Uleam UNIVERSIDAD LAICA ELOY ALFARO DE MANABÍ SAPIENTIAE

ADVANCED MULTIVARIATE MODELS FOR THE OPTIMIZATION OF NUTRITIONAL STRATEGIES IN COMMERCIAL BANANA PRODUCTION (*MUSA AAA*)

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RESUMEN

Este artículo analiza la optimización de los planes nutricionales en la producción de banano, un cultivo clave para la economía de países ubicados en regiones tropicales y subtropicales. Se destaca la importancia de implementar modelos multivariados para mejorar la eficiencia y la productividad en plantaciones comerciales, facilitando la toma de decisiones basadas en datos precisos. La investigación combina el análisis foliar y el análisis de suelo para comprender integralmente el estado nutricional de las plantas. Este enfoque se aplica específicamente al banano. Se utilizaron análisis de componentes principales (ACP) y análisis de conglomerados para identificar patrones y reducir la dimensionalidad de los datos. Se emplearon los métodos de Ward y K-medias para discriminar grupos según la similitud de las condiciones nutricionales. Los resultados permitieron agrupar lotes de banano, identificando estrategias de manejo más efectivas. Además, se observó una alta correlación entre las variables estudiadas, lo que respalda la utilidad de las correlaciones de Pearson en la investigación agrícola. La implementación de modelos multivariados no solo mejora la gestión de nutrientes, sino que también fomenta prácticas agrícolas sostenibles, contribuyendo a la productividad y sostenibilidad del cultivo del banano en un contexto agrícola moderno y dinámico.

Palabras clave: *Modelos multivariados, toma de decisiones, planes nutricionales, banana.*

MODELOS MULTIVARIADOS AVANZADOS PARA LA OPTIMIZACIÓN DE ESTRATEGIAS NUTRICIONALES EN LA PRODUCCIÓN COMERCIAL DE BANANO (MUSA AAA)

ABSTRACT

This article analyzes the optimization of nutritional plans in banana production, a key crop for the economy of countries located in tropical and subtropical regions. The importance of implementing multivariate models to improve efficiency and productivity in commercial plantations is highlighted, facilitating decision-making based on accurate data. The research combines foliar analysis and soil analysis to comprehensively understand the nutritional status of plants. This approach applies specifically to bananas. Principal component analysis (PCA) and cluster analysis were used to identify patterns and reduce the dimensionality of the data. Ward and K-means methods were used to discriminate groups according to the similarity of nutritional conditions. The results allowed grouping banana lots, identifying more sustainable management strategies effective. In addition, a high correlation was observed between the variables studied, which supports the usefulness of Pearson correlations in agricultural research. The implementation of multivariate models not only improves nutrient management, but also encourages sustainable agricultural practices, contributing to the productivity and sustainability of banana cultivation in a modern and dynamic agricultural context.

Keywords: *Multivariate models, decision making, nutritional plans, bananas.*

1. INTRODUCTION

Global banana production, *Musa paradisiaca L.*, plays a fundamental role in the global economy and food security. It is a priority to optimize nutritional plans to maximize the yield and quality of this crop (Ploetz *et al.*, 2015). In this sense, multivariate models are presented as advanced analytical tools that allow accurate and data-driven decisions to be made, addressing the inherent complexity of modern agricultural systems (Ding *et al*., 2018). It is essential to implement the use of statistical mathematical models to optimize efficiency and productivity in commercial banana plantations, therefore, multivariate models seem to provide a wide range of possibilities to be used in decision-making to facilitate agro-productive management (Arias *et al*., 2021).

Multivariate models not only allow for improved decision-making related to nutrient management and more effective management of environmental variables, but also facilitate strategic decision-making based on concrete data, which is critical to meeting the complex and dynamic challenges of modern agricultural systems (Jones *et al*., 2017).

These techniques allow the integration of environmental variables, agronomic management practices and the nutritional status of banana plants, using models such as principal component analysis, cluster analysis and multivariate regression analysis to group by similarity and model the crop's responses to various conditions (Cornejo-Reyes & Inca, 2022). Multivariate regression is a crucial technique to understand how key variables, such as plant nutritional status and environmental conditions, directly influence banana crop yield (Saed-Moucheshi *et al*., 2013).

