Using time series with object-image NDVI/TM for monitoring land cover dynamics in the Brazilian Amazon

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Abstract. Biomes like the Amazon Rainforest are a challenge for change detection analysis due to high frequency of clouds. Moreover, time series analysis to change detection in Tropical Rainforests are still recent. This work investigates how a TM/NDVI time series constructed from object-images can help understand the deforestation process in the Amazon Rainforest over 28 years. The study area is located in the state of Mato Grosso, Brazil, within the 'Arc of Deforestation'. We used the bfastSpatial package to obtain the mean annual behaviour of object-based time series from 1984 to 2011. Moreover, we have also detected deforestation in 2002, extracting the lower mean value of each object in this period. To evaluate the proposed method, we compare the processing time between a time series object-based and pixel level. Deforestation initiated in the 90s, with an intensification of the process in the early 2000s. The peak of deforestation observed from this period can be related to an increase in agricultural commodities prices, especially soybeans and meat in the early 2000's. The validation to deforestation detection in 2002 has resulted in a producer's accuracy of 85%. Construction of time series by applying an object-based methodology reduced the computational time in 95% and removed the influence of salt-pepper effect. The combination of these factors, may have contributed to the quality this result, representing a new approach for time series analysis.

Key words: Arc of Deforestation, BFAST Monitor, change detection, time processing, Arco do Desmatamento, BFAST Monitor, detecção de mudança, tempo de processamento.

1. Introduction

Tropical forests are one of the most biologically diverse biomes in the world (Mittermeier et al., 2003) and contain an enormous stock of carbon (Foley et al., 2007). For that reason, deforestation of tropical forests represents a threats to the stability of natural ecosystems and one of the main causes of the environmental global change (Geist and Lambin, 2002). Even so, this was the forest dominance most deforested in the past decade (Hansen et al., 2013) with Brazil leading the list of countries that most have lost forest cover per year in the world (Fao, 2014). Deforestation in the Brazilian Amazon is resultant of government incentives for the expansion of the agricultural frontier (Fearnside, 2008) and it is closely related to the markets of ranching and soybean (Margulis, 2003). The arc of deforestation – how it is called the region where the agricultural frontier advances toward to forests in the Amazon biome – extends from the east of Pará to Acre going through the Mato Grosso and Rondônia states. However, deforestation is not restricted to private lands and also has been noticed in public lands destined to environmental conservation where the clear-cut is not allowed (Araujo et al., 2015).

Efforts to combat deforestation in that region can be supported by land cover monitoring over time. In that case, the use of remote sensing images is an important aid since that the high repetition rates in the records acquisition provide a satisfactory cost/benefit relation for the long term monitoring of the earth's surface (Jensen, 2006). After the open access policy of the United States Geological Survey (USGS) to the Landsat program's file (Woodcock, 2008), the literature has improved the development of methodologies that use a multitemporal trajectory like the analysis of target changes in land cover (Verbesselt et al., 2012). This paper proposes a new methodology for the construction of object-based time series aiming to reduce data volume and improve the delimitation of landscape elements. The method was applied to understand the historical context of deforestation in the Brazilian Amazon over 28 years. Thus, the objective of this study was to evaluate how an object-based approach can contribute to the time series processing in order to detect deforestation in the Amazon Forest.

2. Material and Methods

2.1 Study area

The study area is located in the Mato Grosso state in the Brazilian Amazon and includes the municipalities of Porto dos Gaúchos (56º 44’ 43” W, 11º 43’ 49” S) e Itanhangá (56º 45’ 18” W, 12º 8’ 22” S) (Figure 1). The main economic activity of the region is cattle ranching (Porto dos Gaúchos) and agriculture (Itanhangá), especially focused on the production of grains such as soybeans, corn and rice (IMEA, 2010). The region is inserted in the Arc of Deforestation and contains municipalities such as Porto dos Gauchos included in the list of municipalities to be considered priority in actions of the Ministry of Environment that aim to control deforestation in the Amazon Biome (MMA, 2016).

