Classifying Grasslands and Cultivated Pastures in the Brazilian Cerrado Using Support Vector Machines, Multilayer Perceptrons and Autoencoders

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Classifying Grasslands and Cultivated Pastures in the Brazilian Cerrado Using Support Vector Machines, Multilayer Perceptrons and Autoencoders

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Abstract. One of the most biodiverse regions on the planet, Cerrado is the second largest biome in Brazil. Among the land changes in the Cerrado, over 500,000km^2 of the biome have been transformed into cultivated pastures in recent years. Categorizing types of land cover and its native formations is important for protection policy and monitoring of the biome. Based on remote sensing techniques, this work aims at developing a methodology to map pasture and native grassland areas in the biome. Data related to EVI vegetation indices obtained by MODIS images were used to perform image classification. Support Vector Machine, Multilayer Perceptron and Autoencoder algorithms were used and the results showed that the analysis of different attributes extracted from EVI indices can aid in the classification process. We obtained accuracies up to 85,96% in the study area, identifying data and attributes required to identify these areas by remote sensing images.

Keywords: Data Mining; Image Processing; Brazilian Cerrado; Support Vector Machine; Multilayer Perceptron; Autoenconder.

1 Introduction

Issues such as population growth, climate change and the continuous demand for energy, water and food are a global threat and may cause serious environmental risks if natural resources are not used properly [1]. Within this perspective, it can be mentioned the problems caused by transformations in land use and cover in the Brazilian Cerrado, the second largest biome in the country. More than half of Brazilian Cerrado's area has been changed, mostly to make room for cattle and cash crops, losing more than 1,000,000 km of its original vegetation [14]. A spacial distribution of these areas is shown in Figure 1.

Cultivated pastures cover more than 500,000 km^2 and croplands surpass 100,000 km^2, while protected areas comprise only about 33,000 km^2. The destruction of the Cerrado vegetation is three times larger than the amount of

the deforested area in the Amazon region. This scenario represents a high environmental cost and implies vegetation degradation, water pollution, loss of biodiversity, soil erosion, instability of the carbon cycle and probable regional climatic changes and variations in fire events, which are typical of the biome [13].
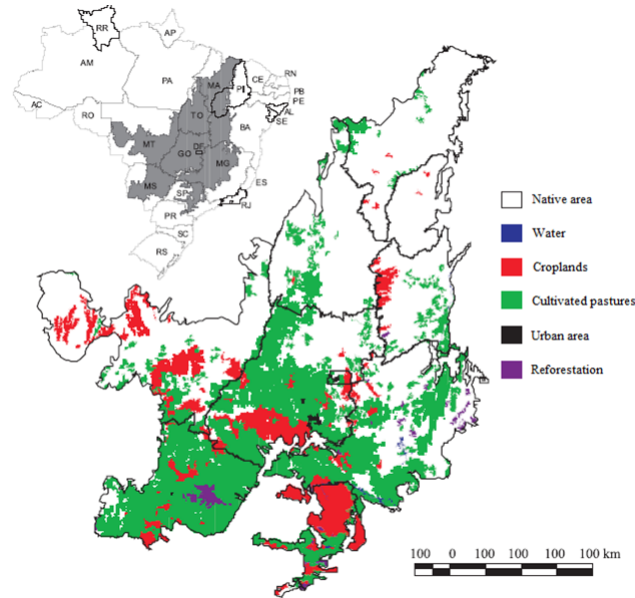

Fig. 1. Spatial distribution of changed areas in the Cerrado biome. Source: [14].

A large number of definitions for Cerrado can be found in the literature and, as a result, there are several proposals for classification of native formations. Among the physiognomic types presented in the biome, there are the grassland formations, which include the physiognomies of Clean Field, Dirty Field and Rocky Field [16]. With the identification and monitoring of these vegetation types using satellite imagery, policies can estimate the productivity of the degraded areas and promote its chemical, physical and biological integrity.

