Monitoring Amazon Forests using LandTrendr and MapBiomas: A Case Study from Trincheira Bacajá, Pará (2018–2023)

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Abstract

The growing pressure on the ecosystems of the Amazon Biorne highlights the need for continuous monitoring of vegetation cover, especially in sensitive areas such as Indigenous lands. This study aims to identify and analyze forest change trajectories in the municipality of São Félix do Xingu, with an emphasis on the Trincheira Bacajá Indigenous lands reservation during the period from 2018 to 2023. ln the analysis, two approaches were compared using Landsat historical series. The first one is the LandTrendr algorithm, which was applied on the Google Earth Engine platform. The second one is based on the yearly land cover maps of the MapBiomas project. The comparison between the methodologies showed that, although they differ in sensitivity and detection criteria, both identify consistent patterns of forest suppression areas in the region. LandTrendr enables a more detailed analysis, while the MapBiomas-based approach is more straightforward. The high spatial convergence of the results reinforces the importance of integrating multiple approaches for forest monitoring in Indigenous territories and land reform settlements, contributing to the support of public policies aimed at conservation and environmental protection.

1. Introduction

With nearly four million square kilometers, the Amazon spans eight Brazilian states and is home to 125 federal conservation units, playing an important role in global climate regulation and carbon sequestration (ICMBio, 2021). Despite its environmental significance, the region has historically been a target of exploitation and occupation due to its abundance of natural resources, as noted by Nogueira *et al.* (2019). This context turns the Amazon rainforest into a space of conflicting interests, especially economic and territorial, resulting in constant pressure on native vegetation. Moreover, the vast areas of Indigenous territories---often inadequately protected against the expansion of illegal and predatory activities-render these populations and their lands particularly vulnerable.

Brazil holds over 50% of the Amazon within its territory, making it one of the richest countries in forest cover in the world. However, in recent decades, Brazil has emerged as one of the world's primary contributors to tree cover loss (Simonet *et ai.,* 2019). Carvalho *et ai.* (2020) emphasize that deforestation in the Amazon is the main factor responsible for the destruction of natural resources and the environment. Uncontrolled urban growth and the expansion ofthe agricultura! frontier, for instance, contribute to the increasing demand for land (Monteiro & Bernardes, 2024).

Faria *et al.* (2018) observed a shift in the deforestation profile in the Amazon in recent years, marked by increasing rates of small-scale deforestation. This includes forest degradation associated with sequential, small-scale clearing, largely driven by the diversification of productive activities linked to family farming. ln the Amazon, the state of Pará stands out due to its strategic location, the significant transformation of natural landscapes resulting from agricultura! expansion, and its key role in the distribution of Agrarian Reform lands.

According to Coelho-Junior *et al.* (2022), satellite monitoring of the Brazilian Amazon shows that deforestation has intensified in the biorne since 2012, increasing by 140% from 2012 to 2020. Between August 2020 and July 2021 alone, the Amazon lost 13,200 km^2-the highest deforestation rate in 15 years. The average size of deforestation polygons has also increased by 61% over the past decade, compared to earlier periods when environrnental policies forced offenders to reduce the size of deforested fragments. ln 2019, the government significantly reduced the budget for environmental agencies and altered procedures for holding violators accountable. As expected, these changes undermined the effectiveness of command-and-control efforts, leading to fewer infraction notices in the Amazon region and fostering a combination of impunity for environmental offenders, worsening climate issues, and accelerating deforestation.

Given this reality, the use of remote sensing time series is very important for continuous monitoring of forested areas in the Amazon rainforest, allowing for the identification of both abrupt and gradual forest loss and the distinction between temporary seasonal variations and permanent disturbances. Such a temporal perspective is essential to understand and track changes in vegetation cover over time, to propose and implement solutions for the rational use of natural resources, and to support conservation policies and sustainable land management. Moreover, continuous monitoring is necessary to ensure the protection of lndigenous territories by overseeing agrarian expansion and settlements, safeguarding both environmental preservation and the traditional ways of life of local populations.

ln this context, the aim of this study is to identify forest change evolution and trends in the municipality of São Félix do Xingu,

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which includes part of the Trincheira-Bacajá Indigenous territory, with an emphasis on detecting disturbances and forest loss between 2018 and 2023. To achieve this, remate sensing time series were analyzed using two approaches: one based on the LandTrendr methodology and another based on the analysis of the MapBiomas maps, in order to assess pattems, trends, and potential discrepancies.

