EXPLORING A DEEP CONVOLUTIONAL NEURAL NETWORK AND GEOBIA FOR AUTOMATIC RECOGNITION OF BRAZILIAN PALM SWAMPS (VEREDAS) USING SENTINEL-2 OPTICAL DATA

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ABSTRACT

The Brazilian Palm Swamps (Veredas) are a vegetation physiognomy of the Cerrado biome. It has a critical importance for biodiversity and also for groundwater sources conservation. With the irrigated agriculture intensification, it´s been significantly impacted. Mapping this physiognomy is important to delimit this vegetation type to provide subsides for public policy and monitoring programs. Pixel-based methods do not succeed, since the spatial context is important for this physiognomy. Object-based methods are a great potential on this sense. Deep Learning methods, particularly the convolutional neural networks (CNN), are increasing considerably as a solution for these challenges. We applied both methods in two regions of the Cerrado and evaluated the model transferability. The results are promising, with training model overall accuracies higher than 90% for both methods. The CNN performed better when transferred a different region. We discussed some advantages and limitations, and pointed out to improvements that can still be done.

Index Terms— Cerrado, Semantic Segmentation, Peatlands, Remote Sensing, Digital Processing Image

1. INTRODUCTION

The Veredas are a specific vegetation physiognomy of the Cerrado biome and has a great ecological importance for biodiversity and also as a regulator of water courses equilibrium [1, 2, 3]. With the development of irrigation techniques, Veredas have been used to build dams for the purpose of accumulating water to be used in irrigation pivots [4]. Properly mapping this physiognomy is very important to delimit this vegetation type in order to provide subsides for informing and enabling public policies and for monitoring. There are also findings that show the potential of this physiognomy as indicator of permanently wet, poorly drained hydromorphic soils [5].

The most usual methods of wetlands inventory are on-site field work, visual interpretation of aerial photography and digital image processing of satellite imagery. The first two have the disadvantage of a relatively long-time lag between data acquisition and map production [6]. Remote sensing is considered the only practicable method for mapping and monitoring wetlands [7]. It has been reported [8] that research is needed in the field of remote sensing to asses habitats that entirely fall into wetlands.

Pixel-based mapping methods usually fail with this physiognomy because of spatial context is particularly important in this case. Veredas consist in an association of other physiognomies [9]. GEOBIA (Geographic Object-based Image Analysis) techniques appears to have a great potential on this sense. Moreover, Deep Learning methods, particularly the convolutional neural networks such as the U-Net, are increasing considerably as a potential solution for mapping this specific vegetation patterns.

Cerrado vegetation mapping has been already done by different authors [10, 11, 12]. Recently, [13] showed the potential of mapping the Cerrado vegetation in a detailed level, applying a hierarchical random forest classification using spectral-temporal metrics derived from dense optical Landsat time series combined with different environmental data.

However, those classifications do not take into account all types of vegetation on the Cerrado. Veredas are usually not considered on the classifications and usually are included

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under savannah vegetation.

In cases where the objective of the study included the mapping of Veredas based on remote sensing, the reported accuracy was low. It is consensual that Landsat-like resolution is too coarse to capture the spatial pattern of Veredas, often leading to confusion with Gallery and Riparian forests, grasslands and savannahs [13].

The objective of this work was to evaluate a traditional GEOBIA classification method and a Fully Convolutional Neural Network classification algorithm for mapping Veredas in two different ecoregions of the Cerrado, and evaluate the model transferability for a different region.

2. METHODOLOGY

We applied both GEOBIA and Deep Learning strategies for mapping Veredas in two different ecoregions of the Cerrado [14], the ”Chapadão do São Francisco”, in the West of Bahia state, and ”Basaltos do Paraná”, in the Nortwest of Minas Gerais (Fig. 1). These ecorregions are relevant for this physiognomy, and they include the main variations of their patterns.

To consider the spatial context and the hierarchical structure in a classification process, GEOBIA techniques are an useful tool, as it considers neighborhood relationships, texture, form and compacity, and other contextual attributes based on segmentation and feature extraction [15]. Multiresolution Segmentation (MRS) algorithm is an image segmentation approach that aims to minimize the variability of a segment, relying on the potential of the local variance.

We performed this classification on the Sentinel 2 selected scenes using the near-infrared, red and green bands with 10 meters of spatial resolution, considering the same weight for all the bands and with the following empirical parameters: scale 100; shape 0.1; and compactness 0.5. The “*eCognition*” software [16] was used to perform segmentation and to extract feature from the segments. The object-based metrics mean, standard deviation and Grey Level Co-occurrence Matrix (GLCM) textures were derived from each band. Shape-based features such as elliptic fit were also extracted, resulting in 22 attributes for each segment/object.

