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Detection of Forest Removal in PRODES Mata Atlântica: Discussion on the Transition from Visual to Semiautomatic Interpretation

PRODES Mata Atlântica: discutindo a transição digital da interpretação visual para a detecção semi-automática da remoção florestal

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Abstract: The Atlantic Forest is a global hotspot rich in biodiversity, but highly threatened by deforestation. The study addresses the PRODES Atlantic Forest monitoring system and its remote sensing techniques, as well as the challenges with the adoption of semi-automatic classification algorithms to process time series of images. We highlight the benefits of transitioning from Landsat series to high spatial resolution Sentinel-2 images, and the combination of Sentinel-2 and Sentinel-1 data to improve visualization in some areas where the landscape is impaired due to clouds. We reviewed existing approaches in the literature for semi-automated deforestation detection, including optical data fusion and SAR, discussing the need to improve the monitoring methodology. We emphasize considering local and seasonal factors to accurately detect the removal of the natural vegetation in the Atlantic Forest and we recommend further testing of algorithms based on time series images. Even though it reveals significant patterns, validation still heavily relies on visual interpretation.
Keywords: Deforestation Monitoring. Remote Sensing. Semi-automation.

Resumo: A Mata Atlântica é um hotspot mundial rico em biodiversidade, mas altamente ameaçado pelo desmatamento. Este estudo aborda o sistema de monitoramento PRODES Mata Atlântica e suas técnicas de sensoriamento remoto, bem como os desafios para a adoção de algoritmos de classificação semiautomáticos para processar séries temporais de imagens. Destacamos os benefícios da transição das séries Landsat para imagens Sentinel-2 de alta resolução espacial, a combinação dos dados do Sentinel-2 e Sentinel-1 para melhorar a visualização em algumas áreas da paisagem prejudicadas pela presença de nuvens. Revisamos na literatura as abordagens existentes para detecção semiautomatizada de desmatamento, incluindo a fusão de dados ópticos e SAR, discutindo as carências para o aperfeiçoamento da metodologia do monitoramento. Ressaltamos a necessidade de considerar fatores locais e sazonais para detectar com precisão a remoção da vegetação natural na Mata Atlântica e recomendamos mais testes com algoritmos baseados em imagens de séries temporais. Embora revele padrões significativos, a validação ainda depende consideravelmente da interpretação visual.
Palavras-chave: Monitoramento do Desmatamento. Sensoriamento Remoto. Semiautomatização.

1 INTRODUCTION

The Brazilian Atlantic Forest is identified as one of the main global hotspots due to its richness and endemic biodiversity, and at the same time, it is one of the most threatened biomes on the planet, making its conservation a priority (Mittermeier et al., 2004; Myers et al., 2000). It is composed of forest and non-forest ecosystems, characterized by high endemism and many species at risk of extinction (Mittermeier et al., 2011). It occupies 15% of the Brazilian territory, 15 states, 3,082 municipalities, and accommodates 72% of the population; (IBGE, 2018). It is the only biome in the country whose predominant land cover class is not original vegetation, with only 12.6% of forest remaining in its extension (IBGE, 2020) (SOS Mata Atlântica, 2023). Atlantic Forest deforestation started when Brazil was a former Portuguese colony in the 1500s and, since then, only less than 8% of its original composition remains (CEPF, 2001).

Despite continued 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 fragments of the biome have been deforested annually, on average, in the last 10 years (Assis et al., 2019; Molinez et al., 2023). Due to its vast geographic extension resulting in diverse phytophysiognomies, monitoring its deforestation is a challenge, however, remote sensing systems enable relatively precise assessments and support territorial management efforts to mitigate environmental impacts (Amaral; Cursino; Almeida, 2023; Joly et al., 2012; Martins-Neto et al., 2021)

In 1978, the National Institute for Space Research (INPE) demonstrated the feasibility of using orbital remote sensing to map deforestation (Tardin et al., 1979), 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, mapping has been carried out by photointerpretation in the TerraAmazon computer system and its results are published online. PRODES uses Landsat 8 or similar images to map deforested areas, with more than 6.25 hectares, compatible with scales between 1:125,000 and 1:75,000.

