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https://doi.org/10.26565/2410-7360-2024-61-24
UDC 911.2:631.41(669.126)

Received 18 September 2024
Accepted 18 November 2024

Spatial variability of some soil properties around Zaria area, Kaduna state, Nigeria

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ABSTRACT

Introduction. Spatial variability of soil properties as influenced by both intrinsic and extrinsic factors, plays a pivotal role in agricultural productivity. Understanding this variability is critical for implementing site-specific management, which optimizes resource allocation while sustaining soil health. This study investigates the spatial variability of selected soil properties in agricultural fields around Zaria, Kaduna State, Nigeria, utilizing geostatistical techniques to provide insights for sustainable land management.

Materials and Methods. The study was conducted in an 85-hectare area located in Zaria, Kaduna State. Seventy soil samples were collected using a grid sampling approach across 85 hectares. Following standard laboratory procedures, the samples were analysed for properties, including particle size distribution, bulk density (BD), pH, organic carbon (OC), and cation exchange capacity (CEC). Geostatistical analysis using Kriging interpolation and semivariogram modelling was employed to determine spatial dependence.

Normal Distribution Test and Data Transformation. Laboratory data from the studied soil properties were tested for normality using the Ryan-Jover test, which revealed that most soil properties did not follow a normal distribution (P<0.05). Johnson trans-formation was hence applied to improve normality for reliable geostatistical modelling, as confirmed by the residuals from QQ Plots.

Descriptive Statistics of Soil Properties. Clay content exhibited the highest variability (CV = 43.09%), ranging from 60 to 420 g kg^{-1}. CEC showed moderate to high fertility potential, ranging from 6.33 to 25.50 cmol kg^{-1}, while OC were generally rated low. BD and pH showed weak spatial variability (CV < 15%) due to the influence of intrinsic soil factors.

Geostatistical Analysis of Soil Properties. Semivariogram modelling revealed strong spatial dependence for most soil properties (nugget ratio < 0.25), including BD, OC, and pH, suggesting intrinsic factors as key drivers. Spatial ranges varied across properties, with clay and CEC extending to 339.9 m and 347.6 m, respectively, while pH and BD showed shorter ranges of 85.4 m and 93.3 m. Spatial patterns in sand and clay demonstrated inverse relationships, as areas with higher clay contents exhibited higher CEC and pH levels.

Spatial Distribution Maps. Kriging interpolation highlighted distinct spatial patterns, such as higher clay and CEC concentrations in specific zones, and lower pH in sandy areas, indicative of leaching effects. Maps showed that the spatial distribution of OC and BD is influenced by short-range processes, requiring localized management strategies.

Conclusion. This study demonstrates the necessity of addressing spatial variability in soil management plans. Strong correlations between clay and CEC emphasize the critical role of texture in influencing soil fertility. Properties like OC and BD, with weak spatial dependence, demand immediate attention through targeted interventions such as organic amendments and improved tillage practices.

Keywords: *Kriging, semivariogram, spatial variability, soil properties.*

In cites: Awwal Yasin Agono, Muhammad Fatihu Ruqayyah (2024). Spatial variability of some soil properties around Zaria area, Kaduna state, Nigeria. Visnyk of V. N. Karazin Kharkiv National University, series "Geology. Geography. Ecology", (61), 303-312. https://doi.org/10.26565/2410-7360-2024-61-24

Introduction. Variability in soil properties exists in nature due to changes that may be inherent such as geologic and pedologic factors [1], or induced, such as effect of landuse and other management practices [2, 3] on land. These intrinsic and extrinsic factors of land formation lead to variability in soil properties [3, 4], consideration of which is important for proper land management [5]. Site-specific management which is an important concept for maximizing agricultural productivity is highly dependent on understanding spatial variability of soil properties [6].

Spatial variability refers to the extent of variation in a given soil property over space [7]. Its assessment is based on the geographical assumption that objects that are closer are more closely related [8 – 11] and has been achieved using classical descriptive statistics such as mean, range, coefficient of variation [3, 12] and/or geostatistical methods such as variograms [6], isotropic variograms [13], semivariogram [14]. Many of these studies also employed the use of ordinary Kriging [15 – 18], co-kriging [6, 19], inverse distance weighting (IDW) [20], and other interpolation methods to estimate variability in soil properties across unsampled locations within a desired study area.

