SUPERVISED CLASSIFICATION APPLIED TO VEGETATION MAPPING IN THE BARÃO DE MELGAÇO MUNICIPALITY (MATO GROSSO STATE, BRAZIL), USING MODIS IMAGERY

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Abstract

The use of remote sensing images and geoprocessing techniques has contributed to a fast and effective monitoring of the Pantanal region. Barão de Melgaço municipality, in Mato Grosso State, has 99.2% of its land area inserted in this biome, with flooding dynamics which result in rapid changes in vegetation cover. Accordingly, this study aimed to map the vegetation of this municipality, in both dry and rainy seasons, using supervised classification (Parallelepiped and SVM) of images from MODIS sensor. The classifications were applied, for each date, both on composite R(MIR) G(NIR) B(RED) and on composite with the fraction images R(wet soil) G(vegetation) B(water) for the rainy season, and R(dry soil) G(vegetation) B(water) for the dry season. The fraction images were derived from a Linear Spectral Mixture Model. A total of eight maps were created and evaluated using an error matrix. The best result for each season was the Parallelepiped classifier applied to the composition with the original bands from MODIS. These results were compared with the map of phyto-ecological regions of Barão de Melgaço. They allowed concluding that the presence of soil in Savanna Woodland and in Tree and/or Shrub Savanna prevented the classification of these vegetation types in the images of the dry season.

Key-words: Digital classification. Error matrix. Linear spectral mixture model. Fraction images.

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Resumo

Classificação supervisionada aplicada ao mapeamento da vegetação do município de Barão de Melgaço/MT utilizando imagens do SENSOR MODIS

O uso de imagens de sensoriamento remoto e técnicas de geoprocessamento tem contribuído para o monitoramento rápido e eficaz do Pantanal. O município de Barão de Melgaço/MT tem 99,2% de sua área territorial inserida no bioma, com a dinâmica de inundação ocasionando mudanças rápidas na cobertura vegetal. Nesse sentido, o objetivo deste estudo foi mapear a vegetação do município mato-grossense de Barão de Melgaço, nas estações seca e chuvosa, através de classificação supervisionada (Paralelepípedo e SVM) de imagens do sensor MODIS. As classificações foram aplicadas, para cada data, tanto na composição R(MIR) G(NIR) B(RED) quanto na composição com as imagens-fração R(solo úmido) G(vegetação) B(água) para a estação chuvosa, e imagens-fração R(solo seco) G(vegetação) B(água) para a estação seca. As imagens-fração foram derivadas do Modelo Linear de Mistura Espectral. Ao todo foram gerados oito mapeamentos, avaliados por meio da matriz de erros. O melhor resultado para cada estação foi o uso do classificador Paralelepípedo aplicado sobre a composição com as bandas originais do MODIS. Estas classificações foram comparadas com a carta de regiões fitoecológicas de Barão de Melgaço, permitindo avaliar que a presença de solo na Savana Arborizada e na Savana Gramíneo-Lenhosa influenciou para a não classificação das mesmas na estação seca.

Palavras-chave: Classificação digital. Matriz de erros. Modelo linear de mistura espectral. Imagens-fração.

INTRODUCTION

Pantanal is considered the largest floodable floodplain in the world, with a size of approximately 160,000 km² and it is located in 3 countries, namely Brazil, Paraguay and Bolivia (JUNK, 2006). According to Silva & Abdon (1998), the Brazilian Pantanal is inserted in the Upper Paraguay river basin, encompassing an area of 138,183 km² distributed in two Brazilian States: 89,318 km² in Mato Grosso do Sul, and 48,865 km² in Mato Grosso. As for Barão de Melgaço municipality, 99.2% of the territory is located within Pantanal and has the Natural Heritage Private Reserve SESC Pantanal, besides being part of the State Park *Encontro das Águas*.

The flooding in Pantanal occurs typically between November and February and the drought period extends from July to August. Adamoli (1995) reports that this flooding frequency is a fundamental ecological factor of this biome, which determines the pulses of the main biotic and non-biotic processes, as well as operative cycles of productive processes, such as cattle raising, tourism, and river navigation. Besides that, the flood regime causes the type and the specific compositions of different landscape units occurring in the biome.

This particularity makes the monitoring of Pantanal a difficult task because, besides its extension and access difficulties, this region suffers cyclic changes caused by changes of vegetation cover. Shimabukuro et al. (1998) inform that the monitoring of natural resources in regions like Pantanal can be improved using remote sensing methods.

Satellite image classification is one of the most frequent remote sensing applications for the production of thematic maps, such as those of land use/land cover. This procedure can be accomplished by both visual analysis and by automatically using a computer (FOODY, 2002).

Among the automatic classifications, Devi & Baboo (2011) report that the so-called Parallelepiped algorithm is computationally efficient to classify data obtained from remote sensors and that it is generally used when the process must be fast. Its disadvantage, however, in many cases, is its low accuracy.