In 1990, SOS Atlantic Forest Foundation and INPE began the mapping of Atlantic Forest remnants, using Landsat images (SOS & INPE, 2002). In 2015, the Ministry of the Environment established the *Programa de Monitoramento Ambiental dos Biomas Brasileiros* (PMABB) through Ordinance 365/2015, which includes satellite monitoring of deforestation in the Atlantic Forest. The project complied with the requirements of the United Nations Framework Convention on Climate Change (UNFCCC), in accordance with the national REDD+ strategy to mitigate global warming. Its objective is to prevent deforestation and guarantee payments for results in reducing Greenhouse Gas (GHG) emissions, in line with the National Climate Change Policy (NCCP). With PMABB, deforestation was mapped biannually between 2000 and 2016, and annually, from 2017 to 2022, giving rise to the PRODES Atlantic Forest Project (PRODES-MA) which will continue the monitoring efforts (Amaral; Cursino; Almeida, 2023).

One provocation that emerged from all these years of digital mapping was the analysis of large time series to automatically detect deforestation. The possibility of using these 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.

Until now there is no fully automatic and direct mapping of deforestation in Brazil based on the spectrotemporal pattern of a certain area, especially in the Atlantic Forest. It is believed that such a system would bring greater precision in detecting the limits of deforestation and greater reproducibility and agility in data production. Therefore, this article aims to discuss the main methodological challenges for the automatic mapping of deforestation.

Initially, the current methodology and the main adversities faced by the PRODES-MA team and other INPE projects are presented, as they are relevant to understanding what is being done today and identifying the points that require attention. Next, to compile technical understandings of how deforestation based on image time series analyses are being detected, research conducted in different biomes is reviewed and discussed. Finally, the methodological possibilities for the automatic detection of deforestation are summarized, considering the geographic extent, heterogeneity, landscape composition, and other particularities of the Atlantic Forest.

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2 THE EXISTING METHODOLOGY AND INITIAL TESTING FOR PRODES-MA

The mapping of deforestation in the Atlantic Forest until 2022 followed the methodology developed and used in the PRODES-Amazônia and PRODES-Cerrado projects (INPE, 2022). This methodology is based on a visual analysis of Landsat images with a spatial resolution of 30m, at a scale of 1:75,000, with manual vectorization of deforestation polygons larger than 1 ha, boundaries of the Brazilian Atlantic Forest biome (IBGE, 2020).

The Landsat program involved the launch of a series of eight Earth observation satellites by the National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS). It originated from the Earth Resources Technology Satellite (ERTS) project, later renamed Landsat, in the 1960s. The mission began with the launch of Landsat-1 in 1972, equipped with Return Beam Vidicon (RBV) and Multispectral Scanner System (MSS) cameras. Subsequent satellites, such as Landsat-5 in 1982 and Landsat-7 in 1999 with Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors respectively, expanded imaging capabilities, while Landsat 8, launched in 2013 as the Landsat Data Continuity Mission (LDCM), continued the series with Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) instruments. Each satellite offers revisit periods ranging from 16 days for the early ones to 8 days for the latest, covering a width of approximately 185 km globally. Equipped with multispectral sensors, Landsat satellites capture data across various spectral bands, including the visible and near-infrared spectrum, providing a valuable database for monitoring changes in Earth's surface since 1972 (USGS, 2024).

PRODES-MA has started using Sentinel-2 images (with a spatial resolution of 10 m) at INPE. The Sentinel-2, a component of the Copernicus programs, comprises three European satellites. With a width spanning 290 km and a revisit frequency of 5 days, they are platforms for the Multi-Spectral Instrument (MSI) that captures data across 13 distinct spectral bands and has provided valuable imagery since 2015. To assess the impact of replacing OLI/Landsat 8 with MSI/Sentinel-2 images for deforestation mapping and estimation, a series of tests were conducted by Passos et al. (2023). These tests considered deforestation data mapped with the PRODES-MA historical series and methodology in 13 cells (758km² each), considering deforestation mapped with the PRODES-MA historical series and methodology. The enhanced spatial resolution of Sentinel images facilitated better differentiation of various land types, such as agricultural areas, and reforested regions. Most importantly, MSI/Sentinel-2 spatial resolution contributed to the detection of better delineated polygons of deforestation than Landsat OLI/Landsat 8. Additionally, 512 additional polygons covering a larger area of 13.6 km² were detected. Furthermore, Sentinel obtained a total area of 36.94 km² with 1,104 polygons, while Landsat obtained a total area of 23.37 km² with 592 polygons.

