Soil Nutrient Status, Depth Variation and Spatial Distribution of Soil Nutrients and Productivity Index in Ebonyi State, Nigeria.

Agada Blessing Iveren[1*], Saweda Lenis Liverpool- Tasie[2], Seiglinde Snapp[3], Obi Martins Eze[4]

[1]Department of Soil Science, Joseph Sarwuan Tarka University Makurdi, Nigeria.

[2]Agriculture, Food and Resources Economics department, Michigan State University. USA.

[3]Soil, Microbial and Plant Sciences department, Michigan State University. USA

[4]Soil Science Department, University of Nigeria Nsukka.

[*]Corresponding author

DOI: https://doi.org/10.51584/IJRIAS.2026.11110026

Received: 01 November 2026; Accepted: 06 November 2026; Published: 23 November 2026

ABSTRACT

Soil fertility across humid tropical landscapes is spatially heterogeneous, yet productivity assessments are often based on limited sampling. This study characterized some soil properties and calculated a cumulative soil productivity index along the profile (CUM/PI) from 708 observations sampled at three depths (0–30, 30–60 and 60–90 cm) across 32 wards in 12 local government areas (LGAs) of Ebonyi State, Nigeria. Potassium (K) was zero in 60.6% of observations, nitrogen (N) in 42.0% and phosphorus (P) in 37.3%. Median N, P and K were 0.0002%, 1 mg kg^{-1} and 0 mg kg^{-1}, respectively. Median organic matter (OM) declined from 2.786% at 0–30 cm to 0.036% at 60–90 cm; exchangeable aluminium (Al) also declined with depth. Sulphate-sulphur (S) was strongly right-skewed and declined with depth. Mean CUM/PI was 0.0304 (median 0.0030) and differed among LGAs (Kruskal–Wallis $H = 73.05$, $p < 0.001$), from 0.1640 in Ohoazara to 0.0033 in Ishelu. CUM/PI did not differ significantly among depth layers ($H = 3.471$, $p = 0.176$). In the bivariate analyses, electrical conductivity (EC; Spearman $\rho = 0.671$) and pH ($\rho = -0.301$) had the strongest observation-level correlations with CUM/PI; the first three principal components explained 46.3% of measured-property variance. Because CUM/PI is derived from soil-property scores, associations with its component variables are partly definitional. A 1-SD increase in log-transformed organic matter was associated with lower odds of the empirical low-PI outcome (OR 0.385, 95% CI 0.259–0.571; Benjamini–Hochberg-adjusted p=0.000025). The findings describe sampled observations, not area-weighted state estimates, and the PI threshold used to classify low values has not been validated against crop yield.

Keywords: Soil fertility; soil productivity index; nutrient heterogeneity; potassium deficiency; Ebonyi State

INTRODUCTION

Crop productivity in humid tropical agricultural systems depends on an integrated set of soil conditions rather than on any single nutrient concentration (Karlen et al., 1997; Pierce et al., 1983; Sanchez, 2019). Nutrient supply interacts with soil reaction, salinity, organic matter, water relations, bulk density, texture and cation-exchange capacity (Bünemann et al., 2018; Fageria & Baligar, 2008; Kane et al., 2021; Pierce et al., 1983). A soil may contain measurable nutrient reserves yet remain a poor production environment when another factor limits nutrient availability or root development (Bado & Bationo, 2018; Fageria & Baligar, 2008; Kopittke et al., 2019). This integrated view is relevant to Southeastern Nigeria, where weathered soils and strongly contrasting parent materials create spatial variation in soil reaction and nutrient status.

Studies of Ebonyi State soils have documented fertility limitations across different locations and production settings (Okorie et al., 2020; Obasi et al., 2023). Okorie et al. (2020) examined physicochemical soil properties

and their relationships with maize and cassava production in Ebonyi. Obasi et al. (2023) assessed rice suitability in upland, lowland and irrigated pedons in northern Ebonyi. A separate assessment evaluated cassava suitability in Southeastern Nigeria using a non-parametric FAO framework (Onyechere et al., 2023; FAO, 1976). Experimental work in Ebonyi has also examined biological management of degraded Paleudults (Anikwe et al., 2026).

The present study extends soil characterization across all twelve LGAs using a larger, depth-stratified set of sampled observations. The objectives were to: (i) characterize nutrient status and related soil properties in the sampled soils; (ii) describe variation in the calculated PI among LGAs; (iii) compare PI across sampled depth layers; and (iv) compare selected soil-property distributions between observations below and above the exploratory PI threshold of 0.01. Objective (iv), is addressed as a group comparison.

MATERIALS AND METHODS

2.1 Study area

Ebonyi State lies in the Southeastern geopolitical zone of Nigeria, approximately between latitudes 5°40′–6°45′ N and longitudes 7°30′–8°30′ E (Obasi et al., 2023; Okorie et al., 2020). The area has a humid tropical climate with a bimodal rainfall pattern, a wet season from April to October and a dry season from November to March; reported annual rainfall is approximately 1,600–2,000 mm and mean annual temperature about 26–28 °C (Obasi et al., 2023; Okorie et al., 2020). Vegetation includes secondary rainforest and derived savanna, and rice, cassava and maize are among the principal food crops (Obasi et al., 2023; Okorie et al., 2020).

2.2 Sampling design and coverage

The study was conducted in purposively selected farmers' fields across 32 wards in 12 local government areas (LGAs) of Ebonyi State. Fields of at least one hectare were identified with assistance from divisional agricultural officers. Composite soil samples were collected with a soil auger at 0–30, 30–60 and 60–90 cm for routine soil analysis. The samples comprised 708 georeferenced observations from 289 unique coordinate pairs: 290 observations at 0–30 cm, 277 at 30–60 cm and 141 at 60–90 cm. The number of observations varied by LGA, from 25 in Ohaukwu to 102 in Ivo. Because sampling was not allocated in proportion to LGA land area, statewide summaries describe sampled observations and are not area-weighted estimates.

2.3 Laboratory analysis

Particle-size distribution was determined by the Bouyoucos hydrometer method (Trout et al., 1987). Bulk density was determined by the core method using a known soil volume (Fuller & Warrick, 1985). Soil pH, N, P, K, electrical conductivity (EC) and moisture content (MC) were measured in situ with a calibrated sensor (Agada and Iorchir 2024). Total carbon was analysed by wet digestion; organic matter (OM) was estimated by multiplying organic carbon by 1.724 (Nelson & Sommers, 1982). Cation-exchange capacity (CEC) was determined using neutral ammonium acetate (Sumner & Miller, 1996). Exchangeable Al^{3+} was extracted with 1 mol L^{-1} KCl and quantified colorimetrically (Abreu et al., 2003). Sulphate-sulphur (S) was extracted from air-dried, 2-mm-sieved soil with 0.01 M $Ca(H_2PO_4)_2$ in 2 M acetic acid (Fox et al., 1964). Absorbance was read at 420 nm within 3–8 min (Chesnin & Yien, 1951; Tabatabai, 1996); concentrations are reported in mg kg^{-1}. S was included to describe the measured nutrient profile; it was not specified as a PI factor in the model reported.

2.4 The soil productivity index modified (PIm)

Soil productivity was quantified using the modified productivity-index approach attributed to Pierce et al. (1983). It is modified from the original soil productivity index with the inclusion of the sufficiency for electrical conductivity (EC). The CUM/PI is described as the sum across the sampled horizons of a product of soil-property sufficiency scores and a horizon-specific root-weighting factor. The equation is shown below. PIm is treated in this study as the calculated, cumulative soil productivity index, not a direct measure of crop yield.

$$PIm = \sum A_i \times C_i \times D_i \times E_i \; x F_i \times L_i \times J_i \times Wf_i$$

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Where:

PIm = Productivity Index

A_i= Sufficiency for available water capacity for the ith soil layer

C_i= Sufficiency for pH for the ith soil layer.

D_i= Sufficiency for bulk density for the ith soil layer.

E_i = Sufficiency for electrical conductivity for the ith soil layer.

F_i= Sufficiency for clay content for the ith soil layer.

L_i= Sufficiency for land slope for the ith soil layer

.J_i= Sufficiency for organic matter content for the ith soil layer.

Wf_i= Root weighting factor (based on depth of root zone).

n = Number of horizons in the rooting zone (soil layer).

The soil parameters in the equation are expressed as a sufficiency index (Table 1). The indexes are multiplicative for each soil horizon (0-30cm, 30-60cm, 60-90cm), and summed, so that the soil productivity index (CUM/PI) varies from 0.0 to 1.0, with 1.0 having the greatest productivity (Nwite, 2016; Agada, 2019; Gani et al., 2020; Agada et al., 2026). The soil productivity index was determined by calculating soil sufficiency values of each soil property listed in the equation above. Other soil properties such as, sulphate sulphur, exchangeable aluminium, nitrogen, phosphorus and potassium were tested, but not included in the equation.

Table 1. Sufficiency values reproduced in the manuscript for selected soil properties used in the PIm calculation.

Available Water Capacity (AWC) (cm/cm)	**Sufficiency**	Bulk Density (BD) (g cm^{-3})	**Sufficiency**	Cation Exchange Capacity (CEC) (cmol(+) kg^{-1} clay)	**Sufficiency**
<0.03	0.0	< 1.30	1.0	< 10	0.0
0.05	0.2	1.29 -1.42	0.8	11 - 28	0.2
0.10	0.4	1.43 -1.56	0.6	29 - 46	0.4
0.15	0.6	1.57 -1.70	0.4	47 - 64	0.6
0.2	0.8	1.71 - 1.84	0.2	65 - 80	0.8
> 0.25	1.0			>80	1.0

Source: Pierce *et al*. (1983).

