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Differentiation of five commercial cultivars *of Saccharum* spp. using computational methods of VIS-NIR spectral analysis

Diferenciación de cinco cultivares comerciales de Saccharum spp. mediante métodos computacionales de análisis espectral VIS-NIR

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ABSTRACT: Precision agriculture is applied to manage spatial variability in agricultural fields and optimize production. The objective of this study was to differentiate five commercial cultivars of *Saccharum* spp. (sugarcane) through computational spectral analysis methods. The vegetal material samples were collected in experimental areas of the Sugarcane Research Institute, located in the municipality of Ranchuelo, Villa Clara, Cuba. The commercial cultivars of *Saccharum* spp. were selected based on their characteristics and importance in Cuba; 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', and 'C86-12' were evaluated. The study focused on the spectral reflectance properties of the cultivars, using the first derivative method and ten spectral matching measures for analysis. It was identified that at 526.2 nm, 723.8 nm, and 1,399 nm, there are differences in the spectral characteristics gradients among the cultivars studied.
Keywords: Precision Agriculture, Sugarcane, Spectral Signature.

RESUMEN: La agricultura de precisión se aplica para gestionar la variabilidad espacial en campos agrícolas y optimizar la producción. El objetivo del trabajo fue diferenciar cinco cultivares comerciales de caña de azúcar (*Saccharum* spp.) mediante métodos computacionales de análisis espectral. Las colectas del material vegetal se realizaron en áreas experimentales del Instituto de Investigaciones de la Caña de Azúcar, ubicado en el municipio de Ranchuelo, Villa Clara, Cuba. Los cultivares comerciales se seleccionaron de acuerdo a sus características e importancia en Cuba; se evaluaron 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', 'C86-12'. El trabajo se centró en el estudio de las propiedades de reflectancia espectral de los cultivares y como métodos de análisis se utilizó el método de la primera derivada y diez medidas de correspondencia espectral. Se identificó que, a 526,2 nm, 723,8 nm y a 1 399 nm existen diferencias en los gradientes de las características espectrales entre los cultivares en estudio.
Palabras clave: agricultura de precisión, caña de azúcar, firma espectral.

INTRODUCTION

Sugarcane (*Saccharum* spp.) is one of the world's major crops (FAOSTAT, 2023). In Cuba, the sugar sector is an important part of agro-industrial production and one of the main sources of income for the country's economy (Reyes *et al*., 2021). Several products are obtained from sugarcane, such as biofuels, ethanol, fibers, and sugar. Depending on these products, there are sugarcane cultivars with specific characteristics. For example, cultivars with high fiber content and cell walls that break easily, favoring the production of ethanol from bagasse; cultivars with a small stem diameter and high fiber content, which increase the strength of sugarcane for use in windy areas, among others (Phuphaphud *et al*., 2019).

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Knowing the real-time distribution of sugarcane cultivars is essential for improving crop productivity and quality (Ramírez-Gonzáles *et al.,* 2019). The conventional method for studying the distribution of these cultivars is based on the use of traditional soil and topography maps, or on visual inspection of the field, which is laborious, requires the transfer of personnel, and, on occasion, the maps may be outdated, which limits accuracy (Espinoza and Luis, 2020). Precision agriculture (PA) is a technology used to respond to and recognize spatial variation in a field, thereby improving the management of agricultural production processes (Udompetaikul *et al.,* 2021). Remote sensing techniques using satellite imagery have been widely applied in various fields of agricultural science. This is because they allow real-time information to be obtained from a given region without the need for travel, avoiding costs and also allowing the creation of more efficient methods for crop management and monitoring (Kai *et al*., 2020).

Visible and near-infrared spectroscopy (VIS-NIR) appears to be a promising alternative due to its ability to detect signals from most of the main structures and functional groups of organic compounds (Camargo-Hernández et al., 2023). This technology allows for easy, fast, accurate, non-destructive, and economical analysis of the spatial variability of a crop without prior sample preparation. In addition, it has the potential for developing online measurement instruments (Udompetaikul *et al.,* 2021).

The objective of this work is to differentiate the commercial cultivars of *Saccharum* spp. 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', and 'C86-12' using computational methods of spectral analysis.

MATERIALS AND METHODS

Determination of the spectral signatures of five commercial cultivars of *Saccharum* spp.

Leaf samples were collected in the morning between 8:00 and 10:00 a.m. in experimental areas of the Villa Clara Sugarcane Research Institute (INICA VC), located in the municipality of Ranchuelo, Villa Clara, Cuba. The prevailing environmental conditions at the time of collection were sunny, with no rain and some clouds. The soil type is classified as Salitic Brown, genetic type brown, subtype soft brown, and genus soft brown carbonate.