2. Literature review

Landsat historical archive provides valuable information for analyzing land-cover time series. Landsat data has been widely used for monitoring environmental changes (Kennedy *et al.,* 201O), especially disturbances, because it allows covering extensive areas with moderate spatial resolution and includes spectral bands in the visible and infrared regions.

However, a criticai challenge in using Landsat time series is the frequent presence of clouds and shadows, which may affect the consistency of spectral information. To address this, cloud and shadow masking algorithms such as Fmask (Zhu & Woodcock, 2012; Zhu et ai., 2015) have been developed and are now widely adopted in large-scale analyses. These algorithrns improve the quality of input data by automatica\ly identifying and removing contaminated pixeis, thus enhancing the reliability of temporal trajectory analyses.

Comprehensive reviews of literature on remate sensing time series analysis are available in Roy *et al* (2017). The approaches can be classified into two main groups: approaches that analyse the land cover evolution based on thematic maps; and approaches that compute the differences of each spectral band and build a temporal trajectory of each pixel within the feature space.

Trajectory-based methods model spectral curves over time to extract attributes such as duration, magnitude, and timing of events (Fragal et ai., 2016). For example, the duration indicates the persistence of forest loss or regeneration; the magnitude reflects the intensity of spectral variation; and the starting date reveals when the disturbance began. These attributes are particularly important in tropical environments, where seasonal vegetation dynamics can obscure or overlap with human-induced disturbances. By analyzing the spectral trajectory at the pixel levei, it becomes possible to distinguish temporary fluctuations from persistent land-cover changes.

Banskota *et al.* (2014) classify these methods into categories such as thresholding, curve fitting, hypothetical curves, and segmentation. Among these, trajectory segmentation approaches have gained increasing attention due to their ability to capture both abrupt and gradual changes across long temporal series. Algorithrns such as LandTrendr (Kennedy *et ai.,* 2007) and CCDC (Zhu & Woodcock, 2014) are well-known examples. LandTrendr, for instance, focuses on detecting high-magnitude events, such as forest clear-cutting or fire, while also accounting for event duration, which reduces confusion with seasonal variability. CCDC, in tum, performs continuous monitoring through harmonic modeling of spectral trajectories, making it particularly effective for identifying gradual or subtle changes. These methods have become central in forest monitoring applications because they allow detecting long-term degradation processes as well as sudden disturbances.

ln parallel, vegetation indices such as NDVI are frequently used to characterize canopy changes, since they are sensitive to vegetation structure while minimizing topographic and illumination effects (Jensen, 2009; Ponzoni & Shimabukuro, 2009). When integrated into trajectory-based methods, NDVI trajectories enhance the ability to detect changes in canopy cover, while also facilitating interpretation by linking spectral variation to ecological processes such as regeneration or degradation.

On the other hand, map-based approaches such as MapBiomas generate yearly land-cover and land-use maps using machine learning. MapBiomas is a collaborative initiative involving public and private institutions, producing annual classifications for Brazil at national scale. Its products include classes such as forest, agriculture, pasture, urban areas, water, and others, thus enabling multi-class land use and cover assessments. The methodology is based primarily on Landsat imagery (TM, ETM+, and OLI), complemented in recent years by Sentinel-2 data. These images are pre-processed into annual cloud-free composites with the aid of the Fmask algorithm and other spectral filters to reduce atmospheric and cloud contamination. Classification is then performed with the Random Forest algorithm, which benefits from a large set of training samples and decision-tree ensembles to improve accuracy. After classification, temporal and spatial filtering procedures are applied to eliminate noise and correct misclassification, thereby increasing the reliability and consistency of the historical database.

ln this study, we analyze vegetation cover within an Indigenous territory and a land reform settlement in the municipality of São Félix do Xingu using both approaches: LandTrendr (trajectory-based) and MapBiomas (map-based). This dual perspective enables us to compare the capacity of each method to detect abrupt versus gradual disturbances, while also assessing their suitability for local-scale monitoring in the Amazon biorne.

3. Study Area

The study was conducted in the Trincheira Bacajá Indigenous territory. According to Beltrame (2019) and Mantovanelli (2016), this lndigenous territory covers an area of 1,651,792.26 hectares and is home to the Xikrin people, who self-identify as Mêbêngôkre. The authors also locate this area along the Bacajá River, a right-bank tributary of the Xingu River, in the Volta Grande do Xingu region. Junior et ai. (2017) mention that, according to the Kõppen classification, the Bacajá River Basin region has a predominantly humid tropical climate (Am type), with an annual average temperature ranging between 25ºC and 27ºC, annual rainfall of 1,885 mm, and relative humidity between 78% and 88%.