2.5 Statistical Analysis

Sampling was unbalanced because some lower-depth samples could not be collected owing to hardpan and security constraints. Given the right-skewed and zero-inflated distributions of CUM/PI and several nutrient variables, non-parametric tests were used for group comparisons. Analyses were performed in Python using pandas, NumPy, SciPy, Matplotlib and Seaborn. Descriptive statistics (mean, standard deviation, median, quartiles, minimum and maximum) were computed overall, by LGA and by depth. Kruskal–Wallis tests assessed differences among LGAs and depth groups; pairwise depth comparisons used Mann–Whitney U tests with Bonferroni-adjusted p-values. Spearman rank correlation assessed CUM/PI–soil-property associations at observation and LGA-mean levels. Observations with CUM/PI < 0.01 were classified as low-index observations and compared with the remaining observations using two-sided Mann–Whitney U tests and rank-biserial effect

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

sizes. No multivariable model of low-index status was fitted. Global Moran's I was calculated for coordinate-level averages using eight-nearest-neighbour weights and permutation testing. Exploratory ordinary least-squares models regressed $\log_{10}(PI + 0.0001)$ on $\log_{1+}$-transformed soil variables, with LGA and depth fixed effects; PCA and one-factor-at-a-time sensitivity analyses were also conducted. Statistical significance was set at $p < 0.05$, with Bonferroni correction for pairwise depth comparisons.

2.6 Soil digital map generation

Digital soil maps of selected soil properties studied and CUM/PI were reportedly generated in ArcGIS Pro (Agada et al., 2023; 2026; Esri, 2024; McBratney et al., 2003). Geo-statistical tools highlighted variations in nutrient contents. Satellite imagery and DEMs in ArcGISPro, modeled how terrain, drainage and vegetation affect soil properties and thematic maps were produced to illustrate the spatial distribution and variability of the measured soil properties and productivity indices across Ebonyi state (Figure 1). The digital soil map can be accessed using the link : https://rb.gy/yfnz2m . Metadata can also be downloaded following the detailed user guide.

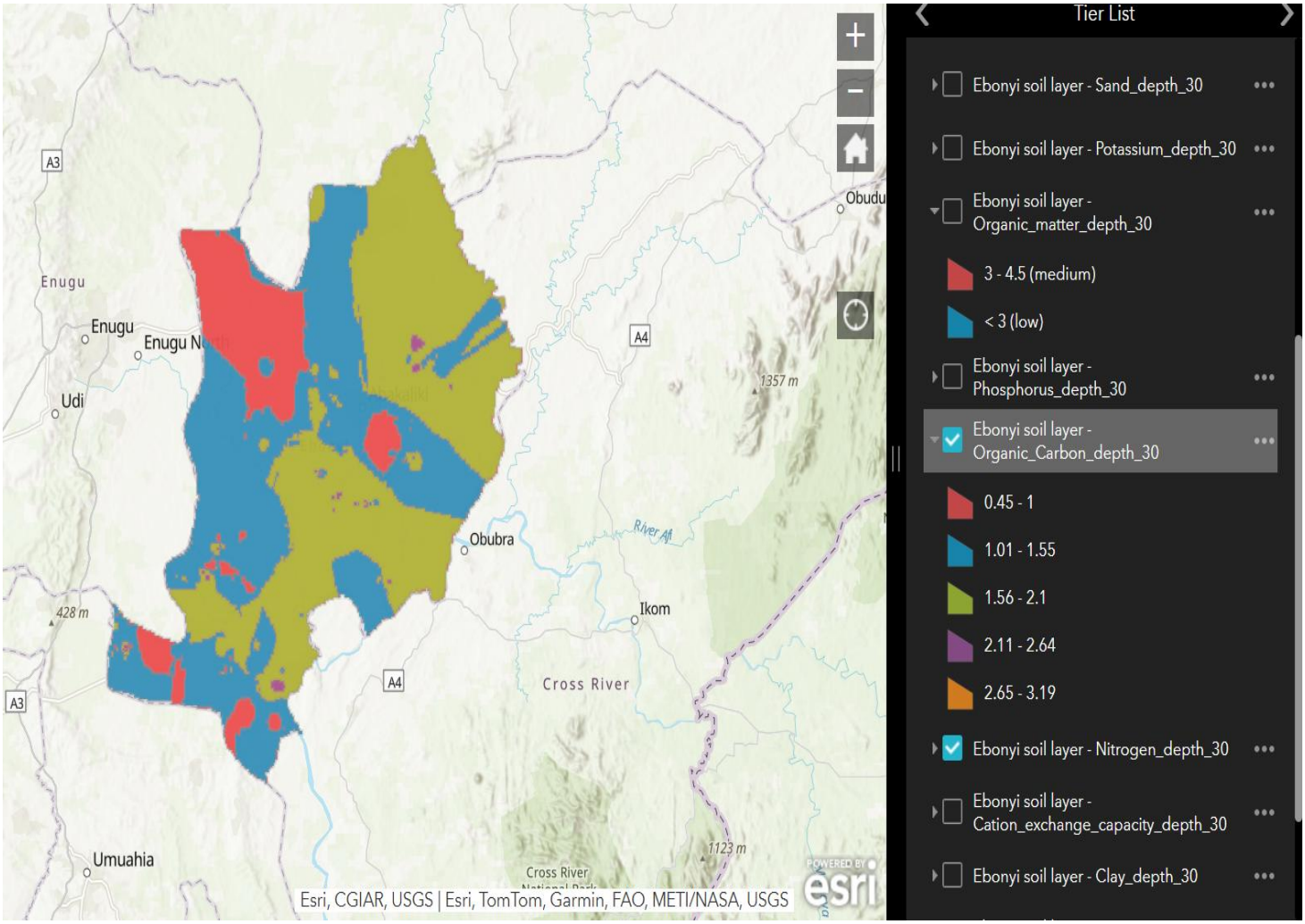

Figure 1: A sample extract of the soil digital map interface for Ebonyi state, Nigeria.

RESULTS

3.1 Nutrient status and distribution

The analysis comprised 708 soil observations from 32 wards in 12 LGAs of Ebonyi State. Samples were collected at three depth intervals (0–30 cm, n = 290; 30–60 cm, n = 277; 60–90 cm, n = 141) from 289 unique coordinate pairs. Sampling intensity varied among LGAs, from 25 observations in Ohaukwu to 102 in Ivo (Table 2). Statewide summaries therefore describe sampled observations rather than area-weighted estimates. N, P, K,

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Al and PI were strongly right-skewed (Table 2). Statewide medians were 0.0002% N, 1 mg kg^{-1} P, 0 mg kg^{-1} K and 0.1 cmol kg^{-1} Al. K was recorded as zero in 429 of 708 observations (60.6%); N was zero in 297 (42.0%), and P was zero in 263 of 705 valid observations (37.3%). OM had a mean of 1.544% and median of 1.187%; pH had a mean of 6.408 and median of 6.50; median EC was 0.019 dS m^{-1}.

Table 2. Descriptive summary of selected soil properties across Ebonyi State (n = 708).

Variable	n	Mean	Median	Q1–Q3	Range
Nitrogen (N, %)	708	0.0386	0.0002	0–0.020	0–3.00
Phosphorus (P, mg kg^{-1})	705	7.20	1.00	0–6.00	0–181
Potassium (K, mg kg^{-1})	708	9.89	0	0–3.00	0–423
Organic matter (%)	707	1.544	1.187	0.628–2.700	0–5.556
Soil pH	708	6.408	6.50	5.70–7.40	2.99–8.90
EC (dS m^{-1})	708	0.0968	0.019	0.004–0.075	0–2.37
Sulphate-sulphur (S, mg kg^{-1})	708	1.155	0.62	0.0075 - 1.49	0 -11.4
Al (cmol kg^{-1})	708	1.040	0.100	0–1.143	0–9.44
CUM/PI	708	0.0304	0.0030	0.0007–0.0170	0–1.00

3.2 Variation across LGAs and wards

CUM/PI varied among LGAs. Ohoazara had the highest mean and median (0.1640 and 0.07425), whereas Ishelu had the lowest (0.00334 and 0.00110). In Ohaukwu, the mean (0.0887) substantially exceeded the median (0.00070), showing that a few high observations influenced the mean. At ward level, the highest mean CUM/PI occurred in Ohoazara–Umchima (n = 25; mean 0.2898; median 0.0850), followed by Ezza North–Okposi (n = 10; mean 0.1346; median 0.0139) and Onicha–Isi (n = 16; mean 0.1091; median 0.1070). The smallest ward medians included Onicha–Enuagu (n = 22; 0.00055), Ezza North–Okaleru (n = 11; 0.00070) and Ikwo–Ekpomaka (n = 23; 0.00080). An omnibus test detected distributional differences in CUM/PI across the 32 LGA–ward units (H = 190.89; FDR-adjusted $p = 2.53 \times 10^{-24}$). N, P, K, pH, EC, moisture, CEC, Al, S and texture fractions also varied across ward units. Organic carbon (adjusted p = 0.060), OM (0.066) and bulk density (0.114) did not meet the FDR-adjusted 0.05 threshold.

At the observation level, Spearman correlation with CUM/PI was strongest for EC (rho=0.671, $p < 0.001$). Associations were weaker for P (rho=0.285), N (0.200), K (0.189), Al (0.126) and sulphate-sulphur (0.112). Soil pH was negatively associated (rho=−0.301). Organic matter (rho=0.069, p=0.066) and organic carbon (rho=0.069, p=0.066) were not statistically significant unadjusted correlates. Correlation does not demonstrate that N, P, K or Al modifies or causes a change in soil productivity index.

The secondary OLS model used 704 complete observations and explained 35.8% of transformed CUM/PI variation (adjusted R^2=0.340). After including LGA and depth indicators, log1p EC (coefficient 2.481, p<0.001), log1p organic matter (0.402, p<0.001) and log1p P (0.106, p<0.001) were positively associated with transformed CUM/PI; log1p pH was negatively associated (−0.763, p<0.001). N (p=0.946) and K (p=0.178) were not statistically significant conditional predictors. These coefficients should not be read as nutrient effects because the index is derived, the observations are clustered by coordinate and the model does not include a site-level random effect.