Four plots (replicas) planted with commercial sugarcane cultivars 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', and 'C86-12', six months old, were selected for collection. One plant per cultivar was randomly selected from each plot. Leaf blades +1 to +7 were collected from each plant according to the Kuijper system (1915). Commercial cultivars were selected based on their characteristics and importance in Cuba. After collection, the samples were stored at room temperature and hydrated. They were then transferred to the Spectroscopy Laboratory at Agricultural Research Center of the Faculty of Agricultural Sciences, located at Universidad Central "Marta Abreu" de Las Villas.

Determination of original spectral reflectance characteristics

To obtain the original spectral reflectance characteristics, a Corona Plus Remote spectrometer from the German company Carl Zeiss was used. This device uses an artificial light source produced by a halogen lamp and an optical system that illuminates the sample at 0° (normal to the sample) in an almost parallel beam. This equipment provides spectral reflectance measurements in 422 bands between 398 and 1,702 nm, with a spectral resolution of 10 nm, thus covering only the visible spectrum (VIS) and near-infrared (NIR) bands. The surveyed area was circular with a radius of 2.5 mm, equivalent to 20 mm². The leaf samples were placed in a linear arrangement in a Petri dish 10 mm deep and 35 mm in diameter, which was placed under the sensor at the center of the coordination point. The reflectance spectra were taken over the central area of the Petri dish, with the sample rotated approximately 30° between subsequent spectral acquisitions. Five reflectance spectra were taken from the base, five from the center, and five from the apex of each leaf collected, for a total of 15 spectra per leaf.

The data obtained with the spectrometer were first processed by Aspect Plus software, version 1.76 (C) on Windows, without smoothing. The reflectance characteristics were limited to the wavelength range between 432.384 and 1,673.385 nm. In addition, markedly atypical reflectance characteristics (outliers) were removed, and to attenuate disturbances in spectral reflectance characteristics that produced high-frequency reflectance noise, a finite impulse response (FIR) moving average (MA) smoothing was used, with a window of five samples (Sonobe and Hirono, 2022).

Principal component extraction was performed using the principal component analysis (PCA) method. The normality of the data was tested using the JB-test, KS-test, L-test, and AD-test for each wavelength, the results of which were calculated from the data grouped and filtered by PCA, with a significance level of 1% (α = 1%), which is equivalent to a 99% confidence level. Under the assumption of normality in the data, the averages of the smoothed reflectance readings were determined for each of the samples of the different sugarcane cultivars, as well as their standard deviation. Subsequently, the First Derivative method was applied.

Comparison of five commercial cultivars of *Saccharum* spp. using ten Spectral Matching Measures

Ten Spectral Matching Measures (SMM) were used as methods of analysis between the cultivars of *Saccharum* spp. Classic SMM were used according to Hong *et al.* (2018); Drumetz *et al.* (2019); Borsoi *et al.* (2021); Pathak *et al.* (2023), where $\rho\_(x)$ and ρ_y are the reflectances of the spectra of samples x and y, respectively, contained in M wavelengths, are defined as follows:

- the spectral Euclidean distance (SED), given by:

$$SED(x, y) = x - \rho_{y2} = \left[\sum_{i=1}^{M} |\rho_{xi} - \rho_{yi}|^2\right]^{1/2} \quad (1)$$

- spectral angle measure (SAM) defined as:

$$SAM(x, y) = \cos^{-1}\left(\frac{\rho_x \cdot \rho_y^T}{\sqrt{\rho_{x2}^2 \rho_{y2}^2}}\right) \quad (2)$$

Where $\rho_x \cdot \rho_y^T = \sum_{i=1}^{M} (\rho_{xi}\rho_{yi})$ represents the domestic product between ρ_x y ρ_y.

- spectral correlation measure (SCM), defined as:

$$SCM(x, y) = \frac{\sum_{i=1}^{M} (\rho_{xi} - \bar{\rho}_x)(\rho_{yi} - \bar{\rho}_y)}{\sqrt{\sum_{i=1}^{M} (\rho_{xi} - \bar{\rho}_x)^2 \sum_{i=1}^{M} (\rho_{yi} - \bar{\rho}_y)^2}} \quad (3)$$

where $\bar{\rho}_x$ is the average of the values of all elements of the reference spectrum vector, as is $\bar{\rho}_y$ for the unknown spectrum.

- spectral information divergence (SID), defined as:

$$SID(x, y) = D(x \,||\, y) + D(y \,||\, x) \quad (4)$$

where $D(x \,||\, y)$ the relative entropy or information distance of Kullback-Leibler de y with respect to x, a which is defined as:

$$D(x \,||\, y) = -\sum_{i=1}^{M} p_{xi}(\log p_{yi} - \log p_{xi}) \quad (5)$$

Here, $p_{xi} = x_i / \sum_{i=1}^{M} \rho_{xi}$ corresponds to a normalized version of the spectrum x in the i-th spectral band.

