FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 13, July, 2026, pp 27 – 38
DOI: https://doi.org/10.33003/fjs-2026-1013-5347

Spatial Distribution of Major Soil Fertility Indicators in Ussa Local Government Area, Taraba State, Nigeria

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ABSTRACT

Spatial variability of soil fertility indicators influences nutrient availability and the effectiveness of soil management practices. This study assessed the spatial distribution of major soil fertility indicators in Ussa Local Government Area (LGA), Taraba State, Nigeria. A base map of the study area showing sampling points was generated in ArcGIS using georeferenced coordinates to stratified coverage. The coordinates were uploaded into a GPS and used as waypoints for field sampling. A randomized sub-sampling approach, following the Soils4Africa configuration, was adopted to capture site variability. Soil samples were collected at two depths (0 - 25 cm and 25 - 50 cm), composited to obtain representative samples, yielding 64 samples. Soil pH, total nitrogen (TN), available phosphorus (AvP), and exchangeable potassium (K^+) were determined using standard laboratory procedures. Ordinary kriging interpolation in ArcGIS 10.5 was used to assess spatial variability and generate nutrient maps. The results revealed considerable spatial variability in the distribution of the investigated soil fertility indicators. Soil pH ranged from 5.56 to 7.50, indicating predominantly slightly acidic to neutral conditions, TN was generally low across the study area, while AvP occurred mainly at medium concentrations with localized low-concentration zones and K^+ was predominantly high and relatively uniform across the area. Nutrient concentration maps delineated distinct zones of nutrient sufficiency and deficiency, highlighting areas requiring targeted fertility interventions. The study demonstrates the effectiveness of geostatistical techniques for characterizing soil fertility variability and provides spatial information for site-specific nutrient management, fertilizer optimization, and sustainable agricultural planning in Ussa LGA.

Received: 21 Jun. 2026

Accepted: 13 Jul. 2026

Published: 3 Aug. 2026

Keywords: Soil Fertility Indicators, Spatial Variability, Ordinary Kriging, Nutrient Mapping, Soil pH, Total Nitrogen, Available Phosphorus, Exchangeable Potassium

INTRODUCTION

The 21st century agriculture grapples with the pressing issues of food security, environmental quality, and soil health, with the global population on the rise, agricultural expansion is inevitable, but it must be balanced with responsible land use patterns and soil management practices (El-Naggar *et al.,* 2019). Soil fertility, which refers to the ability of the soil to provide essential nutrients and favorable conditions for plant development, encompasses the complex interplay of factors including soil pH, soil texture and structure, organic matter, and nutrient availability, which is the foundation of high yielding agricultural systems (Lanki *et al.,* 2023). Consequently, the assessment of soil fertility indicators is fundamental for agricultural potential, supporting land use planning, and promoting sustainable soil resource management (Bünemann *et al.,* 2018).

The spatial variability of soil properties has received considerable attention because soil fertility indicators often exhibit significant heterogeneity across landscapes. This variability is essential for the development of site-specific nutrient management strategies and efficient agricultural resource utilization (Biradar and Ingle, 2023). Soil mapping is a valuable tool for identifying areas with different soil nutrient levels, enabling site specific management strategies and informed decision-making (Bünemann *et al.,* 2018). Ordinary kriging, a geostatistical prediction tool, has emerged as a powerful tool for soil mapping and spatial prediction of soil properties (Rajamani *et al.,* 2020). This technique leverages on the spatial autocorrelation of soil data to estimate values at un-sampled locations, providing a comprehensive understanding of the spatial distribution of soil fertility parameters (Adedeji, 2019). By incorporating spatial dependence and minimizing estimation errors, ordinary kriging proposes a reliable and efficient approach to soil mapping, specifically in areas with limited data availability (Afolayan *et al.,* 2020).

The application of ordinary kriging in soil mapping has gained significant attention due to its ability to quantify the spatial variability of soil properties, which is often characterized by complex patterns and heterogeneity (Huang *et al.,* 2010). Compared with alternative interpolation techniques, including inverse distance weighting and spline interpolation, ordinary kriging takes into account the spatial structure of the data, allowing for more accurate estimations and reduced uncertainties (Keshavarzi *et al.,* 2021). The key advantages of ordinary kriging are its capability to incorporate auxiliary information, such as terrain attributes, remote sensing data, or existing soil maps, into the interpolation process (Afolayan *et al.,* 2020). This integration of secondary data sources can enhance the accuracy and reliability of soil property predictions, particularly in areas with sparse sample points (Sangya *et al.,* 2023).

Despite the agricultural importance of Ussa Local Government Area (LGA), information on the spatial variability and distribution of key soil fertility indicators remains limited, constraining the development of effective and site-specific soil fertility management strategies. This study therefore assessed the spatial distribution and concentration of selected soil fertility indicators; soil pH, total nitrogen (TN), available phosphorus (AvP), and exchangeable potassium (K^+), using geostatistical techniques and ordinary kriging interpolation. The study focused on characterizing soil nutrient status into low, medium, high and generating spatial distribution maps to support targeted nutrient management, optimize fertilizer application, and enhance sustainable agricultural production in the study area.

MATERIALS AND METHODS

The study was conducted in Ussa LGA, Taraba State, Nigeria, located between latitudes 06°55′00″ and 07°15′00″ N and longitudes 09°50′00″ and 10°15′00″ E (Wikipedia, 2024). The area lies within the Southern Guinea Savanna agroecological zone and shares borders in the northeast with Kurmi LGA, in the south and southeast with the Republic of Cameroon and to the north and west with Takum LGA (Asanarimam, 2018). The area experiences a tropical savanna climate characterized by distinct wet and dry seasons. Mean annual rainfall is approximately 2500 mm, while the average temperature is about 31°C (Karima, 2016). Agriculture constitutes the dominant land use in the area, with the cultivation of cereals, legumes, root crops, and tree crops forming the major livelihood activities.