3.3 PCA of soil properties

The primary PCA included 704 complete cases and 15 measured properties, with CUM/PI excluded to prevent the response/index from mechanically influencing the component structure. PC1 explained 21.6% of variance, PC2 13.6% and PC3 11.1% (Figure 2). The first three together accounted for 46.3%. PC1 had the largest positive loadings for organic matter (0.469), organic carbon (0.468) and sulphate-sulphur (0.334), and a negative loading for bulk density (−0.394). PC2 was characterized by Al (0.402) and clay (0.368) loading opposite to pH (−0.487)

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

and sand (−0.431). PC3 had the largest absolute loadings for P (−0.586) and K (−0.587), indicating a joint nutrient axis. These component patterns summarize covariance, not causal mechanisms or fertility classes.

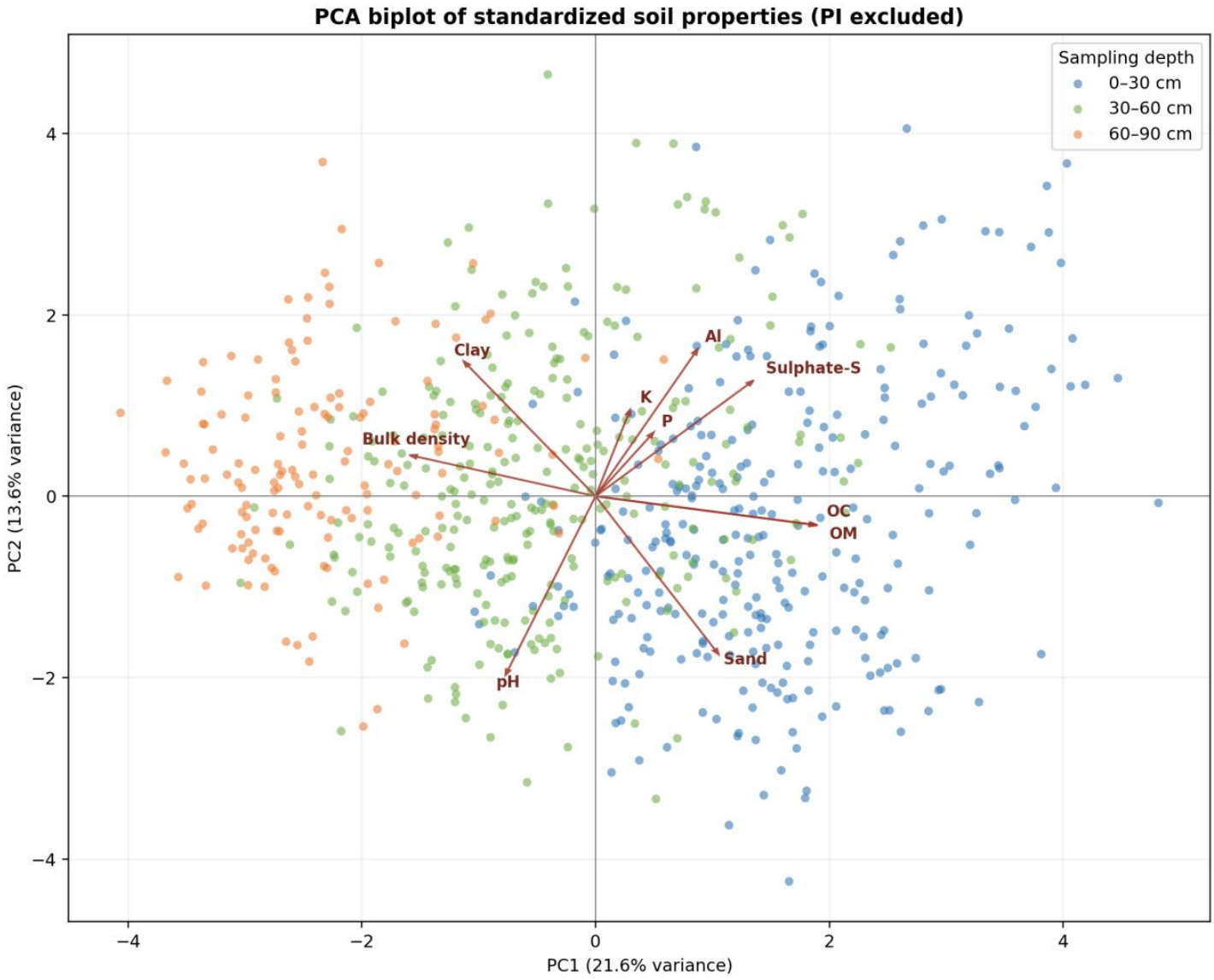

Figure 2: PCA biplot of standardized soil-property scores and selected loadings; PI was excluded from the PCA.

The raw-versus-transformed PCA sensitivity check retained a similar broad structure: PC1 explained 21.6% after transformation versus 20.5% in raw standardized variables; the first three explained 46.3% versus 46.4%. Absolute Spearman score concordance was 0.988 for PC1, 0.978 for PC2 (the sign reversed, which is arbitrary in PCA) and 0.845 for PC3. Thus, the broad first-two-axis structure was stable to the transformation, while the third axis was less stable.

3.4 Sensitivity analysis of the cumulative soil productivity index (CUM/PI)

The one-factor-at-a-time sensitivity analysis used the recorded layer-level Product/Depth calculation, treated here as the same cumulative PI output defined in Section 2.4. Its observed mean was 0.00941. Setting EC sufficiency to 1 while holding other factors fixed increased the counterfactual mean to 0.2029; setting clay and OM sufficiency to 1 increased it to 0.04875 and 0.01606, respectively (Figure 3). EC was the smallest factor in 71.9% of records after scores were clipped to 0–1 for this diagnostic; clay was smallest in 14.7% and OM in 13.0%. Land-slope sufficiency equaled 1 for every record. These scenarios are mathematical diagnostics, not estimated intervention effects. The proportion below the empirical cutoff CUM/PI < 0.01 was 66.9%.

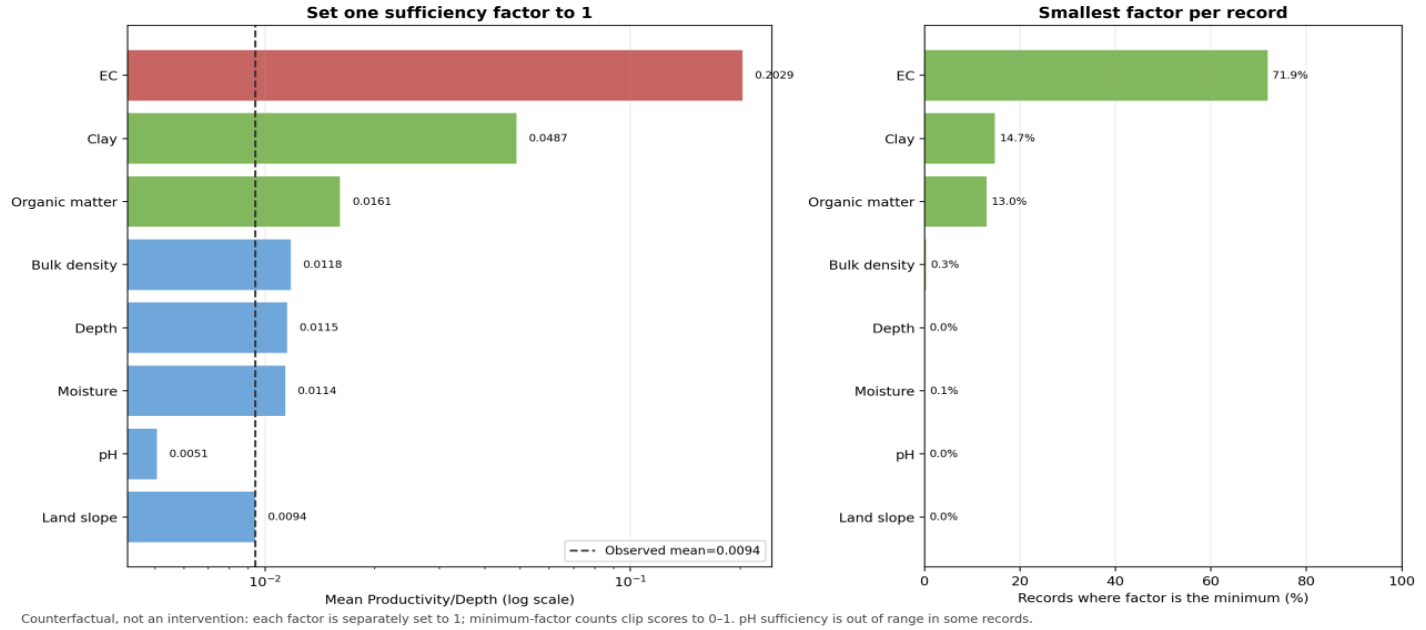

Figure 3: One-factor-at-a-time sensitivity of the recorded cumulative PI calculation. Left: counterfactual mean when one listed sufficiency score is set to 1 and all others are held constant; dashed line shows the observed mean. Right: percentage of records in which each factor was the minimum after scores were clipped to 0–1. The scenarios are diagnostic, not intervention effects.

3.5 Depth changes and complete profiles

Layer-only summaries included unequal numbers of observations (290, 277 and 141; Table 3) because hardpan and security constraints limited sampling at some depths. Median N declined from 0.00055% at 0–30 cm to 0.00010% at 30–60 cm and zero at 60–90 cm. Median OM decreased from 2.786% to 0.980% and 0.036%. Median Al declined from 0.355 to 0.150 and 0 cmol kg^{-1} (Figure 4). The layer-level mean PI values (0.0265, 0.0276 and 0.0439) did not show the same pattern in matched profiles and should not be interpreted as a depth-related productivity increase. Among 139 complete profiles, mean PI was 0.04435, 0.04438 and 0.04436 at the three depths; the median was 0.0046 at each depth. The repeated-measures Friedman test was not significant ($H = 0.67$, $p = 0.717$; Figure 5).

Table 3. Depth-specific medians in all records and matched complete profiles.

