ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.016

JOURNAL OF GEOMATICS AND ENVIRONMENTAL RESEARCH
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RESEARCH ARTICLE

The Analysis of the Spatial Variability of Soil Nutrients using Geospatial Techniques for Improved Precision Agriculture Practices

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Abstract

Soil fertility is rarely uniform across landscapes, yet quantifying this variability is essential for precision agriculture (PA). This study applied geospatial analysis to evaluate the spatial variability of nitrogen (N), phosphorus (P), and potassium (K) on a 1.7-hectare experimental plot at the Federal University of Technology, Minna, Nigeria. Georeferenced soil samples (25 cm depth) were collected and analyzed. The data were processed using Geographic Information System (GIS) techniques, employing both Inverse Distance Weighting (IDW) and Trend interpolation methods to generate distribution maps. Results revealed significant spatial heterogeneity in nutrient levels: nitrogen (N) ranged from 0.50% to 0.76%, phosphorus (P) from 0.024% to 0.038%, and potassium (K) showed the widest variation, from 0.119% to 1.12%. Comparative analysis confirmed that the IDW method provided more accurate and reliable outputs (yielding lower standard deviation values) compared to the Trend method. The study concludes that geospatial analysis, particularly through IDW interpolation, is an invaluable decision-support tool for PA, and recommends its adoption for developing site-specific fertilizer application plans to enhance resource efficiency and promote sustainable agricultural practices in the region.

ARTICLE HISTORY
Received: 13th December, 2025
Accepted: 22nd December, 2025
Published: 23rd December, 2025

KEYWORDS
Soil Fertility, Spatial Variability, Precision Agriculture, Inverse Distance Weighting (IDW), Trend Interpolation.

Citation: Bako M., Makama D., Mohammed G. A., Ibrahim A., Oduyemi A. T. (2025). The Analysis of the Spatial Variability of Soil Nutrients using Geospatial Techniques for Improved Precision Agriculture Practices, *Journal of Geomatics and Environmental Research, 8(2). Pp179-191*

1. INTRODUCTION

Ensuring global food and nutritional security remains a major concern, requiring the agricultural sector to maximize yields while minimizing environmental impacts. Soil fertility, particularly the availability of essential macronutrients like nitrogen (N), phosphorus (P), and potassium (K), is a critical determinant of agricultural productivity (Penuelas *et al.,* 2023; Yingying *et al.,* 2025). However, nutrient availability is rarely uniform across landscapes, a phenomenon known as spatial variability (Bell and Siegel 2022; Havlin and Heiniger, 2010). Ignoring this heterogeneity often leads to the inefficient blanket application of fertilizers, resulting in decreased profitability and environmental degradation (Ghasal *et al.*, 2025; Kumar, 2021).

To address this challenge, Precision Agriculture (PA) has emerged as an integrated information and management system that advocates for site-specific treatment rather than uniform field management (Delgado *et al.,* 2019; Raj *et al.,* 2019). The foundation of PA rests on Geospatial Analysis, which utilizes technologies such as Remote Sensing (RS), Global Positioning Systems (GPS), and Geographic Information Systems (GIS) to capture, store, and analyze spatial data (Panamaldeniya, 2021; Srinivasan, 2006; Gebberi, 2010). GIS-based soil fertility mapping employs spatial statistics and interpolation techniques, such as Inverse Distance Weighting (IDW) and Trend interpolation, to model nutrient distribution across a field. This spatial information is paramount for creating variable rate application maps, which ensure crops receive the right amount of nutrients exactly where they are needed (Patel and Shah, 2022; Kushwaha *et al.,* 2014).

While the benefits of PA are globally recognized, its practical application in regions like Nigeria is still in its nascent stages, with most farmers relying on generalized fertilizer recommendations (Zhang *et al.,* 2021). Recent studies in comparable environments have consistently confirmed that soil parameters exhibit high spatial variation within fields, validating the necessity of variable input strategies (Vasu *et al.,* 2017; Mwendwa *et al.,* 2022). Bridging this local knowledge gap by providing accurate, evidence-based spatial data is crucial for promoting resource efficiency and sustainability within the Nigerian agricultural sector.
Therefore, this study aims to analyze the spatial variability of soil macronutrients (N, P, and K) using geospatial techniques within a 1.7-hectare experimental plot in Minna, Nigeria. Specifically, the research compares the efficacy and accuracy of the Inverse Distance Weighting (IDW) and Trend interpolation methods to determine the most reliable approach for generating site-specific nutrient distribution maps to support improved precision agriculture practices.

2. STUDY AREA

The study area is the 1.7-hectare experimental farm plot situated within the premises of the Federal University of Technology (FUT), Minna, Niger State, Nigeria, which lies at approximately Latitude 9° 41' N and Longitude 6° 31' E as presented in Figure 1, with an elevation of about 258.5 meters above sea level. Minna, located in the North-Central region of Nigeria, falls within the Southern Guinea Savanna ecological zone, characterized by distinct wet and dry seasons (Ibrahim *et al.,* 2024; Ibrahim *et al.,* 2023; Bako *et al.*, 2020). The area experiences an average annual rainfall typically ranging between 1,100 mm and 1,300 mm, with temperatures averaging around 28°C. The dominant soil type in this region is typically classified as sandy loam or loamy sand, often derived from metamorphic and igneous parent materials. The specific experimental plot is an actively managed agricultural field used for research and training, located at the Landscape and Nursery Unit, Department of Horticulture, Federal University of Technology, Minna, Gidan Kwano Campus, Niger State, Nigeria.