In order to promote the recovery of degraded regions and the policies that protect the Brazilian Cerrado, it is pivotal to create maps to analyze the land cover and use of the biome. However, cultivated pastures, similarly to native grasslands, may vary from formations with predominance of grasses to areas that present dominance of pioneer trees and shrub species [9]. Therefore, the mapping of pasture areas and native formations in the Cerrado is a difficult task if only the spectral information obtained by satellite images is used [19].

To overcome this problem, this work proposes a methodology for mapping areas of Cultivated Pasture and Native Field (Clean Field, Dirty Field and

Rocky Grasslands), using Support Vector Machine (SVM), Multilayer Perceptron (MLP) and Autoencoder techniques. Data related to EVI (Enhanced Vegetation Index) obtained by MODIS images were used to perform image classification. Time series extracted from EVI indices were used as attributes in the classification process.

The rest of the paper is organized as follows. In Section 2, we present a brief description of the Brazilian Cerrado, its native formations and the cultivated pastures in the biome. The methodological procedures and data used are depicted in Section 3. In Section 4, we discuss the results obtained in this work. Finally, we describe the conclusion in Section 6.

2   The Brazilian Cerrado

The Brazilian Cerrado has an area of approximately 2 million km^2, comprising about 24% of the Brazilian territory [3]. Cerrado is the richest tropical savanna in the world [13] and the biome occupies the central region of Brazil, extending from the northeast coast of the Maranhão state (MA) to the north of Paraná (PR) state, as seen in Figure 1. Generally, Cerrado can be understood as a grass field coexisting with scattered trees and shrubs [23] and, after Amazonia, it is the second largest of Brazil's major biomes [13].

Cerrado is the Portuguese word for Brazil's plateau of savannas, grasslands, woodlands, and gallery and dry forests [8]. Generally, the grassland formations refer to regions with predominance of herbaceous species and some shrubs, without the occurrence of trees in the landscape [16].

The native vegetation included in the grassland formations comprises areas of Clean Field, Dirty Field and Rocky Field (Figure 2). The phytophysiognomy of Clean Field has a predominance of grasses interspersed with underdeveloped woody plants, without the presence of trees. On the other hand, areas of Dirty Field and Rocky Field present a physiognomic type predominantly herbaceous and shrubby. However, Rocky Field areas usually occupy regions of rocky outcrops at elevations above 900 m, which include micro-relief landscapes with typical species [16].

Fig. 2. Grassland formations in the Brazilian Cerrado. Clean Field (left), Dirty Field (center) and Rocky Field (right).

More than half of Cerrado's original vegetation has been modified into cultivated pasture areas, agriculture and other uses. In addition, studies indicate that changes in land use in the Cerrado take place with greater intensity than in the Amazon region [18].

Henceforth, these transformations in land cover impose substantial threats to ecosystems and species of the biome. Only 2.2% of its area is legally protected and various species of animals and plants are endangered. Besides the vegetation degradation and soil erosion, the introduction of non-native species and the use of fire to create pastures can have an adverse impact on ecosystems and cause significant loss of biodiversity in the biome [13].

2.1   Cultivated Pastures

Comprising about 500,000 km^2 of the biome, nearly 50% of these cultivated pasture areas are severely degraded (Figure 3), causing loss of soil fertility, increased erosion and predominance of invasive species [11]. For that reason, not only can the recovery of these areas increase the producers' income, but also it can reduce the environmental impact by decreasing erosion, emission of carbon dioxide and opening new areas for cattle [6].

Fig. 3. Examples of managed (left) and degraded pastures (right). Source: [9].

Different data sets can be extracted and analyzed to support the detection of these regions, such as climatic, biophysical and radiometric (vegetation indices) data from satellite images [10]. Vegetation indices produced by remote sensing data represent improved measures of surface vegetation conditions and the pattern analysis of these indices can be a useful tool for the observation of land use and cover [21]. Additionally, wet and dry seasons are well defined in the Cerrado and, consequently, this fact may assist to identify the radiometric and biophysical characteristics of the cultivated pasture regions [11].

