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RECEIVED 26 February 2026
REVISED 22 May 2026
ACCEPTED 25 May 2026
PUBLISHED 16 June 2026

CITATION
Potapov P, Turubanova S, Rosa M,
Teixeira L, Shimbo J, Zalles V, Sims MJ,
Stanimirova R, Lima A, Goldman E,
Harris N and Stolle F (2026) Evaluation of
operational satellite-based disturbance
detection products in Brazilian primary
forests for the years 2023 and 2024.
Front. Remote Sens. 7:1818592.
doi: 10.3389/frsen.2026.1818592

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Evaluation of operational satellite-based disturbance detection products in Brazilian primary forests for the years 2023 and 2024

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Operational forest monitoring is essential for the effective implementation of national and international initiatives to reduce deforestation and forest degradation. Such monitoring systems are especially important within Brazilian humid tropical primary forests, where they support enforcement of national policies to prevent deforestation. Several satellite-based forest disturbance monitoring systems are operating in Brazil, including MapBiomas Alerta (MBA), Tree Cover Loss supported by Global Forest Watch (TCL), and Tropical Moist Forest developed by the European Commission's Joint Research Centre (TMF). These systems differ in their forest disturbance definitions, input satellite data, and change detection methodologies. As a result, their annual estimates of primary forest disturbance are not fully consistent, which complicates the implementation of forest conservation policy and introduces uncertainties and potential bias in greenhouse gas emissions accounting. In this study, we followed good practice recommendations to evaluate the performance of these monitoring products to detect humid tropical primary forest disturbances in 2023 and 2024 using a probability reference sample. We compared the map-based and sample-based disturbance areas for each product and estimated their sensitivity and precision for primary forest disturbance detection. Our analysis showed that the MBA product mapped 64%–65% of the sample-based reference deforested area while maintaining the highest mapping precision among the three systems. The TCL product detected the highest percentage of the reference deforested area (82%–94%), while maintaining high precision for mapping high-severity, stand-replacement disturbances. TMF outperformed other products in capturing low-severity disturbances. The detailed comparative evaluation of the three operational monitoring systems highlights their respective strengths and

limitations and explains the differences in forest disturbance reporting. Our results provide guidance for researchers, policymakers, and practitioners in selecting the most appropriate products for specific applications.

KEYWORDS

deforestation, forest change, forest disturbance, forest fires, forest monitoring, Landsat, Planet

1 Introduction

Primary tropical forests have exceptional importance for regulating the Earth's climate and maintaining species diversity. These forests store 49%–53% of the total tropical forest carbon and contribute significantly to carbon sequestration, absorbing up to 13% of the anthropogenic emissions (Mackey et al., 2020). Primary tropical and subtropical forests provide habitat to at least 50% of the terrestrial plant and animal species (Dinerstein et al., 2017), while their degradation and conversion cause a substantial reduction in species diversity (Gibson et al., 2011).

Primary tropical forests are competing with agriculture and forestry for the most productive terrestrial environment on Earth. Growing global demand for food, fiber, and mineral resources has driven their industrial conversion over recent decades (Hansen et al., 2013; Turubanova et al., 2018; Potapov et al., 2022; Sims et al., 2025). At the same time, population growth has led to the expansion of subsistence agriculture, an equally important cause of primary tropical forest degradation (Tyukavina et al., 2017; 2018; Sims et al., 2025). The recent increase in fires within tropical forests (Potapov et al., 2025) illustrates the climate change feedback that intensifies land cover change and may lead to an irreversible tipping point in the humid tropical forest biome (Flores et al., 2024).

Brazil contains the largest share of the remaining primary tropical forests, making their conservation a priority for meeting national zero deforestation commitments and international climate and biodiversity targets (Turubanova et al., 2018). The humid tropical forests of the Amazon Basin are among the most important forest regions on the planet because of the number of species they harbor and the services they provide (Foley et al., 2007). Smaller remnants of primary forests in the Atlantic Forest and Cerrado biomes are important as examples of native ecosystems within these largely converted forest regions (Ribeiro et al., 2009; Pompeu et al., 2024).

