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# Geo-spatial mapping of soil fertility status of Akure South Local Government Area, Ondo state, Southwestern Nigeria

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***Abstract*— *Soil fertility assessment is important for sustainable agricultural productivity and land management, especially in rapidly urbanizing tropical regions. This study evaluated the spatial distribution of soil fertility in Akure South Local Government Area of Ondo State, Nigeria, with a view to assess the influence of land uses on fertility status of soil in the study area. Field-based analysis were conducted on soil samples of the study location, while Geographic Information Systems (GIS) and remote sensing tools were used to map the fertility of soil under the varying land uses. Soil samples at 0-15 cm depth were collected across four land use classes: Built-up, Vegetation, Bare ground, and Outcrop, and analyzed for Nitrogen (N), Phosphorus (P), Potassium (K), Organic Carbon (OC), Organic Matter (OM), and pH. The data were geo-referenced and processed in ArcGIS Pro using the Inverse Distance Weighting (IDW) method to produce spatial distribution maps and a composite Soil Fertility Index (SFI). Results revealed significant spatial heterogeneity in soil fertility. Vegetation areas recorded the highest nutrients, N 10.08 (±9.63 mg/kg), P 12.38 (±10.34 mg/kg), K 30.92 (±28.03 mg/kg), OC 1.27 (±0.82%), OM 2.19 (±1.41%), with pH value of 5.92 (±0.42), while built-up areas were the most depleted. The composite soil fertility index (SFI) map classified the study area into five fertility zones: Very Low (0.048-0.188), Low (0.189-0.271), Moderate (0.271-0.407), High (0.408-0.600), and Very High (0.601-0.994). The study demonstrates that GIS-based soil fertility mapping provides valuable spatial insights for precision agriculture and sustainable land management.*

***Keywords*— Soil Fertility Index; Geographical Information System; Organic Matter; Vegetation Area; Built-up Area; Akure.***

## I. INTRODUCTION

Soil is a fundamental component of ecosystems, playing a crucial role in agriculture, environmental stability, and human activities. It is a complex mixture of minerals, organic matter, water, air, and microorganisms that interact to support plant growth (Hillel, 2008). Soil fertility, a key attribute of soil quality, refers to the ability of soil to provide essential nutrients in adequate amounts for optimal plant growth.

Soil fertility is a major determinant of agricultural productivity and ecosystem sustainability (Brady and Weil, 2016). Physically, factors such as soil texture, structure, and water-holding capacity influence root penetration and nutrient availability. Chemically, pH levels, nutrient composition, and cation exchange capacity (CEC) affect plant growth. Biologically, organic matter and microbial activity contribute to nutrient cycling and overall soil health (Lal, 2015). However, soil fertility is not static; it can be enhanced or degraded by natural processes and human activities. Practices such as crop rotation, organic farming, and the application of appropriate fertilizers can improve soil fertility, while continuous monocropping, deforestation, and poor land management can lead to soil degradation (Ande *et al.,* 2017). The increasing global demand for food, driven by population growth, makes agricultural expansion essential (Singh *et al.,* 2023). Achieving food security and maximizing agricultural productivity require cultivating crops in optimal environments, which depends on the assessment and management of soil fertility. In agriculture, nutrient-rich soils promote high crop yields and better-quality produce, while nutrient-deficient soils lead to poor plant growth and reduced productivity. Beyond agriculture, soil fertility influences forestry, urban planning, and environmental management by affecting carbon sequestration, biodiversity conservation, and water filtration.

In Nigeria, continuous crop cultivation, inadequate fertilizer use, deforestation, and urbanization have contributed to soil degradation, leading to nutrient depletion and reduced agricultural productivity (Adejuwon and Ekanade, 2018). Studies have shown that soil fertility in some southwestern regions in Nigeria, is depleting due to poor soil management practices, overuse of chemical fertilizers without soil testing, and loss of topsoil through erosion (Ande *et al.,* 2023). Rapid urbanization has further worsened the situation by reducing available arable land for farming (Owoeye, 2019). These challenges pose significant threats to food security and sustainable land use in the region. Climate change and erratic rainfall patterns further compound soil degradation, as highlighted by global assessments (FAO, 2017).

In response to the need for detailed soil fertility assessments, advanced digital tools have become essential. Geographic Information Systems (GIS) have emerged as a powerful tool for accessing, analyzing, and visualizing soil properties and fertility levels (Singh *et al.,* 2023). GIS serves as a comprehensive platform for capturing, storing, and processing geographical data. When integrated with intensive field data collection, it enables the creation of detailed soil fertility maps that illustrate nutrient distribution and land suitability for agriculture (Mulder *et al.,* 2011).

Although satellite imagery has been used in some studies, its moderate spatial and spectral resolution in regions like Nigeria often limits the detection of fine-scale variability in soil properties (Mulla, 2013; Zhang *et al.,* 2019). As a result, many researchers advocate relying on ground-collected data analyzed through GIS to achieve more precise soil fertility mapping.

Geographic Information Systems (GIS) enables the integration and analysis of spatial and non-spatial data, facilitating the creation of detailed soil maps that reflect the variability of soil properties across large areas. By incorporating data from various sources, including field surveys and laboratory analyses, GIS can model spatial patterns of soil nutrients, pH levels, organic matter content, and other critical parameters. Akure, a southwestern city of Nigeria faces significant challenges related to soil fertility. Continuous cultivation without adequate replenishment of soil nutrients has led to nutrient depletion, adversely affecting crop yields and food security. These issues collectively threaten the sustainability of agriculture in Akure, necessitating immediate and informed intervention.

Given these limitations, this research focuses solely on leveraging detailed field data integrated with GIS to map soil fertility across Akure. GIS provides a robust framework for analyzing and visually representing ground-based measurements, thereby producing digital soil maps that accurately reflect nutrient distribution and overall soil quality (Nkwunonwo and Okeke, 2013). Studies by Fabiyi *et al.* (2011) have demonstrated the effectiveness of GIS in soil mapping, supporting better decision-making in agricultural practices and land-use planning. Similarly, Olorunfemi *et al.* (2020) and Adejuwon and Ekanade (2018) emphasize the need for sustainable soil management practices in Nigerian regions impacted by rapid urbanization and land-use changes. Despite these attempts, research outputs on GIS mapping of soil fertility remain limited especially in the sub-Saharan Africa. Therefore, this research was aimed at mapping the fertility status of soil in Akure South Local Government Area, in the humid rainforest climate of Nigeria using GIS techniques and comprehensive field data.

## II. METHODOLOGY

### 2.1 Description of Study Location

The study location is Akure, the capital city of Ondo State, Southwestern Nigeria (Adeoye *et al.*, 2025). Akure is situated within the humid tropical rainforest zone, characterized by a bimodal rainfall pattern with an annual average of about 1,500 – 2,500 mm and a mean temperature range of 22°C to 32°C (Olanipon *et al.,* 2025). The climate supports luxuriant vegetation, dominated by tall trees, shrubs, and secondary forest growth, though much of this has been replaced by farmlands, residential areas, and infrastructure due to urbanization (Olujide *et al.,* 2018). Topographically, Akure South is generally undulating with gently rolling hills, while the geology is underlain predominantly by Precambrian basement complex rocks, which influence soil formation and nutrient composition (Olorunfemi *et al.,* 2018). The soils are typically ferruginous tropical soils, known for their weathering, moderate to low fertility, and susceptibility to leaching under intense rainfall (Akande and Adedamola, 2020). The socio-economic activities in the area include farming, trading, government services, and small-scale industries. Agriculture is mainly subsistence-based, with crops such as yam, cassava, maize, and vegetables cultivated in surrounding rural and peri-urban areas (Akinbode *et al.,* 2024). However, increasing urban expansion has reduced the extent of arable land, intensifying pressure on soil resources (Seto and Ramankutty, 2016). These natural and human-induced dynamics make Akure South LGA a strategic location for evaluating soil fertility patterns using GIS techniques, particularly in the context of rapid urbanization and changing land use (Fabiyi *et al.,* 2013; Singh *et al.,* 2023).

### 2.2 Land Use and Land Cover

Land use and land cover (LULC) analysis was conducted to characterize the spatial distribution of surface features across Akure South LGA and to guide soil sampling. The classification was based on four major land cover classes identified within the study area: vegetation, developed areas, barren land, and outcrops. These categories represent the dominant land cover patterns and provide a basis for examining soil fertility across varying land uses (Adeoye *et al.*, 2025). Satellite data were sourced from Landsat 9 Operational Land Imager (OLI-2) imagery for the year 2025, obtained through the Google Earth Engine (GEE) platform. Preprocessing steps included atmospheric and radiometric corrections using surface reflectance products to ensure spectral fidelity. The imagery was clipped to the boundary of Akure South Local Government Area using a shape-file of the study area.

Classification was performed in ArcGIS Pro 3.5.2 using the Support Vector Machine (SVM) supervised classification algorithm, which is widely recognized for its high accuracy in remote sensing applications. The resulting LULC map provided the spatial framework for soil sampling. Soil samples were collected across the four identified land cover classes, ensuring adequate representation of each category for fertility analysis. This stratified sampling approach was designed to capture variations in soil properties attributable to different land uses and surface conditions (Adeoye *et al.*, 2025).

