PRODES Mata Atlântica: discussing the digital transition from visual interpretation to semi-automatic detection of forest removal

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Abstract. *The Atlantic Forest is a biome rich in biodiversity but highly threatened by deforestation. The study addresses the challenges of monitoring deforestation in the PRODES Mata Atlântica monitoring system and its innovations in remote sensing techniques. We highlight the benefits of the transition from Landsat series to high spatial resolution Sentinel-2 images, as well as the challenges with the adoption of semi-automatic classification algorithms to process image time series. This work reviews existing approaches for automated deforestation detection, including the fusion of optical and SAR data. We stressed the need to consider local and seasonal factors for accurately detecting forest removal in the Atlantic Forest.*

1. Introduction

The Brazilian Atlantic Forest is a biodiversity hotspot composed of forest and non-forest ecosystems, characterized by high endemism and 1,923 species at risk of extinction [Mittermeier et al. 2011]. It occupies 15% of the national territory, 17 states, and 3,249 municipalities, and is the only biome in Brazil whose predominant land cover class is not original vegetation [IBGE, 2019; SOS Mata Atlântica, 2022]. Less than 8% of the biome has remained untouched since deforestation began more than 500 years ago [CEPF 2001]. When considering intermediate secondary vegetation and fragments smaller than 100 ha, the estimated natural vegetation coverage ranges from 11.4% to 16% [Ribeiro et al. 2009]. Despite ongoing efforts to restore the Atlantic Forest [Melo et al. 2013; Romanelli et al. 2022; Shennan-Farpón et al. 2022], more than 1,300 km² of biome fragments have been deforested annually on average over the last 10 years [TerraBrasilis 2023]. Furthermore, due to its vast geographic extent and the resulting diverse phytophysiognomies, monitoring deforestation in the Atlantic Forest is challenging for remote sensing systems.

In 1978, the National Institute for Space Research - INPE demonstrated the feasibility of using orbital remote sensing to map deforestation [Tardinet al., 1979 and Tardinet al., 1978], which led to the Monitoring of Deforestation in the Legal Amazon by Satellite Project - PRODES. From 1988 to 2000, deforestation was mapped by visual interpretation on photographic paper and, later, by digital methods [Shimabukuro et al. 2000]. Since 2002, the mapping has been carried out by photointerpretation in the TerraAmazon computer system [Terraamazon, 2021], and its results published online. PRODES uses Landsat 8 or similar images to map clear-cut areas, with more than

6.25 hectares, compatible with minimum and maximum scales, respectively, 1:125,000 and 1:75,000.

In 1990, the SOS Mata Atlântica Foundation and INPE began mapping the forest remnants of the Atlantic Forest, also using Landsat images [SOS & INPE, 1998]. In 2015, the Ministry of the Environment established the Biome Environmental Monitoring Program (PMABB) via satellite, including the monitoring of deforestation in the Atlantic Forest. With the PMABB, deforestation was mapped bi-annually, between 2000 and 2016, and annually from 2017 to 2022, giving rise to the PRODES Mata Atlântica Project (PRODES-MA) which will continue the monitoring task [Amaral *et al*. 2023]. A challenge that arose from all these years of digital mapping was the analysis of large time series to automatically detect deforestation. The possibility of using time series, mosaics, data cubes, and better-resolution images offers promising alternatives for improving PRODES-MA. However, this methodological transition must preserve the quality of monitoring.

In recent years, the expansion and free access to satellite image collections have expanded the potential for monitoring forest cover globally [Hansen *et al*. 2013]. However, the automatic classification of these datasets to monitor deforestation in Brazilian biomes is still inaccurate when compared to the efficiency of human interpretation. Furthermore, large data sets require storage, processing, dissemination, and analysis technologies. Approaches that have used remote sensing images in time series have advanced in the development of algorithms to access, process, evaluate data quality, and analyze the results of automatic classifications related to changes in land use and cover [Ferreira *et al*. 2020; Gomes *et al*. 2020; Gómez *et al*. 2016; Woodcock *et al*. 2020].

