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# Effects of resampling image methods in sugarcane classification and the potential use of vegetation indices related to chlorophyll

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***Abstract*—In methodologies that make use of the remote sensing images obtained by orbital sensors, it is very common the application of resampling methods with the adaptation of images contained bands with different spatial resolutions, for example, the Sentinel-2 sensor, with thirteen bands, four with a resolution of 10m, six of 20m and three with 60m. In this way, to calculate some vegetation indices, the difference of spatial resolution among bands does not allow index calculation, requiring the application of resampling. In the literature, there are several techniques, but the effects derived from that pixel transformation have not been explored much when related to sugarcane classification. Thus, this paper applies different resampling methodologies focused on remote sensing, verifying the effects of each transformation in the vegetation indices calculation to perform sugarcane varieties discrimination. It was possible to observe little variation in accuracy amid the applied methods, showing little influence in the process to identify sugarcane varieties. Thus, the use of indices related to chlorophyll demonstrated great potential for the purpose of discriminating/classifying sugarcane, presenting alternative vegetation indices to be applied for this type of purpose.**

***Index Terms*—Resampling, Classification, Sugarcane, Remote Sensing, Vegetation Indices.**

## I. Introduction

Studies related to sugarcane (*Saccharum officinarum* L.), plant of big economic importance due to the supplier potential, such as ethanol and sugar, aim at creating and improving profitable varieties, valuing productivity and adaptability to different environments. In this way, these studies may involve the improvement of sugarcane varieties, seeking to improve plant characteristics, such as, the sucrose content, drought tolerance, adaptation to adverse environments, resistance to diseases, allowing a wide range of varieties available. Thus, it is possible found the profile of sugarcane variety that best suits adapt to weather conditions found can be purchased.

In addition to developing new varieties, as well monitoring existing ones, approaches involving the growth monitoring of the sugar cane phenological cycle, besides other cultures, allow the crop monitoring in real-time without physical displacement of the specialist. With the wide availability of free images captured by different sensors, remote sensing methods are becoming more popular, and notoriously adopted by researchers due to wide application for diversified purposes in agriculture.

Among methods applied to remote sensing in sugarcane images, we can include image resampling. In this process, bands with lower spatial resolution are resampled to images with more spatial resolution, enable some process, such as different vegetation indices calculation. In case of Sentinel-2 images, containing a total of thirteen spectral bands, four with 10 m of spatial resolution (red, green, blue, and near-infrared), six with 20 m, and three with 60 m, to calculation of vegetation indices, there is a need to adapt the resolution of bands with lower resolution to obtain more information of pixels in each band used to calculate of indices. Thus, pixels must-have spatial resolution compatibility to allow the calculation of the indices selected in the study.

For this study, were applied image resampling methods with objective of increase the spatial resolution in images of Sentinel-2 with lower spatial resolution (20 m to 10 m of spatial resolution). Thereby, various traditional methods as used, as the nearest neighbor, bilinear, and cubic convolution. In the literature, other methods have also been explored and applied to remote sensing problems, such as Lanczos or even artificial neural networks.

From this point, this article will present a study to evaluate the influence of resampling methods on sugarcane classification from Sentinel-2 images, with obtaining vegetation indices related to chlorophyll for the purpose of sugarcane discrimination, presenting the accuracy obtained in the study in addition to other measures, from the application of each resample method selected for this research.

For this, the paper is organized as following: Literature Review in Section 2, follow by Section III with the Materials, results are discussed in the chapter IV, and conclusions in Section V.

## II. Literature Review

### A. Vegetation Index

Vegetation indices correspond to mathematical models that allow extract features by use of two or more spectral bands, resulting in values that correspond to evidenced characteristics, helping in the process of identification and discrimination of cultures and their varieties.

Amidst the most used indices in the literature to classify sugarcane varieties [1] we have the Normalized Difference

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Vegetation Index (NDVI) [2][3][4][5][6] widely used in various studies, Modified Chlorophyll Absorptionin Reflectance Index (MCARI) [2][4][7], Ratio Vegetation Index (RVI) [3][6] and Soil-adjusted Vegetation Index (SAVI) [3][6].