- the SID-SAM hybrid between the SID and SAM methods, called SIDSAM, which is reported to be a better discriminator than its separate components, obtained by:

$$SIDSAM(x, y) = SID(x, y)\tan[SAM(x, y)] \quad (6)$$

- the Bhattacharyya distance (BhattD), taking into account that they are $p_{xi} = \rho_{xi} / \sum_{i=1}^{M} \rho_{xi}$ y $p_{yi} = \rho_{yi} / \sum_{i=1}^{M} \rho_{yi}$ the normalized versions of the spectra ρ_x y ρ_y in the i-th spectral band, is given by:

$$BhattD(x, y) = -\ln \sum_{i=1}^{M} \sqrt{p_{xi} p_{yi}} \quad (7)$$

- the Jeffries-Matusita distance (JMD), where the separability criterion between two classes that are members of a set of classes C($x, y = 1, 2,..., C, x \neq y$), based on the JMD, has been defined as:

$$JMD(x, y) = 2\left(1 - e^{-BhattD(\rho_x, \rho_y)}\right) \quad (8)$$

being BhattD(x, y) l the Bhattacharyya distance between classes ρ_x y ρ_y, given in (7).

In addition, other SMMs were also used, such as the Dice spectral similarity coefficient (DSSC), the Kumar-Johnson spectral similarity coefficient (KJSSC), and the hybrid DSSC-KJSSC (KJDSSC) (Kumar et al., 2021).

- the Dice spectral similarity coefficient (DSSC) is defined as:

$$DSSC(x, y) = \frac{2\sum_{i=1}^{M} (\rho_{xi}\rho_{yi})}{\sum_{i=1}^{M} (\rho_{xi})^2 + \sum_{i=1}^{M} (\rho_{yi})^2} \quad (9)$$

- the Kumar-Johnson spectral similarity coefficient (KJSSC), given by:

$$KJSSC(x, y) = \sum_{i=1}^{M} \left[\frac{(\rho_{xi}^2 - \rho_{yi}^2)^2}{2(\rho_{xi}\rho_{yi})^{3/2}}\right] \quad (10)$$

- the KJDSSC hybrid, which is the hybrid option between KJSSC and DSSC given by:

$$KJDSSC(x, y) = KJSSC(x, y)\tan[DSSC(x, y)] \quad (11)$$

Finally, a metamerism analysis was performed on the SMMs.

RESULTS AND DISCUSSION

In the original spectral reflectance characteristics, it was common for all cultivars to show a noisy band with greater amplitude fluctuations between 932 and 985 nm, with similar amplitude for all cultivars. Because the bandwidth of the spectral bands of the spectrometer used is 10 nm, much greater than that of other commercial spectrometers, which is only 1 nm, the degradation of the signal-to-noise ratio was low.

PCA was used to simplify the handling of the sampled data; this transformation was orthogonal, meaning that the principal components are independent of each other and are organized in such a way that the first captures the greatest variability present in the data, while each subsequent component represents progressively less variance. This allows the most significant characteristics to be identified by focusing on the highest eigenvalues (Che'Ya et al., 2022).

After applying PCA to each of the cultivars, the normality of the data for each of the samples of each cultivar could be assumed. Subsequently, the averages of the smoothed reflectance readings were obtained. These mean values constitute the characteristic spectral signatures of each cultivar and differ mainly in the shape of the characteristic.

Figure 1 shows the average spectral signatures of each cultivar superimposed on a single image, allowing for a better appreciation of the differences between them. For the same cultivar, the set of characteristics varies from one reading to another mainly in amplitude, while from one cultivar to another, the differences are due to the shape of the characteristic. This involves the presence of different gradients between some spectral bands. The gradient (first derivative) does not depend on the amplitude of the reflectance characteristics, but rather on the abrupt changes in amplitude between adjacent wavelengths in these characteristics. These high-gradient changes are generally associated with reflectance peaks characteristic of the constituent elements of the analyzed cultivar (Che'Ya et al., 2022). Figure 2A shows the result of calculating the gradients of the characteristics of the samples of each cultivar, squaring them, averaging them, and smoothing them with a moving average filter with a window of five samples and zero-phase finite impulse response (FIR).

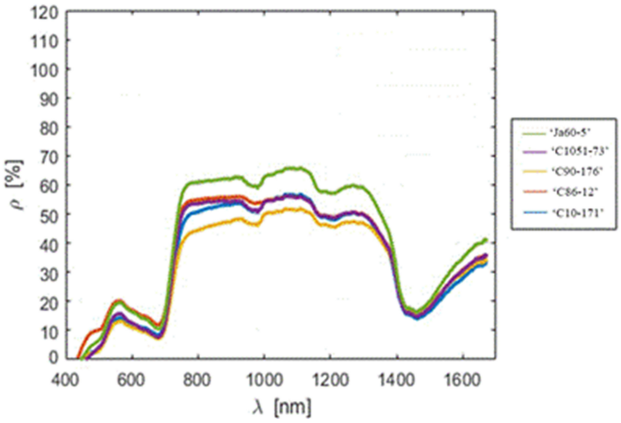

Figure 1. Average reflectance characteristics of cultivars 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', 'C86-12', where ρ is the reflectance of the spectra.

