantile (QQ) plots and trend analysis were conducted for soil nutrient components. Logarithmic transformation and Box-Cox were used to normalize soil properties that did not follow a normal distribution, and trend analysis was performed to adjust soil properties to the trend, which was done primarily to provide acceptable data for ordinary Kriging modeling of the spatial distribution of soil micronutrients in the study area and to provide a basis for mapping of soil micronutrients.

3.0. Results and Discussion

3.1. Descriptive statistics

Table 1 shows the level of pH, manganese (Mn), zinc (Zn), and iron (Fe). The maximum, minimum, mean, standard deviation (SD), and coefficient of variation (CV) of soil for the entire study area are displayed. The results reveal that the pH values ranged from 5.3 to 7.6, with the mean of 6.2, which is within the desirable soil pH range for optimum crop production. Soil pH plays an important role in nutrient availability, solubility, and plant growth (Brady and Weil, 2008). High pH reduces the availability of nutrients like Fe and Zn to plants (Wang *et al*., 2006).

Manganese level in the study area had a mean of 3.0 mg k/g and ranged between 0.01 mg /kg and 13.97 mg /kg. The lowest manganese mean values were found around Kenti, Chinkai, Zebu, Vassa, and Rafin Kada, whereas Arafu, Tapare, and Bantaje had moderate manganese levels (fig. 5). The available zinc concentration of the soil ranged between 0.04 mg/kg and 15.27 mg /kg, with the mean value of 1.96 mg/kg. Zinc concentrations were highest in Wukari, Kenti Arufu, and Gidan Idi, and the lowest was found around Nyankola, Tapare, Gadamayo, and Bantaje(fig 7). The available iron concentration ranged between 0.43 mg kg-1 to 21.20 mg /kg, with the mean value of 11.15 mg /kg recorded in Wukari, Chonku, Rafin Kada, Arufu, and Gindinwaya (fig 6).

3.2. *Fitted Semi-variogram Models of the Spartial Dependence of pH and micro nutrients*

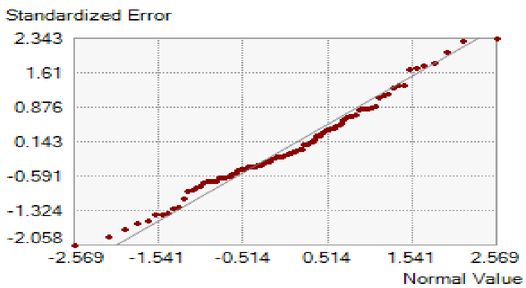
Table 1. Descriptive statistics

Parameter	N	Mean	Max	Min	STD	CV (%)	Kurt	Skew
pH	98	6.2	7.6	5.3	0.47	7.6	0.27	0.51
Mn ($mgkg^{-1}$)	98	3.00	13.97	0.015	2.50	83.25	4.58	1.92
Zn ($mgkg^{-1}$)	98	1.96	15.27	0.04	1.61	82.18	31.54	5.17
Fe ($mgkg^{-1}$)	98	11.15	21.20	0.43	5.36	48.07	-0.90	-0.22

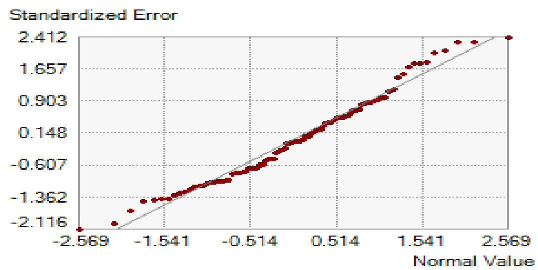
The (Q-Q) plot for pH, Mn, Zn and Fe (Figure 3) shows the ratio of expected to actual values in a normal distribution. This graph is used to test if a distribution is linear in terms of a normal distribution; if so, the dots cluster around a straight line. In this study, Q-Q plots revealed that pH, Mn, Zn, and Fe exhibited normal distributions between actual values and predicted values.

