Anais do XVIII Simpósio Brasileiro de Sensoriamento Remoto - SBSR
ISBN: 978-85-17-00088-1
28 a 31 de maio de 2017
INPE Santos - SP, Brasil

Satellite multisensor spatiotemporal analysis: a TWDTW preview approach

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Abstract. This paper describes the process of multisensor time series composition intended for land-use and land-cover classification. Our objective is to verify the robustness of the Time Weighted Dynamic Time Warp algorithm when applied on images from multiples sensors. Our approach increased temporal resolution to improve the quality of classification. Our data was acquired between 2000 and 2016 and a small area of Mato Grosso, Brazil was analyzed. The results utilizing multisensor composition are promising and consistent with early results of lower resolution images.

Keywords: land use and land cover classification, multisensors, time series .

1. Introduction

Remote sensing technology was first developed in 1960s. Thereby, remote sensing shifts from rustic black and white aerial photography to high resolution image. Currently, more than 1000 operational satellites orbit around Earth. Among them, Landsat satellites series are remarkable, since it provides the longest and the most informative temporal record of space-based surface observations, spanning over 40 years (WOODCOCK; ALLEN et al., 2008). This long term time series dataset represents a great opportunity to monitor land surface and ecological dynamics (KENNEDY; YANG; COHEN, 2010).

Considering the importance of spatiotemporal analysis, many efforts have been made in order to develop and improve algorithms and tools (SCHMIDT et al., 2015; VERBESSELT et al., 2010; MAUS et al., 2016b). In this context, land cover and land use classification algorithms that priorize time dimension have been used to identify forest disturbances (ZHU; WOODCOCK; OLOFSSON, 2012), agriculture and pasture growth (SAKAMOTO et al., 2009; RUFIN et al., 2015), and urbanization dynamics (SETO; FRAGKIAS, 2005) among others. Here, we are particularly interested in the work of Maus et al. (2016a) whose developed an classification algorithm based on DTW (BERNDT; CLIFFORD, 1994) mainly for use on analysis of phenology called Time-Weighted Dynamic Time Warping (TWDTW).

TWDTW provided good classification results when applied on MODIS MOD13Q1 product over the Amazon biome in Mato Grosso brazilian state (MAUS et al., 2016b). Although the results were satisfactory for the characteristics of that region, this may be not the case to more heterogeneous areas, where a 250m spatial resolution would not capture relevant details. However, a more accurate orbital sensor may have a drawback that is to introduce noise into classification process. Moreover, orbital sensors with a higher spatial resolution than MODIS, as Landsat (30m), can be subjected to worse temporal resolution. To overcome this limitation we have composed a time series with different Landsat sensors and MODIS.

We aim to verify the TWDTW algorithm robustness applying it on a multisensor satellite time series with different spatial and temporal resolutions. In this manner, the present work aimed to apply the algorithm by means of both aforementioned sensors data, in order to analyze its performance in comparison to an MODIS only application.

This paper is organized as follows: first, we present the broad context in which our work relates with land-use and land-cover classification; second, we explain our material and methods; third, we present some results and, finally, we make some final remarks.

2. TWDTW

The Dynamic Time Warping (DTW) is an algorithm that compares an unknown time series with a temporal signature (VELICHKO; ZAGORUYKO, 1970). It identifies all possible alignments between two time series and provides dissimilarity measures (RABINER; JUANG, 1993). Based on DTW, the TWDTW algorithm was created to be sensitive to seasonal changes of natural and cultivated vegetation types (MAUS et al., 2016b).

As TWDTW is a supervised classification algorithm, we must provide to it a set of patterns with land cover classes. TWDTW searches all the patterns on time series and similar matches periods are associated with the respective class. TWDTW is able not only to identify the spectral signatures along raw data time series, but also to extract information about the phenomena based on the period that it occurs. For more details about TWDTW see Maus et al. (2016a, 2016b).

3. Materials and Methods

3.1. Study Area

The study area comprehends about $9.6km \times 8km$ and is localized in Ipiranga do Norte (*Mato Grosso*, Brazil) municipality as we can see in Figure 1. Firstly, it was chosen considering the existence of 603 field sample points. Secondly, as we want to compare the result we have choose the same area as used in Maus et al. (2016a). Besides that, it is also important to analyze the perimeter due to its high numbers of agriculture expansion at the expense of the rates of the original forest cover, including in the neighboring municipalities, as *Porto dos Gaúchos*, analyzed by (MAUS et al., 2016b).