The characteristics shown in Figure 2 have a similar trend in terms of the high mean gradient peaks squared associated with the inflection points of the reflectance characteristics of each cultivar. However, these peaks are the key points that denote differences between the cultivars studied. It is important to note that these differences are not influenced by external factors, since all plants of the different cultivars were six months old (which corresponds to the rapid growth stage of the crop), were planted in adjacent areas with the same soil and climate conditions, and the samples were collected on the same day. Therefore, these high mean gradients squared peaks must be associated with the morphological and physiological differences of the cultivars under study. The reflectance characteristics of plants are due to the properties of the surface and internal structure of the leaf, as well as the distribution and concentration of its biochemical components (Peñuelas and Filella, 1998).

As shown in Figure 2B, at 526.2 nm, all reflectance characteristics have a gradient peak, of which the highest gradient is produced by the cultivar 'Ja60-5', while the cultivar 'C90-176' produces the lowest gradient transition. These gradient peaks occur in the VIS region of the electromagnetic spectrum, which is in the range of 400-700 nm. The peaks in this region are related to the effect of chlorophylls and carotenoids (Peñuelas and Filella, 1998). When sunlight strikes the leaves, part of it is absorbed in order to capture energy for photosynthesis. The energy that is not absorbed is reflected (Segarra *et al*., 2020; Singh *et al*., 2020; Sarić *et al*., 2022). This is defined as spectral reflection in the plant and can be described as the process whereby leaves absorb light in the visible blue and red range due to the presence of chlorophyll, leaving the dominant reflection in the green range of the electromagnetic spectrum (between 494-577 nm) (Aboelghar and Khdery, 2017).

The average gradient peaks at 526.2 nm (green zone) differ between cultivars, which may be due to differences in the reflectance of the photosynthetic pigments of each cultivar. The minimum reflectance values correspond to the maximum absorption values (Peña *et al*., 2019). Therefore, it can be deduced that the lower the reflectance value, the higher the absorbance value, which is directly proportional to the light energy used by the plant.

Certain studies have defined wavelengths that are used to calculate reflectance indices, which are used to determine the efficiency of the photosynthetic process (Peña *et al*., 2019). It can be observed that lower reflectance values in the green zone of the VIS region correspond to better photosynthetic efficiency, so there is a negative correlation between them. The above allows us to infer that the cultivar 'C90-176', having the lowest peak at 526.2 nm, is the cultivar with the best photosynthetic efficiency. This corresponds to its characteristics, which, being an energy cane cultivar, requires more energy for biomass production (Abril-González et al., 2019).

Of the three areas of high average gradient peaks squared (526.2 nm, 723.8 nm, and 1,399 nm), the least representative in terms of the differentiation of the cultivars under study is the one occurring at 526.2 nm. This may be because the variability in reflectance between cultivars in the green region of the spectrum is limited because the optical properties of chlorophyll dominate the spectral response. This means that the peaks in this region do not provide relevant information for discriminating between cultivars, as they are less sensitive than the other two regions in the near-infrared region.

