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Farm Level Soil Properties Variability in an Agriculture Landscape of Southwestern Nigeria

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Abstract

Spatial variability of soil properties is a major limitation to precision nutrient management in smallholder farming in Nigeria, where fertilizer is applied uniformly without considering spatial variability within the field. This research examined such variability in a 12.5-ha farmland in the Olowogbo village of Akinyele in Ibadan and using reliable geostatistical fertility maps for characterisation and making recommendations for sustainable soil management. Thirty-four soil samples were collected at 0–30 cm depth and analysed for selected soil properties. Descriptive statistics, Pearson correlation, and geostatistical analyses (semivariogram modelling and ordinary kriging) were used. Total nitrogen ($0.06\text{--}0.17\text{ g kg}^{-1}$, CV = 23.95%, RMSE = 0.03), organic carbon ($6.53\text{--}46.43\text{ g kg}^{-1}$, CV = 33.72%, RMSE = 6.62), calcium ($1.45\text{--}4.37\text{ cmol kg}^{-1}$, CV = 26.54%, RMSE = 0.71), magnesium ($0.45\text{--}1.67\text{ cmol kg}^{-1}$, CV = 35.19%, RMSE = 0.30), and showed considerable variability, with available phosphorus ($1.37\text{--}37.03\text{ mg kg}^{-1}$, CV = 123.49%, RMSE = 8.21), exhibiting extremely high variation and the lowest being exchangeable sodium ($0.15\text{--}0.34\text{ cmol kg}^{-1}$, CV = 16.99%, RMSE = 0.04) and potassium ($0.16\text{--}0.32\text{ cmol kg}^{-1}$, CV = 18.87%, RMSE = 0.04). Most soil properties had moderate spatial dependence and there was significant potential for site-specific nutrient management, and ordinary kriging was used to produce soil fertility maps which clearly identified areas of nutrient sufficiency and deficiency throughout the landscape. Finally, this study also shows the usefulness of GIS and geostatistical methods as decision support tools in sustainable land management in tropical agricultural landscapes.

Keywords: Soil variability, digital soil map, soil management, geostatistical analysis, ordinary Kriging, soil fertility, soil properties.

Introduction

Soils are not only essential for the productivity of the crop but also for maintenance of clean air and water, as well as for the mitigation of greenhouse gas emissions through carbon sequestration, for the maintenance of biodiversity, and for the assurance of food safety [1,2]. The sustainability of agricultural production is a major challenge in the foreseeable future, due to the staggeringly growing human population which the United Nations have projected to rise between 8.3 to 10.9 billion by 2050, hence creating a need for sustainable food production which will require an increment in the current agricultural production by 50 to 75% [3]. Realising this objective requires sustenance of the delicate and dynamic interactions between soil and crops, which fundamentally determines agricultural productivity, soil health and ecosystem resilience [4]. However, climate change, natural disasters and land use constraints can hinder achieving optimum production levels and agricultural sustainability over the long term [5]. These intensifying environmental and anthropogenic constraints have increased pressure on agricultural lands, which are a finite natural resource, and have a negative impact on soil health. To mitigate such challenges, it is imperative to come up with rational agriculture plans and strategies and to efficiently operate agricultural lands. The practise of good nutrient management strategies is necessary for ensuring the long-term sustainability of the agricultural ecosystem, resulting in improved plant productivity. Understanding the role of nutrients in optimal plant growth and development, along with the Soil- Plant-Atmosphere-Continuum (SPAC) relationship, is very important to maintain or improve soil fertility and sustain agricultural production [4,6].

The complex interaction of biological, chemical and physical processes within different intensities and scales results in soils of inherent dynamic nature and considered high spatial variability under different environments and scenarios [7]. Soil properties, along with aspects like crop productivity, disease incidence, weed types, and many other factors, show substantial variation when comparing larger expansive agricultural fields and smaller agricultural plots, an observation that has been reported thoroughly across agricultural studies [8]. In order to maximise the yields and ensure

the optimal application of fertilisers during the crucial stage of crop growth, it is necessary to make a thorough and effective assessment of soil characteristics, with special attention to nutrient composition, before sowing [9]. Assessing the spatial and vertical variability are of paramount importance when evaluating chemical and physical properties of soil and understanding how soil properties fluctuate with geographical location and depth and essential evaluation when it comes to strategically collecting soil samples [2,10]. Such assessments also underlie the implementation of site-specific management practices, which have been proven to increase the productivity of the arable lands through tailoring of inputs according to the spatial requirements of different soils and crops [11-13]. The origins of soil variability are largely based on the complex interactions between topography, geologic formations and climatic conditions, which are further influenced by human land use practises, hence leading to pronounced variability at the macro and micro scales [14]. This occurs at various spatial and temporal scales, and therefore, it requires a higher degree of awareness about heterogeneity to ensure sustainable agricultural practises and increase profitability [15].

The advent of Global Positioning Systems (GPS) and Geographic Information Systems (GIS) has helped manage the spatial variability of soil across a given field, which was once a serious challenge that prevented successful management of agricultural practices. GIS has been highly effective and instrumental in enabling comprehensive evaluations of spatial variability, thus revealing the multifaceted nature of multiple soil properties [7,11]. The processes related to soil sampling and the construction of thematic maps of fertility have been significantly simplified through the integration of GPS and GIS and strengthen the ability of geostatistical analyses intended to characterise the variability of soil properties. The use of digital mapping methods in a GIS framework allows for more accurate estimation of inherent fluctuations of soil parameters in different landscape configurations [16]. Typically, non-geostatistical methods like the Inverse Distance Weighting (IDW) and geostatistical methods such as Ordinary Kriging (OK) and co-Kriging are used for the spatial interpolation of soil attributes [17-19]. Geostatistical interpolation techniques are based basically on directional relationships and distances between known and unknown locations [2,20,21]. Ordinary kriging is preferred over simple kriging because of the greater reliability. An investigation conducted by Gozukara *et al.* [22] showed

that kriging interpolation method yielded a lower Root Mean Square (RMSE) in the analysis of sand, silt and clay content within the soil profile. Moreover, according to [23], in all maps generated with elemental concentrations and indices of weathering, the application of ordinary kriging interpolation methods using an exponential semi-variogram always yielded the lowest RMSE values observed.

Numerous empirical investigations have produced compelling evidence that there are significant differences in soil characteristics in agricultural landscapes with consequent significant differences in crop productivity by region [10,24]. Soil variability, however, is not static and it will change under a complex interplay of multiple factors that operate and interact over spatial (geographical) and temporal scales, thus rendering this variability inherently scale-dependent [25]. Consequently, it is necessary to understand the heterogeneity of soils in order to implement site-specific management strategies that contribute to sustainable resource utilization [26]. Accordingly, in order to effectively deal with the challenge of soil heterogeneity, agricultural scientists also tend to differentiate management zones (MZs) with homogeneous zones within fields with similar soil properties and crop response [7, 27]. Geostatistical methods have been successfully used for establishing these zones in diverse agroecosystems, in favor of targeting interventions and efficient fertilizer use [16]. The effective and efficient management of these soil variabilities requires the comprehensive knowledge of local soil conditions and nutrient dynamics and climatic influences [28]. When combined with spatial analysis, such knowledge improves the timings and accuracies of input applications, thus improving yields and minimising environmental degradation [29]. Sustaining soil health is essential to supporting agricultural productivity and environmental stability. Farmers have to be provided with sufficient knowledge on fertilizer and manure application, proper soil amendments and balanced cropping systems to maintain soil fertility [30-32]. Sustainable land management practises rely on a complete understanding of soil mapping and dynamic interactions that control the variability of soil.