The implementation of multivariate techniques as a basis for decision-making in agriculture is part of the modern era and a new way of doing agriculture. In the specific case of plant nutrition, it will allow a better discernment in the nutritional management of commercial banana plantations, which would translate into significant increases in yields and fruit quality. In this way, sustainable agricultural practices are promoted by reducing the inefficient use of inputs and minimizing environmental impact (Flintlocksmith *et al*., 2023; of God *et al*., 2020; Jayasinghe *et al*., 2022).

The purpose of this research was to evaluate the use of the main techniques of multivariate statistics to facilitate decision-making related to the application of a specific and rigorous nutritional plan that allows zoning according to nutritional characteristics of similarity, as a strategy in order to increase yields potentially. This approach not only seeks to increase yields, but also to promote an integral and responsible management of agricultural systems, highlighting the importance of sustainable practices in agriculture.

2. MATERIALS AND METHODS

Location of the research

The research was carried out at Hacienda Naida, located in the Las Palmitas zone, La Esperanza Parish, Valencia canton, Los Ríos Province, Ecuador. The experimental site is located at the geographical coordinates 0°50'17.3" S latitude and 79°23'33.7" W longitude, at an altitude of 118 meters above sea level.

Experiment Management

The research was carried out in a commercial banana plantation cv. *Williams* established six years ago. Conventional agronomic work on the farm was implemented to maintain standard production and management conditions.

Variables evaluated

Nutritional levels in soil

To carry out the chemical analysis of the soil, 36 sampling points were selected within the banana plantation, considering two sampling points per lot. The samples were sent to the Department of Soils and Water of the Pichilingue Tropical Experimental Station ofl INIAP for detailed analysis. Nitrogen (N), phosphorus (P), calcium (Ca), magnesium (Mg), potassium (K), sulfur (S), copper (Cu), zinc (Zn), boron (B), iron (Fe), manganese (Mn), organic matter, and pH levels were determined using recognized standard methods, such as Olsen's Modified method for phosphorus. These methods can provide more accurate and reliable results, forming a solid basis for assessing soil conditions and developing agronomic management strategies to improve productivity (Khan *et al.*, 2024).

Nutritional levels in plant tissue

Leaf tissue samples were taken from banana plants to evaluate the contents of N, P, Ca, Mg, K, S, Cu, Zn, B, Fe and Mn in the plant tissue. These leaf samples were processed in the Department of Soils and Water of the Pichilingue Tropical Experimental Station of INIAP for detailed analysis, following standardized procedures for the chemical analysis of nutrients in plants. This foliar analysis made it possible to complement the soil data, providing a holistic view of the crop's nutritional status.

Multivariate statistical models used

For the purposes of grouping batches by similarity distances, principal component analysis (PCA) and cluster analysis were applied to identify patterns and reduce the dimensionality of the data. For this, the method of Ward2 and K means=6 was used for the discrimination of the groups.

Subsequently, the groupings obtained and related previously in the cluster analysis were correlated by the PEARSON method and by the batches that made up each grouping. In this way, the intra- batch correlation was validated in order to standardize the data and based on that make subsequent decisions at the nutritional level. This intra-batch approach allows specific recommendations to be established to optimize commercial banana production.

Principal Component Analysis

To address the complexity of the data, we apply principal component analysis (PCA). This technique allowed us to condense the information on soil fertility and nutritional status variables into a few main dimensions, facilitating the identification of key patterns and relationships. The ACP revealed the most influential variables and helped to clarify their impact on production, which allowed to generate practical recommendations to optimize agricultural management.

Cluster Analysis

We used cluster analysis to explore how observations are grouped based on soil fertility variables and crop nutritional status at the foliar level. This methodology allows us to identify natural groupings in the data, revealing how the different variables are related in specific contexts. By identifying these groups, we were able to better understand variations in production and design specific strategies to address the needs of each group, thus optimizing farm management.

Correlation

To check the closeness of the intra-cluster fertilization data, subgroups were selected for both edaphic nutritional variables and foliar nutritional variables resulting from cluster analysis through the K=means method. Subgroup "1" was chosen for the edaphic variables and subgroup "3" for the foliar variables. Validation through intragroup correlation allowed the standardization of the data.

3. RESULTS AND DISCUSSION

Principal Component Analysis (PCA)

Edaphic and foliar nutritional variables

The 11 edaphic nutritional variables (NH_4, P, Zn, Cu, Fe, Mn, B, S, K, Ca and Mg) were selected to differentiate the similarity between the studied batches. According to the Principal Component Analysis (PCA) performed for these variables (Table 1), 100% of the total variation was distributed in 11 principal components (Figure 1A). However, the first two components represented in Figure 1A together explained 46.9% of the total variation, with the first component explaining 29.5% and the second 17.4%.

