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CHARACTERIZATION OF STANDARD HYPERSPECTRAL REFLECTANCE SPECTRA FOR HIGH- AND LOW- PRODUCTIVITY SUGARCANE PLOTS USING FUNCTIONAL DATA ANALYSIS

CARACTERIZACIÓN DE ESPECTROS ESTÁNDAR DE REFLECTANCIA HIPERESPECTRAL PARA PARCELAS DE CAÑA DE AZÚCAR DE ALTA Y BAJA PRODUCTIVIDAD MEDIANTE ANÁLISIS DE DATOS FUNCIONALES

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RESUMEN

Contextualización: La caña de azúcar es un cultivo clave para la agricultura tropical y una fuente de azúcar, etanol y bioenergía. El Valle del Cauca, en Colombia, se encuentra entre las regiones productoras más eficientes del mundo. En este contexto, la intensificación sostenible exige métodos precisos y no destructivos para monitorear el desarrollo del cultivo y predecir su rendimiento.

Vacío de conocimiento: Los índices de vegetación tradicionales, calculados a partir de bandas multiespectrales amplias, como el índice de vegetación de diferencia normalizada, se saturan en doseles densos y presentan una sensibilidad limitada a variaciones fisiológicas y estructurales sutiles, lo que restringe la predicción temprana del rendimiento. Aunque el análisis hiperespectral ofrece un mayor nivel de detalle, la mayoría de los estudios se basa en índices discretos. La aplicación de enfoques estadísticos funcionales al cultivo de caña de azúcar aún es limitada, lo que deja un vacío en la clasificación temprana de la productividad.

Propósito: Este estudio evaluó si el análisis funcional de datos de reflectancia hiperespectral puede mejorar la clasificación temprana de la productividad de la caña de azúcar. Los objetivos fueron distinguir niveles de productividad, comparar mediciones a escala foliar y de dosel, y analizar la influencia de la etapa de crecimiento en la variabilidad espectral.

Metodología: Se recolectaron datos de reflectancia hiperespectral en seis parce-

las del Valle del Cauca durante dos etapas de crecimiento, a los 2,5 y 5,5 meses, tanto a escala foliar como de dosel. Los espectros sin procesar se transformaron en curvas funcionales continuas mediante suavizado con funciones B-spline. Posteriormente, se calcularon medias funcionales y se aplicaron pruebas t basadas en permutaciones para identificar diferencias significativas entre las clases de productividad.

Resultados y conclusiones: Los espectros del dosel permitieron distinguir con claridad las parcelas de alta y baja productividad, especialmente en la región del infrarrojo cercano, donde la mayor biomasa y área foliar de las parcelas con mayor rendimiento produjeron una reflectancia más alta. Los espectros foliares mostraron una capacidad de discriminación menor, en particular durante las etapas posteriores del crecimiento. El análisis funcional preservó características espectrales que los índices tradicionales pasaban por alto, lo que permitió interpretar mejor la variabilidad del cultivo. El análisis funcional de datos hiperespectrales a escala del dosel constituye una herramienta robusta y no destructiva para la evaluación temprana del rendimiento; asimismo, respalda la toma de decisiones en agricultura de precisión relacionadas con la fertilización, el riego y el manejo del cultivo.

Palabras clave: agricultura de precisión, espectrometría, productividad, reflectancia.

ABSTRACT

Contextualization: Sugarcane is a key crop in tropical agriculture, providing sugar, ethanol, and bioenergy. Valle del Cauca Department, Colombia, is among the world's most productive sugarcane-growing regions, where sustainable intensification requires accurate, nondestructive methods to monitor crop development and predict yield.

Knowledge gap: Traditional vegetation indices calculated from broad multispectral bands, such as the Normalized Difference Vegetation Index, saturate in dense canopies and have limited sensitivity to subtle physiological and structural variations, restricting early yield prediction. Although hyperspectral analysis provides greater detail, most studies rely on discrete indices. Functional statistical approaches remain underused in sugarcane research, leaving a gap in the early classification of productivity.

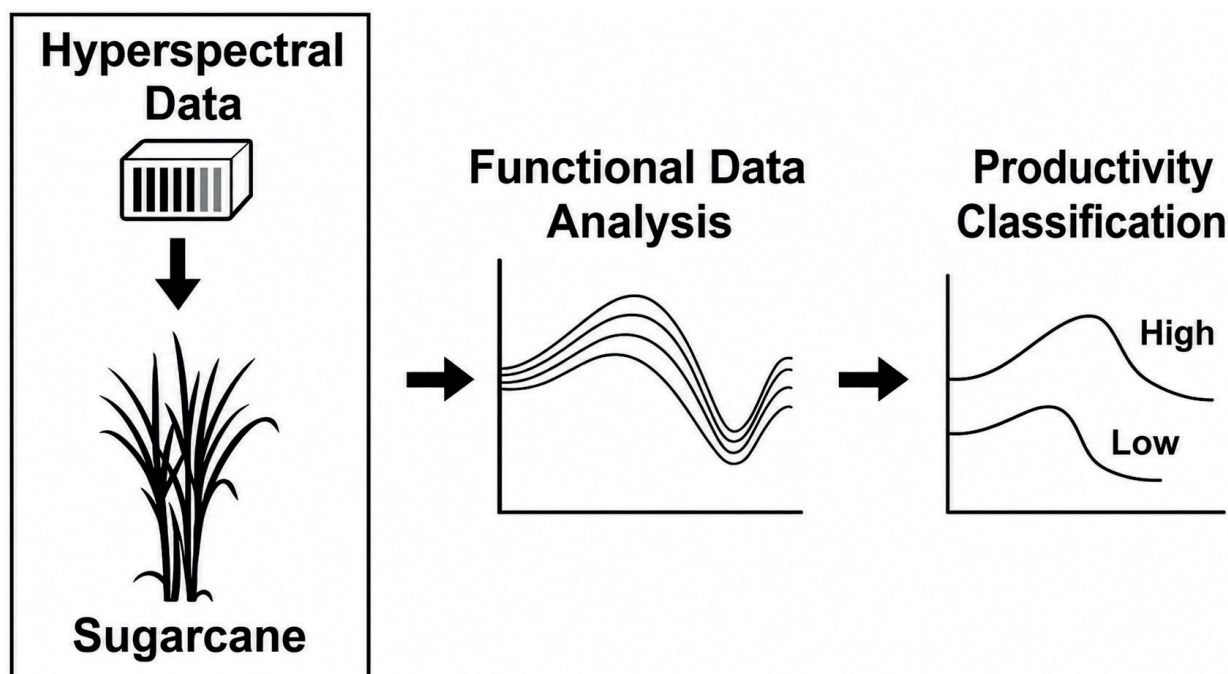
Objective: This study evaluated whether functional data analysis of hyperspectral reflectance can improve the early classification of sugarcane productivity. The specific objectives were to distinguish productivity levels, compare canopy- and leaf-scale measurements, and analyze the influence of growth stage on spectral variability.