Over the past half-century, agricultural expansion has been a major driver of deforestation in Brazil (Zalles et al., 2019). Deforestation in the Amazon reached its maximum in 2004, but declined significantly over the last 2 decades, following the economic crisis of 2008 and the implementation of effective international and national policies (Arima et al., 2014). The Action Plan for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), launched in 2004, enabled a sharp reduction of deforestation (West and Fearnside, 2021). Another important intervention that helped to reduce tropical deforestation was the Amazon Soybean Moratorium, which successfully reduced deforestation directly linked to soybean expansion (Heilmayr et al., 2020).

The implementation of deforestation suppression policies requires a robust and timely forest monitoring system (Heilmayr et al., 2020; Nepstad et al., 2014). The demand for such a monitoring

system was one of the main forces that stimulated the development of satellite-based remote sensing technologies and machine learning methods. From the early approaches using manual image interpretation (Skole and Tucker, 1993; Achard et al., 2002) and coarse resolution data (Hansen et al., 2008) to the globally consistent 30-m operational mapping (Hansen et al., 2013; Vancutsem et al., 2021) and the recent near-real-time monitoring systems employing machine and deep learning techniques (Doblas et al., 2022; Reiche et al., 2021; Hansen et al., 2016; Mullissa et al., 2023; Tang et al., 2023; Pickens et al., 2025), continental and national-scale tropical forest monitoring has been the focal point of Earth observation technology development. Operational forest monitoring systems provide spatially explicit time series data that enable rapid detection of deforestation and degradation, support enforcement actions, and form the basis of national and international reporting. Operational monitoring also improves our understanding of climate-driven forest changes and supports Earth system modeling.

Several satellite-based operational forest monitoring products are currently available for Brazil, including PRODES (Programa de Cálculo do Desmatamento na Amazônia; Almeida et al., 2025) and DETER (Detecção do Desmatamento em Tempo Real; Diniz et al., 2015) developed by the Instituto Nacional de Pesquisas Espaciais (INPE), SAD (Sistema de Alerta de Desmatamento, originally implemented by the Brazilian non-government organization Imazon), Tree Cover Loss and Forest Loss Alerts (Hansen et al., 2013; Hansen et al., 2016; Pickens et al., 2025), and Tropical Moist Forest (Vancutsem et al., 2021), among others. While these products are critical for national forest conservation and reporting, they differ in their definitions of forest disturbance, input data, temporal frequency, and sensitivity to different disturbance types. As a result, they produce varying estimates of deforestation and degradation, which can complicate policy implementation and lead to uncertainties in greenhouse gas emission accounting.

Consistent performance evaluation of these monitoring products is therefore necessary to assess their reliability and identify their strengths and limitations for different applications. Without such evaluation, there is a risk of miscommunication of monitoring results, which could undermine the effectiveness of conservation policies and climate change mitigation strategies. In this study, we present a methodologically consistent evaluation of three operational forest monitoring products within Brazilian humid tropical primary forests using a probability reference sample following good practice recommendations (Olofsson et al., 2014; Tyukavina et al., 2025a). The analyzed products include MapBiomias Alerta (MBA, <https://plataforma.alerta.mapbiomas.org/api>), Tree Cover Loss (TCL, www.globalforestwatch.org), and Tropical Moist Forest (TMF, <https://forobs.jrc.ec.europa.eu/TMF>). Our analysis focuses on their performance for mapping annual primary forest loss and degradation within the Turubanova et al. (2018) primary forest

TABLE 1 Operational forest monitoring products used in our study.

Dataset characteristic	Map biomass alerta (MBA)	Global forest watch tree cover loss (TCL)	Tropical moist forest (TMF)
Source satellite data	Planet	Landsat	Landsat
Product format, spatial resolution, and minimal change detection area	Vector polygons of visually confirmed deforestation events with a minimum mapping area of 0.3 ha	Raster data with a pixel size of 30 × 30 m at the Equator, with a minimum mapping area of one pixel	Raster data with a pixel size of 30 × 30 m at the Equator, with a minimum mapping area of one pixel
Forest type in the preceding year	Natural forest	Tree canopy cover of at least 5 m height, including natural and planted trees	Closed-canopy evergreen or semi-evergreen natural forest
Forest disturbance drivers and types	Mechanical clearing, which is defined as the complete removal of natural vegetation	Human-driven and natural disturbances that caused the removal of at least 50% tree cover within the Landsat pixel	Deforestation (permanent conversion to non-forest land) and degradation (temporary forest loss followed by forest recovery)
Update interval and start year	Weekly updated since 2019	Annually updated since 2001	Annually updated since 1990

extent in the context of the annual World Resources Institute (WRI) Forest Pulse reporting (Goldman et al., 2025). We performed the analysis for the years 2023 and 2024, which differ in terms of forest disturbance dynamics, specifically, the extent of forest fires. Our results provide insight into the performance of these products and offer guidance for their practical use.