Considering remote sensing studies involving sugarcane varieties discrimination, in [8], was obtained an overall accuracy of 86% by use of Random Forest classifier, from three images, using 10 bands and three vegetation indices (Normalized Difference Built-Up Index (NDBI), Red-Edge Normalized Difference Water Index (RENDWI) and Red edge Normalized Difference Vegetation Index (RENDVI)).

However, considering indices with purpose of identify/discriminate sugarcane varieties in literature, little has been explored about indexes related to chlorophyll. The chlorophyll has high importance in the photosynthesis process, corresponding to a green pigment presents in the leaves, responsible for converting light energy into chemical energy. Thus, it is possible to understand the nutritional status of the plant, stress, and other factors. Also, due to absorption in the region of the spectrum corresponding to the blue and red bands, as a result, we have the green color of chlorophyll.

There are several vegetation indices developed to obtain the content present in the leaves. Among some related vegetation indexes, for example, NDRE, NDCI, CVI, CI green, and CI red_edge.

Similar to NDVI, the NDRE (Normalized Difference Red-Edge Index) [9] is a sensitive index to some phases of plant growth, to obtain the health of vegetation by use of the red band and the red edge band, applied in images containing crops between the intermediate and advanced stages, due to the higher concentration of chlorophyll, defined as:

$$NDRE = \frac{NIR - RED\_EDGE}{NIR + RED\_EDGE}$$

The sensitivity of this index is higher than the NDVI due to the adoption of the red edge band, being more capable of penetrating the leaf than the red band used by NDVI.

NDCI (Normalized Difference Chlorophyll Index) [10], calculates the chlorophyll content of the plant using the red band of the visible spectrum and the red edge band, described as follows:

$$NDCI = \frac{RED\_EDGE - RED}{RED\_EDGE + RED}$$

MCARI [11] is a vegetation index that represents the chlorophyll concentration of the leaves, indicating high chlorophyll content for lower values obtained.

$$MCARI = \\ ((VNIR - RED) - 0.2 * (VNIR - GREEN)) * (\frac{VNIR}{RED})$$

The CVI (Chlorophyll vegetation index) is a vegetation index used to calculate the total chlorophyll content found in the leaves.

$$CVI = NIR * \frac{RED}{GREEN^2}$$

In the case of the CIgreen and CI red_edge indices, both have indices that are more sensitive to the variation of the chlorophyll content, in which CIgreen calculates the chlorophyll index using the green band and CIred_edge in obtaining the chlorophyll index by using the red_edge band.

$$CIgreen = \frac{NIR}{GREEN} - 1$$

$$CIred - edge = \frac{NIR}{RED\_EDGE} - 1$$

### B. Resampling

In remote sensing, methods to image resampling can be applied to transform the original image according to the proposed objective. For example, corrections involving reference points, or adjust the spatial resolution to make possible the feature extraction through the joint use of other images. Resampling can be applied by various methods, being the most traditional the nearest neighbor, bilinear, and cubic convolution.

In the literature, other methods have also been explored in researches involving remote sensing, such as Lanczos, Gauss, and others. Information for each method is described below:

- Nearest Neighbor - image resampling by the nearest neighbor comprises in the assigning the value of a pixel based on the nearest neighbor. With a simple approach, this method preserve the original data of the image. However, the use of this method results in duplication of values, loss of information, besides positioning errors.
- Bilinear - uses four closest points that best suit the new pixel value, applying the interpolation between the pixels that intercept the points. Therefore, for each point value obtained, is calculate the weighted average of pixels, corresponding four pixels of the nearest original image, thus generating new output values.
- Cubic - cubic convolution uses sixteen closest pixels of the original image to obtain the value of the new pixel on the specified coordinate of the resampled image, with calculation of the weighted average of these points. Requires a longer calculation time compared to the nearest neighbor but tends to have a smoother image compared to the original due to the use of more points.
- Lanczos - resampling method that preserves details and softens the image, interpolating the signal value by using a Lanczos kernel. It requires more processing time compared to the simplest methods.
- Gauss - Gaussian resampling tends to produce a blur effect in the image, with the application of Gaussian convolution, obtaining the pixel value through a distance-weighted of the four nearest pixels.