According to Ardahanlioglu et al. [21], Kriging and IDW are the most commonly employed extrapolation methods in agriculture. Both methods utilize allocation of weights to observed properties in estimating values of defined properties at unobserved locations. However, Saleh [13] asserted that Kriging is more complicated and laborious to implement than IDW. Kriging provides a more accurate explanation of the spatial distribution of the data, while suggesting valuable information about the error or estimation [22]. The process of Kriging is contingent upon computing accurate semivariogram models from which estimates of variance can be reliably estimated. To develop this accurate semivariogram, a sufficient number of samples that can represent the autocorrelation of the soil property under consideration must be used [23].

Several researchers have utilized Kriging to evaluate variability of physical and chemical properties of soil on agricultural fields [24]. For instance, Masood and Salim [6] utilized Kriging technique to determine spatial variability of hydro-related physical properties of Al-Rasheed Loam in Iraq. The study explored properties such as saturated hydraulic conductivity, initial infiltration rate, Porosity and bulk density, revealing a moderately skewed (-0.5 to 0.5) spatial distribution for the studied characteristics. Saleh [13] studied spatial distribution of particle sizes, utilizing spherical and gausian models for parameter determination of semivariogram models. While Yakub et al. [14] evaluated spatial variability in total nitrogen, organic carbon and pH in Wukari local government area of Nigeria.

Zaria province of Kaduna State includes communities that depend on agriculture as their major source of livelihood. Soils of the area are characterized by a diverse range of soil types, which shape their properties and influence strategies for their management [25]. Several works have been carried out to investigate properties of soils in Zaria [5, 26]. Works have been carried out to investigate variation in soil properties in the area as a result of difference in parent material [27], topography [26, 28], and vegetative cover [25, 29]. However, these studies employed conventional method that were site specific and considered variation in soil units selected as a function of these factors, rather than as a continuum in space. About 25 years ago agronomists realized that geostatistics could be harnessed for precision agriculture, and they have made substantial progress in the technology since [30]. It is used for the site-specific management of crop nutrients, pH, irrigation, weeds and crop pests [31, 32].

Quantitative explanation of the inherent variation in soil properties across agricultural fields help by providing valuable basis for site-specific management, while increasing our knowledge of soils and aid in planning appropriate use for soil resources [33]. Therefore, this study aims to examine spatial variability of selected soil properties across farming fields under continuous cultivation.

Materials and Methods. Location of the study area. The study area consists of 85 ha, and is located between 11° 6' 44.93" N, 7° 37' 24.23" E and 11° 4' 45.67" N, 7° 39' 0.35" E (Figure 1). The region which has a tropical Savanna climate type with distinct wet and dry season [34], falls between Sabon Gari and Giwa local government area, Zaria, Kaduna State, Nigeria and is predominantly agrarian. Majority of the land under agricultural use are cultivated mechanically through conventional tillage. Most of the soils have a sandy to sandy loam texture [26, 35], and have been classified as leached ferruginous tropical soils developed on weathered regolith overlain by a thin deposit of wind-blown silt from the Sahara Desert during many decades of propagation of tropical continental air mass into the area [36].

