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RESEARCH ARTICLE

DISCRIMINANT SOIL DIVERSITY ANALYSIS FOR CROP ENHANCEMENT AND AGRICULTURAL MANAGEMENT STRATEGIES DEVELOPMENT IN SELECTED NIGERIAN OIL PALM AREAS

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ABSTRACT

This study is focused on the empirical investigation of discriminant analysis in the context of land allocation for oil palm plantations in five distinct soil types:. When determining whether a soil type is suitable for oil palm cultivation and if mineral fertilisers are necessary, the chemical properties of the soil are considered more important than the physical properties of the soil. Understanding these soils and their response to cultural management practices is a necessity for any soil user or grower. The analysis employed canonical correlation along with Wilks' Lambda, yielding values of 0.754 and 0.178, respectively, and corresponding chi-square statistics of 82.503, indicating significance at $p < 0.05$. A total of 13 indicator factors were examined, seven out of these were significant, and magnesium (Mg) proved to be the most effective in differentiating between the soil categories. A comparison of the actual classifications of the five soil types with the predictions produced by the discriminant function showed groups 1 and 5 had the highest accuracy. They successfully classified 75% of the observations, while group 3 classified 64.2% of the observations accurately, displaying a moderate level of predictive performance. On the other hand, groups 2 and 4 recorded the lowest accuracy of predictions at 58.3% and 56.8% respectively. The overall discriminant accuracy (hit ratio) was recorded at 67.7% for classifying samples correctly. This study's findings portray discriminant analysis as a valid tool for forecasting novel cases in the five most prevalent soil types in Southern Nigeria's Raphia production zone. Additionally, key soil variables such as magnesium (Mg), phosphorus (P), copper (Cu), pH, calcium (Ca), manganese (Mn), and potassium (K) were noted to have a significant important influence in determining the soil type. As a result, this model demonstrates strong predictive capabilities, making it a valuable tool for classifying new cases in this context.

Keywords: Discriminant analysis, soil diversity, oil palms, raphia growing zone, Southern Nigeria

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1.0. INTRODUCTION

Grown primarily for its commercial production of vegetal oil, oil palm is a tropical tree crop. Additionally, it is seen in village gardens that produce oil for community use. For the tree to grow to its full potential, it needs high temperatures, high relative humidity, high rainfall, and extended daylight hours. The ability to control or eradicate pests and illnesses influences oil palm yield in addition to vegetative growth and production (Biodun et.al, 2020). To accurately classify soils and identify sites or places with comparable oil qualities, it is crucial to understand the amounts and patterns of soil diversity in the research areas.

When assessing land suitability for oil palm cultivation, several environmental factors must be considered, including climatic conditions, existing vegetation, and soil characteristics. The soils conducive to oil palm growth can be categorized into five distinct types based on their morphological properties and the underlying geology that influences vegetation patterns. These categories include crystalline metamorphic and igneous rocks, shale mixed with sandstone, coastal plain sand, coastal alluvium, and freshwater swamps. Each of these soil types is presumed to exhibit variations in physicochemical properties, which are crucial for determining optimal land for oil palm agriculture. While various methodologies can facilitate the classification of soil into one of these five types based on specific properties, this study will implement discriminant analysis, focusing on the physicochemical characteristics of soil samples from the Raphia region of Nigeria.

This study is necessary because not only will it provide the necessary information about the sites in the group, but the results generated for the group will also be useful elsewhere in the cluster, it will not be restricted to a specific location. Compared to site-by-site surveys, dedicated group surveys will help inform management processes and recommendations, thereby reducing research costs and ensuring higher outcomes, especially for farmers and other stakeholders.

1.2. Objectives

The following goals are being pursued by the research in order to utilize discriminant analysis.

1. To determine which properties of the soil sites allow for the greatest soil type discrimination.

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2. To create linear combinations of the predicting variables that discriminates and show significant differences in the group means.
3. To determine the discriminant analysis's accuracy in identifying Nigeria's oil palm-growing soil.
4. To accurately identify and categorise future undiscovered samples into one of the five soil categories, based on established predictors (soil attributes), in soils sustaining Raphia palms in southern Nigeria, using discriminant analysis to predict soil affiliations.