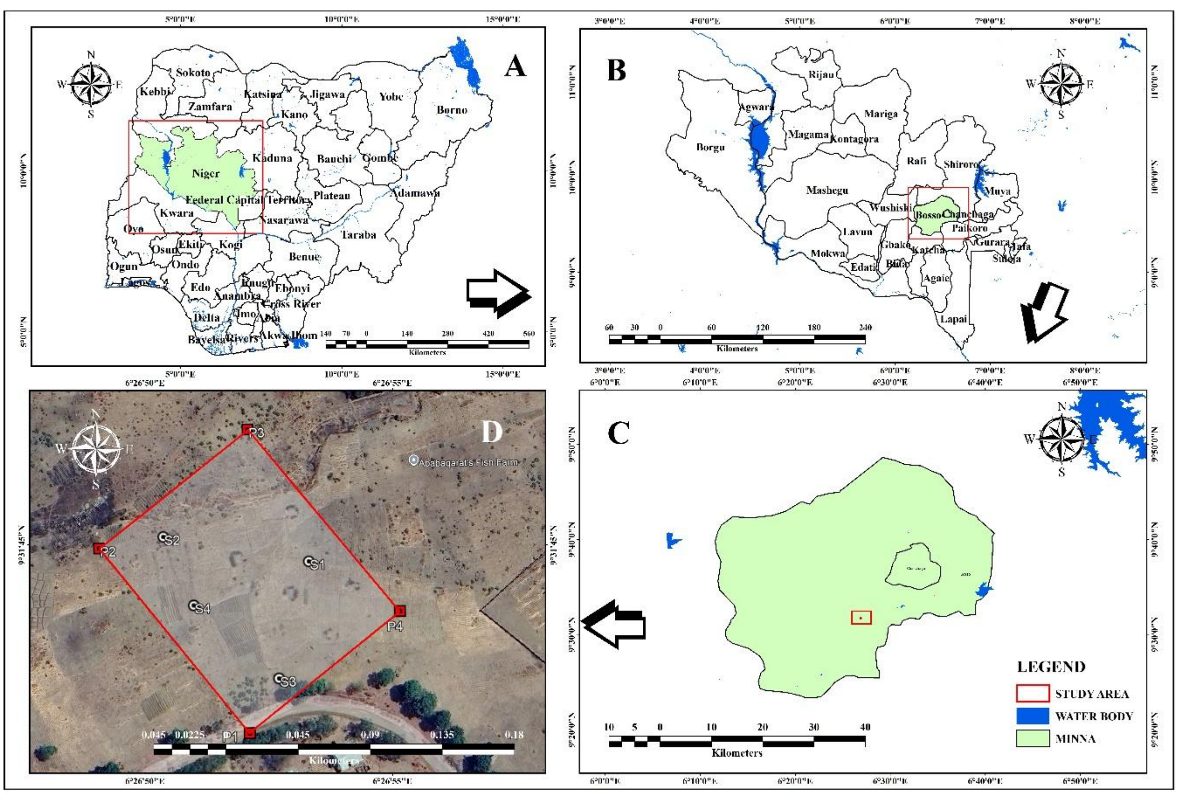

Figure 1. Study Area *(A = Nigeria, B = Niger State, C = Minna, D = Experimental Site)*
Source: (Authors Lab. 2025)

3. METHODOLOGY

3.1 Materials and Methods

3.1.1 Data Acquisition

The dataset for this study is summarized in Table 1. It comprises primary soil samples collected from the field, subsequent laboratory analytical results, and integrated spatial data. To establish a precise geospatial framework, field data acquisition involved the use of handheld Global Positioning System (GPS) devices to record the exact geographic coordinates of each sampling point across the study, see table 2 & 3.

Table 1. Materials Used for the Study

Category	Item(s) Used	Purpose/Application
Field Equipment	Handheld GPS devices	Recording geographic coordinates (Northing/Easting) of soil sampling points.
	Soil sampling tools	Collecting soil samples from a depth of 25 cm at random locations.
Laboratory Materials	2 mm sieve	Sieving air-dried soil samples for analysis.
	Dichromate solution & Ferrous sulphate solution	Used in the oxidation and titration process to determine organic carbon.
	Ammonium acetate (pH 7)	Extracting exchangeable cations of Potassium (K) from soil samples.
Laboratory Methods	Micro-Kjeldahl method	Determining the total Nitrogen (N) concentration.
	Bray P-1 method	Determining the available Phosphorus (P) concentration.
Software & Data	ArcGIS	Primary software for geospatial processing, spatial integration, and generating nutrient distribution maps.
	Microsoft Excel / CSV files	Data entry and storage of nutrient concentrations and Coordinates in a tabular format for import into GIS.
	Google Earth Imagery	Procured as a remote sensing data source and used as raster layers for mapping.
	Shapefiles & Raster layers	Digital boundary of the study area (vector) and continuous surfaces for nutrient analysis.