2 Data and methods

2.1 Forest disturbance monitoring products

We evaluated the performance of three operational annual forest disturbance monitoring products available within the Brazilian humid tropical primary forests (hereafter referred to as “primary forests”) during the full calendar years 2023 and 2024 (Table 1). Each of these products provides annual maps of forest disturbance; however, they use different definitions of forests and forest disturbance. By restricting our analysis to primary forests, we ensured that the analysis extent and the reporting interval (January to December) are consistent between these products. We did not evaluate PRODES, the oldest Brazilian forest monitoring system, due to the difference in reporting intervals (August to July) and the large minimum deforestation mapping area (1 ha; Almeida et al., 2025). We also did not consider near-real-time products, such as GLAD-L (Hansen et al., 2016) and DIST-ALERT (Pickens et al., 2025), which are not designed for annual reporting.

2.1.1 MapBiomass alerta (MBA)

MBA provides maps of deforestation in Brazil, validating alerts from different sources with high spatial resolution satellite imagery. The MBA defines deforestation as the complete removal of native vegetation, including forests and non-forest vegetation, such as savannas. The product is operationally updated weekly by the collaborative network of co-creators comprising non-government organizations, universities, and private companies. MBA does not generate its own deforestation alerts but relies on analyst-based image confirmation and refining deforestation events at locations

detected by the near-real-time forest monitoring systems such as DETER (Diniz et al., 2015), SAD, and GLAD-L (Hansen et al., 2016). For each alert, an analyst visually determines the presence of deforestation and, if confirmed, refines the deforestation polygons using high-resolution Planet imagery. The MBA delivers confirmed and refined vector polygons of deforestation events with a minimum size of 0.3 ha (depending on the biome and alert sources available). Each polygon is attributed to the disturbance date and disturbance driver. The MBA product is available at <https://plataforma.alerta.mapbiomas.org/api>. It comprises weekly updated data from January 2019 to the present. We used all the MBA deforestation polygons available by September 2025 for our analysis.

2.1.2 Tree cover loss (TCL)

TCL is a global annual forest monitoring product that has been developed by the University of Maryland and Global Forest Watch (Hansen et al., 2013). Since 2015, TCL has been produced using the annual change detection algorithm developed by Potapov et al. (2019) using Landsat Analysis Ready Data time series (Landsat ARD, Potapov et al., 2020), which consists of normalized, cloud and cloud shadow-filtered, and consistently gridded imagery optimized for time-series analysis. The TCL algorithm relies on a set of regional tree cover loss detection models, which are implemented annually using an automated workflow. The output of these automated models is thoroughly checked by an analyst to remove artifacts. The TCL objective is to detect tree cover loss events defined as the removal or mortality of woody vegetation at least 5 m in height that affects at least 50% of the Landsat 30-m pixels. The TCL product does not record repeated disturbance events; only the year of the first detected tree cover loss event since 2001 is recorded. Tree cover loss includes disturbances in naturally regenerated and planted forests due to natural and anthropogenic drivers. The TCL product is available through the Global Forest Watch data portal of the World Resources Institute (www.globalforestwatch.org) and is updated annually. Here, we used the years 2023 and 2024 of TCL for product evaluation.

The annual TCL is attributed to “fire-related” and “other” disturbances by two products: the 30-m spatial resolution fire-related TCL product by Tyukavina et al. (2022) and the wildfire

category from the 1-km forest loss drivers product (Sims et al., 2025). Because existing fire attribution products differ in methodology and spatial resolution, we used both products to assess the robustness of fire-related disturbance attribution and to evaluate potential complementarity.