Automatic classification algorithms, such as those available in the package Satellite Image Time Series (SITS), have assisted automatic classification in the systematic mapping of land use and cover, as carried out by INPE in the TerraClass project [Terrabrasilis, 2023]. To facilitate this type of analysis, recent initiatives have produced and made available time series as Analysis Ready Data in data cubes [Killough 2019; Lewis *et al*. 2017]. Specifically, the Brazil Data Cube (BDC) has built a valuable source of data for monitoring Brazilian biomes [Ferreira *et al*. 2020; Picoli *et al*. 2020; Simoes *et al*. 2021].

A commonly used way to detect deforestation is by comparing temporal maps of land use and cover. The MapBiomas project, for example, uses the Random Forest algorithm to classify land use and cover, annually. The classifier is trained with reference samples collected with the aid of maps, historical series, and visual interpretation of satellite images. Then, the MapBiomas automatically classify images into forest, field, agriculture, pasture, urban area, and other classes. The deforestation mapping in this case is attributed to the difference between land cover classes in the maps across the years [Souza *et al*. 2020].

However, to date, there is no completely automatic and direct mapping of deforestation in Brazil based on the spectro-temporal pattern of a given area, especially in the Atlantic Forest biome. It is believed that such a system would bring greater precision in detecting the limits of deforestation, reproducibility, and agility in data production. For that, this article aims to discuss methodological alternatives for the automatic detection of deforestation in the Atlantic Forest to assist the digital transition to PRODES-MA. Two guiding questions are: 1) What are the main methodological challenges for automatic mapping of deforestation? 2) How can image time series classification help the automatic detection of deforestation?

Initially, the current methodology and the main challenges faced by the team in PRODES-MA and by other projects at INPE are presented. These aspects may be relevant in the process of automatic detection of deforestation. Next, articles on detecting deforestation based on image time series analysis are discussed, regardless of the biome. Finally, the methodological possibilities for automatically detecting deforestation are summarized, considering the geographic extent, heterogeneity, and other particularities of the Atlantic Forest.

2. The existing methodology and initial testing for PRODES-MA

The mapping of deforestation in the Atlantic Forest up to 2022 followed the methodology developed and used in the PRODES-Amazônia [INPE, 2023a] and PRODES-Cerrado [INPE, 2023b] Projects. This methodology is based on: visual analysis at 1:75,000 scale; manual vectorization of deforestation polygons larger than 1 ha; use of the biome limit of the Brazilian Atlantic Forest [IBGE, 2019]; use of Landsat images with 30m spatial resolution.

Since 2022, PRODES-MA has been carried out at INPE with MSI/ Sentinel-2 images (10 m spatial resolution). A series of tests were conducted to assess the impact of replacing OLI/Landsat 8 with MSI/Sentinel-2 images for deforestation mapping and estimation. [Passos *et al*., 2023] considered deforestation data mapped with the PRODES-MA historical series and methodology in 13 cells, 758 km² each. The enhanced spatial resolution of Sentinel images facilitated a more accurate delineation of deforested fragments, allowing for better differentiation of various land types, such as agricultural areas, and reforested regions, and the identification of a greater number of polygons compared to Landsat images.

The increase in resolution was confirmed by the PRODES-MA team through a second experiment conducted in 275 cells, representing 15% of the biome and distributed across various phytophysiognomies within the Atlantic Forest. Sentinel images facilitated the detection of 158% of the deforestation area observed with Landsat images. When analyzing deforestation by phytophysiognomies, the following areas were mapped using Landsat and Sentinel, respectively: 38.27 km² and 72.66 km² (189.8%) in the Ombrophylous Forests (Mixed, Open, and Dense); 56.72 km² and 78.03 km² (137.57%) in Seasonal Deciduous and Semideciduous Forests; and 38.77 km² and 54.49 km² (140.54%) in non-forest areas. These results are being prepared for submission.

The wide gradient ranging from approximately 5º to 30º South Latitude in the Atlantic Forest results in climatic and phytophysiognomic variability, making it challenging to establish a single automated procedure for the entire biome. Subdividing the area into homogeneous units, such as ecoregions, can be a strategy to facilitate local adjustments in classification models [Silva *et al*., 2022]. This significant difference in latitude also affects the optimal period for detecting cloud-free images. For the northern region, the preferred time is from October to December, while for the central-southern region, it is from June to August [Almeida *et al*., 2022]. However, in some northern regions, cloud-free images are scarce. To address this issue, tests were conducted using temporal mosaics of Sentinel-2 images, produced by BDC, the preferred times for the north and central-southern regions. The obtained mosaics had undesired effects related to cloud detection and relief removal procedures, which posed challenges for visual interpretation of deforestation. Thus far, it has been concluded that the usefulness of mosaics for automatic deforestation monitoring depends on further tests that consider alternative production methods and different time frames.