A study area of 162,488.9 hectares was used, cons1stmg of approximately 74.2% ofthe Trincheira Bacajá lndigenous Land, 13.1% of the land reform settlement, and 12.7% of the municipality of São Félix do Xingu. This region is located in the southwestern part of the state of Pará, between the municipalities of Altamira, Anapu, São Félix do Xingu, and Senador José Porfirio. The location map (Figure 1) was created

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using UTM coordinates based on the WGS 84 datum.

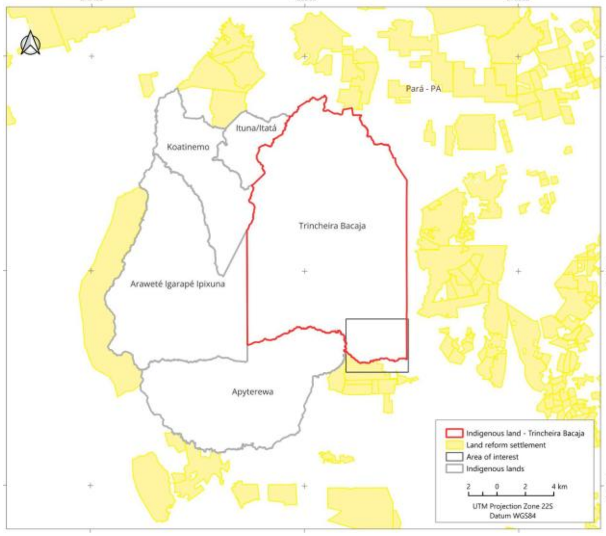

Figure **1** - Study Area: Southem part of the Tricheira Bacajá Indigenous land, the land reform settlement and the municipality of São Félix do Xingu in Brazil

The region has recently become known for the construction of the Belo Monte hydro dam, which had serious consequences for the surrounding region, by affecting the water flow of the Xingu River and its tributaries, including the Bacajá River (Oliveira and Cohn 2014). Xikrin, B., & Bollettin (2022) also say that along with this mega-infrastructure, the region experienced a greatly accelerated process of invasion of the various Indigenous Lands in the region, which had devastating effects on the environment and social life of these people. Although invasions and expropriations of lndigenous Lands are nothing new in the Amazon, they have increased in recent years with the accelerated advance of the exploratory economy in the forest. Severa! invasions have also occurred along the borders of the Trincheira-Bacajá Indigenous Land, and in the surrounding towns, trucks can be seen illegally transporting timber and removing tons of logs from the area.

4. Methods

Land use/Land cover changes in the study area in the period between 2018 and 2023 was monitored using Landsat remate sensing images. The LandTrendr algorithm was applied within the Google Earth Engine (GEE) platform. The result was compared to changes detected within the MapBiomas platform. Additional computations were performed using scripts developed within the Google Colaboratory environment.

For this study, the analysis period was defined from 2018 to 2023, using corresponding Landsat satellite images and the LandTrendr algorithm within the Google Earth Engine (GEE) platform. LandTrendr detects changes within the series of each pixel using the digital values in severa! spectral bands. This included applying masks, temporally segmenting forest trajectories, and mapping their characteristics. ln the study, Landsat 8 (OLI) images were used for the period from 2014 to 2020, and Landsat 9 (OLI-2) for the period from 2021 to 2024. Although the core focus of the analysis is the 2018-2023 period, earlier Landsat images were included to build a more robust 10-year time series. This temporal extension allowed LandTrendr to distinguish gradual processes from abrupt disturbances, enhancing segmentation accuracy. By incorporating this broader temporal range, the model benefits from a richer dataset, enabling a more accurate reconstruction of land use and land cover trajectories over time. This initial approach ensures greater robustness in the modeling process before narrowing the scope to comparative data with MapBiomas.

The presence of clouds, shadows, and water bodies compromises the quality of the analyses, affecting image composition, atmospheric correction, spectral index calculations, land cover classification, and change detection, due to their influence on the spectral bands of optical sensors. To minimize these effects, it was used the Fmask algorithm, which applies automatic masks to remove clouds, shadows, and water, ensuring greater accuracy in data analysis.