On the other hand, the SVM (Support Vectors Machine) method is gaining prominence due to its good performance related to other classifiers, as it was verified by Shao & Lunetta (2012) for the classification of land cover from the Albemarle-Pamlico estuarine system (USA), using temporal MODIS datasets and by Senthilnath et al. (2012), who combined image segmentation and classification to map the Krishna river, in southern India, and to evaluate its flooded regions, also using MODIS images.

The MODIS (Moderate Resolution Imaging Spectro-radiometer) sensor was designed to deliver simultaneous observations of atmospheric, oceanographic, and terrestrial features, at the visible and infrared wavelengths of the electromagnetic spectrum (JENSEN, 2009). Data from this sensor are available free of charge and its spectral bands, besides being geometrically, atmospherically, and radiometrically corrected, are also transformed into other products such as vegetation indices and leaf area indices (LATORRE *et al.,* 2007).

Zhan et al. (2002) inform that the red and infrared wavelength intervals are the most important spectral regions to map vegetation. These bands are found in the module MOD13Q1 from MODIS.

MODIS images and its products have been used in studies at Pantanal, e.g. monitoring of its spatial-temporal dynamics (ADAMI *et al*., 2008); to evaluate the performance of NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index) and LSWI (Land Surface Vegetation Index), considering the main types of land cover and the seasonality of rainfall in Pantanal, the LSWI was the most adequate index for this region (VIANA; ALVALÁ, 2011); and also for the analysis of the vegetation phenology based on a temporal series of EVI (ANTUNES *et al.,* 2011).

Although MODIS data have a high temporal resolution, its moderate spatial resolution frequently becomes a limitation for the automatic image classification, because the spectral response of each pixel is the result of radiance integration from several targets, causing the predominance of an intra-pixel spectral mixture (SILVA *et al*., 2010). According to Shimabukuro & Smith (1991), it is possible to decompose this spectral response using the Linear Spectral Mixture Model (LSMM), which generates fraction images representing the proportions of each component in the pixel formation.

In order to monitor the dynamics of vegetation cover in the Pantanal region, Shimabukuro *et al*. (1998) used, based on Landsat-TM data, vegetation index images and fraction images derived from a LSMM, indicating a higher sensitivity of the fraction image to variations of the vegetation cover when compared with the vegetation index image.

In this context, the use of fraction images for the automatic image classification, especially those with low to moderate spatial resolution, can get the best results for land use evaluation. Every effort to improve knowledge of Pantanal is worthwhile, due to the fast changes of vegetation cover caused by the flooding regime and also due to its conservation, particularly in Barão de Melgaço municipality, where there are two environmental reserves.

OBJECTIVES

The objectives of this study are: (1) to map the vegetation of Barão de Melgaço municipality during both rainy and dry seasons, applying two supervised classification methods (Parallelepiped and SVM) in MODIS images, as well as to evaluate the classifiers performance; (2) to compare the best result for each season with the map of phyto-ecologic regions of this municipality, and to qualitatively analyze the vegetation class.

MATERIALS AND METHODS

The municipality of Barão de Melgaço, located in the geographic micro-region Upper Pantanal, has an area of approximately 11,175 km^2. Figure 1 shows the localization of the study area inserted in the Brazilian Pantanal.

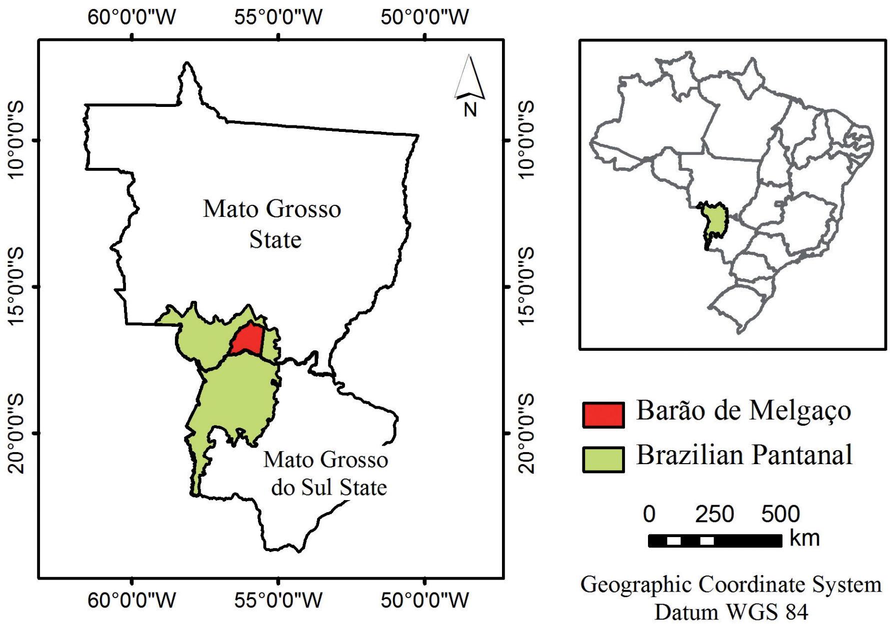

Figure 1 – Localization of the study area: Barão de Melgaço municipality, in Mato Grosso State