Farmers in Nigeria and most especially those within the Olowogbo agricultural landscape usually follows the blanket and uniform agronomic practices despite the likelihood of substantial within-field heterogeneity in soil properties. These practices have resulted in nutrient use inefficiency, reduced crop productivity and leads to increased production costs. Despite the increasing use of geospatial approaches for

precision nutrient management worldwide, previous studies in study area assessed fertility status but did not quantify within-field spatial dependence or generate maps of key soil fertility variability for this agricultural landscape. Currently, there is limited scientific basis for site-specific fertility management and precision nutrient interventions in the area. This study unlike the previous assessments of soil fertility in southwestern Nigeria, advances the intergration of geostatistical modelling, GIS-based mapping and management-oriented interpretation of soil fertility variability to identify spatially distinct areas requiring differential nutrient management in the study area. This study, therefore, thoroughly investigated the selected soil properties variability using GIS-based geostatistical techniques.

Materials and Methods

Description of the study Area

This research was conducted in Olowogbo village, Akinyele Local Government Area, Ibadan, Oyo State Nigeria. The geographical coordinates of the site are between latitude 7°38'10.72" - 7°38'32.90"N and longitude 3°53'25.86" - 3°53'40.52". This area is located in the surveyed area of the Ibadan North-East sheet 261 of the Federal surveyed topographic map dated 1964 [33]. The total area covered by the site is about 12.5-ha and is located on the tropical rainforest ecological zone (Fig. 1). The local population is mainly occupied in small scale agriculture and petty trading. The region has two climatic periods: during the eight month wet season and a four month dry season when the harmattan winds from the northeast prevail. The climate of the study area is characterised by a bimodal distribution of rainfall with peak precipitation usually occurring during the months of May - June and September - October. Annual rainfall is between 1,190mm and 1,342mm [34]. The mean daily maximum temperature is around 32° C and the mean daily minimum is around 21° C. During the rainy season the temperatures tend to go down, about 29° C in July, gradually rise towards the end of the year. Night temperatures in December can drop to 18° C, with absolute minimum sometimes occurring at 9° C due to mostly influence of cool and dry northeasterly (harmattan) wind from the Sahara Desert.

The study area belongs to the very humid Oyo–Ibadan–Ondo–Oka Plains or Zone N agro-ecological zone [35]. Its landscape is predominantly low-lying and gently undulating. The broader Oyo region comprises both sedimentary and basement

complex formations. Sedimentary units include post-Cretaceous sediments and the Abeokuta Formation in the southern parts, while the northernmost parts has basement complex consists mainly of medium-grained, foliated gneisses rich in feldspar, quartz, and biotite. Portions of the northeastern area are underlain by coarse-grained granites. This geological diversity influences soil texture, drainage patterns, and nutrient dynamics across the landscape [35].

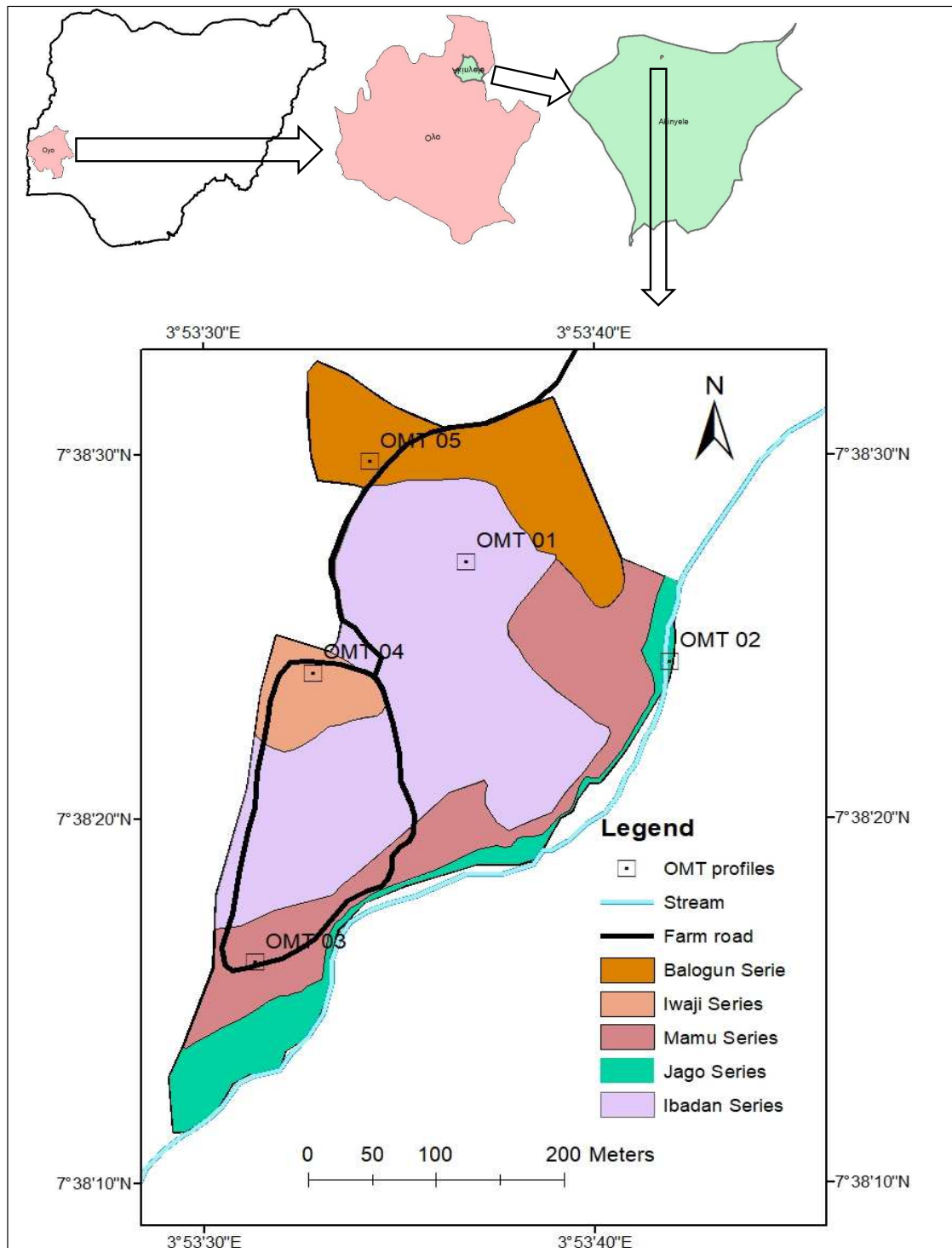


Fig. 1. Map of the Study Area showing the various soil series in the study area

Field Survey and site mapping

A grid-based soil survey approach was adopted. Sampling points were first delineated in a Geographic Information Systems environment, after which their coordinates were uploaded to a GPS device for accurate field navigation. The land was systematically divided into 20 m × 80 m transects, resulting in the identification of 34 sampling locations. Coordinate data from each grid point were transferred into Google Earth Pro to generate a preliminary site map, which was subsequently imported into ArcGIS Pro for further spatial analysis.