Discriminant analysis is a multivariate statistical technique that is useful for forecasting group membership based on a collection of factors or predictors (Tabacchnick and Fidell, 1989). The statistical approaches seem to be crucial for classifying soil, but pedologists haven't given them much thought. In his 1970 paper, Norris outlined several persuasive arguments in favour of using multivariate statistical techniques in soil science research. These techniques have the potential to disclose previously unknown soil structure and relationships among several, often connected components. Multivariate analysis makes it possible to examine the variables objectively and impartially, preventing erroneous or incomplete conclusions from being drawn from preconceived notions. Ultimately, the proficiency in statistical techniques necessary for the appropriate implementation of multivariate analyses ought to yield an accurate and replicable outcome that is unattainable using non-numeric approaches (Norris, 1970).

2.0 LITERATURE REVIEW

Fruit from the palm is produced in bunches weighing between 10 and 40 kg. The fruit, which weighs between 6 and 20 grams, is composed of an exocarp (outer skin), an endocarp (middle nut) with a fibrous matrix carrying the palm oil, and a kernel (inner nut) that has an oil that is considerably different from palm oil and more like coconut oil. The wild oil palm groves of Central and West Africa are predominantly composed of the Dura variety, characterized by its thick shell and thin mesocarp. In contrast, Tenera is a hybrid variant that has been developed through selective breeding, primarily between Dura and the shell-less Pisifera. This hybrid exhibits a notably thicker mesocarp along with a reduced shell thickness, optimizing oil yield

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and extraction efficiency.

This later variety, whose fruits contain significantly more palm oil than the native Dura, is currently the basis for all breeding and planting initiatives. The method that is currently most frequently employed for classifying soil is the natural system approach. This method, which includes the USDA Taxonomy, the FAO, and the French method, Kang (1981), involves classifying soils according to their inherent characteristics (soil morphology). But the most widely utilized systems in Nigeria are the USDA and FAO, which have drawn interest from all around the world (Esu, 2004). A multivariate statistical technique called discriminant analysis can be used to forecast group membership based on a collection of factors or predictors (Tabacchnick and Fidell, 1989). Despite its apparent importance for classifying soil, pedologists have paid little attention to this statistical technique. Important arguments in favour of applying multivariate statistical techniques to soil science research were outlined by Norris (1970). The structure and relationships between the numerous, frequently interconnected characteristics that define soils may become clearer with the use of these techniques. Multivariate studies enable an impartial, objective analysis of the variables, preventing erroneous or incomplete conclusions from being drawn from preconceived notions. Finally, the application of multivariate analyses necessitates a level of statistical expertise that yields precise and reproducible conclusions, which are unattainable through non-numeric methods (Norris, 1970). Prior uses of discriminant analysis in soil science have been to identify typical general classes of soil over large geophysical provinces (Webster and Burrough, 1974) and to classify phases of development on sand dunes (Berg, 1980). Discriminant analysis has proven to be more effective than soil taxonomy in predicting soil response classes, claim Edmonds and Lentner (1987). In addition, Lentz and Simonson (1987) classified soils linked to sagebrush communities using discriminant analysis. Their investigation showed that the key factors for differentiating across soil classes were the characteristics of the soil other than those considered in soil taxonomy.

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3.0 MATERIALS AND METHODS

The data employed in this research was gathered from the Chemistry Division of The Nigerian Institute for Oil Palm Research (NIFOR). The study used soil samples taken from 57 sites and five different soil types in southern Nigeria, a region thought to be suited for growing Raphia palms. The physicochemical properties of each of the 57 samples are detailed below. Detailed below are the physicochemical characteristics for each of the 57 samples.