The results of the spatial data analysis describing the spatial dependence and variation of soil properties fitted to a Gaussian model are presented in Table 2. The area of the semivariogram is the maximum distance between correlated measurements and can be an effective criterion for evaluating sampling designs and mapping soil properties (Fu *et al.*, 2010; Utset *et al.*, 2000). The spatial correlations (ranges) of soil properties varied significantly, from 8933.50 m (zinc) to 16349.81 m (iron) Table 2. In general, nuggets were high in all evaluated micronutrients, indicating moderate to weak spatial dependence. Nugget-sill ratios are used to quantify the spatial variation of soil properties. Nugget-to-sill ratios smaller than 0.25 are thought to exhibit strong spatial dependence. Spatial dependence is classified as moderate when the ratio is between 0.25 and 0.75, and weak when it is greater than 0.75 (Cambardella et al., 1994; Antwi *et al*., 2016).

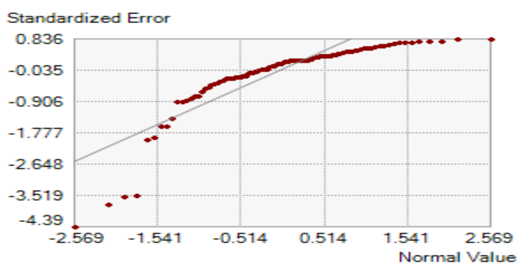
The nugget/sill ratio of the semivariogram model obtained from the study area showed moderate spatial dependence for pH, Mn, and Zn (0.48, 0.49, and 0.42) respectively, but weak for Fe (0.85). The results indicates that their spatial dependence is moderate to weak and controlled by extrinsic variations such as fertilizer application, tillage, soil and water conservation, and other management practices. The moderate to weak spatial dependence of these soil characteristics implies that the degree of correlation between soil properties at different places may increase as distance decreases. This shows that soil characteristics at closer distances within the study area may be the same, and farmers located within a closer distances are more likely to use the same fertilizer management practices regardless of their variation in soil nutrient (Gouri et al., 2018). As the distance increases, fertilizer management strategies may differ, and their dependence could become weaker on the impact of management (Johnson and Moen, 1998). According to the findings of this study, suggest that the moderate and weak spatial dependence of soil fertility parameters is due to soil and crop management practices (Cambardella *et al*., 1994).



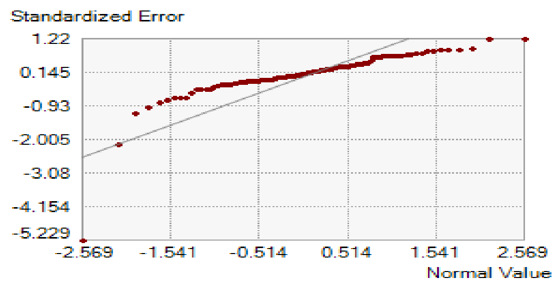
(A) pH



(B) Fe



(C) Mn



(D) Zn

Figure 3. (A, B, C and D)

Table. 2 Fitted Semi-variogramme Models for Soil properties

Properties	Model	Spatial Dependence.	Nugget	Partial Sill	Range (m)	Sill	Nugget/ Sill
pH	Guassian	Moderate	0.125375	0.086965	41829.84	0.259381	0.483362
Fe	Guassian	Weak	0.487135	0.11223	16349.81	0.572951	0.850212
Mn	Guassian	Moderate	0.862406	1.38554	13782.10	1.737404	0.496376
Zn	Guassian	Moderate	0.883679	2.002367	8933.50	2.100456	0.420703