In this study the following MODIS data, flown onboard platform Terra, were used: product MOD13Q1, red (R), near infrared (NIR) and medium infrared (MIR) bands of tile h12v10, with 250 m spatial resolution. This product is a 16 day composition, and it is already atmospherically corrected, i.e. it presents, as a quality parameter, the best pixels of the 16 day image to compose the tile.

The images were acquired in accordance with the dry and rainy seasons of 2011. For the rainy season the image is Julian day 65th (composite from March 6th to 21st 2011) and for the dry season the data taken was Julian day 209th (composite from July 28th to Aug. 12th 2011). For each period a color composite R(MIR) G(NIR) B(RED) as well as the selection of the study area were made.

The fraction images were generated for dry soil, vegetation, and water for the dry season image, and for wet soil, vegetation, and water for the rainy season image. The objective was to enhance the targets with the contribution of each target contained in only one pixel, using the LSMM. The LSMM can be described according to equation (1) as follows:

$$R_i = \text{sum}\,(a_{ij}\,x_j) + e_i$$

Where:

R_i = medium spectral reflectance for the i^{th} spectral band;

a_{ij} = spectral reflectance of the j^{th} component in the pixel for the i^{th} spectral band;

x_j = proportion value of the j^{th} component in the pixel;

e_i = error for the i^{th} spectral band;

j = 1,2…..n (n = number of components assumed for the problem)

i = 1,2…..n (n = number of spectral bands for the sensor system).

For the generation of fraction images, LSMM must select "pure pixels" of each target, also called "endmembers", because they bring new information from the original spectral responses.

For the dry season, pure pixels of dry soil, vegetation, and water were selected, while for the rainy season, pure pixels of wet soil, vegetation, and water were selected. This differentiation among pure soil pixels is due to the fact that this area presents large flooded sections during the rainy season and so the humid soil is more present and consequently it spectrally mixes with the vegetation, that is, the mapping target of this study. Figure 2 shows the spectral curves of pure pixels selected, used at LSMM.

The following step was to apply two automatic supervised classification methods, namely Parallelepiped and SVM, and to extract the vegetation areas afterwards. Both classifiers were applied to each color composite image R(MIR) G(NIR) B(RED) and to the compositions of fraction images R(wet soil) G(vegetation) B(water) and R (dry soil) G(vegetation) B(water), in order to verify if the utilization of fraction images improves the results of the classifications.

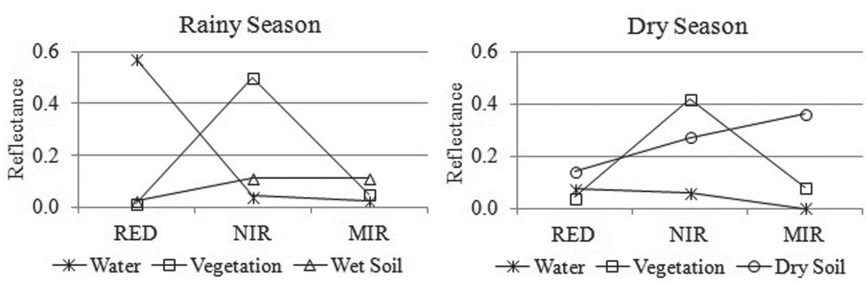

Figure 2 – Spectral curves of pure pixels of water, vegetation, wet soil and dry soil

The Parallelepiped method considers an area (square or rectangular) in the space of attributes around the training set. According to Crósta (1993), each class has decision borders, represented by the lateral sides of the parallelepiped. Therefore all pixels within this area are considered as belonging to the same class. The SVM method is based on the theory of statistical learning (GONÇALVES *et al*., 2006). Its principle is the optimum separation of classes by a decision surface which maximizes the separation margin between such classes. This surface is also known as "ideal hyperplane" and the points which are close to the margin of the ideal hyperplane are called "support vectors" (BROWN *et al*., 2000). Even if SVM is a binary classifier in its simplest form, it can work as a multi-class classifier through the combination of several binary classifiers SVM (PAN *et al*., 2012). In this study, the kernel RBF (Radial Basis Function) was used, which was also considered by Pan *et al*. (2012), Gonçalves *et al*. (2006) and Melgane & Bruzzone (2004).