Study Area

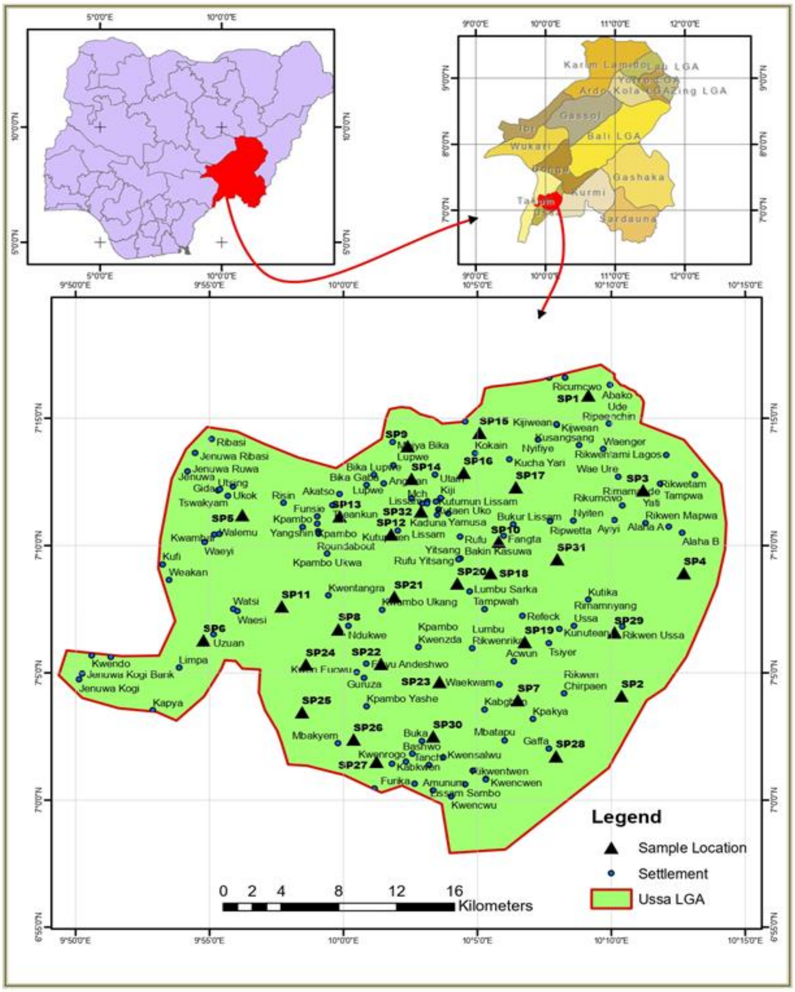

Figure 1: Map of the Study Area Showing Sampling Points

Soil Sampling and Laboratory Analysis

A stratified sampling approach was adopted to ensure adequate spatial representation of the study area. Sampling locations were established using a georeferenced base map generated in ArcGIS. A total of 32 sampling points were selected across the study area (Fig. 2.1) and their coordinates were navigated using a Global Positioning System (GPS) receiver. At each sampling location, four subsamples were collected within a radius of approximately 1 m (Fig. 2.2) and composited to obtain representative samples. Soil samples were collected from two depths: 0 - 25 cm (surface soil) and 25 - 50 cm (subsurface soil), resulting in 64 composite samples. The samples were air dried, gently crushed, passed through a 2 mm sieve, and homogenized prior to laboratory analysis.

Soil pH was determined potentiometrically in a 1:2 soil-to-water suspension (Jaiswal, 2003). Total nitrogen (TN) was determined using the micro-Kjeldahl digestion method (Bremner and Mulvaney, 1982). Available phosphorus (AvP) was extracted using the Bray-1 method and quantified colorimetrically following the procedure of Bray and Kurtz (1945) and Murphy and Riley (1962). Exchangeable potassium (K^+) was extracted using 1 N ammonium acetate ($NH_4CH_3CO_2$) at pH 7.0 and measured with a flame photometer following Thomas (1982).

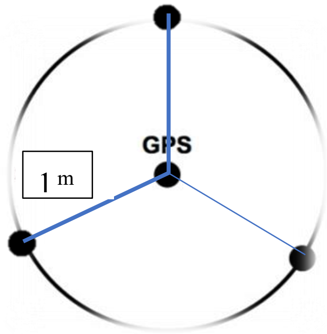

Figure 2: Sampling Layout

Geostatistical Analysis and Spatial Mapping

Geostatistical analyses were performed to characterize the spatial variability of soil pH, total nitrogen (TN), available phosphorus (AvP), and exchangeable potassium (K^+). Experimental semivariograms were developed to evaluate the spatial dependence of each soil fertility indicator, while trend analysis and normal Q-Q plots were used to assess data distribution and spatial correlation. Ordinary kriging (OK) interpolation was employed to estimate values at unsampled locations based on the spatial autocorrelation of measured soil properties (Yesrebi *et al.,* 2009). Geostatistical modelling and interpolation were conducted using the Geostatistical Analyst extension in ArcGIS 10.5. The resulting prediction surfaces were used to generate spatial distribution maps for each soil fertility indicator. Nutrient concentration maps were subsequently produced through raster reclassification based on established fertility rating standards (Waizah *et al.,* 2022), allowing the delineation of nutrient status classes and soil reaction categories across the study area.

RESULTS AND DISCUSSION

Spatial Distribution of Soil Fertility Indicators

The spatial distribution maps generated through ordinary kriging revealed distinct patterns in the distribution of soil fertility indicators across Ussa LGA. The interpolated surfaces highlighted areas of nutrient enrichment and depletion, reflecting the influence of soil forming processes, topography, land use practices, and management history. The spatial variability of each indicator is discussed below.

