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## 2 **Data Mining Using NDVI Time Series Applied to** 3 **Change Detection**

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9 **Abstract:** Quantifying and monitoring woody cover distribution in semiarid regions is challenging,  
10 due to their scattered distribution. Data mining has been widely used in remote sensing data for  
11 information extraction of spectral and temporal data in the analysis of change detection. The main  
12 objective of this study was to characterize the land cover and use over 2000-2010 time period for the  
13 brazilian Caatinga seasonal biome using a temporal NDVI series and Geographic Object-Based  
14 Image Analysis. For each of the target years was obtained NDVI images derived from MODIS  
15 (MOD13Q1, at 250 m spatial and 16-day temporal scale) sensor during the dry season to predict  
16 wood cover in the municipality of Buriti dos Montes, in the state of Piauí, Northeast region of Brazil  
17 (H13V09 *tile*). The images were automatically pre-processed and in the GEOBIA approach was  
18 performed image segmentation, spatial and spectral attribute extraction and labelled according to  
19 the following legend: Tree Cover (TC) and Cropland/Grass (CG), to obtain a classification using the  
20 decision tree supervised algorithm. Our results showed that approach using GEOBIA presented  
21 Kappa Index of 0.58 and Global Accuracy (GA) of 0.81% and showed better accuracy for the Tree  
22 Cover. Finally, we recommend new studies adding others parameters strongly related to vegetation  
23 of semiarid regions.

24 **Keywords:** Land cover change; deforestation; GeoDMA; semiarid; Caatinga.  
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### 26 **1. Introduction**

27 Semiarid regions present low and irregular precipitations, limited to a very short period of the  
28 year in large part of their extension. These regions are mainly characterized by a long period of  
29 rainfall reduction [1]. In Brazil, periods of drought are relatively frequent in the Northeast region as  
30 consequence of high interannual rainfall variability. Northeast Brazil has a type of vegetation adapted  
31 to semiarid conditions denominate caatinga (savanna), and the Caatinga biome cover an area of circa  
32 844,453 km<sup>2</sup> or approximately 11% of the Brazilian territory and in which is populated by more than  
33 27 million inhabitants [2].

34 However, the Caatinga biome is the third most degraded in Brazil and this region has suffered  
35 heavy losses of natural vegetation as a common practice for the preparation of land for agriculture,  
36 contributing to the loss of biodiversity. Moreover, partial or total removal of native vegetation has  
37 caused a reduction in the aerial biomass, a practice that has been carried out in a predatory manner  
38 due firewood be one of the main energy sources in these regions [3].

39 In this context, the monitoring and mapping is crucial to understand the vegetation and  
40 structure changes [4] and their variations over time. Thus, many studies have used remote sensing  
41 techniques to extract information in the analysis of temporal series through mining of spatial and

42 spectral data to changes detection [5]. The Geographic Object-Based Image Analysis (GEOBIA) is  
43 based on topological information and geometric of the objects to the classification of images.

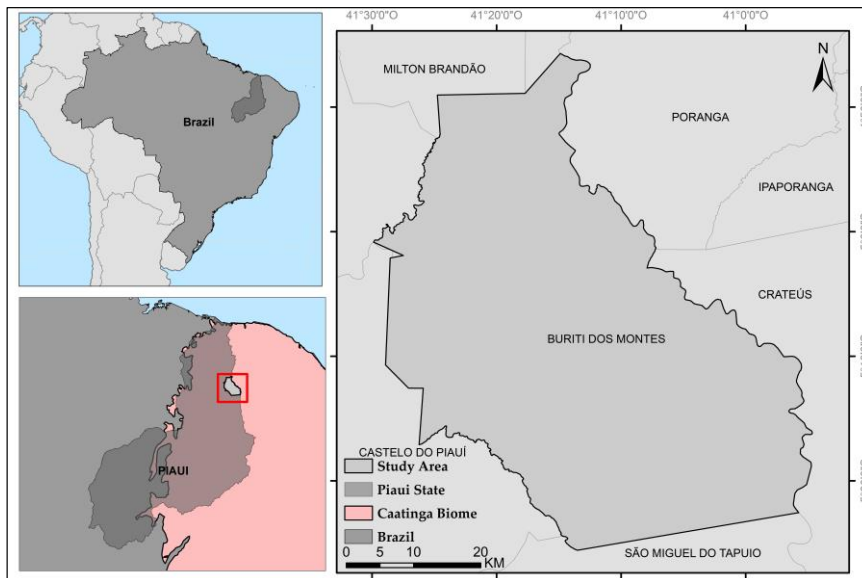
44 In this context, the aim of the present work is to classify the land cover and use of the Brazilian  
45 Caatinga seasonal biome using Geographic Object-Based Image Analysis (GEOBIA) in a temporal  
46 NDVI series over 2000-2010 time period, in the municipality of Buriti dos Montes, Piauí.