In the first component, the most influential variables were Zn (0.46), Mg (0.45), Ca (0.44) and K (0.41). This suggests that batches with medium to high levels shared similar levels of Zn, Mg, Ca, and K. For the second component, the most prominent variables were Fe and Mn (Table 1).

In addition, Figure 1B shows the distribution of the 36 lots, evidencing a wide dispersion in the plane determined by the axes of components 1 and 2, grouped according to the similarity of the edaphic levels of macro and microelements (Figure 1B).

With respect to the foliar variables, the 11 nutritional variables sampled in the plant tissue (N, P, Zn, Cu, Fe, Mn, B, S, K, Ca and Mg) were chosen to distinguish the similarity between the analyzed lots.

According to the principal component analysis (PCA) performed for the leaf variables (Table 2), 100% of the total variation was distributed in 11 principal components (Figure 3A). However, the first two components, shown in Figure 3A, accounted for 33.1% of the total variation, with a contribution of 16.9% from the first component, which grouped the predominant characteristics in the PTA.

The second component contributed 16.2% to the variation (Figure 3A). In the first component, the most relevant variables were S (0.41) and N (0.37). These results suggest that batches with medium to high levels shared similar levels of macroelements S and N.

For the second component, the most prominent variables were Cu and S levels (Table 2). In addition, Figure 3B illustrates the distribution of the points corresponding to the 36 lots, showing a wide dispersion in the plane defined by the axes of components 1 and 2, grouped according to the leaf levels of similarity for the macro and micro elements (Figure 3B).

Lever *et al.*, (2017) states that principal component analysis (PCA) simplifies the complexity of high-dimensional data, while preserving trends and patterns. It does this by transforming data into fewer dimensions, which act as feature summaries. High-dimensional data are very common in biology and arise when multiple characteristics, such as the expression of many genes, are measured for each sample, however, the use of this statistical tool to improve the efficiency in decision-making of nutritional plans for commercial crops is little known.

In the same way, Jolliffe & Cadima, (2016) They state that some types of data present several challenges that PCA mitigates: computational expenses and a higher error rate due to correcting multiple tests when testing each feature for association with an outcome.

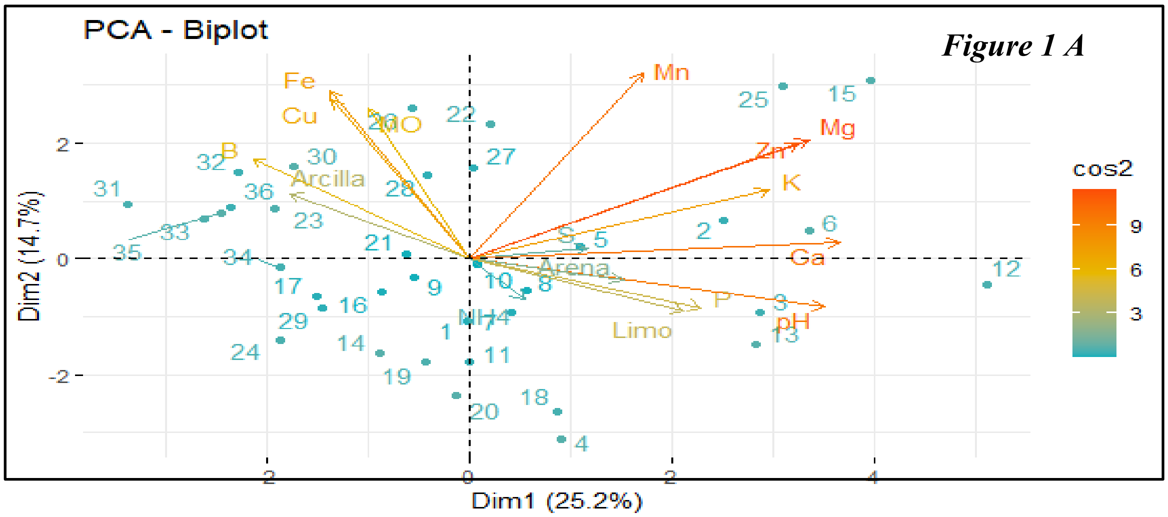
PCA is an unsupervised learning method and is similar to clustering. AndFind patterns without reference to prior knowledge about whether samples come from different treatment groups or have phenotypic differences (Vargas Sanchez *et al.*, 2022).