In order to evaluate the accuracy of obtained maps, error matrices were generated for each classification. In an error matrix, the pattern of class attribution related to reference data is described; i. e. inasmuch the situation considered is classified in conformity with the reference. This is a frequently used method for the accuracy evaluation of data originated from remote sensing (FOODY, 2002). From the error matrix other important elements for such evaluation can be derived, such as overall accuracy, omission error, commission error, and *Kappa* coefficient (LU; WENG, 2007).

The references used were two thematic maps with generic vegetation classes; dry/wet soil and water, which were crossed with the classifications, using the post-classification tool Confusion Matrix, Using Ground Truth ROIs, from software ENVI 4.5. These thematic maps were generated from the visual interpretation of two Landsat-TM images with the composition R(5) G(4) and B(3). One image corresponds to the rainy season, obtained in April 22nd 2011 and the other to the dry season, dated Aug. 12th 2011, close to the interval of imaging dates from MODIS. In the literature there are several methodologies which consider the above mentioned procedure, however, according to Mello *et al.* (2010), it is necessary to consider the fact that the reference map does not truly express field reality, because the result is a visual interpretation. So when the disagreement between the classification and the reference is considered an "error", it is wise to understand that the term is subjective. Among other studies, it is worth mentioning Araújo *et al*. (2011) and Shao & Lunetta (2012), who also followed a similar methodology for accuracy evaluation. The first authors used as a reference a Landsat5-TM mosaic, while the second ones relied on a thematic map.

To reinforce the use of this methodology, this study was based on a discussion of Congalton & Green (1999) where these authors discuss which information source should be considered as a reference, when one is working with data originated from satellite images. These authors inform that the reference data should be the one which considers the earlier step, closer to the terrestrial reference, instead of the one which generated the classified map. In this case, the Landsat-TM images are considered closer to the terrestrial conditions than the map generated from MODIS images.

Aiming at a qualitative analysis of the vegetation mapped, a comparison was made between the best vegetation classification obtained for each date and the map of phyto-ecological regions from the municipality. This map was elaborated as part of the activities from the sub-project "Survey and Mapping of Vegetation Cover Remnants from the Pantanal Biome, in 2002, scale 1:250,000" which is inserted in the thematic "Survey of Vegetation Cover Remnants of Brazilian Biomes", within the Project for Conservation and Sustainable Use of the Brazilian Biologic Diversity, the PROBIO (BRASIL, 2006). The vegetation masks were converted into vectors to cross with the vector data of the database from the map of phyto-ecological regions.

RESULTS AND DISCUSSION

For each season four vegetation maps from Barão de Melgaço municipality were made, resulting from the combination between the classifiers and the color composites of images, represented by the acronyms: PLP-FI referring to the Parallelepiped classifier applied on fraction images; PLP-OB referring to the Parallelepiped classifier applied to compositions R(MIR) G(NIR) B(RED), considered here as original bands (OB); SVM-FI referring to the classifier SVM applied to compositions with fraction images and SVM-OB referring to the SVM classifier applied to the compositions R(MIR) G(NIR) B(RED).

The results of vegetation mapping with the image from the rainy season are presented in figure 3.

Table 1 shows the statistical results derived from the error matrix for this mapping.

