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Original Research

Soil Productivity Index and Soil Constraints Across Ten Local Government Areas (LGAs) in Benue State, Nigeria

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Abstract

This study characterized soil productivity across ten Local Government Areas (LGAs) in Benue State, Nigeria, using 882 soil samples representing coordinate-defined soil profiles at three depth intervals (0–30, 30–60 and 60–90 cm). The cumulative productivity index (PI) values were summarized by profile and LGA. The cumulative PI had a mean of 0.138 and a median of 0.105; 105 of 314 profiles had PI = 0.00. Okpokwu had the highest median entered PI (0.290), followed by Kwande (0.210) and Makurdi (0.180), whereas Ushongu had the lowest (0.000) and 86.7% zero-PI profiles. CEC was the dominant constraint: 99.0%, had CEC sufficiency value, below 0.50 and 48.3% were scored zero. Organic matter was the second major constraint, with 46.5% samples below 0.50. The results support LGA- and ward-targeted soil management, with priority for CEC and organic-matter improvement in Usongu, Apa, Gboko and Konshisha, while Okpokwu and Kwande should be prioritized for productivity maintenance as high-performing sites.

1. Introduction

Soil productivity is the inherent capacity of a soil to sustain crop growth and agricultural sustainability (Nwite & Obi, 2008a; Kopittke *et al.*, 2019). Factors like parent material, topography, and land use create substantial spatial variability, yet decision-making often relies on broad administrative averages (Agber, 2017; Agada *et al.*, 2024). Conventional soil testing focuses predominantly on surface soil (0–15 or 0–30 cm) (Ibrahim *et al.*, 2015). This creates a critical diagnostic blind spot as subsurface dynamics in nutrient availability are ignored (Nwite & Obi, 2008a; Agber, 2011; Bako *et al.*, 2021a, 2021b; Agada *et al.*, 2023). Quantifying productivity through spatial and explicit depthwise models overcomes this limitation (Anucha *et al.*, 2026; Bako *et al.*, 2021a). Parametric productivity modeling integrates complex physical, biological and chemical parameters into standardized indices (Pierce *et al.*, 1983; Nwite & Obi, 2008b; Agada, 2019). Neill's Productivity Index (PI) model converts measurable attributes such as available water capacity, bulk density, pH, organic carbon, cation exchange capacity, and other soil properties into sufficiency values (0.0 to 1.0) aggregated across profile depths (Pierce *et al.*, 1983; Gani *et al.*, 2020; Bako *et al.*, 2021). This model acknowledges that individual soil properties do not operate in isolation but rather interact synergistically to determine overall productive capacity (Kane *et al.*, 2021). The Productivity Index (PI) model has emerged as a comprehensive approach to assessing soil suitability for crop production (Daudu, 2020). Soil productivity indices are useful as it reduces several soil limitations to a common decision-support tool. The interpretation, however, depends on the quality of the underlying factors, the aggregation rule, the depth structure, and the spatial unit used for reporting (Adeyolanu *et al.*, 2020).

While population growth, continuous cultivation, poor soil management, and climatic variability accelerate land degradation, the challenge is severe in smallholder farming systems across Sub-Saharan Africa (Ehui *et al.*, 1995; Bado & Bationo, 2018). Young *et al.* (2021) and Agada *et al.* (2024), reported that site-specific factors substantially modified the effects of agronomic practices on soil and crop outcomes.

Benue State, Nigeria's primary food basket in the Southern Guinea Savanna, experiences yield well below ecological potential due to fertility decline and erosion (Agada & Obi, 2015; Agada *et al.*, 2024). A comprehensive, depth wise productivity assessment across its agro-ecological zones remains lacking (Ibrahim *et al.*, 2015).

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The objective of this study was to characterize and quantify the soil productivity status and its distribution across ten LGAs and at ward-level profiles. Furthermore, we identify the principal soil constraints and constraint zones after the PI index to create digital soil maps for the area.

This research innovates by: (1) employing a comprehensive Productivity Index model that integrates multiple soil parameters rather than treating constraints individually; (2) delineating management zones based on quantitative spatial analysis rather than administrative boundaries (3) provides a replicable framework for precision soil management in semi-arid, smallholder-dominated agricultural systems across sub-Saharan Africa.

