Sahel Journal of Life Sciences FUDMA (SAJOLS)
June 2025 Vol. 3(2): 228-238
ISSN: 3027-0456 (Print)
ISSN: 1595-5915 (Online)
DOI: *https://doi.org/10.33003/sajols-2025-0302-28*

Research Article

Spatial and Geo-Statistical Analysis of Variability of the Soil Particle Size Distribution in River Wudil Floodplain, Kano State, Nigeria

***Yasir Ibrahim Khallah[1], Afiya Kabir Lamido[2], Bala Muhamad[3], and Anas Sulaiman Musa[4]**

[1]Association of Nigerian Authors (ANA), Kano State Branch, Kano Sate, Nigeria
[2]Department of Soil Science, Aliko Dangote University of Science and Technology, Kano State, Nigeria
[3]Audu Bako College of Agriculture, Thomas Dambatta, Kano State Nigeria
[4]Department of Soil Science, Kaduna State University, Kaduna State, Nigeria
****Corresponding Author's email***: yaseerkallah@yahoo.com; **Phone: +2348034629585**

ABSTRACT
This study was conducted to analyze the spatial and geo-statistical variability of the soil particle size distribution in River Wudil floodplain, Kano State, Nigeria. From the study area, 150 soil samples were collected at a depth of 0-30 cm, by 100 × 200 m regular, using systematic grid sampling technique. The soil particle size distribution (sand, silt, and clay) were measured in the laboratory using the Bouyoucos hydrometer method. After data curation, classical and geo-statistical analyses were used to describe soil properties and spatial correlation of soil characteristics. Spatial variability of the sand, silt, and clay particles was quantified through semi-variogram analysis and the respective surface maps were prepared through ordinary Kriging. The result revealed that clay contents have moderate spatial dependence, with nugget/sill ratios between 25-75%, while sand and silt have weak dependence with nugget/sill ratios of greater than 75%. The result showed that all the soil samples varied considerably all over the studied area. The sand distribution was observed to show the least level of variability, while the silt and clay distribution was observed to show moderate variability among the three measured parameters. In conclusion, the spatial distribution of the particle size distribution varied across the study area. The study recommends integrated soil fertility management, combining organic and inorganic fertilizers, due to moderate spatial dependence on clay content. A site-specific nutrient management strategy, accounting for structural and random factors, is suggested to address moderate spatial variability in silt and clay contents.

Keywords: Floodplain; Geostatistical Analysis; Kiriging; Spatial Variability; Soil Particle Size Distribution (PSD)

Citation: Khallah, Y.I., Lamido, A.K., Muhamad, B. & Musa, A.S. (2025). Spatial and Geo-Statistical Analysis of Variability of the Soil Particle Size Distribution in River Wudil Floodplain, Kano State, Nigeria. *Sahel Journal of Life Sciences FUDMA*, 3(2): 228-238. DOI: *https://doi.org/10.33003/sajols-2025-030222-28*

INTRODUCTION

Soil particle size distribution (PSD) is a fundamental soil physical property that governs a wide range of hydrological, ecological, and agricultural processes. It determines soil texture, which influences porosity, permeability, infiltration, erodibility, aeration, and the retention and transport of water and nutrients (Hillel, 2008; Brady and Weil, 2017). A detailed understanding of PSD is therefore critical for soil classification, land suitability assessment, irrigation management, and sustainable agricultural practices, particularly in floodplain ecosystems where natural and anthropogenic factors interact to shape soil heterogeneity (Jabro *et al.,* 2010, Silva Cruz *et al*., 2011).

Globally, numerous studies have highlighted the spatial variability of PSD in floodplains and its implications for soil fertility and land productivity (Yusuf *et al.*, 2020). For example, research along the Mississippi River floodplain demonstrated that sediment deposition and seasonal flooding contribute to significant spatial differences in soil texture, affecting crop yield variability (Allison and Hughes, 1983; Knighton, 1999). Similarly, studies in the Nile floodplain have linked soil texture heterogeneity to sediment transport dynamics and agricultural land use (Abdel-Magid *et al.,* 1987). In sub-Saharan Africa, investigations in the Niger floodplain emphasize the influence of hydrological regimes on spatial soil variability, which has important implications for soil conservation (Vrieling *et al.,* 2013).

In northern Nigeria, floodplains such as the River Wudil floodplain in Kano State are vital for irrigated agriculture due to their seasonal inundation, nutrient-rich alluvial deposits, and relatively high moisture retention (Adeoye *et al.,* 2021). However, despite the socioeconomic importance of these landscapes, comprehensive studies assessing the spatial variability of soil PSD remain limited. Existing regional surveys often focus on broad-scale soil fertility assessments without capturing fine-scale spatial patterns necessary for precision farming (Ibrahim *et al.*, 2016; Yusuf *et al., 2020*).

Geostatistical methods, including variogram modeling and kriging, have proven robust in quantifying spatial variability and providing spatially explicit estimates of soil properties (Goovaerts, 1997; Webster and Oliver, 2007). Recent advances in applying geostatistics in soil science support data-driven decision making for sustainable land management (McBratney *et al.,* 2003). Nevertheless, the application of these techniques remains underutilized in floodplain systems across sub-Saharan Africa, where site-specific soil information is critical for enhancing agricultural productivity and environmental conservation.

The main objective of this study is to assess the spatial variability of the soil particle size distribution in River Wudil floodplain, Kano State, Nigeria, using geostatistical techniques. The specific objectives of the study were to determine the status and degree of spatial variability of soil particle size distribution in the study area; to map out the spatial distribution of soil particle size distribution in the study area and; to assess relationships between the soil properties in the study area.

MATERIALS AND METHODS

Location of the Study Area

The study was conducted along Wudil River, which lies between latitude 11.798180^0 & 11.76196^0 north and longitude 8.8272030^0 & 8.762978^0 east. It covers a distance of 27.326 km, in Wudil Local Government, Kano State (Fig. 1).