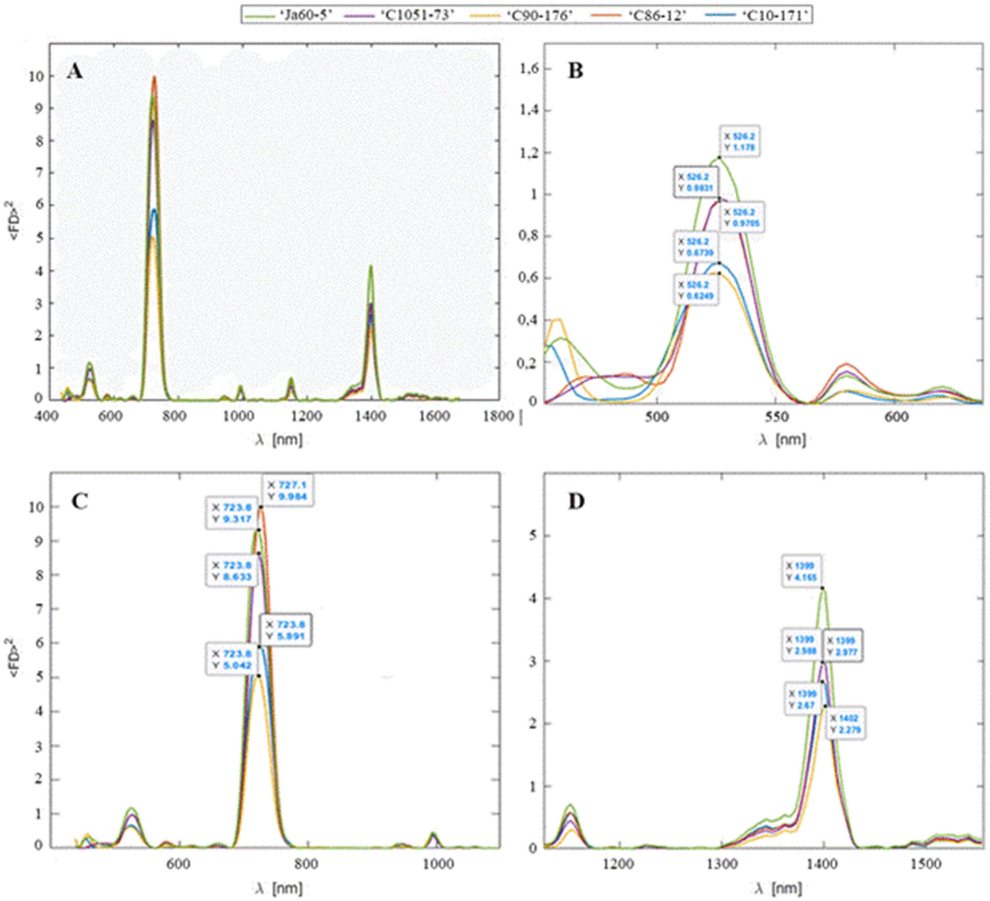

Figure 2. A Average reflectance gradient of the leaves of the cultivars under study, squared and smoothed. B Peaks of average reflectance gradient of the leaves of the cultivars under study at 526.2 nm. C Peaks of average reflectance gradient of the leaves of the cultivars under study at the red edge. D Peaks of average reflectance gradient of the leaves of the cultivars under study around 1,400 nm.

Figure 2C shows the average gradient peaks of the cultivars under study at the red edge (700-745 nm). The rate of change in this zone is greater for cultivar 'C86-12', while cultivar 'C90-176' has the lowest gradient in this band. High reflectance values at the red edge are associated with chlorophyll content in the leaf (Peñuelas and Filella, 1998). The usefulness of derivative analysis of reflectance data in this region for vegetation identification has been highlighted (Thorp and Tian, 2004).

Of the three areas with high mean gradient peaks squared (526.2 nm, 723.8 nm, and 1,399 nm), the most important in terms of differentiating the cultivars under study is the one occurring at 723.8 nm. Although chlorophyll continues to influence this region (as it does in the 526.2 nm zone), reflectance around 700-745 nm is more sensitive to morphological and physiological differences between cultivars (Feng et al., 2013). This is because as wavelengths approach 700 nm, chlorophyll absorption decreases dramatically. After this point, the leaves begin to increase reflectance, marking the beginning of the red edge, a key feature in plant spectroscopy (Gausman, 1974). This abrupt change is sensitive to leaf conditions, such as chlorophyll content or cell structure (Peñuelas and Filella, 1998), making it very useful for distinguishing between cultivars.

For this reason, although chlorophyll remains a determining factor in this region, differences in chlorophyll content between sugarcane cultivars can generate a more pronounced contrast around 723 nm. This allows the spectra to vary more noticeably between cultivars, which is not so much the case in the 526.2 nm range, where reflectance is more stabilized by the strong absorption of chlorophyll.

Finally, around 1,400 nm (NIR), all characteristics produce another zone with gradient peaks, with the highest gradient occurring in the 'Ja60-5' cultivar and the lowest gradient in the 'C90-176' cultivar (Figure 2D). These average gradient peaks at 1,400 nm are due to discontinuities between cell walls and intercellular air spaces in the internal structure of the leaf (Yuan *et al.*, 2014; Katsoulas *et al.*, 2016). Although this wavelength is not directly linked to the biochemical processes of photosynthesis, it has an indirect relationship with them, especially in C4 plants such as sugarcane. These plants have developed a specialized mechanism to perform photosynthesis more efficiently under high light and temperature conditions. Part of this efficiency comes from their leaf structure, which optimizes CO_2 capture and reduces photorespiration (Moore and Botha, 2014), which could be reflected in absorption or reflectance in this region of the spectrum.

The air spaces between cells allow for more efficient transport of CO_2 to the cells specialized in photosynthesis in C4 plants. This characteristic is an advantage that is exploited in the photosynthetic process, as it is crucial in the carbohydrate synthesis phase. If reflectance at 1,400 nm is associated with the proportion of these intercellular spaces, it could be reflecting structural characteristics that favor efficient photosynthesis in C4 plants. Although the absorption of photons that enable chemical synthesis in photosynthesis itself occurs at visible wavelengths, the cellular architecture that facilitates this process manifests itself at NIR wavelengths.