### 2.3 Soil Sampling and Analysis

Soil samples were collected from the topsoil layer (0–15 cm depth). The selection of this depth reflects its importance as the most biologically active portion of the soil profile, where root activity, nutrient cycling, and organic matter accumulation are highest (Hao *et al.,* 2021). Sampling was conducted over a period from August 2025 to September 2025 to coincide with the post-rainy season when soil moisture conditions are stable yet not saturated. A total of 40 sampling points were selected across the study area, stratified by the four major land use / land cover classes (vegetation, developed area, barren land, and outcrops) to ensure representation. At each sample location, the GPS coordinates were recorded using a handheld GPS device and the soil was placed into clean nylon bags. This geo-referencing ensures spatial traceability of the samples for integration with GIS analyses. In the field, coarse debris such as stones, fresh roots, and plant residues were removed. The collected soil was air-dried in the laboratory to preserve microbial activity and the chemical integrity of the sample (i.e., to limit further decomposition or nutrient transformations). After air-drying, the samples were passed through a 2 mm sieve to standardize particle size and remove remaining coarse fragments. The sieved soil serves as the standard "fine earth" fraction for most fertility analyses (Carter, 2007).

The collected soil samples were analyzed for site specific chemical parameters commonly used to assess soil fertility: nitrogen (N), phosphorus (P), potassium (K), pH, organic carbon (OC), and organic matter (OM). The N, P, K of soil were measured directly using soil fertility speed sensor. The handheld soil sensor, based on Frequency Domain Reflectometry (FDR) technology, was employed to determine soil nitrogen (N), phosphorus (P), and potassium (K) concentrations from prepared soil samples. The instrument features a high-sensitivity stainless-steel probe, LCD digital display, and built-in lithium battery (DC 3.7V) for field portability and autonomous operation. It measures multiple soil components in real time, with a detection range of 1–1999 mg/kg and measurement accuracy of ± 2% sensitivity. The sensor operates using the FDR measurement principle, where an electromagnetic wave is transmitted into the soil medium and the reflected frequency signal is analyzed by a micro-control unit (MCU) to estimate the dielectric properties. These dielectric properties correlate with soil moisture, electrical conductivity, and ionic nutrient concentrations (Yao *et al.,* 2025). The FDR method provides rapid and non-destructive assessment of soil nutrient status by translating changes in the electromagnetic response into nutrient estimates (Chen *et al.,* 2019).

During measurement, the probe was vertically inserted into the soil to a depth exceeding 10 cm, ensuring full contact with the medium. To enhance data reliability, multiple points were measured, and the mean value was recorded for each sampling site. After each use, the probe was cleaned and dried to prevent oxidation and maintain accuracy, in line with the manufacturer's guidelines. FDR-based soil sensors such as the Jingxun model are increasingly used in precision agriculture and soil fertility monitoring due to their fast response, low power consumption, and good repeatability compared to conventional laboratory methods (Gao *et al.,* 2021). Their integration of real-time digital display and multi-parameter detection supports efficient field assessment and nutrient management.

### 2.3.1 Analytical Methods

***pH measurement.***

Soil pH was determined using a standard pH meter with soil–water suspension (e.g. 1:2.5 soil to water by weight). This is a widely used technique to measure the acidity or alkalinity of soils, which influences nutrient availability (Brady & Weil, 2017).

***Organic Carbon and Organic Matter Determination* (Walkley–Black Method)**

The organic carbon content of the soil samples was determined using the Walkley–Black wet oxidation method (Nelson and Sommers, 2018). This method quantifies the oxidizable portion of organic carbon in the soil, which serves as a key indicator of soil fertility and organic matter content. Approximately 1 g of each air-dried and sieved soil sample (<2 mm) was weighed into a 250 ml Erlenmeyer flask. To each sample, 10 ml of 0.167 M potassium dichromate ($K_2Cr_2O_7$) was added using a pipette, followed by 20 ml of concentrated sulphuric acid ($H_2SO_4$). The mixture was swirled gently to ensure complete dispersion and allowed to stand for 30 minutes to allow oxidation of the organic matter. After oxidation, 100 ml of distilled water was added to dilute the solution. Subsequently, 3 drops of phenanthroline indicator were added, and the mixture was titrated with 0.5 M iron (II) ammonium sulphate solution until the color changed sharply from dark green to brownish-red (maroon), indicating the endpoint. A blank titration (without soil) was also performed using the same reagents and conditions.

The percentage of organic carbon (% OC) and organic matter in each soil sample was calculated using the equations 1 and 2:

$$\%\,Organic\ Carbon = \frac{(B-T)\times M\times 1.33}{W} \quad (1)$$

where:

B = Titre value for blank (ml)

T = Titre value for soil sample (ml)

M = Molarity of $Fe(NH_4)_2(SO_4)_2{\cdot}6H_2O$

W = Weight of soil sample (g)

1.33 = Correction factor for incomplete oxidation of organic matter

The organic matter (OM) content was subsequently estimated by multiplying the % organic carbon by 1.724.

$$\%\,Organic\ Matter\ (OM) = \%\,Organic\ C \quad (2)$$

This method provides a reliable measure of soil organic carbon, which is an important indicator of soil fertility, nutrient retention capacity, and overall soil health.

### 2.3.2 Evaluation of Soil Fertility Index (SFI)

The Soil Fertility Index (SFI) was calculated using the Expert Opinion (EO) method to integrate multiple soil parameters into a single quantitative index representing the overall fertility status of each sampling location. This approach combines established agronomic principles with empirical soil data to provide a comprehensive assessment of soil fertility across Akure South LGA.

The Expert Opinion Method was adopted to assign relative weights to the selected soil fertility indicators, reflecting their importance in determining overall soil productivity, particularly in tropical environments. This approach draws from established agronomic principles and findings reported in literatures (Chaudhry *et al.,* 2024; Lenka *et al.,* 2022; Vasu *et al.,* 2016; Zhao *et al.,* 2023). Based on a comprehensive review of studies focused on tropical and sub-Saharan African soils, the following weights were assigned: Nitrogen (0.25) and Organic Carbon (0.25) received the highest weights, as they are recognized as the most critical factors influencing soil fertility. Nitrogen is often the most limiting macronutrient in tropical soils and is essential for vegetative growth (Zhang *et al.,*2015), while organic carbon serves as the foundation of soil fertility, acting as the main nutrient reservoir and enhancing microbial activity (Lal, 2020). Phosphorus was assigned a weight of 0.20, reflecting its frequent deficiency in acidic tropical soils due to fixation processes (Shen *et al.,* 2011). Potassium, also weighted at 0.20, plays a vital role in crop quality, stress tolerance, and overall plant metabolism (Römheld and Kirkby, 2010). Finally, pH was given a weight of 0.10, acknowledging its role in modulating nutrient availability and influencing the chemical environment of the soil (Brady & Weil, 2017).

***Selection of Soil Fertility Indicators***

Five key soil parameters were selected as fertility indicators based on their recognized importance in tropical soil systems and their routine use in soil fertility assessment (Chaudhry *et al.,* 2024; Isong *et al.,* 2022; Vasu *et al.,*2016):

i. Nitrogen (N, mg/kg): A primary macronutrient essential for vegetative growth, chlorophyll synthesis, and protein formation
ii. Phosphorus (P, mg/kg): Critical for energy transfer (ATP), root development, flowering, and seed formation
iii. Potassium (K, mg/kg): Essential for enzyme activation, water regulation, osmotic balance, and disease resistance
iv. Organic Carbon (OC, %): A fundamental indicator of soil organic matter content, nutrient retention capacity, soil structure, and biological activity
v. Soil pH: Controls nutrient availability, microbial activity, and chemical reactions in the soil

Organic matter (OM) was excluded from the SFI calculation to avoid multicollinearity, as it is directly derived from organic carbon through the conversion factor 1.724 (Shamrikova *et al.,* 2022), resulting in perfect correlation (r = 1.00) between these two parameters. The inclusion of both would artificially inflate the weight of organic matter in the final index.

***Indicator Transformation and Scoring Functions***

To integrate soil parameters measured in different units (mg/kg, %, unitless) onto a common dimensionless scale, transformation functions were applied. These scoring functions normalize each parameter to a 0-1 scale, where higher scores indicate more favorable conditions for plant growth (Yu *et al.,*2018).

**i. Linear "More is Better" Scoring Function (N, P, K, OC):** For nutrients and organic carbon, a linear scoring function was applied based on the principle that higher values indicate better fertility status:

$$S_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad 3$$

where $S_i$ =normalized score (0-1), $x_i = measured\ value,$ $x_{min}\ and\ x_{max}$ = minimum and maximum observed values

**ii. Optimum Range Function (pH):** In contrast, for soil pH, fertility is not simply proportional to its value; rather, it follows an optimum range, where extreme acidity or alkalinity can reduce nutrient availability. Therefore, an Optimum Range Function was used to normalize pH scores based on established fertility ranges (Brady & Weil, 2017):

$$S_{pH} = \begin{cases} 1.0 & if\ 6.0 \le pH \le 7.0 \\ \frac{pH-4.5}{1.5} & if\ pH < 6.0 \\ \frac{8.5-pH}{1.5} & if\ pH > 7.0 \end{cases} \qquad 4$$

This function assigns the maximum score (1.0) to soils within the optimal pH range (6.0–7.0), where nutrient availability and microbial activity are highest. Scores decrease linearly for values outside this range, reflecting the detrimental effects of both acidity (< 6.0) and alkalinity (> 7.0) on soil fertility.