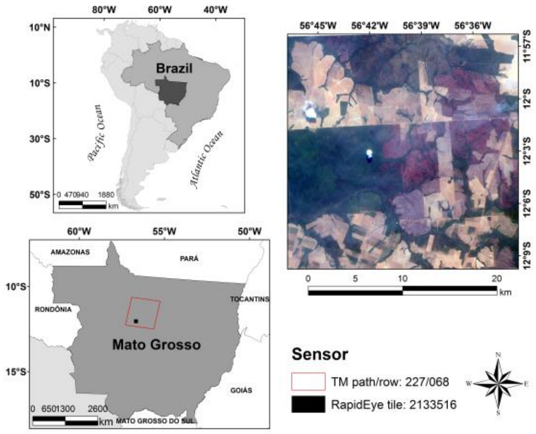

Figure 1. Location of the study area in the Mato Grosso state. The map highlights the subset of the area evaluated for the RApidEye image at 09/21/2011, in the RGB 3-2-1 composition.

2.2 Acquisition of TM images between 1984 and 2011

All the images from the satellite Landsat 5/TM path/row 227/068 available between 1984 and 2011 were acquired from the portal EarthExplorer / USGS (http://earthexplorer.usgs.gov), with a cloud cover below 30%. These data are collected at a revisit frequency of 16 days, with a spatial resolution of 30 meters to the bands in the visible region and infrared of the electromagnetic spectrum and 60 meters to the thermal band. It was used the Landsat CDR product (Surface Reflectance Climate Data Record) and this database resulted in a time series of 236 images.

A RapidEye image provided by the Ministry of Environment regarding to the tile 2133516 and acquired at 09/21/2011 was used to make the subset of the time series for the study area. Next, it was calculated the NDVI for all the images of the time series. Also, the masks available in the CDR product were used to eliminate pixels covered by clouds or shade. This pre-processing resulted in the time series at pixel level $NDVI_{pixel}/TM_{8411}$.

2.3 Object – Images

2.3.1 Construction of an object-image (OI)

We propose the construction of object-images for constructing a object-based time series. In this case, the objects are delimited using a segmentation process to from the grouping of pixels according to its geographic, spectral and spatial characteristics. Then, these objects are used as reference for the extraction of statistical parameters of each image in the time series at pixel level. Also, the total number of objects resultant of the segmentation is used as reference for the construction of a square matrix. The object-image (OI) is obtained by inserting the statistical parameters in the square matrix in which the location of each cell ($A_{i,j}$) is the value of the object (n) in each image of the time series.

Figure 2 shows the steps of constructing a time series with object-images. The total number of objects (N = 10) obtained to from the segmentation is used as a parameter for creating a square matrix with 4 x 4 pixels. Since a square matrix must have the same number of rows and columns, NoData values (NA) are added to the 6 pixels added to the matrix. In the object-image that is resultant, the value of each pixel is the mean value extracted from each object according to each image (I). For example, considering the mean values extracted for the objects in the first image (I_{1984}), the object-image equivalent (OI_{1984}) is obtained as follows: the A_{1x1} cell corresponds to the mean value of the object 1, in the image I = 1984. Likewise, the A_{1x2} cell corresponds to the mean value of the object 2 and so on for the 10 objects. This methodology reduces the number of pixels and hence the amount of data to be processed. In the example, an image with 38220 pixels is reduced to an equivalent object-image with 16 pixels.

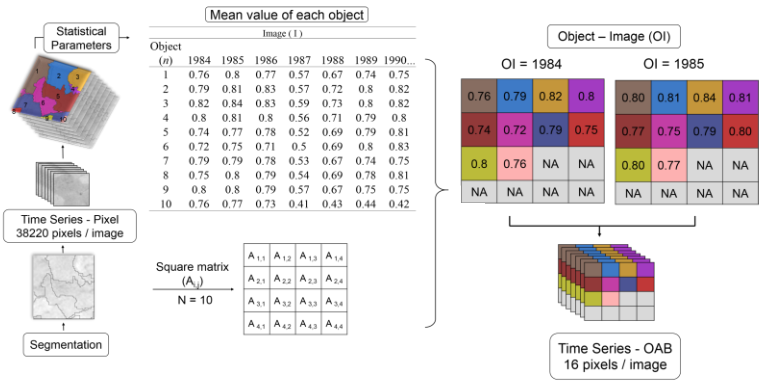

Figure 2. Schematic representation of the methodology for constructing time series with object-images.