3.3. Spatial Variability map

The findings of this study suggest the distribution of soil pH was moderately acidic in most of the study area, with slightly acidic to neutral values in the western part around Arufu and Akwana (Figure 4). The spatial distribution of manganese (Figure 5) showed high concentrations in the south, covering the Arufu and Akwana regions, while low concentrations were observed at Chinkai, Kenti, and Maradu in the eastern region. The distribution of iron (Figure 6) in the study area showed that iron concentrations were high in the central, western, and southern regions, while low concentrations were observed in areas such as Chinkai, Khenti, Gidan Idi, Vassa, and Wotire. The spatial distribution of Zn in the research area (Figure 7) revealed moderate to high concentration in the central and western parts of the study area with low concentration in the eastern part. The spatial distribution map showed the particular area where micronutrients need to be managed. Roslee *et al.* (2012) reported similar findings, using Kriging geostatistical interpolation approach to generate a landslide susceptibility study map for Kota Kinabalu, Malaysia, and identified landslide-prone locations.soil pore size distribution and water characteristics (Wu and Vomocil, 1988).

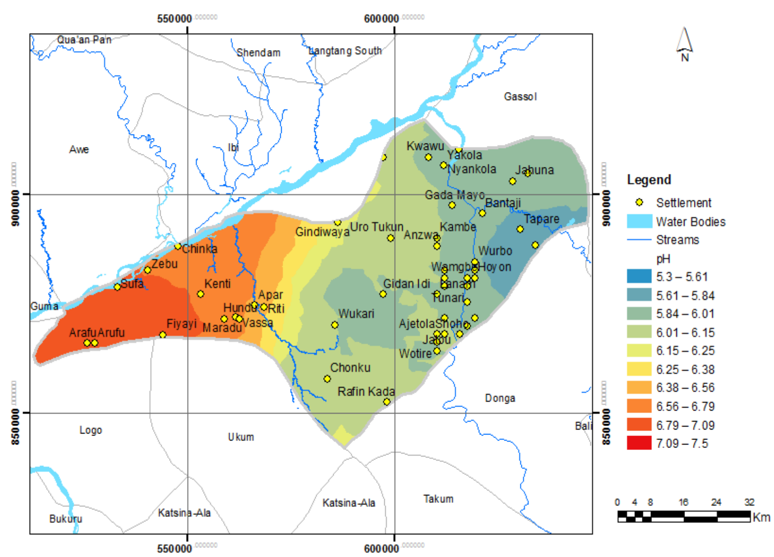


Figure 4. Spatial distribution map of pH

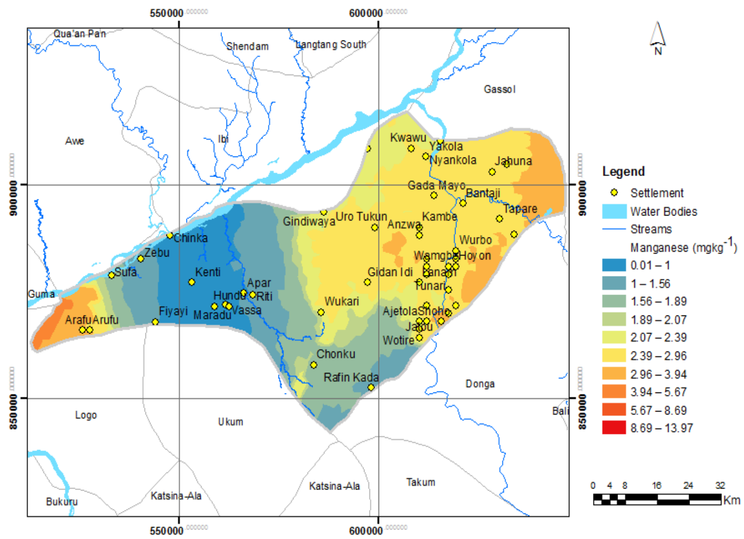


Figure 5. Spatial distribution map of pH

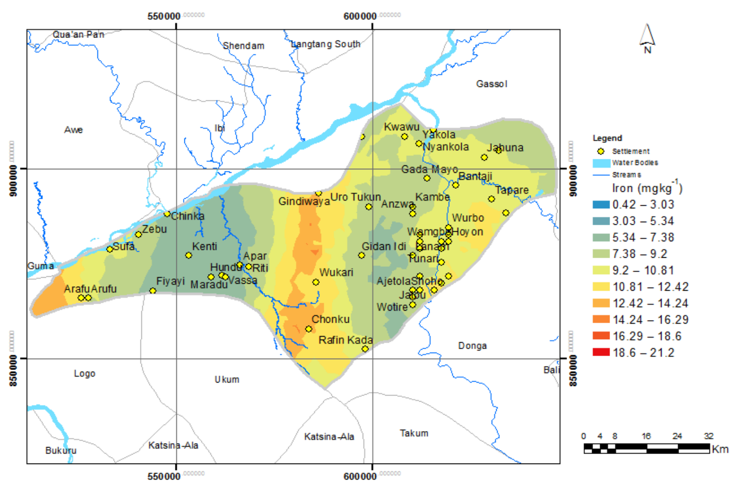


Figure 6. Spatial distribution map of Fe

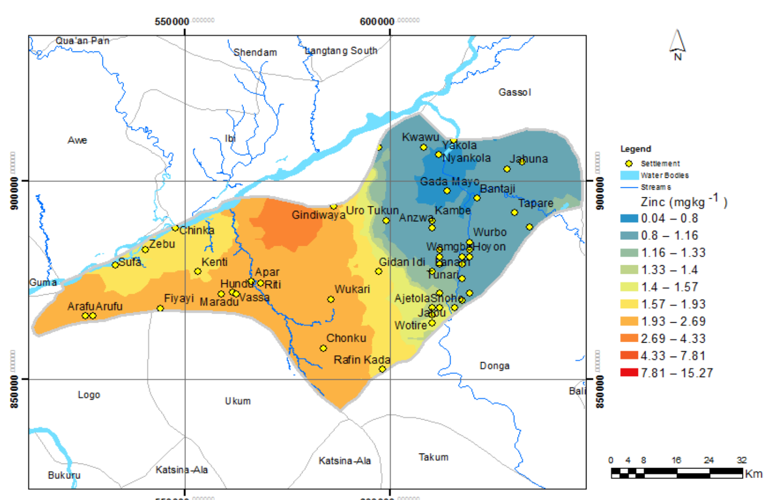


Figure 7. Spatial distribution map of Zn

4.0. Conclusion