The improvement with 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 latitudinal range of the Atlantic Forest results in climatic and phytophysiognomic variability, influencing the ideal period for acquiring cloud-free images. There is a notable heterogeneity concerning the driest quarter of the year, which occurs later in the northern regions and earlier in the southern regions. Given this diversity, the initial approach was to divide the biome into three distinct zones to optimize satellite monitoring: north, center, and south. In the northern zone, the quarter from October to December was identified as ideal, with the possibility of including September, to improve cloud-free image coverage. Similarly, in the central zone, priority was given to the June-August quarter with a potential of including September. The division between the central and southern zones was considered unnecessary, as the period from June to

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September facilitates the acquisition of images of the entire area of the southern biome, given the conditions of cloudiness, sunshine, and precipitation (Amaral; Cursino; Almeida, 2023b).

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 the Brazil Data Cube taking 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. These results are being prepared for publication, but more tests are needed to generate mosaics free of the artifacts caused by cloud cover and relief characteristics of the Atlantic Forest.

3 DEFORESTATION DETECTION USING TIME SERIES OF IMAGES

A time series constitutes an organized sequence of observations or measurements collected at regular intervals over time. Within the domain of satellite image analysis, time series play a pivotal role in monitoring trends, seasonal cycles, and specific events, enabling the observation of environmental changes and natural phenomena over extended periods. Satellite image time series (SITS), comprised of sets of satellite images acquired at specific and regular intervals, are essential for land cover classification and vegetation mapping, facilitating the analysis of seasonal patterns and temporal changes (Drusch et al., 2012; Pelletier; Webb; Petitjean, 2019; Petitjean; Inglada; Gancarski, 2012; Verbesselt et al., 2010). The use of SITS through automatic classification algorithms demonstrates the potential to improve classification accuracy. Although widely used, traditional methods such as Support Vector Machines (SVMs) and Random Forests (RFs) often overlook the temporal dimension of the data. However, approaches that consider time series, such as Temporal Convolutional Neural Network (TempCNN) models, show promise for enhancing classification accuracy.

For the analysis of large Earth observation data sets, Câmara (2020) proposed 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 essential. 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 of Bahia and Minas Gerais states. Near metropolises and cities, urban uses are evident (Bolfe; Sano; Campos, 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; Mitchard; Williams, 2017a). 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).

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).

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.

Based on the discussions presented, one concludes that monitoring deforestation using time series in the tropical zone requires the collection, comprehensive processing, and analysis of 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).

4 CHALLENGES AND RECOMMENDATIONS

4.1 Geographic Extent

The Atlantic Forest is composed of numerous types of phytophysiognomies associated with different soil and climate conditions, which concerns its wide range of latitude (from 5º to 30º south) and altitude (from sea level to 1600m altitude in Itatiaia-RJ). Thus, it is a challenge to establish a single, automated procedure for the entire biome.

Subdividing the biome into homogeneous units, such as ecoregions, can be a strategy to facilitate local adjustments in classification models (Silva; Souza; Vitória, 2022). Despite significant advances in remote sensing tools, the classification of complex land cover remains challenging due to landscape fragmentation and spectral similarity between classes. Integrations of spectral and spatial features have been proposed to address this challenge, including methods such as kernel (Schölkopf; Smola, 2002), Bayesian models (Murat Dundar; Landgrebe, 2002), Markov Random Field (MRF) (Jackson; Landgrebe, 2002) and Conditional Random Field (CRF) (Zhong; Wang, 2010). However, these approaches have limitations in parameter definition and generalization to different cases due to their emphasis on low-level features and dependence on specific contexts (Zhao; Du, 2016).

For the detection of disturbances in the forest and savanna vegetation of the Cerrado in Maranhão state, Campanharo et al. (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 that the user's accuracy for the deforestation class was only 1%. In other words, they substantially overestimated the occurrence of deforestation when compared to 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.

4.2 Seasonality

Identifying and dealing with phenological changes across growing seasons in different forest types is another challenge for deforestation classification. Wu et al. (2014) studied ten forest ecosystems - deciduous broadleaf and evergreen needle forests - considering 8 years of MODIS data associated with CO_2 measurements. Phenology was derived from daily Gross Primary Productivity (GPP) data, defining the beginning and end of the growing season as the days on which the smoothed daily GPP reached 10% of the seasonal maximum. Vegetation indices (VIs) from the MODIS sensor were used to monitor phenological transitions and obtained that seasonally averaged VIs had limited performance in tracking phenology in evergreen needle forests, while models based on these VIs were accurate in evergreen needle and deciduous broadleaf forests. Optimized soil Adjusted Vegetation Index (OSAVI) stood out, which strongly correlated with the end of GPP in evergreen needle forests. Despite the lack of a consistent measure of phenology across plant types, the authors emphasized the potential of multiple indices combination for the estimation of phenology at the local level.

