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Distribution and Interactions of Soil Nutrients and Organic Carbon at University of Calabar Campus, Nigeria

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ABSTRACT
Plant biodiversity depends fundamentally on soil nutrient availability. However, nutrient dynamics within university campuses remain poorly studied, and less attention has been given to soil health, plant biodiversity, and the ecosystem services supported by campus soils. This study evaluated the influence of soil depth on the distribution, relationships, and multivariate interactions of soil nutrients and organic carbon across the University of Calabar campus, Nigeria. Ten randomly selected sampling locations were established using QGIS, and composite soil samples were collected from four depth intervals (0–15, 15–30, 30–60, and 60–100 cm). Soil organic carbon, nitrogen, phosphorus, potassium, calcium, magnesium, silicon, and sulfur were determined using standard laboratory procedures. Data were analyzed using Pearson correlation, one-way ANOVA, principal component analysis, and multiple linear regression. Significant positive correlations were observed between nitrogen and phosphorus ($r = 0.78$, $p = 0.0027$), phosphorus and silicon ($r = 0.72$, $p = 0.0082$), and calcium and potassium ($r = 0.62$, $p = 0.0331$), whereas phosphorus and magnesium were negatively correlated ($r = –0.65$, $p = 0.0227$). Soil depth had no significant effect on organic carbon or nutrient concentrations ($p > 0.05$). The regression analysis showed that the measured nutrients did not significantly predict organic carbon. These findings indicate relatively homogeneous soil conditions within the campus and provide a baseline for future studies on nutrient dynamics and distribution within the University of Calabar campus and similar landscapes.

Keywords: Soil depth, Soil fertility, Nutrient cycling, Nutrient dynamics, Tropical urban soils

INTRODUCTION

Soil organic carbon (SOC) is a fundamental component of terrestrial ecosystems, playing a pivotal role in nutrient cycling, soil fertility, and climate regulation (Zhao et al., 2025). The vertical distribution of SOC and its interactions with nutrients such as nitrogen (N), phosphorus (P), and various micronutrients are highly variable (Qiao et al., 2020). It is influenced by a range of biotic and abiotic factors, including soil depth, mineralogy, moisture, and land use practices (Krüger et al., 2023). SOC is not uniformly distributed throughout the soil profile; instead, its concentration and chemical composition are reported to change markedly with depth (Hu et al., 2024). The interactions between SOC and nutrients are further modulated by factors such as soil moisture and mineral composition, which can enhance SOC stabilization through organomineral associations (Von Fromm et al., 2025).

Studies show that SOC levels in university soils, like other urban landscapes, vary significantly with land cover type (Saha & Handique, 2022; Wachu & Ibrahim, 2025). This variation may be linked to differences in vegetation, management practices, and seasonal changes (Shapkota & Kafle, 2021). SOC not only enhances nutrient cycling and plant growth but also improves soil structure and water retention, supporting the sustainability of campus green spaces (Kabato et al., 2025).

Biodiversity, especially plants, relies on soil for nutrition; however, research on their nutrient dynamics within campus boundaries remains limited. Most sustainability initiatives in higher education and campuses focus on energy, waste, and infrastructure, with relatively little attention to soil health, biodiversity, or ecosystem services (Oliveira & Proença, 2025). There is a lack of comprehensive studies on nutrient cycling, organic carbon dynamics, and the impacts of campus management practices on soil quality especially in southern Nigeria. Campuses serve as living laboratories, providing accessible sites for ecological research, education, and community engagement (Valliere, 2022). Understanding nutrient and carbon dynamics in these settings can inform sustainable land management and enhance urban biodiversity (Colding & Barthel, 2017). Moreover, universities are influential institutions that can model best practices for urban sustainability, contributing to global efforts to mitigate climate change and promote ecological stewardship (Genta et al., 2021). In response to the identified gap, this study aimed to evaluate the distribution, relationships, and interactions of soil nutrients and organic carbon across different soil depths on the University of Calabar campus.