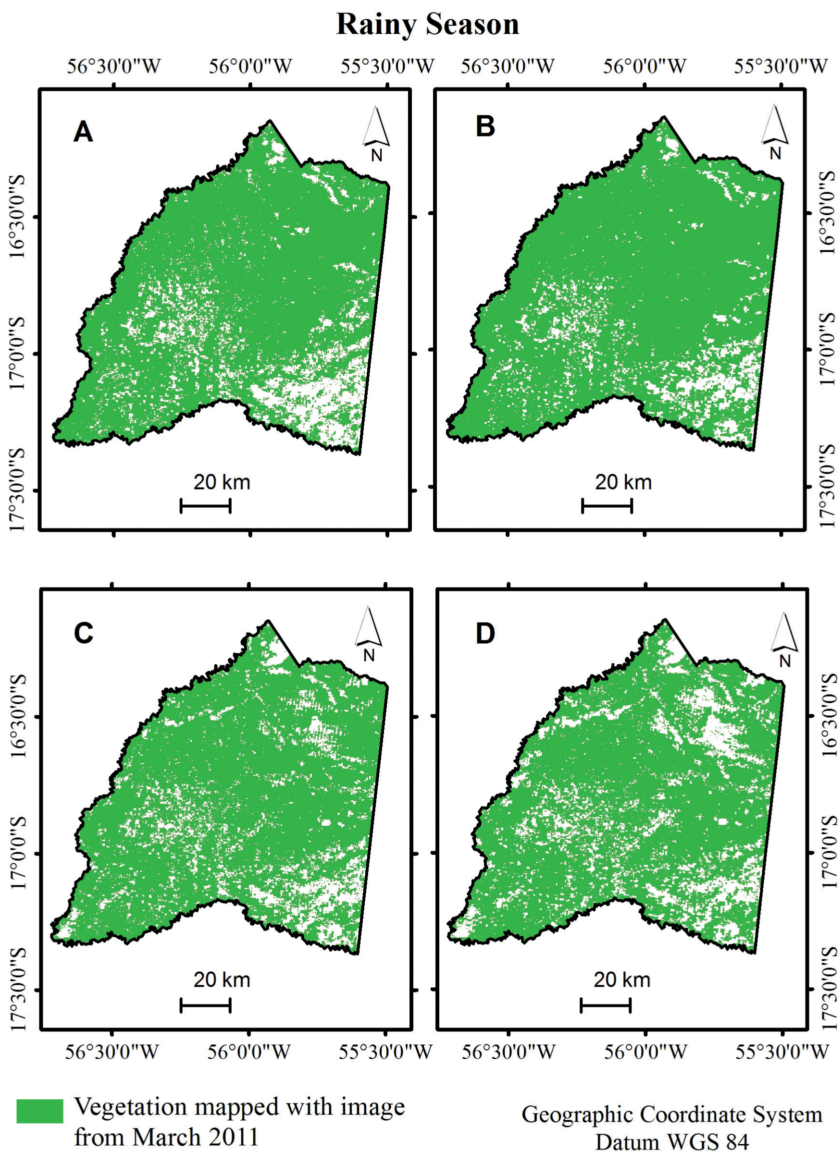

Figure 3 – Vegetation mapped during rainy season from combinations: (A) PLP-FI; (B) PLP-OB; (C) SVM-FI; (D) SVM-OB

Table 1 – Accuracy evaluation for the map of March 2011, rainy season

	PLP-FI	PLP-OB	SVM-FI	SVM-OB
Overall accuracy	86.8%	89.5%	88.8%	83.9%
Kappa coefficient	0.45	0.47	0.54	0.43
Commission error*	1.5%	2.0%	1.6%	1.5%
Omission error*	9.5%	4.7%	10.2%	14.9%
User's accuracy*	98.5%	98.0%	98.4%	98.5%
Producer's accuracy*	90.5%	95.3%	89.8%	85.1%

* refers to class vegetation.

The overall accuracy represents the total correct hits related to the total number of pixels. The combination which presented the highest overall accuracy was PLP-OB, reaching 89.5% correct hits. The lowest index of correct hits was obtained with SVM-OB, reaching 83.9%.

Referring to the *Kappa* coefficient, which is a statistical technique for the evaluation of agreement or disagreement in two situations of interest, varying from 0 to 1 (CONGALTON, 1991), the best result was obtained with SVM-FI, with *Kappa* value of 0.54. SVM-OB got the lowest *Kappa:* 0.43. All values of *Kappa* coefficient for the classifications of the rainy season are considered as of good quality, according to intervals proposed by Landis & Koch (1977).

The commission error occurs when other classes (in this case wet soil and water) are indentified by the classifier as the class of interest (vegetation). As for vegetation, which is the object of the mapping, the commission error was low for all classifications, between 1.5% and 2.0%, i.e. the other classes (wet soil and water) were rarely classified as vegetation. As a consequence, the user's accuracy is the probability of a pixel classified in the map to represent the same target in the terrestrial reference. For the vegetation class, the user's accuracy varied between 98% and 98.5% for all classifications from the rainy season.

Finally table 1 also shows the omission error, which occurs when the class of interest (vegetation) is classified as the other classes (wet soil and water). Consequently the producer's accuracy is the probability that the pixel of interest is correctly classified. For vegetation, the PBL-OB presented the lowest omission error (4.7%) and the highest producer's accuracy (95.3%). SVM-OB came out with the highest omission error and the lowest producer's accuracy, respectively 14.9% and 85.1%.

Antunes *et al.* (2011) showed that the rainfall regime in Pantanal determines an alternation of the soil cover conditions. Comparing the temporal EVI profile with accumulated precipitation data, these authors observed that in areas without human occupation, the biomass peaks coincide with the periods of higher rainfall, even when considering a time interval between the beginning of the rainy season and the response of vegetation.

Due to that, in those sections of dry soils during the dry season, the vegetation grows after the beginning of rainfall, collaborating with the increase of the vegetation mapped area in the rainy season. Figure 4 illustrates vegetation mappings for the image of August 2011, from the dry season. One observes a smaller area mapped with vegetation when compared with figure 3, of the rainy season. The accuracy values for figure 4 are presented in table 2.

