GEOBIA AND MULTITEMPORAL SEGMENTATION FOR LAND USE AND LAND COVER MAPPING: A CASE STUDY IN MATO GROSSO, BRAZIL

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ABSTRACT

With expressive crop production and rampant deforestation rates, the state of Mato Grosso, Brazil, represents the struggle between conservation and economic development. This scenario reinforces the need for accurate land use and land cover (LULC) information to support sustainable development policies. Satellite image time series from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor are relevant to produce up-to-date LULC classifications at pixels level. However, there is a need for understanding how it performs at the geo-objects level. In this study, we used Geographic Object-Based Image Analysis (GEOBIA) to produce a LULC map for Mato Grosso from the 2016/2017 harvest period. We derive spatio-temporal geo-objects of a MODIS data cube via segmentation and use Support Vector Machine (SVM) to perform the classification - comparing it with a reference map. The overall accuracy (0.75) and Kappa (0.64) indicate pros and cons of combining GEOBIA and MODIS for LULC mapping.

Keywords *— Remote Sensing, Time series, Object-based analysis, Data cubes, MOD13Q1.*

1. INTRODUCTION

The importance of accurate land use land cover (LULC) mapping expanded to asseverate the implementation of policies related to food security, climate change, deforestation and agriculture dynamics, for example [1]. Therefore, there is a need to overcome factors that influence their quality to increase the accuracy of maps. A recent trend is the use of Earth Observation (EO) data cubes, a uniform space-time tessellation of EO data with unique space and time reference systems for a specific area over a time interval, offering a solution for storing big data products efficiently, providing access to large spatio-temporal data in an analysis-ready data (ARD) form [2], to improve the reasoning on dynamic landscapes.

This is based on the hypothesis that the temporal auto-correlation of satellite image time series data can be stronger than the spatial, making a pixel more related to its temporal neighbors than spatial ones [4]. Nonetheless, variations of this approach emerge. An example is the use of spatio-temporal correlation to perform mapping with aspects that transcend the pixel's reflectance [5].

The Geographic-Object Image Analysis (GEOBIA) approach considers neighbor relations, texture, form and compactness attributes [6], that can be important to analyze heterogeneous landscapes. The idea is to group spatially adjacent pixels into spectrally homogeneous objects and then conduct the classification using objects as the minimum processing units [7]. GEOBIA proved to be useful for LULC mapping using Sentinel-2/MultiSpectral Instrument (S2/MSI) [8]. However, despite their reported advantages, its adaptation to moderate resolution satellite image time series concerning spatio-temporal information remains an issue. The state of Mato Grosso, Brazil, is a unique place for evaluating mapping approaches, due to their heterogeneous and dynamic landscape. Additionally, the MODIS images, with daily global coverage, a spatial resolution of 250m and products with spectral vegetation indices (VIs), are often used to extract LULC information about this state [9]. However, different approaches using MODIS explore only pixel reflectance, excluding contextual spatial features as in GEOBIA, due to spatial resolution limitations.

Therefore, the goal of this study was to assess the performance of the GEOBIA approach to extract LULC information from the state of Mato Grosso (MT), during the 2016-2017 harvest period, using a MODIS-NDVI data cube.

2. METHODS

2.1 Study area

The study area is the State of Mato Grosso, central–west region of Brazil (Figure 1). Covering an area of approximately 905,000 km², Mato Grosso was chosen due to its landscape heterogeneity derived from an active pioneer frontier shaped by different populations, land uses, practices, and varying natural conditions [10].

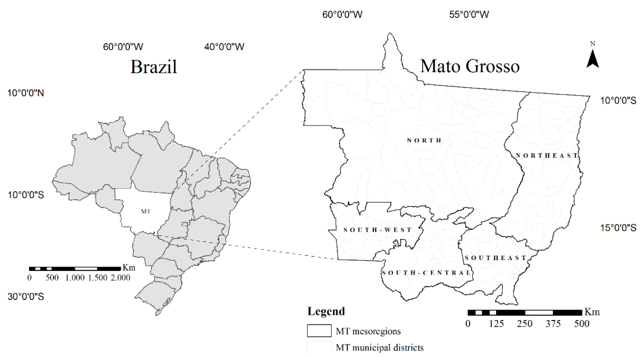

Figure 1. Location of Mato Grosso, Brazil, and its mesoregions.

2.2 Workflow

The methodological procedure (Figure 2) involved three steps: (1) multitemporal segmentation of the MODIS data cube into geo-objects via the Multiresolution Segmentation (MRS) algorithm, which groups the pixels of each object according to six parameters: smoothness, color, weight, and especially scale factor, shape and compactness [11], (2) collection of representative samples of each class of interest and (3) geo-object classification by the Support Vector Machine (SVM) algorithm.