Soil Sampling and Analysis

Thirty-four soil samples were taken at the depths 0 - 30 cm using a Dutch soil auger in 2024. The soil samples were properly labelled and transported to the laboratory for subsequent physical and chemical analyses. Soil samples were air dried, slightly crushed using ceramic pestle and mortar and sieved through a 2 mm sized-hole mesh. Soil pH was measured according to the method described by [36]. Soil texture was analysed using the Bouyoucos Hydrometer Method [37]. Soil organic carbon (SOC) was determined via Walkley and Black dichromate wet oxidation method as modified by [38]. Total Nitrogen was determined using the Kjeldahl digestion-distillation technique [39]. Available Phosphorus was analysed using the Bray-1 extraction method, followed by colorimetric detection [40]. Exchangeable cations (Ca, Mg, K and Na) were extracted using the method described by [41]. Exchangeable acidity ($H^+ + Al^{3+}$) followed the method described by [42]. The extractable micronutrients (Fe, Mn, Cu and Zn) followed the method described by [43]. Effective Cation Exchange Capacity (ECEC) was computed as the sum values of exchangeable cations and exchangeable acidity. The percentage base saturation was calculated as follows:

$$\text{Base saturation (\%)} = \frac{(Ca^{2+} + Mg^{2+} + K^+ + Na^+)}{ECEC} \times 100.$$

Analytical quality control procedures included: use of reagent blanks, duplicate samples, instrument calibration before measurements, and adherence to standard laboratory protocols.

Statistical analysis

Descriptive statistics such as mean, median, range, variance, standard deviation, skewness, kurtosis and coefficient of variation of the soil properties gotten from the laboratory analysis were computed using IBM SPSS Version 22.0 [44]. The level of variation was grouped into three (3) according to the standard set by Wilding and Drees [45] which are least variable ($CV < 15\%$), moderately variable ($CV = 15 - 34\%$) and highly variable ($CV > 35\%$). Pearson correlation analysis was also performed to investigate the relationships between the soil chemical and physical variables.

Geospatial Analysis

Spatial analysis for various soil parameters was conducted utilizing the geo-statistical analyst extension of Esri ArcGIS Pro 3.1 software [46]. Variogram modelling was used to characterize spatial dependence, and ordinary kriging was applied to interpolate soil property values across the study area [47]. Several semivariogram models (e.g., spherical, exponential, Gaussian, rational quadratic, J-Bessel, hole effect) were tested. Model performance was evaluated using: Mean Error (ME), Root Mean Square Error (RMSE), and Spatial Dependence Class (SDC), derived from the nugget-sill ratio. The optimal model for each soil parameter was selected based on ME values near zero and RMSE values closest to one, indicating high predictive accuracy [48]. The equations are presented as follows [49]: variable spatial dependency was calculated by the Nugget to sill ratio, which is the ratio of nugget variance to the total variance (sill) multiplied by 100.

$$\text{Spatial dependency} = \frac{\text{Nugget}}{\text{Sill}} \times 100$$

Nugget (C_0) represents the inaccuracy in the estimate process due to sampling errors, while sill $C_0 + C$ indicates spatially independent variance, occurring when data sites are distanced sufficiently for semi-variance to stabilize. For each parameters, the nugget (C_0), the sill ($C_0 + C$) and the range of influence (measured in meters) were documented. The spatial dependencies (Nugget/Sill ratio) were discovered to be connected to the degree of autocorrelation between the sampling points and expressed in percentages [50]. Geographically dependent variables were categorized as strongly geographically dependent if the ratio was less than 25%, moderately

spatially dependent if the ratio ranged from 25 to 75%, and weakly spatially dependent if it > 75% [51]. The Semi-variogram can be expressed mathematically as:

$$\gamma(h) = \frac{1}{2N(h)} \left[\sum_{i=1}^{N(h)} [z(x_i + h) - z(x_i)]^2 \right]$$

Where, (h) is the semi-variance for interval class h , $N(h)$ is the number of pairs separated by a lag distance (separation distance between sample positions). x_i is a measured variable at spatial location i . $(x_i + h)$ is a measured variable at the spatial location, $i + h$

RESULTS

Descriptive statistics of soil properties

The statistical analysis of the soil chemical properties for the topsoil (0-30 cm) layer is listed in Table 1. With a mean of 5.81 ± 0.46 std. dev., the pH of the soil ranged from severely acid to near neutral (4.92–6.77) (Fig. 3a). At 7.85%, it exhibits minimal fluctuation. It has values of 0.364 for Kurtosis and -0.103 for Skewness. As the precursor of organic matter, it plays an essential role in preserving the structure of the soil and binding nitrogen, which enhances infiltration and plant uptake, respectively. With a mean value of $22.8 \pm 7.68 \text{ gkg}^{-1}$, organic carbon (OC) ranged from 6.53 to 46.43 gkg^{-1} , indicating adequate status (Fig. 3b). The variability is moderate (33.72%). It has values of 59.11 for variance, 0.607 for skewness, and 1.848 for kurtosis. The total N varied from 0.06 to 0.17 gkg^{-1} with a mean value of $0.12 \pm 0.03 \text{ g kg}^{-1}$ and medium CV (23.95%) (Fig. 3c). It has the values of 0.001 for variances of -0.197 for skewness and -0.113 for kurtosis. The available P varied from 1.37 to 37.03 mgkg^{-1} with mean values of $6.62 \pm 8.17 \text{ mgkg}^{-1}$ and has a high CV (123.49%) (Fig. 3d). The variance, skewness and kurtosis values of 66.88, 2.951 and 8.506, respectively. The Exchangeable potassium varied from 0.16 to 0.32 cmolkg^{-1} with mean values of $0.24 \pm 0.04 \text{ cmolkg}^{-1}$ and has a high CV (18.87%) (Fig. 3e). The variance, skewness and kurtosis values of 0.002, 0.166 and -0.904, respectively.

With mean values of $2.98 \pm 0.79 \text{ cmol kg}^{-1}$ and a moderate CV (26.54%), the exchangeable Ca^{2+} ranged from 1.45 to 4.37 cmol kg^{-1} (Fig. 3f). The corresponding values for variance, skewness, and kurtosis were 0.629, -0.138, and -0.941. The exchangeable Mg^{2+} varied from 0.45 to 1.67 cmol kg^{-1} with the mean values of $0.82 \pm$

0.29 and has a high CV (35.19%) (Fig. 4a). The variance, skewness and kurtosis values of 0.085, 1.552 and 2.208, respectively. The exchangeable Na^+ varied from 0.15 to 0.34 cmol kg^{-1} with the mean values of 0.23 ± 0.03 and has a moderate CV (16.99%) (Fig. 4b). The variance, skewness and kurtosis values of 0.002, 0.460 and 1.447, respectively. The ECEC values varied from 3.01 to 6.46 cmol kg^{-1} with the mean values of 4.57 ± 0.97 and has a moderate CV (21.22%) (Fig. 4c). The variance, skewness and kurtosis values of 0.942, 0.238 and -0.904, respectively. The EA values varied from 0.10 to 0.60 cmol kg^{-1} with the mean values of 0.29 ± 0.10 and has a moderate CV (33.20%) (Fig. 4d). The variance, skewness and kurtosis values of 0.009, 1.029 and 1.989, respectively. The Base saturation values varied from 84.62 to 97.47 % with the mean values of $93.33 \pm 2.60\%$ and has a low CV (2.79%) (Fig. 4e). The variance, skewness and kurtosis values of 6.799, -1.364 and 2.567, respectively.