Soil micronutrients are important in crop production, and their deficiencies offer a serious concern in Sub-Saharan Africa. Most people are unaware of the consequences, which therefore have great implications for soil, crops, animals, and humans. The knowledge of the spatial variability of Mn, Fe and, Zn is good for soil and environmental management and helps in the sustainable use of soil resources for optimum crop production. The results of this study revealed that the soil pH is slightly acidic to slightly alkaline, which is within the desirable soil pH for optimum crop production. The nuggets were high in all the micronutrients studied, showing moderate to weak spatial dependence. Moderate spatial dependence was observed for pH, manganese, and zinc, but weak for iron, this indicates that farmers located within a closer distances are more likely to use the same fertilizer management practices. The maps developed as a result of this study showed that there are adequate Mn, Fe and Zn in some areas, while others areas showed inadequacy. The maps developed during this study can be useful in determining plant species based on specific micronutrient fertilization and help in site specific management of Mn, Fe and Zn.

References

Antwi-Gyei P., C. H. Quinn, S. G.K. Adiku, S. N. A. Codjoe, A. J. Dougil, R. Lamboll, D. B. K. Dovie.. (2016) Perceived stressors of climate vulnerability across scales in the Savannah zone of Ghana: a participatory approach. *Regional Environmental. Change*, 17 (2016), pp. 213-227

Brady, N. C., & Weil, R. R. (2008). *The nature and properties of soils*. 14th edition, Prentice Hall Upper Saddle River, NJ: 13, 662-710

Burrough P.A., Rachael A. McDonnell and Christopher D. Lloyd (1998) *Principles of Geographical Information Systems*: 2nd Edition (Spatial Information Systems), Oxford publications

Burrough, P. A., McDonnell, R., McDonnell, R. A., & Lloyd, C. D. 2015. *Principles of geographical information systems*. Oxford University Press.