With a set of W independent variables $X_1, X_{2,\dots\dots} X_{13}$ (Soil Characteristics: Soil pH (pH), Organic Matter (Orgm), Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mn), Magnesium (Mg), Sulphur (S), Iron (Fe), Copper (Cu), Zinc (Zn), Boron (B)), Multiple Discriminant Analysis (MDA) seeks to determine the linear combination (Discriminant Function) of these variables that most effectively distinguishes between the groups of cases $Z_{1,} Z_{2,\dots\dots\dots} Z_5$ (Soil types: Crystalline metamorphic and igneous rocks, shale mixed with sandstone, coastal plain sand, coastal alluvium, and freshwater swamps). A sample of cases in which the group membership is already identified is used to generate the functions. These functions are then used in fresh scenarios where the group membership is unknown but the predictor variables have measurements.

In general form, the discriminant function is expressed as:

$$Z = a + W_1X_1 + W_2X_2 + \cdots + W_kX_k$$

Where

Z = Discriminant Score,

a = Discriminant Constant,

W_k = Discriminant Weight or Coefficients,

X_k = an Independents Variables or Predictors Variables.

The method automatically selects an initial discriminant function that optimally delineates the groups with the highest possible significance. Subsequently, it identifies a second function that minimizes the overlap with the first and maximizes the separation of the groups. This process continues iteratively, adding functions until it reaches the maximum number permissible, determined by the number of predictor variables and the categories within the dependent variable. In the case of two groups, only one discriminant function is applicable. However,

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when extending to multiple groups, the resulting discriminant functions are orthogonal to one another.

The efficacy of each discriminant function is quantitatively assessed through several metrics, including Eigenvalues, Canonical Correlation, and Wilks' Lambda.

The Eigen-value (λ), also known as its distinctive root, represents the relative discriminating strength of discriminant functions. Each discriminant function has a single Eigen-value. When there are many functions, the first is the largest and most significant, followed by the second, which is the next most essential in terms of the explanatory capacity. This may be simply described as:

$$\boldsymbol{\lambda} = \frac{\boldsymbol{BSS}}{\boldsymbol{WSS}} = [\ \Sigma(\check{z}_J - \check{z})^2 / \Sigma(z_{ij} - \check{z}_J)^2$$

Where, BSS stands for between-group variance, while WSS stands for within-group variance

If $\boldsymbol{\lambda}$=0, the discriminant function lacks any meaningful discriminative capability. Conversely, a higher value indicates greater discriminative power.

The Canonical Correlation, eta (η) quantifies the association between the groups formed by the dependent variable and the resultant discriminant function. It is defined mathematically as follows:

$$\eta = \sqrt{\boldsymbol{\lambda}/(\mathbf{1} - \boldsymbol{\lambda})} = \sqrt{\boldsymbol{BSS/TSS}}$$

Here, BSS refers to the between-group variance, and TSS (Total Sum of Squares) encompasses the overall variance in the data

η (canonical correlation) serves as an indicator of the relationship between the predictor variables and the discriminant scores generated by the model, effectively measuring the association among the discriminant scores across the identified groups.

$$\eta^2 = \boldsymbol{coefficient\ of\ determination}$$

$$\mathbf{1} - \eta^2 = \boldsymbol{coefficient\ of\ non - determination}$$

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A high canonical correlation, approaching 1, indicates a robust association between the discriminant functions and the groups, signifying effective discrimination among the groups. Conversely, a correlation of 0 suggests there is no discernible relationship between the groups and the functions.

Wilks' lambda (Λ) serves as a metric for assessing the overall significance of the discriminant function. It is defined as follows:

$$\boldsymbol{\Lambda = (1 - \square^2) = \left[\frac{1}{1+\lambda}\right] = WSS/TSS}$$

Where WSS represents the within-group sum of squares and TSS signifies the total sum of squares. A significant Wilks' lambda allows for the rejection of the null hypothesis, indicating that the groups do not share the same mean discriminant function score.

A significant Wilks' lambda allows for the rejection of the null hypothesis, indicating that the groups do not share the same mean discriminant function score.

To evaluate the significance of differences in mean discriminant scores across groups, the chi-square statistic (χ^2) is utilized, formulated as:

$$\boldsymbol{X^2 = -[(n-1) - 0.5(m+k+1)]1nA}$$

In this context, K-1 denotes the degrees of freedom (df) for a particular function, which is derived from the number of continuous discriminant variables and the number of groups classified by the categorical variables. Here, **k** represents the number of predictor variables, while **m** indicates the number of discriminant functions that have been extracted.