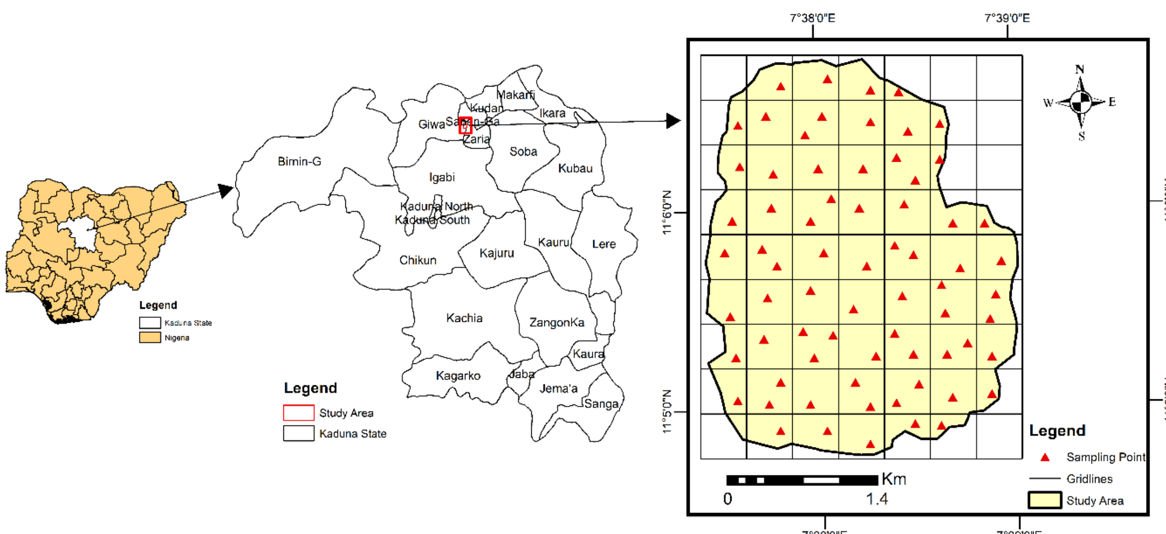

Fig. 1. Map of study area showing sample points

Sampling and soil analysis. A reconnaissance survey was carried out to delineate the study area, which spanned 83 hectares and was predominantly used for cultivating maize, watermelon, millet, cowpea and rice. A grid sampling method was employed, dividing the site into 63 grids (9 × 7), each approximately 120 × 120 m, using ArcGIS 10.5 [37]. Soil samples were collected from a depth of 0 – 45 cm to capture the spatial variability of soil properties. A total of 70 samples were obtained, with at least one sample from each grid, and additional samples from selected grids on observed heterogeneity. All sampling points were carefully georeferenced and recorded for precise spatial analysis (Figure 1).

Laboratory studies. Particle size analysis was determined using the Bouyoucus Hydrometer method as described by Gee and Or [38]. Organic carbon (OC) was determined by Walkley-Black dichromate wet oxidation method [39]. Glass electrode was used to determine soil pH in a 1:2.5 soil/water solution ratio, as described by Uyovbisere et al. [40]. Cation exchange capacity (CEC) was determined by neutral (pH 7.0) NH_4OAc saturation method as described by [41].

Statistical Analysis. Descriptive statistics and Pearson's coefficient of correlation were computed for the studied properties using R software [42]. The Ryan-Jover normality test was performed to test the hypothesis assuming each property has a normal variable distribution using Minitab 17.0. Properties without normal distribution (P<0.05) were subjected to Johnson Transformation. Johnson transformation technique is renowned for its applicability in situations where standard parametric methods require normality. It involves evaluating different transformation functions with four parameters shown in the equation below [43]. The transformation process optimally selects one of three (i.e. bounded, SB, lognormal (SL), and unbounded, SU) families of distributions, which can easily alleviate the non-normality and skewness of the raw data [44]. Johnson transformation is expressed as:

$$Z = \gamma + \delta f\left[\frac{X - \xi}{\lambda}\right] \quad (1)$$

where Z denotes a standard normal variable, γ and δ represent the shape parameters, $f(.)$ is the function of transformation, λ is a scale parameter and ξ is a location parameter. This transformation method defines the lognormal system of distributions, making it suitable for soil data, since earlier researches have shown that soil properties are more closely log-normally distributed [45].

Geostatistical Analysis. The ArcGIS 10.5 software was used to build semivariogram models, $\gamma(h)$ describing degree of spatial dependence of random variable $Z(x_i)$ over certain distance points [46]. The model is given in Equation (2)

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

Where $\gamma(h)$ is the semivariance for the interval distance class h, $N(h)$ is the number of pairs, $Z(xi)$ and $Z(xi + h)$ are the measured sample values at position i and $(i + h)$, respectively. Two semivariogram models were used to describe the studied characteristics. Exponential model was used by default, while spherical models were used when transformation was done [6]. The models are depicted as:

$$\text{Exponential: } \gamma(h) = \begin{cases} C_0 + C\left[1 - exp\left(-\frac{h}{a}\right)\right] & h \le a \\ C_0 + C & h > a \end{cases} \quad (3)$$

$$\text{Spherical: } \gamma(h) = \begin{cases} C_0 + C\left[\frac{3}{2}\left(\frac{h}{a}\right) - \frac{1}{2}\left(\frac{h}{a}\right)^3\right] & h \le a \\ C_0 + C & h > a \end{cases} \quad (4)$$

Where, C_0: nugget variance, C: structural variance, (C_0+C): sill value of semivariogram, a: range of spatial correlation.