Cambardella, C.A., Moorman, T.B., Novak, J.M., Parkins, T.B., Karlen, D.L., Turco, R.F. and Konopka, A.E., 1994. Field scale variability of soil properties in Central Iowa soils. *Journal of Soil Science Society of America*. 58:1501-1511

Cressie, N. 1992, Smoothing Regional Maps Using Empirical Bayes Predictors. *Geographical Analysis*, 24: 75-95. https://doi.org/10.1111/j.1538-4632.1992.tb00253.x

Fu, W., Tunney, H. and Zhang, C. 2010. Spatial variation of soil nutrient in a dairy farm and its implication for site specific for fertilizer application. *Soil Tillage Research.* 106:185-193

Gouri, S. B., Pravat, K. S. and Rabindranath, C. 2018. Assessment of spatial variability of soil properties using geostatistical approach of lateritic soil West Bengal, India. *Anal of Agrarian Science*, 16:436-443

Jaiswal, P.C. (2003). Soil, Plant and Water Analysis.Kalyani Publishers, Ludhiana, New Delhi, *NordaHyderabab*, India.1-399 p

Johnson, B. G. and Moen, J. 1998. Patterns in species associations in plant communities: the importance of scale. *Journal of Vegetation Science*, 9(3):327-332

Khadka, D., Sushil, L., Rita, A., Sushila, J., Shree P. V., Kamal, S. and Netra, H. G. 2019. Soil fertility assessment and mapping spatial distribution of Agricultural Research Station,

Krige, D.G. 1951 A Statistical Approaches to Some Basic Mine Valuation Problems on the Witwatersrand. *Journal of the Chemical, Metallurgical and Mining Society of South Africa*, 52: 119-139.

Lindsay W L, Norvell W A 1978 Development of DTPA soil test for zinc, iron, manganese and copper. *Soil Science Society America Journal.* **42:** 421–428.

Mahesh K., Panwar N.R., Pandey C.B. and Jatav M.K. 2015 Spatial distribution of available nutrients in the potato growing areas of Banaskantha district of Gujarat. *Potato Journal. 42.* (2): 130-136.

Omran E. 2012 Improving the Prediction Accuracy of Soil Mapping through Geostatistics *International Journal of Geoscience.* 3(3): 574-590.

Roslee R., Jamaluddin T.A. and Talip M.A. 2012. Integration of GIS using Geostatistical Interpolation Techniques (kriging) (GEOSTAINT-K) in determine model for landslide susceptibility analysis (LSA) at Kota Kinabalu, Sabah, Malaysia. *Journal of Geography Geology*, 4(1), 18-32.

Utset, A., Lopez, T. and Diaz, M. 2000 a comparison of soil maps, Kriging and a combined methods for spatial prediction of bulk density and field capacity of ferrosols in the Havana Matanzas plain. *Geoderma*, 96:199-213

Waizah Yakub A. M. Saddiq and A. Salem 2022. Fertility capability classification of soils of Wukari, Taraba State, Nigeria. *FUW Journal of agriculture and life sciences.* Vol. No. 1 pp 163-178 *ISSN: 2545-5141; e-ISSN: 2545515X*

Waizah Yakub and Onwu Clement Alex 2024 Effect of cow dung and urea on some soil properties and growth of Amaranthus in Bennubyen flood plain in Wukari. *International Journal of Sustainable Agricultural Research* 11(1) ISSN(e): 2312-6477 ISSN(p): 2313 0393

Wang, J. P., Raman, H., Zhang, G. P., Mendham, N., & Zhou, M. X. 2006. Aluminium tolerance in barley (Hordeum vulgare L.): physiological mechanisms, genetics and screening methods. *Journal of Zhejiang University Science B*, 7(10), 769-787.

Yaser, S., Isa, E. B., Ardavan, K., Mohammad, H. S. and Mosen, B. B. 2013. Mapping soil texture using geostatisticsl methods (A case study of the shahrekord plain central Iran). *Arabianb JournaL of Geosciences*, 6 (9):3331-33.