A global analysis of Normalized Difference Vegetation Index (NDVI) trends from 1982 to 2011 was conducted using the Seasonal Trend Analysis technique (STA), based on a two-stage time series analysis (Eastman et al., 2013). The study examined trends in NDVI seasonality using data from the GIMMS (Global Inventory Modeling and Mapping Studies) NDVI3g and STA archive. STA extracts shape parameters from seasonal curves, including the amplitude and phase of annual and semi-annual sine waves, as well as the Annual Mean NDVI, for each pixel and year. More than half of land areas showed a significant trend in seasonality, with three main classes of seasonal trends dominating the observed changes, associated with different biomes. Trends were identified using the Mann-Kendall contextual procedure to determine statistical significance. Although climate change was observed as a preponderant factor in the trends, it was not possible to attribute a single cause for each identified trend.

4.3 Cloud cover

According to Picoli et al. (2020), data cubes improve environmental monitoring capabilities, such as deforestation mapping, wildfire studies, and LULC temporal analysis. A platform for analyzing and visualizing large volumes of Earth Observation Analysis Ready Data (ARD). Using a "best pixels" approach, BDC selects data free of clouds and shadows, with a time of 16 days, opting for the median as the method of choice (Ferreira et al., 2020). This data is then used to generate mosaics that resolve issues related to large volumes of Remote Sensing images. This approach is crucial to ensuring the accuracy of analysis in environmental applications such as land use and land cover mapping, deforestation monitoring, and environmental change detection. The BDC covers data from medium spatial resolution sensors (10-64 m) from satellites such as Landsat 8/OLI, CBERS-4/WFI, and Sentinel-2/MSI, covering the entire Brazilian territory. Furthermore, the BDC provides data in cloud-optimized formats, such as Cloud Optimized GeoTIFF (COG), and is Spatio Temporal Asset Catalog (STAC) compliant, making data access and analysis easier.

To mitigate the effects of clouds, the BDC has studied this issue extensively. In a specific study, algorithms for cloud and cloud shadow detection and removal in satellite images were employed, such as Fmask for Sentinel-2 and Landsat-8, and CMASK for CBERS-4. These algorithms were chosen based on their accuracy compared to alternative options like MAJA, Sen2Cor, and s2cloudless. Following cloud and shadow detection and removal, images undergo temporal composition, wherein only valid observations are considered, excluding those affected by clouds, shadows, or snow. This composition, carried out by the stack compositing function, prioritizes observations with lower cloud coverage, ensuring their representativeness within the time interval. Subsequently, the data is distributed as Cloud Optimized GeoTIFF (COG) files, enabling efficient access and high performance in cloud environments. These strategies, combined with the use of specialized software such as LaSRC for Sentinel-2/MSI and Landsat-8/OLI, and MS3 for CBERS-4/AWFI and MUX, aim to minimize the impact of clouds on surface reflectance analyses and data cube creation (Ferreira et al., 2020). 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, fully convolutional network (FCN) architectures were chosen for the classification task. In scenarios with a low probability of cloud cover ($\leq 5\%$), the models utilizing optical data achieved an average accuracy of 71%, while the radar models, 61%. However, in other scenarios (> 5%), the optical models exhibited accuracy generally below 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 4% higher accuracy than those by a single data type.

The Synthetic Aperture Radar (SAR) operates at microwave frequencies, allowing it to penetrate clouds and other atmospheric conditions. Using active remote sensing, it emits its microwave signals and measures the reflected signals to create images, independently of cloud cover or weather conditions. The longer wavelengths of SAR signals have lower scattering and absorption properties, facilitating penetration through clouds compared to visible or infrared wavelengths. Additionally, SAR can employ different polarization modes, such as dual polarization or SAR polarimetry, to provide additional information about scattered targets and help distinguish between surface types, including those obscured by clouds. This capability makes SAR a crucial tool for monitoring areas frequently covered by clouds, such as tropical forests, enabling assessments of deforestation and changes in land cover (Moreira et al., 2013).

An approach to mapping vegetation without cloud interference and identifying areas with high variability in cloud cover was presented by Wilson and Jetz (2016), Cloud frequencies were calculated on a global scale using an in-house cloud masking algorithm and the atmospherically corrected surface reflectance product MODIS MOD09. Removal of orbit and albedo artifacts was performed with the Variable Stationary Noise Removal (VSNR) technique, allowing the generation of monthly cloud climatologies for Terra and Aqua MODIS. Validation of these frequencies was carried out by comparing them with data from synoptic meteorological stations. Furthermore, tropical cloud forest and species distribution modeling techniques were applied using logistic regression models and Bayesian methods. The environmental data used included variables such as mean annual temperature, precipitation, and cloud metrics, derived from remote sensing and interpolated datasets. This approach allowed not only the efficient mapping of vegetation without interference from clouds but also the identification of areas with high variability in cloud cover.