The Zn values varied from 0.80 to 2.10 mg kg^{-1} , the mean values of 1.29 ± 0.35 std. dev. (Fig. 4f). It has a high CV (42.99%) and variance, skewness and kurtosis values of 0.123, 0.609, and -0.021, respectively. The Cu values varied from 1.45 to 9.50 mg kg^{-1} , the mean values of 4.26 ± 1.94 std. dev. (Fig. 5a). It has a high CV (45.52%) and variance, skewness and kurtosis values of 3.760, 0.653, and 0.447, respectively. The Fe values varied from 7.0 to 75.0 mg kg^{-1} , the mean values of 36.45 ± 19.87 std. dev. (Fig. 5b). It has a high CV (54.51%) and variance, skewness and kurtosis values of 394.792, 0.362, and -0.574, respectively. The Mn values varied from 9.0 to 124.60 mg kg^{-1} , the mean values of 41.06 ± 24.17 std. dev. (Fig. 5c). It has a high CV (58.94%) and variance, skewness and kurtosis values of 584.408, 2.054, and 4.725, respectively. The values of the Sand particles of the soil varied from 700.00 to 962.00 g kg^{-1} , the mean values of 878.67 ± 49.24 std. dev. (Fig. 5d). It has a low CV (5.60%) and variance, skewness and kurtosis values of 2424.735, -2.015, and 5.630, respectively. The values of the silt particles of the soil varied from 34.00 to 177.00 g kg^{-1} , with the mean of 85.09 ± 28.81 std. dev. (Fig. 5e). It has a moderate CV (28.81%) and variance, skewness and kurtosis values of 830.376, 1.735, and 4.433, respectively. The values of the clay particles of the soil varied from 4.00 to 126.00 g kg^{-1} , with the mean of 36.22 ± 22.44 std. dev. (Fig. 5f). It has a high CV (61.93%) and variance, skewness and kurtosis values of 503.405, 2.327, and 7.294, respectively.

Table 1 General descriptive statistics of soil properties at the study area

Parameters	Range	Min.	Max.	Sum	Mean	Std. Dev	%CV	Variance	Skewness	Kurtosis
pH	1.85	4.92	6.77	197.35	5.81	0.46	7.85	0.207	-0.103	-0.364
SOC(g/kg)	39.90	6.53	46.43	775.16	22.80	7.68	33.72	59.110	0.607	1.848
Total N (g/kg)	0.11	0.06	0.17	3.97	0.12	0.03	23.95	0.001	-0.197	-0.113
Avail P (mg/kg)	35.66	1.37	37.03	225.16	6.62	8.17	123.49	66.877	2.951	8.506
Exchangeable Cations (cmol kg⁻¹)										
Ca	2.92	1.45	4.37	101.59	2.98	0.79	26.54	0.629	-0.138	-0.941
Mg	1.22	0.45	1.67	28.19	0.82	0.29	35.19	0.085	1.552	2.208
Na	0.19	0.15	0.34	7.85	0.23	0.03	16.99	0.002	0.460	1.447
K	0.16	0.16	0.32	8.02	0.24	0.04	18.87	0.002	0.166	-0.969
ECEC	3.44	3.01	6.46	155.56	4.57	0.97	21.22	0.942	0.238	-0.904
BS (%)	12.85	84.62	97.47	3173.28	93.33	2.60	2.79	6.799	-1.364	2.567
EA (cmol/kg)	0.50	0.10	0.60	9.90	0.29	0.10	33.20	0.009	1.029	1.989
Extractable Micronutrients (mg kg⁻¹)										
Zn	1.30	0.80	2.10	43.87	1.29	0.35	27.20	0.123	0.609	-0.021
Fe	68.00	7.00	75.00	1239.15	36.45	19.87	54.51	394.792	0.362	-0.574
Mn	115.60	9.00	124.60	1394.56	41.01	24.17	58.94	584.408	2.054	4.725
Cu	8.05	1.45	9.50	144.80	4.26	1.94	45.52	3.760	0.653	0.447
Particle Size (g kg⁻¹)										
Sand	262.00	700.00	962.00	29875.07	878.67	49.24	5.60	2424.735	-2.015	5.630
Silt	143.00	34.00	177.00	2893.13	85.09	28.81	33.86	830.376	1.735	4.433
Clay	122.00	4.00	126.00	1231.80	36.22	22.44	61.93	503.405	2.327	7.294

Min – Minimum, Max – Maximum, Std. Dev.- Standard deviation, CV- coefficient of variation, Na-Sodium, Mg-Magnesium, Ca- Calcium, K-Potassium, EA- Exchangeable Acidity, P-Phosphorous, Total N- Total Nitrogen, SOC-Soil Organic Carbon

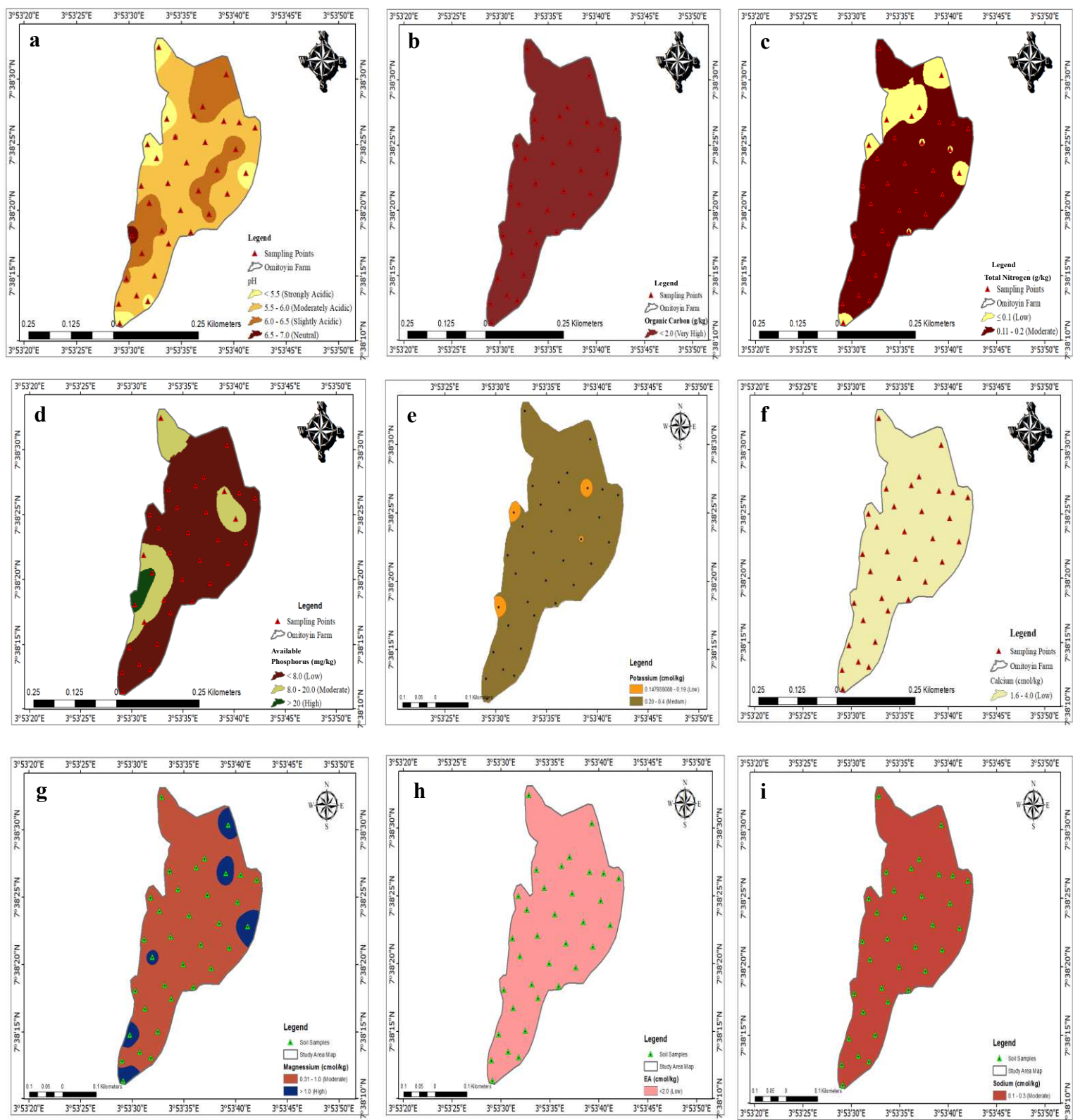


Fig 3 Spatial Distribution of (a) Soil pH (b) Soil Organic Carbon (c) Total Nitrogen (d) Available Phosphorus (e) Potassium (f) Calcium (g) Magnesium (h) Exchangeable Acidity (E.A) (H⁺+Al²⁺) (i) Sodium