A chi-square distribution, characterized by specific degrees of freedom, was deployed to compare against the chi-square statistic. Additionally, the p-value associated with the chi-square statistic was provided. The null hypothesis, which posits that the canonical correlation of a particular function is equal to zero, as well as any lesser canonical correlations, is rejected if the p-value is less than a predetermined significance level, such as 0.05. Conversely, if the p-value exceeds this threshold, the null hypothesis cannot be rejected.

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To evaluate the discriminant function's classification performance, the overall hit ratio—which shows the proportion of initial group cases correctly classified—was employed. The proportional chance criteria, Press's Q statistic, and the Maximum Chance criteria (MCC) are the three benchmarks used in this research. The model is deemed significantly superior to random chance if the hit ratio exceeds both the group maximum and the proportional chance values. The definitions of these statistics are as follows:

Maximum Chance Criterion (MCC) = $(N_I/N_L)(100)$

Where: N_I = number of subjects in the large group; N_L= total number of subjects in the combine; Proportional Chance Criterion

C pro=$\sum p_j^2$

Where,

p_j = Proportional of subjects in each group

- Press Q statistic

Q= $[N-(n)(g)]^2/[N-(g-1)]$

N= total number of subjects

N= number of groups

g= number of groups

Q ~X_{g-1}^2

Since Q is close to the Chi-square value, its value is compared to the Chi-square distribution at g-1 degree of
Freedom. If Q is Q, the null hypothesis that the model hit ratio is not considerably better than chance is rejected; if Q is not, it is accepted.

The cutting score, which, for equal groups, is exactly at the halfway point between the two centroids, was utilised to build the classification matrix. This is defined as;

$Z_{cs} = N_A Z_B + \frac{N_B Z_A}{N_A} + N_B$ Where

Z_{cs}= Optimum cutting score between groups A and B.

N_A= No of observation in group A

N_B= No of observation in group B

Z_A= Centroid for group A

Z_B= Centroid for group B

For unequal group

Z_{cs}= $Z_A + Z_B/2$ Where

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Z_{cs}= Optimum cutting score for equal group size.
Z_A= Centroid for group A
Z_B= Centroid for group B

To ascertain the significance of the predictors, it is essential to conduct tests that evaluate the differences among the groups. In this context, the following hypothesis was examined:

$H_0 := u_1 = u_2 = u_3 = u_4 = u_5$ Where

$H_1 :;= u_1 = u_2 = u_3 = u_4 = u_5$

$u_1 = u_2 = u_3 = u_4 = u_5$ Are the population means of groups 1,2,3,4 and 5, respectively?

The hypothesis outlined above can be evaluated employing Wilks' lambda test statistic, which is defined as follows

$$\lambda = \frac{BSS}{WSS} = [\ \Sigma(\check{z}_J - \check{z})^2 / \Sigma(z_{iJ} - \check{z}_J)^2$$

Wilk's lambda values range from 0 to 1, where lower values signify greater dissimilarity among groups. Conversely, values closer to 1 suggest a lack of distinction between groups. A smaller lambda for a predictor indicates a stronger contribution to the discriminant function. Additionally, the F test associated with Wilk's lambda assesses the significance of each variable's contribution within the context of the model. The F-test can be defined as;

$$F = \left[1 - \frac{\frac{\lambda_k - 1}{\lambda_k}}{\frac{\lambda_k - 1}{\lambda_k}}\right] / \ [(N\text{-}g\text{-}1)/(g\text{-}1)]$$

Where
N= total sample size,
G= number of dependent variables (group),
d.f (N-g-1) and (g-1)
If the significance value is small (<0.05), this indicates that the variable contributes to group differences.