We used a field-work database, kindly provided by the State Environmental Departments of Brazil, to train a Random Forest (RF) [17] model and obtained the GEOBIA classifier in which we empirically determined the parameters *mtry* of 5 and *ntrees* of 500. The “randomForest” package in R was used for our classification tasks. The final maps were validated with 30% of the samples, while the other 70% were used for training. A confusion matrix was calculated, and the average confusion matrix was used to derive the overall accuracy and the class f1-scores for each model.

Deep Neural Networks (DNN), especially the well known Convolutional Neural Networks (CNN), have shown to be greatly effective in scene classification and semantic segmentation tasks. This potential comes from their ability of learning representative contextual features about the images [18]. [19] has imputed to the Deep Neural Networks the responsibility for the major advances in solving some of the hardest pattern recognition problems, which have resisted the best attempts of the Artificial Intelligence (AI) community for many years. In this context, the U-Net, firstly proposed by [20], has demonstrated to be very effective for semantic segmentation tasks, being widely used for Land Use and Land Cover mapping applications [18, 21].

The Deep Learning methodology presented in this paper was developed based in the baseline U-Net architecture implemented by [18], which is available in the DeepGeo package [22].

To generate the chips for the U-Net training process, we randomly selected 500 chips of 316x316 pixels from the field-work database (Fig. 1).

The U-Net parameters were empirically defined as: 50 epochs, batch size of 5 chips, initial learning rate of 0.1, and using an exponential decay with a rate of 0.991 for the learning rate, a L2 regularization rate of 0.0005, and the Average Soft Dice as loss function. Batch normalization was also applied after all the convolutional layers. Besides the cited parameters, 6 data augmentation procedures were used in each chip: 90° rotation, 180° rotation, 270° rotation, flip vertically, flip horizontally, and flip transpose.

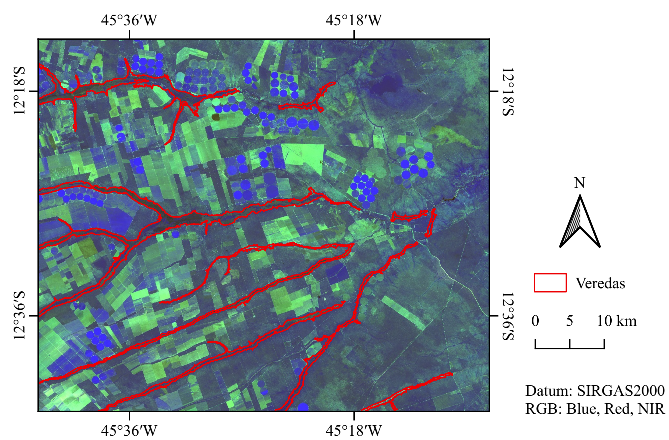

Fig. 1. Training reference.

3. RESULTS

As presented in Fig. 2 and Table 3, we found that the U-Net presented better results when transferring the model. This is a motivating result, since usually deep learning models require a high number of samples, and in this case, even collecting samples only in one region, the model presented a good transferability, with a reasonable promising in a different ecoregion, in which the Veredas present different spatial patterns.