Methodology: Hyperspectral reflectance data were collected from six plots in Valle del Cauca at two growth stages, 2.5 and 5.5 months, at both the canopy and leaf scales. The raw spectra were converted into continuous functional curves using B-spline smoothing. Functional means and permutation-based *t*-tests were then used to identify significant differences between productivity classes.

Results and conclusions: Canopy spectra clearly distinguished high- and low-productivity plots, particularly in the near-infrared region, where greater biomass and leaf area in high-productivity plots resulted in higher reflectance. Leaf spectra showed weaker discrimination, especially at later growth stages. Functional data analysis preserved spectral characteristics often overlooked by traditional indices, enabling a more detailed interpretation of crop variability. Canopy-scale functional hyperspectral analysis provides a robust, nondestructive tool for early yield assessment and supports precision agriculture decision-making related to fertilization, irrigation, and crop management.

Keywords: precision agriculture, spectrometry, productivity, reflectance.

GRAPHICAL ABSTRACT:



Source: Authors.

1 INTRODUCTION

Sugarcane (*Saccharum officinarum*) is a major crop in global agriculture and a primary source of sugar, ethanol, and bioenergy. It occupies more than 26 million hectares worldwide and plays a crucial role in the economies of tropical and subtropical regions (Voora et al., 2023). In 2020, global production reached 1.87 billion tons and is projected to increase to 1.96 billion tons by 2030 due to improved yields and expanded cultivation areas (OECD/FAO, 2021). The sugarcane industry supports more than 100 million jobs in over 120 sugarcane-producing countries, making it vital to rural economies (Voora et al., 2023). Growing demand for sugarcane-derived products un-

derscores the need for advanced methods for analyzing field data to improve yield estimation, optimize resource use, and ensure sustainable crop management (Ungureanu et al., 2022).

Traditional vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index, are widely used to assess crop health. However, these indices have limitations, particularly in high-biomass crops such as sugarcane, because NDVI saturates in dense canopies, reducing its ability to detect subtle differences in productivity (Zhang et al., 2024). Although NDVI has proven useful for predicting sugarcane yield and detecting

stress (Rahman & Robson, 2016), its standard formulation based on broad multispectral bands is highly sensitive to environmental conditions and has limited ability to detect early-stage stress. These limitations compromise its reliability for accurately assessing sugarcane health and productivity (de Lima et al., 2021).

To address these shortcomings, hyperspectral analysis and near-infrared (NIR) spectroscopy have emerged as more precise approaches for assessing sugarcane quality parameters, including Brix, Pol, and fiber content, which are crucial for determining crop quality and processing efficiency (Corrêdo et al., 2021; El-Hendawy et al., 2017).

Hyperspectral reflectance has also been used to estimate nitrogen (N) concentrations in sugarcane fields (Martins et al., 2024; Zhang et al., 2024). A study conducted in Cali, Colombia, used hyperspectral data to assess canopy N content under varying fertilization rates and identified key spectral regions (450–505 nm, 671 nm, and 719–760 nm) that were sensitive to variation in N levels (Reyes-Trujillo et al., 2021). These findings are consistent with broader research showing that hyperspectral indices in the red-edge and NIR regions are closely associated with plant health and nutrient status (Reyes-Trujillo et al., 2021).

Emerging methods such as functional data analysis (FDA) are gaining prominence in remote sensing applications because they enable the continuous representation of spectral variation, improve predictive accuracy, and reduce noise (Grygar et al., 2024; Matsui & Mochida, 2024; Ullah & Finch,

2013). FDA has been successfully applied in agriculture to assess chlorophyll content and canopy structure, and to predict yield (Som-ard et al., 2021).

In viticulture, FDA combined with functional partial least squares and functional principal component analysis has improved canopy vigor classification and stress detection (Vélez et al., 2022). Similarly, integrating machine learning models with FDA has improved sugarcane yield prediction, demonstrating the feasibility of hybrid approaches that leverage both spectral and structural crop information (Li et al., 2023).

Despite its advantages, the application of FDA in sugarcane research remains limited. Most studies continue to rely on discrete vegetation indices, which may overlook key spectral features that distinguish high- and low-productivity areas. Moreover, multi-scale spectral analyses incorporating both canopy- and leaf-scale measurements are needed because leaf-scale measurements can be used to calibrate and adjust canopy-scale models. Canopy architecture influences vegetation spectral responses and affects the sensitivity of measurements to variations caused by nutrient or water stress (Reyes-Trujillo, 2020).

Therefore, the primary objective of this study was to evaluate the effectiveness of FDA applied to hyperspectral reflectance data for the early classification of sugarcane productivity in Valle del Cauca, Colombia. The specific objectives were (i) to assess the ability of FDA to distinguish between high- and low-productivity sugarcane plots using hyperspectral reflectance spectra, (ii) to

compare the discriminatory power of canopy- and leaf-scale spectral measurements for productivity classification, and (iii) to evaluate the influence of crop growth stage on spectral variability and classification accuracy. The findings are expected to con-

tribute to the development of robust, non-destructive remote sensing methods that support precision agriculture strategies for optimizing crop management in intensive sugarcane production systems.

2 MATERIALS AND METHODS

2.1. STUDY AREA AND EXPERIMENTAL DESIGN

The study was conducted on six plots associated with the Ingenio del Cauca sugar mill in the Cauca River Valley, Cauca Department, Colombia. The plots were planted with the CC 01-1940 sugarcane variety (Viveros Valens, 2018), managed using conven-

tional agronomic practices, and had similar soil and climatic conditions, crop ages, and N fertilization regimes. The average vegetative period of sugarcane in the Cauca River Valley is 12.5 months after emergence (MAE), although harvesting the CC 01-1940 variety after 13 MAE is recommended to optimize sucrose production. The total experimental area covered 51.7 hectares (Figure 1; Table 1).

