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ASSESSMENT OF TEXTURE FEATURES FOR BRAZILIAN SAVANNA CLASSIFICATION: A CASE STUDY IN BRASÍLIA NATIONAL PARK

Avaliação de Atributos de Textura para Classificação do Cerrado brasileiro: Um Estudo de Caso no Parque Nacional de Brasília

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ABSTRACT

Distinguishing Brazilian savanna physiognomies is an essential task to better evaluate carbon storage and potential emissions of greenhouse gases. In this study, we propose to evaluate the potential of texture features to improve the discrimination among five physiognomies in the Brazilian savanna: Open Grasslands, Shrubby Grassland, Shrubby Savanna, Savanna Woodland and Gallery Forest. Texture features extracted from RapidEye images and also from Spectral Linear Mixture Model components and Vegetation Index were evaluated. Results showed that texture features based on GLCM can reduce misclassification for Open Grasslands, Shrubby Grasslands and Shrubby Savanna classes.

Keywords: Remote Sensing, Data Mining, RapidEye, *Random Forest*.

RESUMO

Distinguir as fitofisionomias do Cerrado brasileiro é uma tarefa importante para uma melhor avaliação sobre o estoque de carbono e possíveis emissões de gases do efeito estufa. Neste estudo foi proposto o uso de atributos de textura para aumentar a discriminação de cinco fitofisionomias do Cerrado brasileiro: Campo Limpo, Campo Sujo, Cerrado Ralo, Cerrado Típico e Mata de Galeria. Os atributos de textura foram extraídos de uma imagem RapidEye, imagens dos componentes do modelo linear de mistura espectral e de uma imagem de NDVI. Os resultados mostraram que atributos de textura extraídos da matriz GLCM reduziram erros entre as fitofisionomias de Campo Limpo, Campo Sujo e Cerrado Ralo.

Palavras-chave: Sensoriamento Remoto, Mineração de Dados, RapidEye, *Random Forest*.

1. INTRODUCTION

Brazilian savanna, also known as Cerrado, occupies an area of approximately two million square Kilometers in the Brazilian territory, mainly in the central part of Brazil (MMA, 2015). Cerrado is one of the richest biomes in the world and it contains more than 160.000 species of plants, animals and fungi (FERREIRA *et al.*, 2003). Besides that, Cerrado is responsible for storing about 5.9 billion tons of carbon in vegetation and 23.8 billion tons in the ground (MMA, 2014).

The loss of natural vegetation in Cerrado reached 45.5% of its original area by 2013 (MMA, 2015). The loss of biodiversity can lead to problems such as: soil erosion, water pollution, carbon cycle instability, microclimate changes and also biome fragmentation (KLINK & MACHADO, 2005). Considering these negative effects on biodiversity, it is essential to promote strategies to monitor the Cerrado biome.

Mapping of heterogeneous tropical areas, such as Cerrado, should be carried out considering biological, climatic and topographical information. The major natural formations in Cerrado are Grasslands, Shrublands and Woodlands (Figure 1). Their mapping has been the subject of several studies. Sano *et al.* (2009) performed visual interpretation of satellite images to produce maps of Cerrado. This process was very time consuming and difficult to discriminate Grasslands.

The difficulty to map Cerrado patterns is even greater when considering more formations than those mentioned above. For example, the system proposed by Ribeiro and Walter (2008) splits these major formations into 14 physiognomies. Identifying these physiognomies is important to evaluate carbon storage and potential emissions of greenhouse gases for each type of land cover.

Most studies aiming to classify vegetation types in the Cerrado biome rely on the use of spectral information from remote sensing imagery. The NDVI (Normalized Difference Vegetation Index) has been tested to discriminate Cerrado physiognomies (LIESENBERG *et al.*, 2007; OLIVEIRA *et al.*, 2007; COSTA *et al.*, 2014). However, there is still difficulty to discriminate different grassland physiognomies using only NDVI. Spectral Linear Mixture Model (SLMM) has also been used to classify physiognomies on a protected area of Cerrado in Distrito Federal State, Brazil (FERREIRA *et al.*, 2007). The SLMM reduced the classification error between Grasslands and Shrublands, but it was not enough to fully automate the classification.