Depth	All-record n	Complete-profile n	N median (%)	P median (mg kg^{-1})	K median (mg kg^{-1})	Organic matter median (%)	Al median (cmol kg^{-1})	PI median
0–30 cm	290	139	0.00055	2	0	2.786	0.355	0.0030 all records; 0.0046 complete profiles
30–60 cm	277	139	0.00010	1	0	0.980	0.150	0.0030 all records; 0.0046 complete profiles
60–90 cm	141	139	0	1	0	0.036	0	0.0046 all records and complete profiles

Within complete profiles, paired comparisons showed declines in N and OM from the surface toward 60–90 cm (FDR-adjusted $p < 0.001$ for each depth pair). Al also declined across the profile (adjusted $p < 0.001$ for all three pairwise comparisons). P was lower at 60–90 cm than at either upper depth (adjusted $p < 0.001$), whereas the 0–30 versus 30–60 cm contrast was not statistically significant ($p = 0.233$). K medians were zero at every depth; the 30–60 versus 60–90 cm signed-rank test differed despite identical medians, reflecting a distributional rather than median change. PI did not differ pairwise across complete-profile depths after FDR adjustment (all $p \geq$

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

0.593). These results contrast the depth-related declines in OM, N and Al with the nearly unchanged recorded PI.

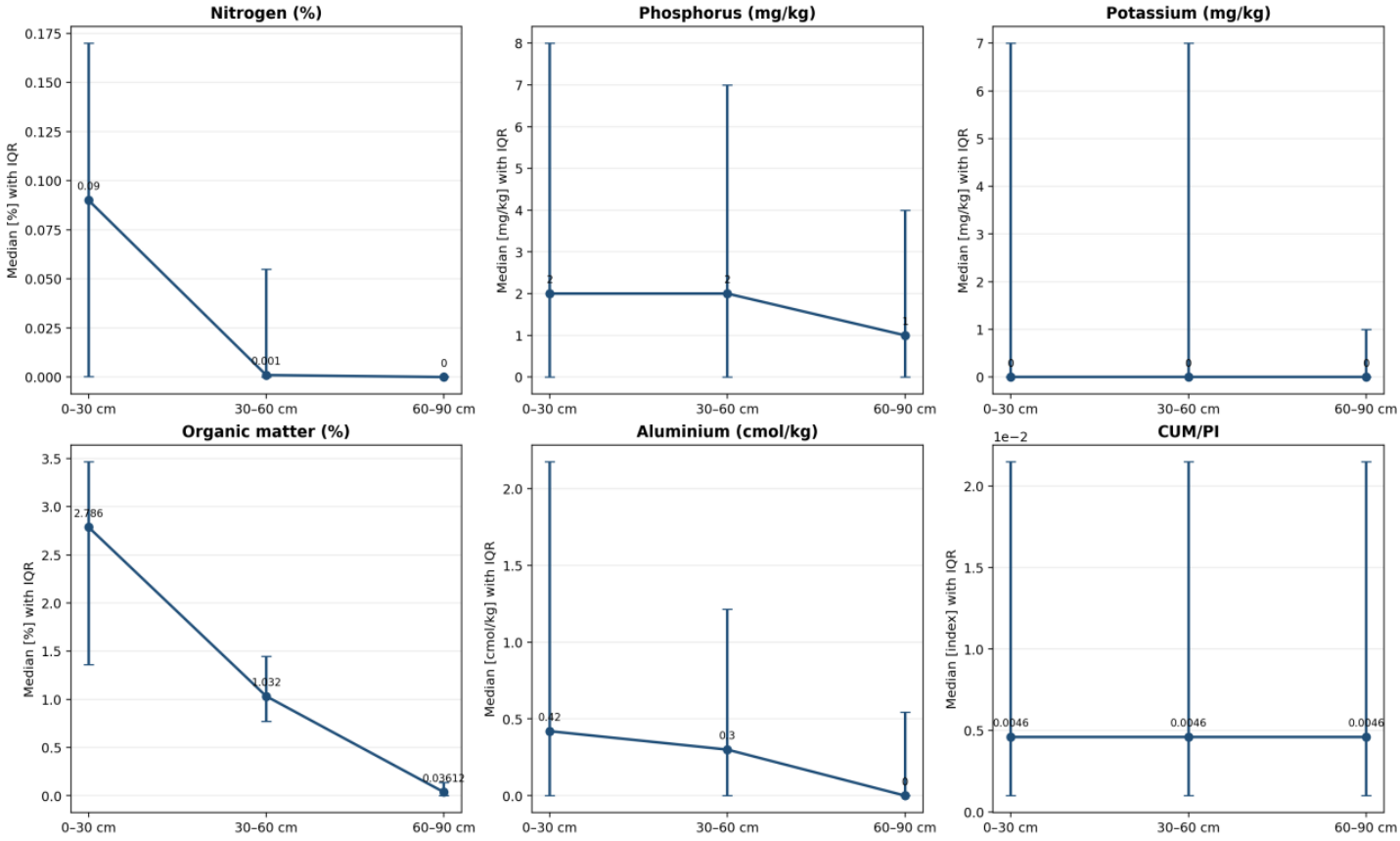

Figure 4: Median N, P, K, OM, Al and cumulative PI by depth among the 139 complete profiles; vertical bars show the interquartile range. The same coordinate locations contribute observations at each depth.

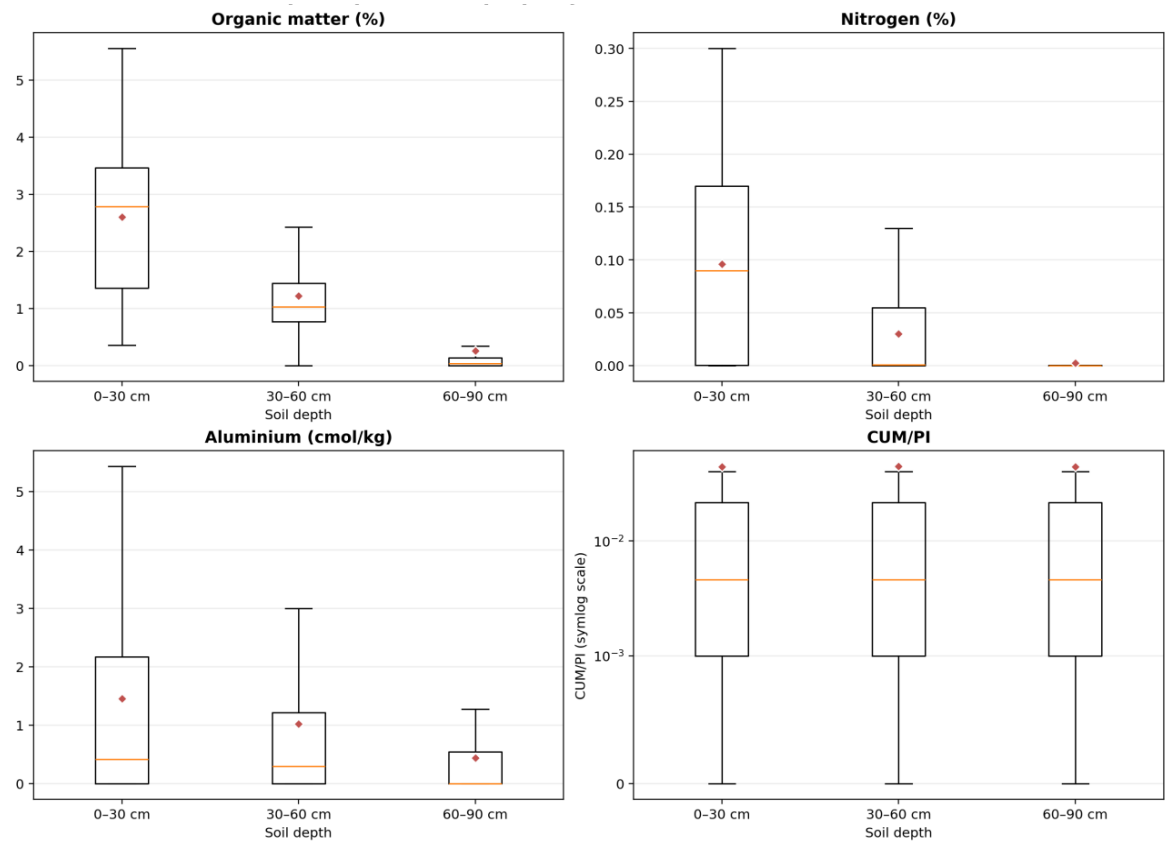

Figure 5: Distributions of OM, N, Al and cumulative PI by depth among 139 complete profiles. Boxes show interquartile ranges, centre lines show medians, whiskers show the plotted ranges, and diamonds show means; the PI panel uses a symlog scale to display zero values.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

3.6 Spatial variability of PI among LGAs

PI distributions differed among the 12 LGAs (Kruskal–Wallis $H = 73.05$, $p < 0.001$; Figure 6). Ohoazara had the highest mean (0.1640) and median (0.07425), whereas Ishelu had the lowest mean (0.0033) and median (0.00110). In Ohaukwu, the mean (0.0887) was much higher than the median (0.00070), illustrating the effect of a small number of high observations. LGA-level heterogeneity was also detected for N ($H = 81.51$, $p < 0.001$), P ($H = 87.13$, $p < 0.001$), K ($H = 301.82$, $p < 0.001$) and pH ($H = 221.63$, $p < 0.001$), but not OM ($H = 17.01$, $p = 0.107$). Ohoazara and Onicha had the highest mean P (18.42 and 18.13 mg kg^{-1}) and K (38.94 and 39.48 mg kg^{-1}); Afikpo North had the highest mean N (0.0855%), and Izzi had the highest mean OM (1.868%). Ishelu had comparatively low mean OM (1.093%). Because the LGA sample sizes ranged from 25 in Ohaukwu to 102 in Ivo, these are comparisons of sampled observations, not area-weighted estimates.

