ASSESSING FOREST CHANGE DETECTION IN TROPICAL SEASONAL BIOMES THROUGH LANDTRENDR ALGORITHM

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ABSTRACT

There is no optimal disturbance detection method without limitations that can be applied to all ecosystems. Different vegetation structures present different responses to seasonal variations inducing disturbance errors along geographical regions. This study applied the LandTrendr algorithm, developed in GEE platform, in order to examine its accuracy in different tropical seasonal biomes: Savanna and Atlantic Forest. LandTrendr was run by a default parameter configuration and compared to a large-scale reference dataset. In general, the Atlantic Forest presented higher accuracies than Savanna in the disturbance. Both biomes presented low producer's accuracy for some years but high user's accuracy for almost all years. These results are explained due to change detection in high seasonal areas is affected by seasonal modifications in spectral signature due to phenology, leading to misclassification of spectral changes as having human-induced changes. Future researches can also follow-up this approach by exploring different disturbance detection algorithms and parameters simulations as well as the implementation of stratification by vegetation class in order to reach higher accuracies, reducing the effects of land cover type on climate fluctuations.

***Key words* —** Landsat time series, change detection, remote sensing, seasonality, google earth engine.

1. INTRODUCTION

Monitor, analyze and detect disturbances in forested systems are critical processes with a myriad of techniques and algorithms [1]. Despite the range of methods in scientific literature, there is no optimal method that applies to all purposes [2], inducing each technique to particular strengths and weaknesses regarding to the omission and commission errors and target disturbance populations [3].

The Brazilian territory is divided into six continental biomes, from which Atlantic Forest and Savanna are considered world's hotspot for conservation of biodiversity [4]. These biomes were subject to the most rapid land conversion in Brazil, almost 75% of the Atlantic Forest and 50% of Savanna were already transformed into pastures and croplands, inducing a consistent understanding of the land cover changes upon these areas [5].

Nowadays, the establishment of Google Earth Engine (GEE) platform provided many advances in change detection studies, such as full access to satellite archives, straightforward management of time series stacks, and agile computation through parallel processing. These advances enable the creation of large-scale disturbance maps and also a user-friendly format to run disturbance detection algorithms [6]. However, estimating disturbance in tropical areas is not a trivial task since phenology affects the spectral signature of vegetation measured by satellites leading to misclassification of seasonal changes as disturbances [7]. Different vegetation domains presents different response to seasonal variations inducing disturbance errors along geographical regions or disturbance regimes [3].

This study examines the accuracy of Landsat-based detection of Trends in Disturbance and Recovery – LandTrendr [8], an automated trajectory based-image analysis algorithm, in its ability to map disturbances over two biomes (Savanna and Atlantic Forest) distributed across Minas Gerais State, Brazil. We were motivated by the following research question: how accurately an automated algorithm detects disturbance in different seasonal biomes?

2. MATERIAL AND METHODS

2.1. Study scenes

Two areas dispersed across the Minas Gerais State were selected for this study (Figure 1a). These areas were delimited by the Worldwide Reference System version 2 (WRS-2) and represented two distinct Brazilian biomes: Savanna (Path/Row: 219/71) and Atlantic Forest (218/75) [9].

The Atlantic Forest biome is characterized mostly by evergreen and semideciduous forest formations. This region receives around 2,000 mm annual rainfall and mostly it does not show a climatological water deficit, leading to a low seasonality noise [9]. On the other hand, the Savanna biomes is characterized by a distinct dry season with monthly precipitation reaching zero millimeters (Figure 1b). This strong seasonality influences the forest dynamics resulting in a wide range of adaptive phenological strategies as leaves fall in Savanna trees [10].

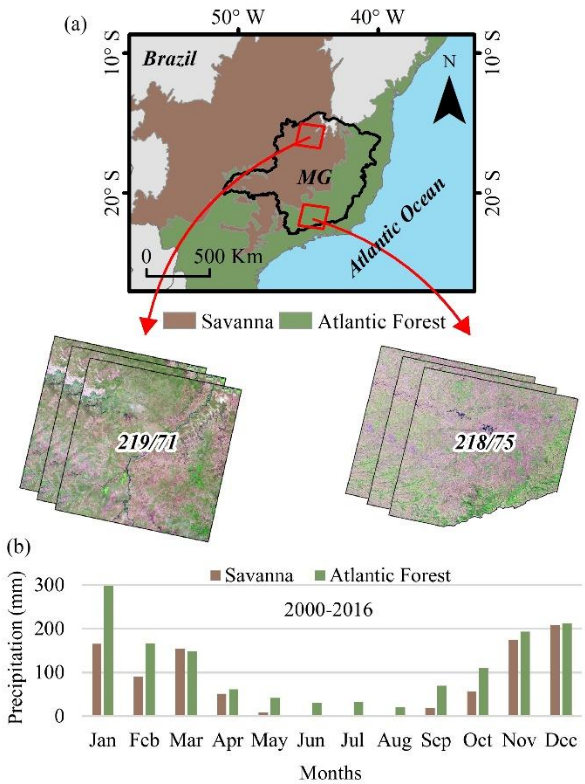

Figure 1. Study area.