4.0 RESULTS AND DISCUSSION

Table 1 displays the analysis findings for the four discriminant functions. Each indicator's comprehensive meaning is provided by the coefficients linked to these discriminant capacities, and the sign denotes the direction of their relationships. The most powerful predictor among the major functions that were statistically significant ($p < 0.05$) was nitrogen (N), closely followed by Soil pH (pH). The soil types show a favourable association with both measures. The

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secondary functions are as follows: K, N, and pH are strong predictors of the second function, whereas K and N are the strongest predictors of the third and fourth functions, respectively. The results of this study indicate that the categorisation of soil types is significantly influenced by the significant coefficients of N, pH, and K.

Table 2 presents the statistical metrics including Eigen-values, Canonical correlation, Wilks' lambda, Chi-square Statistics, and associated p-values, which are crucial for assessing the discriminative power of the functions under investigation. A total of four functions were analyzed (as seen in Table 3), but only one function demonstrated a significant Eigenvalue of 1.315, accounting for 55.6% of the variation in soil types (refer to Table 4).

The calculated Canonical Correlation of 0.754 indicates a strong relationship between the groups and the discriminant scores, suggesting effective separation among the five groups examined. Wilks' lambda value of 0.178 supports the notion of significant variability in the soil types represented in the discriminant model.

In summary, the analysis reveals that 55.6% of the variance can be attributed to the distinctions among groups (1, 2, 3, 4, and 5). The chi-square Statistic value is reported at 82.503, further affirming the robustness of the findings.

Table 1: The linear Discriminant Function Coefficient for the Soil Groups

Variables	Z_1	Z_2	Z_3	Z_4
Constant	-8.403	4.949	-5.567	-5.567
B	0.625	0.090	1.084	0.689
Orgm	-0.032	-0.147	0.023	-0.193
Zn	0.005	0.049	0.035	-0.003
P	0.052	-0.058	0.177	0.005
pH	1.324	-1.104	0.608	0.399
Ca	0.0232	0.600	0.123	-0.077
Cu	0.199	-0.195	0.072	0.052
S	-0.062	0.023	0.009	0.046
Mn	0.024	-0.005	0.009	0.018
Fe	0.003	0.008	0.003	0.001
K	0.546	-2.083	-2.174	0.897
N	3.386	1.029	0.382	-2.702
Mg	0.324	0.449	-0.550	-0.632

Source: Authors' Analysis (2025).

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The results indicate a significant difference between group centroids ($p < 0.05$), leading us to reject the null hypothesis of equal means across the groups. The analysis of Wilks' Lambda and Chi-square statistic provided robust evidence for this distinction. The calculated Press' Q statistic is 8.96, exceeding the threshold for chance, which suggests that the discriminant model demonstrates considerable strength in classifying the soil types within the study area, rendering it suitable for further investigation.

In Table 3, we present a comparison between the actual classifications of the five soil types and those predicted by the discriminant functions. Notably, groups 1 and 5 exhibited high classification accuracy, with 75% of cases correctly assigned, reflecting the efficacy of the discriminant functions. In contrast, groups 2 and 4 had slightly lower accuracy, just below 60%. Overall, the hit ratio for correct classifications was 67.7%, indicating that approximately 33% of the cases were misclassified. This performance aligns well with previous findings, such as the 67% accuracy reported by Fincher and Marie-Louise Smith in 1993 and the 72% accuracy noted by Stacy Campbell.

Using these criteria, the model's prediction accuracy was evaluated. Both the maximum and proportionate chance numbers of 27.59% and 21.22% are exceeded by the total hit ratio of 67.7%. Additionally, the Press Q statistic of 347.57 greatly surpasses the tabulated value of 11.1, confirming that the model's prediction accuracy is significantly higher than what could be attributed to chance alone.

Table 2: Test of Significance for the Discriminant Function.

Function	% of Varian.	Canonical correlation	Eigen values	Chi square	Wilks Lambda	Significant Value
1	55.6	0.754	1.315	82.503	0.178	0.004
2	20.7	0.574	0.491	42.211	0.415	0.221
3	18.3	0.550	0.433	23.039	0.619	0.400
4	5.4	0.336	0.128	5.767	0.887	0.834

Source: Authors' Analysis (2025).