Likewise, some authors have launched the use of PCA as a grouping technique used in agronomy, for example, Garcés-Fiallos *et al.*, (2015) and Villamar-Torres *et al.*, (2018). In bean genotype studies, they used this tool to be able to group the variables that were made up of health variables and productive variables. The genotypes were grouped according to similarity and closeness to the vectors that represented the variables.

Table 1. *Principal component analysis of 11 edaphic and foliar nutritional variables for the 36 banana lots.*

Soil variables	CP1	CP2
NH_4	0,05	-0,24
P	0,27	-0,37
Zn	0,46	0,19
With	-0,05	0,37
Fe	-0,07	0,47
Mn	0,30	0,44
B	-0,17	0,38
S	0,16	-0,12
K	0,41	-0,01
Ca	0,44	-0,14
Mg	0,45	0,21
Foliar variables	**CP1**	**CP2**
N	0,37	-0,29
P	-0,32	0,29
K	-0,39	-0,26
Ca	0,62	-0,05
Mg	-0,12	-0,01
S	0,41	0,35
Zn	0,11	0,51
With	-0,08	0,48
Fe	-0,14	0,09
Mn	-0,04	0,11

Figure 1. *Principal Component Analysis (PCA) of the study soil variables.* ***(A)*** *Biplot of the ACP with lots and variables.* ***(B)*** *Scree plot showing the variance explained by each principal component.*



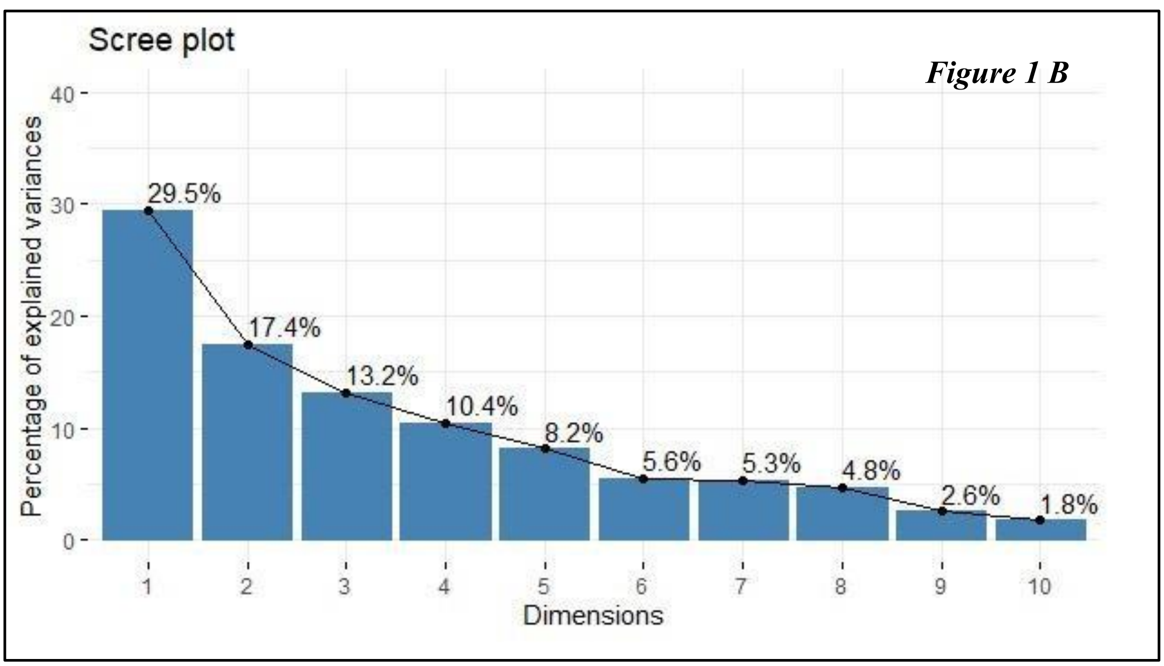
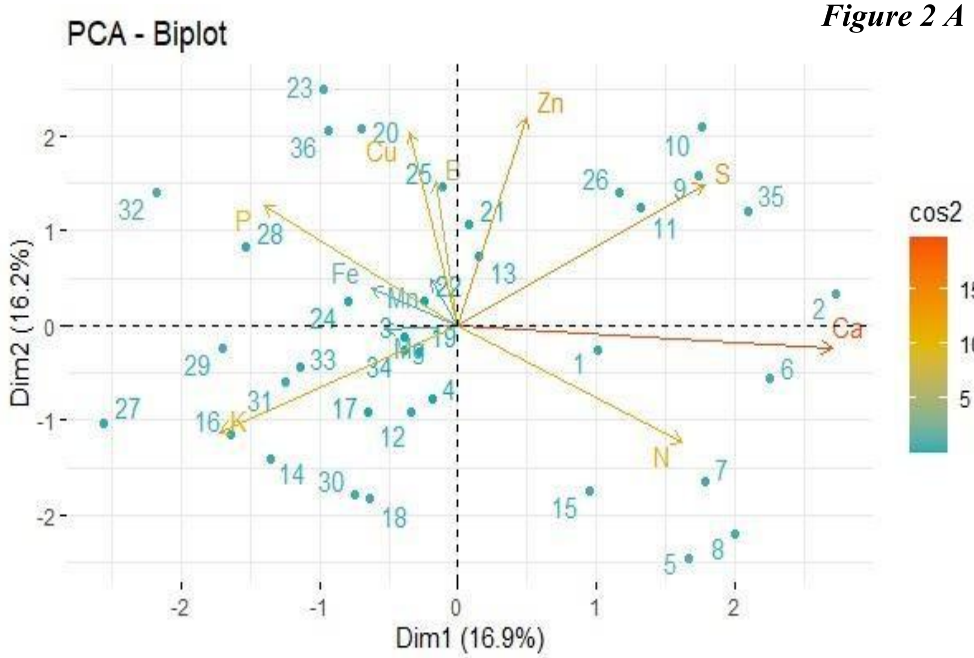