MATERIALS AND METHODS

Study Area

Figure 1 shows the sample points within the University of Calabar campus, Calabar, Cross River State, Nigeria. Calabar is located at 4° 58' N, 8° 20' E. The campus comprises a mix of land uses, including built-up areas, lawns, ornamental plantings, and small patches of semi-natural vegetation. The soils in the region are predominantly derived from coastal sediments and are generally characterized as sandy to sandy-loam. Calabar falls within the tropical equatorial climate characterized by mean annual temperature of about 26 ºC, a mean annual relative humidity >80 %, and abundant mean

annual rainfall exceeding 3000 mm during the wet season (Awuh et al., 2018, Ononyume & Edu, 2026).



Figure 1: Soil sample collection points within campus boundary

Sampling Design and Site Selection

A simple random sampling was adopted to obtain an unbiased representation of soil conditions across the University of Calabar campus. The campus boundary was delineated using the OpenStreetMap layer in QGIS (version 3.44 Solothurn), after which ten sampling points were randomly generated within the study area. The geographic coordinates of the selected points were uploaded to a Garmin GPSMAP 79sc handheld Global Positioning System (Garmin Ltd., Kansas, USA) and used to navigate to each sampling point during fieldwork in December, 2025. Soil sampling was conducted during the dry season to minimize the influence of short-term moisture fluctuations on soil properties.

Soil Sample Collection

At each of the ten sampling locations, soil samples were collected from four depth intervals: 0–15 cm, 15–30 cm, 30–60 cm, and 60–100 cm. Before soil collection, surface litter and other debris were carefully removed from the collection point. At each depth, five soil cores were collected within a 5-m radius of the sampling point using a soil auger. The five subsamples from the same depth interval were thoroughly homogenized to produce one composite sample representative of that depth at each location. The auger was cleaned between sampling points and depth intervals to prevent cross-contamination. Composite samples were placed in labeled polyethylene bags, transported to the Department of Soil Science, University of Calabar and air-dried at room temperature for seven days. Afterwards, the soil was gently crushed, and passed through a 2-mm sieve before laboratory analyses. A total of 40 composite soil samples (10 locations × 4 depths) were analyzed.

Laboratory Experiment

The laboratory analyses were conducted at the Department of Soil Science, University of Calabar, where key soil properties were measured. Soil organic carbon was determined using the Walkley–Black wet oxidation method (Walkley & Black, 1934), while total nitrogen was assessed through the Kjeldahl digestion method (Bremner, 1965). Available phosphorus was extracted with Bray-1 solution and measured colorimetrically (Bray & Kurtz, 1945). Potassium, calcium, and magnesium were determined using the exchangeable cations method (Reyes-Gutiérrez et al., 2008). Silicon was measured by alkali extraction followed by colorimetric analysis (Elliott & Snyder, 1991), and sulfur was analyzed using the method by Kilmer & Nearpass, (1960). All parameters were measured in triplicate to ensure analytical precision.

Data Analysis

Data analysis was performed in R statistical software (version 4.4.3). One-way Analysis of Variance (ANOVA) was used to evaluate the effect of soil depth on soil nutrient content, including soil organic carbon (OC), nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), silicon (Si), and sulfur (S). Soil depth was treated as a fixed factor with four levels (0–15 cm, 15–30 cm, 30–60 cm, and 60–100 cm). Pearson's product-moment correlation analysis was conducted to determine the strength and direction of linear relationships among soil nutrients and organic carbon, with statistical significance assessed at $p < 0.05$.

To further explore multivariate relationships among the measured soil properties, Principal Component Analysis (PCA) was performed to identify the principal components explaining the greatest proportion of variation in nutrient relationships.

A multiple linear regression model was fitted to evaluate the collective influence of soil nutrients (N, P, Ca, Mg, K, Si, and S) on soil organic carbon. Model performance was evaluated using R^2 and adjusted R^2, while overall model significance was assessed using the F-statistic. Individual predictor effects were evaluated using regression coefficients, 95% confidence intervals, and standardized coefficients. Model assumptions were evaluated through the Shapiro–Wilk test for normality of residuals, and Variance Inflation Factors (VIF) to assess multicollinearity among predictor variables.