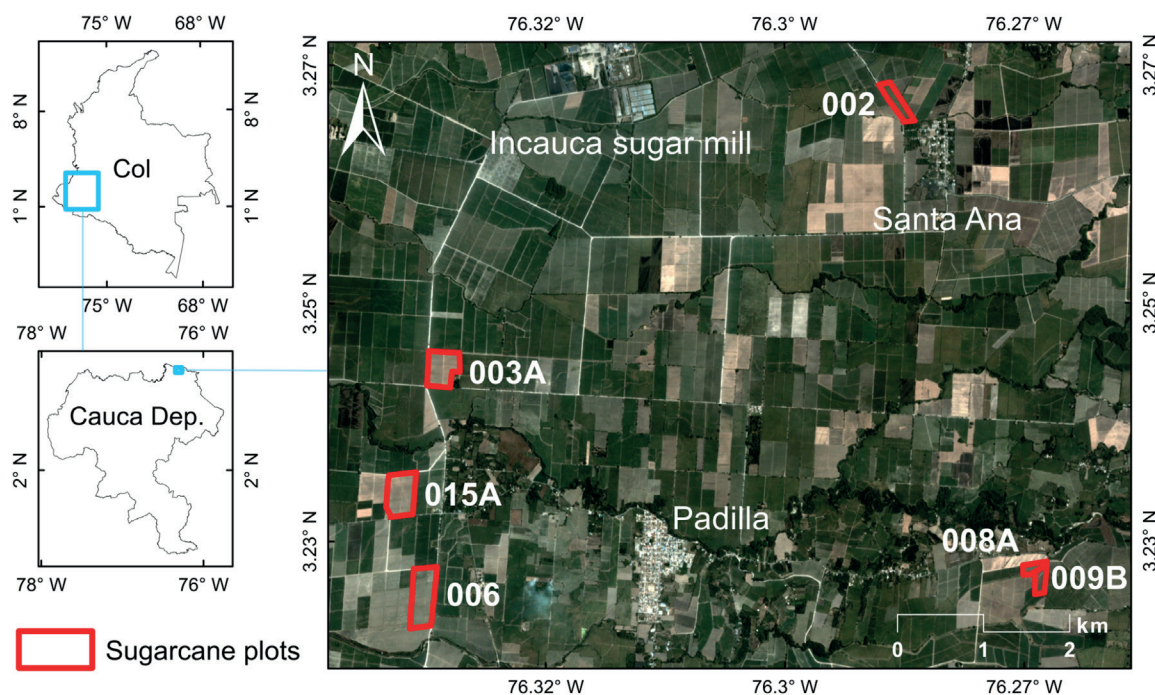


Figure 1. Geographic Location of the Experimental Plots Included in the Study (Col = Colombia; Cauca Dep. = Cauca Department).

Source: Authors.

Table 1.

Physical and Agronomic Characteristics of the Experimental Sugarcane Plots, Including Area, Ratoon Number (RN), Total Cane Yield per Hectare (TCH), Soil Texture, and N Fertilization Rates

Plot	Area (ha)	RN	TCH	Soil texture	Fertilization (kg/ha)
009B	3.11	2	135	L, SL	350
008A	4.55	1	118	CL, SCL, SiL	350
002	5.85	1	86	L, SiL	350
015A	3.74	4	112	L, SiL	350
006	12.68	1	123	L, SiL	375
003A	5.40	1	132	L, SiL	350

Note. L = loam; SL = sandy loam; CL = clay loam; SCL = sandy clay loam; SiL = silt loam. Fertilization consisted of the application of urea (46%).

Source: Authors.

The study area is located in agroecological zone 11H3 (Carbonell González et al., 2011). The soils are characterized by fine, loamy textures over clayey subsoils, and belong to the Mollisol order. These soils are found predominantly on the middle and lower slopes of alluvial fans under an udic moisture regime. Annual rainfall in the region ranges from 200 to 600 mm, with an average temperature of 23.7 °C and an average elevation of 1,005 m above sea level. The experiment was monitored at two key early growth stages: the end of tillering at 2.5–3 months of age in December 2023, and the rapid vegetative growth stage at 5.5–6 months of age in March 2024. Monitoring at these stages enables timely field management decisions to address production constraints during the current crop cycle, whereas assessments at

later phenological stages primarily inform adjustments for subsequent ratoon crops.

2.2. SAMPLING AND ACQUISITION

The hyperspectral data sampling protocol used in this study followed a multistage sampling approach, implemented during two measurement campaigns under an uncontrolled experimental design. First, the primary sampling unit was defined by dividing the total number of rows in each plot by the minimum number of access rows required for machinery, and then adding a random number between 1 and the resulting quotient to select the specific row to sample. Next, the secondary sampling unit was defined as a randomly selected 10-m longitudinal

section nested within each selected row. Finally, a randomly selected 1-m tertiary sampling unit, corresponding to a specific sugarcane plant, was nested within the secondary unit.

Direct optical spectral measurements were performed at the leaf scale within the tertiary sampling unit. Optical spectra were

measured at the canopy scale within the secondary sampling unit. The number of primary sampling units (furrows) selected for each plot was as follows: 9 for plots 009B and 008A, 9 for plot 002, 7 for plot 015A, 8 for plot 006, and 10 for plot 003A. The workflow is shown in Figure 2.

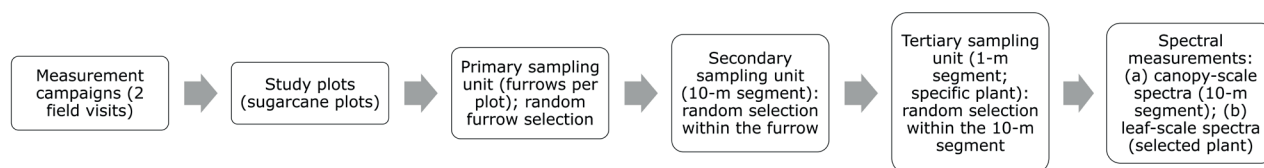


Figure 2. Multistage Hyperspectral Sampling Protocol.

Source: Authors.

2.3. SPECTRAL MEASUREMENTS

A hyperspectral measurement system based on optical spectroscopy in the visible-to-near-infrared (VIS-NIR) range was developed to collect spectral data. The system was configured to acquire diffuse reflectance spectra with an integration time of 200 ms, with five readings averaged per sample. Diffuse reflectance refers to incident radiation that is scattered by a surface in multiple directions, providing a measure of surface properties independent of the viewing angle (Benavides-Bolaños et al., 2025). Measurements were taken at 9:00 a.m. and 3:00 p.m. during the tillering (2.5–3 months) and rapid vegetative growth (5.5–6 months) stages of the sugarcane crop.

For leaf-scale measurements, an STS-VIS-NIR microspectrometer was used (Ocean Optics, Dunedin, FL, United States).