To detect significant vegetation changes, the LandTrendr model parameters were fine-tuned. Nine input variables were adjusted to optimize the spectral-temporal segmentation of the image series. This calibration enabled precise identification and analysis of disturbances on an annual basis, allowing for a focused examination of key periods of interest.

LandTrendr includes nine trajectory analysis parameters, which are adapted according to the physiognomy of the area of interest:

- starting year: 2014;
- final year: 2024;
- starting day: January 1;
- Final day: December 31;
- var-index: NDVI;
- mask: clouds, shadows and water.

After the computation ofthe trajectory, the temporal variation of each pixel was segmented to detect key points along tbe time series. LandTrendr allows computing some features, listed in table **1,** tbat enable detecting peaks tbat characterize rapid cbanges. lt is necessary to adapt tbe LandTrendr trajectory analysis parameters to the physiognomy of the area of interest. This was performed and the values are displayed in Table 1.

Parameter	Value	Definition
maxSegments	10	Maximum number of segments fitted to the time series
spikeThreshold	0.15	Threshold for normalizing spikes
vertexCountOvershoot	4	Extra number of vertices allowed beyond the segment limit to capture potential changes
preventOneYearRecove1y	True	Prevenis a partia! one-year recovery from being classified as a change
recoveryThreshold	0.7	Threshold to determine when a recovery is considered significant
pva!Threshold	0.05	p-value threshold to determine whether a change is statistically significant
bestMode!Proportion	0.15	Removes from the model the vertices above the given value
minObservationsNeeded	8	Minimum number of observations required in a segment for model fitting
time series		Collection of images used to extract trends; the first band is used to detect breakpoints, and ali

		subsequent bands are used to analyze those changes

Table **1** - Segmentation Parameters of LandTrendr. (from: Kennedy, 2018)

By configuring the segmentation parameters of the LandTrendr algorithm, disturbances were successfully identified across the annual time series. Based on these results, the years 2018 to 2023 were selected as the period of interest, during which vegetation changes were captured using NDVI values. These changes were then analyzed through frequency histograms, with ali processing carried out in Google Colaboratory.

The second approach is based on the MapBiomas Collection 9 database. To ensure consistency in this comparison, it was used land use and land cover (LULC) maps from MapBiomas Collection 9, available on the Google Earth Engine platform. The MapBiomas maps were processed to extract forest vegetation cover. **ln** this classification system, each land cover class is represented by a numerical code. For the purposes of this study, the classes "Forest," "Forest Formation," "Savanna Formation," "Mangrove," and "Floodable Forest," corresponding to codes lower than 7, were grouped and interpreted as forest areas, encompassing both primary and secondary forests. This criterion justifies the consideration of values less than 7 as representative offorest cover.

The annual images were extracted, clipped, and processed for the area of interest, which includes the Trincheira Bacajá lndigenous Land. These data allowed for the identification of areas of vegetation suppression, as indicated in the maps. The evolution of these classes was computed in the period 2018-2023, to establish an estimate of forest changes in the study area. This process allowed for a clear and objective representation of the spatial and temporal distribution of vegetation.

A comparative analysis was subsequently carried out to assess the spatial correspondence between disturbance areas identified by both methods. This comparison was conducted using geoprocessing techniques within a GIS environment, employing operations such as *intersect* to quantify the degree of overlap between the results produced by LandTrendr and the official MapBiomas data in detecting changes in vegetation cover within the study area.

Annual composites of relevant spectral bands were generated, with spatial and temporal filtering applied to reduce noise, ensuring higher reliability in vegetation change detection. The processing was conducted on the Google Colaboratory platform, where metrics were extracted to automatically generate polygons corresponding exclusively to deforested areas within the area of interest. The resulting classified maps enabled the identification of vegetation loss over time, supporting the analysis of deforestation trends. These classified maps facilitated the temporal assessment of vegetation loss, providing a robust basis for analyzing deforestation dynamics within the study region.

5. Results and Discussion

After choosing the best parameters in LandTrendr, it was possible to map the occurrence of severe changes in the study area, as displayed in Figure 2.