Veredas can present different patterns, ranging from wet

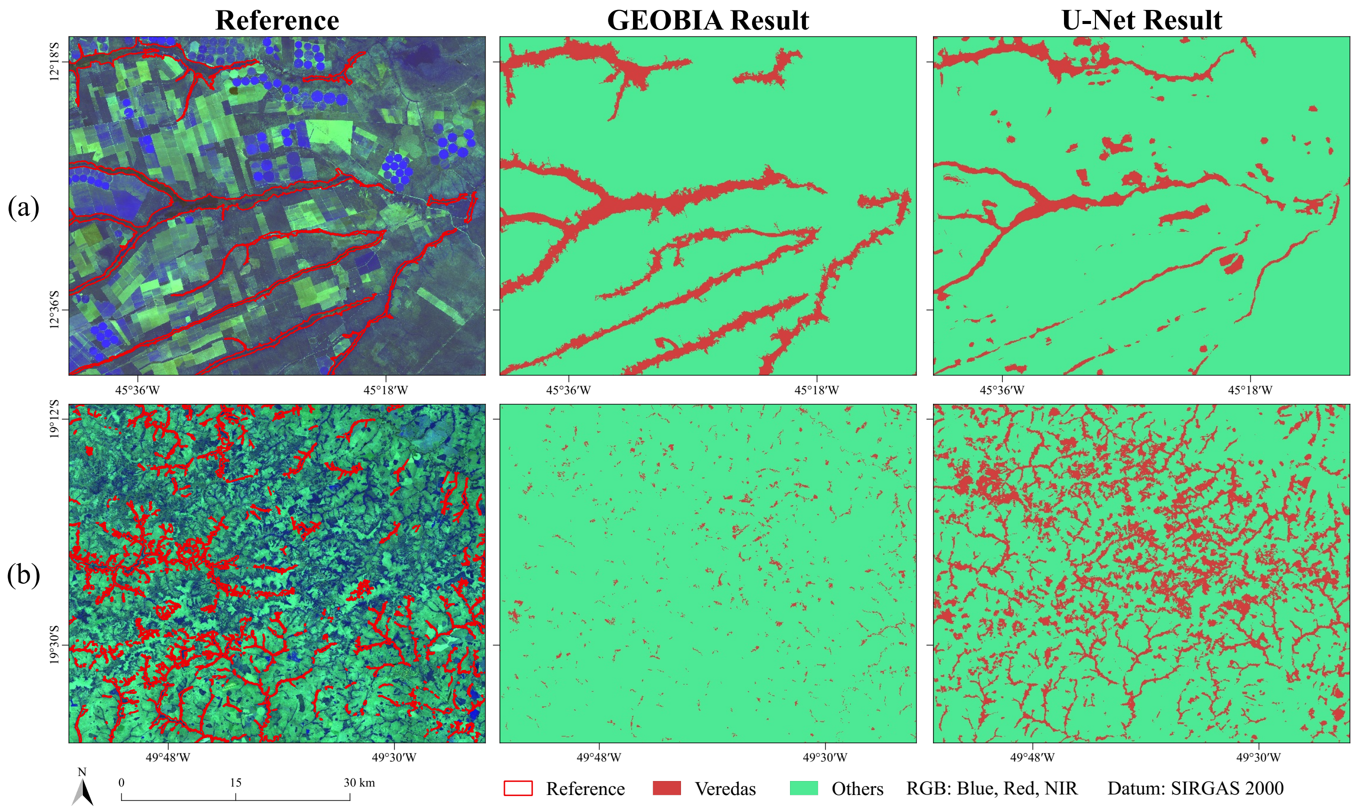

Fig. 2. Reference and results for the training area (a); and reference and results for the different ecoregion area (b).

		Reference			
		Training Area		Different Ecoregion	
		Vereda	Other	Vereda	Other
Mapping	Vereda	1,684,658	1,983,119	142,765	743,598
	Other	0	27,778,895	1,804,875	31,202,074

Table 1. Confusion Matrices for the GEOBIA mapping.

		Reference			
		Training Area		Different Ecoregion	
		Vereda	Other	Vereda	Other
Mapping	Vereda	1,234,075	495,731	1,138,194	6,215,424
	Other	450,583	29,266,283	809,446	25,730,248

Table 2. Confusion Matrices for the U-Net mapping.

	Training Area		Different Ecoregion	
Statistic	**GEOBIA**	**U-Net**	**GEOBIA**	**U-Net**
Accuracy	0.94	0.97	0.93	0.79
Sensitivity	1.00	0.73	0.07	0.58
Specificity	0.93	0.98	0.98	0.80
F1-Score	0.63	0.72	0.10	0.24

Table 3. Metrics for the mapping with GEOBIA and U-Net.

meadows to riparian forest and are associated with the presence of Buriti palms (*Mauritia flexuosa*) [23]. Even regionally, the paths can be presented under different environmental conditions [2].

We can observe some commission errors, including areas of agriculture, specifically from irrigated areas. In case of the analyzed region in the "Basaltos do Paraná", we could see that there was a great inclusion of Riparian and Gallery forests, what is is still a challenge. [24] have found that in most of the mapping initiatives, Veredas often cannot be separated from other riparian formation not classified as wetlands.

The use of auxiliary data can be a solution. [6] have attained high classification success ($< 85\%$) using Landsat ETM+ in combination with topographic and soil data.

The use of SAR data and auxiliary data as the vertical distance to the nearest drainage obtained from HAND algorithm (Height Above the Nearest Drainage) can also improve the results for both methods, as showed by [23].

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