2.3.2 Construction of the time series with object-images NDVI/TM

For the construction of time series, first was made a segmentation aiming delimit the reference objects for the extraction of statistical parameters. Two TM images referring to the first (01/30/2002) and last record (12/21/2002) of 2002 were used. This year was chosen from an a priori analysis of the database that has identified it as an important period in the historical context of the studied area. The multi-resolution image segmentation algorithm was applied and this process resulted in 3559 objects. Next, the methodology described above was applied to obtain the object-images. For this, the segmentation was overlaid to the time series $NDVI_{pixel}/TM_{8411}$ in order to extract the mean value of each object in each image. The total of 3559 objects resulted in a squared matrix of 60 x 60 pixels, in which 41 pixels were configured as NoData. For the construction of 236 object-images, the method was replicated considering the relation between this matrix and the mean values extracted for each object in

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each image $NDVI_{pixel}/TM_{8411}$ series. This process resulted in a time series with object-images $NDVI_{OAB}/TM_{8411}$, in which the value of each pixel corresponds to the mean value of NDVI.

2.4 Analysis of time series NDVI/TM

The bfastSpatial package (Dutrieux et al, 2014) implemented in the R software (R Core Team, 2015), was used to analyze the temporal trajectory aiming understand the dynamics of land cover in the study area. This package provides several tools for manipulation and analysis of change detection in time series.

2.4.1 Computational time: pixel X OAB

Both of time series at the pixel level ($NDVI_{pixel}/TM_{8411}$) and at object level ($NDVI_{OAB}/TM_{8411}$) have the same extension and consist of 236 images. However, the analysis of the $NDVI_{pixel}/TM_{8411}$ required that any processing must be replicated 163,757,804 times, whereas for the $NDVI_{OAB}/TM_{8411}$ this number is reduced to 849,600 times.

That condition can be relevant in analyzes that require a substantial computational time such as the bfastSpatial function. This function applies the BFAST Monitor method to the whole time series and each pixel is divided into a historical period and a monitoring period (Verbesselt et al., 2012). In this paper, the historical period was set between 1984 and 2001 and the monitoring period as 2002. First, a vegetation mask was applied to the $NDVI_{OAB}/TM_{8411}$ series to address the analyses only for forested areas in 2002. Since a regression model is independently adjusted for each pixel of the time series, the processing time for the $NDVI_{pixel}/TM_{8411}$ time series at pixel level was computed in regards to the $NDVI_{OAB}/TM_{8411}$ object-based time series.

2.4.2 Historical context of deforestation in the Amazon

A AnnualSummary function was used for getting the deforestation trajectory over 28 years (1984 – 2011). This function performs statistics to summarize the information about the whole time series in an image/year. In this case, in order to get the historical behavior of deforestation in the area evaluated, the function was applied to calculate the NDVI annual mean for each object. Thus, the $NDVI_{OAB}/TM_{8411}$ time series was summarized in 28 images.

The AnnualSummary function also was used to measure deforestation that occurred in 2002. As the change of interest is characterized by a reduction in the NDVI values, the function was applied to extract the lowest NDVI mean value registered for each object in this period. Deforestation was identified in the resulting image by applying a NDVI value <0.5 to it. A land cover map was elaborated to validate the identified deforestation in 2002. This process generated a cover land map with 1860 vegetation objects (no-change) and 101 deforestation objects (change). The mapping was used as reference for getting the confusion matrix. Then, the producer’s accuracy, user’s accuracy, errors of commission and omission were calculated.

3. Results and Discussion

3.1 Time series with object-images

The Figure 3 shows the time trajectory of an object that was extracted from a method BFAST Monitor in which deforestation was identified in 2002. The black dotted line represents the end of the historical period (1984-2001) and the beginning of the monitoring period (2002). The gray dots characterize the stable historical period identified. The solid black line corresponds to the seasonally-adjusted trend model which was tested for the monitoring period (continuous line with red dots). Deforestation is indicated by the occurrence of a breakpoint (red dotted line).

In this analysis, a regression model is independently adjusted for each pixel of the time series. The comparison between the computational effort spent for the analysis of object-based time series ($NDVI_{OAB}/TM_{8411}$) and for time series at the pixel level ($NDVI_{pixel}/TM_{8411}$) highlighted a reduction of 95% in processing time. Using the object-based approach, the mean processing time was reduced from 13 hours to about 4 minutes.

These results demonstrate the potential use of object-images for the time series analysis. This approach may be particularly relevant for the monitoring of large areas and/or with dense amount of available data that require a quite significant processing time. In addition, this methodology can be implemented for other remote sensors, facilitating various studies that use a temporal approach.