(Authors Lab. 2025)

Table 2. Coordinates of the experimental area perimeter

NAME	NORTHING	EASTING
P1	1054274	219810.1
P2	1054388	219717.5
P3	1054462	219810.7
P4	1054348	219902.6

(Authors Lab. 2025)

Table 3. Coordinates of soil sample points

LOCATION	NORTHING	EASTING
Sample1	1054379	219847.2
Sample2	1054395	219757.6
Sample3	1054307	219828.7
Sample4	1054352	219776.5

(Authors Lab. 2025)

3.1.2 Method

This study utilized a field-based experimental design integrated with geospatial and remote sensing techniques to evaluate the spatial variability of soil macronutrients—nitrogen (N), phosphorus (P), and potassium (K)—within a 1.7-hectare experimental plot at the Federal University of Technology, Minna,

ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.016
Nigeria. The initial phase involved collecting georeferenced soil samples from four randomly selected locations at a depth of 25 cm, with exact coordinates recorded using handheld GPS devices to establish a precise spatial framework. These samples were then air-dried, sieved, and subjected to specific laboratory protocols: the micro-Kjeldahl method for total nitrogen, the Bray P-1 method for available phosphorus, and ammonium acetate extraction at pH 7 for exchangeable potassium, see figure 2.

The resulting laboratory data were compiled into a tabular format and integrated into a Geographic Information System (GIS) environment using ArcGIS software, where all spatial datasets were projected to the WGS 84 UTM coordinate reference system to ensure accuracy. To model the continuous distribution of nutrients across the entire field from these discrete points, the researchers employed and compared two distinct spatial interpolation techniques: Inverse Distance Weighting (IDW) and Trend interpolation. The study then utilized comparative statistical analysis, specifically examining standard deviation values and alignment with primary laboratory data, to determine that the IDW method provided a more reliable and accurate decision-support tool for developing site-specific fertilizer application plans.

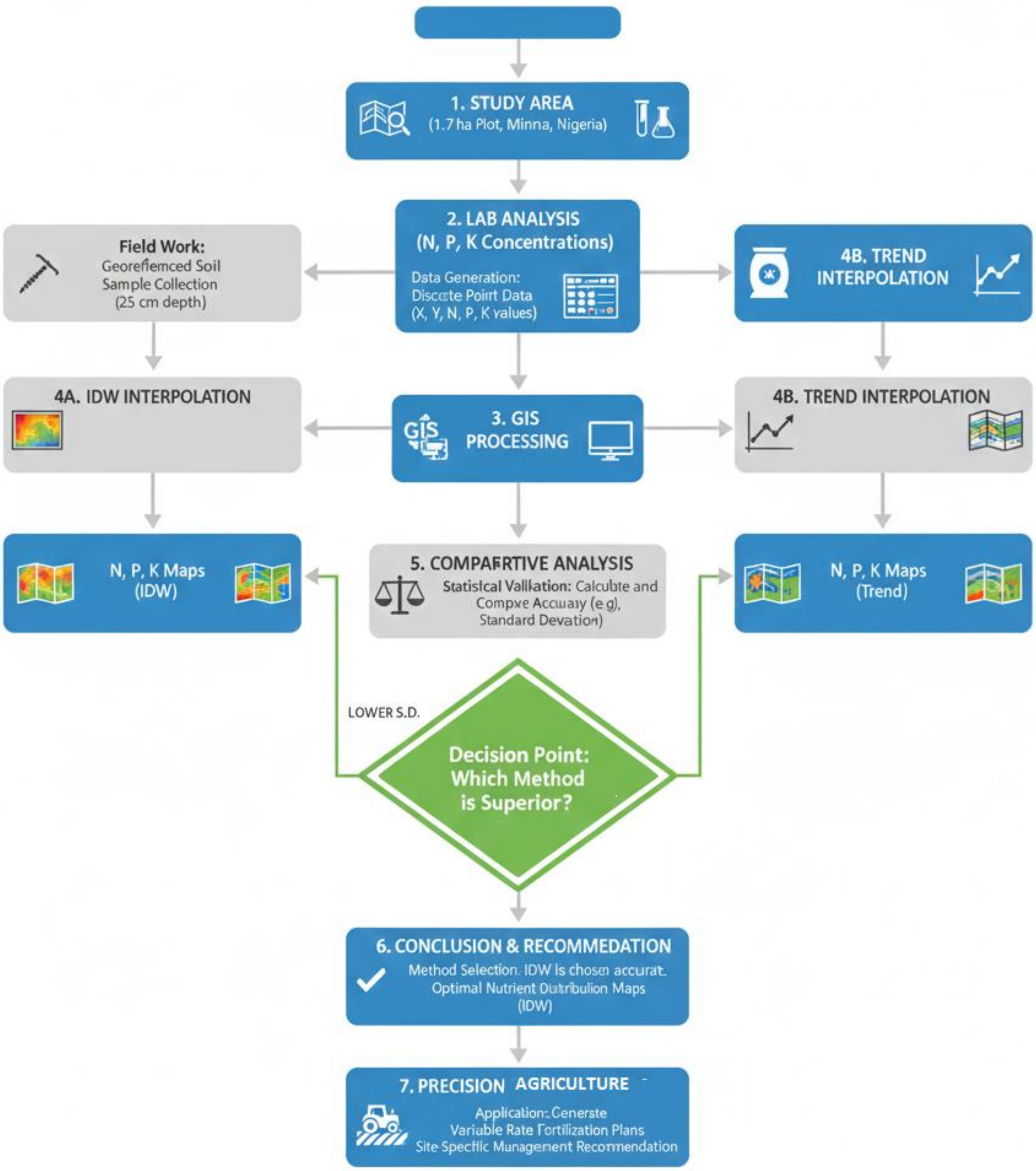

Figure 2. Work Flow Diagram
Source: (Authors Lab. 2025)

3.1.3 Soil Sample Collection Technique

A total of 4 Soil samples to a depth of 25 cm from randomly selected locations across the 1.7-hectare experimental area were taken for laboratory analysis. Each sampling location was precisely recorded using a GPS device, yielding point data with associated geographic coordinates. Subsequent laboratory analysis determined the concentration of N, P, and K for each soil sample. This attribute data was then compiled into a tabular format (CSV file), with distinct columns for spatial coordinates.