Soil pH

The interpolated spatial variability map of soil pH across the study area (Fig. 3) reveals distinct variability, ranging from moderately acidic to neutral. The northeastern zone recorded lower values and are predominantly moderately acidic to slightly acidic, particularly around Kutupwen, Mbiya, Ricumcwo, Alaha B, and Kutika constituting a major landscape. Moving towards the eastern and northcentral regions, including Rikwen Ussa, Waekwam, Kwambo Ukang, and Bika Gaba soils generally exhibit slightly acidic reactions. The southeast towards the northwest exhibited slightly acidic to neutral level of pH notably around settlements such as, Kpakya, Kpambo Yashe and Utsing. In the southern part while moving towards the southwest and part of the north northwest the pH distributions terns to move from slightly acidic to neutral with some patches of slightly acidic soils at the extreme end part of the southwest particularly around Kwendo, Jenuwa Kogi Bank and Jenuwa Kogi respectively, while the central part, especially near Waekwam and Ndukwe, forms a transitional band where slightly acidic soils predominate.

This pattern is likely influenced by variations in parent material, topography, and land use across the landscape. Upland areas in the north and northeast, characterized by minimal leaching and higher base saturation, retain moderately acidic to slightly acidic conditions, whereas lower elevations in the south, which experience higher rainfall and minimal leaching, exhibit reduced acidity. These observations align with findings reported by Waizah *et al.,* (2022) in Guinea savanna soils and are consistent with studies by Aakash *et al.,* (2019) and Kurumaiah *et al.,* (2021), who demonstrated that pH distribution in tropical soils is strongly linked to geomorphology, rainfall intensity, and cultivation practices.

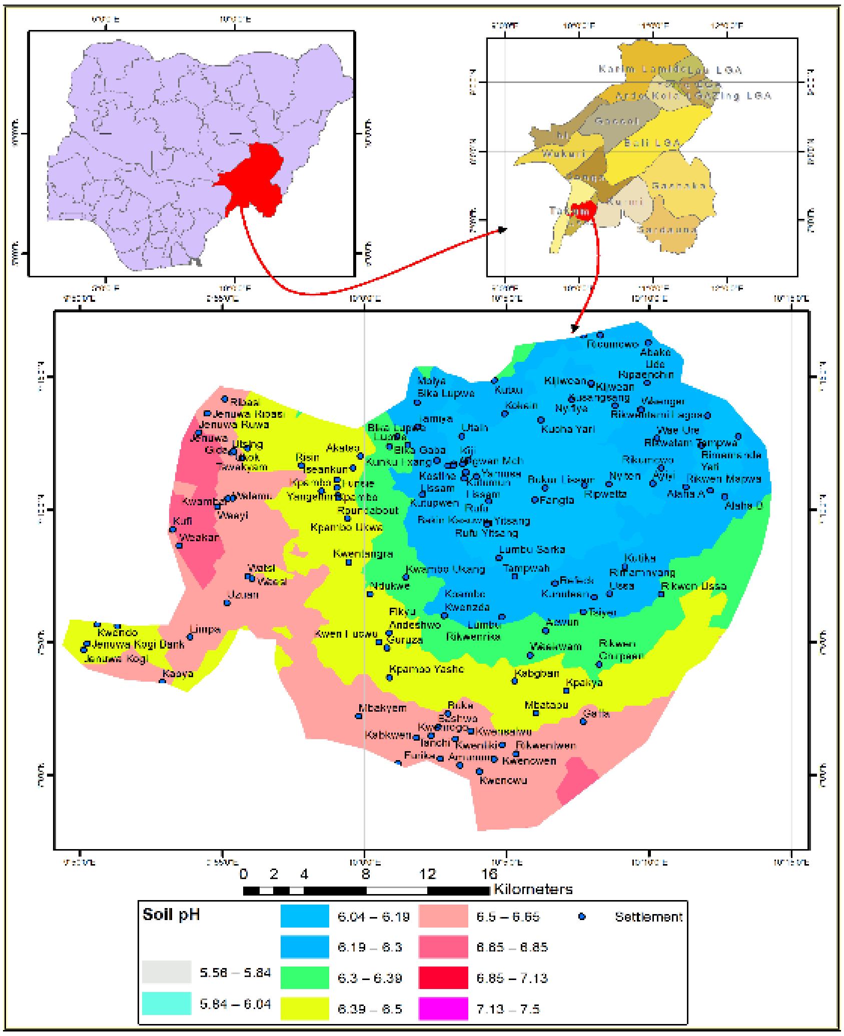

Figure 3: Spatial Distribution Map for Soil pH

Total Nitrogen (TN)

The spatial distribution map of TN (Fig. 4) indicates that the concentration of TN across the entire area is relatively low. Lower level represented by the yellow color dominates the north-north towards the northeast and south with some patches of light green indicating a lower value around settlements such as Waenger and Rikwmcwo. The wide spread of other lower TN concentrations but with higher values moves from the southwest towards the central and up to the northwest where settlements around Ribasi, Walemu and Kpambo Ukwa shows medium concentration of TN.

The spatial distribution of TN in the study area reflects the complex interplay between natural pedogenic processes and anthropogenic disturbances. The generally low TN concentrations observed align with findings from similar watershed studies where agricultural land use and settlement activities deplete soil nitrogen reserves (Tong *et al.,* 2023; Xie *et al.,* 2023). The patchy distribution pattern, with localized higher values around specific settlements, is consistent with Yang *et al.,* (2025), who reported scattered TN hotspots attributable to site-specific vegetation density and organic inputs. Furthermore, the medium TN concentrations observed around Ribasi, Walemu, and Kpambo Ukwa may reflect the combined influence of topography and land management practices, as demonstrated by Tong *et al.,* (2023), who found that slope position and land use interaction significantly affect nutrient accumulation. The predominance of lower TN values in the north-northeast and southern regions suggests the influence of natural pedogenic factors such as soil texture and moisture status (Tong *et al.,* 2023), while the spatial heterogeneity observed is indicative of anthropogenic homogenization effects typical of intensively managed landscapes (Yang *et al.,* 2025).