The sensor had an optical resolution of 1.5 ± 0.05 nm and 1,024 pixels and was coupled to a multimode optical fiber optimized for the VIS-NIR range. The fiber, which had a diameter of 200 μ m and an optical aperture of 0.22, was used to collect leaf-scale spectral data. All measurements were stored on a laptop for subsequent analysis.

For canopy-scale measurements, the system was configured to acquire continuous spectral readings over a 60-s period along a 10-m transect, corresponding to the length of the secondary sampling unit. The system consisted of two main components: (1) an aboveground unit (AGU), responsible for collecting diffuse reflectance spectra, and (2) a ground-based reference unit (GBRU), used for calibration. The AGU comprised a hyperspectral sensor mounted on a mechanically and electronically stabilized platform. The system featured an adjustable

optical aperture ranging from 1° to 28° and was positioned 1 m above the crop canopy to measure reflectance.

The GBRU, used to acquire reference irradiance measurements, incorporated a Spectralon Reference Panel (Ocean Optics, Dunedin, FL, United States) with 99% reflectivity across the 400–1,500 nm spectral range. This configuration made it possible to monitor changes in reference irradiance, prevent saturation, minimize the effects of variations in lighting conditions, and ensure measurement comparability (Reyes-Trujillo, 2020; Reyes-Trujillo et al., 2021). The unit was positioned independently to enable real-time calibration and correction of hyperspectral measurements under field conditions during all measurement campaigns.

2.4. DETERMINATION OF STANDARD SPECTRA

Based on the exploratory analysis of the hyperspectral data collected under the uncontrolled experimental design, standard diffuse reflectance spectra were developed for the tillering and rapid growth stages of the CC 01-1940 sugarcane variety. FDA was subsequently applied (Ramsay & Dalzell,

1991; Ramsay & Silverman, 2005; Ullah & Finch, 2013), using B-spline smoothing to fit hyperspectral reflectance curves across the continuous wavelength range with a set of functions, $\{\phi_k\}_{k \in N}$. These fitted curves are hereafter referred to as functional data.

The B-spline basis functions (Eubank, 1999) allow the functions in the dataset to be approximated, thereby facilitating analysis. The fundamental properties of B-splines are as follows: (a) each basis element $\phi_k(w)$ is a spline function of order m on a partition τ ; (b) any linear combination of spline functions is also a spline function; and (c) any spline function of order m on a given partition τ can be expressed as a linear combination of the basis functions.

In FDA, the dataset is treated as a collection of continuous curves rather than as discrete vectors, as is done in classical multivariate analysis. These functional representations are obtained through regression models optimized by cross-validation. Functional data are formally defined using a set of basis functions, $\{\phi_k\}_{k \in N}$, such that any function can be represented as a linear combination of these basis functions, as follows:

$$\mathbf{x}(w) = \sum_{k=1}^K c_k \phi_k(w) \quad (1)$$

where $\phi_k(w)$ denotes a basis function and c_k is the corresponding coefficient (Equation 1).

Once the functional data have been constructed, classical statistical concepts are extended to the functional domain. This extension enables the derivation of descrip-

tive functions, such as slopes and inflection points, which improve the interpretability of hyperspectral curves. The standard spectra were determined using functional descriptive

statistics, as described elsewhere (Ramsay & Silverman, 2005):

$$\text{Functional mean: } \underline{x}(w) = N^{-1} \sum_{i=1}^N x_i(w) \quad (2)$$

$$\text{Functional variance: } V[x(w)] = (N - 1)^{-1} \sum_{i=1}^N [x_i(w) - \underline{x}(w)]^2 \quad (3)$$

where $x_i(w)$ represents an individual spectral observation and $\underline{x}(w)$ is the functional mean (Equations 2 and 3).

To further analyze the functional data and identify spectral differences between sugarcane productivity classes, a functional t -test based on the permutation method was applied (Coffey & Hinde, 2011). This test generates a null distribution for the test statistic and calculates the corresponding p value to assess statistical significance.

The functional t -test was performed using the permutation procedure proposed by Ramsay and Dalzell (1991), which involves the following steps:

1. Specify the number of points (n) and the number of permutations (d).
2. Shuffle the labels of the functional curves d times and compute the test statistic for

each permutation at all n points. The resulting $T_{null\ values}(w)$ are stored in an $n \times d$ matrix.

3. Determine the maximum difference for each permutation across the n points. These differences form a null distribution represented by $T_{null}(w)$, resulting in a column vector of length d .
4. Compute the original test statistic for the unshuffled dataset, $T(w)$, at the n points. The largest of these values is $T_{Max\ observed}(w)$.
5. Calculate the pointwise critical-value curve as the quantile $[T_{null\ values}(w); \alpha]$ across all permutations at each point. This yields an n -dimensional column vector.
6. Determine the maximum critical value, denoted as $T_{null}(w)$.

3 RESULTS AND DISCUSSION

For this analysis, diffuse reflectance spectra collected at the canopy and leaf scales during two measurement campaigns under an uncontrolled experimental design were compiled into a database. The collected spectra were classified according to the productivity class assigned to each plot.

Table 2 presents the number of diffuse reflectance spectra collected at the canopy and leaf scales during the two measurement campaigns. The table distinguishes between high- and low-productivity plots and provides a breakdown of spectral acquisitions by plot. Plots with TCH > 120 t/ha were

classified as high-productivity, whereas those with TCH < 120 t/ha were classified as low-productivity, based on the national average sugarcane yield in Colombia. Notably, the high-productivity plots (003A: 132 t/ha, 009B: 135 t/ha, and 006: 123 t/ha) consist-

ently had more spectral acquisitions than the low-productivity plots (002: 86 t/ha, 008A: 118 t/ha, and 015A: 112 t/ha), indicating differences in structural characteristics that may have influenced the spectral responses.

Table 2.

Number of Diffuse Reflectance Spectra Acquired at the Canopy and Leaf Scales, Grouped by Productivity Class and Measurement Campaign

Plot	Canopy-Scale R	Leaf-Scale R	Productivity classification
003A	950	50	High
009B	855	45	High
006	760	40	High
002	855	45	Low
008A	855	45	Low
015A	665	35	Low
Campaign 1	4,940	260	
Campaign 2	4,940	260	
Total	9,880	520	

Source: Authors.

After the database was compiled and an exploratory analysis was performed, the spectral data were transformed using functional data analysis techniques, as described below.