Differently, Carvalho *et al.* (2010) used texture features to map the vegetation cover in the Cerrado. In this paper, an initial classification was performed using data based on NDVI, SLMM and spectral features. Afterwards, they included texture information into the dataset and noticed an increase in the classification accuracy. PenequeGalvez *et al.* (2013) also used texture features to classify Cerrado physiognomies in Bolivia. In this case, Woodlands were classified with high accuracy, but some confusionerrors occurred in the discrimination between Grasslands and Shrublands. However, some texture features increased this error, and reduced the overall classification accuracy. Therefore, it is necessary to investigate whether these features may be really effective for Cerrado classification.

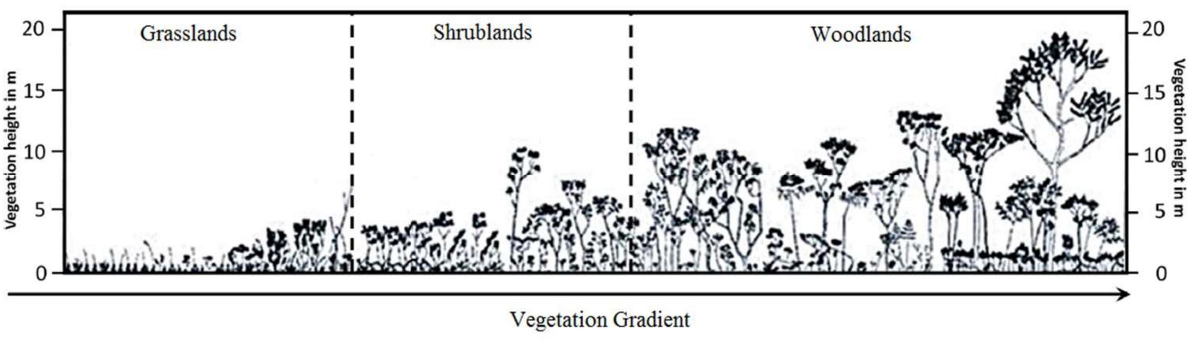


Fig. 1 - Major Cerrado formations describing the vegetation gradient (adapted from SCHWIEDER *et al.*, 2016).

In order to better analyze texture features in the Cerrado classification, we could calculate texture features from NDVI instead of calculating it from original image. The NDVI texture has been used in other applications such as urban studies (NUSSBAUM & MENZ, 2008). It has also been used to detect bushfire prone areas (CHEN *et al.*, 2001) as well as to identify different types of forest and spatial patterns of vegetation structure (NING *et al.*, 2011).

Therefore, we propose in this work to evaluate the potential use of texture information extracted from RapidEye original images, and also from vegetation index and SLMM components to classify the following physiognomies in the Brazilian Cerrado: Open Grasslands, Shrubby Grassland, Shrubby Savanna, Savanna Woodland and Gallery Forest.

This paper was based on Girolamo Neto *et al.* (2016), presented at GEOINFO 2016 (http://www.geoinfo.info/geoinfo2016).

2. METHODOLOGY

Figure 2 presents the methodology flowchart proposed to classify vegetation cover in Cerrado. Each processing step is detailed in the following sections.

2.1 Study Area and Reference Map

The study area is located in the Brasília National Park (PNB), which has approximately 30000 ha of preserved natural Cerrado vegetation. Figure 3 shows the major part of the park, in which a red line highlights the study area. For the experiments, we used a RapidEye image in the path-row 1-318 tile 2331801 of the RapidEye Earth Imaging System (REIS). This image was acquired in 05/30/2014 and processed in level 3A product (BLACKBRIDGE, 2015).

We also used as reference the map of PNB that was produced by Ferreira *et al.* (2007). The authors used the system proposed by Ribeiro and Walter (1998) to classify 5 Cerrado physiognomies described in Table 1. Other classes such as Water Bodies, Marsh, Reforestation, Bare Soil and Constructed Area were removed from the dataset.

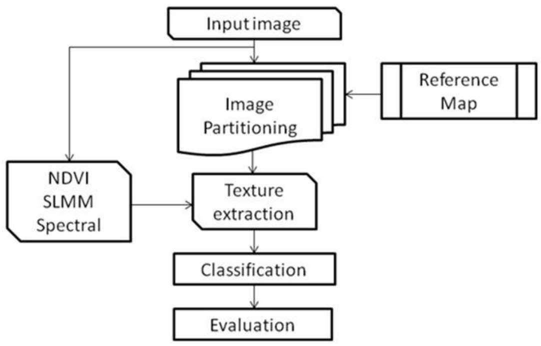


Fig. 2 - Methodology flowchart.