Results and Discussion. Normal Distribution Test and Data Transformation. The Ryan-Jover statistic was used to test the normality of each soil property. Sand content was the only property whose normality was not rejected based on its p-value which was greater than 0.05. The other properties were transformed using Johnson transformation. The transformation of the data improved the normality of the distributions, as indicated by the increased RJ and p-values as shown in Table 1. The necessity of applying transformation techniques on soil properties have been proven in several researches [12, 47, 48].

QQ plots were used to visualize the degree of fitness of the data to normal distribution (Fig. 2). The plots compare the observed residuals to the expected values if the residuals were normally distributed. Few outliers are observed for sand, silt, clay and CEC, however, most of the data points clustered around the normal distribution line, suggesting sufficient normality.

Descriptive Statistics of Soil Properties. Descriptive statistics for soil properties are presented in Table 1. Sand content in the study area ranged from 100 to 740 g kg^{-1} (mean, 503.10 g kg^{-1}), and BD ranged from 1.22 to 1.40 Mg m^{-3} (mean, 1.31 Mg m^{-3}). Clay was the most variable soil separate in the study area, ranging from 60 to 420 g kg^{-1}. Soil pH varied between strongly acidic (5.20) and moderately alkaline (8.40), exhibiting weak variability (<15%).

Table 1

Normal Distribution Test for Each Soil Property

Soil Properties	RJ	Normal Dist.	P-Value	Transformation	RJ	Normal Dist.	P-value
Sand	0.985	NR	>0.100	None	-		
Silt	0.940	R	<0.010	Johnson	0.994	NR	0.167
Clay	0.978	R	0.044	Johnson	0.992	NR	0.331
pH	0.957	R	<0.010	Johnson	0.995	NR	0.380
OM	0.935	R	<0.010	Johnson	0.997	NR	0.930
CEC	0.966	R	<0.010	Johnson	0.995	NR	0.818