2.2. Reference Data

We selected two datasets to play as reference maps: (a) the Global Forest Change 2000 – 2017 (GFC), coming from Landsat time-series analysis in characterizing global forest loss from 2000 to 2017 [11]. Forest, on this map, was defined as canopy closure for all vegetation taller than 5m in height, and (b) the MapBiomas, which is an annual land-use and land use changes from 1984 to 2016 in the entire Brazilian territory [12].

We processed both reference datasets into a three step method: First, we applied a time filter from 2000 to 2016 (common period for both datasets: 16 years) in order to make a comparable time analyze. Second, we created a forest mask by combining the MapBiomas vegetation classification for year 2000, and GFC tree canopy cover for year 2000 as well. Third, an annual change map was created by combining both reference datasets in each year of analysis. The aim of blending the reference datasets was to avoid potential individual misclassifications, keeping only disturbance pixels detected by these two reference maps.

The general methodology is presented in Figure 2.

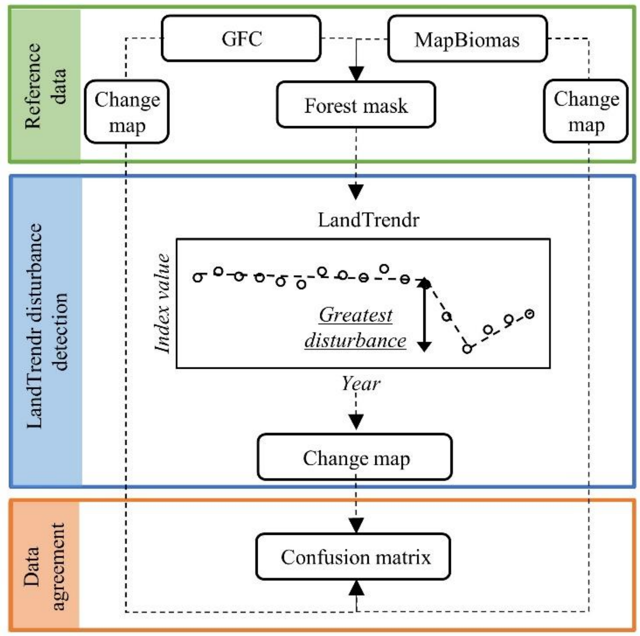

Figure 2. General flowchart of the methodology. GFC: Global Forest Change dataset.

2.3. LandTrendr disturbance detection

Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) time series from 2000 to 2016 were processed through LandTrendr [8]. LandTrendr is an automated trajectory based-image algorithm acting on a pixel level and capturing abrupt disturbance events, which utility has been demonstrated in different geographical regions for a wide range of dynamics related to different disturbance regimes [13].

Both Landsat datasets were derived from Landsat Surface Reflectance collection in GEE, presenting bottom of atmosphere reflectance calculated and high precision data stack generation. LandTrendr implementation was also processed in GEE. We ran LandTrendr with a fixed set of segmentation parameter values [14] and did not make assumptions about parameter testing for the study area.

2.4. Data Agreement

The data agreement step consisted to an accuracy analysis, comparing the LandTrendr disturbance map to the reference dataset created. This pixel level comparison required overlaying LandTrendr change map for each scene and year interval. After the datasets overlaid, we sampled 100 random points in the disturbance class of the reference dataset by each biome and year. The same amount of points was also generated to the not disturbance class (100 points *x* 2 disturbance classes *x* 2 biomes *x* 16 years = 6,400 total).

A confusion matrix was build and overall accuracy, user's accuracy for disturbance class (inversely related to commission error), and producer's accuracy for disturbance class (inversely related to omission error) were calculated by each year and biome. Boxplot charts displayed the dataset variability in order to support the data agreement analysis.

3. RESULTS

Figure 3 illustrates the data agreement analysis of LandTrendr for Savanna and Atlantic Forest in each year of the time series. The LandTrendr agreement with reference data presented overall accuracy ranging from 53 to 80% along the period for Savanna biome, and 58 to 84% for Atlantic Forest. For the disturbance class, producer's accuracy representing disturbance pixels in the reference dataset and omitted by the algorithm, ranged from 8% to 62% for Savanna and 20% to 70% for Atlantic Forest. User's accuracy, representing not disturbed pixels but detected by LandTrendr, showed 69% to 96% of accuracy for Savanna and 80% to 97% for Atlantic Forest.