3.2. Data

To compose our time series, a total of 986 scenes were collected. Image time series for land cover classification requires an adequate temporal resolution and time span, since each land cover class has a distinct phenological cycle (YANG; ZHANG, 2012). All the data are freely available at USGS website (http://www.usgs.gov).

The data used was the time series of Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) from January 2000 to July 2016, of MODIS and LANDSAT products. Differently from NDVI, EVI minimizes canopy background variations, maintains sensitivity over dense vegetation conditions and remove residual atmosphere contamination. Vegetation indexes admit several uses, for instance, to characterize land cover conversions.

The Landsat series EVI indexes were produced from TM, ETM+, and OLI, which temporal resolution is 16 days, 30m spatial resolution and Universal Transverse Mercator (UTM) map projection. he MOD13Q1, from MODIS VI Product Sequence, Terra MODIS, is acquired every 16 days at 250m spatial resolution. The Global MOD13Q1 data are provided as a gridded level-3

ISBN: 978-85-17-00088-1

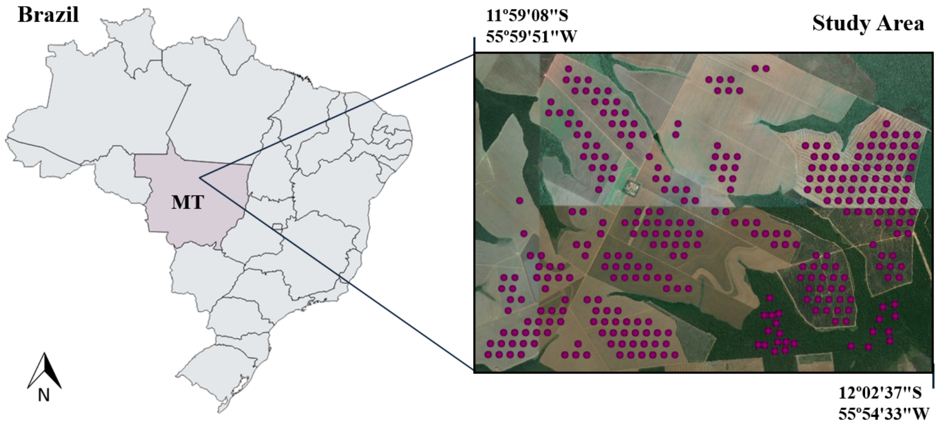

Figure 1: Study Area. The purple points indicate the samples between August 2010 and August 2011.

product in the sinusoidal projection. All images were co-registered.

3.3. Methods

Our multisensors time series have been made by means of stack composition. A total of three stacks, EVI, NDVI and days of the year (DOY) were created, each one with 986 images. All three stacks were time ordered and had the same temporal and spatial extents, analogously to a stacked deck of cards. Furthermore, we resampled MODIS pixels from 250m to 30m through the technique nearest neighbor. This process was required due to image stack alignment. We can see in Figure 2 an example of the NDVI time series of a random pixel and the respective source of each value.

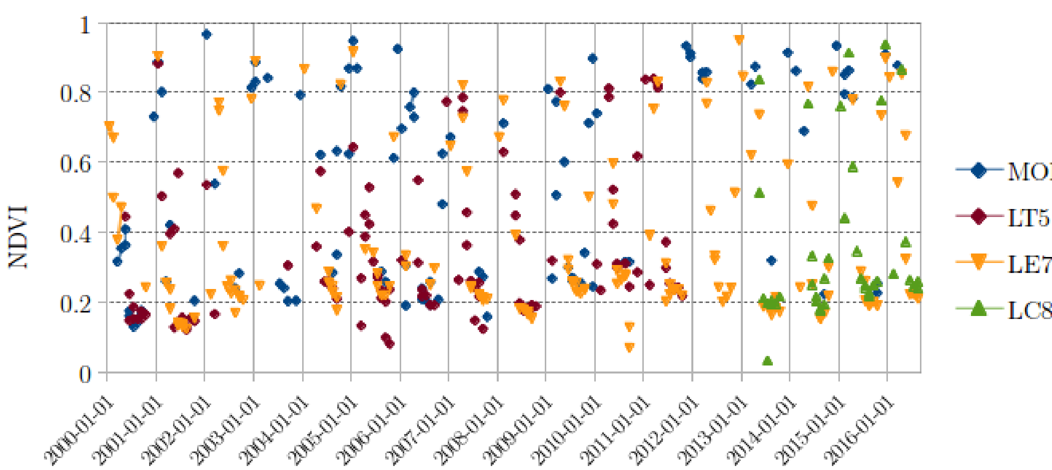

Figure 2: NDVI time series of a random pixel and the source of each value.