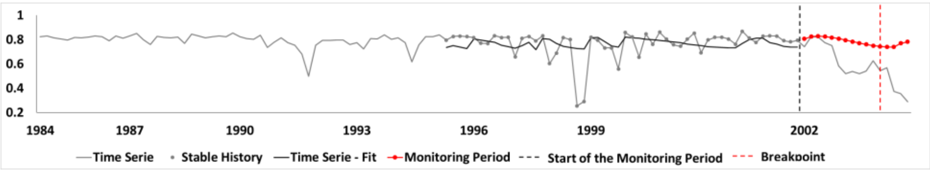

Figure 3. Time profile of the NDVI mean values for a deforestation object.

3.2 Historical of deforestation in the Amazon

Deforestation in the Brazilian Amazon is characterized by the "fishbone" process (Rudel, 2009) and by the removal of large forest areas to the extensive cattle ranching (Oliveira-Filho and Metzger 2006). The figure 4 presents the deforestation pattern over 28 years (1984-2011) in this region. Deforestation in Brazilian Amazon began from 1960’s as a process encouraged by the government based on: 1) the implementation of large infrastructure projects; 2) establishment of agricultural settlements by INCRA; and 3) granting subsidized agricultural credits to the occupation and development of the region (Andersen, 2002). From the 80s, deforestation in the Amazon has become closely related to the meat and soybean markets (Margulis, 2003). The results of the agriculture frontier expansion including cattle ranching were noticed in the early 1990’s when the deforestation rates increased substantially. Between 1995 and 2000, the states of Pará, Mato Grosso and Rondônia were accounted for 100% of the Brazilian herd growth and were the three Amazon states with the highest rates of deforestation (Margulis, 2003). Because of the record deforestation rate in 1995, the Brazilian government adopted more rigorous protection measures to the Amazon Biome including new preservation requirements for landowners. However, deforestation rates rose again in the early 2000’s in strong correlation with the prices of agricultural commodities (Arima et al., 2007). The high deforestation rate perceived in 2004 sparked a series of combined actions by government agencies, NGOs and Federal Prosecutors Office (Ministério Público Federal – MPF) to combat deforestation (Nepstad et al., 2014).

Public policies and interventions in agriculture supply chains could reduce deforestation in the Amazon by 80% between 2004 and 2014 (INPE, 2011). However, the risk of deforestation resumption still exists and the causes are still tied to the global demand for soybeans and to the expansion of pastures (Garrett et al., 2013). Since the new conservation policies, the participation of small clearings (6.25-50.0 ha) in the total annual deforestation increased progressively due the decreased of large clearings amounts (>1000 ha), indicating that reducing small clearings is the next challenge in the fight against deforestation (Rosa et al., 2012). Apparently, farmers have carried out a gradual increase of the productive area of the properties through small forest conversions under the false expectation that small deforestation cannot be captured by the control bodies (Azevedo et al., 2014).