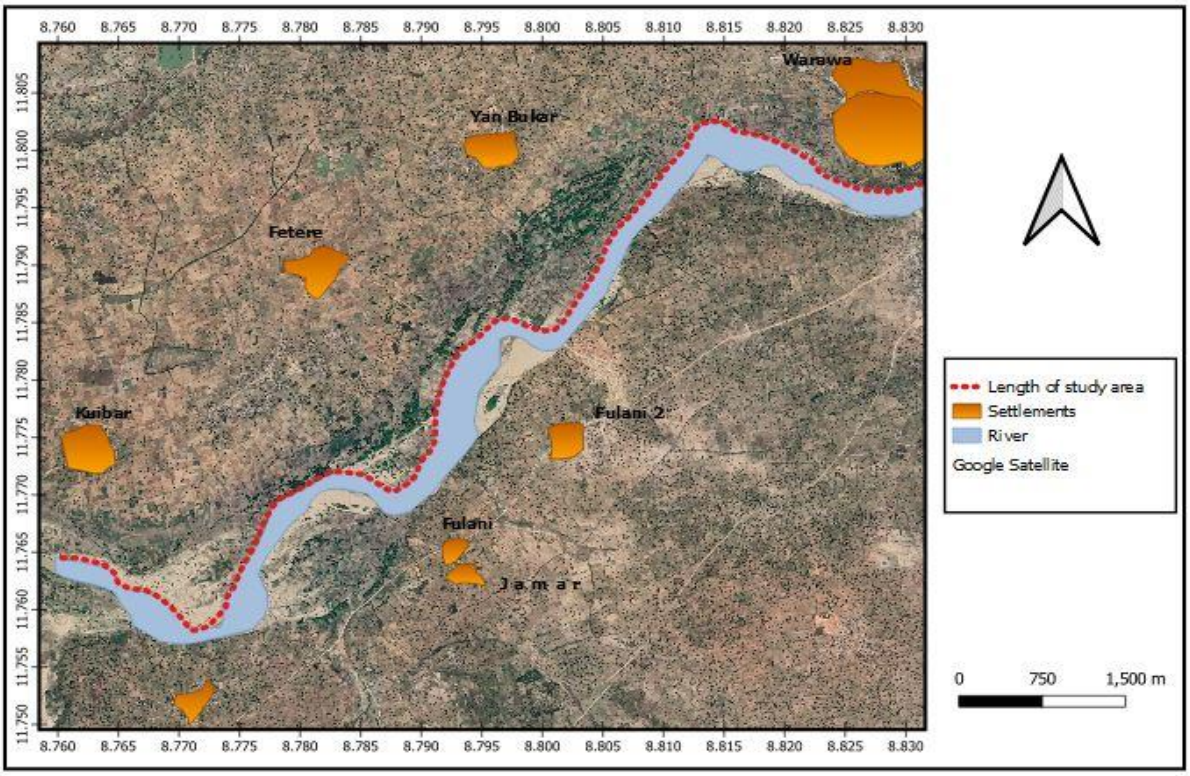

Figure 1: Location of the study area at River Wudil Floodplain
Source: Generated using ArcMap 10.3.1

Field Study

Reconnaissance visits were conducted to determine the extent of the floodplain area. The total extent of the floodplain area was found to be 27.326 km by 0.3 km. A 10 km by 0.3 km area was determined along the floodplain area using Google Maps, and other specific types of data like

coordinates and topographic data of the area were collected during the reconnaissance.
Arc GIS (version 10.3.1) was used to create a 300-meter buffer along the river beds (Fig. 2). The buffer created allows for uniform soil sampling. Grids of 100 by 200 meters were superimposed on the geotag-buffered areas. A total of 150 grid points identified within the buffer, were uploaded into the Geographic Positioning System (GPS) for accurate ground truthing and sampling (Fig. 3). The soil samples were collected at a depth of 0-30cm of each center of the grid points. Soil auger was used for sample collection. The soils were properly labelled, packaged and taken to the laboratory for analysis.

Laboratory Analysis

The collected soil samples were air-dried, ground and passed through a 2-mm sieve. The particle size analysis was determined using the Bouyoucos hydrometer method (Bouyoucos, 1936), using distilled water and Calgon solution (sodium hexametaphosphate) as dispersing agent at the Central Lab of the Center for Dryland Agriculture (CDA) Bayero University, Kano.

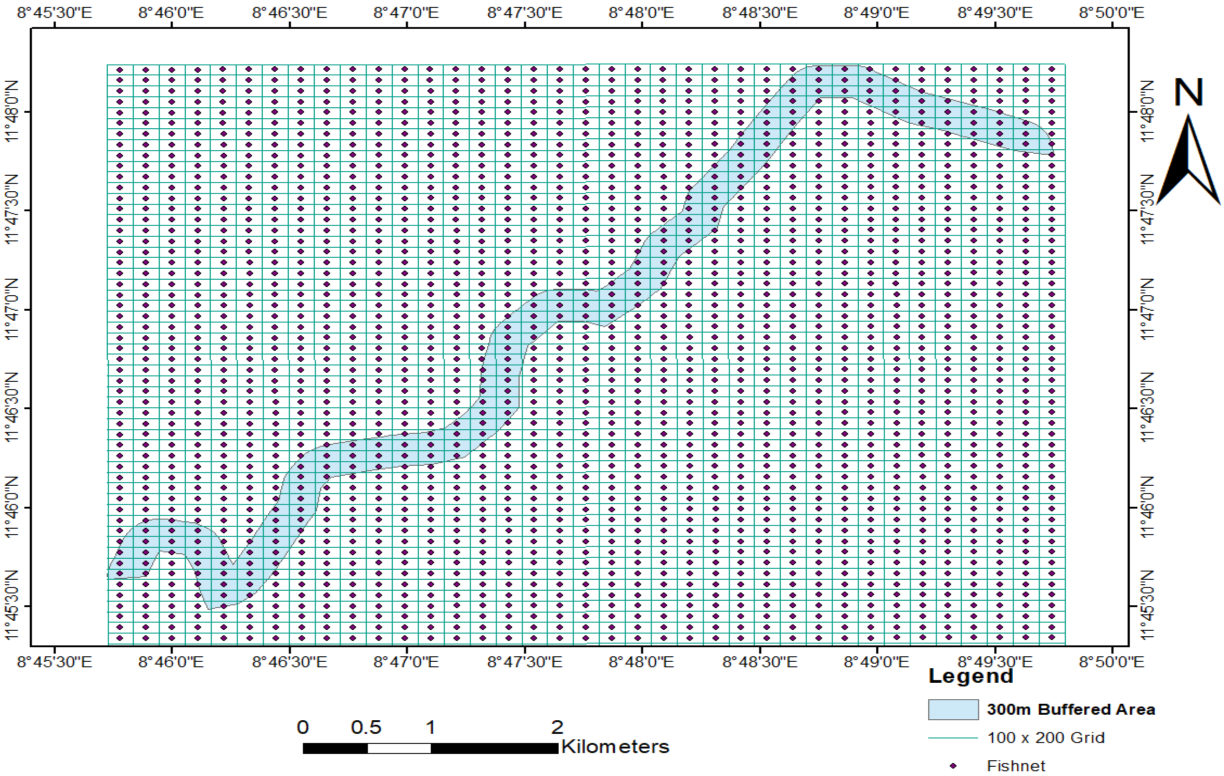

Figure 2: Map Showing the 300 Meters Buffer, a Fishnet and a Grid of 100 by 200 Meters