Figure 2. *Principal Component Analysis (PCA) of the study foliar variables evaluated.* ***(A)*** *Biplot of the ACP with lots and variables.* ***(B)*** *Scree plot showing the variance explained by each principal component.*

Figure 2 A



Cluster A

Edaphic and foliar nutritional variables

Figure 2 B

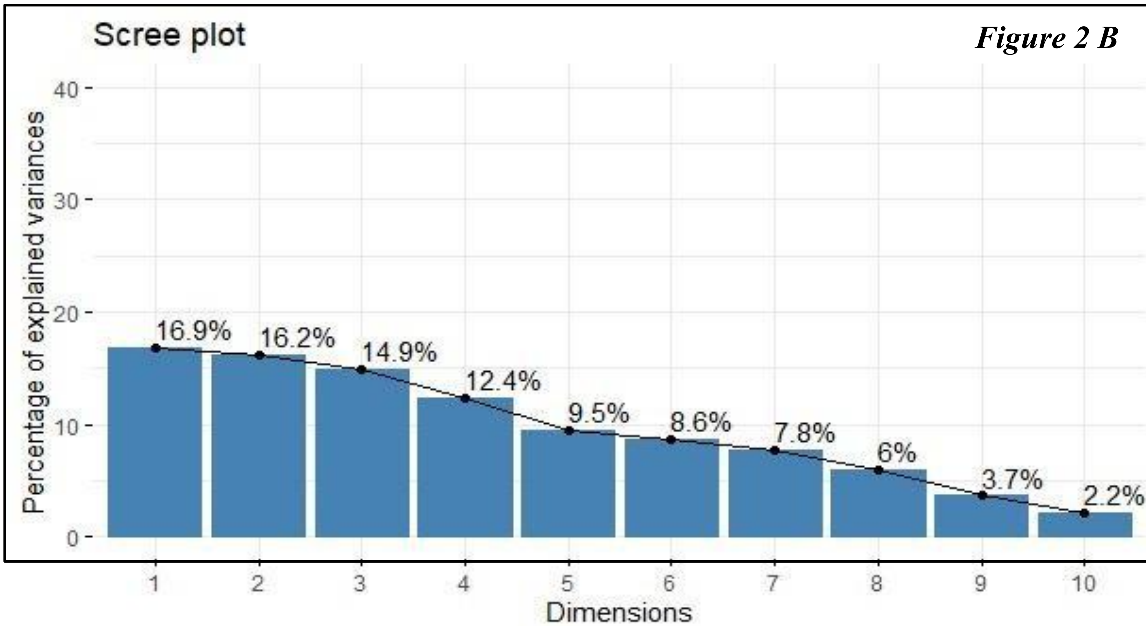
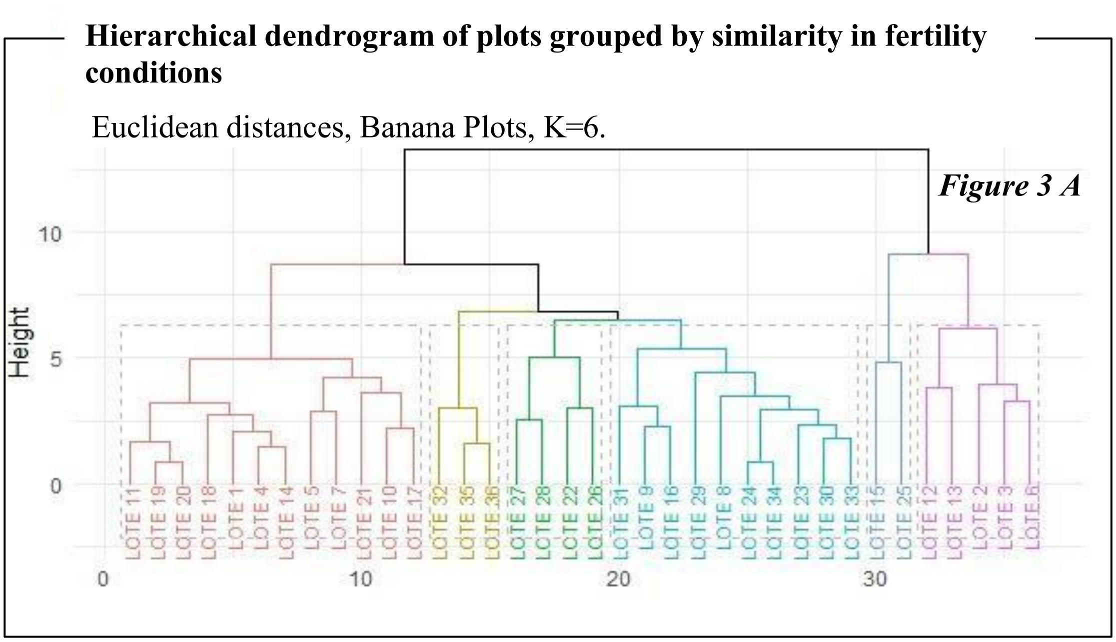
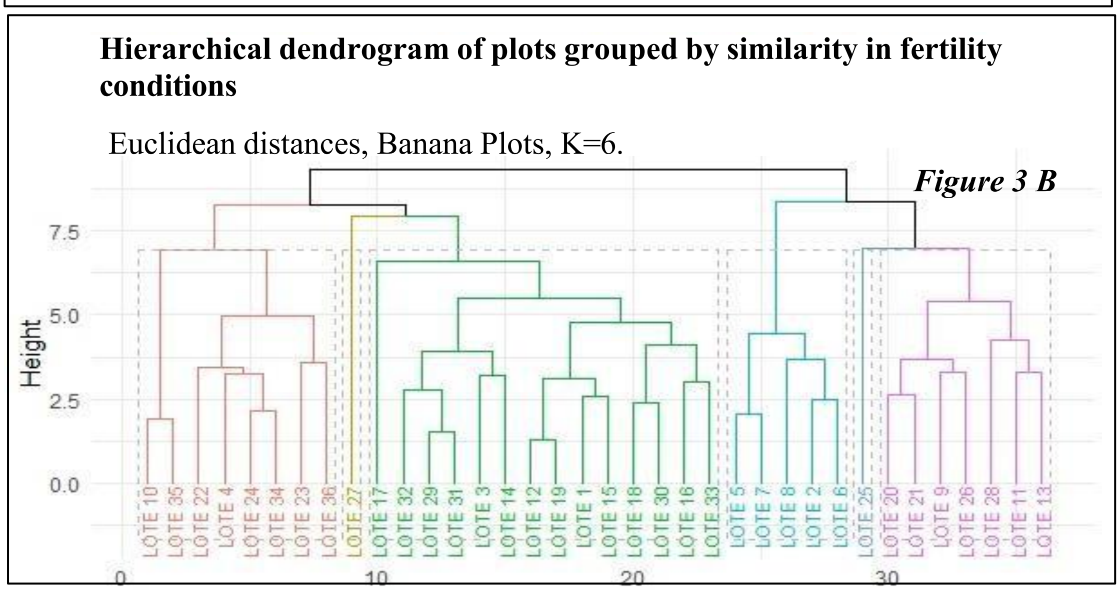