3.1.4 Laboratory analysis

After field collection, Soil samples were air-dried and sieved through a 2 mm sieve and analyzed for N, P and K following the laboratory procedures described by recent researchers. Organic carbon was determined by oxidizing the soil sample with dichromate solution and later titrating with ferrous sulphate solution. The total nitrogen was determined using the micro-Kjeldahl method, and the available P was determined by the Bray P-1 method. The exchangeable cations of K were extracted by leaching 5 g of soil with 100 ml of ammonium acetate at pH 7.

3.1.5 Data acquisition and preprocessing

Field-derived soil sampling coordinates were recorded using a handheld GPS instrument, establishing a precise spatial framework for subsequent analyses. Google Earth imagery was procured. All georeferenced laboratory nutrient data and Google Earth imagery raster layers were imported into ArcGIS for spatial integration. Before analysis, all spatial datasets were projected to a common coordinate reference system (WGS 84 UTM Zone) to eliminate spatial discrepancies. Attribute tables were standardized, and metadata were documented to ensure traceability and reproducibility. A digital boundary of the study area was obtained in a vector format (shapefile). This boundary served as the geographical extent for all subsequent spatial analyses. The prepared datasets were imported into the ArcGIS environment for geospatial processing. The tabular soil sample data (CSV file) was imported into ArcGIS as a point layer using the Layer. The northing and easting coordinates of the perimeter points and sample points, along with their respective nutrient concentrations, were imported into the ArcGIS environment. During this process, the Geometry CRS was set to match the CRS of the source coordinates. This step generated a point vector layer representing the spatial locations of the soil samples with their associated nutrient values. The study area boundary shapefile was imported as a polygon vector layer. This layer served as the foundational geographic reference for the entire analysis.

3.1.6 Interpolation technique for spatial distribution of N. P. and K content and overlay operations for production of soil nutrient variability map.

The values of the nutrients input in Microsoft Excel and saved in comma-delimited (CSV) file format were added as a layer on the map in ArcGIS in the Projected Coordinate Systems WGS 1984 UTM zone 32N. It was added as a layer and exported to a Shape file through the Data/Export Data pathway. To estimate nutrient concentrations across the entire study area from the discrete sample points, two spatial interpolation techniques were applied: inverse distance weighting (IDW) and Trend.

$\hat{z}_{(s_0)} = \frac{\Sigma_i^n=1 \;\; w_i z(s_i)}{\Sigma_{i=1}^n w_i}$ where $w_i = \frac{1}{d_i^p}$ …………………………………..……. *Equation (1)*

$\hat{z}_{(s_0)}$ Is the estimated nutrient concentration at the unmeasured location (s_o)

$\hat{z}_{(s_i)}$ Is the measured nutrient concentration at the *i-th* sampled location s_i , i.e. the N, P, or K concentration at Sample 1, Sample 2, 3 & 4.

n = the total number of sampled points used in the estimation.

di = The distance between the unsampled location s_o and the sampled location s_i.

wi = The weight assigned to the measured value Z(s_i).

p = The power parameter (often 2), which determines the rate at which the influence of the sampled points decreases with distance.

This process generated continuous raster surfaces representing the estimated concentration of each nutrient. The interpolated surfaces were then used to create thematic maps illustrating the spatial concentration of N, P, and K. The continuous nutrient values on the maps were classified into specific ranges to clearly visualize different nutrient zones.

$\hat{z}_{(s)} = \beta_0 + \beta_1 x + \beta_2 y$ …………………………….…….……………. *Equation (2)*

$\hat{z}_{(s)}$ = Estimated nutrient concentration at a location *s* with coordinates (x,y).

x and y = Spatial coordinates, Easting and Northing of the location *s.*

$\beta_0, \beta_1, \beta_2$ = Coefficients estimated from the observed sample data.

4. RESULTS

4.1 Results

From the basic standard soil analysis performed, various distinct modifications on N. P. and K parameters were observed. Topographic variation appears to lead to compositional heterogeneity within the study area, enabling the occurrence of variation in N. P. and K.

The sampling locations were randomly selected across the study area, with each representing an area within a 40 m radius. Table 3 shows the values of nutrient elements, with the mean values as 0.63%, 0.031%, and 0.61%, respectively. Figures 4, 5 and 6 show the spatial concentration of N, P and K, respectively.