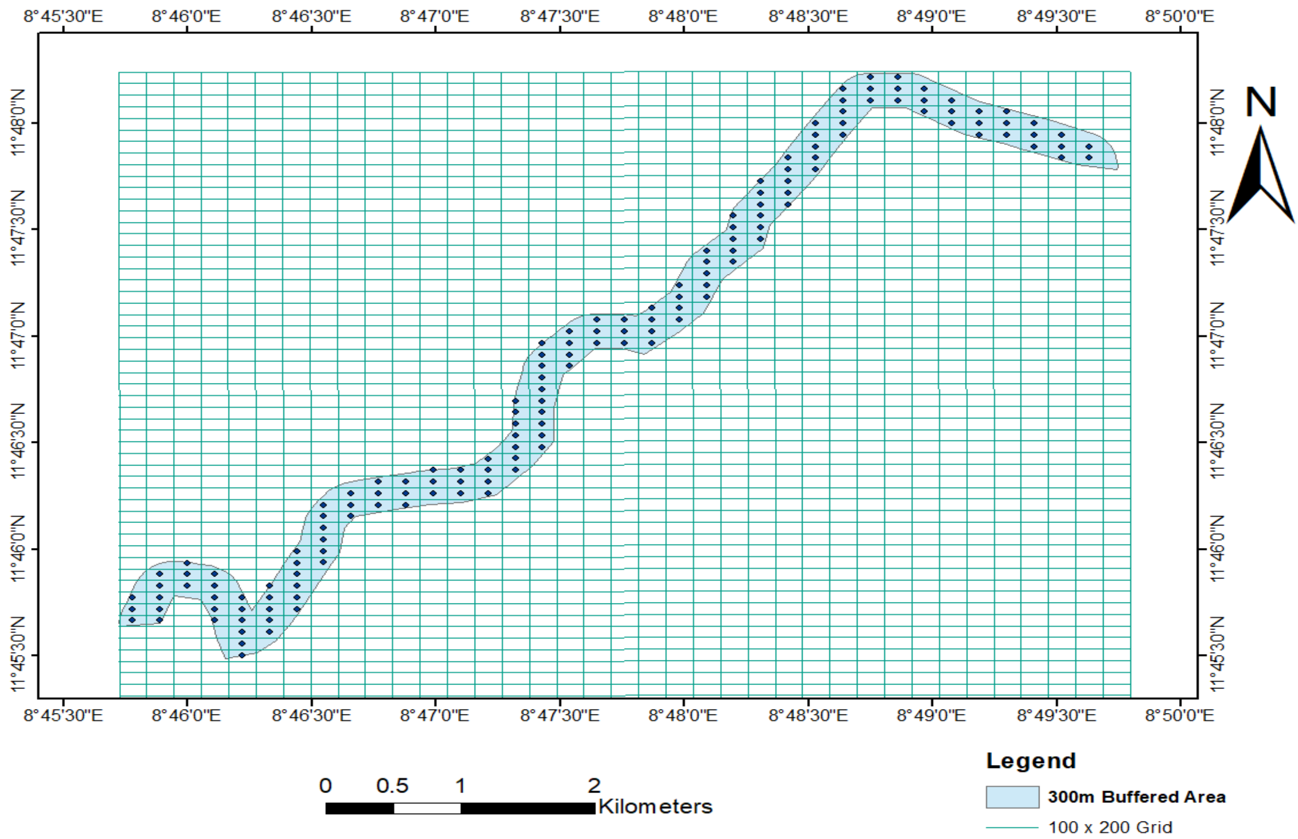

Figure 3: Map Showing the Sampling Points in the Study Area

Data Analysis

Descriptive Statistics

To understand the characteristics of the collected data, descriptive statistics (mean, median, minimum, maximum, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis) were employed using JMP Pro 15.0 Statistical Software. Moreover, a correlation matrix was used to evaluate the relationship between the soil properties.

The degree of spatial variability was determined from the Coefficient of Variation (CV) of the data obtained from the result of the descriptive statistics. Soil properties having a coefficient of variation (CV) between 0 and 15 % are considered least variable, 15 and 35 %, moderately variable, and bigger than 35 % highly variable, as stated by Ogunkunle (1993).

Geostatistical Analysis

Geostatistical software (ArcMap10.3.1) was used to analyze the spatial dependence and to map out the spatial distribution of the soil properties. The degree of spatial dependence for each variable was determined with geostatistical methods using semivariogram analysis and kriging. Ordinary Kriging was selected as a geostatistical method because it is considered one of the most accurate interpolation techniques, which assumes that variables close in space tend to be more similar than those further away (Goovaerts, 1999).

The hypothesis and parities used to calculate semivariograms were described by Burgess and Webster (1980). Experimental semivariograms were obtained from omnidirectional semivariances, $\gamma(h)$, of a set of spatial observations, z (x_i), which were calculated as:

$$\gamma\,(h) = \frac{1}{2N\,(h)}\sum_{i=1}^{N\,(h)}[Z_{(i+h)} - Z_i]^2$$

Where (h) is the number of experimental pairs [Z*(i+h),* Z *i*] of data separated by a vector h.

Experimental semivariograms were fitted by theoretical models with parameters: nugget (Co), sill (Co+C_1), and range of spatial dependence (a). Model selection for semivariograms was performed based on nugget and mean error (ME).

Using the Geostatistical Analyst tool (ArcGIS) and selecting the ordinary kriging methods, a semivariogram was created for each measured property. In the Kriging method, different semivariogram models (spherical, exponential, circular and stable) were evaluated, and the best-fitted model of each parameter was selected using a cross-validation technique, which permits the evaluation of the prediction accuracy. Mathematical models with minimum Mean Error

(ME) and nugget values that are closer to zero were selected.

In the cross-validation techniques, statistical tools involving Mean Error (ME) and nugget values were used to identify the best-fitted semivariogram model. Models with the smallest mean error (ME) and smallest nugget value are the most fitted semi-variogram models, thus indicating the best accurate spatial predictions.