Studies involving automatic classification through the fusion of optical (Sentinel-2) and synthetic aperture radar (SAR) (Sentinel-1) data have also been explored to enhance deforestation detection under various cloud conditions [Ferrari *et al*. 2023]. In this study, convolutional neural network (FCN) architectures were chosen for the classification task. In scenarios with a low probability of cloud cover (≤ 5%), the models utilizing optical data achieved an average accuracy of 0.71, while the radar models, 0.61. However, in other scenarios (> 5%), the optical models exhibited accuracy generally below 0.50. The fusion of optical data and SAR consistently demonstrated an advantage in all scenarios. In most tests, deforestation detected by optical and SAR fusion had at least 0.04 higher accuracy than those by a single data type.

Related to all the above challenges, the results' accuracy prevents the migration to a semi-automatic detection methodology. According to the technical note issued by [INPE, 2022], the accuracies of the PRODES 2022 mapping results for 108 priority scenes in the Legal Amazon and for the Cerrado biome as a whole were 98.8% and 94.3%, respectively. These values are much higher than those found when evaluating automatic classification, such as the study by [Braga, 2023], which showed an accuracy of 66% for an area in the municipality of Campina do Monte Alegre. Another study that also compared the two methodologies was conducted by [Correia, Batista, and Araújo, 2011], in which manual mapping was more viable than automatic mapping. Even though the former took longer time it was easier to identify the features, allowing for greater precision in the interpretation of deforested areas. The automatic mapping was faster but had confusing results specifically for anthropic areas (e.g., deforested areas).

Therefore, some methodological challenges to be considered in the process of automating deforestation detection are the following: processing and analyzing images with adequate spatial resolution to capture small fragments of deforestation; subdividing the biome into ecoregions or phytophysiognomic groups; and developing strategies to map more cloud-prone regions when needed (e.g., temporal mosaics and optical/SAR data fusion). Related to all these challenges, the ultimate concern is the results' accuracy. Finally, a more current challenge but a promising opportunity for improving deforestation mapping accuracy is the classification of time series, which will be discussed in more detail below.

3. Deforestation detection using time series of images

For the analysis of large Earth observation data sets, [Camara, 2020] proposes a theoretical support based on event recognition. Time series analysis encompasses aspects such as pattern matching, trend analysis, change detection, and time series classification, all of which are considered subtypes of event recognition. In contrast to traditional approaches that assign static labels to land use classes in an area, events are identified, such as site-specific temporal transformations. However, adapting machine learning algorithms to handle the time series of satellite images is crucial. This entails developing methods that integrate ecosystem models for a deeper understanding of landscape dynamics and the extraction of information from extensive Earth observation datasets.

In this context, deforestation is considered an event that occurs in a specific time and space, associated with the complete removal of the original vegetation cover. Unlike different land use and cover classes, which may exhibit unique signatures in a time series of images, the deforestation event manifests as a disruption in the primary vegetation time series pattern. Initially, this event is followed by exposed soil, which is later replaced by various patterns of land use and cover. The subsequent cover will generally depend on the local economic activities. In the Atlantic Forest biome, agricultural use predominates in the south, while silviculture prevails in some regions in Bahia and Minas Gerais states; and near metropolises and cities, urban uses are noticed [Bolfe *et al*. 2020].

Despite their potential to classify land use and cover, few studies discuss the limits and advantages of using time series classification to map deforestation. Specifically in forest ecosystems with pronounced seasonal variation, identifying changes in vegetation cover is complex: some forests show notable seasonality in their photosynthetic rate [Gamon *et al*. 1995], making it difficult to accurately detect small-scale disturbances and forest changes [Milodowski *et al*. 2017]. Several studies have investigated forest cover changes, employing locally calibrated algorithms for analysis [Brandt *et al*. 2018; DeVries *et al*. 2015; Hall *et al*. 2009; Hamunyela et al. 2017]. However, monitoring deforestation in the tropical zone requires collecting, comprehensive processing, and analyzing remote sensing data to achieve high accuracy. This requires a significant allocation of financial resources and working time to ensure broad coverage and reliable results [Stehman 2005].