Figure 3. *Dendrogram of banana lots grouped by similarity in edaphic and foliar nutritional conditions using Euclidean distances and K=6.*





Dendrograms were generated using the Euclidean distance matrix for edaphic nutritional variables, applying the WARD2 average distance method. The variability observed between the batches (Figure 2) and the variables used to divide them into six subsets was carried out using the K = means technique (Figure 2), available in the RStudio 4.4.1 statistical package. All the subgroups formed presented common nutritional characteristics. The batches were grouped as follows: subset 1 (15 and 25); subset 2 (12, 2, 13, 3 and 6); subset 3 (4, 18, 11, 7, 1, 19 and 20); subset 4 (22, 26, 8, 5 and 10); subset 5 (29, 34, 30, 33, 32, 36, 21, 23 and 35); and subset 6 (31, 17, 24, 27, 28, 16, 9 and 14). Therefore, the ACP analysis and the dendrogram analysis allowed to identify clear differences between the studied batches, mainly based on their nutritional characteristics.

For the foliar nutritional variables, the same method was used as was proposed for the edaphic variables. The studied batches were grouped into the following subsets: subset 1 (, 35, 22, 4, 24, 34, 23 and 36); subset 2 (27); subset 3 (17, 32, 29, 31, 3, 14, 12, 19, 1, 15, 18, 30, 16 and 33); subset 4 (5, 7, 8, 2 and 6); subset 5 (25); and subset 6 (20, 21, 9, 26, 28, 11 and 13). The methods used in this study coincide with the results of Monsoon *et al.*, (2022), specifically in the dendrograms generated from the Euclidean distance matrix and the K-means clustering technique, which have proven to be robust tools for the analysis of nutritional variables.

The application of the WARD2 average distance method in dendrogram generation allowed for a clear visualization of variability between lots, which is essential for identifying patterns and relationships within complex soil nutrition data. Studies such as that of Miranda *et al.*, (2010) have shown that classification methods play an important role in identifying similarity and hierarchical distances, since the final results have the greatest possible reliability depend on it.