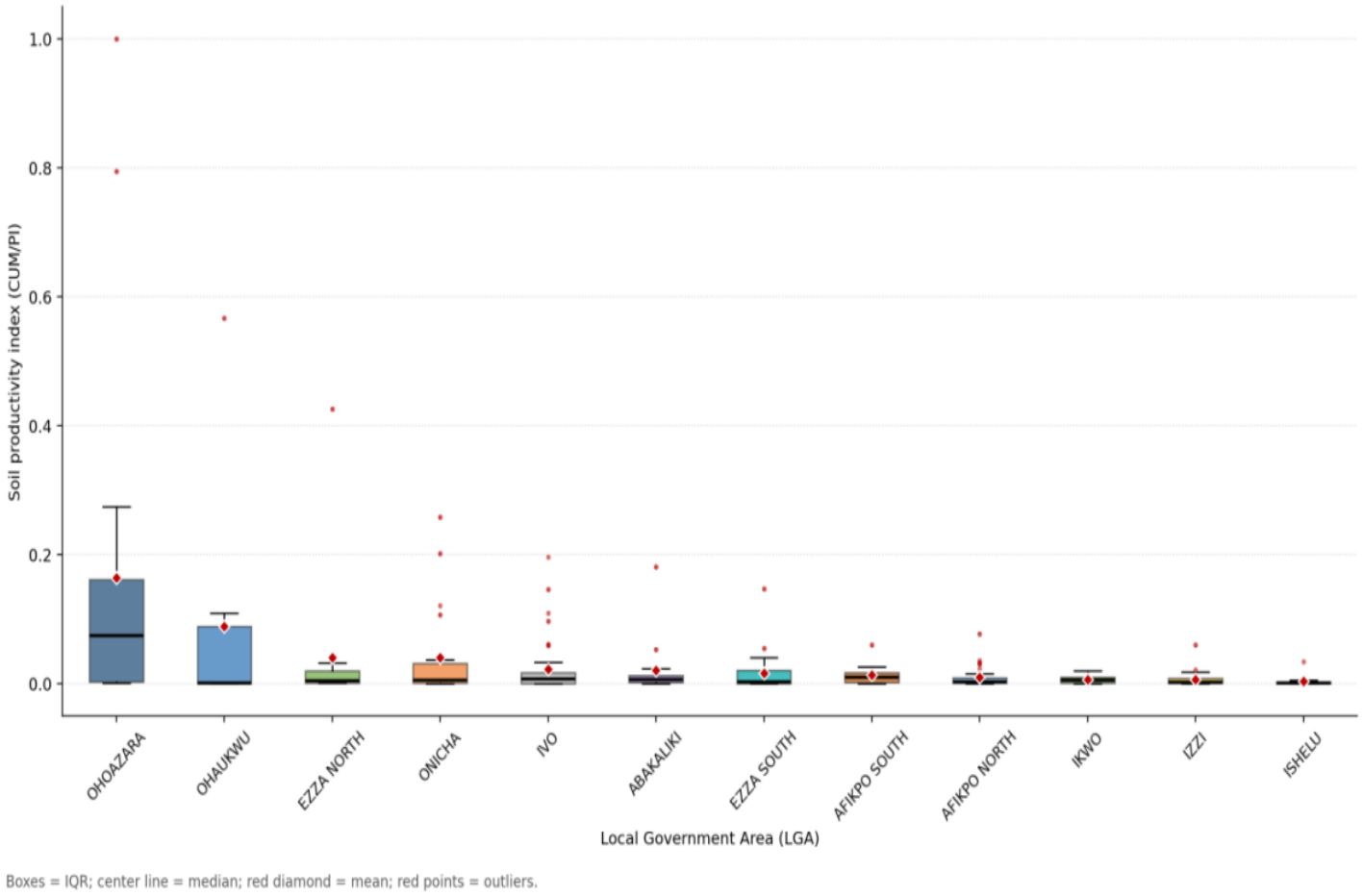

Figure 6: Observation-level CUM/PI distributions by LGA, ordered by descending mean. Boxes show the interquartile range, centre lines the medians, red diamonds the means and red points the plotted outliers. LGA labels follow the spelling in the underlying analysis output.

3.7 Correlates of CUM/PI

At the observation level, EC had the strongest correlation with PI (Spearman $\rho = 0.671$, $p < 0.001$). P ($\rho = 0.285$), N ($\rho = 0.200$) and K ($\rho = 0.189$) had weaker positive correlations; pH was negatively correlated ($\rho = -0.301$; all $p < 0.001$). OM and organic carbon were not statistically significant unadjusted correlates ($\rho = 0.069$, $p = 0.066$ for both), and bulk density showed no association ($\rho = -0.018$, $p = 0.632$). At the LGA-mean level ($n = 12$), EC remained the strongest correlation ($\rho = 0.601$, $p = 0.039$); mean P ($\rho = 0.566$, $p = 0.055$) and pH ($\rho = -0.524$, $p = 0.080$) had similar magnitudes but did not meet the 0.05 threshold. Mean N, K, organic carbon and OM were not statistically significant correlates of mean CUM/PI. Figure 7, shows the descriptive correlations among LGA means; it does not represent the observation-level correlations.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

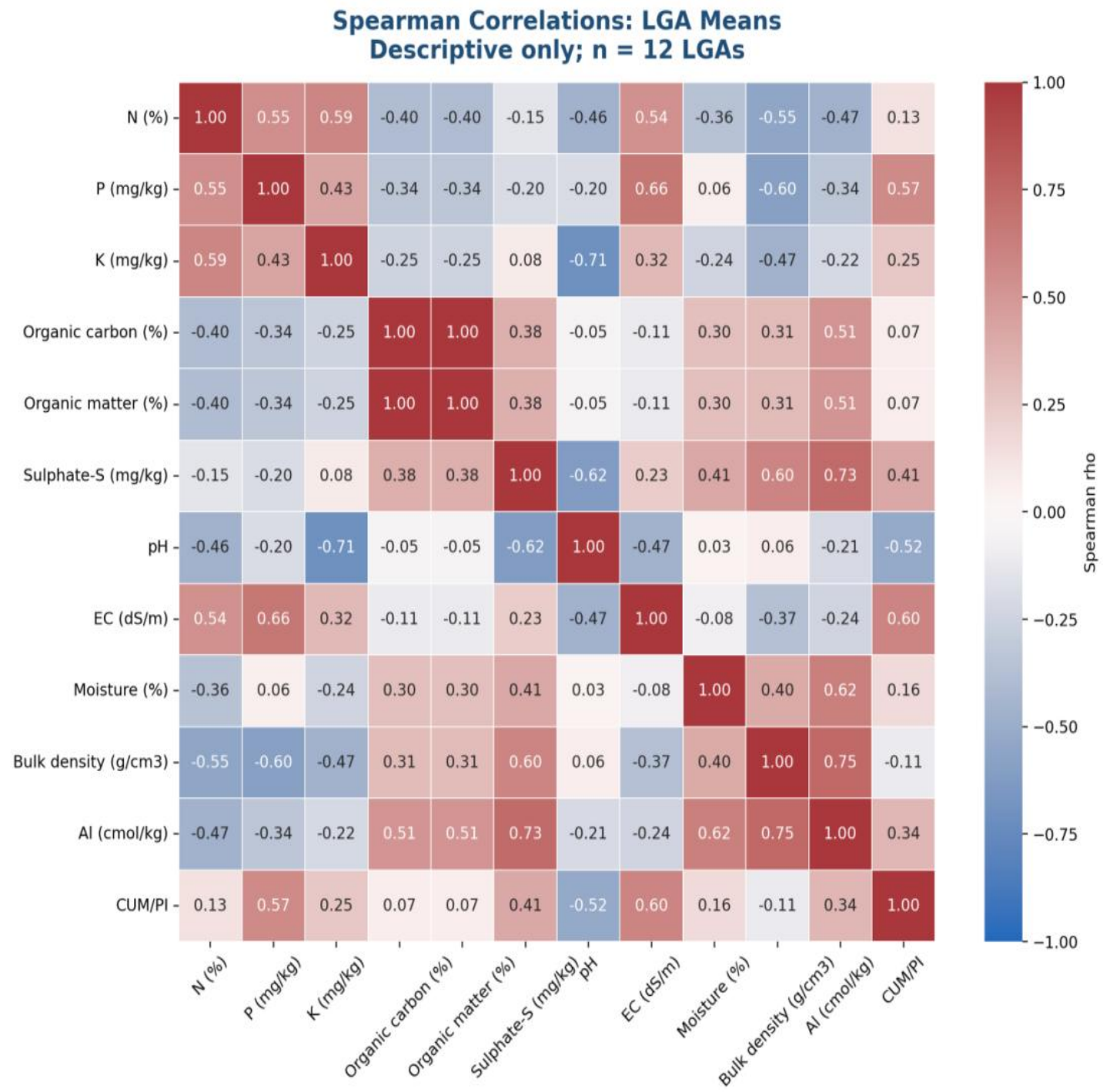

Figure 7: Spearman correlation coefficients among soil-property means and CUM/PI means for the 12 LGAs. The matrix is descriptive (n = 12 LGAs); values should not be interpreted as observation-level correlations or as causal effects.

3.8 Empirical delineation of low-index observations

Using the exploratory threshold CUM/PI < 0.01, 474 of 708 observations (66.9%) were classified as low-index observations. The proportion was highest in Ishelu (95.7%), followed by Ikwo (82.7%), Izzi (79.3%) and Afikpo North (79.1%), and lowest in Ohoazara (38.5%), Afikpo South (52.8%) and Onicha (55.7%). Compared with the remaining observations, the low-index group had a lower median EC (0.010 vs 0.0975 dS m^{-1}), higher median pH (7.0 vs 5.9), lower median P (1 vs 3 mg kg^{-1}), N (0.0001% vs 0.0008%), OM (1.1008% vs 1.3072%) and moisture (19.9% vs 24.0%); median K was zero in both groups. These are unadjusted group comparisons, not a systematic ranking of independent predictors. The CUM/PI< 0.01 cutoff has not been validated against crop-specific yield classes.