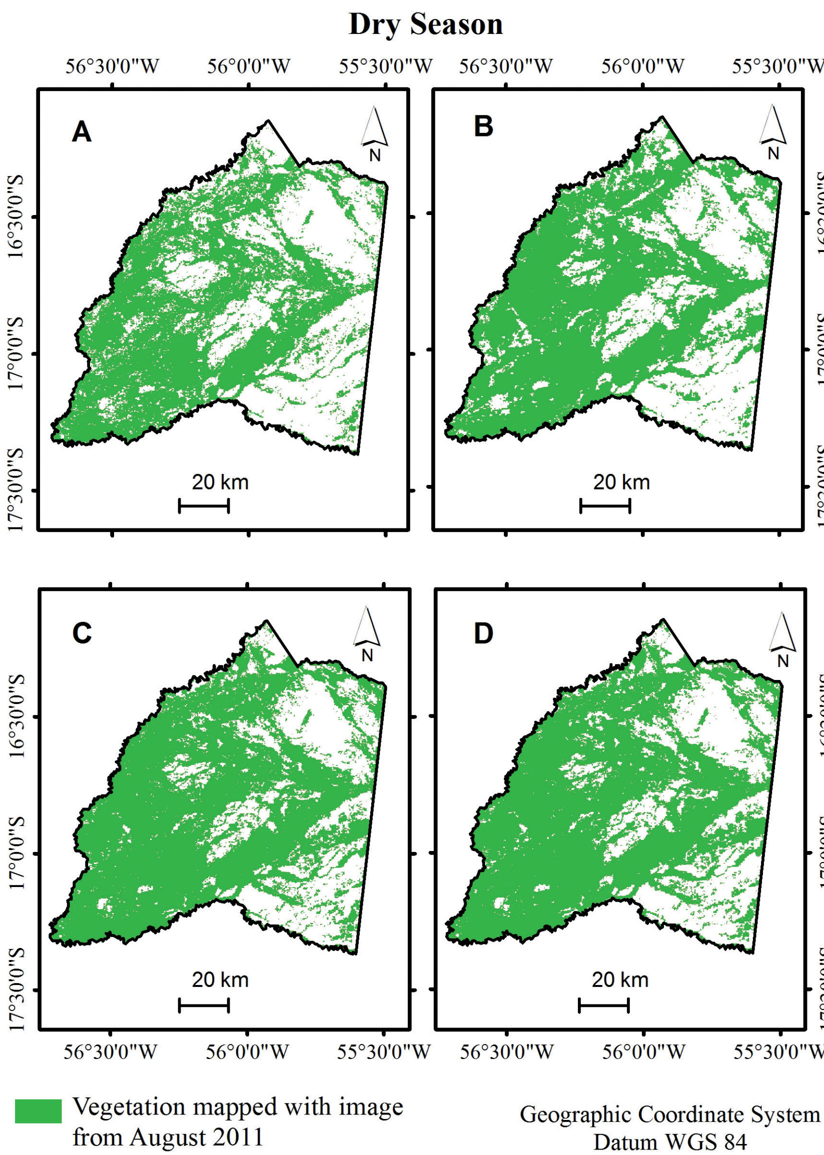

Figure 4 – Vegetation mapped during dry season from combinations: (A) PLP-FI; (B) PLP-OB; (C) SVM-FI; (D) SVM-OB

Table 2 – Accuracy evaluation for the map of August 2011, dry season

	PLP-FI	PLP-OB	SVM-FI	SVM-OB
Overall accuracy	83.2%	93.6%	84.3%	85.6%
Kappa coefficient	0.67	0.87	0.67	0.70
Commission error*	12.1%	9.4%	19.9%	18.8%
Omission error*	16.9%	0.7%	3.0%	2.1%
User's accuracy*	87.9%	90.6%	80.1%	81.2%
Producer's accuracy*	83.1%	99.3%	97.0%	97.9%

* refers to class vegetation.

PLP-OB also obtained the best overall accuracy for the map of August, with 93.6% of correct hits. On the other hand, PLP-FI obtained the lowest percentage of correct hits: 83.2%.

Although the values of overall accuracy for the classifications from the dry season were lower in comparison with those of the rainy season, the *Kappa* coefficient showed an inverse result. PLP-OB reached an excellent quality with *Kappa* of 0.87. The other classifications presented a very good quality with *Kappa* coefficients of 0.67 and 0.70. The quality of classifications was evaluated according to the proposal from Landis & Koch (1977).

Analyzing the vegetation class, commission errors for image classifications from August 2011 were higher compared with those of March 2011 classifications, i.e. the classifiers confused dry soil and water with vegetation. So the user's accuracy presented lower values of correct hits for this season. PLP-OB generated the lowest commission error (9.4%) and the highest user's accuracy (90.6%). On the other, hand SVM-FI presented 19.9% commission error and 80.1% user's accuracy for the vegetation map during the dry season.

All other classifications, except for PLP-FI, presented a lower commission error and a higher producer's accuracy for the results from August, when compared to those from March, i.e. few vegetation pixels were not classified correctly. The best result was reached with PLP-OB with 0.7% omission error and 99.3% producer's accuracy.