Table 3: Classification performance of the estimated Discriminant Function

Actual Group	No of Cases	Predicted	Group	Membership		
		1	2	3	4	5
1	16	12(75%)	2(12.5%)	0(0%)	0(0%)	2(12.5%)
2	12	1(8.3)	7(58.3%)	2(16,7%)	0(0%)	2(16.7%)
3	13	0(0%)	1(7.7%)	9(64.2%)	1(11.%)	5(56.8%)
4	9	1(11.1%)	1(11.1%)	1(11.%)	5(56.8%)	1(11.1%)
5	8	0(0%)	0(0%)	2(25.0%)	0(0%)	6(75.0%)

67.7 of the cases were correctly classified. 32.8 of the cases were not correctly classified.
Source: Authors' Analysis (2025).

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Table 4 presents Wilks' lambda, the F statistics, and their significance levels. Analysis reveals that out of the thirteen indicator factors examined, seven (PH, P, K, Ca, Mg, Mn, Cu) demonstrate statistical significance in the model. Notably, magnesium (Mg) emerges as the most effective discriminator among the groups, closely followed by Soil pH (pH), phosphorus (P), calcium (Ca), manganese (Mn), and copper (Cu), with potassium (K) showing the least discriminative power. These findings indicate that soil types are predominantly influenced by these seven factors. Conversely, the inter-group variability of the remaining six factors—organic matter (orgm), nitrogen (N), sulfur (S), iron (Fe), zinc (Zn), and boron (B)—is insufficient to differentiate among the groups within the surveyed areas, suggesting a relative uniformity in their concentrations.

Table 4: Characteristics of soil location that best discriminate among the soil parents Materials

Variables	Group 1 Mean	Group 2 Mean	Group 3 Mean	Group 4 Mean	Group 5 Mean	Wilks` Lambda	F - Value	P - Value
PH	5.7812	5.2250	5.0538	5.0111	4.9000	.802	3.268	.018*
Orgm	3.2200	3.5850	2.8092	5.8366	4.7512	.912	1.278	.290
N	.1695	.16050	.1261	.2223	.2024	.934	.937	.450
P	5.3750	8.4167	8.9231	14.000	5.5000	.785	3.628	.011*
K	.3000	.14583	.1315	.18556	.0975	.843	2.465	.056*
Ca	2.4037	2.1916	.4961	1.11667	.2938	.810	3.117	.22*
Mg	1.6968	.82917	.30154	.69889	.2238	.596	8.986	.000**
S	11.0312	14.7750	16.8077	17.5000	16.2125	.890	1.641	.178
Fe	77.5625	133.500	75.4615	68.7778	79.000	.907	1.364	.259
Mn	26.7188	14.5333	8.5692	9.8111	3.7125	.810	3.102	.023*
Cu	4.3438	1.89167	1.5231	3.5777	.5375	.787	3.590	.012*
Zn	8.4000	10.0500	3.7846	7.7333	2.5500	.913	1.265	.295
B	.6150	.49750	.50462	.54222	.1938	.937	.895	.474

*Significant ($p<0.05$).
Source: Authors' Analysis (2025).

5.0 CONCLUSION

A small number of variables—specifically, Magnesium (Mg), Phosphorus (P), Copper (Cu), Soil pH (pH), Calcium (Ca), Manganese (Mn), and Potassium (K)—suffice to clarify the nutrient requirements of oil palm within the tract, as demonstrated by discriminant analysis, which successfully condensed the 13 physical characteristics analysed in the study to seven essential components. This decrease suggests that a more condensed collection of soil characteristics can effectively represent the nutrient dynamics required for the best oil palm development, as well as provide insight into the general significance of each property in describing the soil.

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Based on comparable soil features, cluster analysis was able to successfully divide the 57 agricultural fields into five unique groups. This showed that the oil palm belt's soil variability could be adequately categorised into these five clusters based on their respective attributes.

Our understanding of soil variability in Nigeria's oil palm region is improved by the results, which highlight the usefulness of many multivariate statistical approaches as useful instruments for soil evaluation. This information will be crucial for assessing soil diversity for crop enhancement projects and developing agricultural management strategies especially suited to the region's oil palm industry.

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Competing Interest
The authors declared that no competing interest exited in this manuscript.

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