***SFI Calculation***

The Soil Fertility Index (SFI) was computed using the equation 5:

$$SFI = (0.25 \times S_N) + (0.20 \times S_P) + (0.20 \times S_K) + (0.25 \times S_{OC}) + (0.10 \times S_{pH}) \quad \ldots 5$$

where:

$S_N$ is Normalized score for Nitrogen, $S_P$ is Normalized score for Phosphorus, $S_K$ is Normalized score for Potassium, $S_{OC}$ is Normalized score for Organic Carbon, and $S_{pH}$ is Normalized score for soil pH

This weighted additive approach assumes that soil fertility is a composite property determined by the combined effects of multiple parameters, with each contributing proportionally to its assigned weight (Vasu *et al.,* 2016). The index theoretically ranges from 0 (all parameters at minimum values) to 1 (all parameters at maximum values), though actual values typically fall within a narrower range depending on the degree of parameter co-variation.

***Interpolation of Soil Fertility Parameters***

Spatial interpolation was carried out using the Inverse Distance Weighted (IDW) method available in ArcGIS Pro under the Spatial Analyst Tools (Mirzaei and Sakizadeh, 2022; Childs, 2022). The IDW technique was chosen for its simplicity and effectiveness in estimating values at unsampled locations based on the proximity and influence of nearby sampled points (Burrough *et al*, 2015). The method assumes that points closer to each other are more similar than those farther apart, assigning greater weight to nearer observations. The process involved importing the point data containing soil sample locations and their corresponding laboratory results into ArcGIS Pro. For each soil fertility parameter, namely nitrogen (N), phosphorus (P), potassium (K), pH, organic carbon (OC), and organic matter (OM), the respective attribute was selected as the Z-value to generate continuous raster surfaces representing their spatial distribution across the study area. This interpolation was performed separately for each parameter, producing individual spatial distribution maps that visualize variations in soil fertility across the region.

### 2.3.3 Soil Fertility Index Mapping

The Soil Fertility Index (SFI) was calculated by combining the normalized raster layers of nitrogen, phosphorus, potassium, organic carbon, and pH using the Raster Calculator tool (Spatial Analyst Tools) in ArcGIS Pro (Abdellatif *et al.,* 2021; Belayneh *et al.,* 2019). The weighted additive formula applied was the Soil Fertility Index formula as stated in equation 3.6, where each S represents the normalized score (0-1 scale) for the respective parameter. The resulting SFI raster, with values ranging from 0 to 1, was classified into five fertility classes (Very Low, Low, Moderate, High, and Very High) using manual classification breaks.

## 2.4 Statistical Analysis

Following laboratory analysis, descriptive statistics were computed for all soil fertility parameters to characterize their central tendency, dispersion, and variability across the study area. The statistical measures calculated included mean, median, mode, standard deviation, minimum, and maximum values for nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), organic matter (OM), and soil pH.

To quantify the degree of spatial heterogeneity in soil fertility, the coefficient of variation (CV) was calculated for each parameter using the formula:

$$\textit{Coefficient of Variation CV}\ (\%) = \frac{\textit{Standard Deviation}}{\textit{Mean}} \times 100 \qquad 6$$

The CV provides a standardized measure of variability that facilitates comparison across parameters with different units and magnitudes. Variability classes are interpreted as follows: low variability (CV < 15%), moderate variability (15% ≤ CV ≤ 35%), and high variability (CV > 35%) (Tesfahunegn *et al.,* 2011). CV values exceeding 35% typically indicate strong spatial heterogeneity requiring site-specific management interventions, a classification widely applied in soil fertility studies across tropical and subtropical regions (Behera & Shukla, 2015).

Pearson's correlation coefficient (r) was employed. This statistical measure quantifies the strength and direction of linear relationships between pairs of variables and is expressed as:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \qquad 7$$

where:

$x_i, y_i$ is observed value of two soil parameters (e.g., OC and N)

$\bar{x}, \bar{y}$ is mean value of each parameter

r ranges from -1 to +1

Positive r values indicate direct relationships, negative values indicate inverse relationships, and values near zero suggest no linear correlation. Correlation coefficients were tested for statistical significance at $p < 0.05$ and $p < 0.01$ levels. The correlation matrix was constructed to examine interactions among N, P, K, OC, OM, and pH, providing insights into nutrient dynamics and interdependencies within the soil system.

# III. RESULTS AND DISCUSSION

## 3.1 Soil fertility parameters

The descriptive statistics of soil fertility parameters is presented in Table 1. The mean nitrogen concentration across the samples was 7.50 mg/kg, with a wide range of 1.00 - 38.00 mg/kg. Available phosphorus averaged 9.48 mg/kg, but similarly exhibited large variations (1.00 - 41.00 mg/kg). Potassium also showed high variability, with mean value of 23.45 mg/kg and values ranging from 2.00 to 108.00 mg/kg. Organic carbon content averaged 1.01%, with a minimum of 0.40% and a maximum of 3.34%. Organic matter followed a similar pattern (mean 1.74%), reflecting the expected conversion between OC and OM. Soil pH values were relatively stable, ranging from 5.00 to 6.60, with an overall mean of 5.87, indicating that soils of Akure South are slightly acidic.

*Table 1: Descriptive statistics of soil fertility parameters in Akure South LGA*

| Parameter | Mean | Median | Mode | Std. Dev. | Min | Max | CV(%) | Variability |
|---|---|---|---|---|---|---|---|---|
| Nitrogen (N) | 7.50 | 5.00 | 2.00 | 7.30 | 1.00 | 38.00 | 97.30 | Very High |
| Phosphorus (P) | 9.48 | 7.00 | 2.00 | 8.98 | 1.00 | 41.00 | 94.70 | Very High |
| Potassium (K) | 23.45 | 17.00 | 13.00 | 22.99 | 2.00 | 108.00 | 98.00 | Very High |
| Organic Carbon (OC) | 1.01 | 0.83 | 0.40 | 0.66 | 0.40 | 3.34 | 65.60 | High |
| Organic Matter (OM) | 1.74 | 1.43 | 1.34 | 1.14 | 0.69 | 5.76 | 65.50 | High |
| pH | 5.87 | 6.00 | 6.00 | 0.47 | 5.00 | 6.60 | 8.00 | High |

The results highlight clear differences in soil fertility status across the study area. Nitrogen, phosphorus, and potassium exhibited high ranges and standard deviations, which suggests significant spatial heterogeneity in nutrient distribution. This variability is typical of tropical soils where continuous cropping, nutrient mining, and fertilizer application patterns differ widely (Chandrakala *et al.,*2018; López-Granados *et al.,*2002). In contrast, soil pH was relatively uniform, with a standard deviation of 0.47, indicating that the soils are consistently acidic. This acidity has important implications for nutrient availability, particularly phosphorus, which tends to be immobilized in acidic conditions (Agegnehu *et al.,* 2021).

The coefficient of variation results indicate heterogeneity in the soil fertility parameters of Akure South. Nitrogen, phosphorus, and potassium all recorded CV values above 90%, reflecting extreme spatial variability. This suggests that fertility management in the area cannot rely on uniform recommendations, but rather requires site-specific nutrient management strategies. Soil pH showed very low variability (8%), confirming that soil acidity is relatively uniform across the study area.

High CV values (>35%) are generally interpreted as strong heterogeneity, typical of tropical soils that are subject to intensive cultivation, erosion, and uneven fertilizer application (Chandrakala *et al.,*2018; López-Granados *et al.,*2002). The relatively stable soil pH suggests that acidity is a consistent fertility constraint for Akure South, aligning with reports from other tropical humid regions where weathering and leaching processes dominate (Agegnehu *et al.,* 2021).

### 3.2 Soil Fertility Variation across Land Use Types

The mean values and standard deviations of soil fertility parameters across different land use types are presented in Table 2. The results reveal distinct fertility gradients linked to land use and management practices. Vegetation areas recorded the highest average nutrient levels with N 10.08 (±9.63 mg/kg), P 12.38 (±10.34 mg/kg), K 30.92 (±28.03 mg/kg), OC 1.27 (±0.82%), and OM 2.19 (±1.41%) reflecting continuous organic inputs from litter and minimal disturbance. Similarly, bare ground soils showed moderately high nutrient concentrations with N 11.50 (±12.66), P 12.50 (±12.66), K 26.17 (±32.14), likely due to natural accumulation and limited cultivation.