The statistical summary of IDW N, P and K within the study area (Table 4) provides insights into soil fertility and variability. Nitrogen (N%) ranges from 0.5% to 0.768%, with a mean of 0.63% and a standard deviation (SD = 0.139), indicating moderate to high fertility and uniform distribution, suggesting uneven nitrogen distribution requiring site-specific fertilization. Available phosphorus P ranges widely from 0.0248%, to0.0388%, with a mean of 0.031 and a low SD (0.048), indicating significant spatial variation, where some areas may need phosphorus supplementation. Potassium (K) levels range from 0.128% to 1.18%, with a high mean of 0.622 and SD of 0.571, showing moderate to high availability but varying across the area. Overall, the soil exhibits moderate fertility with some nutrient imbalances, requiring site-specific soil management strategies to optimise agricultural productivity, see table 4 & 5.

Table 4. Laboratory analysis results of N. P. and K concentration at each sample location

LOCATION	NORTHING	EASTING	N(%)	P(%)	K(%)
Sample1	1054379	219847.2	0.53	0.024	0.121
Sample2	1054395	219757.6	0.5	0.024	0.119
Sample3	1054307	219828.7	0.74	0.038	1.12
Sample4	1054352	219776.5	0.76	0.038	1.098

(Authors Lab. 2025)

Table 5. Statistical summary of IDW interpolation of nutrient status within the study area

Parameters	Min	Max	Mean	S.D.
N (%)	0.522	0.656	0.589	0.139
P (%)	0.03	0.032	0.031	0.048
K (%)	0.528	0.716	0.622	0.571

(Authors Lab. 2025)

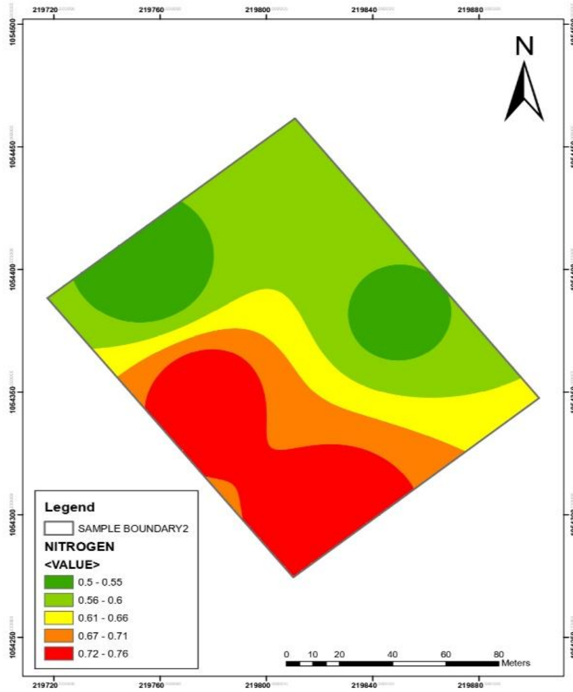

Figure 3. Spatial concentration of Nitrogen
Source: (Authors Lab. 2025)

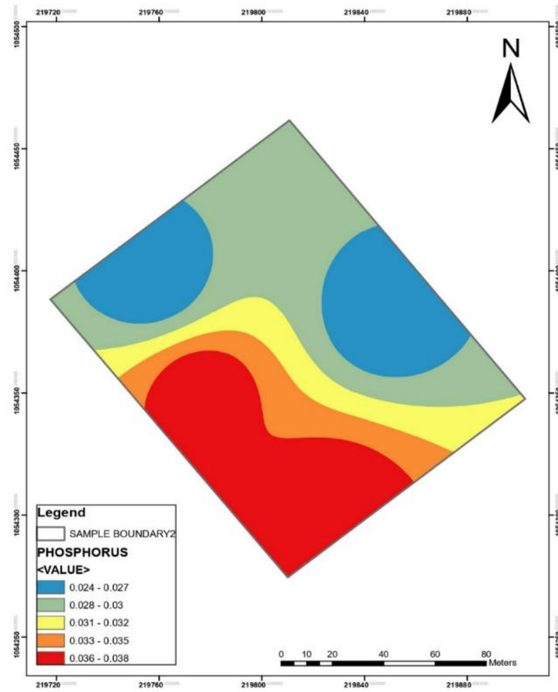

Figure 4. Spatial concentration of Phosphorus
Source: (Authors Lab. 2025)

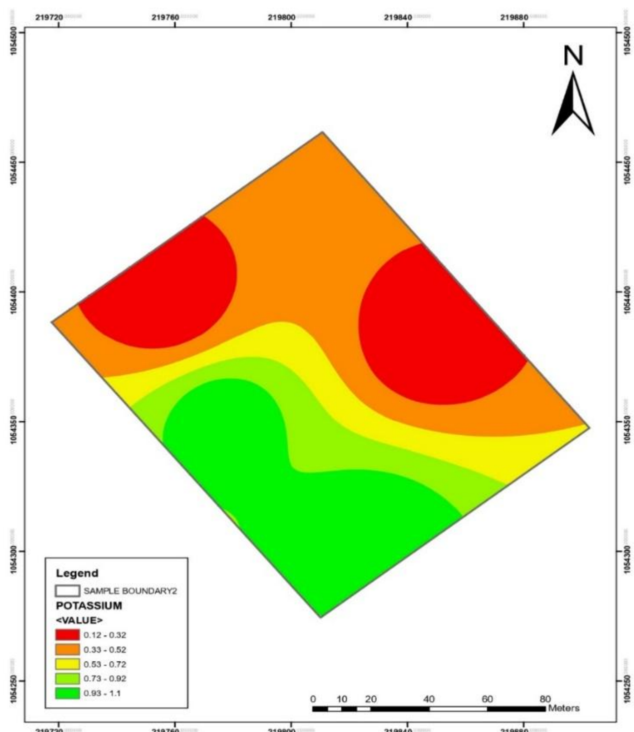

Figure 5. Spatial concentration of Potassium
Source: (Authors Lab. 2025)

4.1.1 Identification of Nutrient Zones

The study investigated the spatial distribution of nitrogen N, P, and K within the study area. The perimeter of this area was defined by four points with specific northing and easting coordinates. Soil samples were collected from four distinct locations within this boundary, and their coordinates were also recorded. Laboratory analysis was then conducted to determine the concentration of N, P, and K at each sample point.