## 47 2. Materials and Methods

### 48 2.1. Study Area

49 To accomplish our study goal, we investigated the municipality of Buriti dos Montes (Figure 1)  
50 located in the state of Piauí in the northwest Brazil. The municipality occupies an area of  
51 approximately 2653 km<sup>2</sup>. Mean altitude is 500 meters and presents tropical climatic classification with  
52 dry season between July to October [6, 7].

53 The area is characterized by representative vegetation of semiarid regions, presenting tree and  
54 shrub savanna cover [8] and the main agricultural products are rice, beans and corn where native  
55 plants have been replaced [6].



56  
57 Figure 1 – Location of the study area in Piauí – Brazil.

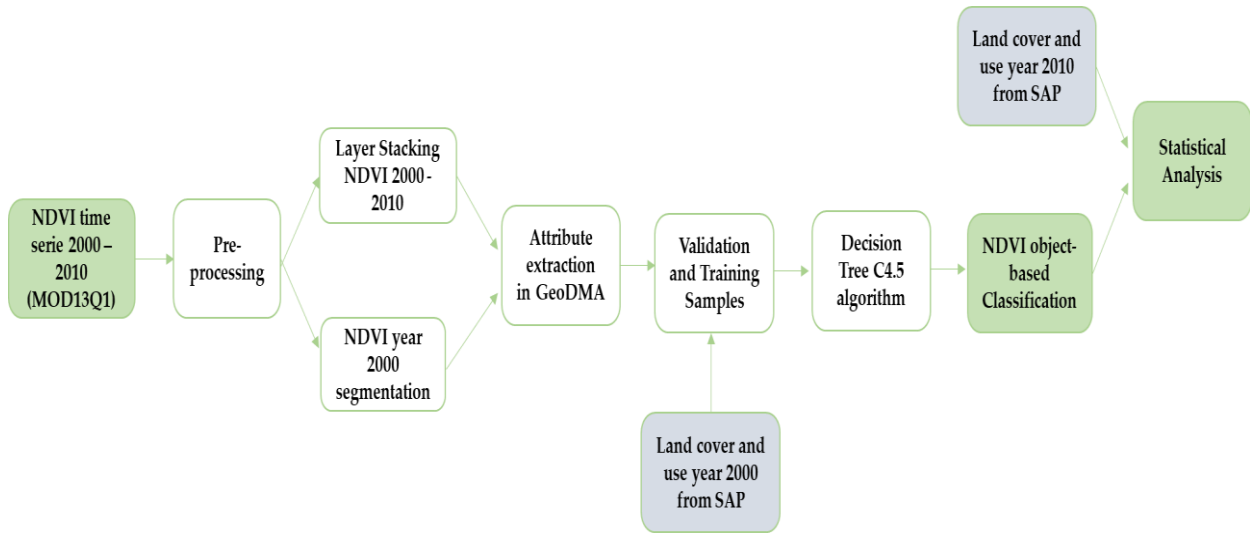
### 58 2.2 Acquisition and pre-processing data

59 This study uses MODIS (Moderate Resolution Imaging Spectroradiometer) sensor imagery from  
60 MOD13Q1, a NDVI (Normalized Difference Vegetation Index) product available at a 250 meters  
61 spatial resolution [9], composed by a mosaic of 16 days of imaging. Based on the supposition that  
62 only trees and shrubs have active photosynthesis during dry season, we applied the methodology  
63 process only for the months of August, over the period 2000-2010 to the tile H13V09 available at  
64 EarthData – NASA (<<https://ladsweb.modaps.eosdis.nasa.gov>>) corrected atmospherically.

65 Two land use and cover maps were used for the years 2000 and 2010 as a reference for this study.  
66 The data were obtained from SAP (*Sistema de Alerta Precoce contra a Seca e Desertificação* – CCST / INPE)  
67 at a 30 meters spatial resolution derived from Landsat TM (Thematic Mapper) and Landsat ETM+  
68 (Enhanced Thematic Mapper) sensors [8].

69 Very high spatial resolution sensor images from GeoEye 1 satellite were visualized in Google  
70 Earth Pro software. The images were used for visual interpretation of the targets and illustration of  
71 the land cover changes detected in MODIS time series.

72 In the pre-processing stage, the images of NDVI product were cut to the interest area in the limit  
 73 of the municipality and then it were stacked to a single raster cube file in ENVI 5.1 environment and  
 74 all the images were normalized to a range of 0 to 1 (Figure 2).



75 **Figure 2** - Methodological work-flow including earth observation data for assessing changes in the  
 76 vegetation.