2. Materials and Methods

2.1 Study area

The study was conducted in ten profiled and selected farmers' field in three wards each of ten (10) Local Government Area (LGAs) of Benue State, Nigeria. The farmers' fields were in a minimum, 1ha in size and under cereal-based systems. Benue state is located in the Southern Guinea Savannah agro-ecological zone of Nigeria and has 2 distinct seasons; wet and dry. The wet season starts from April and ends in October, with mean Annual rainfall of 1500mm and mean air temperature of 28°c. Composite soil samples were collected with soil auger at 0-30 30-60 and 60-90 cm depths for routine soil analysis.

2.2. Laboratory analysis

The collected samples were analyzed to determine soil physical, chemical and biological properties. Particle size distribution was determined by Bouyoucos hydrometer method of mechanical analysis (Trout *et al.*, 1987). The bulk density was determined by the core Method of known soil volume (Fuller and Warrick, 1985). Available water capacity (AWC) was derived from moisture retention at field capacity (10 kPa) and permanent wilting point (1,500 kPa) using pressure plate extractors (Klute, 1986). Soil pH, total nitrogen, phosphorous and potassium were read insitu with a sensor device after calibrations (Agada and Iorchir, 2024).

Total carbon was analyzed by wet digestion and the organic carbon content was multiplied by a factor (1.724) to get the percentage organic matter (Nelson and Sommers, 1982). Cation Exchange Capacity (CEC), was determined using neutral ammonium acetate leachate method Summer and Miller, (1996).

2.3. The Neill soil productivity index

The Neill Productivity Index (PI) model modified by Pierce *et al.* (1983), was used. This model was based on quantifying simple measurable soil properties. The equation is:

$$PI = \sum A \times C \times D \times F \times L \times J \times Wf \quad (1)$$

Where:

PI = Productivity Index
A= Sufficiency for available water capacity for the ith soil layer
C= Sufficiency for pH for the ith soil layer.
D= Sufficiency for bulk density for the ith soil layer.
F= Sufficiency for clay content for the ith soil layer.
L= Sufficiency for land slope for the ith soil layer
.J= Sufficiency for organic matter content for the ith soil layer.
Wf= Root weighting factor (based on depth of root zone). n = Number of horizons in the rooting zone (soil layer).

The parameters in the equation are expressed as a sufficiency index (Table 1). The indexes are multiplicative for each soil horizon and summed so that the productivity index (PI) varies from 0 to 1.0, with 1.0 having the greatest productivity (Nwite, 2016; Agada, 2019; Gani *et al.*, 2020).

Productivity index was determined by calculating soil sufficiency values of each soil property. All statistical calculations were performed with Python using pandas, NumPy and Matplotlib. Descriptive statistics included counts, means, medians, minima, maxima and proportions. LGA summaries included the number of profiles, mean and median entered cumulative PI, the percentage of zero-PI profiles, the percentage of profiles with PI > 0.20.

Table 1. Sufficiency values for soil some soil properties used in the Soil Productivity Index

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).

2.4 Statistical and graphical analysis

2.5 Soil digital map generation

Digital soil maps of selected soil nutrient properties and soil productivity indices for Benue State Nigeria, was generated using ArcGISPro. Spatial soil datasets were geo-referenced, and point data interpolated with geo-statistical tools to highlight variations in nutrient contents. Satellite imagery and DEMs in ArcGISPro, model 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 the respective study areas to support site-specific soil management and fertilizer-use recommendations. The digital map can be assessed here: https://rb.gy/l3si6h (Figure 1).