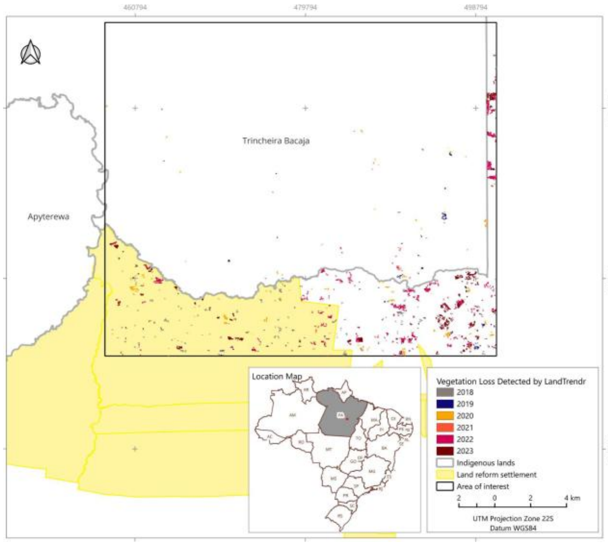

Figure 2: Map of vegetation suppression according to LandTrendr

As observed in the map, the algorithm detects abrupt changes in land use and land cover, being particularly sensitive to areas where vegetation loss occurred and did not recover within a one-year period. The resulting map shows that the changes increased over time, being stronger in the year 2022 and a similarly high number of vegetation loss in the year 2023. ln spatial terms it is also visible that the vegetation was substituted by agriculture in the Southem portion of the image during the first years. This is expected, as this region lies outside of the protected area. The results also point out that the changes during the last years also happen within the protected area, enhancing the invasion of the farmers in the area.

Figure 3 illustrates the evolution of vegetation loss, calculated from the pixeis identified in the analyses performed by LandTrendr. It can be observed that, in the initial years of the analysis (2018-2021), there was an average suppression of approximately 160 hectares per year, followed by a significant increase to about 730 hectares per year in the last two years (2022-2023). This indicates that the annual deforestation in this recent period was approximately 4.6 times higher compared to the average ofthe initial years in the study area.

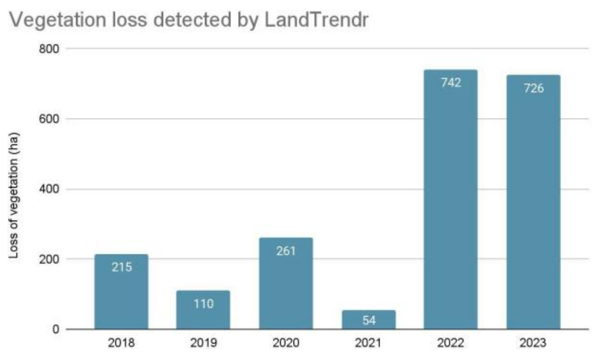

Figure 3 - Temporal evolution of vegetation loss detected by LandTrendr (in hectares)

ln the case of MapBiomas (Figure 4), the analysis focused on the annual detection of deforestation events, with each color representing the year in which vegetation loss occurred. This allows the visualization ofthe spatial and temporal dynamics of land cover change in the study area. The map reveals that vegetation suppression has progressively advanced from the southem portion towards the northern sectors, with more recent events (2022-2023) occurring inside the protected area.

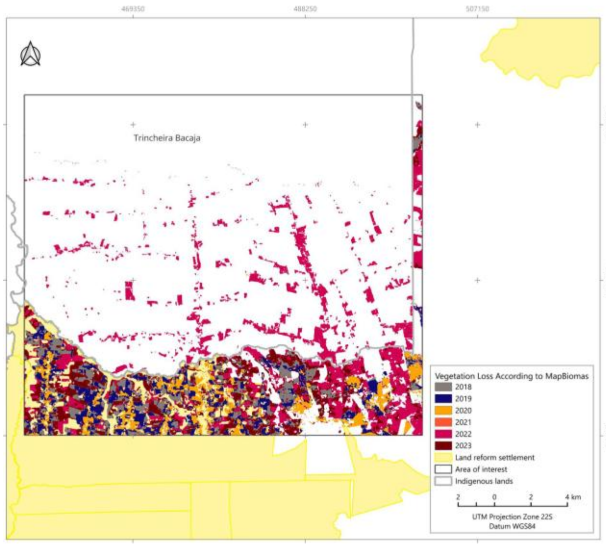

Figure 4: Map of vegetation suppression according to MapBiomas

The histogram of detected trajectories (Figure 5) highlights six dominant patterns of change, corresponding to different combinations of years in which deforestation was registered. The largest peak corresponds to areas where vegetation was removed in recent years (2022 and 2023), confirming the intensification of forest loss during this period. Earlier peaks (2018-2020) reflect the initial stages of agricultura! expansion in the southern region, while intermediate values (2021) indicate the continuity ofthe process before the marked increase observed in the last two years.