We were careful to remove the pixels without data, as cloudy pixels, shade pixels and possible sensor errors. As a result, some pixels may have more data than others. The Landsat 8 image is

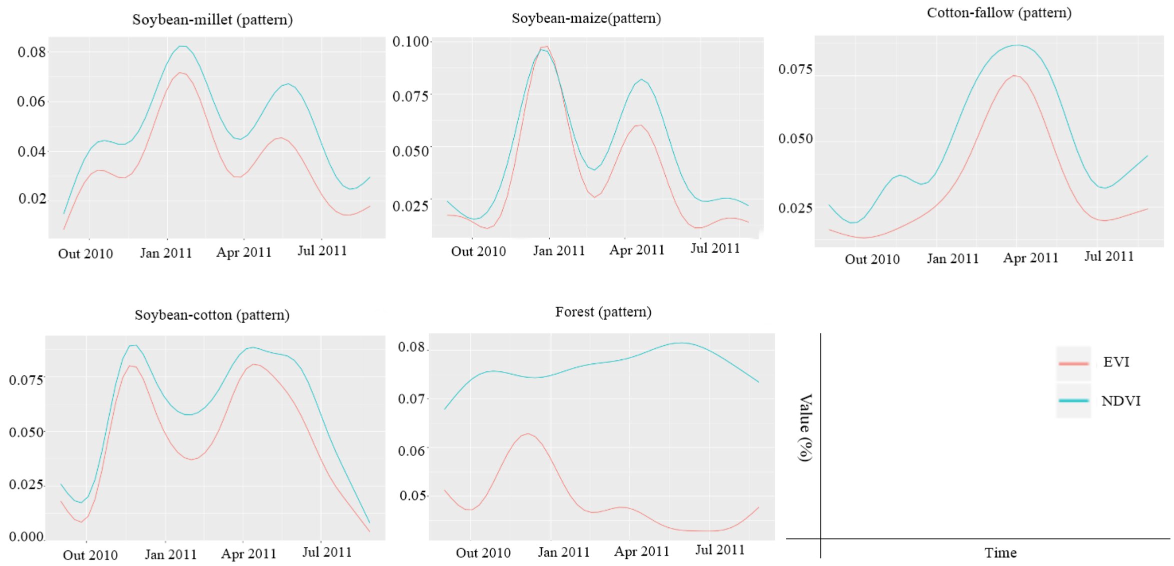

Figure 3: Identified spectral signature patterns

located on the left side with remarkable clouds pixels. We used the cloud mask provided by product data. It is also important to notice that although it has been removed a large portion of clouds, some of them persisted on several regions. We fixed the value `NO_DATA` to those pixels with more than 13% of clouds confidence, which means that they were not considered in the TWDTW algorithm.

The data inputs were three components, the previously created bricks, a text file *timeline* containing the years of the images, and a set of ground truth samples. Those samples have spatial locations (longitude and latitude), date of acquisition and label for each field sample. The field samples were divided in 6 main classes: cotton-fallow, forest, soybean-cotton, soybean-maize, soybean-millet and others.

After that, we build a raster time series, with the bricks and *timeline*. Through the field samples, the *dtwSat* package provides a possibility to create spectrotemporal patterns using a function that fits a Generalized Additive Model (WOOD, 2011). This function provides better fit to satellite data than purely parametric models (MAUS et al., 2016b). The patterns created can be viewed in Figure 3.

Before the classification step, we pre-classify the data assessing quality and information that contain the template pattern. It is realized in order to produce consistent results for the following classification step. Finally, to classify the raster time series, we applied TWDTW in each pixel for both vegetation indices.

4. Results and Discussion

Spectro-temporal signature patterns were obtained by *dtwSat* for each analyzed target through the sample type provided by the package. Although it was analyzed from 2000 to 2016, a sequence of 6 years were selected to present the local land-cover development Figure 4.

Although the Figure 4 presents some classification, it is not possible to assert with high accuracy that they represent the ground truth. In this manner, no detailed explanation was made. However, it is possible to notice a close relation with MODIS only classification made in Maus et al. (2016a) as we can see by comparing with Figure 5.

