Discrimination of Sugarcane Varieties by Remote Sensing: A Review of Literature

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***Abstract*—Remote sensing techniques by satellite imagery have been widely applied in various fields of agrarian sciences due to allowing real-time information, allowing data retention in a given region without the need for displacement, avoiding costs, and also enabling the creation of more efficient methods for the task of monitoring crops. In special to remote sensing applied to sugarcane varietal identification, the possibility of discrimination among the varieties is important due to allows the monitoring of the crop growth concerning characteristics by plants, measures controls, and the preservation of copyright of developed varieties. Among the researches involving studies with sugar cane regarding varietal identification, the purpose of the paper implies to present a review of the literature, conferring methods, and checking state of the art about the subject of discrimination of sugarcane varieties by remote sensing.**

***Index Terms*—Remote Sensing; Sugarcane Varieties; Image Processing.**

I. Introduction

The sugarcane (*Saccharum officinarum* L.), where Brazil currently ranks as the world's largest producer, with 2019/20 estimated crop in 615,98 millions of tons, provides the most varied products such as sugar, fibers, energy production and the growing demand by ethanol [1]. To maintain industry profitability, related studies to productivity growth of sugarcane are conducted, including genetical enhancement of varieties as sucrose content, drought tolerance, increased in the ethanol acquisition and biomass [2], resulting in new varieties that adapt to different environments and soils to posteriorly to be available for large-scale planting, allowing the farmer to select the variety that most fits the climate conditions, region soil and crop disease resistance.

Besides that, the importance of monitoring and discriminating sugarcane varieties, based on law no. 9456, of April 25, 1997, of Protection of Cultivars of Brazil (LPC) [3], enable what plant breeding specialists protect their new varieties with the acquisition of rights over them. Thus, methods for tracking crop development are developed, providing the advantage of real-time monitoring without the need for physical displacement. As an example of this we have the popularization of remote sensing methods, increasingly used by specialists applied in agriculture.

The use of remote sensing has been widely applied due to the fact that it can provide data that allows the extraction of updated information in addition to other important factors such as soil salinity [4], crop monitoring [5][6], burning emission [7], discrimination between crops and varieties, nutritional assessment, pest and disease detection [8], weather forecasting, water requirement assessment, and other purposes [9]. Based on multispectral images from reflectance characteristics of sugarcane varieties, in [10], discriminated four stages of sugarcane growth.

Several studies have been performed with the use of remote sensing applied in sugarcane crops purposes of identifying, discriminating, or otherwise classifying varieties. Identify these varieties are an important task because it allows following the growth of the plant-based characteristics, besides the harvest prediction, allowing the producer to select the variety that best fits the climatic and soil conditions found, as well as reducing the incidence of crop diseases. Due to this, this paper presents a Review of Literature, bringing papers with researches of sugarcane variety discrimination, aiming to verify the state of the art for the development of future research.

From this point on, this paper is structured as follows: Section II presents the Review planning and execution. In Section III brings the synthesis of the study, bringing answers regarding the main research question. Section IV presents the discussion and Section V the conclusion of review.

II. Review of Literature

In this report, to answer the research question, data considered relevant from the studies were extracted, exhibiting the existing techniques applied by the authors, to investigate the state of the art associated with the identification/classification of sugarcane varieties by remote sensing.

A. Research methods analysis

In this review we have the following research question:

Q: What are the techniques used to perform sugarcane varieties discrimination by satellite images?

To answer this question, with the help of a list with nomenclatures available in the Table I, studies that perform the identification, discrimination, and classification of sugarcane varieties are presented, with data extracted from the articles.

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Table I: Nomenclature

CDA	Canonical Discriminant Analysis
F'DA	Fisher's Discriminant Analysis
FDA	Factorial Discriminant Analysis
JM	Jeffries-Matusita Distance
LDA	Linear Discriminant Analysis
LWIR	Long Wavelength Infrared
MDA	Multiple Discriminant Analysis
NIR	Near Infrared
PCA	Principal Component Analysis
PDA	Penalized Discriminant Analysis
PLS-DA	Partial Least-Squares Discriminant Analysis
RF	Random Forests
ROI	Region of Interest
SAM	Spectral Angle Mapper
SFDA	Stepwise Forward Discriminant Analysis
SVM	Support Vector Machine
SWIR	Short Wavelength Infrared

In advance of the abstracted content of the selected papers in this review, a brief description of the multivariate methods used by the authors will be exhibited.