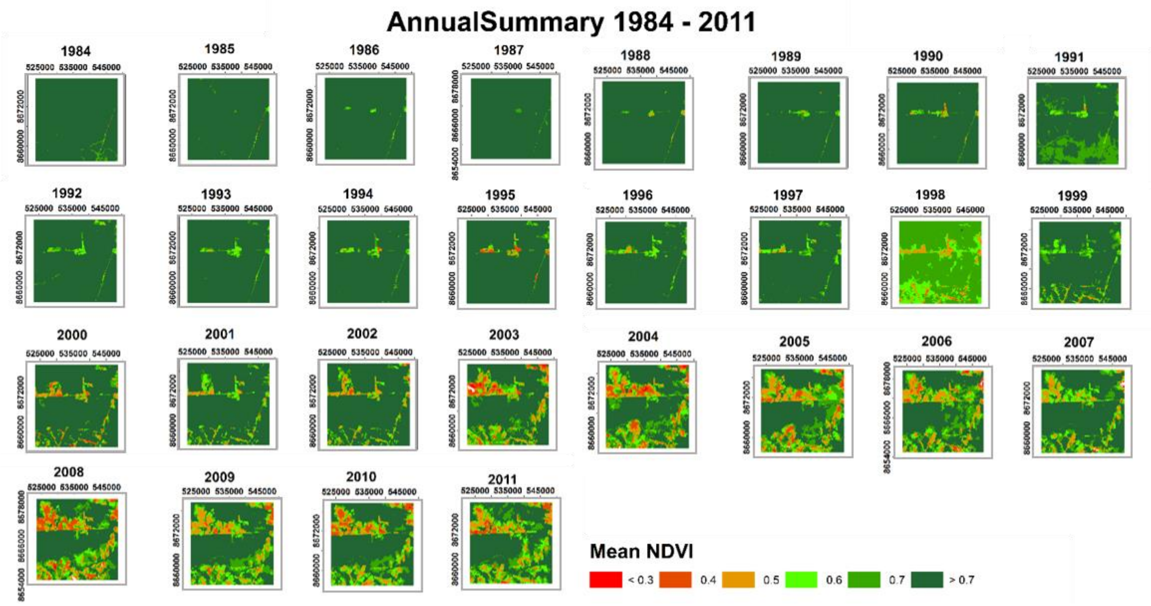

Figure 4. Deforestation pattern over 28 years in the Forest Amazon.

3.3 Deforestation in 2002

The figure 5 shows the map of land cover for 2002 that is resulting from the reference analysis (analyst) and AnnualSummary function. During this period, deforestation resulted in removal of 1,297 hectares of native vegetation. The mean size of the deforestation object was 13 ha, ranging between 1 - 52 ha. Table 1 shows the confusion matrix for deforestation and non-change classes between the reference map for the land cover and the results from the applied function. It was observed a high correlation between deforestation identified by the analyst and automatically. In this case, the automatic detection has achieved a producer's accuracy of 85% (Table 2). Furthermore, the use of object-based approach reduced the salt-pepper effect, resulting in a low error of commission (23%).

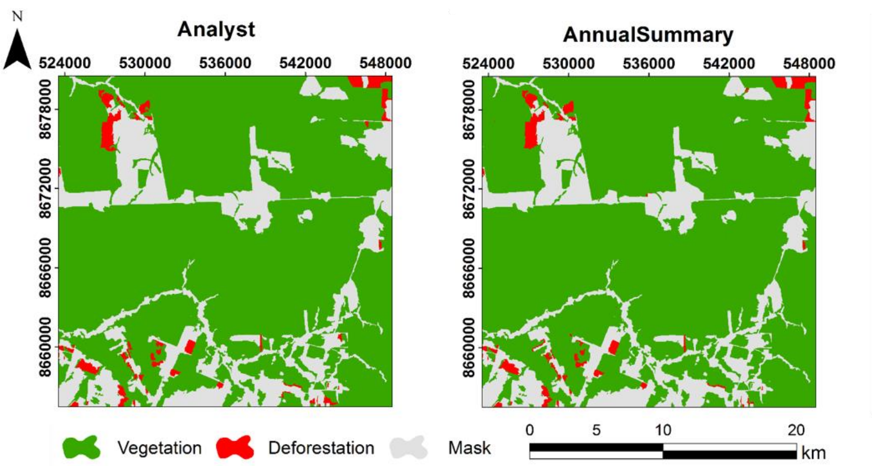

Figure 5. Deforestation in 2002.

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Table 1. Confusion matrix for the land cover map of 2002.

	Actual		
AnnualSummary	**Deforestation**	**No Change**	**Total**
Deforestation	86	25	111
No Change	15	1860	1875
Total	101	1885	1986

Table 2. Percentage value for the producer's accuracy, user's accuracy and errors of commission and omission for the land cover map of 2002.

	Accuracy		Error	
Class	**Productor**	**User**	**Comission**	**Omission**
Deforestation	85.15	77.48	22.52	14.85
No Change	98.67	99.2	0.80	1.33

4. Conclusion

This study was developed in order to elaborated a methodology to reduce processing time of time series. Therefore, it was proposed the construction of object-images. The approach was applied to understand the historical context of deforestation in the Forest Amazon over the past 28 years. It was possible to note the increase of deforestation in the early 1990's that is atributed mainly to the cattle ranching expansion. After a short period of stability, deforestation increased again in the 2000's triggering a series of measures aiming to control deforestation. The comparison between of computational time spent for time series analysis at the pixel level and for the object-based analysis, has highlighted the relevance of the proposed method. In this case, the use of object-image reduced the processing time in 95% over the analysis at the pixel level. In addition, this approach also contributed to the reduction of the error of commission due to less influence of the salt-pepper effect. In summary, the use of the object-images approach was essential to the substantial reduction in the computational time, appearing as a new alternative for the time series analysis.

5. Acknowledgement

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