To map and monitor deforestation and forest degradation in Guyana, Reiche et al. (2013) proposed remote sensing data fusion, combining information from the ALOS PALSAR sensor in Fine Beam Dual (FBD) mode with Landsat TM/ETM+ images, for 2007 and 2010. Using a decision tree classifier, features extracted from these data are integrated to classify the Forest Land Cover (FLC) and detect changes in FLC over time. Overall accuracy was 88% for mapping forest cover and 89.3% for detecting changes. The annual rates of deforestation (0.1%) and degradation (0.08%) observed from 2007 to 2010, mainly due to the expansion of mining, exceeds the country's reported average, emphasizing the importance of the region to Guyana’s REDD+ program. The approach offers a solution to cloud coverage challenges and data gaps directly contributing to Guyana's REDD+ monitoring and verification (MRV) objectives.

4.4 Land Use and Land Cover

To detect disturbances in tropical forests Joshi et al. (2015) presented a methodology for mapping both deforestation and forest degradation over time, as continuous progressions in space and time instead of discrete events, using radar in Madre de Dios, Peru. They utilized the L-band Synthetic Aperture Radar (SAR) sensor aboard the Advanced Land Observing Satellite (ALOS), from the dry season of 2007 to 2010, removing speckles, and variations unrelated to anthropogenic disturbances. The Enhanced Lee Filter algorithm was applied, and multiple backscatter change maps over time were utilized to identify disturbance areas. Disturbances were classified into slow and fast recovery changes based on the persistence of altered backscatter signal relative to 2007. To validate the algorithm, satellite imagery, visual inspection of known disturbance areas, and timber harvest data were employed. The temporal series was utilized to observe the same pixels on multiple occasions over time, allowing for a better determination of an area's status and increasing confidence in disturbance detection. This aided in distinguishing changes related to human activities from natural variations in backscatter. There was a 63% accuracy rate in identifying disturbances in agriculture and pasture areas, with a 0.3% false positive rate in detecting disturbances in remote forest areas. There were disturbances not detected by optical products, highlighting the effectiveness of radar in detecting forest disturbances and its importance for monitoring land use dynamics in tropical forests.

Zanotta et al. (2019) carried out a study to map the loss of forest cover in the Brazilian Amazon between 1984 and 2000 for the state of Rondônia, using the TM-Landsat 5 satellite, in comparison to the PRODES Amazônia system. The method involved identifying deforestation in the first image in the series, by using a supervised decision tree with forest samples and different types of deforestation, to create an intuitive decision rule and recursive detection, carried out continuously and employing a color-based method to identify deforestation polygons. This method considers the color tones of polygons, transforming the Red, Green, Blue (RGB) system into the Hue, Saturation, Value (HSV) system and using only the hue component, replicating the visual process of photo-interpreters. The results provide vector maps, allowing continuous mapping of deforestation fragments over time. According to the study, the deforestation rates recorded through the semi-automatic method carried out are consistent with the quantities verified by the tables published by the PRODES analog monitoring system of 41456.084 km² in Rondônia, Brazil. However, the lack of detail regarding the algorithm used and the omission of the precision of the results obtained make it difficult to evaluate and replicate the methods.

Ten years of deforestation data, detected by the Global Forest Change (GFC) initiative and SOS Mata Atlântica (SOS MA), were validated by Andreacci and Marenzi (2020) in the municipality of Araquari (384 km²), Santa Catarina. The GFC uses Landsat temporal reflectance metrics and assigns to deforestation pixels the name of the class equivalent to the year in which the loss of natural vegetation was recorded, starting in 2000. (Hansen et al., 2013). SOS MA classifies biannual or annual deforestation greater than 3 ha via visual interpretation. The study conducted a manual visual inspection of the deforestation polygons in each dataset to determine whether they corresponded to actual deforested areas. This analysis was performed using specific software tools, such as Open Foris Collect®, Collect Earth®, and Google Earth®. 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, despite not having no classification errors, identified only 31% of the deforestation accurately 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.