*Table 2: Mean and standard deviation of soil fertility parameters across different land use types in Akure South LGA.*

| Land use | N(mg/kg) Mean(Std.) | P(mg/kg) Mean(Std.) | K(mg/kg) Mean(Std.) | OC(%) Mean(Std.) | OM(%) Mean(Std.) |
|---|---|---|---|---|---|
| Vegetation | 10.08 (±9.63) | 12.38 (±10.34) | 30.92 (±28.03) | 1.27 (±0.82) | 2.19 (±1.41) |
| Built-up | 5.44 (±4.27) | 7.19 (± 5.97) | 15.69 ( ±12.84) | 0.78 (±0.45) | 1.35 (±0.78) |
| Outcrop | 7.40 (±7.47) | 10.80 (±11.36) | 28.60 (±32.93) | 0.51 (±0.14) | 0.88 (±0.24) |
| Bare Ground | 11.50 (±12.66) | 12.50 (±12.66) | 26.17 (±32.14) | 1.13 (±0.95) | 1.95 (±1.64) |

In contrast, built-up areas exhibited the lowest fertility, with markedly reduced nutrient contents, N 5.44 (±4.27), P 7.19 (±5.97), K 15.69 (±12.84), OC 0.78 (±0.45%), OM 1.35 (±0.78%), attributed to soil compaction, surface sealing, and low organic input. Outcrop soils were similarly poor in organics, OC 0.51 (±0.14%), OM 0.88 (±0.24%) but retained moderate nutrient levels due to residual mineral weathering.

Overall, these results confirm that land use strongly influences soil fertility in Akure South. Vegetated and fallow lands maintain higher nutrient reserves through organic recycling, while built-up and rocky areas show significant degradation. The large standard deviations across all parameters further indicate high spatial variability within each land use, consistent with findings from Chandrakala *et al.* (2018) and López-Granados *et al.,* (2002), and underscore the need for site-specific fertility management.

### 3.3 Correlation Matrix of Soil Parameters

The correlation analysis carried out among nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), organic matter (OM), and soil pH is presented in Table 3. The strongest positive correlation was observed between organic carbon (OC) and organic matter (OM) ($r = 1.00$), which is expected since OM is derived directly from OC through a conversion factor. This close relationship validates the consistency of the laboratory results and reinforces the importance of organic matter as a key fertility indicator (Chandrakala *et al.,* 2018). Nitrogen (N) also exhibited strong positive correlations with both OC ($r = 0.84$) and OM ($r = 0.85$), reflecting the role of organic matter as the primary reservoir of nitrogen in tropical soils. Similar findings have been reported in India and Spain, where higher organic matter content was associated with increased nitrogen availability (López-Granados *et al.,* 2002). Furthermore, phosphorus (P) and potassium (K) were strongly correlated with N ($r = 0.94$ and 0.94, respectively) and with each other ($r = 0.96$), suggesting that areas with higher fertility tend to have simultaneous enrichment of these macronutrients. These patterns are consistent with the synergistic accumulation of nutrients in soils under favorable land-use and organic matter conditions (Agegnehu *et al.,* 2017).

*Table 3: Correlation matrix of soil fertility parameters in Akure South LGA (Pearson's r)*

| | N | P | K | OC | OM | pH |
|---|---|---|---|---|---|---|
| **N** | 1.000 | | | | | |
| **P** | 0.942 | 1.000 | | | | |
| **K** | 0.939 | 0.964 | 1.000 | | | |
| **OC** | 0.841 | 0.831 | 0.774 | 1.000 | | |
| **OM** | 0.845 | 0.836 | 0.780 | 1.000 | 1.000 | |
| **pH** | 0.144 | 0.130 | 0.133 | 0.222 | 0.222 | 1.000 |

**Note:** All correlations among N, P, K, and OC/OM are strong and statistically significant ($p < 0.01$). Correlations involving pH are weak and not statistically significant ($p > 0.05$).

The correlation analysis revealed important interactions among soil fertility parameters in Akure South. By contrast, soil pH exhibited only weak positive correlations with N, P, K, and OC ($r \approx 0.13$–$0.22$), and these were not statistically significant ($p > 0.05$). This indicates that in the study area, soil acidity does not co-vary strongly with nutrient concentrations. However, studies in other tropical environments have shown that under more strongly acidic conditions, nutrient availability, particularly phosphorus can be reduced through fixation processes, while leaching may worsen nutrient losses (Jia *et al.,* 2023). Overall, the results highlight the central role of organic matter management in improving soil fertility in the area. Enhancing soil OC through organic amendments, residue incorporation, or biochar application would support nitrogen availability and general nutrient retention. The strong co-variation among N, P, and K suggests that fertility enrichment practices could yield broad improvements in nutrient status. Nevertheless, the weak relationship between pH and soil nutrients underscores the need to monitor soil acidity independently, as it remains a potential limiting factor for nutrient availability even if not strongly expressed in this dataset.

### 3.4 Fertility Classification

The soil fertility distribution classes is presented in Table 4. About 60% of the sampling points (24 out of 40) exhibited low or very low fertility ($SFI < 0.45$), while only 12.5% (5 sampling points) demonstrated high or very high fertility ($SFI \geq 0.60$). The dominant fertility class across the study area was "Low," accounting for 47.5% of all sites. The mean SFI value of 0.379 indicates widespread fertility constraints across Akure South LGA, reflecting significant soil degradation. This pattern aligns with previous findings in southwestern Nigeria, where declining soil fertility has been linked to intensive cultivation, inadequate organic matter inputs, and rapid urbanization (Dhayanan *et al.,* 2016; Olorunfemi *et al.,*2018). Spatially, high-fertility zones ($SFI \geq 0.60$) were concentrated in the northwestern and northeastern sectors, predominantly in vegetated and agricultural areas. These zones benefit from continuous organic inputs through litter decomposition, reduced erosion, and stable nutrient cycling, resulting in higher organic carbon content (2.2–3.3%) and elevated levels of nitrogen, phosphorus, and potassium. In contrast, low-fertility zones (SFI < 0.45) were dominant in the central and southern parts, corresponding largely to built-up and barren lands. These areas experience soil sealing, topsoil removal, and minimal organic matter additions, leading to low organic carbon (<0.7%) and depleted nutrient levels (Chang *et al.,* 2022; Weng, 2012). The pronounced spatial variability (CV = 41.2% for SFI and >90% for individual nutrients) highlights the need for site-specific nutrient management rather than uniform fertilizer recommendations. Tailored interventions guided by SFI classifications are essential to enhance input efficiency and restore soil productivity in degraded zones (Chandrakala *et al.,* 2018).

*Table 4: Soil fertility distribution classes*

| Fertility Class | Number of Sites | Percentage |
|---|---|---|
| Very Low | 5 | 12.5% |
| Low | 19 | 47.5% |
| Moderate | 11 | 27.5% |
| High | 3 | 7.5% |
| Very High | 2 | 5.0% |

### 3.5 Spatial Distribution of Soil Nutrients

The spatial distribution of soil nutrients provides critical insights into the fertility status of Akure South LGA. The spatial analysis reveals how these nutrients vary across the landscape under different land use and land cover (LULC) conditions. This approach makes it possible to identify nutrient-rich hotspots, areas of deficiency, and the underlying drivers of spatial variability, including farming practices, vegetation cover, topography, and human activities. The use of GIS-based Inverse Distance Weighted (IDW) interpolation method shows the spatial variability of key fertility indicators: Nitrogen (N), Phosphorus (P), Potassium (K), Organic Carbon (OC), Organic Matter (OM), and Soil pH.

#### 3.5.1 Spatial Distribution of Organic Carbon (OC)

The spatial distribution of organic carbon (OC) in the study area is presented in Figure 1. The maps reveal considerable heterogeneity, with higher concentrations predominantly occurring in the northern and northwestern zones. These areas are largely associated with vegetation-dominated land uses, including forest cover and farmlands, where litter deposition, root turnover, and incorporation of organic residues enhance carbon accumulation in the soil. In contrast, the central and southeastern sectors, particularly those under built-up and barren land uses, exhibit lower OC concentrations. This depletion is likely due to soil sealing, reduced organic inputs, and intensive disturbances associated with construction activities and surface exposure.

The spatial clustering of high OC zones aligns closely with natural vegetative cover, supporting the findings of Lima *et al*. (2025), who reported that forested and agricultural soils sustain higher carbon content due to continuous biomass input. Conversely, the low OC levels observed in urbanized and barren areas mirror patterns of nutrient depletion driven by topsoil erosion and organic matter oxidation (Chang *et al.,* 2022). Collectively, these results underscore the strong dependence of organic carbon enrichment on land use.

#### 3.5.2 Spatial Distribution of Organic Matter (OM)

The spatial distribution of organic matter (OM) in the study area is presented in Figure 2. The maps indicate a pattern that closely mirrors the distribution of organic carbon, as expected due to their direct proportional relationship. High OM concentrations are observed in the northern and western parts of Akure South, coinciding with vegetation-dominated and cultivated lands. These areas benefit from the incorporation of organic residues, manure application, and natural litter accumulation, all of which contribute to humus formation and sustained soil fertility. In contrast, lower OM concentrations are dominant in the southern and central sectors, particularly within developed and barren land covers. These areas are characterized by minimal organic inputs, erosion, and soil sealing, which collectively reduce organic matter content.