Available Phosphorus (AvP)

Available phosphorus across the study area (Fig. 5) as showed in the spatial distribution map indicate a pronounced variability. Higher AvP concentrations are predominantly located in the central towards the north and northeastern part of Ussa, whereas southern and northwestern areas display comparatively lower concentrations, with notably spots which occurred around Kwendo, Ndukwe, and Jenuwa Gida suggesting discrete areas of intensified nutrient input or distinct soil characteristics. This pattern of AvP concentration is likely arising from the combined influence of parent material variation, topography, and localized land management practices. The differences in mineral weathering and soil texture may govern baseline phosphorus availability, while discrete spots may correspond to areas of concentrated fertilizer or organic amendment application. In tropical farming systems, phosphorus mobility is limited, and thus such spots often reflect anthropogenic inputs or unique soil mineralogy. Similar spatial variability in AvP has been reported in related studies conducted by Waizah *et al.,* (2022) who observed patchy distribution of AvP across Wukari LGA, attributing it to both land use intensity and topographic differences. Similarly, Nalin *et al.,* (2023) reported that available phosphorus variability is strongly affected by environmental factors, including topographic characteristics and land use patterns. These findings corroborate the relationship between terrain, land management, and phosphorus distribution (Fig. 5).

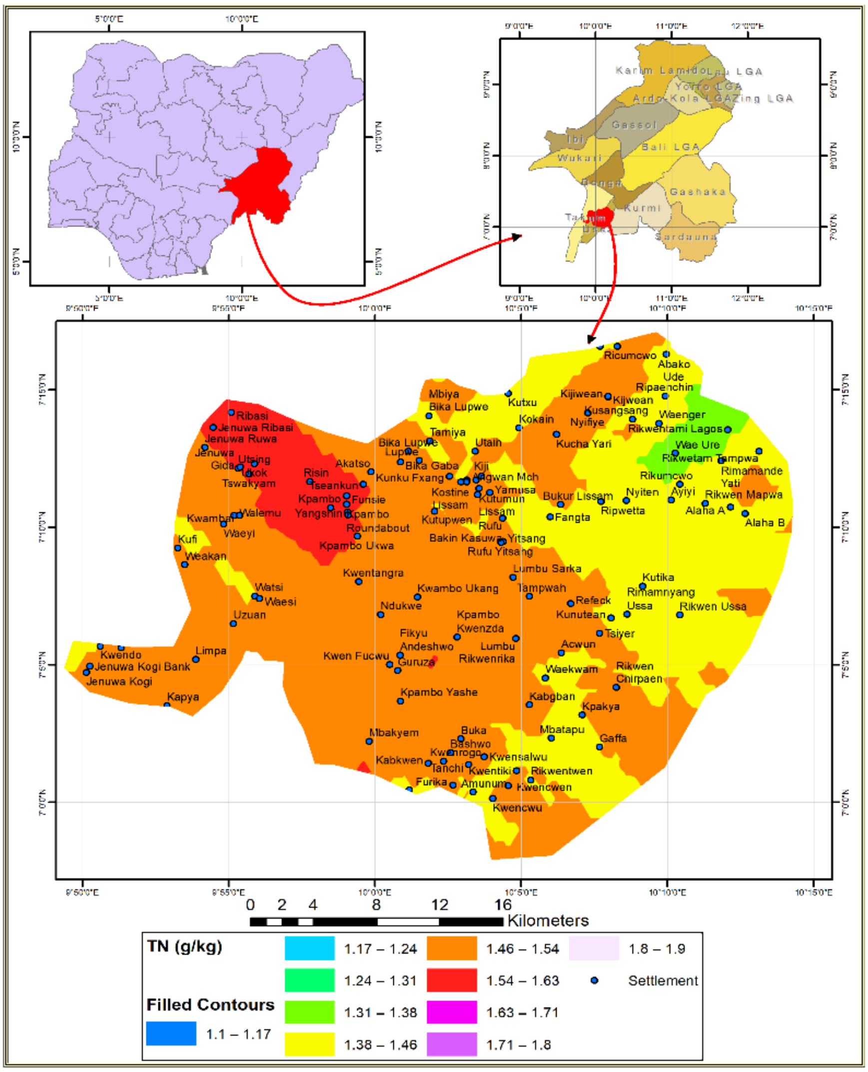

Figure 4: Spatial Distribution Map for Total Nitrogen

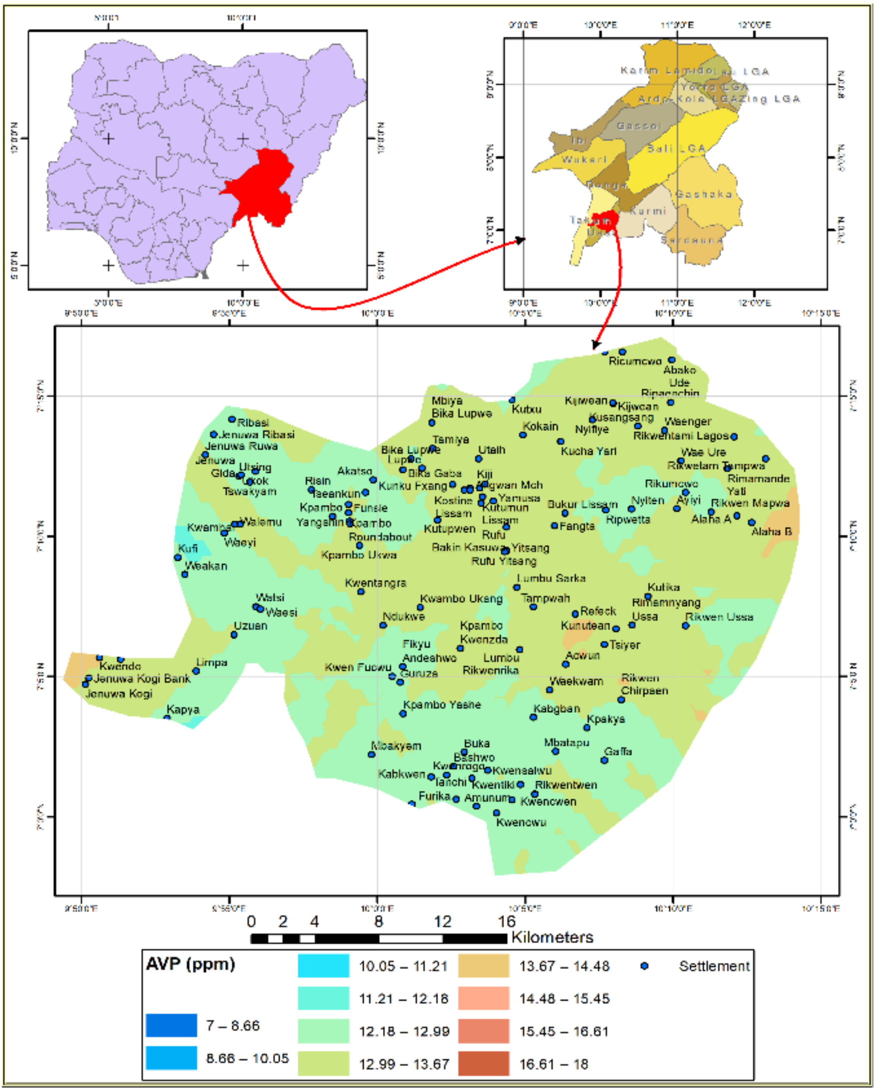

Figure 5: Spatial Distribution Map for Available Phosphorus

Potassium (K)