Note: RJ: Ryan-Jover statistics; NR: not rejected; R: rejected

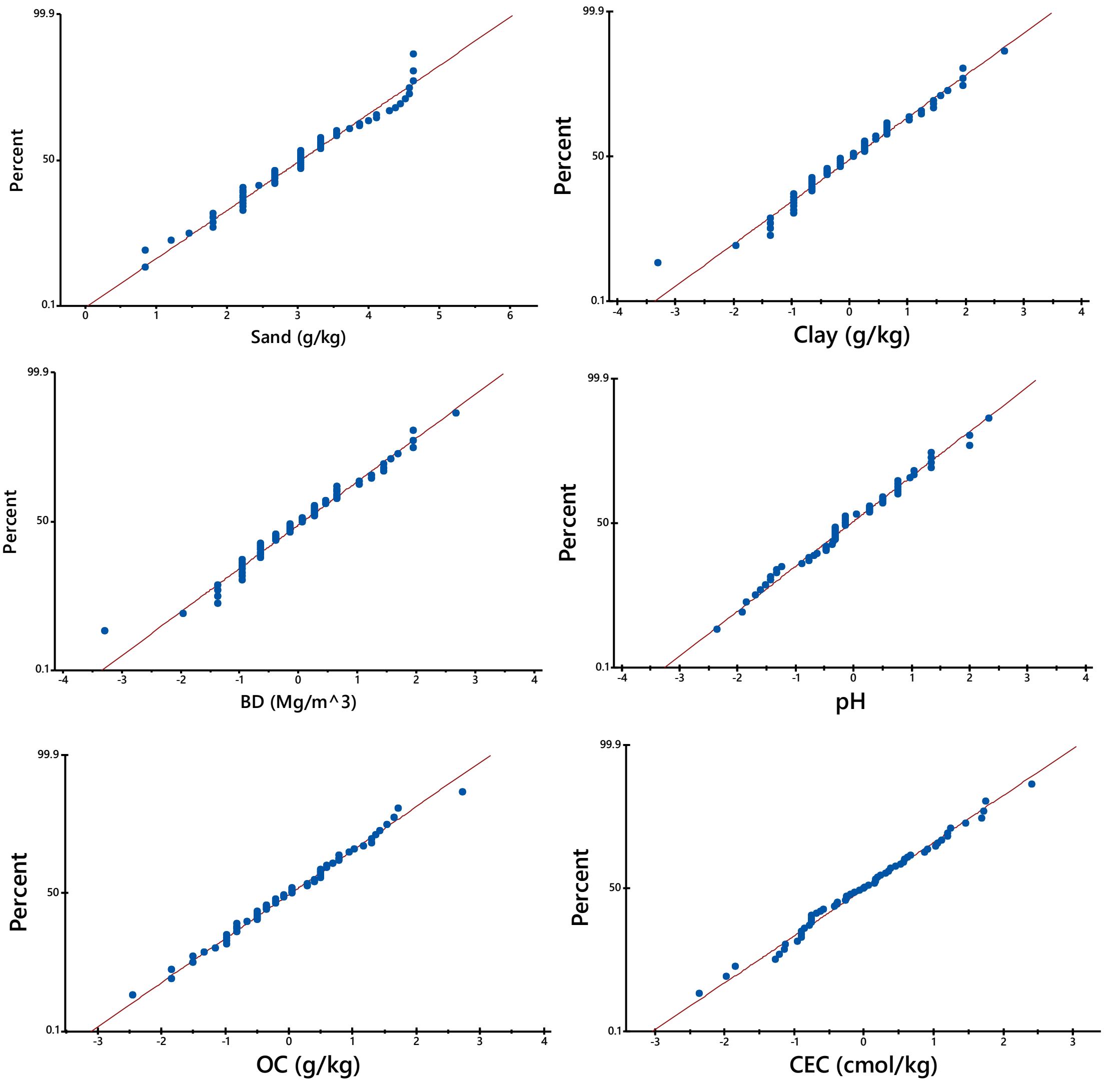

Fig. 2 (a-f). QQ Plots for the soil properties before (sand) and after normalization

Soil OM ranged from low (1.10 g kg^{-1}) to moderate (12.1 g kg^{-1}), which is typical in savanna soils [5, 49], while CEC ranged from moderate (6.33 cmol kg^{-1}) on maize fields to high (25.50 cmol kg^{-1}) on rice fields. Asides BD and pH which showed weak variability, other soil properties studied showed moderate to high variability, which is typical of soils formed in undulating planes of the savanna [50]. Sand and pH were left-skewed, while clay, OM and CEC were right-skewed. Clay and CEC exhibited flat distribution from their negative kurtosis values. Close association between the two properties is expected due to high association between these properties around the study location as reported by [26].

Pearson coefficient of correlation was used to analyse the nature of relationship among the soil properties, and the values are presented in Table 3. Clay content positively correlated significantly with CEC ($r = 0.990^{***}$). Clay particles containing silicate minerals have a net negative charge due to the substi-

Table 2

Descriptive Statistics for Soil Properties

	Min.	Max.	Mean	SD	CV	Skew.	Kurt.
Sand (g kg^{-1})	100.00	740.00	503.10	141.90	28.21	-0.49	0.08
Clay (g kg^{-1})	60.00	420.00	210.00	90.50	43.09	0.54	-0.68
BD (Mg m^{-3})	1.22	1.40	1.31	0.053	4.02	0.00	-1.00
pH	5.20	8.40	7.39	0.65	8.84	-1.14	1.34
OC (g kg^{-1})	0.06	0.70	0.23	0.10	44.86	1.70	5.55
CEC (cmol kg^{-1})	6.33	25.50	13.27	5.10	38.45	0.66	-0.62

Note: OC: organic carbon; CEC: cation exchange capacity; CV: coefficient of variation (%); SD: standard deviation

tution of silica (Si^{4+}) by aluminum (Al^{3+}) in the mineral structure. This attracts positively charged ions such as calcium (Ca^{2+}), magnesium (Mg^{2+}), and potassium (K^{+}) held through weak electrostatic interactions. This allows the clay to retain and exchange cations with the surrounding soil solution [51]. Conversely, sand content negatively correlated with it CEC ($r = -0.650^{***}$). This may be due to the relatively poor surface charge nature of sand particles in soils [26]. Soil pH also positively correlated with clay particles ($r = 0.413^{**}$), implying that higher clay content were associated with higher pH, likely due to accumulation of basic cations on clay exchange sites [52, 53].