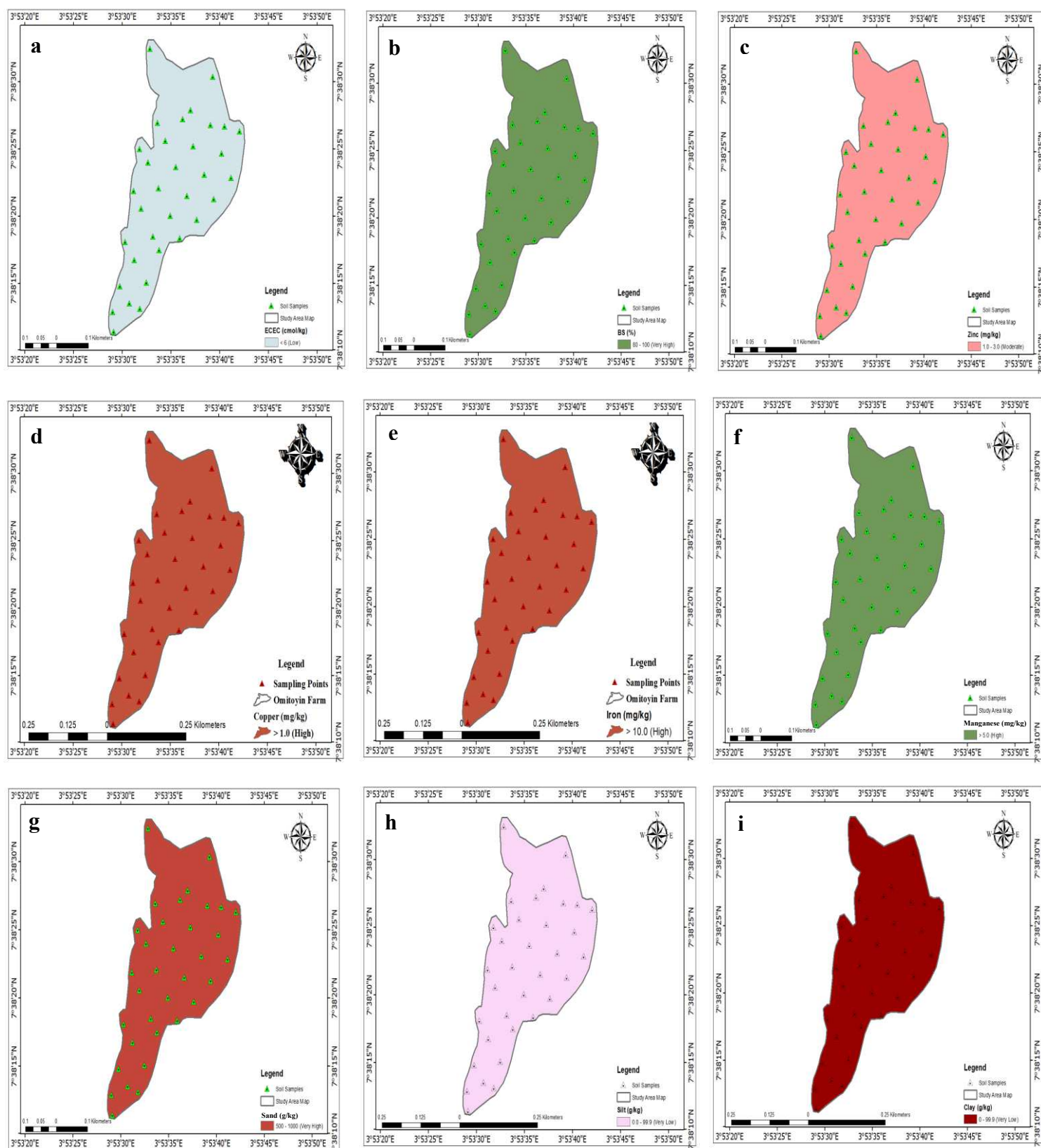


Fig 4 Spatial Distribution of (a) ECEC (b) Base Saturation (c) Zinc (d) Copper (e) Iron (f) Manganese (g) Sand (h) Silt (i) Clay

Geostatistical analysis of soil properties

Table 2 and Fig. 5 provides findings on the semi-variance analysis of the soil properties. Semi-variogram models, including Gaussian, spherical, exponential, stable, and J-Bessel, were applied to each soil chemical properties and the model with the least Mean Error (ME) and Root Mean Square Error (RMSE) using the standard kriging interpolation approach was selected. The spherical semi-variogram model fit pH, P₂O₅, Ca²⁺, Zn, and clay the best, whereas the exponential model only suited Na⁺ the Gaussian model fit TN, OC, Fe²⁺, Mn⁺, and Cu⁺ the best. J-Bassel was the best fit for K⁺, Acidity, and Silt, while Stable was the best fit for Mg⁺, ECEC, and Sand.

Table 2: Semi-variance analysis of soil properties

Soil parameters	Ordinary Kriging Model	ME	RMSE	Nugget	Sill	Nugget/ Sill (%)	Spatial Class
Total N	Gaussian	8.4454	0.0292	0.7539	1.0316	73	Moderate
pH	Spherical	0.0293	0.3933	0.3542	1.2567	28	Moderate
Avail P	Spherical	-0.3977	8.2145	26.5661	78.7509	33	Moderate
Org Carbon	Gaussian	0.1885	6.6203	29.4229	63.0224	46	Moderate
Calcium	Spherical	0.0065	0.7088	0.5813	1.2501	46	Moderate
Magnesium	Stable	-0.0075	0.3011	0.9464	1.7169	55	Moderate
Sodium	Exponential	-0.0005	0.0401	0.9749	1.0719	90	Weak
Potassium	J-Bassel	-0.0002	0.0428	0.5070	0.9807	52	Moderate
ECEC	Stable	0.0299	0.9420	0.8024	0.8038	99	Weak
EA	J-Bassel	-0.0008	0.0951	0.8939	0.9575	93	Weak
Zinc	Spherical	0.0054	0.3461	1.0898	1.1225	97	Weak
Iron	Gaussian	0.4095	19.7776	1.0593	1.3853	76	Weak
Manganese	Gaussian	0.2183	22.5298	0.7102	1.303	54	Moderate
Copper	Gaussian	0.0900	1.8088	0.8007	1.4901	53	Moderate
Sand	Stable	1.774	45.2561	0.7622	1.419	53	Moderate
Silt	J-Bassel	-0.6285	23.8405	379.2930	868.0733	43	Moderate
Clay	Spherical	-0.1181	22.2849	0.7431	1.3473	55	Moderate

Notes: ME: Mean standard error; RMSE: Root-Mean-Square error; EA: Exchangeable Acidity; ECEC: Effective Cation Exchange Capacity.