Figure 3 illustrates the transformation of raw reflectance spectra into smooth, functional curves using FDA at the canopy scale. The raw spectral data exhibit noise and fluctuations caused by environmental conditions and sensor variability, particularly

in the 770–800 nm region. After FDA was applied, the spectra retained key absorption features, while random noise was reduced, improving interpretability. The smoothed curves provide a clearer representation of spectral variation attributable to differences in leaf area, canopy structure, and solar radiation interception; the latter is influenced by pronounced fluctuations in incident solar radiation caused by changes in cloud cover that are characteristic of tropical climates.

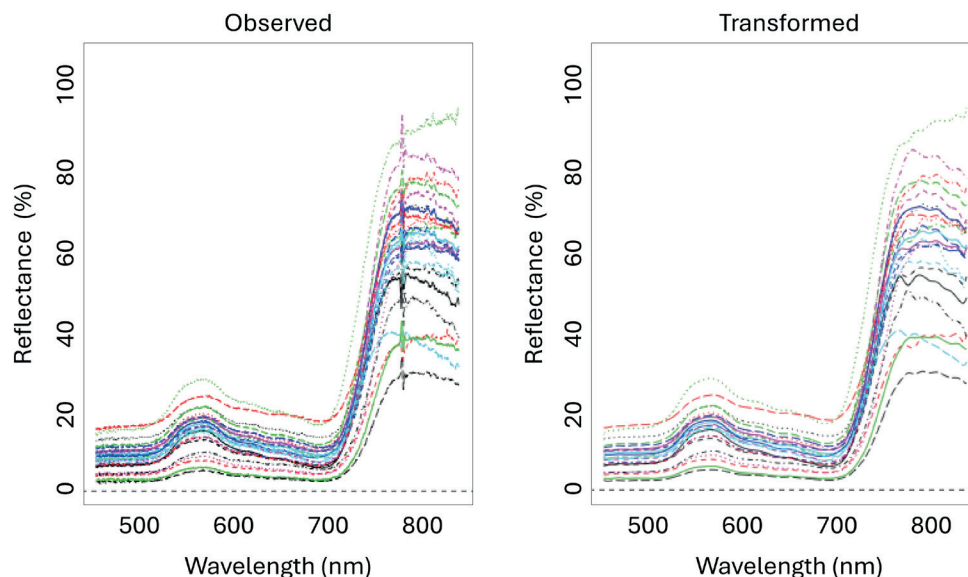


Figure 3. Comparison of Observed and Functionally Transformed Reflectance Spectra at the Canopy Scale, Illustrating the Preservation of Key Spectral Features.

Source: Authors.

The functional mean reflectance was then calculated for each type of spectral data and for plot groups classified by productivity level. Figure 4 presents the functional mean reflectance spectra at both the canopy and leaf scales for Campaign 1. These curves exhibit the characteristic spectral response of vegetation, with a reflectance peak in the green region and a pronounced increase in the NIR region.

At the canopy scale (Figure 4a), high-productivity plots show lower reflectance across the visible region and higher reflectance in the NIR region, suggesting greater chlorophyll content and better overall plant health. At the leaf scale (Figure 4b), differences in spectral reflectance between high- and

low-productivity plots are much less pronounced across all wavelengths, indicating that canopy-scale analysis is more effective for distinguishing productivity levels.

The spectral differences observed in low-productivity plots within the 750–820 nm NIR range, characterized by higher reflectance, may indicate water stress due to increased scattering associated with reduced leaf water content and a lower refractive index (Katsoulas et al., 2016). They may also reflect physiological changes, such as alterations in xanthophyll pigments affecting the photochemical reflectance index (PRI) detectable in this region (Gamon et al., 1992; Nakamura et al., 2024). These findings reinforce the need for multiscale spectral assessment.

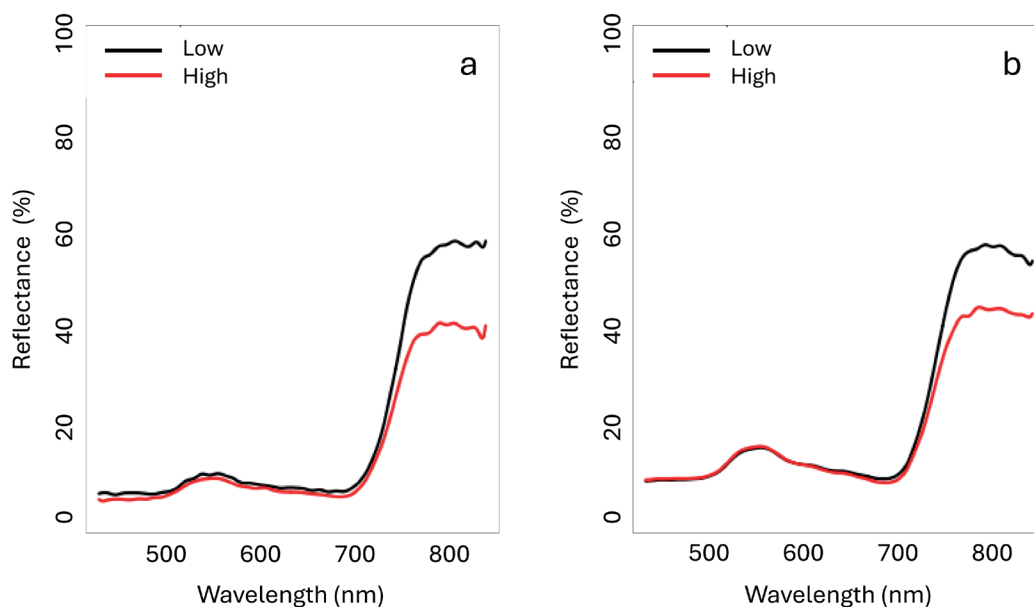


Figure 4. Functional Mean Reflectance Spectra at (a) the Canopy Scale and (b) the Leaf Scale, Grouped by Productivity Class.

Source: Authors.

The observed spectral patterns require stage-specific interpretation that accounts for measurement scale and physiological context. At the early growth stage (2.5 months), leaf development is limited; therefore, differences in the NIR region (750–820 nm) primarily reflect variations in leaf water content, rather than canopy structure. Low-productivity plots exhibit higher NIR reflectance, indicating water stress due to increased scattering associated with reduced leaf water content and refractive index (Katsoulas et al., 2016).

At the canopy scale, higher reflectance in the VIS region in low-productivity plots suggests stress-induced reductions in photosynthetic pigments and enzymes (Katsoulas et al., 2016; Peñuelas et al., 1994). These find-

ings highlight the ability of FDA to reveal subtle, physiologically meaningful spectral differences that cannot be detected using broadband indices.