Geostatistical Analysis of Soil Properties

Exponential model was used to express semivariogram of sand content, while spherical model was utilized for the other properties. The reason for this disparity was because sand content had a normal distribution, while the other properties were transformed [6]. Earlier researches also suggested the use of spherical models, especially for pH, clay [54], and other chemical properties as it gave better results [13]. Nugget effect, sill, range and nugget-sill ratio were used to analyse the spatial distribution in this study. Nugget effect represents the variance at a lag distance of zero, capturing measurement error and spatial variation at distances smaller than the sampling interval [55, 56].

The nugget values were higher in sand (0.89) and clay (0.45) than in other soil properties, but were generally close to zero, suggesting that variances in soil properties were reasonably accounted for at the sampling distance used in this study [12]. The range refers to the distance over which spatial autocorrelation exists [57]. Beyond this distance, data points are considered spatially independent. The range for CEC, sand and clay where relatively large, ranging from 297.2 to 347.6 m, while pH, silt, and OM had lower ranges from 85.4 to 124.8 m, indicating that the optimum sampling interval varies greatly among different soil properties. The similar range for sand and clay is due to the inverse nature of their relationship,

Table 3

Pearson correlation analysis of soil properties

	O.C	pH	Clay	BD	Sand
CEC	0.433	0.415^{**}	0.990^{***}	0.042	-0.650^{***}
O.C		-0.053	0.035	-0.129	0.095
pH			0.413^{***}	0.207	-0.395^{**}
Clay				0.035	-0.774^{***}
BD					-0.074

LOS: * = $P < 0.05$; ** = $P < 0.01$; *** = $P < 0.001$

Table 4

Semivariogram model types and parameters of soil properties

Soil Properties	Model	Nugget (C_0)	Sill (C_0+C)	Range (m)	Nugget/Sill (C_0/C_0+C)	Spatial Dependence
Sand (g kg^{-1})	Exponential	0.89	2.82	297.20	0.31	moderate
Clay (g kg^{-1})	Spherical	0.45	2.00	339.90	0.22	strong
BD (g kg^{-1})	Spherical	0.00	0.92	93.30	0.00	strong
pH	Spherical	0.17	1.17	85.40	0.14	strong
OC (g kg^{-1})	Spherical	0.00	1.20	124.80	0.00	strong
CEC (cmol kg^{-1})	Spherical	0.35	1.62	347.60	0.21	strong

whereby one increases as the other reduces as further buttressed by the significant negative correlation between them ($r = -0.774^{***}$). Also, the similarity between the range of clay and CEC is explained along same lines, since they are significant correlators.

The nugget to sill ratio or nugget ratio was used to evaluate the degree of spatial dependence of the properties [58]. A nugget ratio less than 0.25 indicates strong dependency, between 0.25 and 0.75 indicates moderate dependency, and there is said to be weak spatial dependency when nugget ratio is greater than 0.75 [59, 60]. Bulk density (0.00), clay (0.22), pH (0.14), OM (0.00) and CEC (0.21) were all strongly spatially dependent, suggesting that their spatial auto-correlation are affected by intrinsic properties such as parent material, mineralogy, climate, and other structural factors [61]. This is similar to the findings of Yakub et al. [14], whose research showed strong spatial correlation for OM (nugget ratio, 0.00). Gülser et al. [12] similarly reported strong autocorrelation with a nugget ratio of 0.13 for clay content in cultivated fields. Several researchers have linked soil properties like pH to parent material [53, 62] and leaching of basic cations [26] in the study area. Likewise, the strong spatial dependence of OM is attributed to climatic factors such as radiation and high temperature, which leads to high mineralization [26, 50] and frequent crop residue removal for feeding livestock, fuel, and building purposes [27, 49]. Sand content showed moderate spatial dependency (0.31), reflecting the effect of the dominant local conditions in explaining its spatial dependence. This was similar to the findings of Kilic et al. [3] and Saleh [13] who also reported moderate spatial dependency for sand content. Kilic et al. [3] showed that continuous cultivation tends to reduce spatial autocorrelation of soil properties such as sand, silt and clay content when comparing native grassland to 20-year cultivated land.