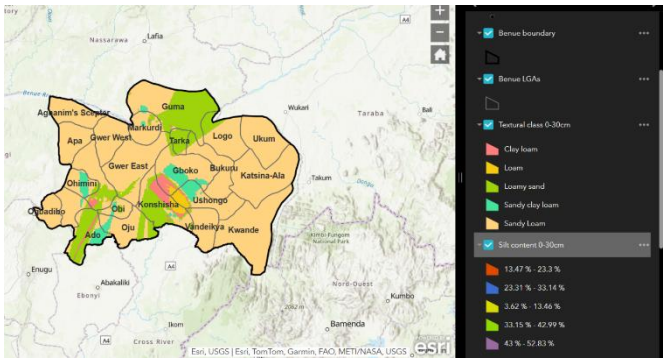

Figure 1. A sample extract of the soil nutrient and soil productivity index map interface

3. 0. Results

3.1 Overall soil productivity status

The total samples, had a mean cumulative PI of 0.138 and a median of 0.105. The distribution was strongly uneven: 105 profiles had PI = 0.00, 52 had PI >0.00–0.10, 71 had PI > 0.10–0.20, 54 had PI > 0.20 – 0.30 and 32 had PI > 0.30. Thus, one-third of profiles had zero-PI profiles, while only 32 profiles exceeded 0.30. The highest cumulative PI was recorded for Utabar in Gboko (0.76), Uam in Makurdi (0.56), Mbake in Konshisha (0.48), Baa in Makurdi (0.45), and Agan in MakurdiI (0.46). The supplied depth-specific PI had a mean of 0.044 and median of 0.000 across all 882 rows. The highest mean depth-specific PI occurred at 30–60 cm (0.059), followed by 60–90 cm (0.044) and 0–30 cm (0.030). (Figure 2).

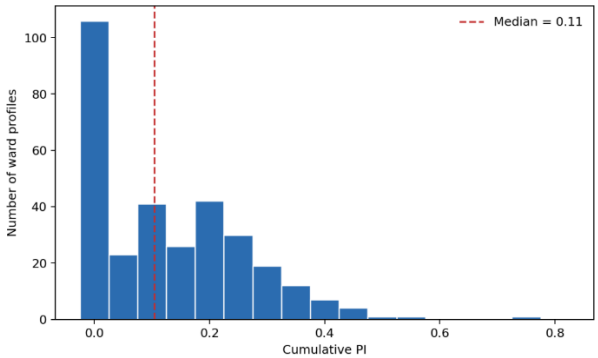

Figure 2. The overall distribution of Productivity index across Farmers field

3.2 Soil-property sufficiency and calculated PI

CEC was the clearest system-wide limitation. Its mean sufficiency was 0.109 and its median was 0.200. Of 882 soil samples, 873 (99.0%) were below 0.50 and 426 (48.3%) were exactly zero. Organic matter was the second major constraint. Its mean sufficiency was 0.564 and its median was 0.500; 410 records (46.5%) were below 0.50 and 46 (5.2%) were exactly zero. Bulk-density sufficiency was intermediate, with a mean of 0.697 and median of 0.600, although only 14 samples (1.6%) were below 0.50. Available-water-content sufficiency was generally higher, with a mean of 0.849 and median of 0.800; 57 records (6.5%) were below 0.50. The pH factor had a median of 1.000 and no data was below 0.50, while root-weighting and slope factors had medians of 1.000 and were not low (Figure 3; Table 2).

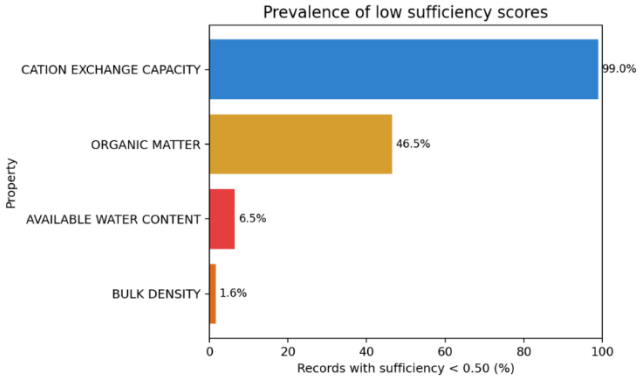

Figure 3. CEC and organic matter were the principal low-sufficiency factors; bulk density and available water were less frequent constraints