RESULTS AND DISCUSSION

The effect of soil depth on organic carbon and nutrient concentrations is presented in Table 1 and Figure 2. One-way ANOVA showed that soil depth did not significantly influence organic carbon ($F = 0.065$, $p = 0.977$) or any of the measured nutrients (all $p > 0.05$). Among the nutrients,

magnesium exhibited the largest depth-related effect ($F = 2.267$, $p = 0.158$; $\eta^2 = 0.459$), although this effect was not statistically significant. In contrast, organic carbon showed the smallest effect of depth ($\eta^2 = 0.024$), while nitrogen, phosphorus, potassium, and silicon exhibited moderate effect sizes despite the absence of significant differences among depths.

Table 1: Analysis of Variance (ANOVA) and Corresponding Effect Sizes for Soil Nutrients and Organic Carbon

Variable	F value	p-value	Between SS	Residual SS	η^2 (proportion of total variance explained)
Organic carbon	0.065	0.977	0.000367	0.015	0.0239 (2.39%)
Nitrogen	0.75	0.552	0.000225	0.0008	0.2195 (21.95%)
Potassium	0.891	0.486	0.001425	0.004267	0.2504 (25.04%)
Phosphorus	0.862	0.499	1.241	3.838	0.2443 (24.43%)
Calcium	0.494	0.696	0.0667	0.36	0.1563 (15.63%)
Magnesium	2.267	0.158	0.1133	0.1333	0.4594 (45.94%)
Silicon	0.865	0.498	4.047	12.48	0.2449 (24.49%)
Sulfur	0.496	0.695	0.03562	0.19167	0.1567 (15.67%)

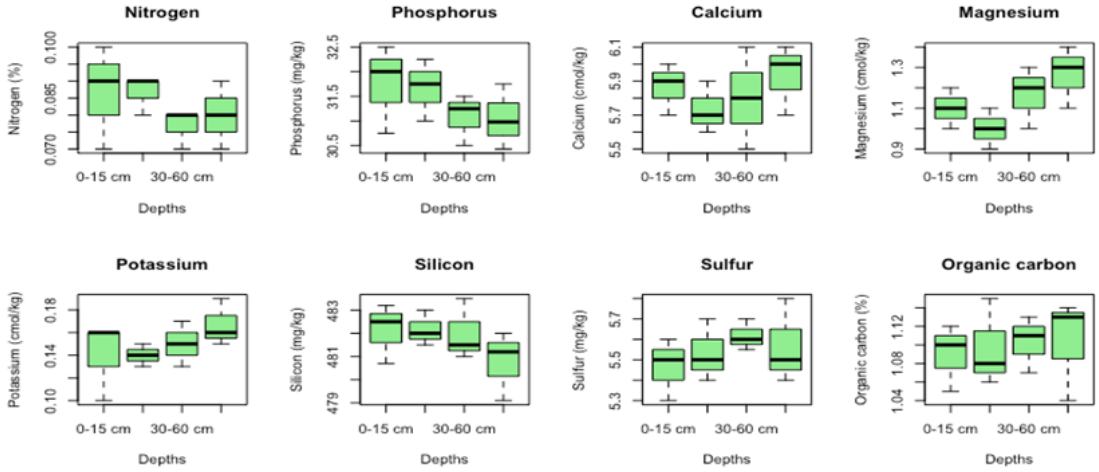


Figure 2: Mean Distribution of Nutrients and Organic Carbon Concentrations Across Depths

The Pearson correlation matrix is presented in Figure 3. Significant positive correlations were observed between nitrogen and phosphorus ($r = 0.78$, $p = 0.003$), phosphorus and silicon ($r = 0.72$, $p = 0.008$), and calcium and potassium ($r = 0.62$, $p = 0.033$). In contrast, phosphorus was negatively correlated with magnesium ($r = -0.65$, $p = 0.023$), while magnesium was negatively correlated with silicon ($r = -0.63$, $p = 0.029$). Organic carbon showed no significant correlations with the measured nutrients, although its strongest association was a moderate positive relationship with calcium ($r = 0.52$, $p = 0.087$).