To determine the spatial dependence, the nugget-to-sill ratio (nugget ratio expressed in percentage), is used to define spatial dependence of soil properties: if the ratio is < 25%, there is strong spatial dependence; if it is 25 to 75%, there is moderate spatial dependence; and if the ratio is > 75%, spatial dependence is weak (Cambardella *et al.,* 1994). The nugget ratio was determined by dividing the nugget value of each parameter by its sill value and subsequently multiplying the result by 100.

RESULTS AND DISCUSSION

Status and Degree of Spatial Variability of the Soil Parameters

The particle size distribution of the soil revealed a high content of sand in the study area, with a mean value of 60%. However, the sand content ranged from 41 to 79% across the study area (Table 1). The coefficient of variability (CV) of 12.62% for sand indicates the lowest level of variability. Generally, Soil properties having a coefficient of variation (CV) between 0 and 15 % are considered less variable, 15 and 35 %, moderately variable, and bigger than 35 % highly variable (Ogunkunle, 1993). The sand content deviated to the left from the normal distribution curve for skewness (-0.16) and has a light-tailed kurtosis of -0.12 (Table 1).

Table 1: Descriptive statistics for the soil particle size distribution

Properties	Min	Max	Mean	Median	SD	Variance	CV (%)	Skewness	Kurtosis
Sand (%)	41	79	60	61	8	57.29	12.6	-0.16	-0.12
Silt (%)	2	49	26	25	8	65.39	31.1	-0.15	0.46
Clay (%)	5	25	14	13	4	16.863	29.3	0.252	-0.254

Source: Generated using JMP Pro 15.0 Statistical Software

Silt has a CV of 31.1 %, indicating a moderate level of variability, and this result follows the findings of Ogunkunle (1993). The silt contents ranged from 2 to 49 % across the study area, and have a mean value of 26 %. It also deviated to the left from the normal distribution curve by showing a skewness of (-15) and a heavy-tailed kurtosis of 0.46 (Table 1).

Clay contents varied moderately with CV 29.3 % and values ranged from 5 to 25 %. It has a mean value of 14 %. It deviated to the right from the normal distribution curve by having a skewness value of 0.252 and heavy-tailed kurtosis of 0.254.

The low variability in sand contents across the sampling sites confirmed the findings of Voncir *et al.* (2008), Malgwi *et al.* (2000) and Shehu *et al.* (2015) who reported that sand and fine texture dominated the common soils of Nigerian savanna which occur as a result of sandstone nature of parent material and Aeolian deposit. Low to medium variability in soil separates may be attributed to the fact that soil texture is one of the inherent soil physical properties less affected by management practices. It is thus clear that textural fractions tend to have a low spatial variation. The results are in agreement with the observations of Some'e *et al.* (2011) who found medium variation for the silt and clay whereas low variation for sand. Also, the result agrees with the finding of Malgwi & Abu (2011) who reported that soils of the savanna region are physically fragile because the topsoil contains a large proportion of sand, weak aggregation and low level of organic matter.

Spatial Distribution and Pattern of the Soil Properties

As shown in Table 2, the nugget ratio values indicated the presence of moderate to weak spatial dependence for the three soil parameters (values between 73.3 and 98.4%).

There was moderate spatial dependence in clay (73.28%) and silt (78.23%), while weak spatial dependence was observed in sand (98.4491%).

The weak spatial dependence observed in sand may be controlled by both intrinsic variations of soil properties and extrinsic factors such as human-induced activities (Liu *et al.,* 2013; Wu *et al.,* 2010), while the moderate level of spatial dependence observed in clay and silt contents might be caused largely by extrinsic variations such as tillage, soil and water conservation, other management practices (Cambardella *et al*., 1994) and topographical land features (Zheng *et al.,* 2009; Denton *et al.,* 2017). The weak spatial dependence observed in silt may be controlled by both intrinsic variations of soil properties and extrinsic factors such as human-induced activities (Liu *et al.,* 2013; Wu *et al.,* 2010).

Table 2: Semivariogram Models and Parameters for the Soil Properties

Variable	Model	Nugget, (C_0)	Sill, (C_0+C)	Range (m)	ME	RMSSE	Nugget ratio (%)
Sand (%)	Spherical	53.9349	54.7846	2.17	0.2752	1.0169	98.4491
Silt (%)	Exponential	54.3587	69.4551	4.70	-0.1993	1.0330	78.2646
Clay (%)	Exponential	12.6184	17.2192	3.59	-0.0001	1.0239	73.2808

Generated using ArcGIS (version 10.3.1)

Spatial Distribution and Pattern of Sand, Silt and Clay

The geostatistical analyses of particle size distribution are presented in Table 2. The spherical model was the best-fitted semivariogram model for sand distribution, and that corroborated the study of Fazle Rabbi *et al.* (2014), who observed the spherical model as the best fit for sand. The kriged map showed a range of 41 to 79 % sand content. A smaller range value of 2.17m for sand indicates that observed values of the soil property are not influenced by other values of this property over greater distances (Isaaks and Srivastava, 1989; Oliver & Webster, 2015).

Lower interpolated range values of sand contents of the soil were observed towards the northeast of the study area; some patches of the lower-class value were observed across the study area. The lower range values of sand contents of the study area, as depicted by the interpolated map of sand (Figure 4), occupied a total area of 0.71 (km)^2, which is equivalent to 23 % of the total study area (Table 3). Middle interpolated range values of sand contents were observed around the southwest of the study area and towards the extreme northeast end of the study area. The middle range values of the sand content occupied a total area of 1.38 (km)^2, which is equivalent to 45 % of the study area (Table 3). Upper interpolated range values of sand contents were observed at the two extreme northeast and southwest ends of the study area, and some of its patches were observed around the centre. The upper range values of sand occupied an area of 0.97 (km)^2, which is equivalent to 32% (Table 3). Having a Root Mean Square Standardize Error (RMSSE) value of 1.0169 indicated a slight overestimation of sand contents. The nugget effect, which is an indication of micro variability, was 53.93 for sand content, which indicate large errors in measurements (Vieira, 2000; Oliver & Webster, 2015) and high random variance in the study area.