3.3. Soil Depth Effects on Constraint Expression

Analysis across soil profile depths (0-30 cm topsoil, 30-60 cm subsoil, 60-90 cm deep subsoil) reveals differential constraint expression: For the topsoil (0-30 cm), the highest PI per depth was 0.030, but paradoxically lowest CEC value of 0.080. Organic matter was most abundant in topsoil (0.589) but water retention was lowest (0.825) (Table 3). For the subsoil (30-60 cm), highest PI per depth value was 0.059 despite lower organic matter 0.587. CEC improved to 0.124, and water retention increased to 0.853 (Figure 4). The deeper subsoil (60-90 cm), had Intermediate PI 0.044, lowest organic matter 0.516, but maintained CEC 0.123 and highest water retention 0.868. The deep layer provides water storage capacity but minimal nutrient supply (Azuma *et al.*, 2022). This depth-dependent variation indicates that productivity constraints operate through depth-specific mechanisms: topsoil limitations center on nutrient retention, subsoil provides transitional conditions, and deep layers contribute primarily to water storage. Successful interventions must address these layered constraints differentially (Williams *et al.*, 2016). The PI was highest on average at 30–60 cm, but the median remained low at all depths.

3.4 Distribution across LGAs

Okpokwu had the strongest productivity distribution. Its 29 profiles had a median entered PI of 0.290, a mean of 0.286 and

Table 2. Soil property sufficiency and the operational sufficiency classification.

Soil property	Mean sufficiency	Median sufficiency	Samples below 0.50	Samples at zero	Samples above 1.00	Ascribed sufficiency
Organic matter	0.564	0.500	46.5%	5.2%	0.1%	Limited
pH	1.181	1.000	0.0%	0.0%	32.2%	Adequate by median
Cation exchange capacity	0.109	0.200	99.0%	48.3%	0.0%	Critical
Bulk density	0.697	0.600	1.6%	0.1%	0.2%	Limited
Available water content	0.849	0.800	6.5%	0.1%	0.1%	Adequate
Root weighting factor	0.997	1.000	0.0%	0.0%	0.0%	Adequate
Slope factor	1.000	1.000	0.0%	0.0%	0.0%	Adequate

Table 3. Depth-specific PI obtained by multiplying the seven bounded sufficiency factors.

Soil depth	Valid PI	Mean PI per depth	Median PI per depth	Maximum PI per depth
0–30 cm	296	0.0292	0.0000	0.2016
30–60 cm	295	0.0476	0.0384	0.2000
60–90 cm	289	0.0339	0.0336	0.1700

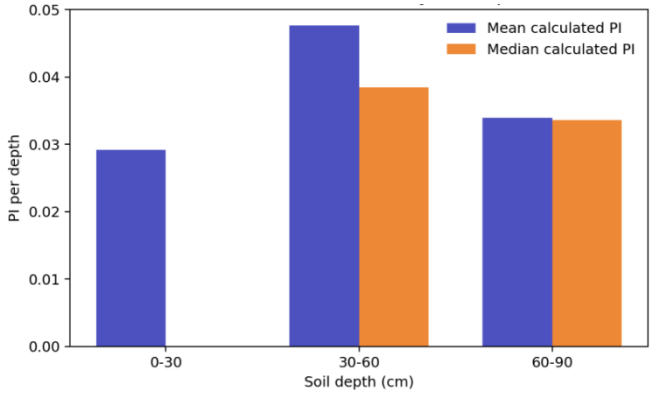

Figure 4. Mean Productivity Index by Soil Profile Depth

no zero-PI profile; 89.7% exceeded 0.20. Kwande ranked second, with a median of 0.210, a mean of 0.220 and 58.1% of profiles above 0.20. Makurdi was heterogeneous but comparatively productive, with a median of 0.180, a mean of 0.186 and 43.9% above 0.20. OTUKPO occupied an intermediate position, with a median entered PI of 0.160 and 24.0% of profiles above 0.20. Guma had a median of 0.110 and only 3.2% of profiles above 0.20; its mean of 0.154. OBI had a median of 0.095 and 25.0% zero profiles. The lowest distributions occurred in Gboko, Apa, Konshisha and Ushogu. Their zero-PI proportions were 62.5%, 60.0%, 66.7% and 86.7%, respectively. Ushongu had a mean entered PI of 0.014, a median of 0.000 and no profile above 0.20 (Figure 5).