Spatial Distribution Maps. The interpolation of spatial distribution maps using ordinary Kriging for the soil properties are presented in Figure 3 (a-f). Raster values were grouped into five classes using natural breaks for all soil properties. The map of sand content reveals a gradient from higher values in the north to lower values in the south, while the inverse gradient is observed for clay content map. Comparing the map of clay and CEC, it is evident that areas with higher clay contents also had higher CEC values as a result of the relationship between these properties. Map of pH distribution showed a similar trend of lower values in the north, which progressively increased towards the south. Lower pH values were recorded around northern areas with higher sand content, due to effect of leaching of exchangeable cations from the sandy soils. Organic carbon content is highly variable across the study area, with notably higher values in the center corner, likely due to the presence of fallow lands towards this area. The lack of nugget effect and a range of 124.80 m indicate strong spatial dependence and little measurement error.

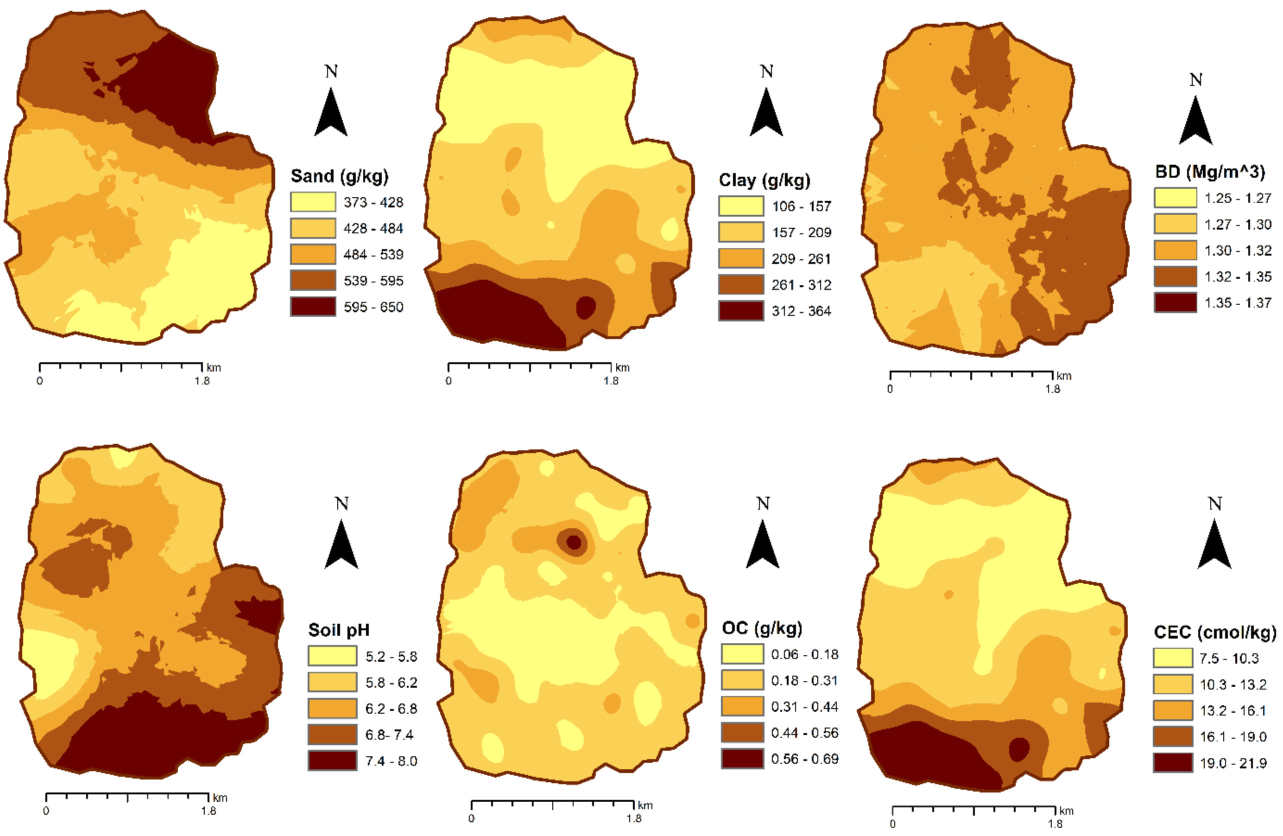

Fig. 3 (a-f). Spatial distribution of sand, clay, BD, pH, OM and CEC in the study area