Figure 5 presents the results of a functional *t*-test comparing mean reflectance spectra at the canopy scale between high- and low-productivity plots. Statistically significant spectral differences were observed across nearly the entire spectral range, particularly in the NIR region, where the structural and physiological properties of the canopy strongly influence reflectance. This finding suggests that hyperspectral canopy data are highly effective for distinguishing productivity levels and may serve as a reliable predictor of sugarcane performance.

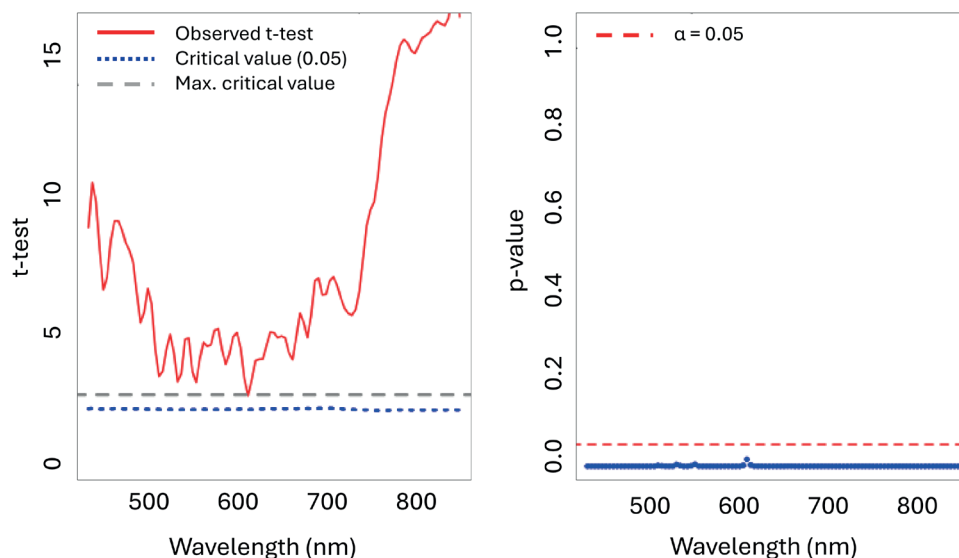


Figure 5. Functional t -test Results Comparing Mean Reflectance Spectra at the Canopy Scale, Highlighting Significant Differences Across the Entire Spectral Range.

Source: Authors.

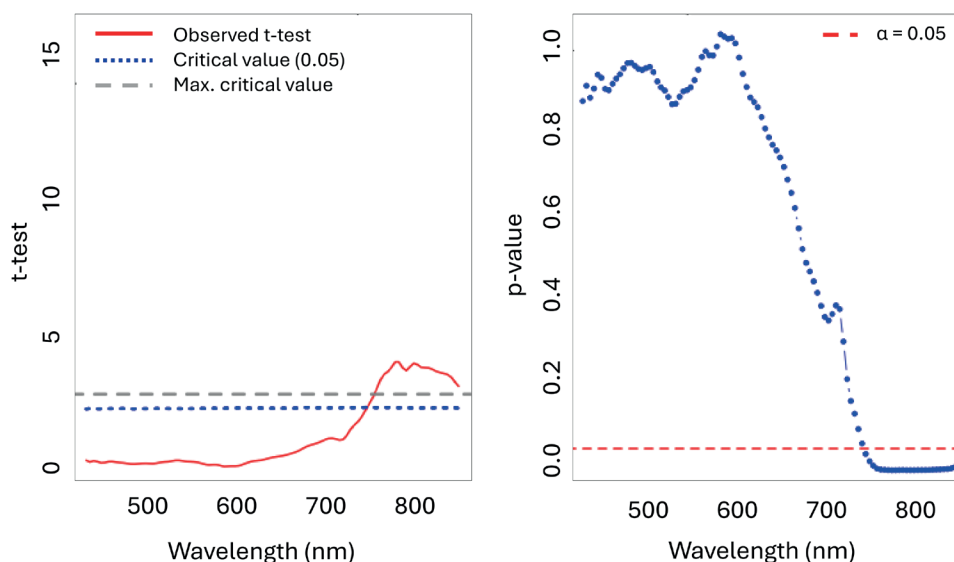


Figure 6. Functional t -test Results Comparing Mean Reflectance Spectra at the Leaf Scale, Showing Significant Differences Only in the NIR Region.

Source: Authors.

Figure 6 presents the results of the functional t -test at the leaf scale, showing that statistically significant spectral differences

are limited to the NIR region. This finding indicates that, although leaf reflectance contains useful information, it is less robust than

canopy-scale measurements for detecting differences in productivity. The lower spectral sensitivity at this scale may be attributed to localized variation in leaf properties that does not fully reflect the broader physiological condition of the crop (Carter & Knapp, 2001; Katsoulas et al., 2016; Reyes-Trujillo, 2020).

Figure 7 compares the functional mean reflectance spectra at the canopy and leaf scales during the later growth stage (5.5 months). At the canopy scale (Figure 7a),

high-productivity plots exhibit higher NIR reflectance than low-productivity plots, consistent with a more developed canopy architecture and greater aboveground biomass, which modify internal light scattering as the crop matures. At the leaf scale (Figure 7b), spectral differences remain small across wavelengths, reinforcing the greater sensitivity of canopy-scale measurements for productivity classification compared with leaf-scale measurements.

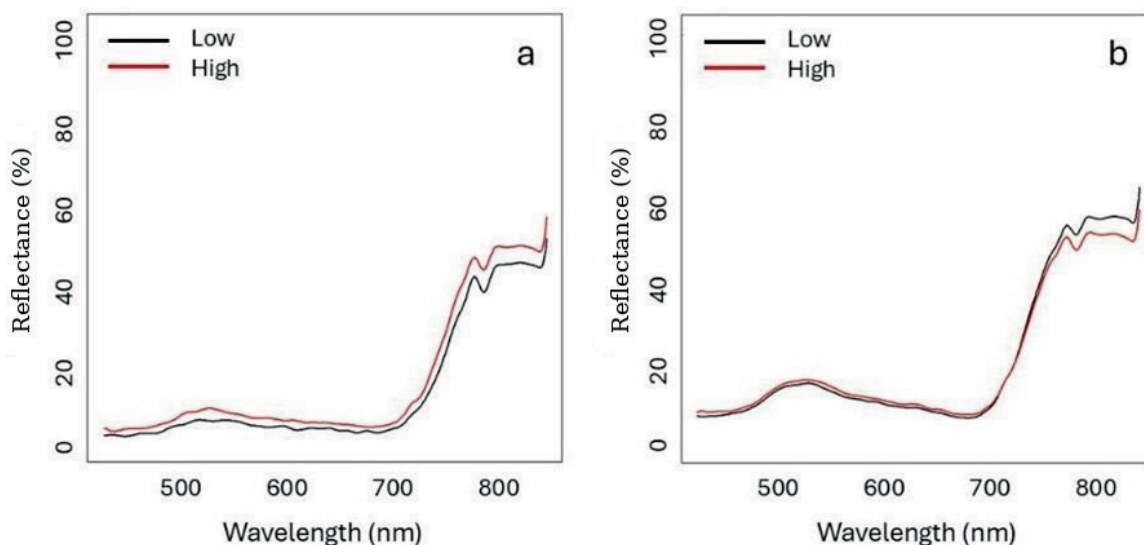


Figure 7. Functional Mean Reflectance Spectra at (a) the Canopy Scale and (b) the Leaf Scale for Growing Season 2 (5.5 Months), Grouped by Productivity Class.