The spatial distribution of potassium across the study area (Fig. 6) reveals a broadly elevated baseline of high potassium levels extending across most of the region, with some notably patches indicating a higher concentration than the others as observed in the northeastern part arround: Tampwa, Yamusa, Kuttika, and Gaffa; in the northwestern zone, particularly around Ribassi; and southwestern zones encompassing Limpa, Jenuwa Kogi, among others. This widespread enrichment of K patches likely reflects underlying geological substrate variability, as potassium rich parent materials such as mica or feldspar bearing formations can release potassium during weathering. Additionally, agricultural practices, especially fertilizer application and residue incorporation into cultivated plots, tend to elevate exchangeable potassium levels.

This aligns with earlier research conducted by Akbaş, Gunal, and Acir (2017) where they investigated the spatial variability of soil potassium in a Mediterranean upland, revealing that parent material and land use are significant drivers of potassium distribution. They found that soils derived from potassium rich lithologies and areas with intense cropping exhibited elevated potassium concentrations, while leached or intensely weathered zones displayed lower levels.

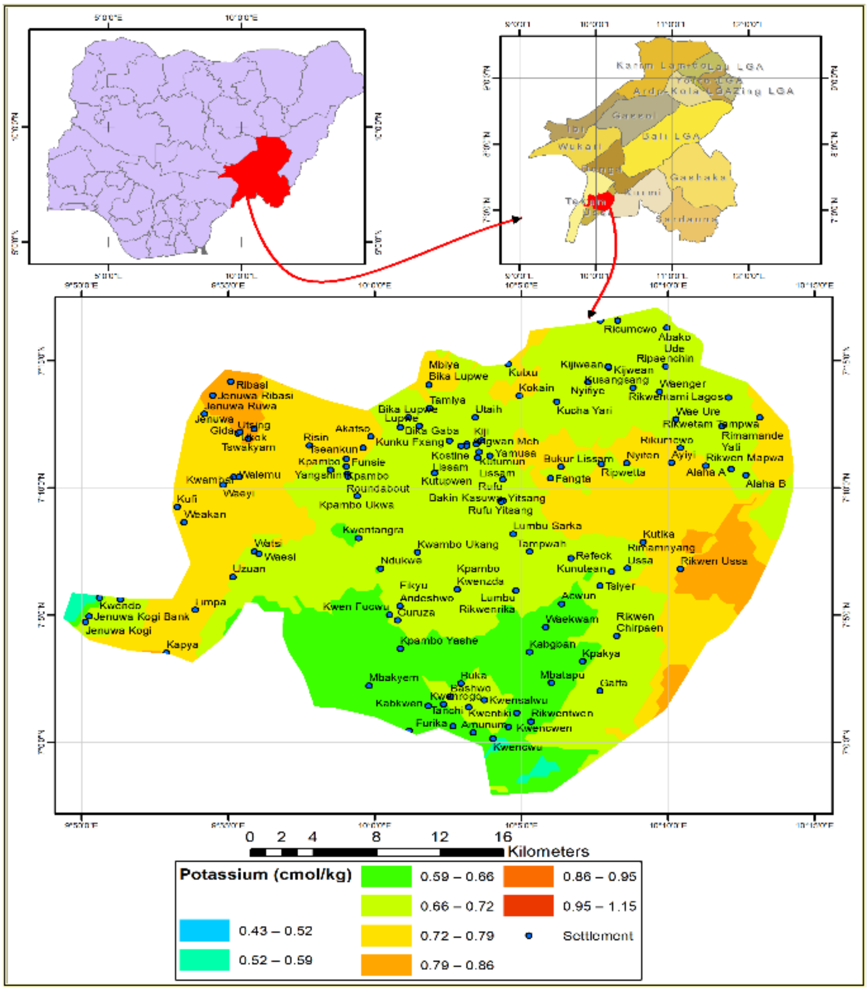

Figure 6: Spatial Distribution Map for Potassium

Nutrient Concentration Maps of Soil Fertility Indicators
To facilitate interpretation of soil fertility status and management recommendations, the interpolated surfaces were reclassified into 3 nutrients concentration levels (Low, medium and high) respectively, based on established rating standards. The resulting nutrient concentration maps provide a spatial representation of nutrient sufficiency levels and identify areas requiring targeted soil fertility interventions.