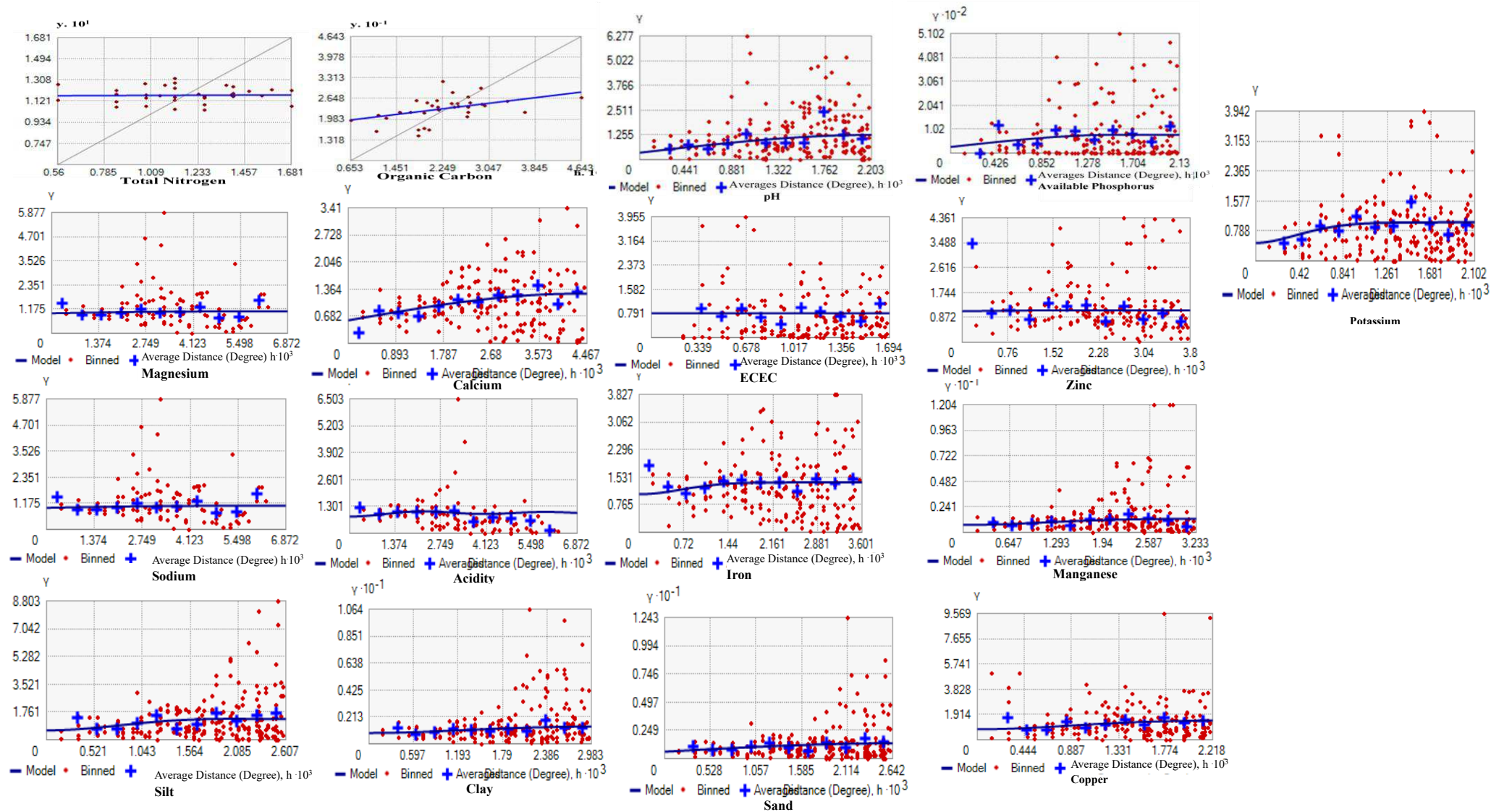


Fig. 5. Semi-variogram analysis of the Soil Physical and Chemical Properties for best-fit models based on ME and RMSE values.

Pearson Correlation of the Soil Physical and Chemical Properties

To determine the degree of relationship between soil parameters, the Pearson correlation coefficient was used (Table 3). N, OC, and P had positive correlations with pH, while Ca, Mg, Na, K, ECEC, BS, Acidity, Zn, Fe, Mn, Cu, Sand, Silt, and Clay had negative correlations. Total nitrogen had a negative correlation with zinc, copper, and sand and a positive correlation with pH, OC, P, Ca, Mg, Na, K, BS, acidity, silt, and clay. P, Ca, Mg, Na, K, ECEC, Acidity, Zn, Fe, Mn, Silt, and Clay all had positive correlations with soil organic carbon, whereas BS, Cu, and sand had negative correlations. There was a negative correlation between the available phosphorus and Zn, Cu, silt, and clay, and a positive correlation with Ca, Mg, Na, K, ECEC, BS, Acidity, Fe, and Mn. While calcium had a negative correlation with sand, Na, Zn, and Cu, it had a positive correlation with Mg, K, ECEC, BS, Acidity, Fe, Mn, Silt, and clay. Magnesium showed a negative correlation with Zn and Sand, but a positive correlation with Na, K, ECEC, BS, Acidity, Fe, Mn, Cu, Silt, and Clay. In contrast to its negative correlation with ECEC, Acidity, Cu, and Sand, sodium had a positive correlation with K, BS, Zn, Fe, Mn, Silt, and Clay. Potassium had negative correlations with Acidity, Cu, Sand, Silt, and Clay, and positive correlations with ECEC, BS, Zn, Fe, and Mn. There was a negative correlation between the effective cation exchange capacity and Zn, Cu, and Sand, and a positive correlation with BS, Acidity, Fe, Mn, Silt, and Clay. The exchangeable acidity had a negative correlation with Sand, Cu, and Fe, and a positive correlation with Silt, Clay, and Fe. Zinc had a negative correlation with sand and a positive correlation with silt, clay, iron, magnesium, and copper. Iron had a negative correlation with Mn, Cu, and clay and a positive correlation with silt and sand. Manganese has a negative correlation with Cu and Sand and a positive correlation with Silt and Clay. Copper has a negative correlation with sand and a positive correlation with silt and clay. The sand concentration of the soil was inversely connected with Silt and Clay whereas Silt was positively correlated with Clay.

Table 3 Pearson Correlation of the Soil Physical and Chemical Properties

Par	pH	Total N	OC	Av.P	Ca	Mg	Na	K	ECEC	BA	EA	Zn	Fe	Mn	Cu	Sand	Silt	Clay
pH	1																	
Total N	0.021	1																
Org. Carbon	0.244	.398*	1															
Avail P	0.176	0.179	0.145	1														
Ca	-0.046	.609**	.451**	0.280	1													
Mg	-0.216	.358*	0.130	0.034	.449**	1												
Na	-0.139	0.022	0.104	0.072	-0.103	0.132	1											
K	-0.308	0.337	0.072	0.218	0.193	0.197	.431*	1										
ECEC	-0.035	.586**	.388*	0.263	.958**	.596**	-0.073	0.236	1									
BS	-.536**	0.319	-0.006	0.065	.446**	0.329	0.038	.371*	.381*	1								
Acidity	.505**	0.071	0.250	0.065	0.071	0.075	-0.039	-	0.168	0.180	-.801**	1						
Zn	-0.052	-0.015	0.151	-0.133	-0.005	-	0.145	0.243	-0.028	-0.102	0.108	1						
Fe	-0.192	.371*	0.207	0.146	.346*	0.078	-0.028	.390*	0.307	.416*	-0.184	0.050	1					
Mn	.398*	.504**	0.300	0.289	.445**	0.116	0.189	0.201	.431*	-0.004	0.268	0.123	-	1				
Cu	-.351*	-0.271	-0.028	-.385*	-0.059	0.045	-0.020	-	-0.070	0.023	-0.120	0.265	-.361*	-0.116	1			
Sand	0.064	-0.313	-0.189	0.188	-.378*	-.346*	-0.277	-	-.442**	-0.004	-0.226	-0.254	0.110	-.402*	-	1		
Silt	-0.059	0.308	0.158	-0.139	.443**	0.329	0.153	-	.499**	0.020	0.261	0.236	0.042	.461**	0.230	-.916**	1	
Clay	0.010	0.233	0.051	-0.224	0.289	.412*	0.283	-	.377*	0.011	0.142	0.099	-.345*	0.236	0.109	-.837**	.619*	1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Discussion

Descriptive statistics of the soil properties

The spatial distribution of the soil properties showed that all the soil properties exhibited considerable variability across the study region (Table 1). The soils were generally high in sand in the surface layer and subsoil levels. This is in agreement with the previous studies of [52,53]. The soil texture across the field was dominated by loamy sand followed by sandy loam, then sand and few sand clay loam. This textural class is particularly noted for its high infiltration rate making it very good for cultivation. The sand fraction has a low variability while the silt has a moderate variability and the clay was highly variable.