B. Multivariate methods

Multivariate analysis is composed of statistical methods responsible for extracting information of datasets widely used in object classification with simultaneous measures in many variables [11]. A brief description of methods involving multivariate analysis used by the studies to identify sugarcane varieties is presented.

- Linear Discriminant Analysis (LDA): is a generalization of Fisher's discriminant linear, being very similar to the PCA method, with data dimensionality reduction and linear transformation techniques aiming to separate two or more classes.
- Principal Component Analysis (PCA): is a method that aims to reduce the dimensionality of data, increases the variance between classes, in which correlated variables are transformed into uncorrelated variables. The number of variables resulting from the method will be less than or equal to the original quantity.
- Canonical Discriminant Analysis (CDA): aims to reduce data dimensionality using canonical variables, being linear combinations of original variables, the way to maximize the variation between classes, searching two sets of linear combinations, to are as highly correlated as possible [12]. This technique is respect to principal component analysis and canonical correlation.
- Factorial Discriminant Analysis: factors are used in the factorial analysis to represent variables through linear combinations, varying from individual to individual, aiming to decrease the number of factors, and consequently, the redundancy of data [13].
- Penalized Discriminant Analysis (PDA): create by Hastie et al. [14], was developed for situations involving many highly correlated variables, applying penalties to Fisher's discriminant.
- Partial Least-Squares Discriminant Analysis (PLS-DA): This supervised technique is an adaptation of Partial least squares regression (PLS regression) to dimensionality reduction, applied to variable with a categorical response. The PLS-DA method finds a linear regression model that makes a regression between classes and your descriptors.
- Stepwise Forward Discriminant Analysis (SFDA): based on PCA analysis, this algorithm uses a discrimination step-by-step analysis selecting the best variables [15].The method starts without predictors and each step verifies the best variable to be included in the model.
- Support Vector Machine (SVM): create by Vapnik *et al.* [16], is a supervised algorithm that aims to find an optimal hyperplane (decision limits) with n-dimensional space to the separation between classes. The support vectors, corresponding to nearby data of limits of the hyperplane, are used to maximize the margin.
- Random Forest (RF): being supervised learning, also called random decision forests, it combines decision trees to perform the classification of a new individual or object by tree votes. Votes are based on attributes of individuals.

1) Related Works:

- *Schmidt's method* [17]: with high-resolution Digital Multispectral Video imagery, by multivariate analysis, PCA was applied for noise removal in the multispectral data of 24 sugarcane varieties. Edge effects, accommodation, and factors associated with water stress influenced the separability between varieties. In addition, he reported the need to investigate the spectral signature of varieties also based on the growth stage.
- *Gers's method* [10][18]: exposed no significant differences between the top five sugarcane varieties using Landsat-7 ETM+ data. Suggested that the results of discrimination varieties can be associated with the resolution of the sensor and the higher influence of the growth stage in contrast to the physical characteristics of the leaves.
- *Apan's method* [19]: The separation of eight sugarcane varieties was performed by discriminant analysis from 152 bands and 40 vegetation indices derived from another study [8]. For preprocessing to Hyperion sensor imaged data include re-calibration, selection of sensor bands, conversion of reflectance values using ACORN (Atmospheric CORrection Now), and pixel value repair. The classification obtained for 8 varieties was 72.4% with better separability between some varieties in the range of 550 nm, 680 nm, 800 nm, and 1660nm and 2220nm.
- *Galvão's method* [20] [21]: with use of from the selection of variables such as band reflectance values, band reflectance ratios and sensitive indices for chlorophyll, leaf water and lignin-cellulose, was possible discriminate the variety SP80-1842, using canonical discriminant analysis (also denominate Multiple Discriminant Analysis)

for the others 4 varieties, of which: RB72-454, SP80-1816, SP81-3250, and SP87-365, with region of study located in Brazil's Southeastern. Use of 198 bands (242 in total) with exclusion of bands around 1400nm and 1900nm due to strong atmospheric absorption by water vapor. Differences in reflectance values of varieties were observed in the following ranges: 750-1300, 550-690 and 1500-1750.