However, the classification of cultivated pastures is difficult because the degradation of these regions can, for instance, influence the percentage of vegetation cover and the response of vegetation indices. Misclassification may happen when pastures are managed improperly, since those areas might be infested by

invasive species or even it may occur the revival of species of native shrubs and trees in these regions [11].

Therefore, in order to improve the discrimination of such targets it is necessary to use temporal and field data and also to better understand the biophysical properties of these areas [11]. Thus, the analysis of these areas using time series extracted from satellite images can allow a more accurate identification of temporal patterns of these targets in the biome.

3   Data and Methods

The study area covers a Cerrado's location that encompasses a region of Serra da Canastra National Park and neighboring regions, illustrated in Figure 4. It is located in the south-central state of Minas Gerais, southeastern of Brazil. The chosen scene contains the targets of interest, both native grassland areas and cultivated pastures.
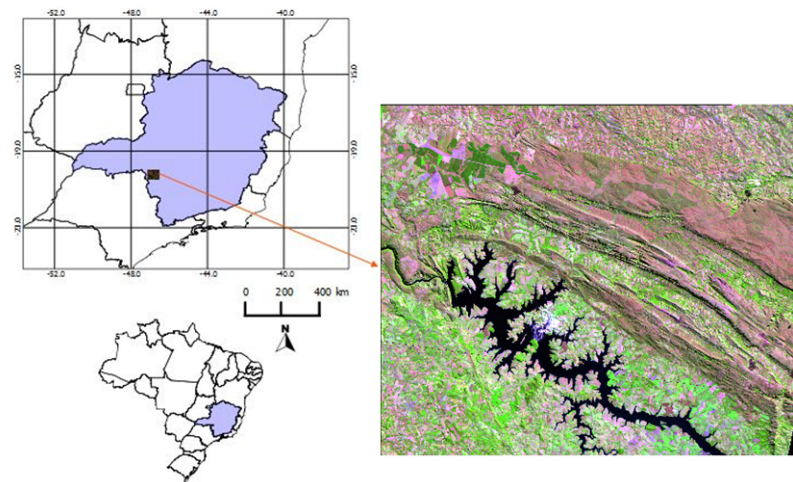

Fig. 4. Location of the study area. Crop of a Landsat-5 TM (R5B4G3) image of the study area.

Information on cultivated pasture areas, for the year 2006, were provided by the Brazilian Ministry of the Environment. The regions of native areas, for the year 2009, were obtained from the Forest Inventory of Minas Gerais State, created by the University of Lavras (UFLA), which ranks the grassland formations into two classes: Field (Clean and Dirty Fields) and Rocky Field [20]. These two reference data are shapefiles with polygons categorized with the classes of interest. As a means to evaluate the classification results, these data were merged

and used as ground truth. The classes used in this work includes the following standards: Cultivated Pasture, Native Field and Others. The class Native Field combined the Field and Rocky Field classes into a single class, whereas the class Others covered all other native formations in the study that are neither Field nor Rocky Field.