Soil chemical characteristics varied widely across the study area. The soils' pH values, which ranged from 4.92 to 6.77, corresponded to a strongly to moderately acidic, attributable to the leaching of basic cations under humid conditions marked by substantial and heavy rainfall. Additionally, this may also stem from the intrinsic properties of the soils in the study area, regardless of their parent materials [53]. Ajayi *et al.* [54] and Orimoloye *et al.* [55] documented similar results in soils derived from basement complex geology. Crop output may suffer as a result of soil acidity's effects on nutrient availability, herbicide persistence, and heavy metal toxicity [56]. Brady and Weil [57] stated that 5.5 to 7.0 is the preferred range for most crops. The impact of soil pH on crop nutrient availability is so profound that the majority of essential nutrients are available to most plants in the range of 6.0 to 6.5 [58]. Maintaining ideal soil pH levels throughout the field is crucial for both crop quality and yield as well as soil health. The soil pH CV readings showed minimal variability ($CV < 15$). Because pH is regarded as a stable soil characteristic, these values were lower than the CV values of other measured soil chemical parameters [59]. Ajayi and Okonokhua [58] found similar results, indicating that pH had the lowest CV (6.29%) and the least variation. The concentration of soil organic carbon was very high indicating favorable accumulation of carbon based on the rating given by [60,61]. The SOC varied moderately also possessing a positive skewness and kurtoses. The concentration of total nitrogen varied from low to moderate and moderately variable. The spatial distribution of the farm (Fig. 3c) showed that TN is moderate in most part of the farm. The low to moderate nature of Nitrogen recorded in this study correlates with studies of [54,62] possibly due to uptake by plants or mineralization, volatilization, leaching, and nitrification processes which is necessitated by the humid climate.

The spatial distribution of available P contents of the soil in the study area was dominated by low (< 8 mg/kg) followed by moderate (8 – 20 mg/kg) then high (> 20 mg/kg) (fig. 3d). Also, the available P content was highly variable ($CV > 35\%$) as shown in Table 1 and were lower than those reported in soils in similar area as observed [63]. The dominance of low available P at most points could have been due to leaching of plant nutrient or to some losses through plant uptake. The findings were similar to [53], who reported that among soil properties, available P was more variable compared to

others. The deficit might also be caused by soil formation from phosphorus-deficient parent material; the observation is consistent with [15,64], who found that parent materials greatly influenced the soil's phosphorus level. Phosphorus depletion in soils is a global issue threatening the attainment of United Nations Sustainable Development Goal Two, Zero Hunger; this claim has been supported by earlier studies [65]. Energy metabolism and transformation depend on phosphorus as do the development of plant branches [15,64].

The spatial distribution of Potassium in the soil in the study area showed that it was medium ($< 0.20 - 0.4$ cmol/kg) in most parts except in some few areas being low (> 0.2 cmol/kg) (fig. 3e). Also, the K content was moderately variable ($CV > 15 < 35\%$) as shown in Table 1. The maintenance of normal physiological processes, protein synthesis, and plant water balance is a crucial process by Potassium [66]. Sobulo and Adepetu [67] identified a critical potassium level of $0.15-0.30$ cmol/kg, with the soils exhibiting values exceeding this threshold. The sufficient potassium concentration in the soil may be attributed to the parent materials, corroborating the findings of Swoboda *et al.* [68], which indicated that parent materials significantly affect soil potassium availability. The spatial distribution of the exchangeable calcium in the studied area showed that it was low ($1.6 - 4.0$ cmol/kg) and moderately variable (26.54%). Turyasingura *et al.* [69] asserted that an exchangeable calcium level exceeding 6 cmol/kg of soil is deemed sufficient for the nutritional requirements of the majority of crops. Calcium is recognised for its role in regulating plant responses to endogenous stimuli and stress signals [70]. The reduced calcium concentration in the soil may arise from leaching caused by the humid environmental conditions [71].

The spatial distribution of exchangeable magnesium in the research area ranges from moderate ($0.31 - 1.0$ cmol/kg) to high (> 1.0 cmol/kg) and exhibits significant variability (35.19%). It performs several essential functions, including enzyme catalysis, photosynthesis, and the production of genetic material in plants [72]. The magnesium level in the soil is optimal for plant growth. The spatial distribution of exchangeable sodium in the research area indicates a moderate range ($1.0 - 3.0$ cmol/kg) and a moderate variability of 16.99%. It is monovalent, allowing it to serve as a substitute for potassium in plant nutrition; nevertheless, its excess may adversely affect soil structure due to sodicity. The moderate distribution signifies the absence of soil sodicity, indicating that sodium is not a constraint for plant production. The soil's ECEC concentration was low and exhibited moderate variability (21.22%). These figures indicate the limited potential of these soils to retain nutritional components, attributed to the inadequate quantity of organic matter and the soil's acidic nature [73]. The diminished ECEC values indicate that some exchangeable cations in the soil were deficient. The exchangeable acidity of the soils was low (< 2.0 cmol/kg) and exhibited significant variability (33.20%). The percentage base saturation (PBS) values were very high and has a low variability (2.79%). The high %BS suggest high soluble forms of basic cations in soil solution. This finding is in total agreement with [63], who reported consistent high values of BS in the soils of similar areas. The high base

saturation might be due to the nature of parent materials or the presence organic matter which serves as an exchange sites.

The micro-nutrients (Zn, Fe, Mn, Cu) in the soils indicated that Zn is at a moderate level, whereas Cu, Fe, and Mn are at high levels. Zinc is essential for gene replication and significantly impacts plant metabolism by modulating hydrogenase and carbonic anhydrase activity, facilitating cytochrome synthesis, and stabilising ribosomal fractions [74]. Iron is the fundamental micronutrient due to its function in chlorophyll production and electron transport. It affects nitrification, respiration, and the production of genetic materials [75]. The elevated iron levels in all samples can be ascribed to effective drainage and the availability of iron in the exchange complex following base leaching. The elevated concentration of iron indicates a strong likelihood of the presence of iron-rich minerals such as haematite, goethite, olivine, magnetite, and siderite. This may also result from Fe complexes with phosphate compounds in the soil, reducing the likelihood of leaching losses. Nutrients such as phosphorus, potassium, manganese, and zinc must be well regulated, as their availability is compromised by elevated iron levels [15]. Copper enhances mitochondrial respiration, hormone signaling, photosynthetic electron transport, and enzyme activation in plants [76]. Mwendwa *et al.* [15] reported that sufficient copper levels and its higher accumulation in the surface horizon are mainly associated with clay minerals and organic matter, respectively. In soils, copper occurs largely as the divalent Cu^{2+} ion, where it is retained through adsorption onto clay particles or complexation with organic materials. The observed copper status may also be linked to low soil phosphorus levels, as phosphorus is known to antagonize copper availability. Manganese primarily derives from the breakdown of ferromagnesian rocks. It has a crucial role in photosynthesis, nitrogen absorption, root disease resistance, and enzyme activation [77,78].