This spatial pattern highlights the critical role of land cover in regulating organic matter dynamics. Vegetated lands act as sinks of organic matter, whereas urbanized and exposed lands serve as zones of degradation. Similar associations between OM and vegetation cover have been reported in tropical soils, where land management practices strongly influence soil organic matter content (Li *et al.,* 2022).

#### 3.5.3 Spatial Distribution of Soil pH

The spatial distribution of soil pH in the study area is presented in Figure 3. The maps indicate a relatively uniform distribution, with most locations exhibiting slightly acidic conditions (pH 5.5–6.5). Marginal variations, however, are observable: slightly higher pH values occur in the central and western portions of the LGA, which coincide with vegetation and agricultural land uses, whereas lower pH values (<5.5) are concentrated in the southern and built-up zones. These areas of reduced pH are likely attributable to soil compaction, limited organic matter inputs, and acidifying anthropogenic activities such as surface runoff and waste deposition.

The predominance of acidic conditions across Akure South aligns with the characteristics of humid tropical environments, where high rainfall and intense leaching processes contribute to base cation loss and soil acidification (Bationo *et al.* 2007). Although the overall variability in pH is limited, localized acidity may significantly affect nutrient availability, particularly by promoting phosphorus immobilization and disrupting cation exchange balance. As such, periodic liming or other pH correction measures may be necessary in more acidic zones to optimize nutrient uptake and improve overall soil fertility.

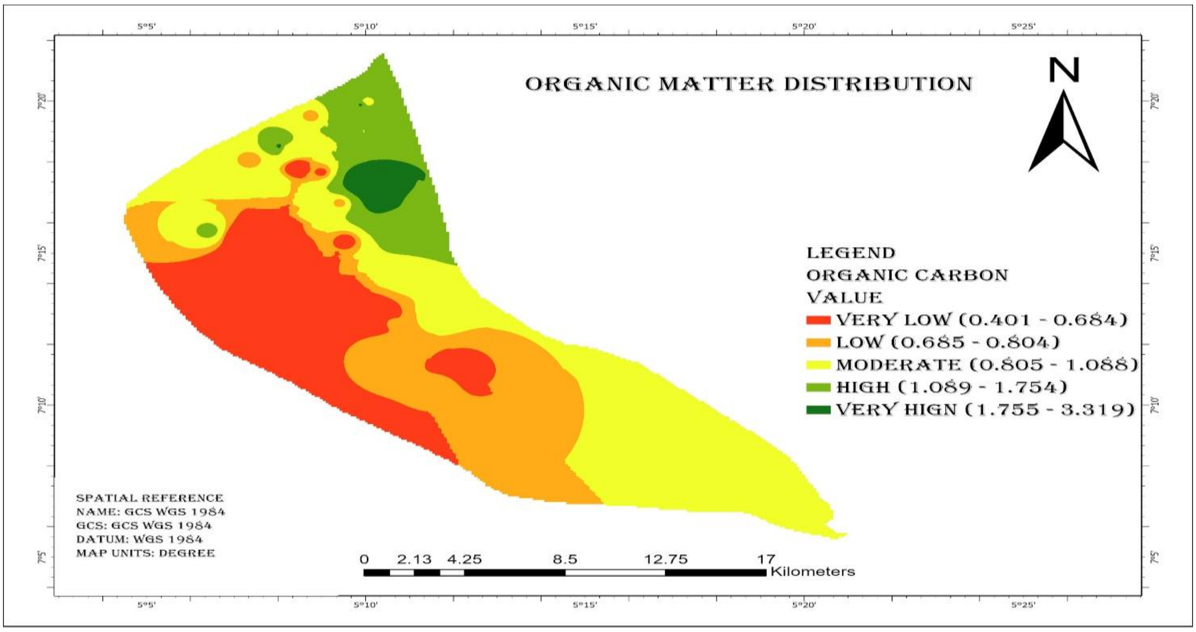


*Fig.1: Organic carbon distribution in Akure South LGA*

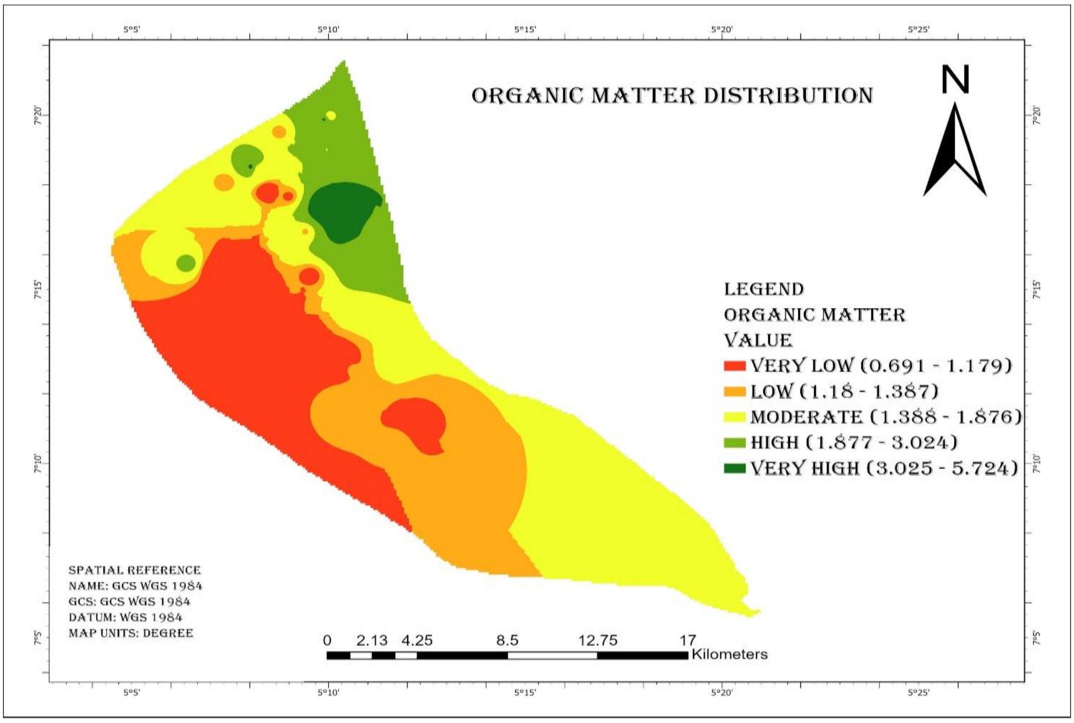


*Fig.2: Organic matter distribution in Akure South LGA*

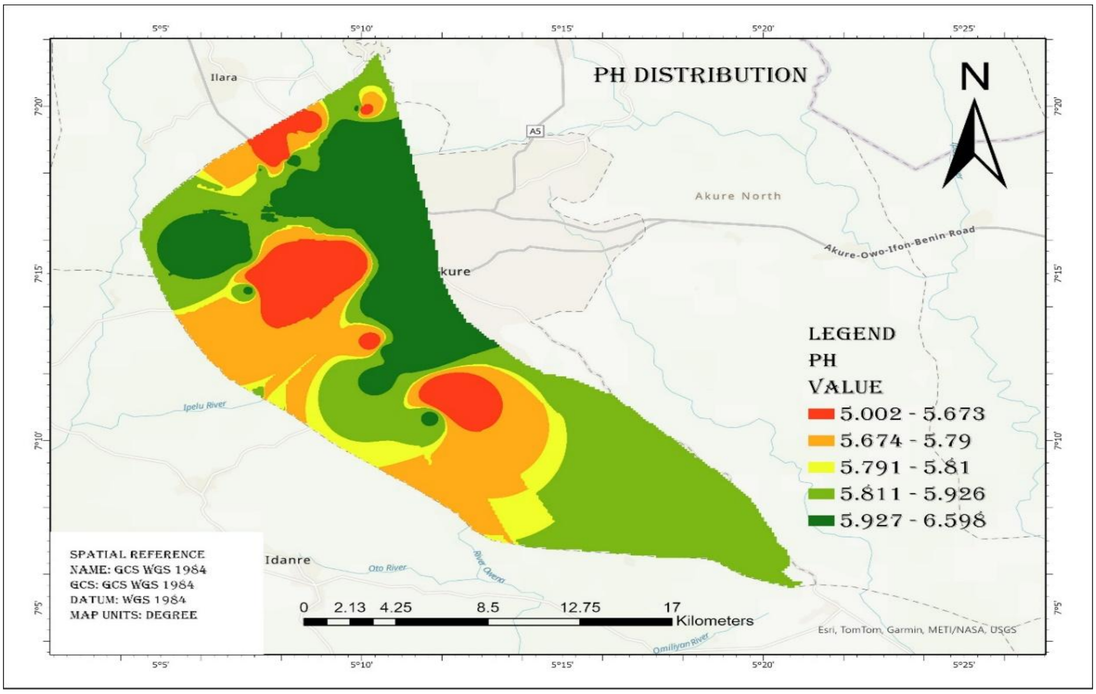


*Fig.3: pH distribution in Akure South LGA*

### 3.5.4 Spatial Distribution of Potassium (K)

The spatial distribution of potassium (K) in the study area is presented in Figures 4. The maps reveal pronounced spatial variability, with high K concentrations occurring predominantly in the northwestern and northeastern zones. These areas are largely associated with vegetative and agricultural land covers, where potassium enrichment is likely attributable to natural weathering processes and organic recycling from plant residues. Similar findings have been reported in studies showing that soils under natural vegetation and grassland maintain higher extractable potassium compared to disturbed croplands due to continuous organic inputs and nutrient cycling (Abindaw *et al.,* 2023). Moderate concentrations are observed in the central portions of the LGA, while low K values dominate the southern and southeastern sectors. The latter coincide with urban and barren lands, where nutrient depletion is likely a consequence of runoff, soil erosion, and insufficient replenishment through organic or mineral nutrient inputs.