Source: Authors.

Figure 8 presents the results of the functional *t*-test for canopy reflectance spectra at the later growth stage (5.5 months). Statistically significant differences were detected across nearly the entire spectral range, indicating that canopy-scale hyperspectral measurements remain highly sensitive to productivity-related variation at later growth

stages. Consistent with the functional mean spectra shown in Figure 7a, these differences reflect the influence of a more developed canopy structure in high-productivity plots, where leaf area, aboveground biomass, leaf angle, and leaf age exert greater control over spectral behavior (Lepine et al., 2016). Consequently, canopy-scale measurements

provide more informative data than leaf-scale measurements for capturing the com-

bined effects of nutrient accumulation and canopy architecture on productivity.

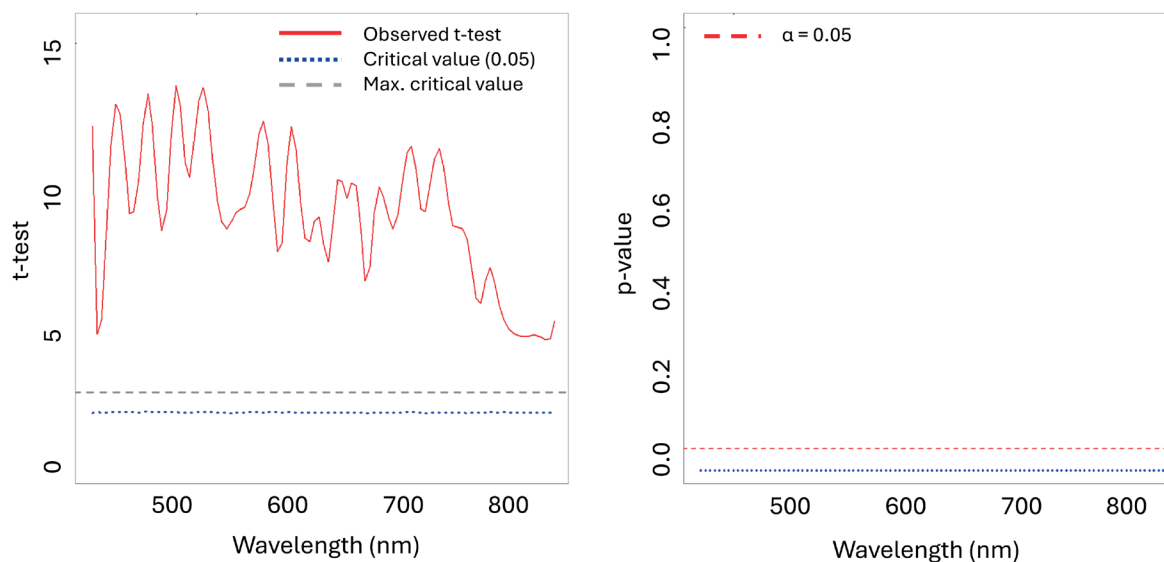


Figure 8. Functional *t*-test Results Comparing Reflectance Spectra at the Canopy Scale for Growing Season 2, Highlighting Significant Spectral Differences.

Source: Authors.

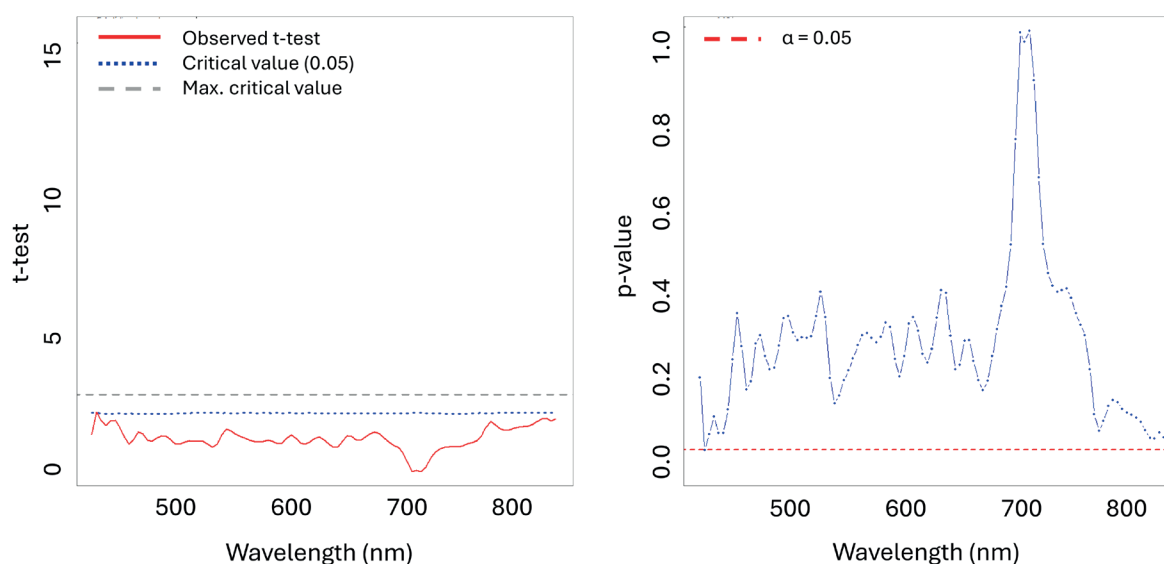


Figure 9. Functional *t*-test Results Comparing Reflectance Spectra at the Leaf Scale for Growing Season 2, Showing No Statistically Significant Differences.

Source: Authors.

Figure 9 presents the results of the functional t -test for leaf reflectance spectra at the later growth stage. Unlike the canopy-scale results, no statistically significant differences were detected at the leaf scale, suggesting that, as the crop matures, leaf spectral variation becomes less indicative of differences in productivity. This finding may be attributed to nutrient redistribution dynamics and canopy homogenization, which reduce the spectral contrast between high- and low-productivity plots (Reyes-Trujillo, 2020).