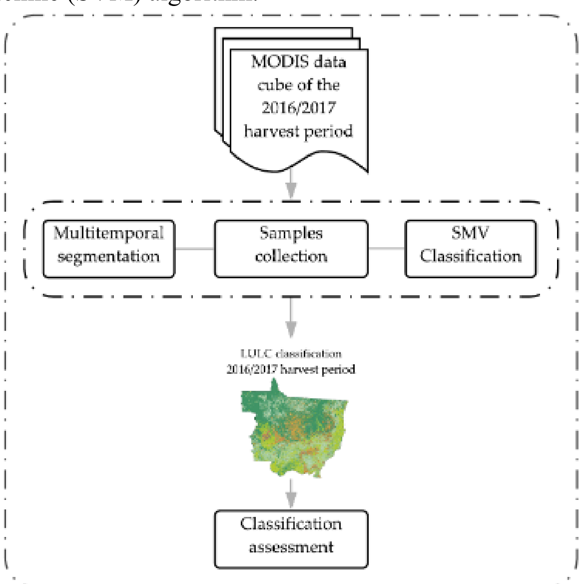

Figure 2. Workflow of the methodological procedure.

The segmentation parameters were: 25 (scale factor), 0.9 (shape), and 0.8 (compactness), based on tests. The sample dataset used to train the SVM was based on a dataset made available by Camara et al. (2018) [12].

2.3 Satellite data

MODIS provides reflectance time series with moderate resolution and frequency, showing potential for large-scale mapping [10]. A suitable product is the MOD13Q1, a 16-day composite with 250m of spatial resolution, which has the Enhanced Vegetation Index (EVI) [13] and Normalized Difference Vegetation Index (NDVI) [14]. We chose NDVI because it is the most widely used for LULC mapping in Mato Grosso [4,9]. We used the 16-day MODIS-NDVI from MOD13Q1 to create a data cube corresponding to the 2016-2017 harvest period, from September/2016-August/2017. This data cube is composed by a mosaic of the H12V09, H12V10, H13V09, H13V10 MODIS tiles in a consistent ARD product.

2.4 Sample data

To train the SVM algorithm, a sample dataset was produced, derived from the *in situ* dataset made available by Camara et al. (2018) [12]. It is composed with 1,892 samples of nine LULC classes: *Cerrado* (380 samples), *Forest* (132), *Pasture* (345), *Fallow-cotton* (single crop) (30), *Soy-fallow* (single-crop) (88), *Soy-corn* (double-crop) (365), *Soy-cotton* (double-crop) (353), *Soy-millet* (double-crop) (181), and *Soy-sunflower* (double-crop) (27). They were collected by an experienced analyst, using the *in situ* dataset and high-resolution images to guide the acquisition.

2.5 Feature extraction

To obtain object-based information, features were extracted using the segments produced with the MRS algorithm and MODIS-NDVI time series. For each moment of the time series, the average NDVI value of each segment was calculated and used for classification. Also, for each date in the time series, six attributes (contrast, dissimilarity, entropy, homogeneity, correlation and second angular moment) were derived from Gray Level Co-occurrence Matrix (GLCM). Along with them, 16 geometrical features were also used. A total of 72 attributes of each segment were extracted.

2.6 Classification approach

The classification was performed using the SVM, a supervised, non-parametric machine learning algorithm that separates classes by using a small number of training data, called support vectors, and performs well with a limited number of training samples, finding complex land cover patterns in high-dimensional feature sets [15].

2.7 Classification assessment

We used the classification generated by Camara et al. (2018) [12] as a reference to assess our classification. Its overall accuracy (OA), using 5-fold cross-validation of training samples, was 0.96. We used the *sits_kfold_validate* function of the *Satellite Image Time Series Analysis on Earth Observation Data Cubes* package [16] to compare each pixel of both classifications. The accuracy was assessed via error matrix, deriving Kappa index, OA, user accuracy (UA), and producer accuracy (PA).

3. RESULTS AND DISCUSSION

The LULC classification of Mato Grosso corresponding to the 2016/2017 harvest period (Fig. 3), emphasizes its heterogeneous landscape.

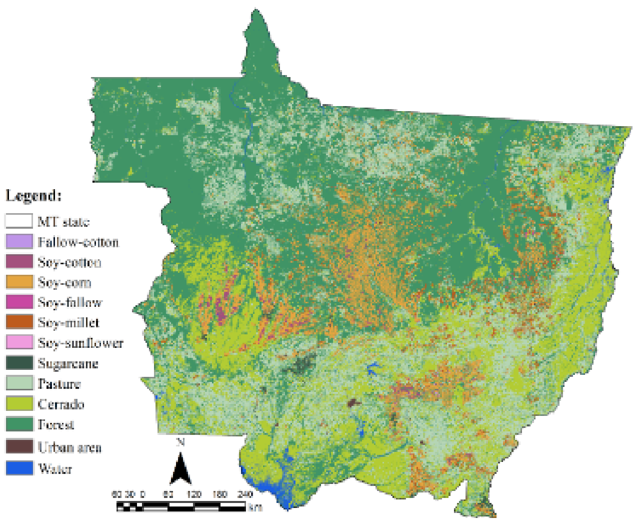

Figure 1. Classification using the GEOBIA approach.