Table 3: Area and Percentages of the Interpolated Ranges of Sand, Silt and Clay

Range	Area (km)^2	Area (%)
Sand (%)		
Lower	0.71	23
Middle	1.38	45
Upper	0.97	32
Silt (%)		
Lower	0.75	24
Middle	1.10	36
Upper	1.21	40
Clay (%)		
Lower	0.86	28
Middle	1.51	49
Upper	0.69	23

Generated using ArcGIS (version 10.3.1)

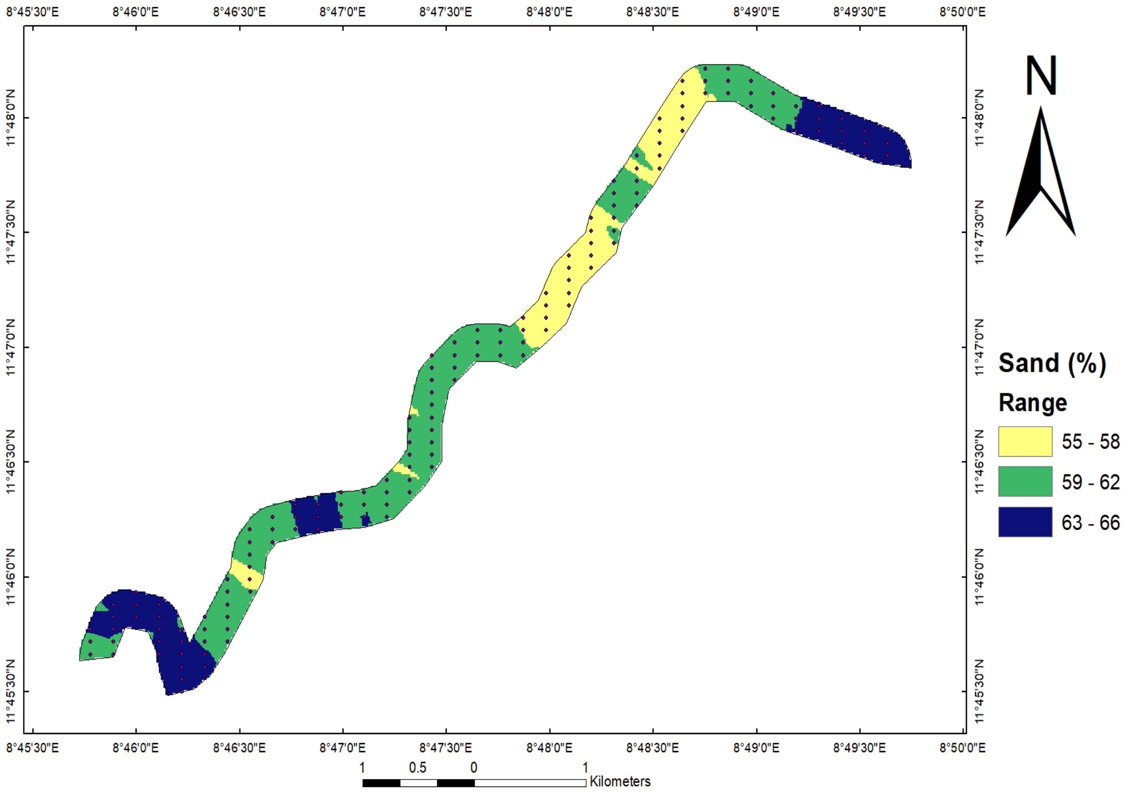

Figure 4: Interpolated map of sand distribution in the study area
Source: Generated using ArcGIS (version 10.3.1)

Lower interpolated range values of silt contents of the study area, as depicted by the interpolated map of silt (Figure 5), occupied a total area of 0.75 (km)^2, which is equivalent to 24 % of the total study area (Table 3). The lower range contents were observed at the extreme northeast end of the study area. A clear patchy distribution of the lower content was observed across the study area (Figure 5). Middle interpolated range values of silt contents of the study area. Which occupied an area of 1.1 (km)^2, equivalent to 36 %, was distributed across the study area (Figure 5). The upper interpolated range values of silt contents of the study area were observed around the middle when moving from the northeast towards the southwest of the study area. It occupied an area of 1.21 (km)^2, which is equivalent to 40 % of the total area (Table 3). The nugget effect, which is an indication of micro variability, was 54.3587 for silt content.

The exponential model fitted the semivariogram of silt contents, and the finding contradicted the study of Fazle Rabbi *et al.* (2014), who revealed that a spherical model was chosen for silt. High values of the nugget effect (69.46) observed in silt contents indicated large errors in measurements (Vieira, 2000; Oliver & Webster, 2015) and high random variance in the study area. A smaller range value of 4.70 m for silt indicates that observed values of the soil property are not influenced by other values of this property over greater distances (Isaaks and Srivastava, 1989; Oliver & Webster, 2015).

Clay contents ranged from 5 to 25 % across the study area (Table 1). The result of the clay was fitted to an exponential model based on the cross-validation method (Table 2). Upper interpolated range values of clay contents of the study area were observed at the extreme northeast end of the study area. The total area it occupied is 0.69 (km)^2, which is equivalent to 23 % of the total study area (Table 3). The middle-interpolated range values of clay contents of the study area were observed around the middle part of the study area and towards the southwest end of the study area (Figure 6). It occupied an area of 1.51 (km)^2, which is equivalent to 49 % of the total study area (Table 3). Lower interpolated range values of clay contents of the study area occupied an area of 0.86 (km)^2, which is equivalent to 28 % of the total study area (Table 3). It was observed to have a high value of nugget effect of 12.62 and a smaller range value.59 m. RMSS value of 1.0239 indicated a slight overestimation of the content.

The exponential model fitted to clay contents corroborated the study of Coşkun *et al.* (2016), who revealed that an exponential model was chosen for clay. High values of the nugget effect in clay (12.62) indicated large errors in measurements and high random variance in the study area (Vieira, 2000;

Oliver & Webster, 2015). A smaller range value of 3.59 m for clay contents indicates that observed values of the soil property are not influenced by other values of this property over greater distances (Isaaks and Srivastava, 1989; Oliver & Webster, 2015).