### C. classificatory models

- k-NN - a classificatory model with output associated with a class, based on the information of the k nearest neighbors.
- SVM - supervised learning algorithm that finds a hyperplane that best distinguishes the analyzed classes.
- Random Forest - creates randomly several decision trees generating a forest with combinations of decision trees to increase the overall classification result.

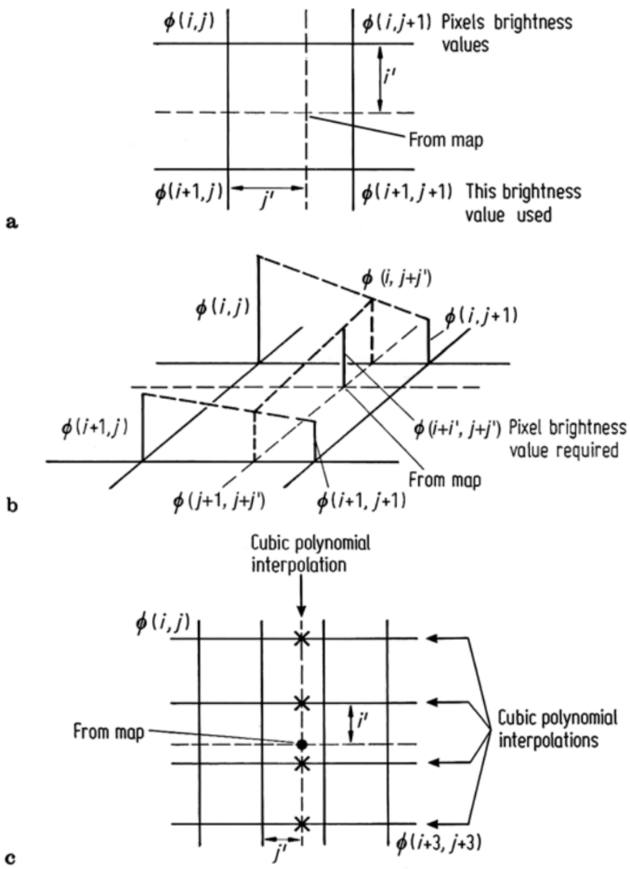


Fig. 1: Resampling methods: (a) resampling of the nearest neighbor, (b) bilinear interpolation, and (c) cubic convolution interpolation [12]

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Table I: Image Data

| Data | Sigle | variety |
|---|---|---|
| 02/05/2020 | KFF | RB92579G e RB966928G |
| 27/05/2020 | | |
| 16/07/2020 | | |
| 31/07/2020 | | |
| 02/05/2020 | KEF | RB88082D |
| 17/05/2020 | | |
| 27/05/2020 | | |
| 16/06/2020 | | |
| 30/05/2020 | KCF | RB966928AE |
| 24/06/2020 | | |
| 14/07/2020 | | |
| 24/07/2020 | | |
| 02/05/2020 | LGJ | RB988082JM |
| 12/05/2020 | | |
| 27/05/2020 | | |
| 01/06/2020 | | |
| 10/05/2020 | KCE | RB92579S |
| 30/05/2020 | | |
| 14/06/2020 | | |
| 19/07/2020 | | |

## III. Materials

### A. Image

For this study, images of Sentinel-2, product 1C was used, encompassing an orthorectified image of 100 km x 100 km, in the UTM/WGS84 projection, with pixel values provided in top reflectances of the atmosphere (TOA), containing a total of thirteen bands, with resolutions between 10 m and 60 m (four with a spatial resolution of 10m, six with 20 m and three with 60 m. In this study, bands with a resolution of 10 m and 20 m were used.

For each sugarcane variety, through the EOS LandViewer website (https://eos.com/landviewer/), Sentinel-2 images Level-1C were obtained and selected the following bands: bands of the visible spectrum (B02, B03, B04), near-infrared band, and the red edge band (B8A).

The vegetation indices were calculated using the bands of the visible spectrum (red, green, and blue), in addition to the near-infrared bands (NIR) and short wave infrared band (SWIR). Due to different spatial resolutions present in Sentinel-2 bands, resampling methods were applied to allow the calculation of chlorophyll-related vegetation indices, exploring which technique most impacts the accuracy regarding in the classification of sugarcane varieties.