- *Fortes's method* [22]: study performed with the selection of area located in the state of São Paulo (Brazil), using multispectral images applying atmospheric correction (5S model - Simulation of Satellite Signal in the Solar Spectrum), analyzing each band individually, which are: B1, B2, B3, B4, B5 and B7, with method by dispersion graph of pixels and regression equations to discriminate four sugarcane varieties (RB835486, RB855536, RB855113 and SP81-3250) from vegetation indices with specific characteristics of varieties. Used a method by step-wise discrimination analysis to select the best variables to discriminate varieties. A percentage of 93.55% was obtained from sugarcane varieties classification.
- *Everingham's method* [23]: from the use of hyperspectral sensor (EO-1/Hyperion), to classify 9 sugarcane varieties located in Australia denominated 20, 121, 124, 135, 136, 138, 159, 185 and 190, was used Linear Discriminant Analysis, Penalized Discriminant Analysis, Random Forests and Support Vector Machine. Used 150 of Hyperion's 242 bands, eliminating nonuniform bands after calibration procedures. The approach made use of areas without mixed vegetation and free of edge effects, performing the classification in two ways, using pixel and paddock, being a paddock composed of several pixels, performing the training of cross-validation samples with value of v = 10. For the nine discriminated sugarcane varieties, support vector machines and random forests obtained the highest correct ratings. LDA and penalized discriminant analysis have more variations accuracy to different sample sizes.
- *Johnson's method* [24]: using a fiber optic spectroradiometer with wavelength range of 350 - 850 nm at 0.4 nm intervals (the total wavelength range of device is between 200 - 1100 nm), investigating plant pigment, this research combined wavelength reflectance data (5nm and 20nm) and three vegetation indices to distinguish seven sugarcane varieties by cross-validation discriminant analysis and canonical discriminant analysis. Reflectance data resulted in better classification of varieties concerning the use of pigments.
- *Rao's method* [25] [26]: with selected region located in India by hyperspectral image, made use of Spectral Angle Mapper (SAM), which determines the spectral similarity between two spectrum calculating the angle among them as vectors with dimensionality equal to the number of bands, to identify and classify three sugarcane varieties (CO6097, 85A261 and 84A125).
- *Murillo's method* [27]:to measure the spectral separability of two sugarcane varieties from Colombia, the Jeffries-Matusita statistical distance was applied resulting in global precision of 80.8%. Bands, vegetation indices and transformation indices (Principal Component 1 (CP1), Principal Component(CP2) and Greenness Vegetation Index (GVI)) was used to discriminate the varieties.
- *Neto's method* [28]: In this study, the authors used multivariate analysis (PCA, FDA, SFDA and PLS-DA) to classify four varieties of sugarcane by the visible/near-infrared spectral reflectance obtained from the stalks by a portable device, the varieties RB867515, RB855453, RB928064 and RB92579. Was observed good separability between the RB928064 and RB92579 varieties, but there was an overlap in the Score plot of PCA between B867515, RB855453 varieties and confusion in classification by the other 3 methods. The discrimination by FDA with cross-validation considering the four sugarcane varieties was between 80.65% and 100%.
- *Duft's method* [29]: To investigate Sentinel-2b's ability to discriminate sugarcane varieties, obtained an overall accuracy of 86% using RF, from three images, using 10 bands and 3 vegetation indices, being the indices Normalized Difference Built-Up Index (NDBI), Red-Edge Normalized Difference Water Index (RENDWI) and Red edge Normalized Difference Vegetation Index (RENDVI).

From this information, we extracted the following data from the selected studies in order to answer the research question:

1) *Data extraction fields*: D1. Type Image, D2. Sensor, D3. Used Bands, D4. Quantity of varieties, D5. Spectral Indices used, D6. Discriminant method, D7. Local and D8. Accuracy.

Among this set of information captured from research involving sugarcane varietal discrimination, the extracted data can be seen in the Table IV.

III. Results

The following section presents the result of the review of studies and other pieces of information with subsections than include the temporal distribution of published papers, the number of citations and other information.

A. Methodology to varietal discrimination

Based on the selected studies related to sugarcane varietal discrimination, the following flowchart was constructed containing the basic steps for sugarcane varieties classification. The flowchart is available in Figure 1.

Firstly, images are acquired from the use of sensors and then applied the atmospheric correction to minimize the influence of atmospheric effects to improve image classification accuracy. In geometric correction distortions are corrected between the image and the coordinates of the earth's surface.