Soil pH
The nutrient concentration map showing the distribution of soil pH (Fig. 7) indicates that a substantial portion of the study area is slightly acidic, a condition that spans across most geographical zones with dominance in the northeast. Moderately acidic soils were confined to smaller portions in the central region, particularly around Lumbu Sarka, Kokain, and Ripwetta, while areas transitioning from the southeastern base toward the northwestern edge generally exhibited neutral reactions a condition indicating a balance concentration of acidity and alkalinity, with isolated pockets of slightly acidic soils were also seen in the southwestern zones, notably around Kwendo.
These observed pattern of slight to moderate acidity dominance in the study area is a typical characteristic of tropical regions where high rainfall promotes leaching of basic cations, thereby enhancing soil acidification (Mustapha *et al.,* 2011). The presence of neutral soils along the southeastern to northwestern axis (Fig. 7) can be attributed to variations in parent material and topographic influence, which affect weathering intensity and base saturation. Similar spatial trends were reported by Waizah *et al.,* (2022) in Wukari LGA Taraba State, where slightly acidic soils dominated most areas with occasional neutral zones in low lying or colluvial landscapes. Equivalent observations have also been documented by Aakash *et al.,* (2021) and Kurumaiah *et al.,* (2021) in related agroecological settings, emphasizing the role of lithology, organic matter accumulation, and land use in moderating soil pH across landscapes.

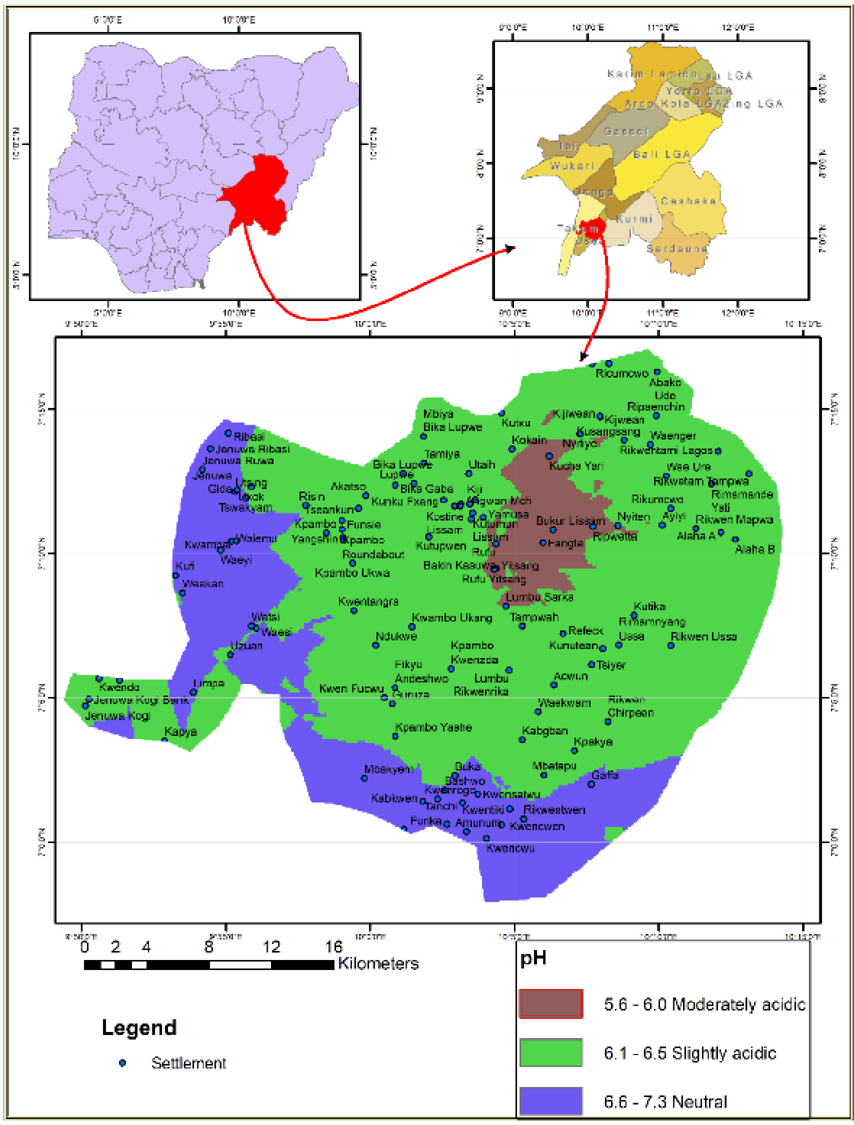

Figure 7: Nutrient Concentration Map for Soil pH

Available Phosphorus (AvP)

The nutrient concentration map for AvP (Fig. 8) reveals that most parts of the study area are dominated by medium AvP concentrations, which extend across all regions. However, some notable variations exist, with patches of lower AvP concentrations observed in the southern zones as well isolated portions in the northeast particularly around Rikwen Ussa and other scattered lower variation occurring in the region of the northwest around Kwambai, Kuffi, Weaken, Wetsi, and Uzuan respectively.

This pattern can be attributed to the inherent characteristics of tropical soils, where phosphorus fixation is high due to the dominance of iron and aluminum oxides in highly weathered soils. Such fixation reduces the availability of phosphorus even when total P content may be adequate. Additionally, lower concentrations in some areas could result from continuous cropping and minimal organic input, which accelerate depletion (Mustapha *et al.,* 2011). Similarly, Aakash *et al.,* (2021) also documented a comparable distribution pattern in tropical environments, highlighting the impact of soil mineralogy and management practices on P availability.

Total Nitrogen (TN)

Nutrient concentration map of TN reveals that the entire study area is dominated by low concentration of TN which spans across all geographical zones as seen in (Fig. 9) with some patches of medium TN concentration which can be observed in the southwest towards the central and northwest region respectively. This pattern reflects the inherently low nitrogen content typical of highly weathered tropical soils, where intense leaching and minimal organic matter input contribute to widespread depletion of nitrogen. Geostatistical studies in similar contexts reinforce this pattern. Han *et al.*, (2022), mapping soil fertility in Southwest China, reported that TN displayed strong spatial dependence primarily controlled by intrinsic factors such as soil texture, parent material, and vegetation, rather than agricultural practices or climate dynamics. These findings reflect the situation in Ussa LGA, where soil forming factors predominantly define the nitrogen distribution (Fig. 9). Additionally, regional and global mapping efforts like those by Hengl *et al.*, (2017) using high resolution machine learning models across Sub-Saharan Africa consistently find out that TN is one of the nutrients with the clearest geospatial patterns, generally confined within moderate ranges unless enriched through localized management.