To discriminate and classify sugarcane, classificatory models widely used in the literature to identify sugarcane varieties have been explored, including k-NN, SVM, Random Forest, as well as with the use of neural networks, increasingly applied for various purposes in agriculture.

The conversion of the coordinates referring to the points containing the growing varieties was performed with Qgis software, converting the shapefile to the same EPSG of Sentinel-2 images. The implementation of codes to resampling images, selection of ROI by shapefile, and classificatory models are developed in Python language.

The process for sugarcane classification by remote sensing images can be visualized through flowchart in Figure 2.

### B. Varieties

In this study, three sugarcane varieties were selected, with use of images between the months of May and June, presenting phenological stages of growth and maturation. Two regions are selected for each variety, with four images to each localization, eight images for each sugarcane variety, totaling 20 images. The sugarcane varieties in this study are RB92579, RB966928 e RB988082.

### C. Resampling

In this article, resampling methods traditionally applied in studies involving the identification of sugarcane varieties were selected. Resampling was applied using the five methods (nearest neighbor, bilinear, cubic, Lanczos, and Gauss) to band 5 and band 8A of Sentinel-2, converting images with

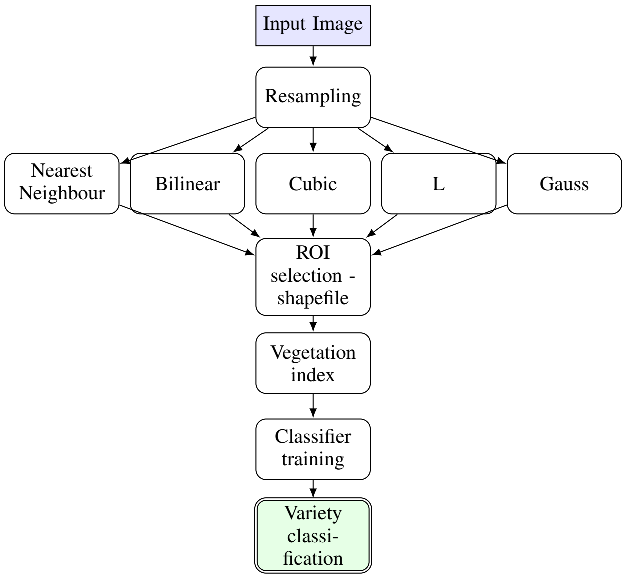


Fig. 2: Process for sugarcane variety classification.

20m spatial resolution to 10m. In total, was generate ten new resampled images (five images of band 5 and five to band 8A).

### D. Area selection

For ROI selection, corresponding to the locations with the growing varieties (Figure 3) between the phenological stages of stalk growth and maturation, coordinates obtained in situ were used through a portable GPS. The subsequent acquisition of shapefiles, coordinates with extension .kml are converted to the same coordinate system as the images obtained from Sentinel (EPSG: 32721).

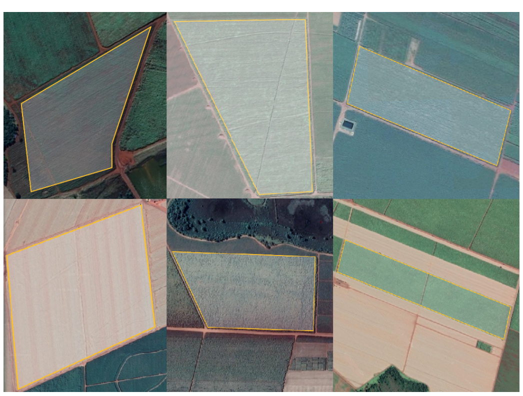

Fig. 3: Selected areas with sugarcane varieties.

Each shapefile selected (6 shapefiles in total, 2 for each variety of sugarcane) served as a mask for ROI selection. This step is performed before the vegetation indexes values calculation due to processing necessary is more quickly than the image with original size, in addition to allowing the obtaining only of pixels relevant to the study.