77 The second part of the study was carried out in the TerraView 4.2.2 software to the processes  
 78 involving data mining technique. The image segmentation, attribute extraction and sampling for  
 79 training were the stages performed specifically through the GeoDMA (Geographical Data Mining  
 80 Analyst) plug-in [10] which is used by GEOBIA for image classification [11].

81 For this procedure, the segmentation process was performed in the NDVI product referred to  
 82 2000 year. We used the segmentation algorithm based on the region growing [12], which Euclidean  
 83 distance and minimum area parameters are used to divide the image in homogeneous spectrally  
 84 regions. During this procedure, several segmentations were tested but the threshold that best fit the  
 85 analyzed data was the values of 30 and 10 for Euclidean distance and minimum area respectively.

86 Subsequently, the spectral and spatial metrics were extracted using the segmentation results and  
 87 the NDVI cube over the period. Thus, each object generated through segmentation has an attribute  
 88 value calculated from the selected metrics.

89 For the classification process, it is necessary to select training and validation samples, which  
 90 consists in the selection of pixels or homogeneous regions that best represent each one of the classes  
 91 resulting in an object-based classification map. In this study we used the land cover and use mapping  
 92 from SAP as a reference for year 2000. The selected samples were used for the classification based on  
 93 decision tree by algorithm C4.5 contained in the GeoDMA plug-in. Objects were classified into two  
 94 land cover classes: The Tree Cover (TC) class was defined in trees and shrubs savannas and  
 95 Cropland/Grass (GC) class.

96 Due to the lack of appropriate field data required for assessing the quality of land cover map  
 97 produced for our study, we opted to compare the land cover map from SAP of year 2010 as a reference  
 98 mapping with the classification obtained by decision tree to evaluate the accuracy. The Kappa Index  
 99 Kappa Index (Equation 1), obtained by the error matrix, Global Accuracy (Equation 2), Hypothesis  
 100 Test by Z test (Equation 3), Producer Accuracy (Equation 4) and Consumer Accuracy (Equation 5).

101 
$$\hat{k} = \frac{\theta_1 - \theta_2}{1 - \theta_2}, \quad \text{where: } \theta_1 = \frac{\sum_{k=1}^c X_{kk}}{n} \quad e \quad \theta_2 = \frac{\sum_{k=1}^c X_{+k}}{n^2} \quad (1)$$

102 
$$\text{Global Accuracy: } \frac{\sum_{k=1}^c X_{kk}}{n} \quad (2)$$

103 
$$\text{Z Test} = \frac{\hat{k} - k}{\sqrt{\text{Var}(\hat{k})}} \sim N(0,1) \quad (3)$$

104 
$$\text{Producer Accuracy: } k = \frac{x_{kk}}{x_{+k}} \quad (4)$$

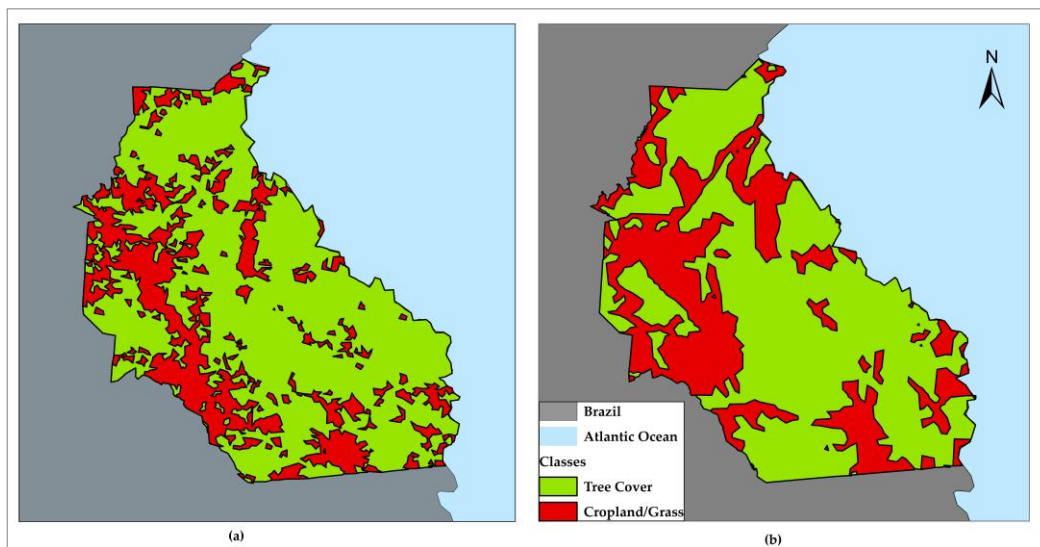
105 
$$\text{Consumer Accuracy: } k = \frac{x_{kk}}{x_{k+}} \quad (5)$$

106 Where  $x_{kk}$  is the sum of each element of the diagonal,  $x_{+k}$  is the total of the column of each class  
 107 and  $x_{k+}$  is the total of the row of each class.