The available P, Mg, %BS, EA, Mn, Sand, Silt and Clay were highly skewed with skewness values +1 and above (right-handed skewness) or -1 (left-handed skewness). SOC, Zn, and Cu were moderately skewed with skewness values between 0.5 and 1 or between -0.5 and -1. Soil pH, total N, Ca, Na, K, ECEC, and Fe had skewness values between -0.5 and 0.5 and which are considered to be normally distributed. Kurtosis values for SOC, available P, Mg, Na, %BS, EA, Mn, Sand, Silt and Clay were greater than one, indicating leptokurtic kurtosis.

Semi-variance analysis of soil properties

The semi-variance analysis presented in the table 2 evaluates the spatial distribution of various soil properties using the Ordinary Kriging geostatistical method. The analysis involves key geostatistical indicators such as the nugget, sill, nugget-to-sill ratio, and cross-validation metrics (mean error and RMSE), which are essential for understanding and classifying the spatial structure of soil attributes. The nugget-to-sill ratio, in particular, serves as an indicator of spatial dependence, where values less than 25% suggest strong dependence, 25–75% imply moderate dependence, and

above 75% indicate weak spatial dependence [51], helping to determine the extent to which soil variables can be spatially predicted or managed.

The findings reveal that most soil properties exhibited moderate spatial dependence such as total nitrogen (73%), pH (28%), available phosphorus (33%), organic carbon (46%), calcium (46%), magnesium (55%), potassium (52%), and soil textural components (sand, silt, and clay). This implies that their distribution is influenced by both natural factors (such as parent material and topography) and anthropogenic activities (such as land use or fertilization practices), implying that their spatial variability can be effectively managed through site-specific interventions [79]. In contrast, parameters such as sodium (90%), exchangeable acidity (93%), ECEC (99%), zinc (97%), and iron (76%) showed weak spatial dependence, indicating a more random distribution that may not be well captured by spatial interpolation techniques. This suggests a more random spatial pattern, making them less responsive to precision management strategies. The spatial class of the soil properties across the farm are generally weaker than in the comparator studies, [81] reported moderate to strong spatial dependence in parameters like organic carbon, total nitrogen, and pH in Iowa soils. Similarly, [81] observed moderate spatial dependence in pH, P and OC in soils of Irepo local government area of Oyo state, which corresponds with the present findings. The weak structure found in ECEC and EA in this study can be attributed to anthropogenic influences.

Pearson Correlation Matrix of the Soil physical and Chemical Properties

The table 3 presents a Pearson correlation matrix that analyzes the relationships among various soil physical and chemical properties. This statistical approach is essential in understanding how soil parameters interact, and it aids in identifying patterns of nutrient dynamics and physical structure within the soil profile. Such relationships, when combined with spatial analysis techniques like geostatistics, provide critical insights for land use management, soil fertility optimization, and precision agriculture.

From the matrix, significant positive correlations were observed between several key nutrient indicators. Total nitrogen (N) showed strong positive correlations with organic carbon ($r = 0.398^*$) and calcium ($r = 0.609^{**}$), suggesting that nitrogen availability in the soil is closely tied to organic matter content and cation exchange capacity. This finding is consistent with [15,81,82] emphasizing that areas high in organic matter also tend to be nutrient-rich due to the mineralization of organic materials. Also, [83] found a positive and significant correlation between TN and OC in their study in Ibadan southwest local government area of Oyo state. Moreover, effective cation exchange capacity (ECEC) also correlated strongly with calcium ($r = 0.958^{**}$) and magnesium ($r = 0.596^{**}$), which is expected since these cations significantly contribute to the soil's exchange capacity.

A negative relationship was observed between base saturation (BS) and acidity ($r = -0.801^{**}$), indicating that soils with higher acid content tend to have lower base

saturation levels. This disagreed with studies by [83], which reported very strong positive relationships between pH-related factors and base saturation in acidic agricultural soils. Similarly, sand content showed a strong negative correlation with clay ($r = -0.837^{**}$) and silt ($r = -0.916^{**}$), which reflects the inverse proportionality of soil texture components, a common result also observed by [81] in their assessment of soil texture and fertility in tropical regions.

Micronutrients such as iron (Fe) and manganese (Mn) showed positive correlations with total nitrogen (Fe: $r = 0.371^*$, Mn: $r = 0.504^{**}$), indicating that microelement availability may also be influenced by organic matter decomposition and nutrient cycling. However, copper (Cu) exhibited weak or negative correlations with most variables, particularly with available phosphorus ($r = -0.385^*$), possibly due to antagonistic interactions in the soil matrix or low mobility. In the study of [16, 84], they found a negative correlations and significance difference between pH and Zn and a negative but not significant differences between pH and Cu. pH in this study was positively correlated and significantly different from Mn and positively but not significantly different from Fe which aligns with [84].

The findings in this study align with broader patterns observed in spatial soil studies. Liu *et al.* [85] emphasized the importance of organic matter and pH in shaping nutrient availability and their spatial distribution. Similarly, [80] showed that organic carbon, nitrogen, and pH had strong spatial structures and significant correlations, supporting site-specific nutrient management strategies. The correlation matrix provides a foundational understanding of the interrelationship among soil variables, many of which also exhibit spatial variability. These relationships highlight the need for integrated soil fertility management that considers both chemical interactions and spatial distribution. This supports the design of more efficient nutrient application regimes and sustainable land use planning.

Conclusion

The soils showed significant variation in the distribution of some specific soil properties across the study area. While some properties such as pH and sand showed low variation and strong structure, whereas available phosphorus, sodium and ECEC were highly variable or weakly structured, demonstrating randomness and heterogeneity in soil fertility status. These variations suggest to a non-uniform fertility level across the terrain, underlining the need for site-specific soil management approaches. All but a few of the attributes showed little spatial dependence, suggesting that precision agriculture methods could be used to improve the efficiency of fertiliser use.

In addition, high correlations between the key properties (organic carbon, total nitrogen, calcium and ECEC) emphasize the need for whole-farm nutrient and soil health management. Availability of adequate micronutrients, particularly Fe & Mn are encouraging, but care needs to be taken with interactions, e.g. antagonism between P & Cu. The present study aims at geostatistically characterizing the main soil parameters and their spatial representation within the study area by using GIS

technique for the first time. The resulting maps showed significant spatial variation, and illustrate the potential for site-specific nutrient management strategies. Apart from the traditional soil fertility assessment, the study sets up a spatial decision-support Sustainable Agricultural Intensification in tropical farming systems. The establishment of soil fertility maps is one of the steps towards precision agriculture in the study area and it provides a basis for the evaluation of soil fertility spatial heterogeneity and site specific nutrient management. The maps created can be used to optimise nutrient application, reduce the need for inputs that are not required, prevent environmental degradation and enhance the productivity and profitability of smallholder farms, as the maps indicate where nutrients are in deficient or surplus amounts. The study also illustrates how GIS and geostatistical techniques can be useful for sustainable land use in agricultural landscapes as decision support tools. These should be included in future studies to further improve precision soil management recommendations for the area by incorporating terrain attributes and remote sensing data.

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Declarations

Data Availability Statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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