### E. Vegetation Index

Each pixel had the calculation of the following vegetation indices: NDRE, NDCI, MCARI, CVI, CI green, and CI red_edge, with storage of values in tables, where each row of the table represent only pixel and the columns features (different vegetation indexes related to chlorophyll). For this process, 4000 pixels per variety were selected (two distinct areas per sugarcane variety), therefore containing 500 pixels from each image (four images with different dates result in 2000 pixels in total).

The averages of the pixel reflectance values for different dates were also calculated with their respective vegetation indices.

### F. Classification

Sugarcane varieties classification through three supervised classificatory models widely used in remote sensing. Among them are k-NN (k-nearest neighbor), SVM (Support Vector Machine), and RF (Random Forest).

### G. Accuracy assessment

Was performed 10-fold cross-validation to the evaluation of the classification models. The dataset has split into 70% of the data for training and 30% for tests. The k-neighbors in k-NN and C parameter in SVM were selected based on the highest accuracy obtained after ten runs for each parameter. In the case of k-NN, the k parameter was tested between 1 to 20 neighbors. For parameter C, the following values were tested: 0.01, 0.1, 1, 10, 100, and 1000, with Radial basis function kernel. Random Forest was carried out with the standard configuration of parameters, using n_estimators equal to 10. Besides the accuracy, other measures were collected, such as precision, recall and f1-score.

## IV. Results and Discussion

In this section, the results of study will be presented for the discrimination/classification among sugarcane pixels of different varieties and differentiation between regions (sugarcane and non-sugarcane), ending with a discussion of the results obtained.

### A. Sugarcane varieties classification

To classification among three sugarcane varieties, k-NN, SVM, and Random Forest classifiers were trained with 70% of the data. The dataset is composed of values referring to six vegetation indices related to chlorophyll (NDRE, NDCI, MCARI, CVI, CI green, and CI red_edge). Each pixel has the features calculated stored per row, totaling 12000 rows (4000 per variety), with data obtained in two locations per variety. Tests were performed with 30% of unused data in the training step. Also, averages per pixel of the vegetation index of the four dates covered in the study were computed (1000 pixels per variety).

Among the experiments, it was possible to observe little variation in the classification from the resampling methods applied to the Sentinel-2 images. Thus, it is possible to see in the table II the result of each resampling method and the accuracy for each classificatory model. Notably, the accuracy of the k-NN and SVM method is close to all methods, showing that classic resampling methods have little effect on the later process of discrimination of sugarcane varieties.

Table II: Varieties classification per pixel

| Method | Classifier | Accuracy |
|---|---|---|
| | k-NN | 84.5% |
| Nearest Neighbour | SVM | 86.2% |
| | Random Forest | 72% |
| | k-NN | 86.2% |
| Bilinear | SVM | 87.1% |
| | Random Forest | 71% |
| | k-NN | 83.93% |
| Cubic | SVM | 85% |
| | Random Forest | 72% |
| | k-NN | 86.93% |
| Lanczos | SVM | 85% |
| | Random Forest | 70% |
| | k-NN | **87.84%** |
| Gauss | SVM | 87% |
| | Random Forest | 71% |

In the case of the use of data containing the average of pixels composed by four different dates between the months of May and June, the vegetation index obtained also had little variation in the classification accuracy (Table III). Using k-NN, the accuracy for the five resampling methods was above 96%.

Table III: Mean Data

| Method | Classifier | Mean |
|---|---|---|
| | k-NN | 98.23% |
| Nearest Neighbour | SVM | 98.58% |
| | Random Forest | 87% |
| | k-NN | 98.58% |
| Bilinear | SVM | **99.1%** |
| | Random Forest | 86% |
| | k-NN | 98.64% |
| Cubic | SVM | 98.9% |
| | Random Forest | 87% |
| | k-NN | 98.79% |
| Lanczos | SVM | 98.89% |
| | Random Forest | 88% |
| | k-NN | 96.87% |
| Gauss | SVM | 98.13% |
| | Random Forest | 87% |

The SVM classifier presented the highest accuracy among the three classificatory methods used, with 99.1 % based on the calculation of vegetation indices by the joint use of bilinear resampling, demonstrating the viability of chlorophyll-related indices for purposes of classifying sugarcane varieties

### *B. Sugarcane identification*

In addition to verifying the effects of different sampling techniques on Sentinel-2 images to classify sugarcane varieties, the influence of these techniques on identifying crops containing sugarcane has also been studied using chlorophyll-related vegetation indices.