4.1.2 Spatial distribution of available N

Figure 3 presents the spatial distribution of available N content across the study area. The nitrogen concentration varies significantly, ranging from a minimum of 0.5% to a maximum of 0.76%, as depicted in the legend. The spatial concentration map for nitrogen visually corroborates these findings, illustrating areas where N content falls within distinct ranges: 0.5-0.55%, 0.56-0.6%, 0.61-0.66%, 0.67-0.71%, and 0.72-0.76%. The color gradient illustrates these variations, where red areas indicate higher nitrogen availability, and blue shades represent lower nitrogen levels. The majority of the study area exhibits moderate nitrogen content. The uneven distribution of nitrogen suggests spatial variability in soil fertility, possibly influenced by land-use patterns, crop rotation, and organic matter content, and fertilization practices. The low nitrogen levels in a small area indicate potential nitrogen deficiency, which may limit crop productivity and necessitate supplementary nitrogen fertilization to maintain soil fertility. Conversely, areas with higher nitrogen concentrations may have received more organic inputs or fertilizers, enhancing soil nutrient availability. Therefore, targeted nutrient management strategies are essential to balance nitrogen levels across the municipality, ensuring sustainable agriculture.

4.1.2 Spatial distribution of available P

The map presented in Figure 4 illustrates the spatial distribution of available P across the study area, with values ranging from 0.024 to 0.038. The spatial concentration map for phosphorus provides a visual representation of these ranges, categorizing the distribution into 0.024-0.027%, 0.028-0.03%, 0.031-0.032%, 0.033-0.035%, and 0.036-0.038%. The color gradient, from blue (low P) to red (high P), highlights significant variability in soil fertility across the region. Areas with higher phosphorus availability, shown in red, are likely to support better crop growth, whereas blue zones with lower phosphorus levels may require nutrient supplementation. This variation is influenced by factors such as land use, soil type, topography, and farming practices. The map provides valuable insights for targeted soil management and sustainable agricultural planning.

4.1.3 Spatial distribution of available K

Figure 5 depicts the spatial distribution of available K in the study area, with values ranging from 0.12 to 1.1 is the most pronounced variability among the three nutrients observed in potassium concentrations. The spatial concentration map for potassium vividly displays this wide range of distribution, with distinct zones representing concentrations of 0.12-0.32%, 0.33-0.52%, 0.53-0.72%, 0.73-0.92%, and 0.93-1.1%. The map uses a colour gradient where green represents areas with higher potassium availability, indicative of more fertile soils, while red indicates regions with lower K levels, suggesting potential nutrient deficiencies. This variation in K distribution could result from differences in soil characteristics, agricultural practices, and topographical features. The map serves as an essential tool for identifying nutrient-deficient areas and implementing targeted soil fertility management strategies to enhance agricultural productivity. The statistical summary of the Trend interpolation of nutrients within the study area (Table 5) provides insights into soil fertility and variability. N% ranges from 0.268% to 0.91%, with a high mean value of 0.59 and a standard deviation (SD = 0.206), indicating moderate to high fertility and uniform distribution, suggesting uneven nitrogen distribution requiring site-specific fertilization. Available phosphorus P ranges widely from 0.008 to0.048 %, with a mean of 0.028 and a low SD (0.017), indicating significant spatial variation, where some areas may need phosphorus supplementation. K levels range from -0.991 to 1.83%, with a mean of 0.448 and high SD of 1.173, showing low to high availability but varying across the area. Overall, the soil exhibits moderate fertility with some nutrient imbalances, requiring site-specific soil management strategies to optimize agricultural productivity.

ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.016

Table 6. Statistical summary of the Trend interpolation of nutrient status within the study area.

Parameters	Min	Max	Mean	S.D.
N (%)	0.51	0.67	0.59	0.206
P (%)	0.023	0.033	0.028	0.107
K (%)	0.121	0.774	0.448	1.173

(Authors Lab. 2025)

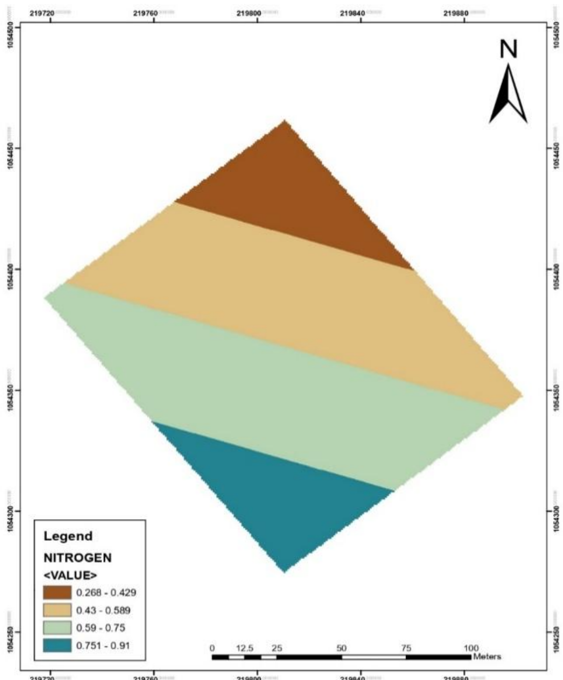

Figure 6. Trend Interpolation of Nitrogen
Source: (Authors Lab. 2025)