Images of EVI MODIS sensor were used to collect the attributes, with atmospheric correction and spatial resolution of 250 m. Specifically , annual profiles were used as feature vectors for 2006 and 2009. Each annual profile was extracted from EVI composition of 16 days from MODIS, resulting in 23 instants for each profile. Figure 5 shows a summary of the sequence of images obtained from MODIS data for the 23 instants of 2006 and 2009. For each image, each pixel corresponds to a vegetation index value (EVI), so that the values of this ordered sequence of images result in a time series, as shown in Figure 6.
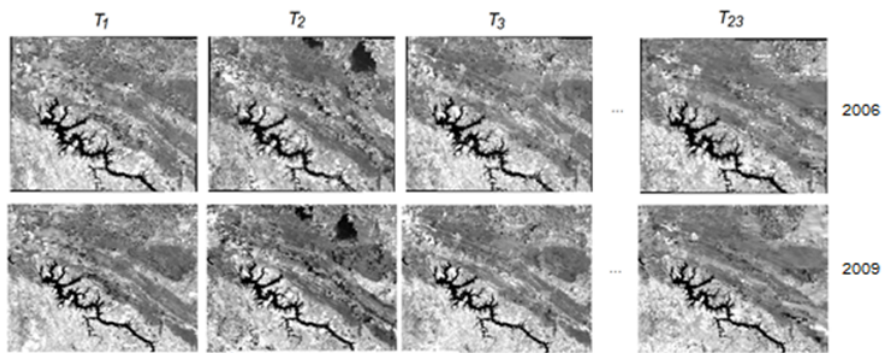

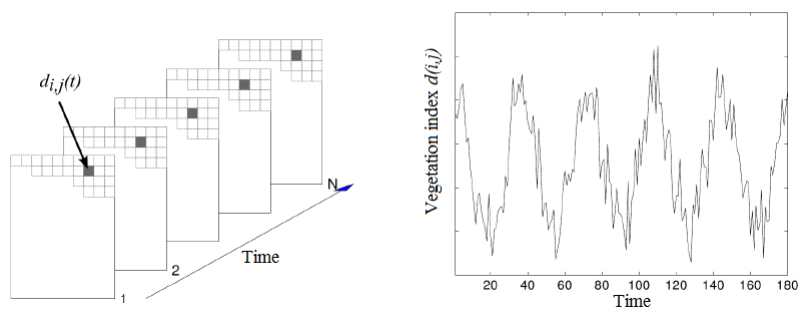**Fig. 5.** Sequence of images to compose the EVI time series for 2006 and 2009.

Fig. 6. Example of time series of vegetation index in the pixel d(i,j)

For the extraction of predictive attributes, each sample was considered as the set of information relating to a polygon of the file created from the reference data. For each of the 23 images of EVI indices, attributes related to vegetation indices were extracted from the implementation of algorithms using the library TerraLib 5 [4]. TerraLib is an open source class library written in C++ that allows collaborative work between the development community of geographic applications.

It was necessary to implement an algorithm to assign the mean of all pixel values (EVI, in this case) of each polygon. The attributes correspond the mean of the values of the pixels within each polygon for each EVI image at the instant $T_i(i = 1, 2, \cdots, 23)$.

To avoid the problem of edge pixels, an approach was used to define the attributes of EVI for each polygon. Using TerraLib 5, an algorithm was implemented that sets the value of the attribute for each polygon in each one of the images T_1 to T_{23}, equal to the mean of "pure" pixels of a given polygon.

It was considered only the pixels whose neighbors also belong to the same class in the calculation of EVI value for a given polygon in each one of the 23 instants. As a result, this approach avoids edge pixels that influence the calculation of the mean of EVI values of a given polygon. Figure 7 shows two examples of pixels in the decision-making process of the algorithm. The first pixel is "pure" and it would be considered in the calculation of attributes, whereas the second one would be disregarded.
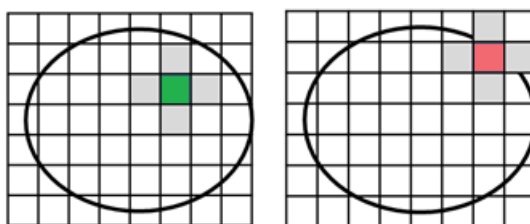

Fig. 7. For each polygon, the pixel highlighted in the figure on the left is considered "pure", while the second pixel does not follow the spatial relation defined in the algorithm and, therefore, it is not taken into consideration.

With the generation of the time series for each polygon, the algorithm developed in this work also calculates the variables derived from the extracted time series. These variables are also used as attributes in the experiments. The variables extracted from the time series are the values of: minimum, maximum, amplitude, sum, mode, mean and standard deviation.