2.1.3 Tropical moist forest (TMF)

The TMF product developed by the European Commission's Joint Research Centre (Vancutsem et al., 2021) provides annual maps of closed-canopy forest extent and change within the humid tropical biome. The fully automated TMF mapping algorithm relies on Landsat image classifications in Google Earth Engine and uses temporal trajectory analysis to generate annual forest maps. The annual maps include the following categories: undisturbed natural forest, degraded natural forest, deforested land, regrown secondary forest, other land cover, and water. Undisturbed forests are defined as closed-canopy natural forests with no recorded disturbance since 1990. A degraded forest is defined as one affected by short-duration disturbances observable within 1 year (logging, surface fires, and other natural disturbances) or one that has been temporarily cleared and subsequently regrown within 2.5 years (mainly high-severity fires). Most forest degradation events detected by TMF were observed within a short interval of less than 6 months (Vancutsem et al., 2021). Deforested land refers to the permanent conversion of forest into non-forested land use. The TMF only maps deforestation within the forest extent of the preceding year. Similarly, forest degradation is only mapped within undisturbed forests of the preceding year. This design therefore emphasizes sequential, year-to-year change detection, with results contingent on the forest and disturbance status mapped in the preceding years. The annual TMF data are available at <https://forobs.jrc.ec.europa.eu/TMF>.

2.2 Analysis extent and forest disturbance maps

We conducted our analysis within the primary forest extent (Turubanova et al., 2018), which we restricted to Brazil using GADM version 4.1 country boundaries (<https://gadm.org/data.html>). Turubanova et al. (2018) define humid tropical primary forest as a mature natural forest area that has not been completely cleared and regrown in recent history. The original primary forest map shows its extent for the year 2001. To create the primary forest extent map for each analysis year, TCL data before 2023 were excluded when defining the 2023 primary forest extent, and similarly, TCL data before 2024 were excluded when determining the 2024 extent. Due to the commission errors of the primary forest mask and the omission errors of 2001–2022 TCL, a small area of non-primary forest was included in the analysis. Similarly, due to omission errors in the original primary forest extent map, a small area of primary forest may be excluded from the analysis.

Each operational forest monitoring product was converted into an annual forest disturbance map using the Landsat ARD pixel grid (Potapov et al., 2020). All map products were resampled to geographic coordinates with a pixel size of $0.00025 \times 0.00025^\circ$ (approximately 30×30 m at the Equator). Disturbance maps

were limited to the Brazilian primary forest extent of the years 2023 and 2024, respectively. Each 30 m pixel served as a sampling unit, and all pixels within the Brazilian primary forest extent for 2023 and 2024, respectively, were eligible for selection in the corresponding annual sample analysis.

To create an annual MBA forest disturbance map for performance evaluation, we extracted vector polygons where deforestation was detected during the corresponding year (2023 or 2024, respectively). These vector maps were rasterized to the 30 m grid by assigning each pixel to the deforestation polygon containing its centroid. This approach, however, resulted in the omission of small fragments of vector polygons that did not include pixel grid centroids. To account for this omission, we created a second version of the rasterized MBA data, where we attributed a 30 m pixel to the disturbance class if at least 25% of the pixel was within a deforestation polygon. The second map version was used only for forest disturbance detection sensitivity analysis.

The annual TCL map represents forest disturbances detected during the corresponding year. The TCL raster data format is identical to the Landsat ARD pixel grid. We used the intersection of the TCL events for each year with the fire-related disturbance attribution from Tyukavina et al. (2022) and Sims et al. (2025) products to evaluate the disturbance driver attribution. For stratification, we used only the Tyukavina et al. (2022) product, and for the analysis, we used both products separately and combined them by attributing a disturbance event to fire if it was included in any of these two products.

The TMF annual forest type maps for the years 2022, 2023, and 2024 were resampled to the TCL pixel grid using the nearest neighbor resampling method. To create the 2023 forest disturbance product for evaluation, we labeled pixels classified as forest in 2022 but deforested in 2023 as “deforested”. Pixels that represented undisturbed forests in 2022 and degraded forests in 2023 were labeled as “degraded.” The same approach was applied to derive the 2024 deforestation and degradation map using the 2023 and 2024 annual TMF maps. Because there is an uncertainty in the differentiation between deforestation and degradation classes during the two latest years of TMF data (<https://forobs.jrc.ec.europa.eu/TMF/>), we did not differentiate these two classes for our analysis; we considered that both classes represent forest disturbance events. The TMF is different from the MBA and TCL products as it only considers disturbances within forest areas mapped during the preceding year. As TMF disturbance detection is based on the preceding year's forest extent, earlier classification errors (e.g., disturbance commission or missed forest recovery) may influence the extent eligible for TMF disturbance mapping. To align the TMF sensitivity analysis with the product methodology, we used only samples within the TMF forest extent of the preceding year.