108 **3. Results and Discussion**

109 After performing the steps in GeoDMA, the C4.5 classifier generated the decision tree from the  
 110 calculated spatial and spectral metrics, using those that best fit the data set.

111 Using the decision tree generated by the classification algorithm, we obtained the land cover and  
 112 use classification map based on the NDVI time series. The generated map was compared in relation  
 113 to the reference map of the year 2010 also of the SAP in order to generate the statistical analyzes  
 114 (Figure 3).



115 Figure 3 – (a) NDVI time series object-based Classification Map and (b) Land cover and land use  
 116 reference data for the 2010 year by SAP adapted by author.

117 Based on the map generated and the reference map, it was calculated the extension for each  
 118 class obtaining a result of 1927 km<sup>2</sup> for Tree Cover and 725 km<sup>2</sup> for Cropland/Grass using the  
 119 classification based on the NDVI time series. On the other hand, for the reference map, the TC area  
 120 covers approximately 1746 km<sup>2</sup> of the municipality of Buriti dos Montes and 907 km<sup>2</sup> for  
 121 Cropland/Grass (Table 1).

122 Table 1. Area of Tree Cover and Cropland/Grass classes for object-based Classification and SAP  
 123 Mapping for the year 2010 as a reference.

	Area 2010 (Km <sup>2</sup> )	
	NVDI classification	SAP Reference
Tree Cover	1927	1746
Cropland/Grass	725	907
Total	2653	2653

124 According to [8] the municipality of Buriti dos Montes had about 81.5% of it is entire territory  
 125 covered by Caatinga (tree and shrub savanna) in year 2000, however, there was a reduction to 65.82%  
 126 in 2010, while there was a considerable increase of 15, 64% in agriculture.

127 In addition, the authors report twice the average of the outbreaks of fires for the year 2010,  
 128 ranging from an average of 50 to 100 fires detected. They also point to the increase of the

129 environmentally susceptible area index (IAS) reaching attributes of moderate and high susceptibility  
 130 to the municipality.

131 The error matrix (Table 2) was generated after crossing the 265 sampling points with the  
 132 mapping obtained with object-based classification. The Kappa Index found for this classification  
 133 process was 0.58 and Global Accuracy of 81%. The main source of error occurred in the classification  
 134 of 31 TC as a CG class. This pattern found in this study suggest that there are large variations between  
 135 classes due to the patchiness of tree cover, also to scattered distribution of wood plants and  
 136 distribution of cultivated fields. As well as values of producer and consumer accuracies are observed  
 137 (Table 3).

138 Table 2. Error matrix for object-based classification.

Classes	Tree Cover	Cropland/Grass	Total
Tree Cover	151	31	182
Cropland/Grass	19	64	83
Total	170	95	265
<i>Kappa Index</i>			0,58
<i>Global Accuracy</i>			0,81
<i>Z Test</i>			10,88

139 Considering the application of the Z test, at 5% significance, in order to verify if there is  
 140 agreement between the NDVI time series in a objet-based classification and the reference map fot the  
 141 year 2010 used, we observed that a Z value of 10,88 means that there is agreement between both  
 142 maps.

143 Table 3. Producer and Consumer Accuracy for NDVI Classification (%).

Classes	Producer Accuracy	Omission Error	Consumer Accuracy	Inclusion Error
Tree Cover	88,82	11,17	82,96	17,03
Cropland/Grass	67,36	32,63	77,10	22,89

144 It can be attributed that the result of the classification obtained from the time series of the NDVI  
 145 did not obtain excellent results possibly due to differences in spatial resolution of the data used and  
 146 the reference data.

#### 147 4. Conclusions

148 The use of the GeoDMA computational application for extracting spatial and spectral metrics  
 149 through data mining has proved to be an efficient and accessible tool for classifying orbital images of  
 150 temporal NDVI series using the C4.5 algorithm.

151 The results indicate that the process of classification by data mining method allows to detect  
 152 changes in land cover through from the NDVI product in a long period, especially in what concerns  
 153 the expansion of agriculture in the municipality of Buriti dos Montes.

154 Finally, we recommended new approaches using earth observation data in a higher spatial  
 155 resolution for better comparison with the reference data used in this work, as well as the addition of  
 156 other parameters strongly related to vegetation of semiarid regions.

157  
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 159 CAPES.

160  
 161 **Conflicts of Interest:** The authors declare no conflict of interest.

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