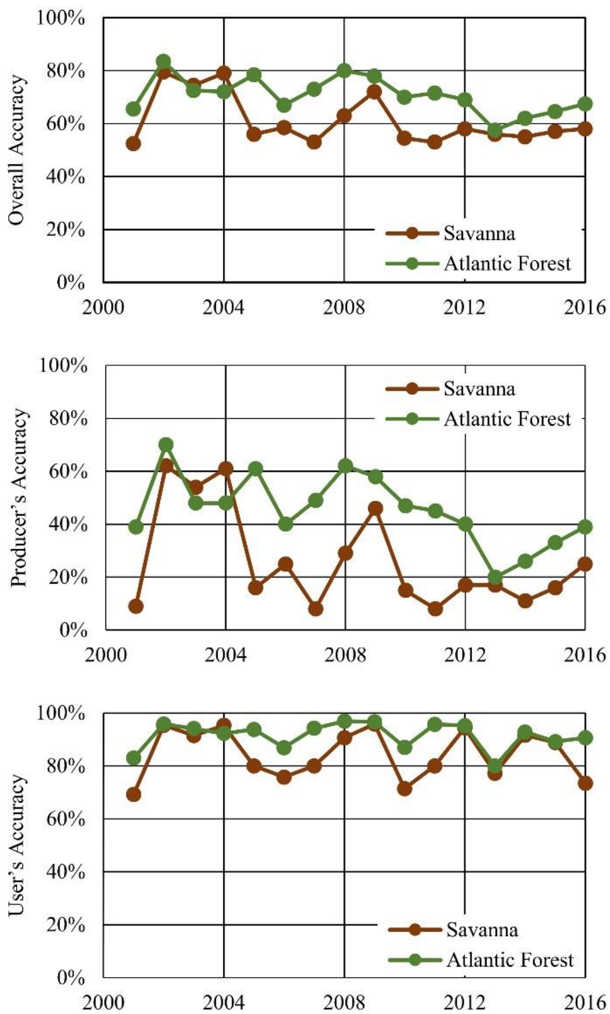

Figure 3. Accuracy analysis.

Boxplot charts demonstrated higher mean accuracies for the Atlantic Forest biome and lower accuracies variability along the period comparing to the Savanna biome (Figure 4).

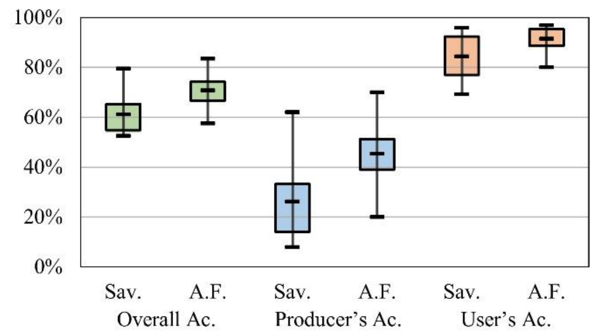

Figure 4. Savanna (Sav.) and Atlantic Forest biome (A.F.) accuracy boxplots along the time series.

4. DISCUSSION

Accuracy measures demonstrated a contrast between the Savanna and Atlantic Forest domain. The lower accuracies in Savanna regions indicated a troublesome disturbance detection, which can be related to the seasonal noise. Most of the woody Savanna species are deciduous formations, and the total or partial leaf fall during the dry season can be a noise in disturbance detection studies [7], [15].

Comparing producer' and user's accuracy, we demonstrated that the rate of disturbance pixels omitted by LandTrendr is higher than pixels included to the disturbance class. This low commission error indicated that LandTrendr is barely affected by seasonal noise in these regions, since the leaf fall by seasonality induces to the inclusion of not disturbed pixels to a disturbance class.

The LandTrendr run through default parameter configuration, which was set in a different forest region across the globe [14]. Since our aim was not reach the best detection accuracy through simulations, perhaps a better algorithm configuration could provide higher accuracies in the study area. In addition, the idea of stratification should be applied running LandTrendr with distinct parameter configuration for each biome, focusing on a particular accuracy measure as producer's accuracy, which presented low values for both areas.

According to boxplot charts, the Atlantic Forest presented lower variability along the years than Savanna for all three measures of accuracies. These results also emphasize the natural disturbances in Savanna regions, indicating how unpredictable the seasonal noise can be in a time series [7].

Another valuable point is the user-friendly characteristic of GEE to access and analyze disturbance data. This singular aspect allows the user to run simulations from different algorithms. In addition, the cloud-based format performs massive computation capabilities supporting forest disturbance detection in large-scale applications.