2.3 Stratification and sampling

We conducted an independent sample analysis of forest disturbance for each year, 2023 and 2024. In both years, we employed a stratified sampling design to increase the precision of the annual forest disturbance area estimate and to target areas with disagreement between the monitoring products. In total, nine strata were defined for each year (Table 2).

TABLE 2 Stratified sampling design for the years 2023 and 2024.

Strata	2023		2024	
	Percentage of total area	Sample size (pixels)	Percentage of total area	Sample size (pixels)
1. MBA and TCL (non-fire)	0.102	25	0.084	25
2. MBA and TCL (fire)	0.003	25	0.003	25
3. MBA, no TCL	0.008	25	0.010	25
4. TCL non-fire	0.092	50	0.082	100
5. TCL low certainty fire	0.078	50	0.142	100
6. TCL high certainty fire	0.088	50	0.594	50
7. TMF only (no MBA or TCL)	0.267	50	0.609	50
8. Potential change omission	1.954	50	3.079	50
9. No change	97.41	50	95.40	50

Strata 1-3 included pixels mapped as deforestation by MBA. Strata 1 and 2 consist of pixels with MBA and TCL forest disturbance detection agreement that were separated by the TCL driver (fire-related and other loss). Stratum 3 includes pixels mapped as disturbance by MBA, but not by TCL. Strata 4-6 included pixels mapped as tree cover loss by TCL, but not by MBA. We separated these pixels into fire-related TCL (stratum 6) and other TCL using Tyukavina et al. (2022) data. We further separated the other TCL areas into stratum 5, which includes pixels with above-zero fire-related TCL probability from Tyukavina et al. (2022), and stratum 4, which includes the rest of the pixels. Pixels that were mapped as deforestation or degradation only by the TMF product were assigned to stratum 7.

Strata 8 and 9 included pixels that were not mapped as forest disturbance by any of the analyzed products. Following the approach of Olofsson et al. (2020), we included areas of potential forest disturbance omission into stratum 8. We used two criteria that indicate potential disturbance omission: (i) proximity to any mapped loss (a 60 m buffer from strata 1-7), and (ii) potentially burned forest areas omitted by all the analyzed products. To map the burned forest areas, we aggregated the MapBiomas burned area extent (this criterion was used only for the year 2024) and the active fire detection product generated by NASA using the S-NPP Visible Infrared Imaging Radiometer Suite (VIIRS) instrument data (Schroeder et al., 2014). The active fire detection product has a spatial resolution of 375 m at the Equator. We selected fire detection events of the corresponding year (2023 and 2024, respectively) with “nominal” and “high” confidence and “presumed vegetation fire” type to ensure that only valid active fire detections were included in the analysis. We used the 540 m buffer around the active fire detection points at the 30-m resolution to include (i) the VIIRS pixel where the fire event was detected, and (ii) a one-pixel buffer around it at the VIIRS data resolution. The rest of the primary forest mask pixels for the corresponding year were allocated to stratum 9 (“no change”).

The total sample size was constrained by project duration and funding. Sample allocation was guided by the anticipated disturbance detection variance. For strata 1-3, where disturbances were mapped by the analyst-driven MBA method

that was expected to be highly accurate, we allocated 25 sampled pixels each. For strata with possible confusion between fire and non-fire forest disturbance drivers during the extreme fire season (strata 4 and 5 of 2024), we allocated 100 sampled pixels each. For all other strata, we allocated 50 sampled pixels each following the minimum sample size recommendation (Tyukavina et al., 2025a). In total, we processed 375 sampled pixels for the year 2023 and 475 sampled pixels for the year 2024. Sampled pixels were randomly selected within each stratum using GLAD Tools software (<https://glad.geog.umd.edu/ard>).