Were used 12000 pixels from areas not belonging to sugarcane (pasture, land, river, and forest) concatenated with 12000 pixels with varieties features previously extracted for classification among RB92579, RB966928, and RB88082 variety. In this way, five arrays were obtained, with calculated values for each vegetation index according to the type of resampling approached applied.

The selection of pixels for training and testing for later classification by the k-NN, SVM, and Random Forest models were random for each loop. The 10-k-fold cross-validation was performing to train and validate the best parameters to k e C, employing the execution of ten times to find an average value for the performance of the classifiers, as well as to find the best k parameter fork-NN and C for SVM.

The Table IV it is possible to observe the average value of the accuracy obtained for classificatory models in each resampling method performed and the best parameter found. Among the experiments using k-NN, the values of k parameters were mostly 5, 7, and 9 neighbors for all resampling methods, in which k = 5 obtained the highest accuracy values by using bilinear resampling, Lanczos and Gauss, and k = 7 for the use of nearest neighbor and cubic, but with little variation in the classification in general regardless of the approached method. Furthermore, the study demonstrated the feasibility of applying the vegetation indexes related to chlorophyll in contrast to the routine use of NDVI to discriminate cultures and their varieties.

Table IV: Sugarcane discrimination

| Method | Classifier | Mean | Parameter |
|---|---|---|---|
| | k-NN | 94.7% | k = 7 |
| Nearest Neighbor | SVM | 95.2% | C = 1000 |
| | Random Forest | 88.6% | – |
| | k-NN | 95.4% | k = 5 |
| Bilinear | SVM | 95.8% | C = 1000 |
| | Random Forest | 89.5% | – |
| | k-NN | 95.1% | k = 7 |
| Cubic | SVM | 95.5% | C = 1000 |
| | Random Forest | 88.4% | – |
| | k-NN | 95.2% | k = 5 |
| Lanczos | SVM | 95.3% | C = 1000 |
| | Random Forest | 89.8% | – |
| | k-NN | 94.1% | k = 5 |
| Gauss | SVM | 94.6% | C = 1000 |
| | Random Forest | 85.7% | – |

Classification performance measures of k-NN and SVM models extracted from the confusion matrix are displayed in the table V) related to discrimination between sugarcane and non-sugarcane pixels with nearest neighbor resampling.

Table V: Classification performance measures with Nearest Neighbor method.

| Class | Precision (%) | | Recall (%) | | F1-score (%) | |
|---|---|---|---|---|---|---|
| | KNN | SVM | KNN | SVM | KNN | SVM |
| $C_1$ | 94.0 | 94.8 | 95.5 | 95.6 | 94.8 | 95.2 |
| $C_2$ | 95.5 | 95.6 | 93.9 | 94.8 | 94.7 | 95.2 |
| Avg | 94.7 | 95.2 | 94.7 | 95.2 | 94.7 | 95.2 |

($C_1$ – sugarcane, $C_2$ – non sugarcane)

For the discrimination between pixels using SVM, the best parameter found, regardless of the type of resampling, was C = 1000, with parameter value obtained in all execution of the algorithm. Regarding the classifier's performance, the accuracy was between 94.6 % to 95.8 %, with values close to the applied resampling methods, as well as for the precision, recall, and f1-score measures.

The class corresponding to the sugarcane pixels obtained higher precision compared to pixels representing other regions. Results with the Random Forest classifier were omitted due to the lower accuracy in comparison to other models used.

From the experiments with images from Sentinel-2 in the discrimination between pixels belonging to sugarcane and other regions, it was possible to observe little variation in accuracy about the resampling method used, demonstrating that the approach has little influence on the sugarcane discrimination/classification problem. Thus, simplistic methodologies for this subject may be more beneficial due to less complexity in processing images with large spatial resolution.

Also, it was possible to verify the applicability of vegetation indices related to the content present in the leaves, more precisely focused on chlorophyll for the identification of sugarcane and non-sugarcane pixels in addition to the classification among varieties of the crop.