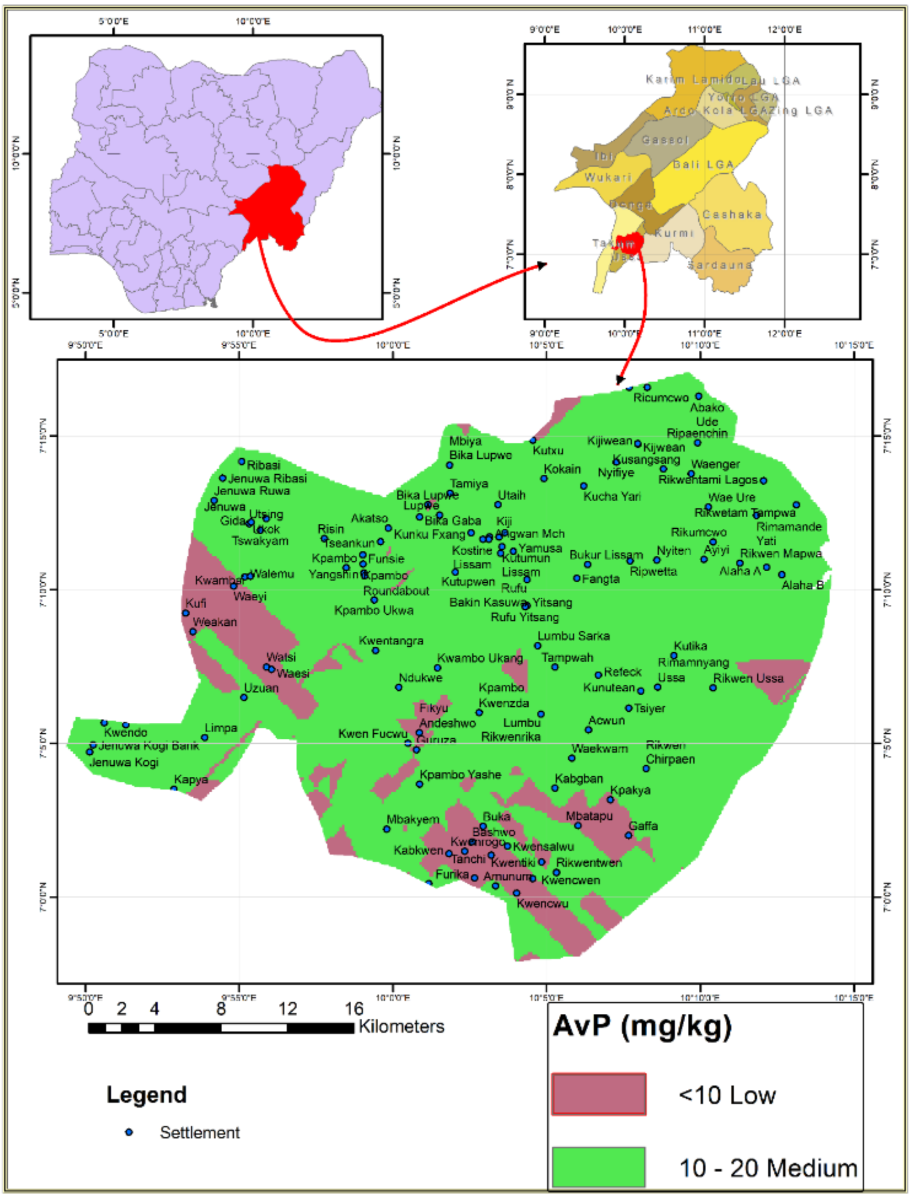

Figure 8: Nutrient Concentration Map for AvP

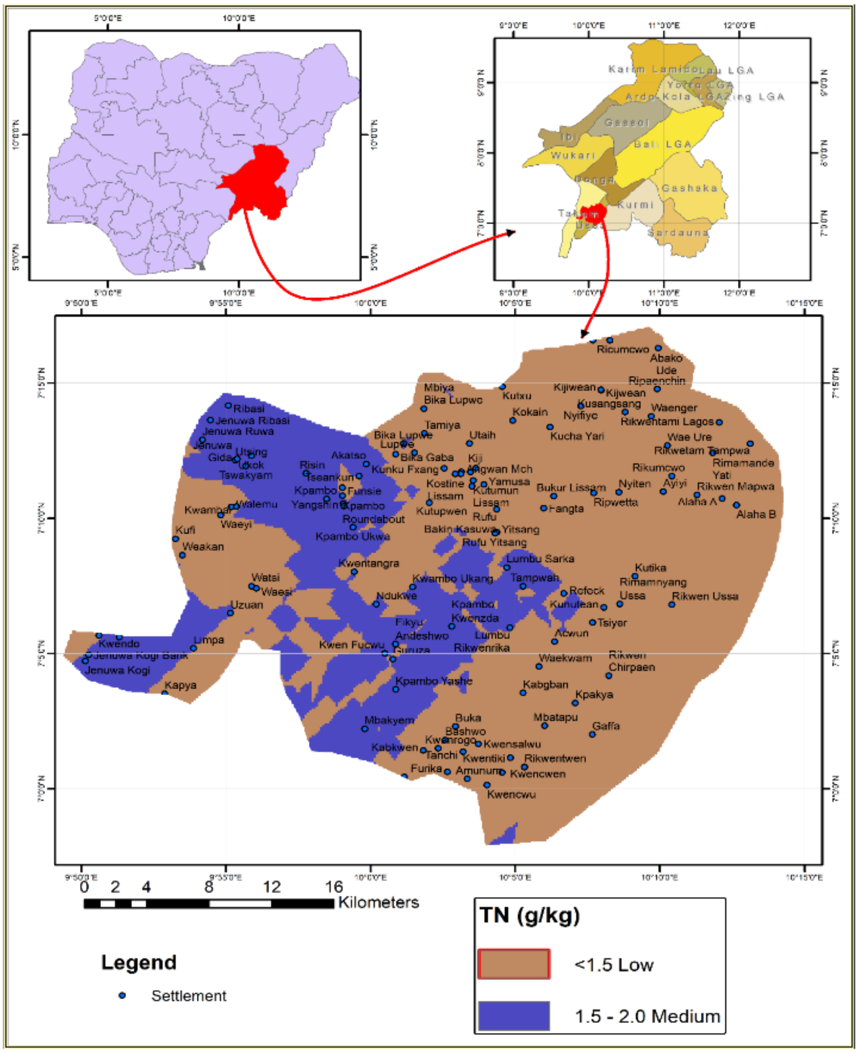

Figure 9: Nutrient Concentration Map for Total Nitrogen

Potassium (K)