The strong correspondence between high potassium concentrations and vegetated land covers highlights the influence of land management practices and vegetation density on soil nutrient status. This observation is consistent with findings reported by Matano *et al.* (2015), who noted that vegetation enhances nutrient cycling and soil fertility, whereas urbanization and land degradation contribute to nutrient decline. These results emphasize the need for targeted potassium supplementation, particularly in barren and built-up areas, as a strategy to restore soil fertility balance across the study area.

### 3.5.5 Spatial Distribution of Phosphorus (P)

The spatial distribution of phosphorus (P) in the study area is presented in Figure 5. The maps reveal pronounced spatial variability, indicating that available phosphorus is not uniformly distributed across Akure South LGA. High concentrations are observed in the northern and northwestern zones of Akure South, which largely coincide with vegetated and cultivated land uses. These areas are enriched through organic residue decomposition, manure application, and phosphorus cycling via plant root systems. In contrast, the central and southern sectors, particularly those under built-up and barren land covers, exhibit comparatively lower phosphorus concentrations. This depletion is likely a result of topsoil erosion, surface sealing, and reduced organic matter input.

The clustering of high-P zones in vegetative and agricultural lands is consistent with the strong positive association between organic matter and phosphorus availability reported in tropical soils (Gao *et al.,* 2019). Given the slightly acidic soil pH observed in the area, phosphorus availability may be constrained by immobilization through adsorption to iron and aluminum oxides (Shen *et al.,* 2011; Ezeaku, 2021). Therefore, site-specific phosphorus management strategies, including the application of organic amendments and the use of phosphate-solubilizing bio-fertilizers to enhance fertility and crop productivity in low-P zones may be necessary.

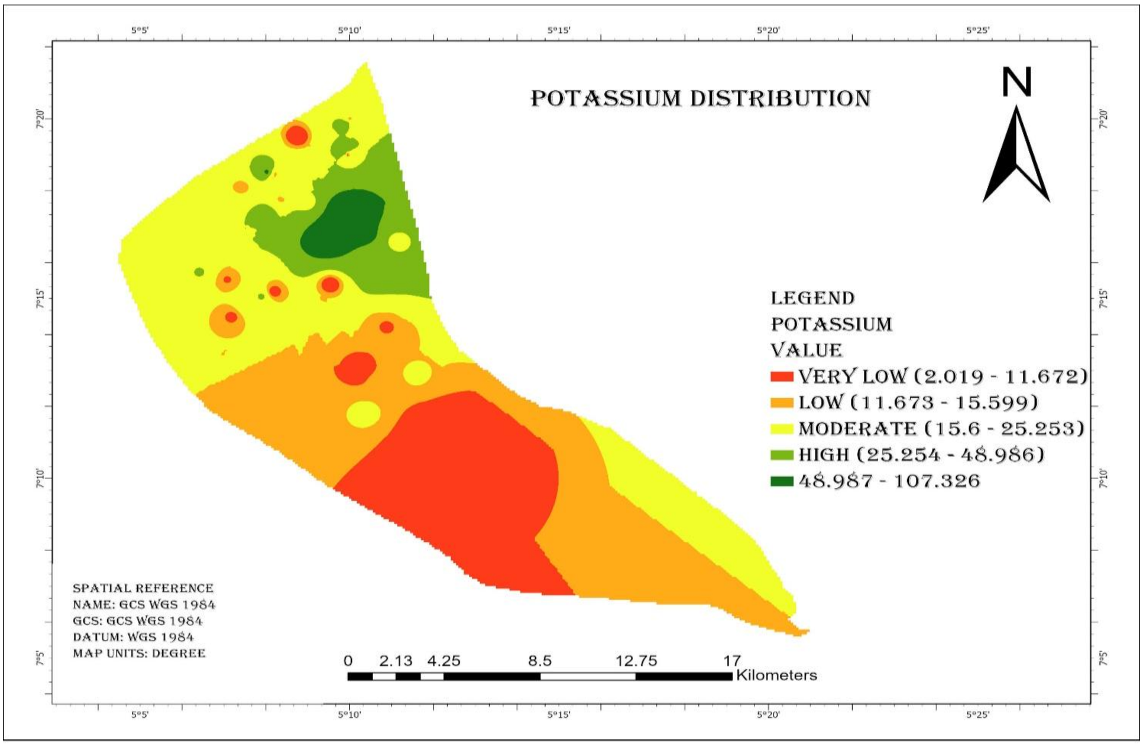


*Fig.4: Potassium distribution on Akure South in Akure South LGA*

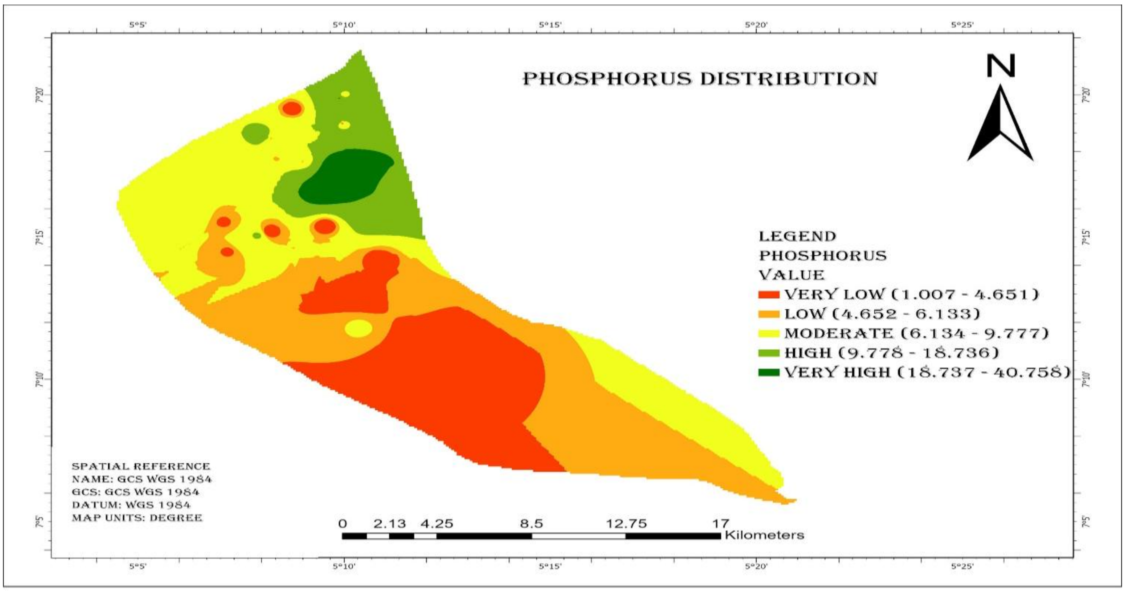


*Fig.5: Phosphorus distribution in Akure South LGA*

### 3.5.6 Spatial Distribution of Nitrogen (N)

The spatial distribution of nitrogen (N) in the study area is show in Figure 6. The maps reveal considerable spatial heterogeneity, with high nitrogen concentrations concentrated in the northern and western sectors of Akure South. These zones correspond primarily with vegetated and agricultural land uses, where substantial organic inputs from leaf litter, crop residues, and root exudates enhance nitrogen accumulation through mineralization processes. In contrast, the southern and central parts of the LGA, particularly under built-up and barren land covers, exhibit comparatively low nitrogen levels. This reduction is likely attributable to soil compaction, erosion, and depletion of organic matter, which collectively constrain nitrogen availability.

The observed pattern reflects the strong dependence of nitrogen status on organic matter, as further supported by the strong positive correlation (r = 0.84) between N and OC obtained from the correlation matrix analysis. Similar spatial associations have been reported in tropical regions, where vegetation cover and land management practices are key determinants of nitrogen distribution (Ogunleye and Agele, 2025). Furthermore, the high coefficient of variation (97.3%) recorded for nitrogen underscores the extreme spatial variability of this nutrient, driven by differences in land cover, organic inputs, and anthropogenic activities.