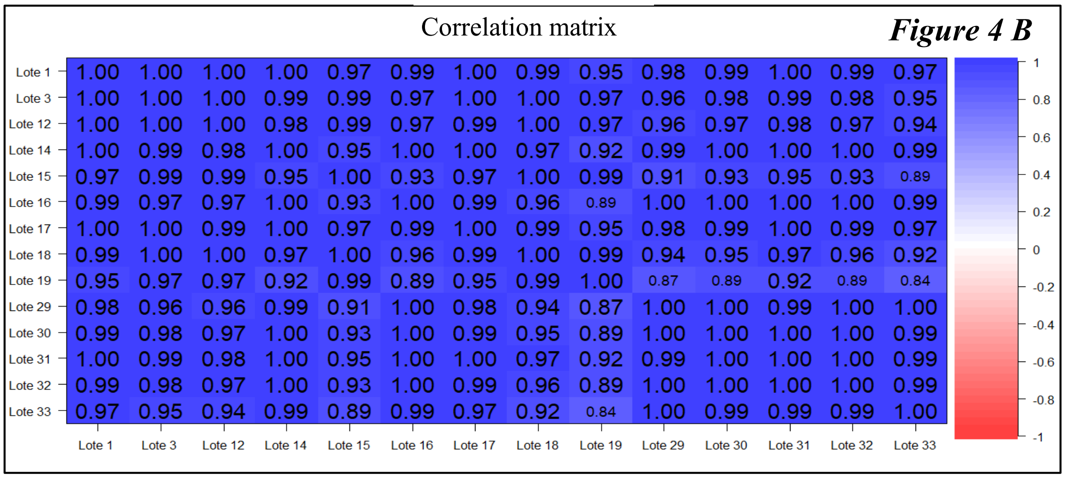
Intra-lot correlations

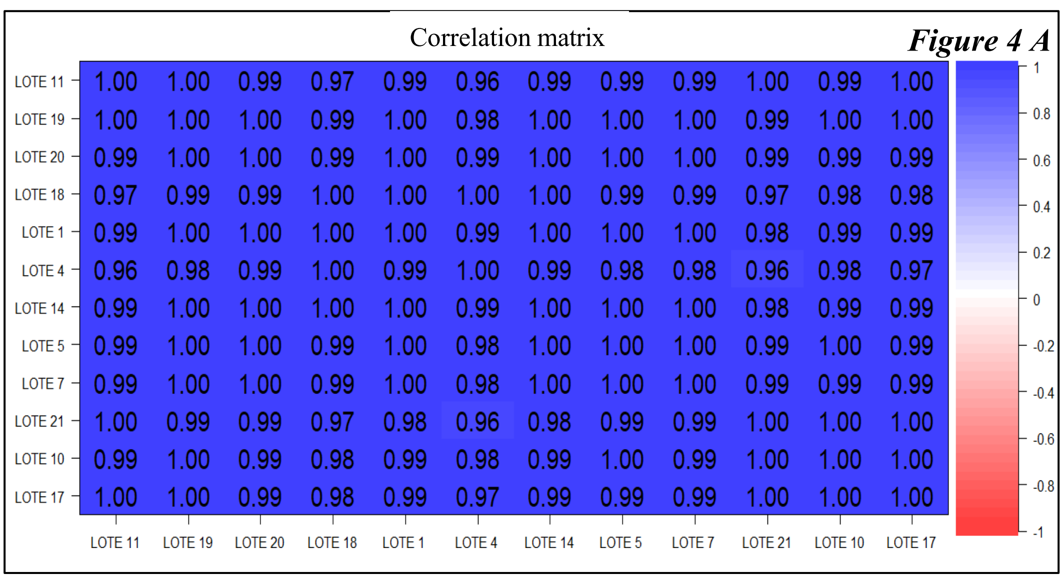
The results of the Pearson correlation coefficients between the edaphic and foliar nutritional variables are presented to establish relationships between the different batches. Figure 4, both subfigures A and B show the correlations corresponding to the batches selected in the dendrogram of subgroup "1" for the edaphic variables and subgroup "3" for the foliar variables, due to the greater number of batches represented in these subgroups. For all comparisons, positive R2 values close to 1 (CP > 0.8) were observed, which indicates a directly proportional correlation between all the variables under study. In Figure 4A, the correlations of these subgroups are high, with R2 values ranging from 0.96 to 1.00. In Figure 4B, lots 33 and 19 show a relationship with an R2 of 0.84, this being the lowest correlation within subgroup 3, while the other correlations between the lots vary between 0.87 and 1.00.

All these results have a concordance, as they denote the degree of association between the lots, being considered of vital importance for nutrient management in commercial banana plantations. Lalinde *et al.*, (2018) indicates that Pearson's correlation coefficient is a measure that is widely used in various areas of scientific work, from technical, econometric or engineering studies. It is precisely this extensive and profuse dissemination that would explain the improper use given to this statistical tool, especially in those scenarios in which it must be interpreted correctly or in which the mathematical assumptions that support it have to be verified.

On the other hand, the high correlation observed in Figures 4A and 4B, with R2 values close to 1, suggests a strong correlation between the batches grouped by similarity characteristics. This finding is consistent with previous studies that have demonstrated the usefulness of Pearson correlations in the evaluation of the relationship between agronomic variables (Tofiño-Rivera *et al.*, 2016).

Figure 4. *Correlation between banana lots grouped by similarity in edaphic and foliar nutritional conditions using Pearson.*





4. CONCLUSIONS

Principal component analyses (PCAs) and cluster analysis have identified significant patterns in soil and foliar nutritional variables, facilitating the zoning of banana plantations according to their specific nutritional needs. The application of Pearson's method to assess the correlation between nutritional variables has shown that there is a strong association between soil conditions and plant nutritional status, supporting the importance of an integrated approach to nutrient management.

The validation of the similarities between batches through the statistical techniques employed has provided a solid basis for the formulation of accurate recommendations in the implementation of nutritional plans, which can result in a significant increase in the yield and quality of the banana crop. The implementation of multivariate models not only improves efficiency in the use of inputs, but also promotes sustainable agricultural practices by reducing the environmental impact associated with the inefficient use of fertilizers and other resources.

5. Acknowledgement

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6. Authors' Conflict of Interest Statement

The authors declare no conflict of interest.

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