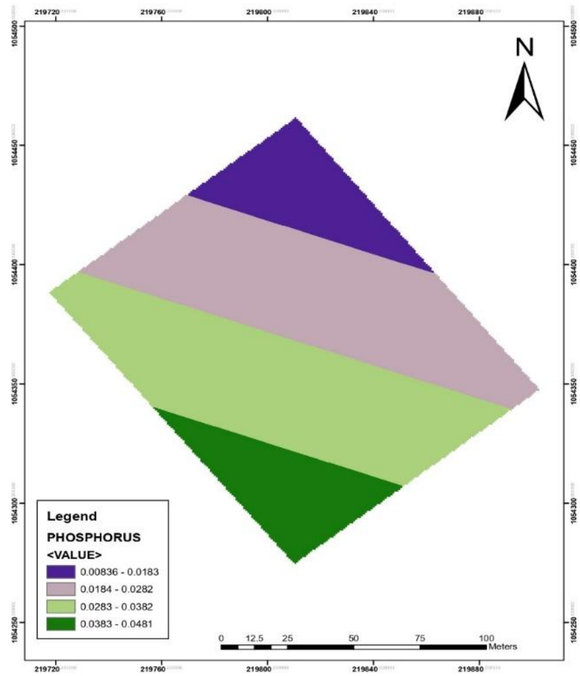

Figure 7. Trend Interpolation of Phosphorus
Source: (Authors Lab. 2025)

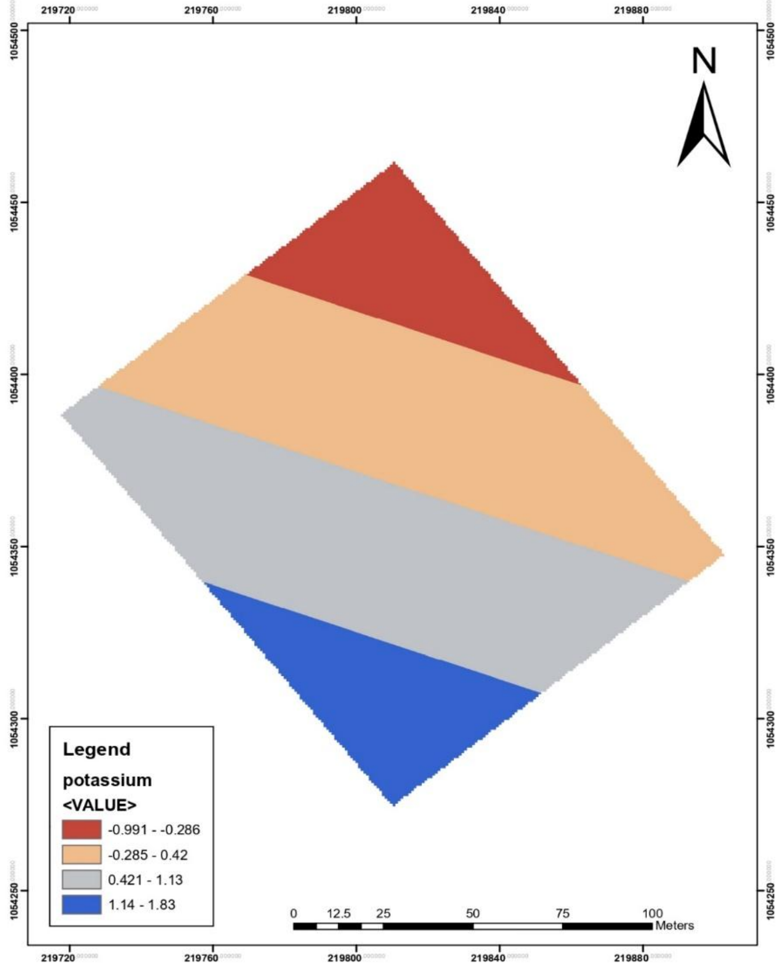

Figure 8. Trend Interpolation of Potassium
Source: (Authors Lab. 2025)

Based on trend interpolation, the distribution of N, P, and K within the experimental area is as follows. Figure 6 presents the spatial distribution of available N content across the study area. The map shows a trend of increasing concentration from the northwest towards the southeast. The areas with the highest N concentration (0.59% - 0.75%) are located in the southeastern part of the experimental area, represented by a light brown colour. The lowest concentrations (0.268% - 0.429%) are found in the northwestern section, indicated by a teal color. The sample points with the highest N concentrations are Sample 3 (0.74%) and Sample 4 (0.76%). Figure 7 illustrates the spatial distribution of available P across the study area. The P map shows a similar trend to N, with higher concentrations in the southeastern portion of the area. The highest phosphorus concentrations (0.038% - 0.048 %) are represented by dark green, located in the southeastern corner. The lowest concentrations (0.008% - 0.018%) are in the northwestern part, shown in dark purple. The highest P concentrations were found at Sample 3 (0.038%) and Sample 4 (0.038%). Figure 8 depicts the spatial distribution of available K in the study area. The potassium map also indicates a trend of higher concentrations in the southeast. The highest K concentrations (1.14% - 1.83%) are found in the southeastern section, depicted in dark blue. The lowest concentrations (-0.991% to -0.286%) are in the northwestern part, represented by a red colour. The highest K concentrations were found at Sample 3 (1.12%) and Sample 4 (1.098%).