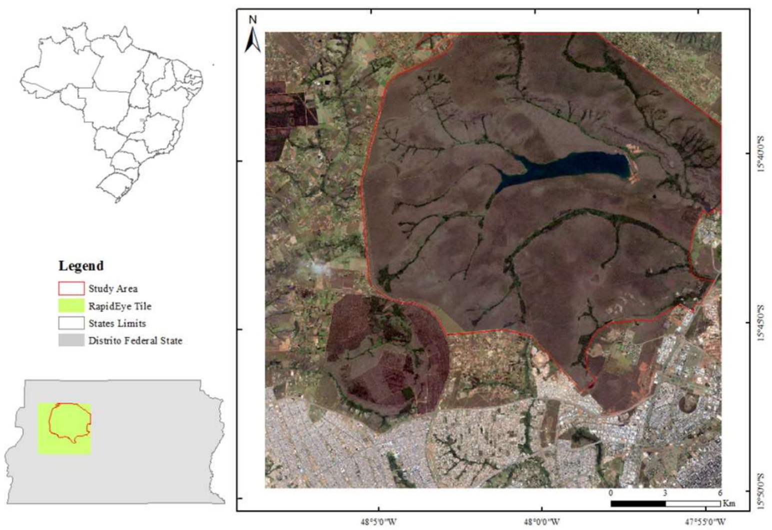


Fig. 3 - Study area in the Brasília National Park.

Table 1: Cerrado physiognomies characteristics (Adapted from FERREIRA *et al.*, 2007 and RIBEIRO & WALTER, 2008)

Physiognomy name	Vegetation description	Tree cover (%)	Tree height (m)
Open Grassland (OG)	Grasses	0	-
Shrubby Grassland (SG)	Grasses and Shrubs	0-5	-
Shrubby Savanna (SS)	Shrubs and a few trees	5-20	2-3
Wooded Savanna (WS)	Trees and a few Shrubs	20-50	3-6
Gallery Forest (GF)	Trees	70-95	15-30

2.2 Image Partitioning

In order to extract texture features, the image was partitioned into square objects of ***s*** x ***s*** pixels size. The use of square objects instead of polygons extracted from segmentation algorithms based on similarity allows us to evaluate texture features that capture the natural heterogeneity in the image. This procedure prevents detecting texture as a possible rule in the classification process, once we intend to evaluate texture potential for classifying Cerrado vegetation cover.

Following, the image was linked with the reference map to identify the square objects represented within each class in the map. The larger is the square object size, the fewer number of objects can be extracted from the image. We tested different object sizes ranging from 10 to 35, with a step of 5. The maximum value 35 was chosen because the number of samples for Gallery Forest reached almost zero. Figure 4 illustrates the influence of object size in relation to the number of samples for Gallery Forest.

After the partitioning process, some segments presented two or more classes, which can lead to misclassification (FERREIRA *et al.*, 2007; OLIVEIRA *et al.*, 2007; CARVALHO *et al.*, 2010). To reduce this problem these elements were removed from the dataset. Figure 5 illustrates the cleaning up procedure.

2.3 Feature Extraction

Spectral features were obtained from Digital Numbers (DN) of RapidEye (RE) bands. The description the spectral features is presented in Table 2.

The NDVI and SLMM components (*soil*, *shadow* and *vegetation*) were computed according to Tucker (1979) and Shimabukuro and Smith (1991), respectively. Texture features were computed from Gray Level Co-occurrence Matrix (GLCM) as shown in Table 3. GLCM is a second order histogram in which each entry reports the join probability of finding a set of two gray levels at a certain distance and direction from each other over some pre-defined window (HARALICK *et al.*, 1973). Additionally, some texture measures were computed from Gray Level Difference Vector (GLDV), as shown in Table 3. GLDV indicates occurrence of the absolute difference between a reference pixel and its neighbor. It can be calculated for 4 different directions (0º, 45º, 90º and 135º). In this study, we used only direction 0º.