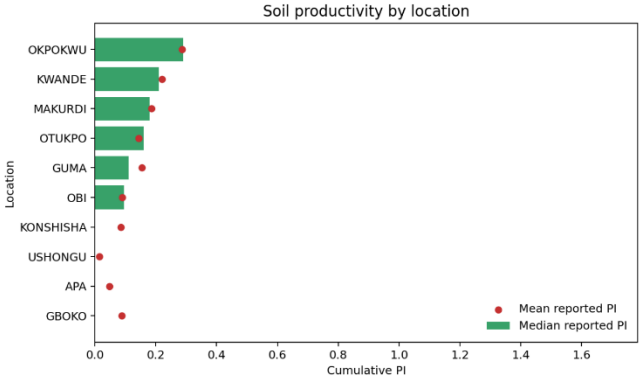

Figure 5. Mean Cumulative Productivity Index by Local Government Area

3.5. Ward-level productivity pattern and distribution constraints

The highest entered ward-profile values were Utabar in Gboko (0.76), Uam in Makurdi (0.56), Mbake in Konshisha (0.48), Baa and Agan in Makurdi (0.46 each), Baa2b in Mahurdi (0.45), and

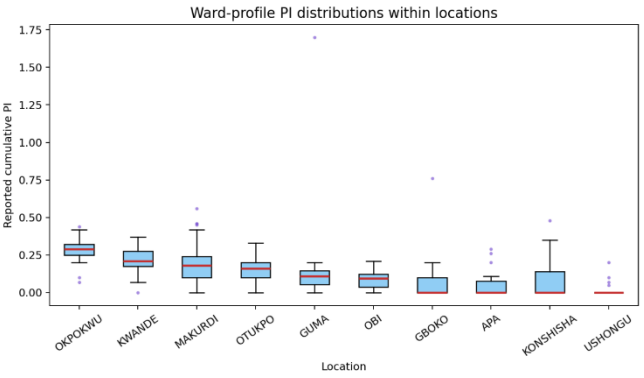

Figure 6. The boxplots showing within-LGA variation and the influence of high or low ward-profile values

several Okpokwu profiles at 0.42–0.44 (Figure 6). The spatial analysis across the state revealed stark geographic variation in soil productivity, with Mean Cumulative Productivity Index ranging from 0.014 (Ushongu) to 0.286 (Okpokwu) a 20-fold difference. This extraordinary variability demonstrates that Benue State comprises fundamentally different soil fertility environments requiring differentiated management approaches (Girish *et al.*, 2026).

3.6. Major constraints and constraint zones

CEC limitation was widespread across all ten LGAs. The percentage of sample below 0.50 was 100% in every LGA. The percentage of zero CEC scores was highest in Ushongu(94.4%), Gboko (82.9%), Apa (80.0%) and Konshisha (75.3%). These four LGAs also had the greatest concentrations of zero-PI profiles, linking the spatial productivity pattern to the dominant factor in the multiplicative formula. Organic-matter limitation was strongest in Guma, Apa, Obi and Konshisha. The proportion of records below 0.50 was 79.8% in Guma, 77.8% in APA, 55.6% in OBI and 55.1% in Konshisha. In contrast, the corresponding proportions were 26.4% in Okpokwu and 27.0% in Makurdi. This contrast indicates that the high productivity of Okpokwu and Makurdi were supported partly by better organic-matter sufficiency, although CEC remained low across the entire dataset (Figure 7).