Physical units such as temperature, radiance or reflectance are not represented quantitatively by Digital Numbers (DN). Thus, the process of converting the DN to radiance and reflectance data allows the obtainment of other important

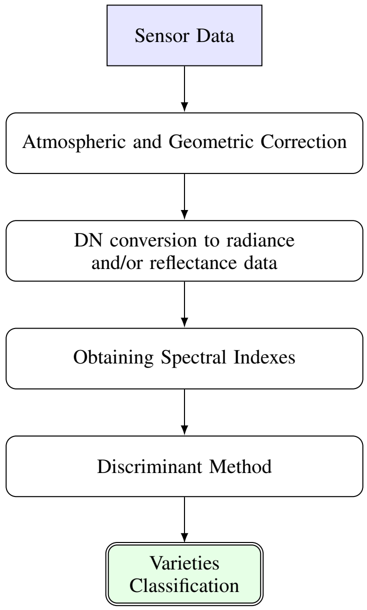

Fig. 1: Flowchart for sugarcane varieties identification/classification.

information, such as, for example, the calculation of the vegetation indices and others transformation.

Various discriminating methods have been used in studies related to the identification of sugarcane varietals, in particular, to discriminant analyzes as well as their variations. The use of other multivariate methods, such as SVM and RF, has also been explored by some studies.

B. Temporal distribution of publications

The majority of published studies were mostly concentrated between 2003 and 2008, 10 in total. The distribution of papers can be visualized in Figure 2.

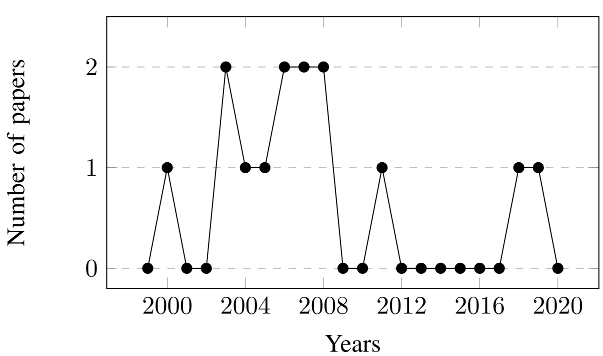

Fig. 2: Distribution of publications over the years

Most publications concentrate on journals, with studies published in the International Journal of Remote Sensing [21][22][25], and Remote Sensing of Environment [20].

C. Citation analysis

The citation is an important point, considering it allows checking the number of studies by referencing particular research. For verification purposes of citation quantity, the analysis of selected papers was made through the Google Scholar. Other databases were considered to obtain information on the number of citations. However, due to the lack of results for some studies, we opted by Scholar.

Table II: Number of citation per paper

Authors	**Total**	**Average citation per year**
[20] Galvão et al. (2005)	260	17.33
[26] Rao et al. (2007)	83	6.38
[25] Rao et al. (2008)	42	3.50
[22] Fortes et al. (2006)	35	2.50
[23] Everinghan et al. (2007)	29	2.23
[21] Galvão et al. (2006)	29	2.07
[24] Johnson et al. (2008)	14	1.16
[18] Gers (2003)	12	0.70
[10] Gers (2003)	10	0.58
[19] Apan et al. (2004)	9	0.56
[17] Schmidt et al. (2000)	7	0.35
[27] Murillo et al. (2011)	2	0.22
[28] Neto et al. (2018)	0	0
[29] Duft et al. (2019)	0	0
	532	**26.60**

Among articles, the most cited is the research of Galvão et al. [20], published in February 2005, addressing the theme of the classification of 5 sugarcane varieties in southeastern Brazil, with a total of 260 citations, with average of 17,33 citations per year (Table II), highlighting the other published works related to the identification/classification of this culture. The study of Rao et al. [26] also received some prominence from the results obtained with the spectrum classification of various cultures, with 83 citations to date, and an average of 6,38 per year. Although there are few articles currently published on sugarcane discrimination, it is possible to observe the continuing interest in the subject.

D. Sensor

Sensors are responsible for transforming the energy obtained from the object into an acceptable signal to be converted into useful environmental information. Amidst the sensors related by the studies selected in this review, are divided into studies using data from multispectral and hyperspectral sensors, present in various investigations, of which Landsat the Landsat 7 ETM+ and EO-1 Hyperion, both of which are currently decommissioned. Characteristics of the two most used sensors to sugarcane identification/classification are available in Table III.

In Rao [26][25], besides to Hyperion data, a field spectroradiometer was used, like in Johnson [24], to information in

Table III: Sensors features

Features	Landsat 7 ETM+	EO-1 Hyperion
Launch date	April, 1999	November, 2000
Number of bands	7	220
Spatial resolution	30m	30m
Spectral range	0.4-2.4μm	0.4-2.5μm
Spectral resolution	Variable	10nm
Spectral coverage	Discrete	Continuous
Swath width	185Km	7.7Km
Bands	VNIR, SWIR, and panchromatic	VNIR, SWIR

situ. In most recent paper by Neto [28] the data were obtained by a portable spectrometer.