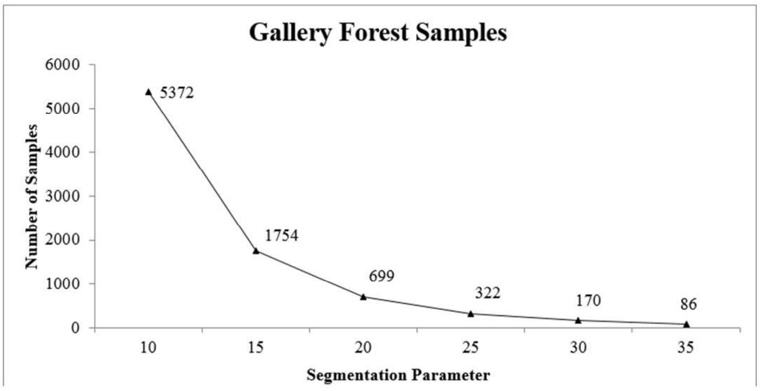
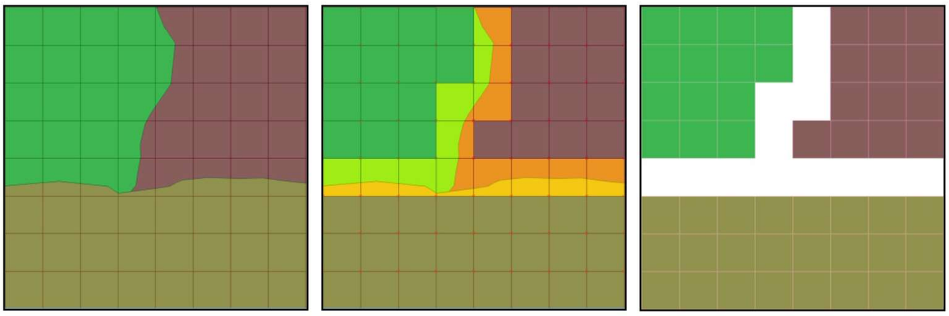


Fig. 4 -The influence of objects size in relation to the number of samples of Gallery Forest.

Texture features were also extracted from image bands, from NDVI, and from each SLMM component (*soil, shadow and vegetation*). Therefore, 9 texture features (Table 3) were extracted from five images (vector of bands, NDVI, SLMM), which produced a total of 45 features. The features of BT and MD were not used for extracting texture.



a b c

Fig. 5 - Clean up process. a) original map with 3 different classes; b) highlighted objects for removal; c) map of samples after cleanup process.

Table 2: Spectral features extracted from the RapidEye image

Feature	Description
Band_1	DN from band 1 (Blue 440 – 510 μm)
Band_2	DN from band 2 (Green 520 – 590 μm)
Band_3	DN from band 3 (Red 630 – 685 μm)
Band_4	DN from band 4 (Red Edge 690 – 730 μm)
Band_5	DN from band 5 (NIR 760 – 510 μm)
Brightness (BT)	Average of the sum of means for bands 1-5
Maximum Difference (MD)	Maximum of the difference between bands
NDVI	Normalized Difference Vegetation Index
SLMM_*soil*	SLMM component of soil
SLMM_*shadow*	SLMM component of shadow
SLMM_*vegetation*	SLMM component of vegetation

Table 3: Textural features (HARALICK *et al.*, 1973). Pi,j is the normalized co occurrence matrix, N is the number of rows/columns, σi and σj are standard deviation of row i and column j, μi and μj are means of row i and column j, Vk is the normalized gray level difference vector and k = |i-j|.

Feature	Formula	Feature	Formula
GLCM Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}\,(-\ln P_{i,j})$	GLCM Dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\,\lvert i-j\rvert$
GLDV Entropy	$\sum_{k=0}^{N-1} V_k\,(-\ln V_k)$	GLCM Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
GLCM Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}\,(i-j)^2$	GLCM Mean	$\mu_i = \sum_{i,j=0}^{N-1} i\,(P_{i,j})$
GLDV Contrast	$\sum_{k=0}^{N-1} V_k\,(k^2)$	GLDV Mean	$\mu_i = \sum_{i,j=0}^{N-1} V_k\,(k)$
GLCM Correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(1-\mu_i)(1-\mu_j)}{\sqrt{(\sigma_i)^2\,(\sigma_j)^2}}\right]$		

2.4 Classification

In the classification phase we performed two experiments. In the first experiment, we used four datasets in the classification phase, as shown in Table 4. This was the baseline to evaluate the classification accuracy gain by including each feature into the datasets one at a time. The idea of this experiment is to evaluate classification accuracy for each spectral feature and also the spectral texture, which has been pointed out by Carvalho *et al.* (2010) and PenequeGalvez *et al.* (2013) as features that improve Cerrado classification. In Table 4, Spectral Texture means texture features extracted from RapidEye bands only.