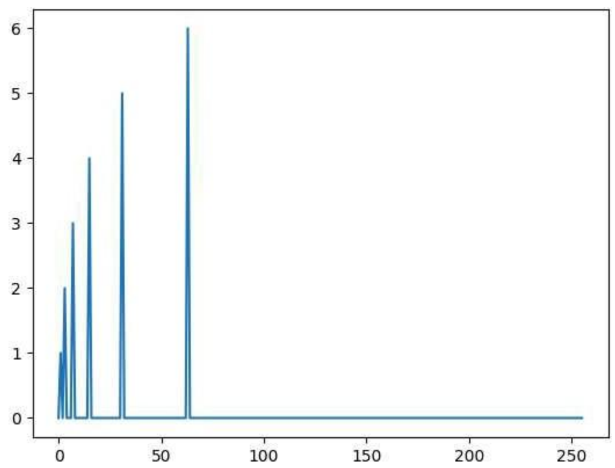

Figure 5: Histogram according to MapBiomas

Unlike LandTrendr, which is optimized to detect abrupt breaks in spectral time series, the MapBiomas approach assigns a specific year of suppression, providing an annualized perspective of deforestation dynamics. This makes it possible to trace the temporal trajectory of forest loss in a straightforward manner, evidencing both the consolidation of agricultura! frontiers outside the protected area and the increasing encroachment into lndigenous lands.

Overall, the MapBiomas results confinn the patterns identified by LandTrendr but present them in a categorical and temporally explicit way, reinforcing the conclusion that deforestation accelerated significantly after 2021 and has expanded into areas that were previously preserved.

As MapBiomas provides a thematic image every year, the analysis is restricted to the yearly variation. Therefore, it is evident that Landtrendl can provide a more detailed view on the evolution of land cover. Nevertheless, a yearly analysis can be considered enough to map problems like deforestation and vegetation recovery.

The comparison ofthe LandTrendr product and the MapBiomas analysis revealed that both approaches enable detecting vegetation suppression events, but there are some differences. LandTrendr detected three significant events during the analyzed period, while MapBiomas identified six. This difference occurs because LandTrendr is designed to detect high-magnitude events, which are directly tied to pixel-levei variations. ln our study, such events are related to vegetation suppression like clear-cutting or fire. Furthermore, LandTrendr considers the duration of the change, requiring that the suppression is visible in continuous sequences for more than one year. This accounts for the seasonal variations typical ofthe Amazon biome's vegetation structure.

On the other hand, the MapBiomas based approach detects changes analyzing individual pixeis through year-to-year comparisons, a method that tends to generalize areas of vegetation suppression on an annual basis. The Mapbiomas thematic maps are carefully produced, on a yearly basis. For each specific year, it is used training samples derived from previous years and validated through field verification.

Figure 6 illustrates the polygons identified by MapBiomas and their spatial convergence with the disturbances detected by LandTrendr. However, it is also evident that MapBiomas, dueto its classification methodology based on annual mosaics, identifies a greater number of change areas that are not confirmed by LandTrendr. This discrepancy may be attributed to MapBiomas' higher sensitivity to subtle or short-term changes that do not persist across multiple years in the time series, a key criterion used by LandTrendr to validate a disturbance.

Anotber relevant aspect is the linear pattem of many of these areas of vegetation loss, associated with the opening of roads and access routes, which act as vectors of penetration into the territory. The convergence between the MapBiomas polygons and the LandTrendr results reinforces the consistency in detecting degraded areas, confirming the significant overlap between different data sources.

ln general, the cartographic analysis demonstrates that, although deforestation in Trincheira Bacajá is a historical process, its recent intensification, particularly after 2018, indicates an accelerated advance into previously preserved areas, threatening both forest conservation and the territorial integrity of lndigenous lands.