E. Spectral indices

As shown in table 4, the field "Q. Indices" represents the number of spectral indices used together with the number of bands of the sensors. Among the commonly calculated indices, the most used for the discrimination of varieties of sugar cane are the Normalized Difference Vegetation Index (NDVI) [20][20][22][19][27][24], Modified Chlorophyll Absorptionin Reflectance Index (MCARI)[20][21][19], Ratio Vegetation Index (RVI)[22][27], Soil-adjustedvegetation index (SAVI)[22][27] and Global Vegetation Index (GVI)[22][27].

IV. Discussion

In this literature review, the selected studies focused mainly on large sugarcane producing regions, comprising countries such as Australia, South Africa and Brazil, the largest sugarcane producer.

Considering studies related to the identification and discrimination of sugarcane varieties, few articles on the subject were found. Many studies have used multivariate methods applied for identification purposes, discrimination and classification of sugarcane varieties. One of the factors for choosing these methods is the lower computational load required unlike more current ones, such as deep neural networks. Besides, although the frequent use of these multivariate methods, it is necessary investigate if the performance can be affected in comparison to other techniques that demand more of computational processing. Thus, the possibility of developing different approaches that accomplish this task can be explored and implemented.

Despite the more frequent use by data authors using the Hyperion sensor, the accuracy obtained for the identification or discrimination of sugarcane varieties by Landsat-7 data exceeded 80%. Using data from more than one sensor could aid in gaining more information to improve classification precision. Due to both sensors, Landsat-7 and Hyperion, are currently decommissioned, to get updated data, other satellites/sensors need to be considered for investigations with more recent crop areas.

In addition, some studies have pointed to the importance of using other plant information, such as pigment, leaf angles, the calculation of known vegetation indices relevant to the varietal identification task, and also the influence of image resolution on the results. It was addressed in some studies about the importance of verifying the stability of a spectral signature by growth phases, which may influence the obtained spectral signatures, adding more information about the varieties, helping to distinguish and consequently in the classification between them.

V. Conclusion

Sources for obtaining land surface data have become increasingly popular and accessible over the years, with the use of sensor data such as Hyperion and Landsat-7 being largely observed for the large availability of information.

In this literature review, studies related to the identification/discrimination of sugarcane varieties were presented and features extracted from the complete reading of the articles. The use of several multivariate methods was observed to identify, discriminate and classify sugarcane varieties in remote sensing.

The application of methods involving multivariate analysis is still very present when related to crop identification or classification, and is also advantageous when related to the low computational load required when compared to other methods, such as deep neural networks.

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Table IV: Data

Study	Type Image	Sensor	Used Bands	Q. Var	Q. Indices	Method	Local	Accuracy
[17]	Multispectral	Digital Multi-Spectral, Video camera (DMSV)	4 bands	24	–	PCA	South Africa	–
[10][18]	Multispectral	Landsat 7 ETM+	6 bands	–	6	PCA	South Africa	–
[19]	Hyperspectral	EO-1 Hyperion	152 bands	8	192	LDA	Australia	74%
[20]	Hyperspectral	EO-1 Hyperion	198 bands	5	13	CDA	Brazil	100%(SP80-1842) 87,5%
[22]	Multispectral	Landsat 7 ETM+	6 bands (B1-B5, B7)	4	12	SFDA	Brazil	93.55%
[21]	Hyperspectral	EO-1 Hyperion	198 bands	5	13	CDA	Brazil	87%
[23]	Hyperspectral	EO-1 Hyperion	150 bands	9	150	LDA, PDA, RF SVM	Australia	100%(RF-paddock) 90%(SVM-pixels)
[24]	Hyperspectral	fiber optic spectroradiometer (Ocean Optics SD-2000)	+1000 bands (350-850nm with 0.4nm intervals)	7	11	CDA LDA	USA	95% - 100%
[25][26]	Hyperspectral	Hyperion, field spectroradiometer (GER 3700)	–	3	–	SAM	India	86,5% - 88,8%
[27]	Multispectral	Landsat 7 ETM+	6	2	14	JM distance	Colombia	80.8% - 66.8%
[28]	Hyperspectral	Portable spectrometer (JAZ-EL350)	all bands	4		PCA, FDA, SFDA, PLS-DA	Brazil	80.65% - 100% (FDA)
[29]	Multispectral	Sentinel-2b	10 bands	25	13	RF	Brazil	86%

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