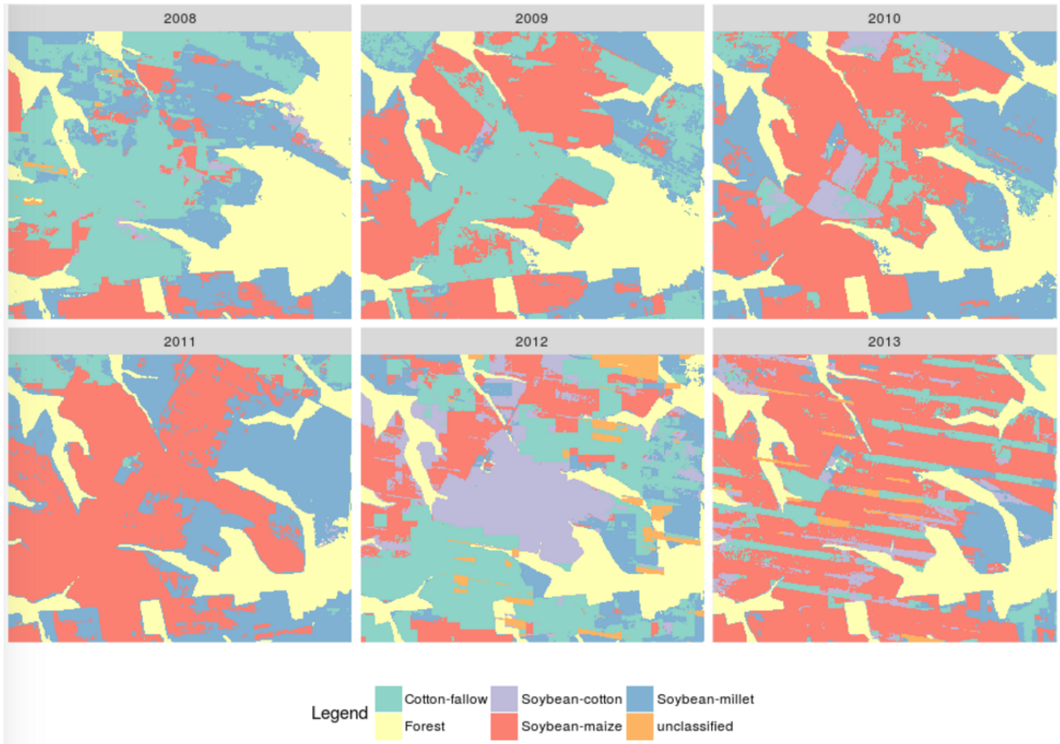

Figure 4: Multisensors time series classification results for 2008-2013.

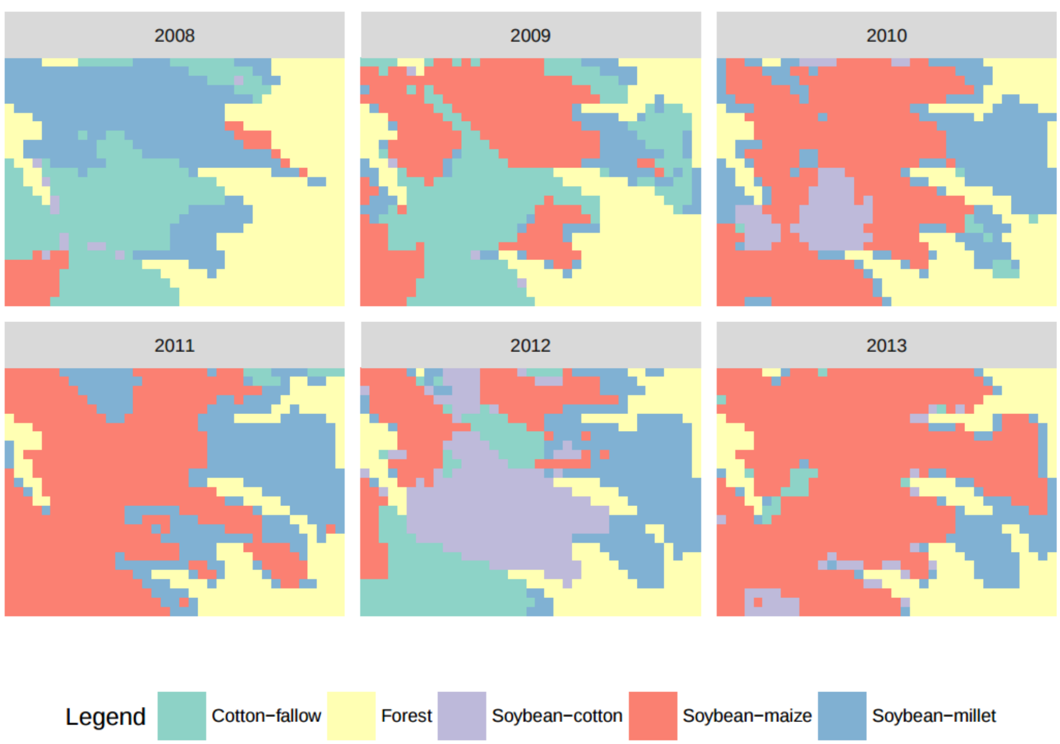

Figure 5: MODIS only time series classification results for 2008-2013. Source: Maus et al. (2016a).