Other authors have described that the NIR region comprising wavelengths of 1,300-1,400 nm is related to the interaction of incident energy with the mesophyll structure of the leaf (de Souza et al., 2020). Sugarcane is a monocotyledonous plant, and the leaves of this type of plant have more air spaces within the mesophyll than dicotyledonous species. Thus, this effect has a direct influence on the radiation scattering of *Saccharum* spp. cultivars. In addition, other mid-gradient peaks useful for the discrimination of cultivars and species have been described. For example, when differentiating between four Brazilian sugarcane cultivars using VIS-NIR spectroscopy, it was found that all wavelengths contributed to discriminating between sugarcane cultivars, but the 600-750 nm range was the most relevant (Neto *et al*., 2018). Also, when differentiating sugarcane plants from weeds by the spectral behavior of the leaves, it was possible to simplify the spectrum into only four bands of interest (500-550 nm; 650-750 nm; 1,300-1,450 nm; and 1,800-1,900 nm) (de Souza et al., 2020). This indicates that the bands used in the differentiation may vary, as the spectral properties of plants depend on their physiological state, such as the concentration of chlorophyll and other photosynthetic pigments, the content and internal structure of the leaves, and the influence of biotic and abiotic stress.

The three high-gradient bands are clearly shown as peaks with maximum values that form different combinations for each cultivar, making it possible to create a feature space. This allows for the characterization of spectral variations, which makes it possible to identify the significant wavelengths from which discrimination and classification strategies can be implemented (Agarla *et al*., 2021).

The results confirm that, based on the VIS-NIR spectra, the cultivars show characteristic features that allow them to be differentiated from one another. In this way, it is possible to differentiate the presence of the five cultivars in the area based on the internal structure of the leaf, the variability in the constituent elements of each plant tissue, and their concentrations among the cultivars analyzed.

Comparison of five commercial cultivars of *Saccharum* spp. using ten spectral matching measures

Table 1 shows the results of the ten SMMs analyzed, representing the mean value and standard deviation among all samples of each cultivar, using reflectance characteristics with an amplitude between 0 and 1. In the measures that determine correlation (DSSC, SCM), the maximum values are represented in green, while the minimum values are represented in red. In the measures that determine distance (SED, BhattD, JMD), similarity (KJSSC, KJDSSC), measure (SAM), or divergence (SID, SIDSAM), the minimum values are represented in green, while the maximum values are represented in red.

The SED, given by (1), was scaled by 0.5 as it depends on amplitudes. When it increases, it indicates a greater Euclidean distance between the spectra, which occurs between the cultivar ‘Ja60-5’ and the rest of the cultivars, with the highest value when compared to the cultivar ‘C90-176’. The lowest values for SED were obtained when comparing cultivars ‘C1051-73’ and ‘C10-171’. The SAM, given in (2) and converted to degrees (°), increases when there is greater angular separation between spectral characteristics, which is obtained between cultivars ‘C86-12’ and ‘C1051-73’, or ‘C90-176’, in that order. This is not the case for the SAM between cultivars ‘C1051-73’ and ‘C10-171’ or ‘Ja60-5’, in that order. The SCM, given in (3), when it decreases indicates lower spectral correlation, which is obtained between cultivars ‘C86-12’ and the rest of the cultivars; presenting the lowest value with cultivar ‘C1051-73’; This is not the case between cultivars ‘C1051-73’ and ‘C10-171’, ‘C1051-73’ and ‘Ja60-5’, and ‘C10-171’ and ‘Ja60-5’, where the first case has the highest spectral correlation. For SED, SAM, and SCM, the standard deviation values did not exceed the measured values.

On the other hand, the SID, given by (4) and (5) scaled by 10, when it increases indicates greater divergence of information between the reflectance spectra, with the maximum divergences being obtained between cultivar ‘C86-12’ and the rest of the cultivars. The same does not occur between cultivars ‘C10-171’ and ‘C1051-73’, as the lowest divergence is obtained between them. The SIDSAM, given by (6), also indicates greater spectral discrepancy when its value increases, which is obtained between cultivar ‘C86-12’ and the rest of the cultivars. As with SID, the smallest difference is obtained between cultivars ‘C10-171’ and ‘C1051-73’; however, the standard deviation in this case exceeds the mean value of the measurement for most values. The BhattD, given in (7) and scaled by 10, when its value increases denote more distance between the spectral characteristics, with the greatest distance being obtained between cultivars ‘C86-12’ and ‘C1051-73’. The smallest distance value was found between cultivars ‘C1051-73’ and ‘C10-171’.

The JMD, given by (8), like the BhattD, when its value increases, denotes more distant spectra and has a nonlinear relationship with the BhattD, showing that the greatest distance values occur between cultivar ‘C86-12’ and the rest of the cultivars, with ‘C1051-73’ being the greatest of all. The smallest distance value occurs between cultivars ‘C10-171’ and ‘C1051-73’.