## V. Conclusions and Future Work

In this paper, the influence of traditional resampling methods on Sentinel-2 images was studied to the subject of discriminate regions containing sugarcane in addition to differentiating between varieties of culture by calculating vegetation indices reported to chlorophyll. Also, the use of these indices demonstrated great potential for the purpose of discriminating/classifying sugarcane, presenting alternative vegetation indices to be applied for this type of purpose.

Besides, there was little variation in accuracy between the applied methods, showing little influence of the same in the process to identify sugarcane. For the classification of the training and test samples, the k-fold cross-validation methodology was used by using the k-NN, SVM, and Random Forest classifiers, performed ten times. Thus, simple methods may be preferable to problems that require more speed than more complex techniques that require longer processing time, such as cubic resampling and Lanczos.

As future works, we intend to apply methods that include image fusion for the improvement of details to increase the method's accuracy. Furthermore, experiments with more sugarcane varieties, images, in addition to other techniques such as the application of neural networks will allow us to further explore the problem. Thus, our experiments presented promising results, demonstrating the potential for the classification of sugarcane varieties by the use of indices related to chlorophyll, independent of the resampling method applied.

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## References

[1] P. M. Kai, R. M. da Costa, B. M. de Oliveira, D. S. Fernandes, J. Felix, and F. Soares, "Discrimination of sugarcane varieties by remote sensing: A review of literature," in *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*. IEEE, 2020, pp. 1212–1217.

[2] L. S. Galvao, A. R. Formaggio, and D. A. Tisot, "Discrimination of sugarcane varieties in southeastern brazil with eo-1 hyperion data," *Remote Sensing of Environment*, vol. 94, no. 4, pp. 523–534, 2005.

[3] C. Fortes and J. A. M. Demattê, "Discrimination of sugarcane varieties using landsat 7 etm+ spectral data," *International Journal of Remote Sensing*, vol. 27, no. 7, pp. 1395–1412, 2006.

[4] A. Apan, A. Held, S. Phinn, and J. Markley, "Spectral discrimination and classification of sugarcane varieties using eo-1 hyperion hyperspectral imagery," in *Proceedings of the 25th Asian Conference on Remote Sensing (ACRS 2004)*. Asian Association on Remote Sensing, 2004, pp. 1–5.

[5] R. M. Johnson, R. P. Viator, J. C. Veremis, E. P. Richard Jr, and P. V. Zimba, "Discrimination of sugarcane varieties with pigment profiles and high resolution, hyperspectral leaf reflectance data," 2008.

[6] P. Murillo-Sandoval, J. Carbonell-Gonzalez, and C. Osorio-Murillo, "Evaluation of landsat 7 etm+ data for spectral discrimination and classification of sugarcane varieties in colombia," *J. Agric. Sci. Technol.*, vol. 5, pp. 101–107, 2011.

[7] L. S. Galvão, A. R. Formaggio, and D. A. Tisot, "The influence of spectral resolution on discriminating brazilian sugarcane varieties," *International Journal of Remote Sensing*, vol. 27, no. 4, pp. 769–777, 2006.

[8] D. G. Duft, A. C. dos Santos Luciano, and P. R. Fiorio, "Sentinel-2b and random forest algorithm potential for sugarcane varieties identification." in *GEOINFO*, 2019, pp. 188–193.

[9] E. Barnes, T. Clarke, S. Richards, P. Colaizzi, J. Haberland, M. Kostrzewski, P. Waller, C. Choi, E. Riley, T. Thompson *et al.*, "Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data," in *Proceedings of the Fifth International Conference on Precision Agriculture, Bloomington, MN, USA*, vol. 1619, 2000.

[10] S. Mishra and D. R. Mishra, "Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters," *Remote Sensing of Environment*, vol. 117, pp. 394–406, 2012.

[11] C. Daughtry, C. Walthall, M. Kim, E. B. De Colstoun, and J. McMurtrey Iii, "Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance," *Remote sensing of Environment*, vol. 74, no. 2, pp. 229–239, 2000.

[12] J. A. Richards and J. Richards, *Remote sensing digital image analysis*. Springer, 1999, vol. 3.