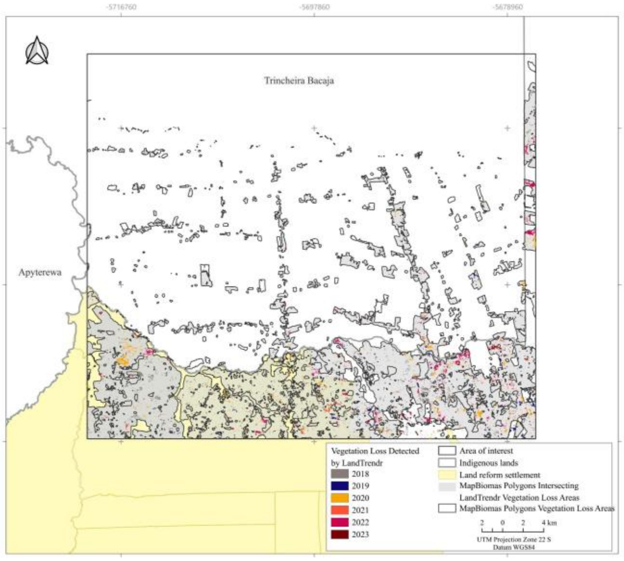

Figure 6: Maps of vegetation suppression according to MapBiomas and LandTrendr.

It is important to highlight the differences between the methods. **ln** the case of LandTrendr, digital values from ali possible satellite images are employed to identify disturbances computing the temporal trajectory of each pixel, thereby enabling the detection of deforestation events based on significant changes in spectral pattems over time. MapBiomas, on the other hand, adopts a machine Jearning-based approach.

Visualizing the satellite imagery (Figure 7), both the areas identified by MapBiomas and those detected by LandTrendr predominantly correspond to zones where forest vegetation suppression has occurred. The visual pattems in the imagery, such as abrupt changes and spectral response, support the interpretation that these regions have undergone significant disturbances, likely dueto activities such as clear-cutting or fire. This visual confirmation reinforces the reliability of both datasets in identifying deforestation events, particularly in regions where vegetation remova! is more evident.

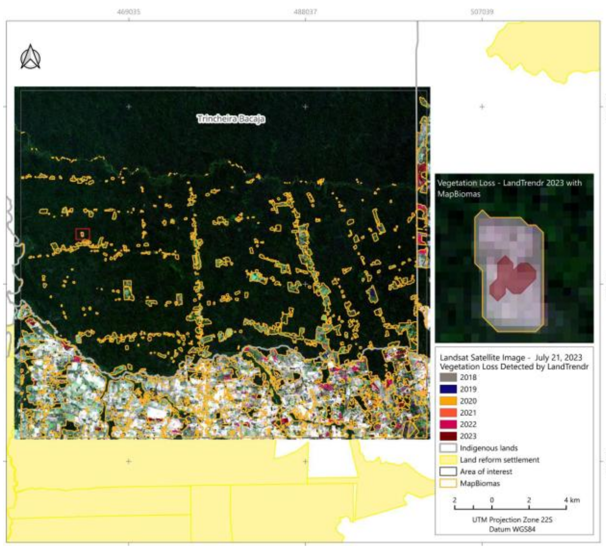

Figure 7: Maps of vegetation suppression according to MapBiomas and LandTrendr.

Despite these methodological differences, a high levei of convergence between the results is observed: more than 93% of the pixeis identified as disturbed by the LandTrendr algorithm between 2018 and 2023 coincide with areas classified as vegetation suppression by MapBiomas. This consistency suggests that the combined use of these tools can enhance the accuracy of environmental monitoring, particularly in sensitive areas such as Indigenous territories and regions under intense human pressure. Both methodologies demonstrate strong capabilities for validating affected areas

6. Conclusion

ln the paper, a comparative study ofthe evolution ofvegetation cover within an Indigenous lands and Jand reform settlement was introduced. Two methodologies were compared: LandTrendr and Mabpiomas thematic maps. We can conclude that these are two distinct methodologies for assessing vegetation suppression in Amazon forest areas. The results revealed that both have different sensitivities to suppression, yet they identify very similar areas, albeit in different proportions. Additionally, we observed that these areas converge on the same vegetation suppression zones, validating both methods through visual interpretation.

We emphasize the importance of these findings in regions facing environmental issues, such as the Amazon biorne. We understand that expanding the study area, conducting field evaluations, and carrying out further research are necessary steps toward identifying these areas more accurately and supporting the development of public policies aimed at addressing vegetation suppression.

The combined application of these methodologies can be further explored in future studies, with the goal of validating the vegetation suppression detection data released annually by MapBiomas. Cross-application between the methods strengthens the reliability of the results and increases the robustness of analyses in criticai areas such as the Amazon biorne.

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