The principal component analysis showed that five components explained most of the variability in the dataset (Table 2 and Figure 4). The first principal component (PC1) explained 38.78% of the total variance. The second principal component (PC2) accounted for an additional 26.68%, resulting in a cumulative variance of 65.46% for the first two components. Inclusion of the third principal component increased the cumulative variance explained to 78.36%.

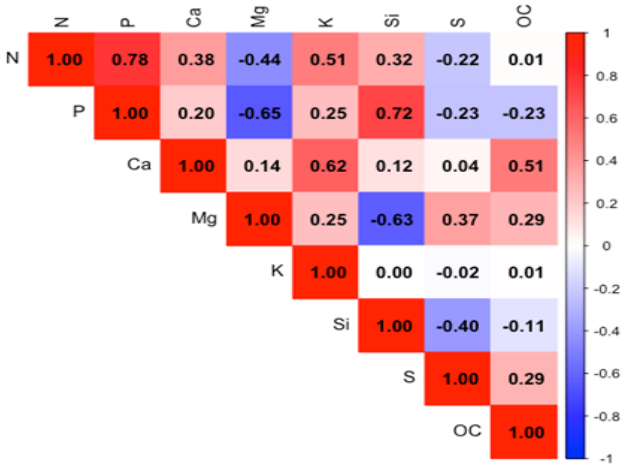


Figure 3: Correlation Matrix of Nutrients and Organic Carbon in Soil

Table 2: Eigenvalues and Proportion of Variance Explained by the Principal Components

Principal Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
PC1	3.103	38.78	38.78
PC2	2.135	26.68	65.46
PC3	1.032	12.9	78.36
PC4	0.805	10.06	88.42
PC5	0.501	6.26	94.68

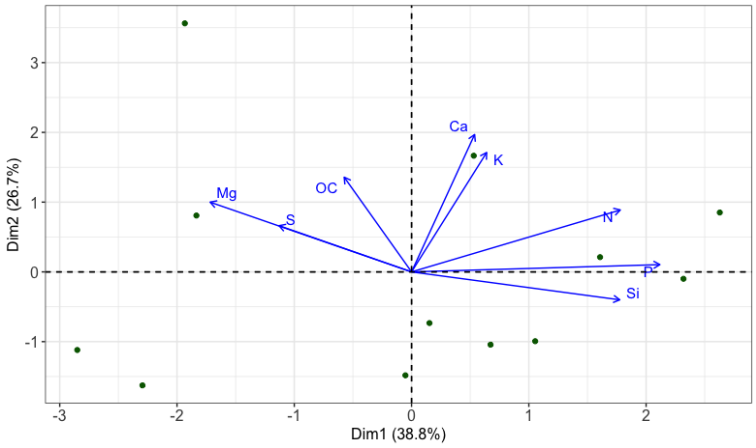


Figure 4: Principal Component Analysis of the Associations Between Soil Nutrients and Organic Carbon

The multiple linear regression model explained 79.2% of the variation in soil organic carbon (Multiple R^2 = 0.792). However, after accounting for the number of predictors relative to the sample size, the explanatory power decreased to an adjusted R^2 of 0.428. The overall regression model was not statistically significant ($F_{7,4}$ = 2.174, p = 0.236), indicating that the measured soil nutrients did not collectively predict soil organic carbon (Table 3). Nitrogen showed the largest positive regression coefficient (β = 4.868, p = 0.097), while potassium (β = −1.204, p = 0.119) and phosphorus (β = −0.077, p = 0.111) exhibited negative coefficients. Nevertheless, none of the regression coefficients were statistically significant (Table 4).

Standardized regression coefficients indicated the relative contribution of each predictor after accounting for differences in measurement scale. Phosphorus exhibited the largest standardized negative coefficient (β = −1.406), whereas nitrogen had the largest standardized positive coefficient (β = 1.257). However, because none of these predictors were statistically significant in the regression model, these coefficients should be interpreted only as relative contributions rather than evidence of significant effects (Table 4).