Actually, TWDTW identifies spectro-temporal signatures along the time according to the extracted spectral patterns of sample areas. To assess the classification accuracy of this process, (MAUS et al., 2016a) have splitted the ground truth samples into training and validation sets. Their results showed that User's Accuracy and Producer's Accuracy were high, demonstrating TWDTW accuracy confidence and robustness for MODIS only time series. However, here we did not made those measurements here.

In 2013 (Figure 6), it is also possible to notice the manifestation of a noise pattern, observed as alternating lighter and darker bands. In the darker bands, we fixed the value NO_DATA, which means that are not taken going to be taken into account for the extraction of time series.

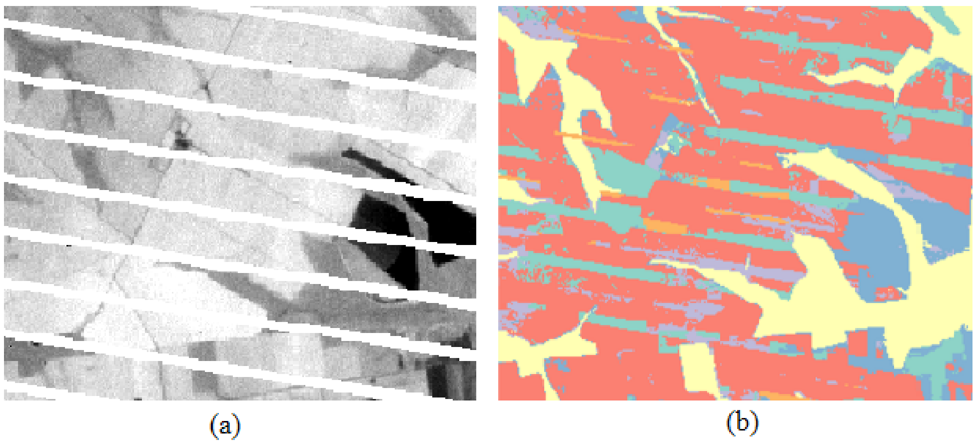

Figure 6: Comparison between 2013 EVI Landsat 7 Original (a) and classified image 2013 (b)

5. Conclusion

A composition of multi sensors Landsat and MODIS was defined, aiming to decrease the period of time between the collected images. As a first approach, we intended to test the robustness of TWDTW algorithm in dealing with multi sensor composition without taking into account its radiance sensibility differences.

It is possible to apply the algorithm developed by (MAUS et al., 2016b) for more accurate spatial resolution sensor, considering that the obtained results were satisfactory. However, some caveats must be done mainly regarding to adjustments.

Integrating multisensors have as a disadvantage the difference in resolutions and in radiance sensibility sensors. This last one can be notice among LANDSAT series (HOLDEN; WOODCOCK, 2016). In this manner, to reduce deleterious atmospheric and sun surface-sensor spectral variations, a radiometric normalization based on nearest temporal satellite image from Landsat 7 should be made. Nonetheless, according to the aim, different normalization strategies can be used by authors (HANSEN et al., 2008). This technique was not used in this work, which may have led to errors in the final classification. Besides that, clouds and errors create gaps in time series and this also impacted the final classification.

In this context, more supporting studies should be performed to refine the data here presented, including: i. analyze the influence of different normalization processes in classification result; ii. aim to fill the gaps found in the time series; iii. map crossing tests; iv. use of different cloud detectors to proceed a better cloud removing process; v. adjustment of the space/time for each class; vi. verify potential adaptations of TWDTW algorithm in order to overcome ETM+ SLC failure (black straps).

Acknowledgments

The authors would like to thank CNPq, CAPES, and FAPESP for the financial support. Landsat Surface Reflectance and Landsat Spectral Indices products courtesy of the U.S. Geological Survey Earth Resources Observation and Science Center.

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