The application of FDA transformed hyperspectral reflectance spectra into continuous functions, enabling more nuanced statistical analysis and interpretation of spectral variation. Unlike traditional approaches that rely on discrete spectral bands or vegetation indices, which often fail to capture subtle but important differences, FDA preserves key spectral features, such as inflection points, peak widths, and local minima and maxima (Oliveira et al., 2020; Rincón-Fonseca et al., 2021). This approach enabled a more detailed assessment of spectral responses across sugarcane plots in different productivity classes.

A key finding of this study was the higher mean reflectance observed in the 750–820 nm range in low-productivity plots during the early growth stage (Figure 4). At this stage, canopy architecture is still poorly developed; therefore, differences in NIR reflectance are driven primarily by leaf-level water status rather than canopy structure. Previous studies have established an inverse relationship between leaf water content and NIR reflectance, with water-stressed plants exhibiting higher reflectance because of in-

creased light scattering and changes in the refractive index (Holzman et al., 2021; Jin et al., 2017; Katsoulas et al., 2016; Liu et al., 2024). This finding highlights the potential of hyperspectral sensing for the early detection of water stress, which could support timely irrigation adjustments and improve overall productivity.

Significant differences in reflectance were also observed in the VIS region at the canopy scale (Figure 4a). These variations likely reflect differences in crop physiological status associated with field water and nutrient availability, ranging from limiting to nonlimiting conditions, that affect chlorophyll concentration and photosynthetic performance. Chlorophyll content, particularly in the spectral regions around 550 nm and 670 nm, has been shown to be strongly correlated with leaf reflectance, making VIS-region spectral analysis a useful tool for monitoring plant health (Arruda et al., 2024; Gai et al., 2024; Tavares et al., 2023; Zhang et al., 2023).

Functional t -tests confirmed statistically significant differences in canopy reflectance across the entire spectral range (Figure 5), whereas at the leaf scale, significant differences were evident only in the NIR region (Figure 6).

During the second growing season (5.5 months), reflectance spectra were analyzed for plots with different productivity levels (Figure 7). At the canopy scale, clear differences were detected between the functional mean reflectance spectra of high- and low-productivity plots (Figure 8). At the leaf scale, no statistically significant differences were found (Figure 9), likely because of the

rapid nutrient accumulation that characterizes this growth stage in the CC 01-1940 variety (Viveros Valens, 2018). Previous research has shown that sugarcane takes up the greatest proportion of major nutrients between 5 and 6 months of growth, influencing its spectral responses (Kumar et al., 2023; Leal Junior et al., 2025).

Canopy-scale spectral measurements provided more reliable assessments of productivity-related variation, as higher reflectance values were consistently associated with high-productivity plots (Figure 7a). These differences are likely attributable to variation in canopy structural traits, including leaf area, aboveground biomass, leaf angle, and leaf maturity, all of which directly affect spectral signatures (Quemada et al., 2021; Tang et al., 2023). These findings suggest that canopy-scale hyperspectral analysis is better suited to productivity assessment than leaf-scale measurements because it integrates both physiological and structural attributes that influence crop performance.

Conventional spectral indices, such as the NDVI, are often constrained by their reliance on scalar transformations, which can

obscure subtle spectral variations by averaging complex signals. Recent studies have shown that hyperspectral data, particularly when analyzed using advanced statistical techniques, provide a more detailed and accurate assessment of vegetation status than broadband indices (Chanchí-Golondrino et al., 2024; Liu et al., 2024).

The interpretation of functional mean reflectance spectra should account for the influence of agroecological conditions, agronomic practices, temporal nutrient dynamics, and canopy architecture. This study demonstrates that hyperspectral analysis combined with FDA offers a scalable and efficient approach to monitoring crop variability and predicting sugarcane yield during early growth stages. Using this methodology, sugarcane producers could optimize fertilization, irrigation, and canopy management strategies, thereby improving resource-use efficiency and yields. The results underscore the importance of multiscale spectral analysis, particularly at the canopy scale, for detecting early signs of stress and facilitating targeted interventions to enhance crop productivity.

4 CONCLUSIONS

This study demonstrated that FDA significantly improved the interpretation of hyperspectral data for the early classification of sugarcane productivity. By transforming raw spectral measurements into continuous functions, FDA enabled the detection of subtle but statistically significant

differences in reflectance, particularly in the NIR region.

Canopy-scale reflectance data provided the greatest discriminatory power between high- and low-productivity plots at both the early (2.5 months) and mid-growth (5.5 months) stages. These differences were con-

sistent with known physiological indicators, such as leaf area index and biomass accumulation, which were more pronounced in high-productivity plots. In contrast, leaf-scale reflectance spectra were less effective, showing limited sensitivity to differences in productivity and fewer spectral regions with statistically significant differences.

The functional t -test consistently identified the canopy NIR region as a key diagnostic zone, whereas the leaf-scale approach showed limited utility under open-field conditions because leaf-level measurements are more sensitive to exogenous measurement artifacts (e.g., variable ambient illumination, bidirectional reflectance effects, and background and canopy scattering) that can mask subtle physiological signals. These findings suggest that integrating FDA with canopy-scale hyperspectral reflectance provides a robust, nondestructive approach to early-stage yield assessment in sugarcane.

This method supports precision agriculture by facilitating timely, site-specific deci-

sions related to irrigation, fertilization, and stress management. Future research should focus on combining FDA with machine learning algorithms and expanding its application across different sugarcane varieties and agroecological zones.

As a corollary, the FDA-derived functional mean curve serves as a relative standard hyperspectral reflectance spectrum for each productivity class under the specific agroecological and management conditions evaluated. In this study, the standard spectra are defined by class-specific functional means and their associated variability envelopes, with the most stable and diagnostically informative separation occurring in the canopy NIR region. However, these standard spectra should be interpreted as context-dependent references rather than universal signatures because their shape and amplitude are expected to vary with the agroecological zone, agronomic practices, crop phenology, nutrient accumulation dynamics, and canopy structural development.

AUTHOR CONTRIBUTIONS

First author: Methodology, investigation, data analysis, conceptualization, and writing of the original draft.

Second author: Investigation, conceptualization, data analysis, and writing of the original draft.

Third author: Data analysis, review, and editing of the final version of the manuscript.

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USE OF ARTIFICIAL INTELLIGENCE

Not applicable.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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Conflicto de intereses

Los autores declaran no tener ningún conflicto de intereses.



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