3.9 Spatial autocorrelation

Of the 289 sampled coordinate pairs, 286 met the plausibility criteria for spatial analysis. Repeated depth observations at each coordinate were averaged before analysis. CUM/PI showed positive spatial autocorrelation (Moran's I = 0.164, permutation p = 0.001), indicating that nearby sampled locations had more similar CUM/PI values than expected under random spatial assignment. pH showed the strongest autocorrelation (I = 0.416, p = 0.001), followed by K (I = 0.257), P (I = 0.200), EC (I = 0.156) and OM (I = 0.124; all p = 0.001); N showed weak, non-significant spatial structure (I = 0.028, p = 0.089). S also showed positive autocorrelation (eight-nearest-neighbour Moran's I = 0.206; 999 permutations; p = 0.001). These statistics describe clustering among sampled locations and do not provide continuous statewide predictions.

3.10 Exploratory multivariable model of CUM/PI

An exploratory ordinary-least-squares model of $\log_{10}(PI + 0.0001)$, including $\log_{1+}$-transformed N, P, K, OM, EC and pH with LGA and depth fixed effects, explained $R^2 = 0.357$ (adjusted $R^2 = 0.339$) of transformed CUM/PI variation across 705 complete observations (Table 4). After adjustment for LGA and depth, $\log_{1+}$ EC (coefficient = 2.480, $p < 0.001$), $\log_{1+}$ OM (0.400, $p < 0.001$) and $\log_{1+}$ P (0.107, $p < 0.001$) were positively associated with transformed CUM/PI; $\log_{1+}$ pH was negatively associated (−0.763, $p < 0.001$). N (−0.026, p = 0.944) and K (−0.043, p = 0.174) were not statistically significant conditional predictors. The index is derived from soil properties, so these coefficients are not independent agronomic effects.

Table 4. Selected coefficients from the exploratory model of $\log_{10}(PI + 0.0001)$; LGA and depth fixed effects were included but are not tabulated.

Predictor (log1p-transformed)	Coefficient	p
Electrical conductivity	2.480	<0.001
Organic matter	0.400	<0.001
Phosphorus	0.107	<0.001
pH	−0.763	<0.001
Nitrogen	−0.026	0.944
Potassium	−0.043	0.174

Model: $R^2 = 0.357$, adjusted $R^2 = 0.339$, n = 705; LGA and depth were included as fixed effects.

3.11 Distribution of sulphate-sulphur across locations and depth

The statewide mean S exceeded the median, reflecting a long upper tail (maximum 11.4 mg kg^{-1}; Figure 8). A Kruskal–Wallis comparison across layers was significant ($H = 113.90$, $p < 0.001$; $\varepsilon^2 = 0.159$), although it treated repeated-depth observations as independent. A paired analysis of 140 coordinate-matched sites with valid S at all three depths (duplicate records averaged within coordinate and depth) also showed lower S with depth: median paired changes were −0.66 mg kg^{-1} from 0–30 to 30–60 cm (95% bootstrap CI −0.97 to −0.46), −1.10 mg kg^{-1} from 0–30 to 60–90 cm (−1.345 to −0.89), and −0.42 mg kg^{-1} from 30–60 to 60–90 cm (−0.58 to −0.275); all paired Wilcoxon p-values were < 0.001. Median S varied among LGAs, from 1.00 mg kg^{-1} in Ohoazara, 0.94 in Ohaukwu and 0.865 in Izzi to 0.26 in Onicha, 0.31 in Ikwo and 0.405 in Ishelu. The LGA omnibus test was significant but the effect size was small ($H = 29.84$, $p = 0.0017$; $\varepsilon^2 = 0.027$). At coordinate-by-depth means, S was positively correlated with Al and negatively correlated with pH at all three depths (Al ρ = 0.538, 0.354 and 0.263; pH $\rho = -0.561$, −0.435 and −0.388; FDR-adjusted $p < 0.01$). In 0–30 cm samples, median S was 2.43 mg kg^{-1} in the acid/Al-associated zone (58 records), 1.115 mg kg^{-1} in the low-P/K, low-index zone (182 records) and 1.025 mg kg^{-1} in the relatively higher-P/K zone (50 records); the across-zone test was significant ($H = 40.23$, $p < 0.001$; $\varepsilon^2 = 0.133$). S was measured as a descriptive soil property and was not included as a PI sufficiency factor; its observed distribution therefore does not indicate that S should or should not be added to the index. A greenhouse study from southeastern Nigeria found significant crop responses to S fertilization at 20 of 45 locations, but its incubation-based extraction and crop-response design do not provide a directly comparable concentration threshold for the present extraction method (Enwezor, 1976). Accordingly, the present S values are not classified as deficient or sufficient using an unvalidated regional cutoff.

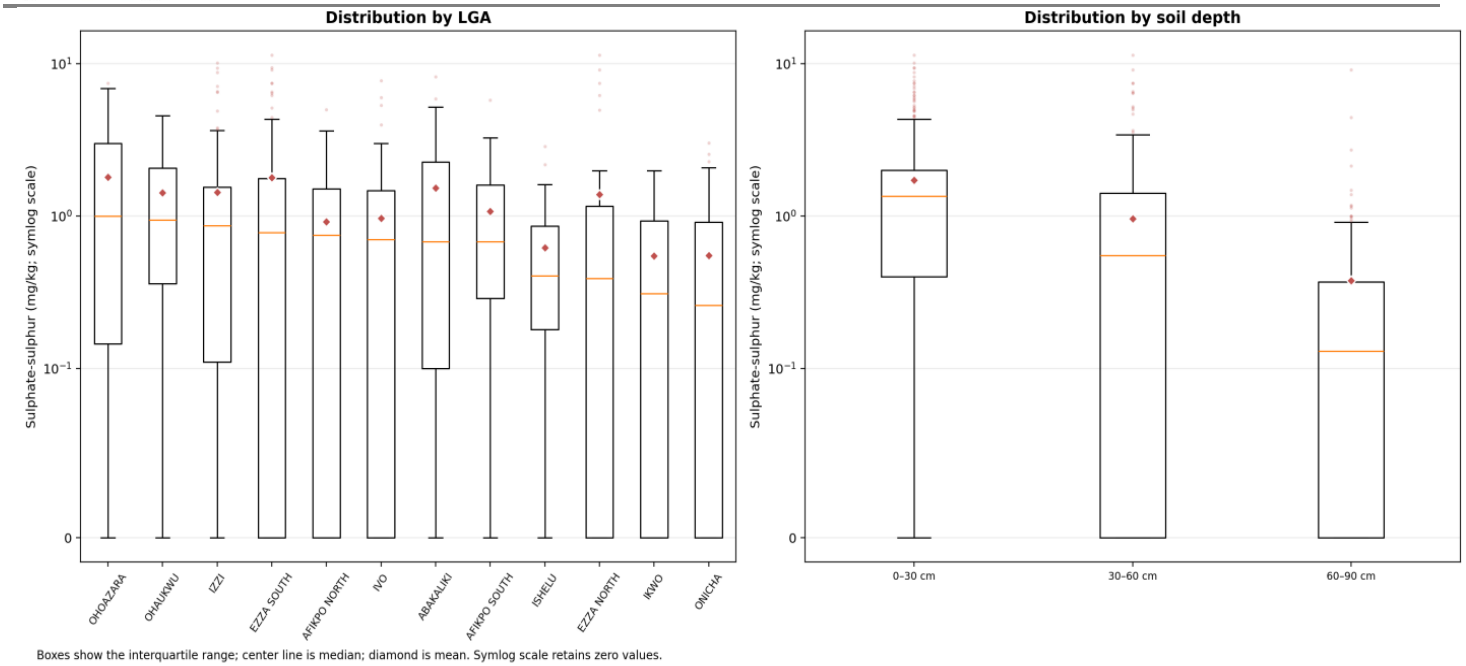

Figure 8: Sulphate-sulphur concentrations by LGA and sampled depth. Boxes show the interquartile range, centre lines the medians and diamonds the means; the symlog scale accommodates recorded zero values. Concentrations are in mg kg^{-1}.

3.12. Logistic regression and validation of low recorded CUM/PI

A logistic model was fitted to the data, using the empirical outcome CUM/PI< 0.01. This is an analytical cutoff, not a validated crop-productivity class. 701 observations from 286 coordinate groups across 12 LGAs, of which 474 (67.6%) were below the cutoff. The model used 12 measured soil predictors (N, P, K, organic matter, EC, pH, Al, sulphate-S, moisture, bulk density, clay and CEC), with LGA and depth included as adjustment variables. Repeated five-fold stratified group cross-validation was carried out, assigning every record at a coordinate to the same fold so repeated depths from one location could not appear in both training and test data. A model using LGA and depth alone was evaluated on the same folds as a comparator. The full model showed good internal discrimination: pooled out-of-coordinate ROC-AUC was 0.831 (coordinate-cluster bootstrap 95% CI 0.790–0.870); precision–recall AUC was 0.886 (0.835–0.931) (Figure 9). The Brier score was 0.149 (0.128–0.172). The LGA-and-depth-only comparator had ROC-AUC 0.565 and Brier score 0.217. The full model's ROC-AUC improvement was 0.266 (cluster-bootstrap 95% CI 0.206–0.324), and its Brier score improved by 0.068 (0.049–0.086). At a probability threshold of 0.5, sensitivity was 0.916 and specificity 0.533 (balanced accuracy 0.724). Thus, this threshold identifies most observations below the empirical cutoff, and calibration was not perfect (calibration slope 0.717; intercept 0.203), so probabilities should not be presented as well-calibrated individual risk estimates without recalibration and threshold selection for a defined use.