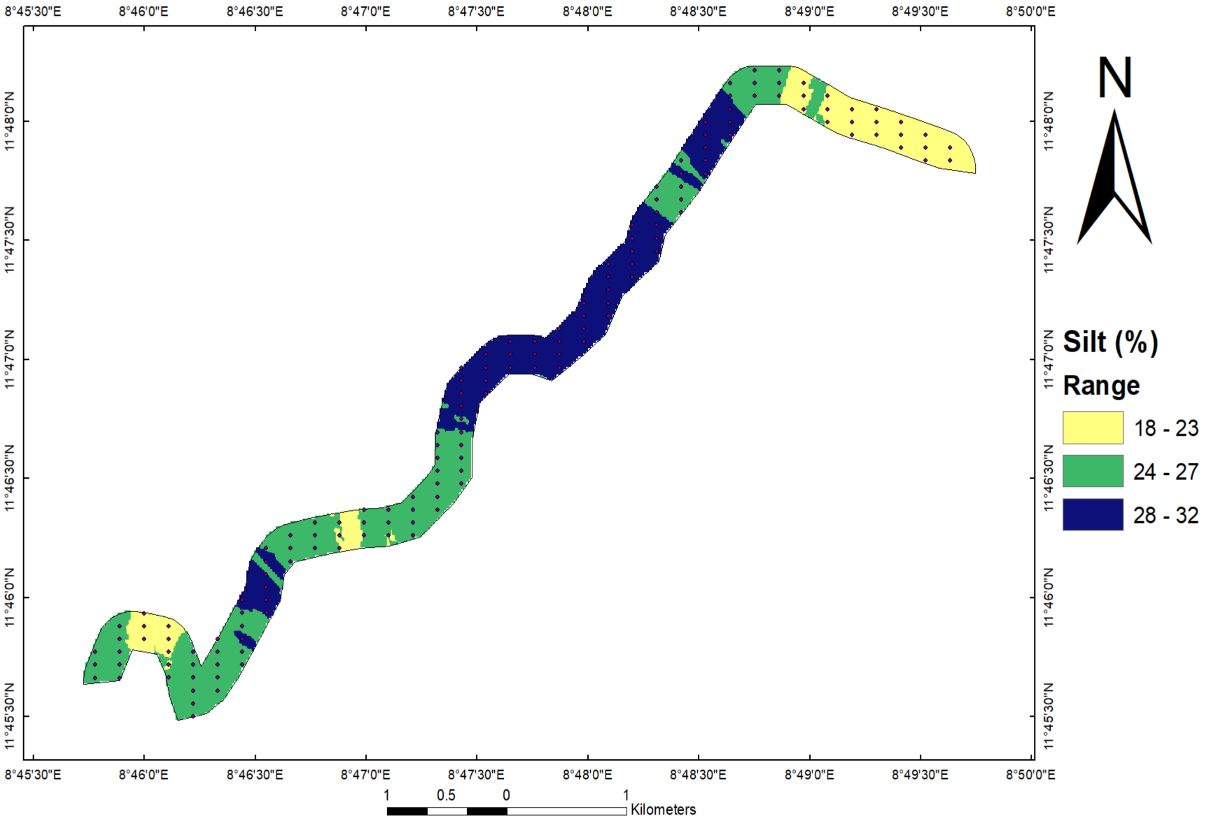

Figure 5: Interpolated Map of Silt distribution in the study area
Source: Generated using ArcMap (Version 10.3.1)

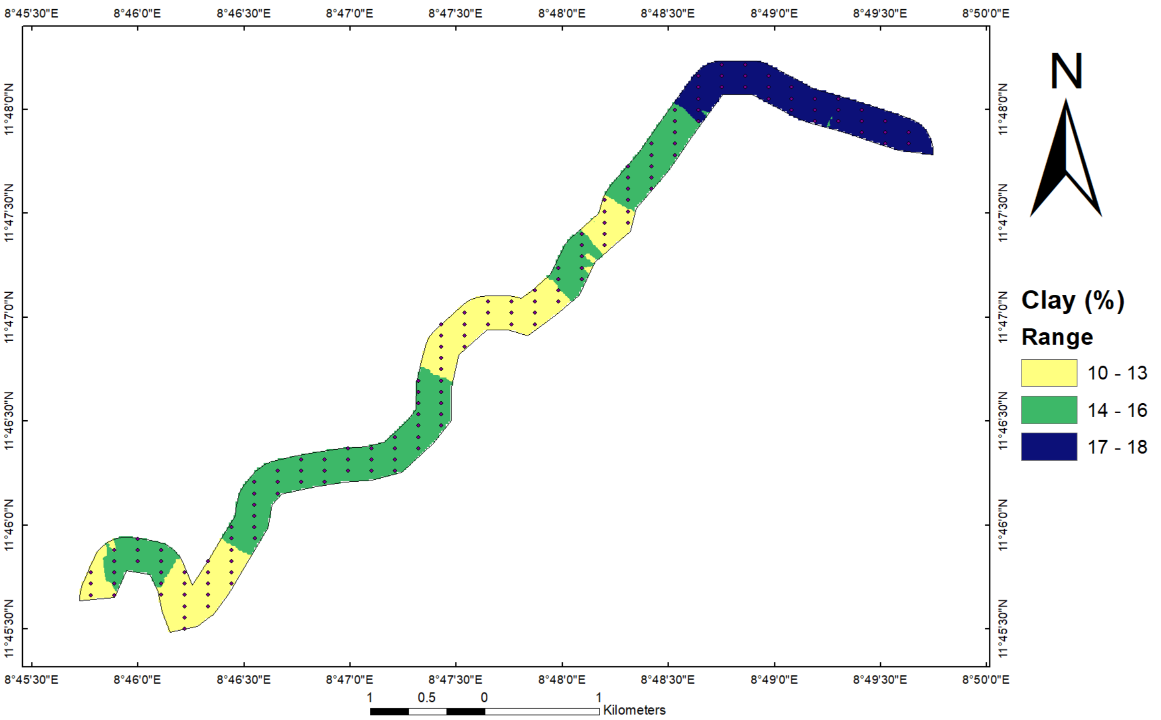

Figure 6: Interpolated Map of Clay distribution in the study area
Source: Generated using ArcMap (Version10.3.1)