In the experiment 2, we evaluated all 45 texture features, adding one at a time in each one of the datasets 1-3. The idea was to evaluate the improvement or not in the classification accuracy for each texture feature.

For comparison, we established the same classification algorithm and parameters for all tests. We used *Random Forest* classification algorithm (BREIMAN, 2001), implemented in *Weka* software (HALL *et al.*, 2009), and set the number of trees to 100 in order to construct each forest.

Table 4: Combination of groups of features to evaluate the best subset for classification

	RE bands, BT, MD	NDVI	SLMM	Spectral Texture
Dataset 1	X			
Dataset 2	X	X		
Dataset 3	X	X	X	
Dataset 4	X	X	X	X

The experiments were carried out using a 10fold cross validation. For the validation process, we used Global Accuracy, Precision and Recall values to summarize the confusion matrix in the experiments:

$$GlobalAccuracy = \frac{TP + TN}{n} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

in which TP = True Positive, FP = False Positive, TN = True Negative, FN = False Negative and n = number of samples.

Recall and Precision mean, respectively, percentage of instances of one class that are correctly classified and the map accuracy.We proposed a ranking system to evaluate the inclusion of textural features into the datasets. It is based on accuracy percentage gain (or loss), *Acc*, when a certain feature is added into the dataset:

$$Acc = \frac{Acc_f}{Acc_i} \quad (4)$$

in which *Acc* is the accuracy percentage gain, Acc_i is the initial accuracy and Acc_f is the accuracy when a texture feature is included in the set of features.

Each one of the 45 features was ranked from 1-45, being 1 the feature that presented more percentage gain and so on. This was performed for datasets 1-3 and segmentation of size equal to 30. A final rank considered the average performance. Table 5 shows an example for 3 hypothetical features.

3. RESULTS

This section presents results obtained from experiments mentioned in section 2.4.

3.1. Experiment 1: Spectral texture features analysis

Figure 6 presents the accuracy classification for all 4 datasets (Table 4) in relation to the segmentation parameter ***s***. We observe that for datasets 1, 2 and 3, the classification values did not presented meaningful difference. That is, the addition of NDVI and SLMM features into the feature set did not improve the classification result. Nevertheless, inclusion of spectral texture features (dataset 4) improved the classification result, which corroborates with Carvalho *et al.* (2010) and PenequeGalvez *et al.* (2013). Another observation is that the classification for segmentation parameter equals to 30 presented better result than others (Figure 7).

Table 5: Ranking system example for 3 hypothetical features

Dataset #	1	2	3	Average rank	Final Rank
Feature 1 Rank	1st	1st	1st	1,00	1st
Feature 2 Rank	2nd	2nd	3rd	2,33	2nd
Feature 3 Rank	3rd	3rd	2nd	2,66	3rd

In order to better investigate this result, we evaluated Precision and Recall values for each class for the classification for the segmentation parameter of 30 (Table 6). We can observe that Shrubby Savanna (SS) and Shrubby Grassland (SG) classes presented the worst classification. Open Grassland (OG) and Wooded Savanna (WS) presented better precision values, but not as good as the ones for Gallery Forest (GF) class. GF class is the only physiognomy with forest structure and it was expected that it would present better classification accuracy than the others.