For the classification of the areas, this work used the algorithms of Support Vector Machine [22] [2], Multilayer Percetron [17] and Autoencoder [15], using the tools Weka [12] and LibSVM [5]. We used the strategy of percentage division

of the set of all samples, with 2/3 of the samples for the training set and 1/3 for the test set.

In evaluation process, confusion matrices were used. From the confusion matrix can be calculated descriptive statistics, such as the accuracy of the results, so that the confusion between classes can be clearly presented and understood [7]. In the case of SVM classification, the calculations of the confusion matrix were implemented in R and C++ algorithms.

In addition to classification with SVM and MLP using the 23 spectral attributes and the 7 attributes derived from the time series, we applied a Autoencoder trained with all 30 attributes. Two new data sets with the attributes generated by Autoencoder were used. These new data sets were then trained and classified with the SVM and MLP networks.

After using and evaluating the classifiers, it can be constructed as output of the classification process a thematic map for each of the classified experiments. Therefore, it is possible to generate an information layer by integration and processing of the input data, derived from satellite images.

4   Results

For observation and analysis of results, three experiments were performed. Each experiment uses a specific set of attributes in the classification process, as described in Table 1.

Table 1. Summary of the datasets used in each experiment.

Experiment	Predictive attributes used
1	23 attributes (time series)
2	Attributes extracted from the time series
3	Time series and attributes extracted from the time series

The classes used in this study includes: Native Field, Cultivated Pasture and Others. The SVM and MLP networks were used in all experiments. The SVM parameters were adjusted for each test using exhaustive search with cross-validation. On the other hand, results using 1 and 2 hidden layers were observed for MLP networks. Values of η and *momentum* were defined as 0.3 and 0.2, respectively.

Furthermore, in the Experiment 3, classifications were also performed with SVM and MLP from the attributes generated by the Autoenconder, trained with the 30 original attributes. Two sets of data were created from the Autoencoder. One set contains 15 (half of the original attributes) and the other has 25 attributes.

Based on algorithms implemented in TerraLib 5 using the "pure" pixel approach, described in the previous section, a data set was extracted with a total of 508 samples to perform all experiments, in which each sample is related to

the mean of pixels values (EVI) of a polygon. Thus, the training set had 337 samples and the test set contained 171.

In Experiment 1, the potential of time series of EVI images as unique set of attributes in the classification was evaluated, in order to analyze the contribution of time series itself. The best classification resulted in an accuracy of 84.21% using SVM. The results of Experiment 1 are shown in Table 2.

Table 2. Experiment 1 results

Classifier	Accuracy (%)
SVM	**84.21**
MLP (1 hidden layer)	77.19
MLP (2 hidden layers)	83.04

In Experiment 2, the contribution of variables extracted from each of the time series was assessed. Seven predictive attributes were used: minimum, maximum, amplitude, sum, mode, mean and standard deviation. All of them were also extracted and implemented using TerraLib 5. Table 3 shows the accuracies obtained for Experiment 2. It was noted that using only this information did not result in good classifications, if compared with Experiment 1 accuracies. The highest accuracy was only 77.19% using the MLP network with two hidden layers.

Table 3. Experiment 2 results

Classifier	Accuracy (%)
SVM	76.60
MLP (1 hidden layer)	71.35
MLP (2 hidden layers)	**77.19**

Lastly, in Experiment 3 it was analyzed whether the combination of the attributes of Experiment 1 and Experiment 2 would achieve better results. Table 4 shows the results obtained. From the evaluation of the results, it can be noticed a small increase in the accuracy of the classifiers regarding the other experiments applied. Experiment 3 obtained the best result of the classifications and achieved an accuracy of 85.96% using SVM classifier. It was reached an increase in accuracy of 1.75% compared to Experiment 1 with SVM, without providing more significant growth.