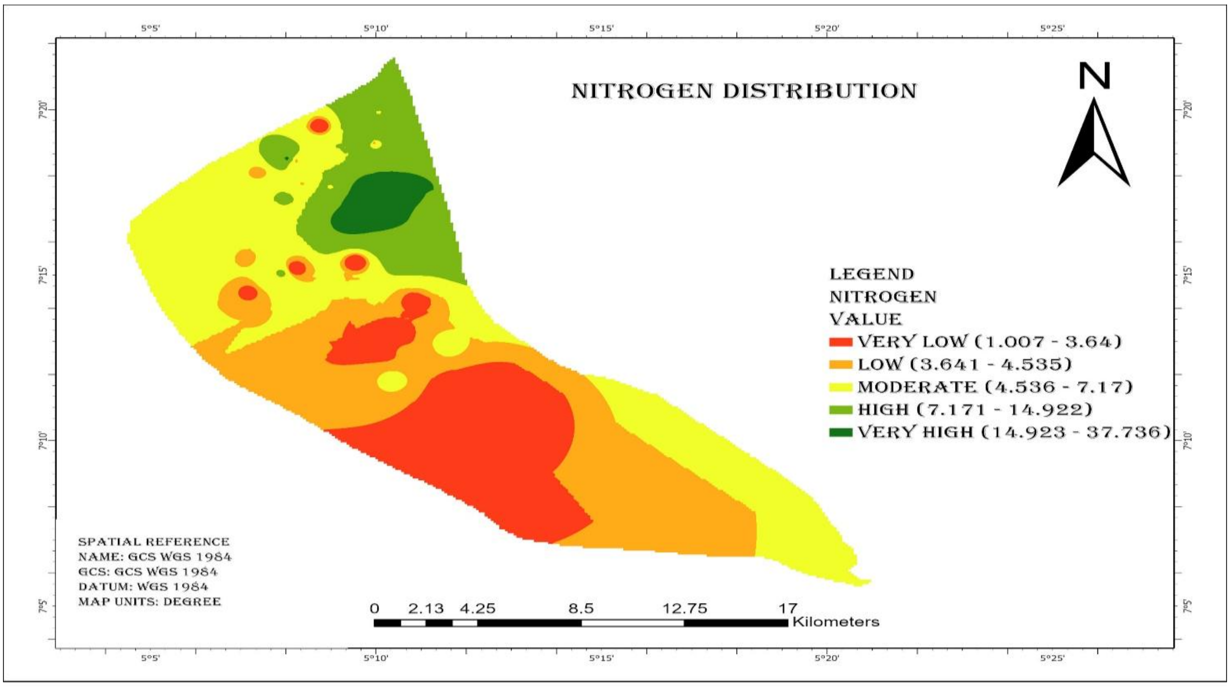


*Fig.6: Nitrogen distribution in Akure South LGA*

### 3.6 Overall Soil Fertility Map

The Soil Fertility Index (SFI) map generated through weighted overlay analysis of normalized soil parameters reveals distinct spatial patterns of fertility across Akure South LGA as shown in Figure 7. The SFI values ranged from 0.048 to 0.994, indicating extreme spatial heterogeneity in soil fertility status across the study area.

The fertility classification identified five distinct zones based on SFI values: Very Low (0.048-0.188), Low (0.189-0.270), Moderate (0.271-0.407), High (0.408-0.600), and Very High (0.601-0.994). The spatial distribution demonstrates a clear north-south gradient, with higher fertility concentrated in the northwestern sector, while lower fertility dominates the central and southern portions of the LGA.

Very Low and Low Fertility Zones (SFI < 0.271) occupy the largest portion of the study area, predominantly in the central and south-central regions, reflecting severe soil degradation due to urbanization, soil sealing, and topsoil removal. The extensive red and orange zones indicate widespread fertility constraints requiring intensive soil management interventions, including substantial organic matter additions and balanced fertilization (Olorunfemi *et al.,* 2018). Moderate Fertility Zones (SFI 0.271-0.407), shown in yellow, form transitional areas between high and low fertility regions, primarily in the western and eastern peripheries. These areas represent mixed agricultural lands and grasslands where soil fertility is adequate but requires regular maintenance through organic amendments and balanced nutrient management to prevent further degradation (Vasu *et al.,* 2016). High and Very High Fertility Zones (SFI > 0.408) are confined to relatively small areas in the northwestern and northeastern corners, appearing as light and dark green patches. These zones coincide with vegetated areas and well-managed agricultural lands where continuous organic matter inputs from litter decomposition, minimal soil disturbance, and active nutrient cycling maintain elevated fertility levels (Isong *et al.,*2022). The spatial pattern observed aligns closely with the individual parameter distribution maps, where high nitrogen, phosphorus, potassium, and organic carbon concentrations clustered in the northern and western vegetated areas, while depleted nutrient levels characterized the central built-up zones. This concordance validates the SFI as a meaningful integration of multiple fertility parameters into a single composite metric (Zhao *et al.,* 2023). The predominance of low fertility zones (red and orange colours covering approximately 60-70% of the mapped area) is an indication of urgent need for soil restoration programs in Akure South. The spatial heterogeneity revealed by the SFI map (with values spanning nearly the entire theoretical range of 0 - 1) confirms that blanket fertilizer recommendations are inappropriate for the area. Areas classified as Very Low and Low fertility require priority attention with intensive soil amendment programs, while High and Very High fertility zones can serve as reference sites for best management practices that could be replicated in degraded areas.

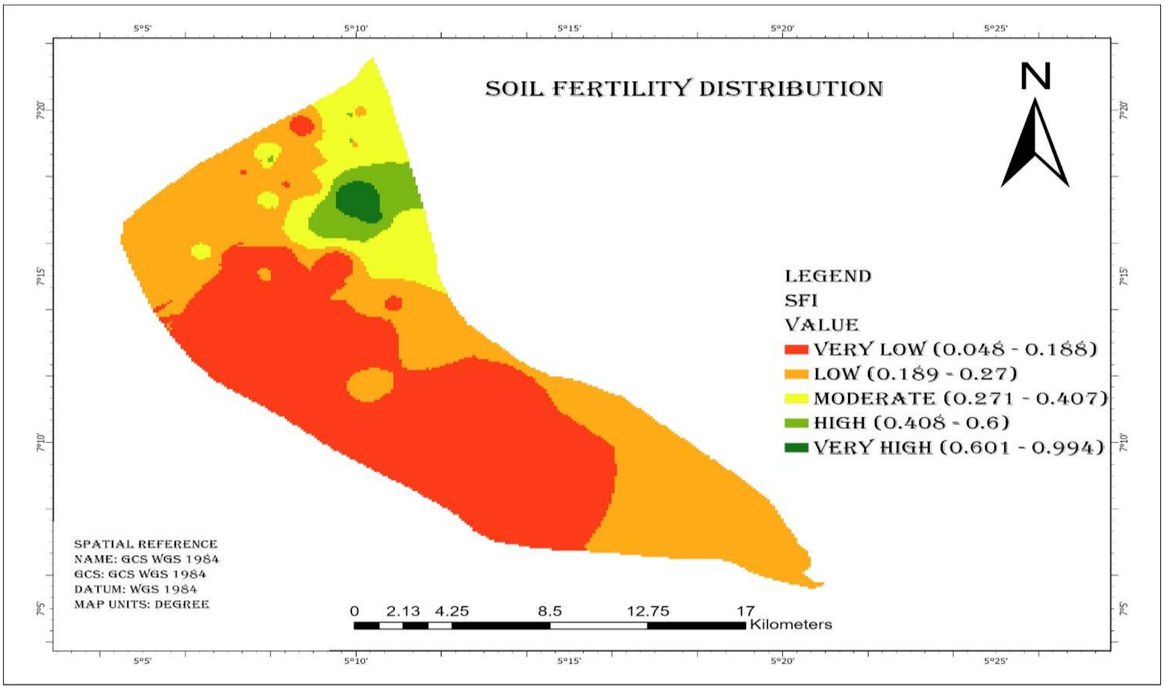


*Fig.7: Soil fertility distribution map of Akure South LGA*

The mean values of nitrogen, phosphorus, and potassium were low to moderate, indicating the general low fertility of the soils in the area. Organic carbon showed a moderate mean value, while the soil pH indicated a slightly acidic condition, which is typical of soils in the humid tropics. The high coefficients of variation (CV) for macronutrients such as nitrogen (97.3%), phosphorus (94.7%), and potassium (98.0%) indicate strong spatial heterogeneity in nutrient distribution. The Soil Fertility Index (SFI) results also showed that most parts of Akure South fell under low to very low fertility classes, accounting for about 60% of the study area (Table 4.).

The findings from the present research highlight a pronounced imbalance between nutrient-rich and nutrient-depleted zones across Akure South. The low mean values of nitrogen (7.50 mg/kg), phosphorus (9.48 mg/kg), and potassium (23.45 mg/kg) coupled with high CV values suggest that nutrient cycling and redistribution processes are highly localized (Table 1; Figure 4). This degree of heterogeneity is consistent with tropical landscapes characterized by complex land use mosaics, varying vegetation density, and differential management inputs (Kongor *et al.,* 2019). The relatively stable pH values (5.0–6.6) indicate a mildly acidic regime that, while suitable for most crops, may constrain phosphorus availability due to Fe/Al oxide fixation typical of ferrallitic soils (Balemi and Bayissa, 2012).