Table 1. Results of the ten SMMs analyzed, representing the mean value and standard deviation among all samples of each cultivar, using reluctance characteristics with an amplitude between 0 and 1.

	'Ja60-5'	**'C10-171'**	**'C90-176'**	**'C1051-73'**	**'C86-12'**
	SED				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,8775±0,3750	0,0000±0,0000			
'C90-176'	1,1121±0,2320	0,5751±0,3462	0,0000±0,0000		
'C1051-73'	0,8114±0,3700	0,4800±0,4132	0,6553±0,4357	0,0000±0,0000	
'C86-12'	0,9122±0,3076	0,6997±0,3372	0,6097±0,3444	0,5064±0,2046	0,0000±0,0000
	SAM				
'Ja60-5'	0,0000±0,0000				
'C10-171'	3,7128±1,8715	0,0000±0,0000			
'C90-176'	5,1013±1,6607	4,8122±1,3868	0,0000±0,0000		
'C1051-73'	3,4983±1,5855	3,3288±1,5049	5,1397±1,7213	0,0000±0,0000	
'C86-12'	5,5087±2,5736	4,7847±2,9583	6,0161±2,5451	6,0556±3,4557	0,0000±0,0000
	SCM				
'Ja60-5'	1,0000±0,0000				
'C10-171'	0,9909±0,0087	1,0000±0,0000			
'C90-176'	0,9873±0,0088	0,9876±0,0108	1,0000±0,0000		
'C1051-73'	0,9909±0,0079	0,9911±0,0082	0,9844±0,0148	1,0000±0,0000	
'C86-12'	0,9781±0,0336	0,9801±0,0399	0,9769±0,0317	0,9691±0,0463	1,0000±0,0000
	SID				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,1310±0,1169	0,0000±0,0000			
'C90-176'	0,2177±0,1730	0,1738±0,0881	0,0000±0,0000		
'C1051-73'	0,1444±0,1184	0,1254±0,1082	0,2569±0,1395	0,0000±0,0000	
'C86-12'	0,3295±0,3064	0,2760±0,4364	0,3560±0,2952	0,4884±0,4919	0,0000±0,0000
	SIDSAM				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,0119±0,0175	0,0000±0,0000			
'C90-176'	0,0240±0,0278	0,0160±0,0123	0,0000±0,0000		
'C1051-73'	0,0115±0,0139	0,0099±0,0121	0,0265±0,0214	0,0000±0,0000	
'C86-12'	0,0451±0,0762	0,0454±0,1175	0,0499±0,0613	0,0810±0,1347	0,0000±0,0000
	DSSC				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,7316±0,0133	0,0000±0,0000			
'C90-176'	0,7240±0,0107	0,7402±0,0103	0,0000±0,0000		
'C1051-73'	0,7338±0,0116	0,7417±0,0114	0,7367±0,0139	0,0000±0,0000	
'C86-12'	0,7318±0,0121	0,7367±0,0104	0,7388±0,0109	0,7426±0,0064	0,0000±0,0000
	KJSSC				
'Ja60-5'	0,0000±0,0000				
'C10-171'	3,6963±2,2523	0,0000±0,0000			
'C90-176'	5,4460±3,8620	2,0686±1,5693	0,0000±0,0000		
'C1051-73'	3,1767±1,9155	1,7244±1,9981	2,8639±2,3213	0,0000±0,0000	
'C86-12'	4,8575±3,0803	3,0374±3,0098	2,7792±2,3586	3,2666±3,2931	0,0000±0,0000
	KJDSSC				
'Ja60-5'	1,0000±0,0000				
'C10-171'	3,2709±1,9369	1,0000±0,0000			
'C90-176'	4,7620±3,2647	1,8627±1,3667	1,0000±0,0000		
'C1051-73'	2,8283±1,6631	1,5407±1,7439	2,5450±1,9921	1,0000±0,0000	
'C86-12'	4,3072±2,5909	2,7148±2,6437	2,4937±2,0725	2,9617±2,9057	1,0000±0,0000

	BhattD				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,0158±0,0143	0,0000±0,0000			
'C90-176'	0,0266±0,0209	0,0211±0,0106	0,0000±0,0000		
'C1051-73'	0,0174±0,0142	0,0152±0,0131	0,0313±0,0168	0,0000±0,0000	
'C86-12'	0,0401±0,0374	0,0334±0,0520	0,0433±0,0358	0,0589±0,0591	0,0000±0,0000
	JMD				
'Ja60-5'	0,0000±0,0000				
'C10-171'	0,0313±0,0279	0,0000±0,0000			
'C90-176'	0,0520±0,0401	0,0417±0,0207	0,0000±0,0000		
'C1051-73'	0,0343±0,0277	0,0301±0,0257	0,0614±0,0324	0,0000±0,0000	
'C86-12'	0,0774±0,0690	0,0632±0,0933	0,0836±0,0673	0,1113±0,1061	0,0000±0,0000

Note: In measures that determine correlation (DSSC, SCM), maximum values are represented in green, while minimum values are represented in red. In measures that determine distance (SED, BhattD, JMD), similarity (KJSSC, KJDSSC), measure (SAM), or divergence (SID, SIDSAM), minimum values are represented in green, while maximum values are represented in red.