Semivariograms of the Soil Particle Size Distribution

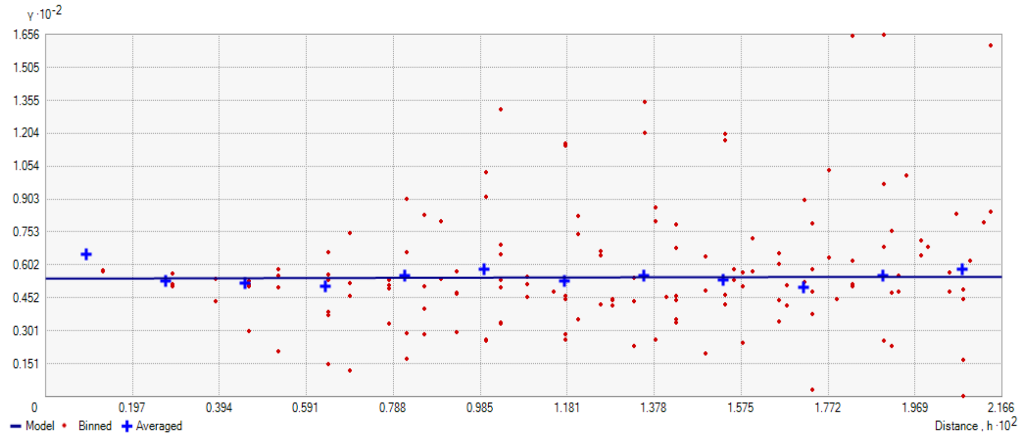

Figure 7: **Semivariogram of Sand**

Source: Generated using ArcMap (Version10.3.1)

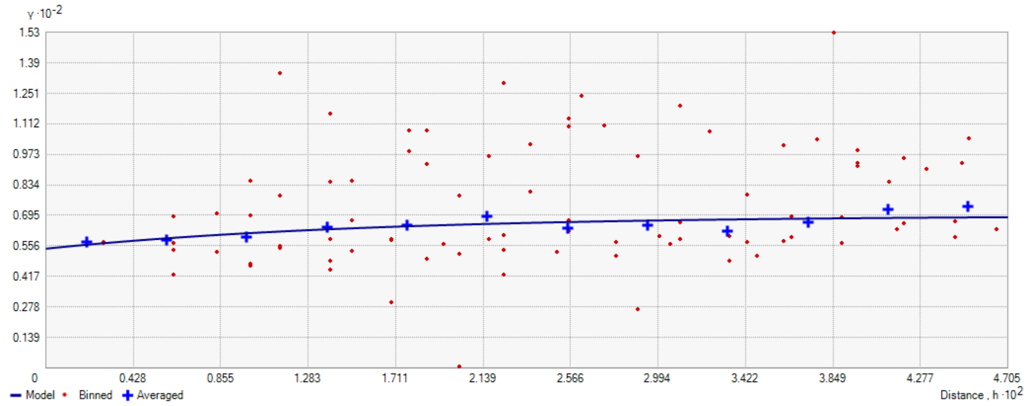

Figure 8: **Semivariogram of Silt**

Source: Generated using ArcMap (Version10.3.1)

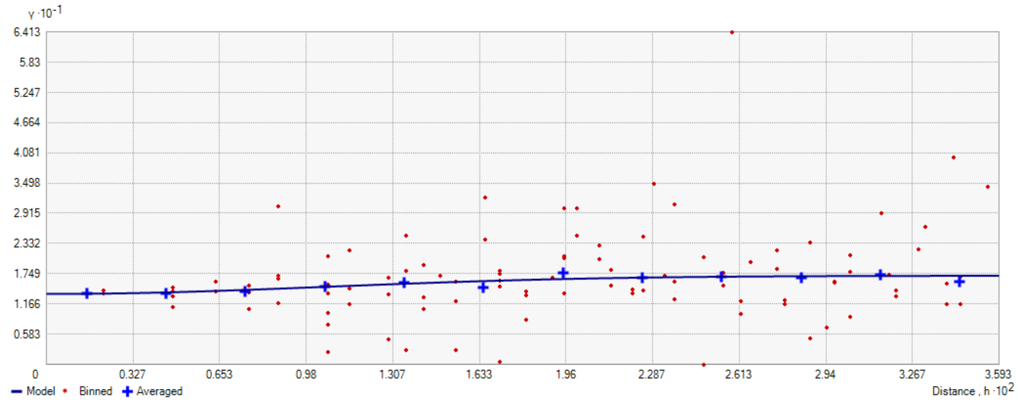

Figure 9: Semivariogram of Clay

Source: Generated using ArcMap (Version10.3.1)

Relation between the Soil Properties

Significant negative relationships were observed between sand and silt (-0.9) and between silt and clay (-0.4), (Table 4).

A significant relationship exists among soil physicochemical properties, which either positively or negatively impact availability (Onwudike, 2020). The negative relationships observed between sand and silt, and between silt and clay mean that the increase of any one of them would lead to a corresponding depletion of the other (Tale and Ingole, 2015), and texture is one of the major factors that caused the negative relationship between the soil properties (Plante *et al.,* 2006; Sakin, 2012).

Table 4: Relationship among the Soil Properties

Variable	Sand	Silt	Clay
Sand (%)	1.0		
Silt (%)	-0.9**	1.0	
Clay (%)	-0.1	-0.4**	1.0

**Correlation is significant at 0.01 level, *correlation is significant at 0.05 level

Source: Generated using JMP Pro 15.0 Statistical Software

CONCLUSION

This study identified low to moderate spatial variability in soil particle size distribution across the Wudil River floodplain in Kano State, Nigeria. Variability was attributed to natural soil formation processes, flooding-induced sedimentation, erosion and deposition dynamics, as well as human-induced factors such as tillage and fertilizer use. Sand was found to be the dominant soil fraction. The findings provide a scientific basis for site-specific nutrient management, crop planning, and precision agriculture. Furthermore, the geostatistical prediction maps developed offer valuable tools for supporting sustainable soil use and agricultural productivity in the region.

Based on the study's findings, it is recommended that integrated soil fertility management—combining organic and inorganic fertilizers—be implemented in the study area due to the moderate spatial dependency of clay content. Additionally, developing site-specific nutrient management strategies that consider both structural and random factors is advised, given the moderate spatial variability observed in silt and clay fractions.

REFERENCES

Abdel-Magid, H., Walkley, A., & Nelson, D. W. (1987). Sediment characteristics and their influence on floodplain soils of the Nile. Geoderma, 39(1-2), 83–95. https://doi.org/10.1016/0016-7061(87)90022-3

Adeoye, K. B., Bello, N. J., & Ibrahim, B. I. (2021). Assessment of floodplain soils for agricultural suitability in the Sudano-Sahelian zone of Nigeria. Nigerian Journal of Soil Science, 31(1), 44–56.

Allison, L. E., & Hughes, J. R. (1983). The floodplain soils of the lower Mississippi Valley: Soil texture and spatial variation. Soil Science Society of America Journal, 47(3), 461–467. https://doi.org/10.2136/sssaj1983.03615995004700030022x

Bouyoucos, G.J. (1963). Hydrometer method for making particle-size analysis of soils. Journal of Agricultural Science, 59(2), 179-183.