Depending on the mapping objective, the overall accuracy can be sufficient to evaluate its quality. However, if some specific classes are important or are of higher interest than others, it is absolutely necessary to evaluate each class individually, taking into account omission and commission errors and the user's and producer's accuracy. In this context, according to the results described, we conclude that the best method to map the vegetation from Barão de Melgaço municipality was PLP-OB, i. e. the Parallelepiped classifier applied on the composition R(MIR) G(NIR) B(RED) for both rainy and dry seasons.

It was expected that the use of fraction images, derived from the Linear Spectral Mixture Model (LSMM), would improve the classifiers performance, if compared to the use of the traditional original bands. According to Lu & Weng (2007) the presence of mixed pixels is one of the biggest problems which affects the image classification based on pixels. Classification methods which consider the sub-pixel have been developed to deliver a more appropriate land cover with higher accuracy, especially when using data with moderate to low spatial resolution, such as MODIS data.

It must be emphasized that, in this study, it was generally helpful to use the SVM classifier with the fraction images, for the rainy season. A similar result was found by Ferreira & Galo (2010) when they evaluated the influence of input data on the quality of

Landsat-TM image classification by artificial neural networks. The analysis showed that use of fraction images with input data in the classification did not allow a significant increase on the classifier performance, presenting a lower *Kappa* value in the results.

With these results in mind, it is interesting to highlight that the automatic satellite image classification does not depend only on the chosen classification method being adequate for each objective. Lu & Weng (2007) report that this is a complex process which requires the consideration of several factors, and the most important are: the availability of high quality images and auxiliary data (e.g. relief and meteorological data), the design of the classification procedure, and the abilities and experiences from the analyst. These authors point out that it is difficult to identify the best classifier for a specific study, due to the non-existence of both a guide for its selection and the availability of an adequate classification algorithm, which justifies the realization of comparative studies with different classifiers.

The best result for each season was qualitatively compared with the map of phyto-ecological regions of Barão de Melgaço (Figure 5). The main phyto-ecological regions in this municipality are Savanna Woodland (Sa), Savanna/Pioneer Formations (SP), Savanna/Seasonal Forest (SN), Savanna Woodland + Tree/Shrub Savanna (Sa + Sg) and Seasonal Semi-Deciduous Alluvial Forest (Fa).

Figure 5B shows, among all vegetation classes, that only few sections of Savanna Woodland (Sa) were mapped during the dry season. According to the Technical Handbook of Brazilian Vegetation (IBGE, 2012) this type of vegetation has a characteristic thin nanophanerophyte, a continuous hemi-crytophytic grass physiognomy. These dominant sinuses form a rachitic physiognomy in degraded terrains, which helps to understand the difficulty of the classifier, because there is a higher soil exposition during the dry season. Other vegetation types with poor mapping due to more bare soil were: Tree/Shrub Savanna (Sg), characterized by grasses mixed with rachitic woody plants, the composed class Savanna Woodland + Tree/Shrub Savanna (Sa + Sg) and pasture areas which were formerly covered by Savanna (Ap.S).

The classes mapped with good performance are: Seasonal Forest/Pioneer Formations (NP), Savanna/Seasonal Forest (SN), Woodland (Sd) and Seasonal Semi-Deciduous Alluvial Forest (Fa).

Figure 5C shows the vegetation mapped in the rainy season, divided in accordance with the phyto-ecological regions. One observes that Savanna Woodland (Sa) had almost its entire area mapped. Savanna Woodland + Tree/Shrub Savanna (Sa + Sg) presented a slight improvement in its classification. This could be explained by the increase of vegetative vigor of these formations during the rainy season. Other vegetation types mapped with good performance during the rainy season were: Tree/Shrub Savanna (Sg), Woodland (Sd), Savanna Woodland + Tree/Shrub Savanna (Sd+Sa) and Seasonal-Semi-Deciduous Alluvial Forest (Fa).

One also observes that the classes Savanna/Seasonal Forest (SN), and Pioneer Formations with fluvial or lacustrine influence (Pa) present a discontinuous mapping of its vegetal formations when compared to the dry season, due to the formation of spatially distributed small lakes dispersed in this area during the rainy season.

As stated by Evans & Costa (2013), it is necessary to point out that the mapping derived from Project PROBIO was based on Landsat images, of improved spatial resolution, acquired in July and October, during the dry season as the authors did not consider the dynamics of flooding for the classification, not including, therefore, the component lake.

Although the objective of this study was not to individually map the phyto-ecological regions from Barão de Melgaço, this visual comparison can guide future studies, indicating the limitations and possibilities for each vegetal formation during the different seasons.