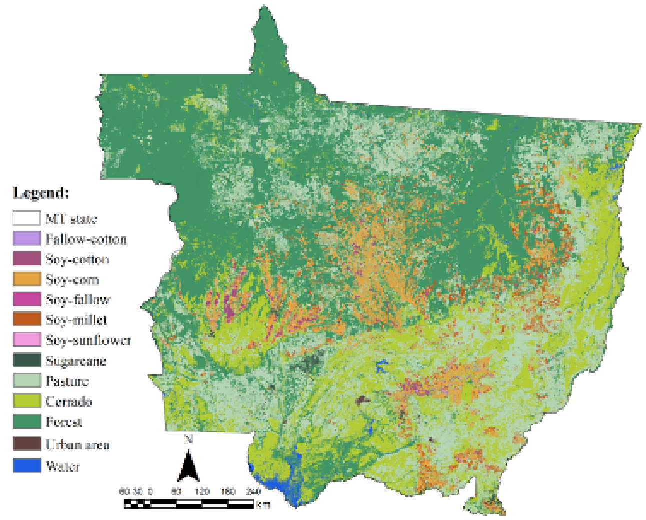

Figure 1. Classification made by Camara et al. (2018) [12].

Double-cropping systems were well detected, but with confusion among crops with similar phenologies, which may have occurred due to the limited number of samples of some classes in the reference dataset and the difficulty to collect samples in MODIS images. The spatial context of some classes, located in specific small fields (such as *Soy-sunflower* and *Soy-fallow*, near Sapezal, and *Fallow-cotton*, near Campo Verde) also made mapping difficult. Considering the spatial resolution, this context may have caused spectral mixing, aggregating different land uses within a single pixel, limiting the formation of homogeneous geo-objects and pattern recognition.

The class "*Forest*" agreed well. Its vegetative vigor is less affected by the rainy seasonality, which marks a spectral homogeneous pattern due to the more linear behavior over time. *Cerrado* and *Pasture* presented misclassification, especially in the portion of the Cerrado biome, where the mix of phytophysiognomies and the rainy seasonality affect LULC mapping [17]. Several studies showed the pertinence of MODIS to identify croplands and forestlands, even though it fails to capture fine-scale patterns and separate pasturelands from natural savanna, due to spatial resolution and the heterogeneous gradient of these classes [10]. We used texture and form to mitigate it, but both were limited by the spatial resolution. Visually, form helped to better delineate fields, which may have mitigated confusion in field boundaries. Despite this, the temporal patterns of pasturelands under different managements over time were fuzzy, and the samples collected do not fully capture its variability. Results were compared with the classification generated by Camara et al. (2018) [12] (Figure 4). To equalize the number of classes, we used the masks used by [12] corresponding to sugarcane [18], urban area [19], and water [20].

Afterwards, we derived accuracy measures from the error matrix. The Kappa was 0.64, representing a substantial statistical strength of agreement between the two maps [21]. The overall accuracy was 0.75. We also assessed individual producers and users accuracy of mapped classes (Table 1).

Class	Producer Accuracy	User Accuracy
Cerrado	0.61	0.60
Forest	0.85	0.90
Pasture	0.72	0.62
Soy-corn	0.63	0.88
Soy-cotton	0.95	0.66
Soy-fallow	0.58	0.35
Soy-millet	0.71	0.61
Soy-sunflower	0.06	0.00
Fallow-cotton	0.51	0.08

Table 1. Producer's and user's accuracy values.

The differences between the two maps can be explained by three factors: (1) suitability of each approach with MODIS, (2) input data, and (3) results' refinement. MODIS favors pixel-based approaches [4]. GEOBIA performs better when pixel size is smaller than targets of interest. It avoids under-segmentation and the occurrence of multiple targets in a pixel/geo-object [6,8]. About input data, an earlier analysis of a similar dataset [22] detected *Soy-sunflower* and *Fallow-cotton* as the least separable using NDVI, and similarity with *Soy-corn* and *Soy-cotton*. Here, crop misclassification involved these classes. In both cases, *Soy-sunflower* and *Fallow-cotton* were undersampled. In contrast, well-sampled classes had better UA and PA. Also, they used features beyond NDVI: EVI, near-infrared, and mid-infrared, which may have increased class separability [4]. On refinement, they used Bayesian smoothing with a 3x3 window to reclassify pixels with low certainty (high entropy) to neighborhood classes with high certainty.

Thus, we recommend the integration between GEOBIA and MODIS data cubes to map large targets. For fragmented areas, we suggest the use of medium spatial resolution data. In Brazil, the Brazil Data Cube [23], developed by the National Institute for Space Research (INPE) creates multidimensional data cubes from medium-resolution data for all Brazilian territory, providing options to this.

4. CONCLUSIONS

This study assesses the integration between GEOBIA and MODIS data cubes for LULC mapping in Mato Grosso. The spatial resolution of MODIS resulted in large geo-objects, causing under-segmentation of images and, hence, limiting class separability. Other limitations were the unbalanced sampling and the use of a single spectral feature for LULC mapping. This integration is appropriate for LULC mapping at a broad level (e.g., croplands and forestlands), optimizing the delineation of features. As it can perform better with other spatial resolutions, future studies should focus on using data cubes from medium-resolution satellite images.

5. ACKNOWLEDGEMENTS

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