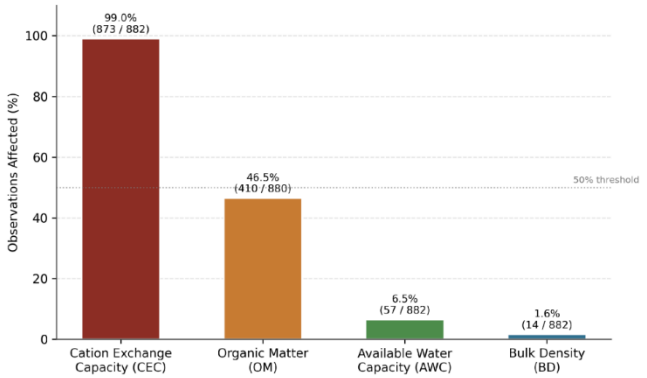

Figure 7. Primary soil Constraints limiting soil productivity in Benue state

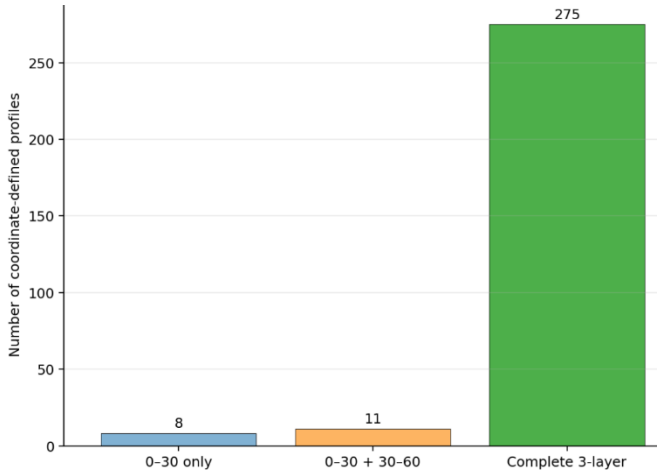

Figure 8. Profile coverage by sapled soil-depth layers across Benue state

Figure 7 also shows bulk-density limitation was spatially less dominant. Only 14 samples were below 0.50, with most LGA-level proportions at zero; Gboko had the highest proportion at 22.0%. Available-water limitation was also localized: 23.6% of Makurdi and 14.4% of Obi were below 0.50, compared with no low values in Kwande, Guma and Okpokwu. The slope factor was 1.00 in all observations, so it did not differentiate the mapped productivity pattern.

4. Discussion

4.1 Interpretation of the spatial productivity gradient

The results show a pronounced productivity gradient among the ten LGAs, but they also show that LGA means alone would conceal important within-LGA variability. Okpokwu had both a high median PI and a high proportion of profiles above 0.20, indicating relatively consistent productivity. Kwande also performed well, while Makurdi combined a relatively high median with a broader range of values. By contrast, Ushongu, Apa, Konshisha and Gboko contained many zero-PI profiles. This pattern is consistent with the rationale for spatial land-suitability assessment in Benue State (Ujoh *et al.*, 2019). The spatial contrast also supports a management strategy based on zones rather than uniform state-wide recommendations. (Adebayo *et al.*, 2026).The difference between Guma's mean and median illustrates why robust summaries are necessary. The profile-level distribution therefore provides a more defensible description of the typical soil condition than the mean alone. The same principle applies to Gboko, where a small number of higher values coexisted with a zero-PI majority.

4.2 CEC and organic matter as the main constraints

CEC was the strongest constraint because it was below 0.50 in 99.0% of samples and zero in nearly half. The effect was amplified by the multiplicative PI calculation: a zero CEC score makes the depth PI zero even when pH, water and bulk-density scores are favorable. The result showed low sufficiency CEC values, and not that all laboratory CEC measurements were intrinsically zero. The large number of zero scores reflected real low exchange capacity. This CEC pattern is nevertheless agronomically plausible as a management concern in low-organic-matter or coarse-textured tropical soils (Ahukaemere and Obasi, 2018; Aberagi *et al.*, 2024). These studies support the need to treat nutrient-retention capacity and organic inputs as linked management targets rather than focusing only on mineral fertilizer supply.

Organic matter was the second major constraint and showed a clearer LGA gradient than CEC. Guma and Apa had the largest proportions of low organic-matter scores, whereas Okpokwu and Makurdi had lower proportions. The result is consistent with evidence from tropical soils that management can alter organic matter, nutrient retention and physical condition. (Abdulmajid, 2025; Adeyolanu *et al.*, 2020). In the present study, organic matter should be treated as a priority constraint in Guma, Apa, Obi and Konshisha, and as a maintenance variable in the higher-PI zones.