The experiments with Autoenconder showed that similar accuracies were found reducing the amount of attributes via this network. For example, the MLP with two hidden layers using the 30 original attributes obtained the same accuracy that the experiment with the 25 attributes generated by the Autoencoder, using a MLP with the same equivalent number of hidden layers.

Table 4. Experiment 3 results

Classifier	*Accuracy (%)*
SVM	**85.96**
MLP (1 hidden layer)	77.19
MLP (2 hidden layers)	84.21
Autoencoder (15 attributes) > SVM	75.44
Autoencoder (25 attributes) > SVM	82.46
Autoencoder (15 attributes) > MLP (1 hidden layer)	75.44
Autoencoder (15 attributes) > MLP (2 hidden layers)	81.87
Autoencoder (25 attributes) > MLP (1 hidden layer)	77.19
Autoencoder (25 attributes) > MLP (2 hidden layers)	84.21

Afterwards, the information plan regarding the thematic map with the best result (Experiment 3 with SVM) was generated, as illustrated in Figure 8.
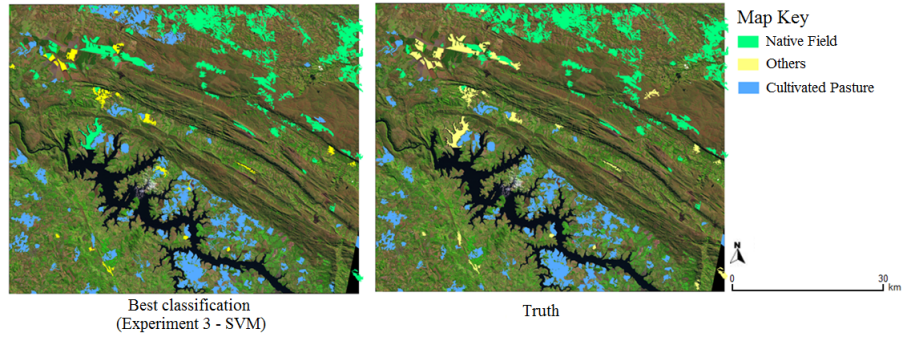

Fig. 8. Thematic map created from the best result of Experiment 3 (left) and thematic map with ground truth (right). The classification are superimposed on a Landsat-5 TM image (R5B4G3).

Concerning the computational cost, the algorithm implemented in TerraLib 5 for extracting attributes regarding only "pure" pixels of the polygon obtained a processing time of nearly 5 hours to complete the extraction of the attributes set. Observing the classification by SVM and MLP, these classifiers performed the predictions of classes in less than a second.

From an operational point of view, the creation of a classification model by SVM with the attributes of Experiment 3 showed results similar to Experiment 1, since the improvement in accuracy was small for the mapping of the three classes. Looking at the results with AutoEncoder, they showed that accuracies using this network were similar to those tests that uses the 30 original attributes. Henceforth, this network can decrease the amount of attributes in the classification processs and, consequently, reduce the data dimensionality.

Furthermore, this work can contribute to the classification and integration of remote sensing data in geographic information systems from the construction of thematic maps as output of the classification process, since it was possible to generate a layer of information from the input data.

5   Conclusion

By comparison pattern recognition techniques, such as Support Vector Machines, Multilayer Perceptrons and Autoencoders, this work aimed to classify and create thematic maps of areas of native grasslands and cultivated pasture areas in the Brazilian Cerrado using times series extracted from satellite images.

With regard to the processing time, attributes extraction had a cost of approximately five hours to execute the algorithm implemented in TerraLib 5. SVM and MLP networks showed a minimum computational cost for classification of results. The SVM algorithm showed better results in separation between classes Native Field and Cultivated Pasture. The best result obtained an accuracy of 85.96% accuracy by combining all the attributes related to time series and variables derived from it. The results also showed that tests using a smaller number of attributes from the autoencoder had accuracies similar to those obtained in the tests that used all original attributes, emphasizing the ability of this network to reduce the dimensionality of the data.
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