For the detection of disturbances in the forest and savanna vegetation of the Cerrado in Maranhão state, [Campanharo *et a*l., 2023] utilized the BFASTmonitor algorithm on NDVI index calculated from Landsat-8 data cubes spanning from 2016 to 2020, available in BDC. The authors compared their results with the 2020 MapBiomas deforestation product and identified a commission error of 99% for the deforestation class. In other words, they observed a much higher number of deforestation than MapBiomas. The algorithm may be highly sensitive to NDVI values calculated for Cerrado physiognomies. Therefore, conducting additional tests with other spectral indices and performing separate analyses for each physiognomy could be valuable, as these ecosystems may exhibit different seasonal dynamics.

Deforestation and degradation of forest landscapes in the state of Rondônia were detected using spectral mixture analysis and a time series of Landsat images spanning from 1990 to 2013, as reported by [Bullock *et al*., 2020]. Spectrally unmixed data, derived from spectral fractions and the Normalized Degradation Fraction Index (NDFI), were employed for disturbance monitoring and land cover classification. The Random Forest algorithm was used for this purpose. The results showed that degradation and deforestation were mapped, respectively, with 88.0% and 93.3% user accuracy, and 68.1% and 85.3% producer accuracy. Time series analyses proved to be efficient in differentiating deforestation from degradation and highlighted spatio-temporal patterns that can serve as a baseline for identifying sudden changes in the landscape.

Additionally, in two distinct regions of the Amazon, [Milodowski *et al*. 2017] conducted a comparative analysis of the accuracy of three forest loss products: GFW, PRODES, and FORMA, concerning high-resolution imagery (RapidEye). The results reveal that the spatial patterns of change detected by GFW and PRODES products align with the changes observed in the high-resolution images. However, they exhibit a significant negative bias, especially when dealing with smaller deforested areas. For instance, in Acre, where smaller clearings predominate, both products fail to detect a substantial amount of forest loss (approximately -27% for GFW and -49% for PRODES).

Ten years of deforestation data, detected by the Global Forest Change (GFC) initiative and SOS Mata Atlântica, were validated by [Andreacci and Marenzi, 2020] in the municipality of Araquari (384 km²), Santa Catarina. The GFC uses Landsat temporal reflectance metrics and classifies as loss year the pixels that lose forest vegetation from the year 2000 onwards [Hansen *et al*. 2013]. SOS Mata Atlântica classifies biannual or annual deforestation greater than 3 ha via visual interpretation. It was found that 55% of GFC forest loss was associated with classification errors (i.e., the removal of non-forest cover), 24% with the removal of forest plantations, and only 21% with the removal of native forest cover. Automating classification based on optical data faces the significant challenge of distinguishing native forests from forest plantations established before the base year of the analysis. SOS MA, on the other hand, did not exhibit a classification error but correctly identified only 31% of the native forest deforestation correctly mapped by the GFC. This evidence underscores the importance of complementing automated deforestation detection with visual inspection routines of high-resolution images to validate the results.

In the Atlantic Forest, [Tramontina and Pereira, 2019] investigated the time series of the NDVI and EVI vegetation indices across different types of land cover. They observed a direct relationship between climate seasonality and vegetation, characterized by distinct seasonal patterns in the time series. These patterns were marked by higher peaks during the rainy season and lower values during the dry season. Deforestation polygons were determined by comparing the time series thresholds for NDVI (0.77) and EVI (0.40), which served as a reference for forest cover between the years 2013 and 2016. While NDVI facilitated the visualization of deforestation, the EVI index exhibited greater annual variability and sensitivity to changes.

4. Recommendations

To further analyze the implications of automatic mapping deforestation in the Atlantic Forest, Table 1 summarizes how some biome’s particularities relates to methodological aspects, opportunities, and challenges presented so far, as well as possible recommendation for the PRODES-MA digital transition. This emphasizes the importance of considering the biome's complexities considering the methodological opportunities and limitations in automatically detecting deforestation.