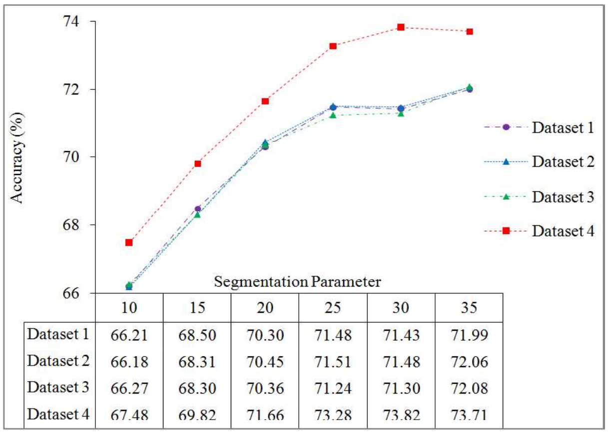


Fig. 6 - Accuracy values (%) for datasets 1-4 according to the segmentation parameter.

When spectral texture is added, we noticed an increase in the recall values for all classes, except for GF. The SG class presented the highest precision gains when spectral texture was added. Oliveira *et al.* (2007) pointed out that discrimination between OG and SG classes is difficult. Costa *et al.* (2014) even suggested merging both classes to decrease classification error. Ferreira *et al.* (2007) also reported confusion between SG and SS classes. However, our results show that the use of spectral texture can improve considerablytheir discrimination.

Table 6: Precision (P) and Recall (R) values for each class from dataset 1 and 4 for the segmentation parameter of 30

	Open Grassland	
	P	R
Dataset1	0,761	0,829
Dataset4	0,757	0,866
	Shrubby Grassland	
	P	R
Dataset1	0,519	0,411
Dataset4	0,578	0,486
	Shrub Savanna	
	P	R
Dataset1	0,620	0,510
Dataset4	0,666	0,507
	Wooded Savanna	
	P	R
Dataset1	0,761	0,827
Dataset4	0,781	0,842
	Gallery Forest	
	P	R
Dataset1	0,947	0,941
Dataset4	0,970	0,935

3.2 Experiment 2: Texture features analyses

In this part, we analyze the texture potential of improving the classification in relation to the 5 Cerrado classes and $s = 30$. As mentioned on section Section 2.4, each one of the 45 texture features were added separately on datasets 1-3. Final rank of the best features is presented in Table 7.

Considering SLMM components and NDVI, the best ranks were achieved by ‘GLCM Entropy’ features. Homogeneous objects have high entropy values while heterogeneous ones have low entropy. In Cerrado, tree density and canopy formation are responsible for more or less homogeneity.

Figure 7 shows the mean values for the "GLCM Entropy *vegetation*" for the five Cerrado physiognomies. It shows us that, SG and SS classes presented the lowest mean values for 'GLCM Entropy *vegetation'*. Although SG does not have continuous canopy it presents bushes more frequently when compared to OG. This makes SG less homogeneous than OG and, therefore, producing lower entropy vegetation than OG.

Regarding to SS class, Ribeiro and Walter (2008) stated that there is a canopy formation, however it is much sparser and with a lower tree cover percentage than the WS class. These vegetation patterns were captured by features such as "GLCM Entropy *vegetation"* and "GLCM Entropy NDVI", which achieved the best rankings (1st and 2nd, respectively).

Table 8 presents Recall and Precision values when "GLCM Entropy *vegetation"*, first feature in the ranking, was added to dataset 3. We noticed a slightly classification improvement for all classes, except for GF Precision. The SG and OG classes presented a little increase in the Recall values.

The use of features such as 'GLCM Entropy *vegetation*' and 'GLCM Entropy NDVI' improved the discrimination of both classes, as can be noticed in Recall values. We also observed a little improvement of Recall for SS class.

Table 7: Ranking the 10 best texture features. Vegetation, shadow and soil represent the features obtained from SLMM images

Feature Name	Average Rank	Final Rank
GLCM Entropy *vegetation*	1,3	1st
GLCM Entropy NDVI	2,3	2nd
GLCM Entropy *shadow*	2,6	3rd
GLCM Entropy *soil*	4,6	4th
GLDV Entropy spectral	9,6	5th
GLCM Contrast *shadow*	10,0	6th
GLCM Contrast spectral	11,0	7th
GLDV Contrast *shadow*	11,0	
GLCM Dissimilarity spectral	11,0	
GLCM Correlation *shadow*	11,6	10th