4.3 Physical factors and depth behavior

Bulk-density sufficiency was generally limited by the median score of 0.60, as only 1.6% fell below 0.50. This suggests that bulk density contributed to reduced PI in some profiles but did not explain the widespread zero values as strongly as CEC. Available-water sufficiency was adequate overall, although Makurdi and Obi contained localized low scores.

The importance of measuring both chemical and physical dimensions is supported by (Adaikwu *et al.*, 2025) who found that selected

Makurdi soils, suggested different degradation and vulnerability interpretations. Similarly Woldemariam *et al.* (2025), reported elevated bulk density, low organic carbon and low nutrient levels as interacting indicators of poor soil health across slope and landscape positions . These comparisons reinforce that productivity index should not be interpreted as a single fertility score detached from physical condition, water storage and landscape position.

4.4 Implications for land management and zoning

The priority zone for CEC and organic-matter intervention comprises Ushongu, Apa, Gboko and Konshisha. These LGAs had high zero-PI proportions and high prevalence of zero CEC scores. Management should begin with locally appropriate organic-resource management, balanced nutrient application and pH correction.

Guma and Obi form a second priority group characterized by organic-matter limitation and low-to-intermediate typical PI. Their management should emphasize residue retention, organic amendments, erosion control and monitoring of water-related limitations. Makurdi and Okpokwu contain high-productivity zones but also substantial internal variation. These zones should be managed through targeted maintenance rather than assuming to be uniformly fertile. Kwande also showed a strong productivity distribution and a low zero-profile percentage. The high-performing wards in these LGAs are suitable candidates for validation sampling, crop-response trials and transfer of locally successful practices.

5. Limitations

First, the dataset had unequal numbers of depth records and profiles among LGAs. Coordinate-defined grouping reduced this problem but did not replace it. Data was analyzed as an unbalanced design as some plots had their effective depth at 30 cm or 60cm following a hardpan (Figure 8)

Secondly, the analysis did not include crop, yield, soil mineralogy, exchangeable bases, total nitrogen, available phosphorus nor potassium, but was limited to the parameters needed in the Neill productivity index equation. Consequently, the PI describes a soil-factor scoring system and should not be interpreted as a direct estimate of crop yield.

Thirdly the twenty-three (23) Local government areas for the state of Benue, and some locations within the ten LGAs studied could not be accessed given security concerns for team members.

6. Conclusion

Across the ten LGAs, the results indicated low and highly variable soil productivity indices. The cumulative PI had a median of 0.105, and 105 of 314 coordinate-defined profiles were recorded as zero-PI profiles. Okpokwu and Kwande were the strongest and most consistent productivity zones, while Ushongu, Apa, Konshisha and Gboko had the greatest concentrations of zero-PI profiles. Makurdi and Guma contained several high-performing profiles but was internally heterogeneous.

CEC was the principal constraint and organic matter was the second major constraint. Bulk density and available water were generally less limiting but remained important at selected wards. The management implication is a targeted rather than uniform strategy: address CEC and organic matter in Ushongu, Apa, Gboko and Konshisha; prioritize organic-matter and site-specific water management in Guma and Obi; while maintaining organic matter in the high-performing wards of Okpokwu, Kwande and Makurdi.

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Data Availability

Data can be downloaded as a Metadata from the digital soil map link provided in the text. Statistical analytics script, are available upon request.

Author Contributions

Agada, B.I.: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing original draft- Introduction, review & editing. Saweda Lenis Liverpool- Tasie : Project supervision, Project Fund and Administration; Conceptualization.; Methodology. Seiglinde Snapp: Conceptualization; Project supervision, Methodology. Obi M.E. : Proof reading.

Conflict of Interest

The authors declare no conflict of interest.

Generative AI Statement

During the preparation of this manuscript, the authors used ChatGPT to support language editing, grammar correction and improvement of clarity. After using this tool, the authors reviewed, edited, and verified the manuscript content and take full responsibility for the final version.

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