Conclusion. The spatial distribution maps reveal distinct patterns for each soil property, influenced by a combination of geological, climatic, topographical and landuse factors. Clay and CEC show the strongest spatial dependence over larger distances, while organic matter and pH content exhibits the weakest dependence over a very short distance. Land management practices should focus on improving soil properties with weak spatial dependence, like organic matter, as they are more susceptible to short-term changes. This can be achieved through planting of cover crops and residue incorporation. Heterogeneity of these soil properties should be considered for implementing successful site specific management, especially in selecting appropriate tillage practices.

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Authors Contribution: All authors have contributed equally to this work
Conflict of Interest: The authors declare no conflict of interest

Просторова мінливість деяких властивостей ґрунту навколо району Зарія, Штат Кадуна, Нігерія

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Просторова мінливість властивостей ґрунту під впливом як внутрішніх, так і зовнішніх факторів відіграє ключову роль у продуктивності сільського господарства. Розуміння цієї мінливості має вирішальне значення для впровадження індивідуального управління, яке оптимізує розподіл ресурсів, одночасно зберігаючи здоров'я ґрунту. У цьому дослідженні вивчається просторова мінливість вибраних властивостей ґрунту на сільськогосподарських полях навколо Зарії, штат Кадуна, Нігерія, використовуючи геостатистичні методи, щоб надати пояснення для сталого управління земельними ресурсами. Дослідження проводилося на території площею 85 гектарів, розташованій у місті Зарія, штат Кадуна. Сімдесят зразків ґрунту було зібрано за допомогою відбору проб на 85 гектарах. Дотримуючись стандартних лабораторних процедур, зразки були проаналізовані на властивості, включаючи розподіл частинок за розміром, об'ємну щільність (BD), pH, органічний вуглець (OC) і ємність катіонного обміну (CEC). Для визначення просторової залежності використовувався геостатистичний аналіз з використанням інтерполяції Крігінга та моделювання варіограми. Моделювання варіаграми виявило сильну просторову залежність для більшості властивостей ґрунту (відношення самородків < 0,25), включаючи BD, OC і pH, що свідчить про внутрішні фактори, як ключові чинники. Просторові діапазони змінювалися залежно від властивостей, при цьому глина та CEC досягали 339,9 м та 347,6 м відповідно, тоді як pH та BD показали коротші діапазони 85,4 м та 93,3 м. Просторові структури в піску та глині продемонстрували зворотні зв'язки, оскільки області з вищим вмістом глини демонстрували вищі рівні CEC та pH. Інтерполяція Крігінга виявила чіткі просторові закономірності, такі як вищі концентрації глини та CEC у певних зонах та нижчий pH у піщаних областях, що вказує на вплив вилуговування. Карти показали, що на просторовий розподіл OC і BD впливають короткочасні процеси, які вимагають локалізованих стратегій управління. Це дослідження демонструє необхідність звернення до просторової мінливості в планах управління ґрунтами. Сильні кореляції між глиною та CEC підкреслюють критичну роль текстури у впливі на родючість ґрунту. Такі властивості, як OC і BD, зі слабкою просторовою залежністю, вимагають негайної уваги за допомогою цілеспрямованих втручань, таких як органічні поправки та вдосконалені методи обробітку ґрунту.

Ключові слова: *Крігінг, семіваріограма, просторова мінливість, властивості ґрунту.*

Внесок авторів: всі автори зробили рівний внесок у цю роботу

Конфлікт інтересів: автори повідомляють про відсутність конфлікту інтересів

Надійшла 18 вересня 2024 р.

Прийнята 18 листопада 2024 р.