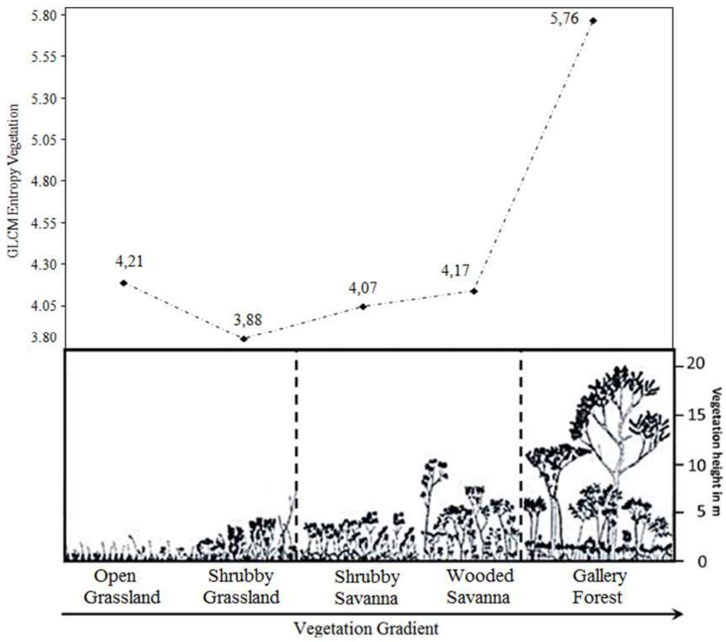


Fig. 7 - GLCM Entropy vegetation mean values for Cerrado physiognomies (adapted from SCHWIEDER *et al.*, 2016).

Table 8: Precision (P) and Recall (R) for each class with addition of textural entropy

	Open Grassland		Shrubby Grassland		Shrub Savanna		Wooded Savanna		Gallery Forest	
	P	R	P	R	P	P	R	P	R	P
Dataset 3	0,760	0,824	0,516	0,450	0,611	0,504	0,763	0,824	0,958	0,941
+ GLCM Entropy vegetation	0,782	0,864	0,567	0,488	0,649	0,529	0,791	0,846	0,936	0,953

Figure 8 shows an example of how important it is to correctly choose the best features to improve the classification accuracy. GLCM Entropy features were much more consistent than the others in all classifications, obtaining always the best ranking. Using some texture features may not really improve the classification results as mentioned by PenequeGalvez *et al.*(2013).

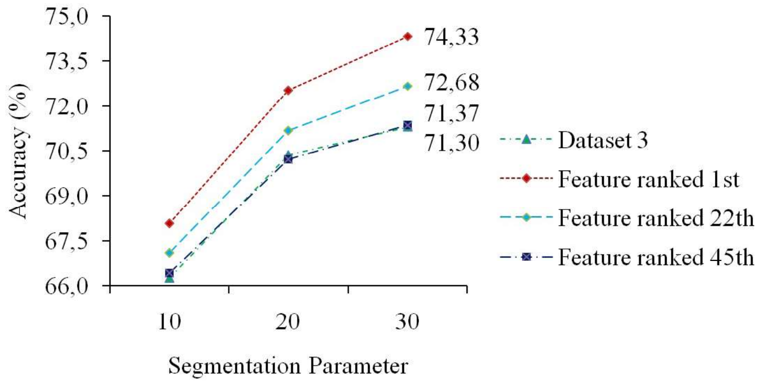


Fig. 8 - Influence of some features in the final classification accuracy. Feature ranked as 1st is "GLCM Entropy *vegetation*", 22th is "GLDV Contrast NDVI"and 45th is "GLCM Mean *spectral*".

4. CONCLUSION

In this study, we presented the assessment of texture features (spectral, NDVI and SLMM) to improve the discrimination of Cerrado physiognomies. Considering only spectral features, the initial accuracy was about 71.3%. The spectral texture improved the classification accuracy to 73.8%. Spectral texture was responsible for reducing the misclassification between grassland physiognomies (Open Grassland and Shrubby Grassland). However, the texture based on GLCM entropy extracted from NDVI and SLMM components, especially vegetation, improved even more the classification accuracy reaching 74.3%.

They not only reduced the confusion between grassland physiognomies mentioned before but also increased the discrimination of Shrubby Grassland and Shrubby Savanna. Gallery Forests had high accuracy on all cases. As future works, we suggest using temporal data analysis and combining spectral texture with NDVI and SLMM textures.

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