The DSSC, given by (9) and scaled by 0.75, decreases when the reflectance characteristics are less similar, which occurs between cultivar 'Ja60-5' and the rest of the cultivars, with the lowest value when compared to cultivar 'C90-176'. The highest DSSC value is obtained between cultivars 'C86-12' and 'C1051-73'. The KJSSC, given by (10) and scaled by 0.1, increases in value when the spectral characteristics are less similar, with the coefficients between cultivar 'Ja60-5' and the rest of the cultivars being the highest. In contrast, the cultivar 'C10-171' compared to 'C1051-73' obtains the lowest KJSSC value. Finally, the KJDSSC, given by (11), also increases in value when the spectral characteristics are less similar, with its results coinciding with those of the KJSSC.

The results of the ten SMMs show as a general pattern that cultivars 'Ja60-5' and 'C86-12' are the most different from the rest. In this sense, the cultivar 'C86-12' achieved the most significant values when compared to 'C1051-73'; and the cultivar 'Ja60-5' obtained its most representative values when compared to 'C90-176'. On the other hand, cultivars 'C10-171' and 'C1051-73' are the most similar to each other.

Only when a cultivar is compared with itself do the values of distance, similarity, measure, or divergence take on a value of zero, or the correlations take on a value of one; otherwise, metamerism would occur. Metamerism is the effect that occurs when two different spectra produce the same perception of the sources that reflect those spectra (Agarla *et al*., 2021). In this case, metamerism will occur between two spectral reflectance readings of different cultivars if the SMMs that determine distance (SED, BhattD, JMD), similarity (KJSSC, KJDSSC), measurement (SAM), or divergence (SID, SIDSAM) between them result in a value of zero, as well as when the SMMs that determine correlation (DSSC, SCM) result in a value of one.

In the analysis of the SMMs, none of the minimum values are zero, with SIDSAM producing the values closest to zero, mainly when comparing cultivar 'C1051-73' with 'C10-171' (0.0099); however, the SIDSAM values for these cultivar pairs are also low. On the other hand, the correlation measures (SCM and DSSC), which take a value of one when metamerism occurs, or when a species is compared with itself, obtain their highest value for the SCM when comparing cultivar 'C1051-73' with 'C10-171' (0.9911).

Finally, it can be noted that based on the results shown and after testing the normality of the reflectance values for the various readings of the same sample, the mean and standard deviation characteristics of each were determined. The bundle of these mean characteristics of the cultivars studied represented their variability. It was identified that, at 526.2 nm, 723.8 nm, and 1,399 nm, there are differences in the gradients of the spectral characteristics of the five cultivars studied. Various SMMs corroborated that it is possible to discriminate between cultivars without metamerism occurring. Of these, SED, SAM, and SCM provide the best results. In addition, these were the three spectral correspondence measures in which none of the standard deviation values exceeded the mean values.

Computational spectral analysis methods have been used to distinguish species and cultivars based on the assumption that each has certain characteristics that can be used to differentiate them from others, which are generally the shape, size, and reflectance of the leaves (Cisternas *et al*., 2020). In a similar study, other wavelengths were identified for the discrimination of commercial cultivars of Saccharum spp. ranging from 560 to 720 nm (Johnson *et al*., 2008). The results indicate that the bands for discriminating cultivars may vary and should be investigated more closely to allow for adequate mapping of sugarcane cultivars, taking into account the area and characteristics of the cultivars under study.

The spectral signature of each cultivar has a different graphical curve depending on its specific characteristics. Therefore, a spectral library can be used to compare the reflectance of sugarcane cultivars in a field and estimate their frequency; in addition, this library can be used to discriminate and identify the location of the plant (Kai *et al*., 2020).

CONCLUSIONS

- It is possible to determine the spectral signatures of commercial cultivars of *Saccharum* spp., 'Ja60-5', 'C10-171', 'C90-176', 'C1051-73', 'C86-12', at 526.2 nm, 723.8 nm, and 1,399 nm, where at a reflectance wavelength of 526.2 nm, 723.8 nm, and 1,399 nm, there are differences in the gradients of their spectral characteristics.
- The ten spectral correspondence measurements allow commercial cultivars of *Saccharum* spp. to be differentiated without metamerism occurring.

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