Variance inflation factor analysis showed moderate to relatively high multicollinearity among several predictors. Phosphorus had the highest VIF (9.13), followed by nitrogen (6.54). Calcium, sulfur, potassium, and magnesium exhibited comparatively lower VIF values (<5), indicating lower levels of collinearity (Table 4). The Shapiro–Wilk test indicated that the regression residuals did not deviate significantly from normality (W = 0.967, p = 0.882).

Table 3: Summary Statistics of Multiple Linear Regression of Soil Nutrients Predicting Soil Organic Carbon

Statistic	Value
Number of observations (n)	12
Multiple R^2	0.792
Adjusted R^2	0.428
Residual standard error	0.028
F-statistic	2.174
Degrees of freedom	7, 4
Model p-value	0.236

Table 4: Multiple Linear Regression Analysis of Soil Nutrients Predicting Organic Carbon

Predictor	Estimate	Standard Error	t-value	p-value	95% Confidence Interval	Standardized β	VIF
Intercept	-10.64	6.648	-1.601	0.185	-29.097 to 7.817	-	-
Nitrogen	4.868	2.259	2.155	0.097	-1.404 to 11.140	1.257	6.54
Phosphorus	-0.077	0.038	-2.04	0.111	-0.183 to 0.028	-1.406	9.13
Calcium	0.113	0.059	1.909	0.129	-0.051 to 0.277	0.595	1.87
Magnesium	0.104	0.101	1.031	0.361	-0.177 to 0.385	0.418	3.16
Potassium	-1.204	0.609	-1.977	0.119	-2.896 to 0.487	-0.733	2.64
Silicon	0.026	0.015	1.723	0.16	-0.016 to 0.068	0.857	4.76
Sulfur	0.104	0.072	1.441	0.223	-0.096 to 0.303	0.398	1.47

Discussion

The lack of depth effects on organic carbon and nutrient concentrations is critical, as organic matter is central to nutrient retention, cation exchange, and the solubility of key nutrients such as P, Fe, and Cu (Gerke, 2022). At the same time, the moderate effect sizes observed for several nutrients, especially Mg, but also N, P, K, and Si, indicate that subtle depth-related trends may exist beneath this apparent uniformity. The distribution of organic carbon and nutrients across soil depths in the campus reflects the management practices, vegetation cover, and near constant human disturbance typical in urban areas, which homogenize soil profiles and gradients (Mwendwa et al., 2022; Omokaro et al., 2024; John et al., 2020; Kotze et al., 2021; Li et al., 2020). For instance, disturbances such as landscaping can redistribute organic matter and nutrients vertically, and reduce stratification when compared to natural systems which usually show nutrient declines with depth. (Pattnaik et al., 2023; Wang et al., 2021). One implication for plant communities is that, a relatively homogeneous soil profile allows roots at various depths to access comparable nutrient pools. This may support consistent nutrient uptake, and promote aboveground productivity to some extent (Seabloom et al., 2020). These trends, though statistically unresolved here, mirror findings from managed and disturbed soils where weak or inconsistent gradients can mask underlying vertical processes until higher-resolution sampling or more targeted study designs are employed (Müller et al., 2025; Abrar et al., 2025; Alvarez, 2025). Such latent gradients may have ecological relevance, potentially influencing nutrient cycling rates and long-term soil development in university landscapes.