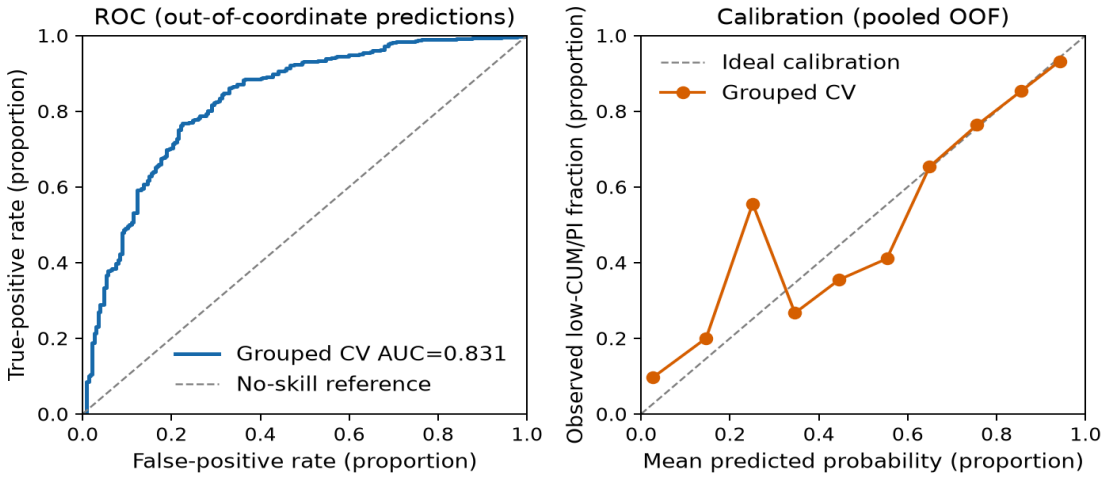

Figure 9: Empirical low-PI classification: Coordinate-grouped validation

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

A coordinate-clustered logistic model fitted to 697 complete predictor records and adjusted for LGA and depth, a 1-SD increase in log-transformed organic matter was associated with lower odds of the empirical low-CUM/PI outcome (OR 0.385, 95% CI 0.259–0.571; Benjamini–Hochberg-adjusted p=0.000025). Moisture also remained associated after correction (OR 0.599, 95% CI 0.433–0.829; adjusted p=0.0118). EC had a nominal association (OR 0.145, 95% CI 0.032–0.665; unadjusted p=0.013), but did not meet the 0.05 threshold after correction across 12 predictors (adjusted p=0.052). The pH association was also not significant after correction; N, P, K, Al, sulphate-S, bulk density, CEC and clay were not statistically clear conditional associations in this model.

3.13. Soil constraints across Ebonyi LGAs

A summary of the 0–30 cm topsoil in 288 unique coordinates across 12 LGAs. The clearest statewide signal in the sampled fields is frequent recorded zero potassium, with phosphorus and nitrogen also often zero. Acidity and elevated aluminium are concentrated in a smaller set of LGAs. These are candidate constraints, not confirmed crop deficiencies or crop-specific critical values, and sampling was purposive rather than area-weighted (Figure 10).

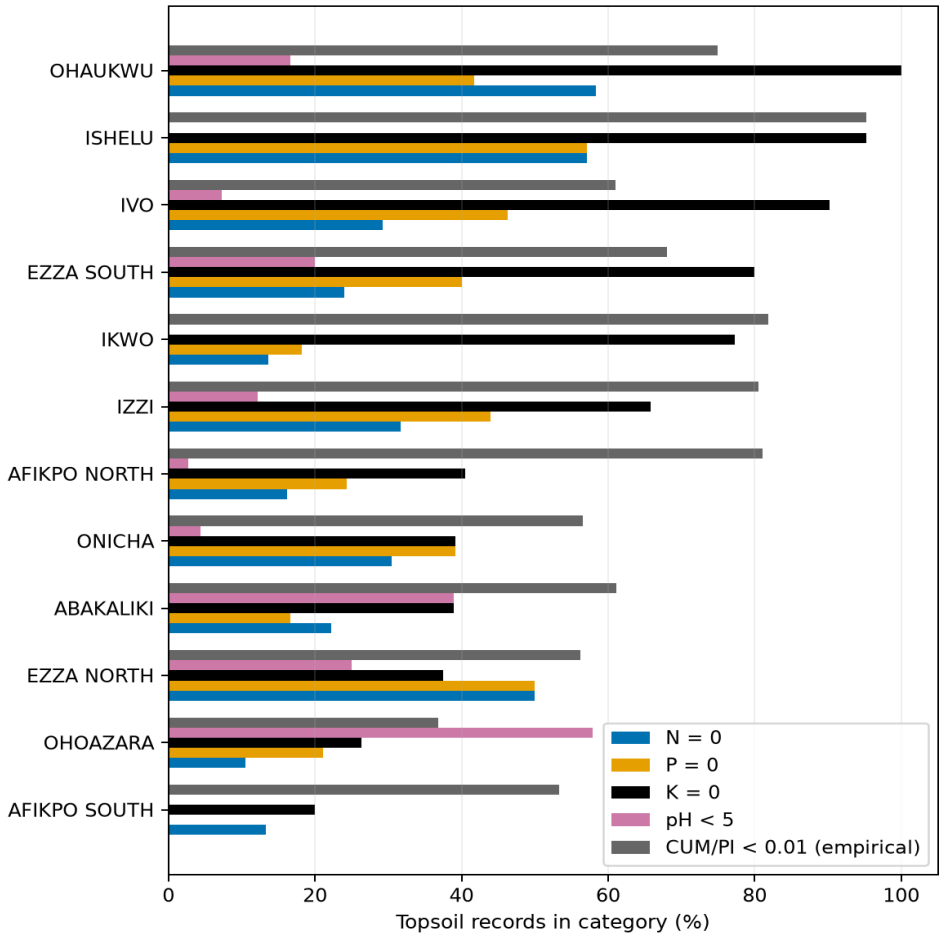

Figure 10: Topsoil constraint indicators by LGA for Ebonyi state

DISCUSSION

4.1 Nutrient status: a state-wide pattern of potassium and nitrogen limitation

The frequent zero and near-zero recorded values for K and N across the sampled Ebonyi soils extend findings from more geographically limited assessments. Obasi et al. (2023) reported fertility constraints across rice land-use settings in northern Ebonyi, and Okorie et al. (2020) described relationships between soil properties and maize and cassava production in Ebonyi. In this study, K was recorded as zero in 60.6% of observations and had a statewide median of zero. This pattern is consistent with evidence that K can constrain production on weathered tropical soils under continued cultivation without nutrient replenishment (Taiwo et al., 2010).

4.2 Depth patterns

The declines in organic carbon, OM and N with depth are consistent with the general concentration of organic inputs near the soil surface. In the matched profiles, CUM/PI did not differ significantly by depth despite declines in OM, N and Al. Because the index combines several soil-property scores, its depth pattern need not track any single property.This corroborates the findings of Nwite (2013) that individual soil properties influenced soil productivity index. The depth comparisons should be interpreted in light of the unequal numbers of records by layer and the repeated-measures structure of observations from the same coordinates.

4.3 Spatial heterogeneity and clustering

Significant LGA-level heterogeneity in PI, N, P, K and pH, together with positive Moran's I for PI and several soil properties, indicates that the sampled conditions were spatially structured. These data support describing local differences in the sampled observations, consistent with the moderate-to-strong spatial dependence reported for pH, phosphorus, and effective cation exchange capacity across Southeastern Nigerian soils using semivariogram-based geostatistics (Onyechere et al., 2023). The present analysis complements that geostatistical evidence with a different spatial statistic (global Moran's I with a nearest-neighbour weight matrix) at finer within-state resolution, and reaches a broadly similar conclusion: soil fertility and the derived productivity index are not randomly distributed across the Ebonyi landscape but form spatial clusters, most evidently around the contrast between the comparatively high productivity index of Ohoazara and the low index of Ishelu, Izzi, and Ikwo. This pattern supports LGA- or locality-targeted fertility interventions over uniform state-wide recommendations.

4.4 Electrical conductivity and pH as correlates, and the risk of mechanical association

EC and pH had the strongest correlations with PI in the reported bivariate analyses, and their coefficients remained statistically significant in the exploratory multivariable model. However, EC, pH and OM are among the soil-property inputs named in the PI method, so their associations with the derived index are partly mechanical and should not be interpreted as independent causal effects. The low-index group had a higher median pH (7.0) than the remaining group (5.9), while the observation-level correlation between pH and PI was negative. These results show that the direction of the association depends on the comparison and may reflect the index scoring, LGA composition or other unmeasured site differences. They do not support a simple statewide liming recommendation rather highlight the influence of site-specific soil conditions on productivity (Nwite et al., 2022).

4.5 Major fertility constraints and implications for management zones

In 0–30 cm topsoil, the reported patterns included low recorded K and P, spatially restricted acidic/Al-associated observations, and strong declines in OM with depth. K had a median of 0 mg kg^{-1}; P had a median of 2 mg kg^{-1}, and the median exchangeable Al was 0.355 cmol kg^{-1}. OM had a surface median of 2.786% and declined to 0.036% at 60–90 cm. S also declined with depth and varied spatially, but it was not included in the PI calculation and should be interpreted descriptively. Low CUM/PI values (< 0.01) characterized 69.0% of topsoil samples, a threshold that has not been validated against crop-specific yield classes. These patterns justify further site-specific field validation.

LIMITATIONS

1. LGA sample sizes were unequal and not allocated in proportion to land area, so LGA comparisons describe the sampled observations rather than area-weighted parameters.
2. PI is a derived multiplicative index built from pH, and CEC, Available water content, Bulk density and organic matter, EC; the correlations reported between PI and these same variables can be partly mechanical rather than independent agronomic relationships.
3. The empirical low-productivity threshold (PI < 0.01) is an analytical convenience specific to this dataset and has not been validated against crop-specific critical limits.

4. The present analysis was limited to the properties needed for the productivity-index equation and did not include crop yield, exchangeable bases, or soil mineralogy; PI should therefore be read as a soil-factor scoring system rather than a direct estimate of crop yield.
5. Security concerns in some areas and presence of hardpans within the soil profile limited the collection of complete samples in some locality.

CONCLUSION

This depth-stratified survey of 708 soil observations across 32 wards in 12 LGAs of Ebonyi State found substantial variation in recorded soil properties and CUM/PI, frequent zero values for N and K, and marked declines in OM, N and Al with depth. CUM/PI differed among LGAs and showed positive spatial autocorrelation, but did not differ significantly among the sampled depth layers. EC and pH were associated with CUM/PI in bivariate and exploratory multivariable analyses; because these properties contribute to the index, their associations are partly definitional. The results describe the sampled observations and do not establish causal effects, crop yield, or fertilizer requirements.