Table 1. Summary of perspectives, challenges and recommendations for automatic detection of deforestation in the Atlantic

Atlantic Forest Issues	Methodological aspects	Opportunities/ possibilities/ perspectives	Challenges	Recommendations	Reference
Land Use and Land Cover	Automatic detection of forest removal year-by-year from a base year	Detecting many more deforestation fragments non-observed by manual mapping initiatives	Noisy map, confusing loss of native forests with forestry (25%) or non-forest areas (55%)	To cross-validate the results by a team that has local experts	[Andreacci & Marenzi, 2020]
Seasonality	Vegetation Index thresholds	Determining thresholds of NDVI and EVI to differentiate forests from non-forests.	Indices sensitive to seasonality: values are high in the rainy and low in the dry season	To analyze in other study areas the sensibility of optimal thresholds to detect deforestation	[Tramontina & Pereira, 2019]
	Partition of the biome into homogenous areas	Locallyadjusting classification by ecoregions	New studies are required to divide the biome or test previous and established division	To study automatic classification after the partition of the biome	[Silva *et al.*, 2022]
	Data cubes	Providing analysis ready data for regional and local analyses	A mosaic in time can mask seasonality effects on vegetation	To investigate how some seasonally affected physiognomies of the Atlantic Forest would benefit from mosaics	[Simoes et al., 2021]
	BFAST algorithm	Mapping deforestation based on breaks in time series trend	High commission error observed using NDVI as the explanatory variable	To evaluate the sensitivity of the algorithm to other spectral indices and in different phytophysiognomies	[Campanharo et al., 2023]
Cloud cover	Partition of the biome	Search for cloud-free images in different regions of the Atlantic forest	A combination of methodologies should be created to map the whole Atlantic Forest	To study automatic classification after the partition of the biome	[Silva et al., 2022]
	Data cubes	Providing analysis ready data with minimal cloud contamination	Undesired effects from cloud masking procedure can interfere with visual interpretation	To run new tests with different mosaics and time frames are needed	PRODES-MA Team
	Fusion optic/SAR	Facilitating better detection of deforestation in scenarios with cloud cover greater than 5%	A study carried out based on a Convolutional Network trained and tested by not homogeneous tiles	To test fusion with other classifiers like RandomForest, being careful with sample quality	[Ferrari et al., 2023]

Small fragments	Spatial resolution to detect deforestation fragments	Increasing spatial resolution allows from 37% to 89% more deforested fragments detection. This was noticed when comparing maps from Sentinel-2 and Landsat 8 images	The remaining fragments are very small and changes detected in the landscape can be minimal	To prioritize satellite images with the highest available spatial resolution to ensure accurate detection and precise delineation of landscape changes	[Passos et al., 2023]

4. Conclusion

Automatic deforestation detection in the Atlantic Forest presents many methodological challenges. The transition to Sentinel-2 images has brought improvements in spatial resolution for mapping deforested areas, as well as for distinguishing different types of land use, such as agricultural areas and reforestation. However, the region's climatic and phytophysiognomic variability requires adaptive approaches, such as subdivision into ecoregions. Combining Sentinel-2 and Sentinel-1 data has been promised for detecting deforestation under cloud cover conditions that exceed 5%. Overcoming these challenges is essential to enhance the accuracy of deforestation detection in the Atlantic Forest.

Classifying image time series for deforestation detection is a valuable approach, as it involves identifying breaks in landscape composition trends. However, identifying deforestation in forest ecosystems is challenging due to the seasonality and complexity of vegetation changes, which are not necessarily related to the removal of vegetation cover. Algorithms like BFASTmonitor have demonstrated sensitivity to these seasonal variations, leading to overestimated deforestation detection. Therefore, conducting more tests with this and other algorithms is essential to overcome the challenges associated with analyzing time series data. While temporal analysis reveals significant spatial and temporal patterns, visual inspection of high-resolution images remains crucial for validation.

The PRODES-MA represents an important step in enhancing the process of monitoring deforestation in this biodiversity hotspot. Two important recommendations to consider are (1) employing high spatial resolution images and (2) improving and testing algorithms for automated deforestation detection based on time series images. However, methodological challenges such as accounting for seasonality, addressing the diversity of phytophysiognomies, and making precise distinctions between deforestation, degradation, and other land uses still require further discussion and in-depth study to enhance mapping accuracy and overall quality.

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