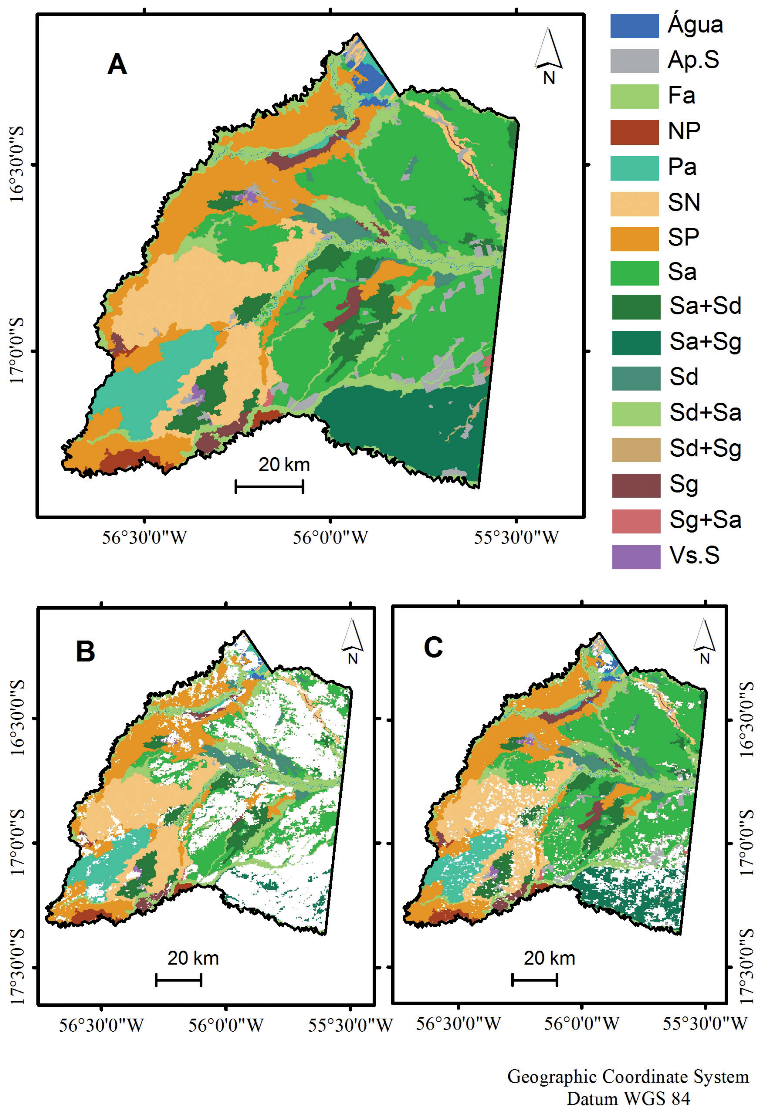

Figure 5 – Overlay of vegetation mapped with the phyto-ecological regions of Barão de Melgaço municipality. (A) Phyto-ecological regions; (B) Best classification for the dry season: PLP-OB; (C) Best classification for the rainy season: PLP-OB

Legend: Ap.S: Cattle raising (pasture) / Savanna; Fa: Seasonal Semi-Deciduous Alluvial Forest; NP: Seasonal Forest / Pioneer formations; Pa: Pioneer formation with fluvial and/or lacustrine influence; SN: Savanna / Seasonal forest; SP: Savanna / Pioneer Formations; Sa: Savanna Woodland; Sa + Sd: Tree/Bush Savanna + Woodland; Sa + Sg: Woodland + Tree/Shrub Savanna; Sd: Woodland; Sd + Sa: Woodland + Woodland Savanna; Sd+Sg: Woodland + Tree/Shrub Savanna; Sg: Tree/Shrub Savanna; Sg+Sa: Tree/Shrub Savanna + Savanna Woodland; Vs.S: Natural Secondary Succession / Savanna.

CONCLUSIONS AND SUGGESTIONS

Mapping vegetation of Barão de Melgaço municipality, during both rainy and dry seasons, presented quality indices between good and excellent. In spite of that, the use of fraction images derived from the Linear Spectral Mixture Model as input data for the classifications did not present the result expected to improve the performance of the classifiers, except for the SVM applied on the image fraction composition for the rainy season, which obtained the best *Kappa* (0.54) for such season.

Considering the vegetation as the target of interest in the mapping, the best results were obtained by the Parallelepiped classifier applied on the original spectral bands of sensor MODIS for both seasons. Although during the rainy season the vegetation is more vigorous, mapping during the dry season presented a higher level of correct hits and a lower level of errors due to the improvement of the spectral discrimination among the targets.

The qualitative comparison between the classifications and the phyto-ecological regions from the municipality showed that those smaller classes mapped during the dry season were the Woodland Savanna and the Tree/Bush Savanna, considering their physical characteristics. During the rainy season, due to the increase of the vegetative vigor, such classes could be identified.

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