Spatial interpolation using IDW (Figures 2 –7) revealed nutrient enrichment primarily in the northern and northwestern sectors of the LGA i.e. areas associated with dense vegetation and lower anthropogenic disturbance. Conversely, nutrient-depleted areas dominated the built-up southern and central zones, reflecting the impact of soil sealing, erosion, and organic matter loss. The strong positive correlation between organic carbon and macronutrients (r > 0.77) further underscores the pivotal role of organic matter in nutrient retention and cycling (Paltineanu *et al.,* 2024). The mean SFI of 0.379 ± 0.156 (Figure 7) and its corresponding fertility classes confirm that most of the soils are below optimal productivity levels and will require intensive management for sustained agricultural performance. This spatial insight allows agricultural planners and policymakers to identify low-fertility zones for targeted intervention, fertilizer optimization, and restoration measures (AbdelRahman *et al.,* 2022; Prabhavati *et al.,* 2015).

### 3.7 Discussion

The observed low to moderate mean macronutrient concentrations and the pronounced spatial heterogeneity (very high CVs for N, P and K) in Akure South are consistent with previous GIS-based and field studies conducted across humid tropical regions in Africa and elsewhere. Several regional studies reported similar baseline fertility constraints in West African agricultural soils, with characteristic low plant-available phosphorus and nitrogen, coupled with modest organic carbon stocks. The studies emphasized strong small-scale variability driven by land-use, management and geomorphic position (Kongor *et al.,* 2019; Wells *et al.,* 2022).

Studies in West and East Africa using soil mapping and fertility indices have found comparable distributions of fertility classes and often identify organic carbon as a primary explanatory variable for nutrient status gradients. For example, detailed assessments of cocoa and mixed-cropping landscapes in Ghana and nearby West African zones documented low to moderate macronutrients and used composite soil quality indices to distinguish management units concluding that organic matter inputs strongly explain spatial fertility patterns (Kongor *et al.,* 2019). Studies showed that in highly weathered, ferrallitic soils, enhancements in organic carbon translate into improvements in N availability and greater nutrient retention overall.

At the landscape and national scale, comparisons of soil-organic-carbon mapping efforts highlight the challenge of predicting SOC and nutrient status from coarse datasets and underscore the utility of local, high-resolution sampling for management. Global and continental studies including national mapping efforts and reviews of digital soil mapping performance emphasize that SOC (and by extension nutrient status) is strongly controlled by edaphic factors (texture, mineralogy), land-use and topography, and that locally-targeted organic amendments are among the most effective mitigation strategies to improve fertility in tropical soils (Feeney *et al.,*2022; Xiang *et al.,* 2023).

Experimental trials and applied studies in southwestern Nigeria also demonstrate practical benefits from organic amendments (compost, manure, biochar) for increasing SOC, improving K and N retention, and raising crop yields outcomes that align with the present recommendation to prioritize organic-matter enrichment as a cost-effective strategy to increase nutrient retention and reduce reliance on blanket mineral fertilizer (Adekiya *et al.,* 2023; Agbede *et al.,* 2024).

Together, these studies indicate that Akure South's fertility profile, a landscape of low to moderate mean nutrient pools with high small-scale variability fits within the broader pattern observed across humid tropical agricultural systems.

#### 3.7.1 Geoscience Interpretation of Fertility Distribution

Akure South LGA lies within the Precambrian Basement Complex of southwestern Nigeria, where migmatite–gneiss, granitic intrusions and related lithologies form the dominant bedrock. These basement rocks weather to produce deep lateritic profiles (residual soils) commonly classified in the WRB as Ferralsols and Acrisols under humid tropical conditions (WRB, 2014). The humid tropical climate (pronounced wet season, considerable annual rainfall) promotes intense chemical weathering and leaching, driving loss of base cations and accumulation of sesquioxides (Fe/Al oxides) in the soil profile (Falowo, 2018); this pedogenic pathway explains the ferrallitic character and generally low total nutrient pools observed in Akure South (Figures 1–6).

#### 3.7.2 Parent material and mineralogical controls.

Parent-rock composition (migmatite–gneiss versus granitic or charnockitic intrusions) exerts first-order control on the primary mineral reservoir of nutrients (notably K and P bound to primary minerals). Where the parent rock contains higher K-feldspar or biotite contents, residual soils can retain slightly elevated K in coarse fragments and weathering residues; conversely, highly leached Ferralsols derived from silica-rich gneisses tend to show low extractable K despite total K stored in resistant minerals (Adeoye *et al.,* 2018). This geological control explains why some local samples show very high K (point concentrations up to 108 mg $kg^{-1}$) while the landscape mean is low, localized pockets reflect either residual mineral fragments or concentrated anthropogenic inputs on specific lithologies or borrow-pit fill (Adeoye *et al.,*2018; Falowo, 2018).

#### 3.7.3 Weathering intensity, sesquioxides and phosphorus dynamics.

Intense weathering characteristic of humid tropical terrains produces high proportions of amorphous and crystalline Fe/Al oxides and oxyhydroxides. These sesquioxides strongly adsorb and occlude phosphate, reducing plant-available P even when total P is moderate ("P fixation" phenomenon). The slightly acidic topsoil pH (5.0–6.6) enhances the availability of $Al^{3+}$ and $Fe^{3+}$ at micro-scales, increasing the sorption of orthophosphate onto oxide surfaces and oxyhydroxide coatings, which is consistent with the low mean Bray-P/available-P values reported in Table 1 despite localized high-P samples (Johan *et al.,*2021). Strategies to improve P availability must therefore consider both chemical (liming, P placement) and organic (addition of biomass or compost to complex Al/Fe and reduce fixation) routes (Kiflu *et al.,* 2017).

#### 3.7.4 Erosion, deposition and nutrient redistribution.

The spatial clustering of high-fertility patches in the northern and northwestern areas of Akure south (Figures 1– 6) together with depleted central/built-up zones suggests active landscape redistribution processes. On basement-complex terrain, ridges and convex hilltops often have thin, heavily weathered soils (nutrient-poor), while concave hollows, footslopes and depositional zones accumulate organic matter and fine sediments, concentrating nutrients (Falowo, 2018). Additionally, human activity such as tillage, manure application, dumping and construction fill can create point-source enrichment. Thus, the observed SFI hotspots likely reflect the combined influence of (a) depositional micro-sites that concentrate org-matter and fine particles, and (b) localized anthropogenic inputs. Targeting foot slope/depositional areas for conservation and management could therefore protect nutrient "sinks" and help restore adjacent depleted slopes (Herrmann *et al.,* 2020).

#### 3.7.5 Anthropogenic/urban geomorphic modifications and anthroposols.

Urbanization and peri-urban land conversion in Akure South have reworked natural soil profiles through topsoil removal, compaction, and import of fill material and creation of anthroposols. These processes reduce organic matter stocks, disrupt structure, and can both dilute and concentrate nutrients depending on the fill source (e.g., construction debris vs. fertile topsoil). The low OC and nutrients observed in built-up zones closely mirror global patterns of urban soil convergence and degradation reported in multiple cities: urbanization tends to homogenize and often reduce SOC and nutrient heterogeneity at short distances, causing loss of ecosystem service potential unless remediated (Pouyat *et al.,*2010; Herrmann *et al.,*2020). Addressing these modifications requires both site remediation (topsoil replacement, decompaction) and planning measures to minimize further soil sealing.

#### 3.7.6 Implications for Sustainable Soil Management and Land Use

***Prioritized, landscape-based interventions*.**

Given the strong spatial heterogeneity (high CVs) and the SFI map (Figure 5; Table 4), management should prioritize targeted interventions rather than uniform, area-wide fertilizer application. High-priority actions include: (1) mapping and protecting nutrient sink areas (depositional zones) to maintain OC and nutrient reservoirs; (2) targeted organic amendments (compost, manure, residue retention) in Low/Very Low SFI zones to build OC and improve cation exchange capacity; and (3) site-specific P management (banding, combined organic–mineral P applications, and judicious liming where pH <6.0) to overcome fixation losses (Fan *et al.,*2019; Johan *et al.,*2021). These recommendations are aligned with successful approaches reported in other humid tropical contexts.

## IV. CONCLUSION

This study successfully evaluated the spatial distribution of soil fertility across Akure South Local Government Area using an integrated approach that combined field-based soil analysis with Geographic Information System (GIS) techniques. The results revealed notable variability in soil nutrient levels across different land use types, emphasizing the strong influence of land use and management practices on soil fertility. Areas with continuous vegetation cover and agricultural activity exhibited comparatively higher fertility index, while built-up and barren lands showed signs of nutrient depletion and reduced soil quality due to limited organic matter and surface sealing. The study highlights the central role of organic matter in maintaining soil fertility and the need for targeted interventions, such as organic amendments, conservation practices, and pH management, to enhance soil health. This research confirms that GIS-based soil fertility mapping is a valuable tool for visualizing spatial patterns of soil properties, guiding precision agriculture, and supporting evidence-based decision-making for sustainable land management in rapidly urbanizing tropical regions.

## DECLARATION OF CONFLICT OF INTEREST

We hereby declare that the research was jointly sponsored and conducted by the authors, and not financed by any external sources. There are no conflict of interest of any form regarding the submission of this manuscript. No financial or personal relationship with a third party whose interests could be positively or negatively influenced by the article's content. Data from this research are all originally collected from the investigations conducted from this research and never a primary or secondary data from any other source.

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