5. CONCLUSIONS

In this study, we have exploited the LandTrendr algorithm in GEE to detect forest disturbance in two distinct Brazilian vegetation domains, Savanna and Atlantic Forest. We demonstrated that LandTrendr has potential to detect disturbance in forest environments, and the user-friendly format of GEE platform provides easy user access, besides the faster computation in large-scale applications.

In general, LandTrendr algorithm presented higher accuracies for Atlantic Forest, which is less disturbed by seasonal noise than Savannas. The overall accuracy and user´s accuracy of Atlantic Forest was satisfactory showing agreement with the reference dataset. Although Savanna biome presented poor accuracies, it also earns attention since the high seasonality affects change detection in this biome.

Future researches can also follow-up this approach by exploring different disturbance detection algorithms and parameters simulations as well as the implementation of stratification by vegetation class in order to reach higher accuracies, reducing the effects of land cover type on climate fluctuations.

6. REFERENCES

[1] M. Hussain, D. Chen, A. Cheng, H. Wei, and D. Stanley, “Change detection from remotely sensed images: From pixel-based to object-based approaches,” *ISPRS J. Photogramm. Remote Sens.*, vol. 80, pp. 91–106, Jun. 2013.

[2] A. P. Tewkesbury, A. J. Comber, N. J. Tate, A. Lamb, and P. F. Fisher, “A critical synthesis of remotely sensed optical image change detection techniques,” *Remote Sens. Environ.*, vol. 160, pp. 1–14, Apr. 2015.

[3] W. Cohen, S. Healey, Z. Yang, S. Stehman, C. Brewer, E. Brooks, N. Gorelick, C. Huang, M. Hughes, R. Kennedy, T. Loveland, G. Moisen, T. Schroeder, J. Vogelmann, C. Woodcock, L. Yang, and Z. Zhu, “How Similar Are Forest Disturbance Maps Derived from Different Landsat Time Series Algorithms?,” *Forests*, vol. 8, no. 4, p. 98, Mar. 2017.

[4] C. Marchese, “Biodiversity hotspots: A shortcut for a more complicated concept,” *Glob. Ecol. Conserv.*, vol. 3, pp. 297–309, Jan. 2015.

[5] MMA, “Monitoramento do Desmatamento nos Biomas Brasileiros Por Satélite: Cerrado 2008-2009.,” Brasília, 2011.

[6] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, “Google Earth Engine: Planetary-scale geospatial analysis for everyone,” *Remote Sens. Environ.*, vol. 202, pp. 18–27, Dec. 2017.

[7] E. Silveira, I. Bueno, F. Acerbi-Junior, J. Mello, J. Scolforo, and M. Wulder, “Using Spatial Features to Reduce the Impact of Seasonality for Detecting Tropical Forest Changes from Landsat Time Series,” *Remote Sens.*, vol. 10, no. 6, p. 808, May 2018.

[8] R. E. Kennedy, Z. Yang, and W. B. Cohen, “Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — Temporal segmentation algorithms,” *Remote Sens. Environ.*, vol. 114, no. 12, pp. 2897–2910, Dec. 2010.

[9] P. L. Silva de Miranda, A. T. Oliveira-Filho, R. T. Pennington, D. M. Neves, T. R. Baker, and K. G. Dexter, “Using tree species inventories to map biomes and assess their climatic overlaps in lowland tropical South America,” *Glob. Ecol. Biogeogr.*, vol. 27, no. 8, pp. 899–912, Aug. 2018.

[10] C. A. Klink and R. B. Machado, “Conservation of the Brazilian Cerrado,” *Conserv. Biol.*, vol. 19, no. 3, pp. 707–713, Jun. 2005.

[11] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend, “High-Resolution Global Maps of 21st-Century Forest Cover Change,” *Science (80-.).*, vol. 342, no. 6160, pp. 850–853, Nov. 2013.

[12] C. Souza Júnior and T. Azevedo, “MapBiomas General Handbook,” 2017.

[13] A. Banskota, N. Kayastha, M. J. Falkowski, M. A. Wulder, R. E. Froese, and J. C. White, “Forest Monitoring Using Landsat Time Series Data: A Review,” *Can. J. Remote Sens.*, vol. 40, no. 5, pp. 362–384, Sep. 2014.

[14] R. Kennedy, Z. Yang, N. Gorelick, J. Braaten, L. Cavalcante, W. Cohen, and S. Healey, “Implementation of the LandTrendr Algorithm on Google Earth Engine,” *Remote Sens.*, vol. 10, no. 5, p. 691, May 2018.

[15] R. Trancoso, E. E. Sano, and P. R. Meneses, “The spectral changes of deforestation in the Brazilian tropical savanna,” *Environ. Monit. Assess.*, vol. 187, no. 1, p. 4145, Jan. 2015.