The lack of statistically significant correlations between organic carbon and most of the nutrients show that the relationship between organic carbon and nutrient elements can be complex and context-dependent (Luo et al., 2025). The strong positive correlation between nitrogen and phosphorus aligns with findings by Bashir et al. (2024) and Wu & Yu (2023) that report co-increment of nitrogen and phosphorus due to shared sources, plant uptake, and microbial processes that couple their cycling in soils. Similarly, a strong positive correlation between phosphorus and silicon indicates that silicon fertilization can enhance the availability of both nitrogen and phosphorus, likely through effects on soil microbial activity and nutrient mineralization (Liang et al., 2021). In contrast, the significant negative correlations between phosphorus and magnesium, and between magnesium and silicon, suggest antagonistic interactions, possibly due to competition for adsorption sites or to differing roles in soil mineralogy and plant nutrition (Gao et al., 2017; Neu et al., 2017). These negative relationships are consistent with broader soil nutrient mapping studies, which have shown that certain cations (such as Mg and Ca) can be inversely related to other nutrients depending on soil parent material and management practices (Hengl et al., 2017; Wu & Yu, 2023). The moderate positive correlation between calcium and potassium reflects their similar geochemical behavior and co-occurrence in many soil types (De Freitas Aurivan et al., 2017). Strong positive correlations among nutrients (N, P, Si, K, Ca) indicate efficient mobilization and high productivity potential, if antagonistic interactions are managed.

The PCA revealed substantial covariance among the measured soil nutrients. Abdel-Fattah et al. (2021) reported that the major sources of variation in soil fertility can often be summarized by a few principal components representing dominant pedogenic processes. The amount of variation captured by the leading principal components agrees with observations reported in other soil studies. For example, Ellur et al. (2024) found that a small number of principal components explained most of the variability in cultivated soils, demonstrating that soil nutrients tend to respond collectively to common environmental drivers. Similar to the results of this study, Tokgöz (2026) showed that three principal components adequately represented the majority of variation in soil physicochemical properties.

The regression model explained a relatively high proportion of the variation in soil organic carbon (SOC). However, the substantial decline from the multiple R^2 to the adjusted R^2, together with the non-significant overall F-test, suggests that the model was overfitted rather than strongly predictive (Dertli et al. 2024). Although nitrogen showed the strongest positive relationship with SOC, none of the measured nutrients significantly predicted SOC. Dai et al. (2022) demonstrated that nitrogen enrichment can enhance SOC accumulation in many ecosystems, while Hu et al. (2024) emphasized that nutrient–SOC relationships are highly dependent on local soil and environmental conditions. The absence of significant nutrient effects in the present study therefore suggests that SOC dynamics on the University of Calabar campus are influenced by factors beyond nutrient concentrations alone.

The elevated variance inflation factors for nitrogen and phosphorus indicate substantial multicollinearity among the predictors, which likely reduced the precision of the regression coefficients. Kyriazos & Poga (2023) explained that multicollinearity inflates standard errors and can obscure genuine predictor effects, while Tesfay et al. (2025) recommended variable selection or dimension-reduction techniques to improve model stability. The regression analysis suggests that the measured nutrients did not independently predict soil organic carbon in the study area. Rather, SOC appears to be influenced by multiple interacting factors, highlighting the need for larger datasets and more parsimonious modelling approaches in future studies. Future research integrating spatial analysis of soil–plant indicators may help to detect subtle interactions (Macci et al., 2025). These results represent a snapshot of nutrient and organic carbon dynamics within the University of Calabar campus and is therefore limited in its spatial and temporal scope. The relatively small sample size may also have reduced the statistical power to detect subtle relationships. Consequently, the findings should not be generalized beyond the study area but could serve as a baseline for future investigations involving broader spatial coverage and seasonal sampling.

Conclusion

This study evaluated the influence of soil depth on the distribution, relationships, and interactions of soil organic carbon and selected nutrients across the University of Calabar campus. Soil depth had no significant effect on organic carbon or nutrient concentrations, indicating a relatively homogeneous soil profile across the sampled depths. Nevertheless, significant associations among several nutrients indicate that their distributions are interconnected despite the absence of pronounced vertical gradients. Multiple regression further showed that the measured nutrients did not significantly predict soil organic carbon. These findings should be interpreted cautiously because the relatively small sample size may have limited the detection of subtle depth-related patterns. Furthermore, the single-time sampling provides only a snapshot of soil conditions in the area. The findings are specific to the University of Calabar campus and should not be extrapolated beyond the study area. Despite these limitations, the integrated statistical approach

provides a useful baseline for future investigations of soil nutrient distribution and organic carbon dynamics on the campus and in comparable landscapes.

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