Potassium as seen in (Fig. 10) the nutrient concentration map shows predominantly high concentration of K throughout the study area. Wang *et al.,* (2021) report that available potassium (AK) exhibited a relatively uniform spatial distribution across the study area compared with other nutrients, indicating that K variability was lower and less spatially structured by topographic gradients in that landscape. The abundance of K in Ussa soils could be attributed to the nature of the parent material, particularly K-rich minerals such as feldspars and micas, which undergo weathering and release exchangeable potassium into the soil (Brady and Weil, 2019). In highly weathered tropical soils, K tends to be less mobile compared to nitrate or sulfate and is retained in soil exchange sites, especially in soils with moderate clay content and higher CEC (Obi *et al.,* 2018). This explains why even areas with sandy loam textures still exhibit relatively high K levels, as exchange sites on clay and organic matter maintain available K in the soil solution.

The relatively uniform distribution of high potassium observed across Ussa LGA, aligns with findings from other Nigerian studies. Tijjani and David (2017) reported that potassium distribution along a toposequence on basaltic soils in Vom, Jos Plateau, showed no consistent relationship with topographic variation. Similarly, Abdullahi and Sadiq (2020) observed localized high potassium concentrations in Mubi Adamawa State, North-Eastern Nigeria, that were not clearly associated with land-use intensity or terrain features. Other report by Kurumaiah *et al.,* (2021) in Indian Vertisols and by Aakash *et al.,* (2021) in subtropical soils, where high spatial homogeneity of K was attributed to the mineralogical composition and long-term management practices.

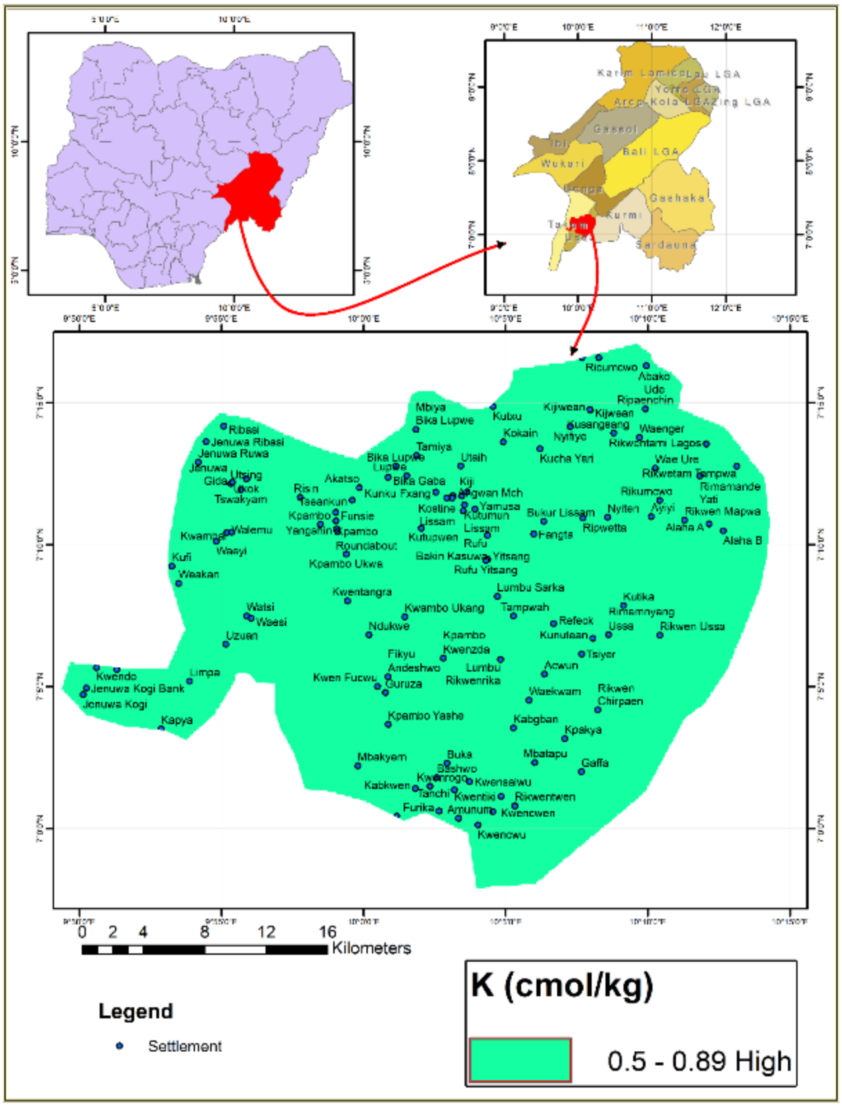

Figure 10: Nutrient Concentration Map for Potassium

CONCLUSION

This study demonstrated significant spatial variability in the distribution of soil fertility indicators across Ussa Local Government Area, Taraba State, Nigeria. Ordinary kriging effectively characterized the spatial patterns of soil pH, total nitrogen (TN), available phosphorus (AvP), and exchangeable potassium (K^+), revealing predominantly slightly acidic to neutral soils, widespread nitrogen deficiency, moderate phosphorus availability, and generally high potassium concentrations. The generated spatial distribution and nutrient concentration maps identified distinct zones of nutrient sufficiency and deficiency, highlighting the heterogeneous nature of soil fertility within the study area. These findings underscore the need for site-specific nutrient management, particularly targeted nitrogen replenishment and location-specific fertilizer interventions, to improve nutrient use efficiency and support sustainable agricultural production in the area.

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