Declarations

Competing interests: The Authors declare no conflict of interests

Funding: We wish to thank the USAID Feed the Future Nigerian Agricultural Policy Project for providing funds to conduct the soil sampling, soil analysis and administration.

Author contributions: Blessing Iveren Agada: Conceptualization, Methodology, Soil Sampling, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing.

Saweda Lenis Liverpool-Tasie: Methodology, Supervision, Resources, Funding acquisition, Project administration.

Sieglinde Snapp: Conceptualization, Methodology Investigation, Supervision, Writing, Review & editing.

ACKNOWLEDGMENTS:

We acknowledge the Dean and staff of Faculty of Agriculture, Joseph Sarwuan Tarka University (JOSTUM), The Permanent Sec., and Technical staff of the Ministry of Agriculture Ebonyi State. Technical staff of JOSTUM and students from Ebony State University (EBSU).

Declaration of Generative AI Use

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) and Claude (Anthropic) to assist with script development, language refinement, and drafting and structuring portions of the manuscript. All AI-assisted outputs were critically reviewed, verified, and edited by the authors, who take full responsibility for the accuracy, originality, interpretation, and integrity of the final published work.

Suplementary Material

Metadata for individual soil property, and PI can be downloaded as an excel file from the digital map generated using the link https://rb.gy/yfnz2m . Also statistical analysis scripts are available upon request.

REFERENCES

1. Abreu, C. H., Muraoka, T., & Lavorante, A. F. (2003). Exchangeable aluminum evaluation in acid soils. Scientia Agricola, 60(3), 543–548. https://doi.org/10.1590/S0103-90162003000300020
2. Agada, B. I. (2019). Soil productivity indices and soil tolerance limits of soils in Makurdi, Benue State [Unpublished PhD thesis]. Department of Soil Science, University of Agriculture, Makurdi, Benue State.

3. Agada, B. I., Snapp, S., & Liverpool-Tasie, L. S. O. (2023). Soil management, fertilizer types and associated practices for maize in Benue State (NAPA Research Paper 7). Michigan State University, Feed the Future Nigeria Agricultural Policy Activity. https://www.canr.msu.edu/fsg/projects/Benue%20State%20Report%20FINAL.pdf
4. Agada B.I and Iorchir C. (2024). Providing Assessable Soil Information: A Case of the Land Potential Knowledge System (LandPKS) in Benue State, Nigeria Asian Soil Research Journal 8(3):30-38 DOI: 10.9734/asrj/2024/v8i3154
5. Agada, B., Tasie, S. L. L., Snapp, S., & Eze, O. M. (2026). Soil Productivity Index and Soil Constraints Across Ten Local Government Areas (LGAs) in Benue State, Nigeria.. Nigerian Journal of Soil Science, 35(2), 109 - 116. https://doi.org/10.67042/njss.2026.7cooiw84
6. Anikwe, M. A. N., Ikenganyia, E. E., & Diobi, B. A. (2026). Arbuscular mycorrhizal fungi biofertilization improves Cyperus esculentus growth, yield, and nutrient uptake while restoring degraded Paleudults in Southeastern Nigeria. Frontiers in Sustainable Food Systems, 10, 1847883. https://doi.org/10.3389/fsufs.2026.1847883
7. Bado, V. B., & Bationo, A. (2018). Integrated management of soil fertility and land resources in Sub-Saharan Africa: Involving local communities. Advances in Agronomy, 150, 1–33. https://doi.org/10.1016/bs.agron.2018.02.001
8. Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J. W., & Brussaard, L. (2018). Soil quality – A critical review. Soil Biology and Biochemistry, 120, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030
9. Chesnin, L., & Yien, C. H. (1951). Turbidimetric determination of available sulfates. Soil Science Society of America Proceedings, 15, 149–151.
10. Enwezor, W. O. (1976). Sulphur deficiencies in soils of southeastern Nigeria. Geoderma. https://doi.org/10.1016/0016-7061(76)90044-6
11. Esri. (2024). ArcGIS Pro (Version 3.x) [Computer software]. https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview
12. Fageria, N. K., & Baligar, V. C. (2008). Ameliorating soil acidity of tropical Oxisols by liming for sustainable crop production. Advances in Agronomy, 99, 345–399. https://doi.org/10.1016/S0065-2113(08)00407-0
13. FAO. (1976). A framework for land evaluation (FAO Soils Bulletin 32). Food and Agriculture Organization of the United Nations.
14. Fox, R. L., Olson, R. A., & Rhoades, H. F. (1964). Evaluating the sulfur status of soils by plant and soil tests. Soil Science Society of America Proceedings, 28(2), 243–246. https://doi.org/10.2136/sssaj1964.03615995002800020034x
15. Fuller, W. H., & Warrick, A. W. (1985). Soils in waste treatment and utilization (Vol. 1). CRC Press.
16. Gani T., Ali, A., Agber, P. I. and Abagyeh, S. O. I. (2020). Evaluating the Effectiveness of Some Productivity Models on Floodplain Soils of Wukari Area, Northern Guinea Savanna, Nigeria. Asian Journal of Soil Science and Plant Nutrition6(3): 8-17. DOI:10.9734/AJSSPN/2020/v6i33008
17. Kane, D. A., Bradford, M. A., Fuller, E., Oldfield, E. E., & Wood, S. A. (2021). Soil organic matter protects US maize yields and lowers crop insurance payouts under drought. Environmental Research Letters, 16(4), Article 044018. https://doi.org/10.1088/1748-9326/abe492
18. Karlen, D. L., Mausbach, M. J., Doran, J. W., Cline, R. G., Harris, R. F., & Schuman, G. E. (1997). Soil quality: A concept, definition, and framework for evaluation (A guest editorial). Soil Science Society of America Journal, 61(1), 4–10. https://doi.org/10.2136/sssaj1997.03615995006100010001x
19. Kopittke, P. M., Menzies, N. W., Wang, P., McKenna, B. A., & Lombi, E. (2019). Soil and the intensification of agriculture for global food security. Environment International, 132, Article 105078. https://doi.org/10.1016/j.envint.2019.105078
20. McBratney, A. B., Mendonça Santos, M. L., & Minasny, B. (2003). On digital soil mapping. Geoderma, 117(1–2), 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4
21. Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. Biometrika, 37(1), 17–23. https://doi.org/10.2307/2332142

22. Nelson, D. W., & Sommers, L. E. (1982). Total carbon, organic carbon, and organic matter. In A. L. Page, R. H. Miller, & D. R. Keeney (Eds.), Methods of soil analysis: Part 2. Chemical and microbiological properties (pp. 539–579). American Society of Agronomy.
23. Nwite, J. N. (2013). Evaluation of the productivity of automobile oil contaminated soil amended with organic wastes in Abakaliki, Southeastern Nigeria [Doctoral dissertation, University of Nigeria, Nsukka]. 142 pp.
24. Nwite, J. N. (2016). Predicting grain yields of maize in an Ultisol amended with organic wastes using modified productivity index in Abakaliki, Southeastern Nigeria. African Journal of Agricultural Research, 11(44), 4434–4443. https://doi.org/10.5897/AJAR2016.11302
25. Nwite, J. N., Ajana, A. J., & Alinchi, I. (2022). Effect of pH on soil chemical properties and maize performance in Abakaliki, Nigeria. Agricultural Science Digest, 42(3), 337–340. https://doi.org/10.18805/ag.DF-409
26. Obasi, S. N., Obasi, C. C., Onweremadu, E. U., & Madueke, C. O. (2023). Quality and suitability of soils of Northern Ebonyi, Southeastern Nigeria for rice production. Reviews in Food and Agriculture, 4(2), 54–60. https://doi.org/10.26480/rfna.02.2023.54.60
27. Okorie, F. C., Njoku, J. D., Onweremadu, E. U., & Iwuji, M. C. (2020). Physico-chemical soil properties and their correlations with maize and cassava production in Ebonyi, Nigeria. American Journal of Climate Change, 9, 34–51. https://doi.org/10.4236/ajcc.2020.91004
28. Onyechere, A. U., Onweremadu, E. U., Aririguzo, B. N., & Ahukaemere, C. M. (2023). Geographical information system approach to suitability assessment of cassava production in Southeastern Nigeria. Bulgarian Journal of Soil Science, 8(1), 41–56. https://www.bsss.bg/issues/Issue1_2023/BJSS_2023_1_4.pdf.
29. Onyechere, A. U., Ukabiala, M. E., Amanze, C. T., & Onyechere, I. C. (2023). Application of GIS in the study of spatial variability of selected soil properties in Southeastern Nigeria. ASRIC Journal on Agricultural Sciences, 4(1), 60–71. https://www.suaire.sua.ac.tz/bitstreams/2adcac06-56e3-4cd8-b1af-d686646e9ece/download?utm_source=chatgpt.com
30. Pierce, F. J., Larson, W. E., Dowdy, R. H., & Graham, W. A. P. (1983). Productivity of soils: Assessing long-term changes due to erosion. Journal of Soil and Water Conservation, 38(1), 39–44.https://doi.org/10.1080/00224561.1983.12436244
31. Sanchez, P. A. (2019). Properties and management of soils in the tropics (2nd ed.). Cambridge University Press.
32. Sumner, M. E., & Miller, W. P. (1996). Cation exchange capacity. In D. L. Sparks (Ed.), Methods of soil analysis: Part 3. Chemical properties (3rd ed., pp. 1201–1229). American Society of Agronomy.
33. Tabatabai, M. A. (1996). Sulfur. In D. L. Sparks (Ed.), Methods of soil analysis: Part 3. Chemical methods (SSSA Book Series No. 5, pp. 921–960). Soil Science Society of America; American Society of Agronomy.
34. Taiwo, A. A., Adetunji, M. T., Azeez, J. O., & Bamgbose, T. (2010). Potassium supplying capacity of some tropical alfisols in southwest Nigeria as measured by intensity, quantity and capacity factors. Nutrient Cycling in Agroecosystems, 86, 341–355. https://doi.org/10.1007/s10705-009-9296-1
35. Trout, T. J., Garcia-Castillas, I. G., & Hart, W. E. (1987). Soil engineering field and laboratory manual. Perks.