Brady, N. C., & Weil, R. R. (2017). The nature and properties of soils (15th ed.). Pearson.

Burgess, T. M. and R. Webster, 1980. Optimal interpolation and isarithmic mapping of soil properties. I. The semi-variogram and punctual kriging. Journal of Soil Science, 31: 315-331.

Cambardella, C. A., Moorman, T. B., Novak, J. M., Parkin, T. B., Karlen, D. L., Turco, R. F., and Konopka, A. E.: Field-scale variability of soil properties in Central Iowa soils, Soil Sci. Soc. Am. J., 58, 1501–1511, 1994.

Coşkun Gülser, Imanverdi Ekberli, Feride Candemir, Zeynep Demir, 2016, Spatial variability of soil physical properties in a cultivated field, Eurasian Journal of Soil Science, C.Gülser et al. / Eurasian J Soil Sci 2016, 5 (3) 192 - 200

Denton, J., Kumar, A., & Singh, A. (2017). Spatial variability of soil micronutrients in agricultural landscapes: A review. Journal of Environmental Biology, 38(5), 851-863.

Fazle Rabbi S. M., Roy B. R., Masum M., Miah, M. Sadiqul Amin, and Tania Khandakar, 2014, Spatial Variability of Physical Soil Quality Index of an Agricultural Field, Applied and Environmental Soil Science Volume 2014, Article ID 379012, 10 pages http://dx.doi.org/10.1155/2014/379012

Goovaerts, P. (1997). Geostatistics for natural resources evaluation. Oxford University Press.

Goovaerts, P. (1999). Geostatistics in soil science: State-of-the-art and prospects. Geoderma, 89(1-2), 1-45.

Hillel, D. (2008). Soil in the environment: Crucible of terrestrial life. Academic Press.

Ibrahim, H., Akinola, A. O., & Abdulrahman, I. (2016). Soil fertility and management practices in Kano floodplain agriculture. Journal of Agriculture and Environmental Sciences, 5(1), 45–54.

Isaaks E.H., Srivastava R.M. (1989): An introduction to applied geostatistics. Oxford Univ. Press, New York. ISSS-ISRIC-FAO (1998): World reference base for soil resources. World Soil Res. Rep. FAO, Rome, 84: 92.

Jabro J.D., Stevens W.B., Evans R.G., Iversen W.M. (2010). Spatial variability and correlation of selected soil properties in the AP horizon of a CRP grassland. Appl. Eng. Agric. 2010;26(3):419–428.

Knighton, D. (1999). Fluvial forms and processes: A new perspective. Arnold.

Lui Z, Zhou W, Shen J, Lei Q and Liang G (2013), A simple assessment on spatial variability of rice yield and selected soil chemical properties of paddy fields in South China, *Geoderma* **235 236:** 39-47. DOI: org/10.1016%2Fj.geoderma.2014.06.027

Malgwi, W. B., & Abu, S. T. (2011). Variation in some physical properties of soils formed on a hilly terrain under different land use types in Nigerian Savanna. International Journal of Soil Science, 6(2), 150-163.
Malgwi, W.B, A.G. Ojanuga, V.O. Chude, T. Kparmwang and B.A Raji, 2000. Morphological and physical properties of some soils at Samaru, Zaria. Nigeria. Nijer. J. Soil Res., 1:58-64.
McBratney, A., Mendonça Santos, M. L., & Minasny, B. (2003). On digital soil mapping. Geoderma, 117(1-2), 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4
Ogunkunle, A.O., 1993. Variation of some soil properties along two toposequence on quartzite schist and banded gneiss in South-western Nigeria. *GeoJournal* 30(4): 399-402.
Oliver, M. A., & Webster, R. (2015). Basic Steps in Geostatistics: The Variogram and Spatial Autocorrelation. Springer.
Onwudike, S. U. (2020). Soil Physicochemical Properties and Nutrient Availability. Journal of Sustainable Agriculture, 14(3).
Plante, A.F., R.T. Conant, C.E. Stewart, K. Paustian and J. Six, 2006. Impact of soil texture on the distribution of soil organic matter in physical and chemical fractions. Soil Sci. Soc. Am. J., 70: 287-296.
Sakin, E., 2012. Relationships between carbon, nitrogen stocks and texture of the Harran Plain soils in southeastern Turkey. Bulgarian J. Agric. Sci., 18: 626-634.
Shehu, B.M., Jibril, J.M., Samndi, A.M. (2015). Fertility status and of selected soils in the Sudan Biome of Northern Nigeria. *International Journal of Soil Science*, vol 10, 2:74-83.
Silva Cruz J., de Assis Júnior R.N., Rocha Matias S.S., Camacho-Tamayo J.H. (2011). Spatial variability of an Alfisol cultivated with sugarcane. Cien. Inv. Agr. 2011;38(1):155–164.
Tale, K.S. and S. Ingole, 2015. A review on role of physico-chemical properties in soil quality. Chem. Sci. Rev. Lett., 4: 57-66.
Vieira, S.R. Geoestatística em estudos de variabilidade espacial do solo. In: NOVAIS, R.F.; Alvarez V., V.H. & Schaefer, C.E.G.R., eds. Tópicos em ciência do solo. Viçosa, MG, Sociedade Brasileira de Ciência de Solo, 2000. p.1-54.
Vrieling, A., de Leeuw, J., & Kyagulanyi, J. B. (2013). Influence of flood regimes on soil spatial variability in the Niger floodplains. Journal of African Earth Sciences, 79, 142–151. https://doi.org/10.1016/j.jafrearsci.2013.03.004
Voncir. N., S. Mustapha. V.A. Tenebe A.L Kumo and S. Kushwaha. (2008). Content and profile distribution of exchangeable zinc (Zn) and some physicochemical properties of soil along topo sequence at Bauchi, Northern Nigeria. *Int J. Soil Sci*., 3: 62-68.
Wu CF, Luo YM and Zhang LM (2010), Variability of copper availability in paddy fields concerning selected soil properties in Southeast China, *Geoderma* **156:** 200-206.
Yusuf, M. A., Abdullahi, U. S., & Shehu, A. (2020). Soil quality assessment of floodplains in Kano State. Nigerian Journal of Agricultural Sciences, 24(1), 89–98.
Zheng, H., Wu, J., Zhang, S., 2009. Study on the spatial variability of farmland soil nutrients based on the kriging interpolation. AICI, International conference on artificial intelligence and computational intelligence, November 7-8, Shanghai, China, Vol:4, p. 550-555.