4.5 Small Fragments

Remote sensing methods for detecting small patches of deforestation, as in the case of the Atlantic Forest, face specific challenges, for which several techniques and approaches have been explored. In addition to the traditional Maximum Likelihood Classification (MLC), other techniques such as Classification and Regression Trees (CART), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and the Random Forest (RF) classifier have been used successfully. Additionally, methods such as AdaBoost and Oblique Tree Models have been explored to improve the detection of small patches of deforestation. These techniques are particularly useful when dealing with hyperspectral or multi-source images, where detecting small patches of deforestation can be defiant due to the complexity and presence of noise in the data (Belgiu; Drăguţ, 2016).

To ensure classification accuracy, in addition to reliable and precise data, the context and particularities of the classes must be taken into account. Lee et al. (2020) employed deep learning algorithms in remote sensing for the classification and segmentation of objects in high-resolution images, with an emphasis on the precise construction of training datasets to ensure the effectiveness of machine learning models, highlighting the use of convolutional neural networks (CNNs) such as CNN, LeNet-5, AlexNet, and GoogLeNet, and fully convolutional neural networks (FCNs) such as SegNet and U- Net. These models are trained using KOMPSAT-3 satellite imagery, for adequate spatial resolution, and algorithms such as SegNet and U-Net, with hyperparameter tuning to optimize accuracy, and a pre-processed AI dataset to eliminate errors. The results indicate that U-Net outperforms SegNet in overall accuracy, reaching 74.8%. Conversely, SegNet is better at classifying forests and bare land while classification accuracy varies with the size of the areas, being higher for forests and lower for smaller areas. Deep learning algorithms proved to be effective in classifying land cover from satellite images, however, it depends on an appropriate algorithm choice. Also, more research to improve accuracy in smaller areas is necessary.

To further analyze the implications of automatic mapping deforestation in the Atlantic Forest, Table 1 summarizes how some biome's particularities relate to methodological aspects, opportunities, and challenges presented so far, as well as possible recommendations 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 from remote sensing in the Atlantic forest.

Atlantic Forest Issues	**Methodological alternatives**	**Opportunities/ possibilities/ perspectives**	**Challenges**	**Recommendations**	**Reference**
Seasonality	Vegetation Index thresholds	Determining thresholds of NDVI and EVI to differentiate forests from non-forests.	Indices sensitive to seasonality: high values in the rainy and low values 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	Locally adjusting classification by ecoregions	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 the cloud masking procedure can interfere with the visual analysis	To run new tests with different mosaics and time frames are needed	PRODES-MA (paper being prepared/sub mitted for publication)
	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)

Continue

Atlantic Forest Issues	Methodological alternatives	Opportunities/ possibilities/ perspectives	Challenges	Recommendations	Reference
Land Use and Land Cover	Automatic detection of annual forest removal 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)
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)

Source: The authors (2024).

5 CONCLUSIONS

Automatic deforestation detection from remote sensing data in the Atlantic Forest presents many methodological challenges. The transition to Sentinel-2 images in the PRODES-MA 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 promising 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 deforestation based on image time series 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 spatial resolution images remains critical for validation.

The PRODES-MA represents an important instrument to support the deforestation monitoring in this biodiversity hotspot. To improve the system to a semiautomatic interpretation, this article highlights two main considerations: (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.

Beyond all challenges noted in this review, maintaining adequate results accuracy is a prerequisite for migrating to a semi-automatic detection methodology. The accuracies of PRODES 2022 mapping, based on human visual image interpretation, for 108 priority scenes in the Legal Amazon and the Cerrado biome as a whole were 98.8% and 94.3%, respectively (INPE, 2022). These values are much higher than those found when evaluating automatic classification, such as Braga (2023) which showed an accuracy of 66% for an area in the municipality of Campina do Monte Alegre, São Paulo state. Correia et al. (2011) justified that manual mapping was more viable than automatic mapping. Even though the PRODES took longer time it was easier to identify the land cover change, allowing for greater precision in the interpretation of deforested areas. The automatic mapping was faster but had confusing results specifically for deforested areas.

In summary, some methodological challenges to be considered in the process of automating deforestation detection are: 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-free 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, although challenging, a promising opportunity for improving deforestation mapping accuracy is the classification of time series.

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Author’s Contribution

The five authors were responsible for the research, conceptualization, writing, revision, and final edition.

Conflict of Interest

The authors explicitly state that they have no conflicts of interest to disclose, affirming that neither funders nor personal relationships have influenced any aspect of the study, including its development, data analysis, manuscript composition, or decision to publish the findings.

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