5 DICUSSION

Given the spatial variability of nutrient concentrations observed in the research area, the most appropriate fertilizer recommendation strategy would be a precision nutrient management approach. This strategy moves away from uniform fertilizer application across the entire field and instead tailors fertilizer inputs to the specific needs of different zones within the experimental area. This research clearly shows distinct areas of varying nutrient levels for N, P, and K. For N, areas with concentrations of 0.5-0.55% would likely require higher nitrogen applications compared to zones with 0.72-0.76%. For P, areas showing 0.024-0.027% would benefit from more P fertilizer than those in the 0.036-0.038% range. For K, the stark differences, with some areas as low as 0.12-0.32% and others as high as 0.93-1.1%, necessitate highly differentiated K applications. Zones with lower K levels would require substantial inputs, while those with high levels might need minimal or no additional potassium to avoid excess and potential nutrient imbalances.

The discussion of this study highlights the significant spatial heterogeneity of soil macronutrients within the 1.7-hectare experimental plot, emphasizing that nutrient availability is rarely uniform across agricultural landscapes. Laboratory analysis and subsequent mapping revealed that while nitrogen and phosphorus showed moderate variation, potassium exhibited the most pronounced fluctuations, with some areas signaling potential deficiencies and others showing high fertility. These findings underscore the inefficiency of "blanket" fertilizer applications and advocate for the adoption of Precision Agriculture (PA) strategies, specifically site-specific nutrient management and variable-rate application (VRA), to optimize resource efficiency and prevent environmental degradation caused by over-fertilization.

A critical portion of the discussion evaluates the efficacy of different geospatial modeling techniques, concluding that Inverse Distance Weighting (IDW) is a more reliable decision-support tool than Trend interpolation for this study area. The researchers found that IDW provided closer statistical alignment with primary laboratory data and maintained lower standard deviation values[55555]. In contrast, the Trend method produced significant mathematical artifacts, such as unrealistic negative values for potassium in the northwestern section of the field. Consequently, the study recommends the integration of GIS-based fertility mapping and the IDW method into broader agricultural policies to support sustainable farming practices and improve crop productivity in the Nigerian agricultural sector, see table 5.

Table 5. Summary of Discussion

Feature	IDW Interpolation	Trend Interpolation
Statistical Alignment	Closer to primary laboratory data	Significant discrepancies from lab data
Standard Deviation	Lower (N: 0.139, P: 0.048, K: 0.571)	Higher (N: 0.206, P: 0.107, K: 1.173)
Data Representation	Captured localized nutrient "islands	Produced a simplified linear gradient
Anomalies	Maintained realistic positive values	Produced unrealistic negative K values (-0.991)

5.1 Limitation

A primary limitation of this study is the constrained sample density, as the geospatial analysis was based on only four georeferenced soil sampling points within the 1.7-hectare experimental plot. While these points provided initial insights into nutrient heterogeneity, the limited number of discrete observations may restrict the precision of the spatial interpolation models in capturing high-frequency variability across the landscape. This low sampling intensity likely contributed to the significant statistical discrepancies and higher standard deviations observed in the Trend interpolation method, particularly for potassium, compared to the laboratory-determined primary data. Consequently, while the study successfully establishes a framework for precision agriculture in the region, the results highlight a need for future research to employ higher-density sampling grids and multi-depth analyses to enhance the granularity and predictive accuracy of site-specific nutrient maps.

6. CONCLUSION AND RECOMMENDATIONS

This study demonstrates that geospatial analysis and GIS-based soil fertility mapping are effective tools for characterizing spatial nutrient heterogeneity, as evidenced by the laboratory-determined variability in nitrogen (0.50–0.76%), phosphorus (0.024–0.038%), and potassium (0.119–1.12%) observed across the study area. A comparative evaluation of spatial interpolation techniques established that Inverse Distance Weighting (IDW) provided a superior representation of soil status compared to Trend interpolation; specifically, the IDW results (N: 0.522–0.656%, P: 0.03–0.081%, and K: 0.528–0.716%) demonstrated closer statistical alignment with primary laboratory data and a lower standard deviation than the Trend method (N: 0.51–0.67%, P: 0.023–0.033%, and K: 0.121–0.774%), which exhibited significant discrepancies, particularly in potassium levels. Consequently, it is recommended that site-specific management strategies utilizing variable-rate application (VRA) be implemented to address these nutrient imbalances and optimize resource efficiency in the adoption of developing site-specific fertilizer application plans. Furthermore, agricultural stakeholders should prioritize the IDW method for high-precision mapping, establish regular spatial monitoring frameworks, and integrate these geospatial tools into broader agricultural policies, while future research should expand on these findings by increasing the sample size and incorporating multi-depth soil analyses and a wider range of micronutrients to achieve a more comprehensive understanding of environmental sustainability and long-term productivity.

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