2.4 Reference data collection

We used Planet monthly basemaps with a spatial resolution of approximately 4.8 m per pixel as primary imagery data for forest disturbance interpretation within each sampled pixel. We define forest disturbance as tree canopy removal or mortality within at least 10% of the sampled pixel area. The sampled pixel interpretation was done using a monthly time series from 2022 to 2025, visualized using the QGIS Planet Explorer plugin. The 2022-2025 high-resolution images from Google Earth were used as supplementary image data. The 2022-2025 16-day Landsat image composites extracted from the Landsat ARD time series (Potapov et al., 2020) were used to detect low-severity and ephemeral disturbances, to separate disturbance events from seasonal changes in spectral properties of forests, and to verify the disturbance detection dates.

For each sampled pixel, we visually interpreted: (i) the presence of the forest disturbance, (ii) the type of disturbance, (iii) the year of occurrence, and (iv) the percentage of the area affected by the disturbance event within the Landsat pixel. Disturbance event types included mechanical tree removal, other high-severity disturbances, and low-severity disturbances (Table 3).

The mechanical tree removal category consists of two sub-categories: “deforestation”, defined as the clearing of natural forests for other land uses, and “other mechanical removal”, which primarily comprises selective logging and shifting cultivation. The latter sub-category also includes tree removal within non-primary forests, which were occasionally included in the analysis due to the commission error of the primary forest

TABLE 3 Reference disturbance types that were visually interpreted using satellite imagery.

Disturbance category	Disturbance sub-category	Definition
Mechanical tree removal	Deforestation	Mechanical clearing of natural forests for agriculture, infrastructure, construction, or mining
	Other mechanical tree removal	Other mechanical tree removal events including selective logging, clearcuts, shifting cultivation, and the removal of secondary regrowing vegetation
High-severity disturbances	High-severity fires	Stand-replacement fires with complete or near-complete tree mortality
	Other high-severity natural disturbances	Landslides, wind damage, and floods with complete or near-complete tree mortality
Low-severity disturbances		Surface fires and temporary flooding events that caused partial tree mortality

map. Mechanical tree removal includes instances where fire was used to clear land after tree felling.

The high-severity disturbances category includes events of complete or near-complete tree cover removal due to fires, landslides, wind damage, and floods. Fires (both naturally occurring and those set by humans) are included in a separate sub-category of high-severity disturbances. As mentioned above, the fire category does not include cases where the trees were first mechanically felled and then burned.

The low-severity disturbances category includes surface fires and floods that caused partial tree mortality. We applied a formal criterion of 50% tree canopy loss within the disturbance footprint (i.e., burned forest area) to separate high-severity and low-severity disturbances. However, the insufficient spatial resolution of Planet data does not allow for the precise quantification of the tree mortality within sampled pixels. Thus, our visual attribution of forest disturbance severity may be imprecise.

The year of the disturbance event was determined using Planet monthly basemaps and Landsat ARD 16-day image composites. The percentage of a disturbance event refers to the portion of the sampled pixel that was affected by the disturbance. Since we estimated these percentages visually, we used a simplified scale with seven levels: 0%, 10%, 25%, 50%, 75%, 90%, and 100%. For fires and floods, we considered the entire area of forest affected by the disturbance event, not the tree mortality within the disturbance footprint. For instance, if a sampled pixel was located completely within a low-severity burn area, we recorded this as a 100% disturbance event within a pixel. We implemented this approach because the spatial resolution of Planet data did not allow us to precisely estimate tree mortality within burned and temporarily flooded forests.

When disturbance events were absent within a sampled pixel, we recorded disturbances that occurred within a neighboring 30-m pixel. Such sampled pixels were categorized as adjacent to the disturbance. This information helped us to understand the reasons for the disturbance detection commission.

The visual image interpretation was first completed by the World Resources Institute and the University of Maryland team, and then the results were revised by the MapBiomass Alerta team. All disagreements were discussed, and the reference data were consolidated using a consensus approach, where all experts agreed on the interpretation results. Overall, we corrected the original interpretation for 4.5% and 3.1% of all samples for

2023 and 2024, respectively, after the discussion between the two sample interpretation teams.

2.5 Area estimation and product evaluation

The map-based forest disturbance area for each of the three analyzed products was calculated using the annual raster data layers with a spatial resolution of 30 m (Section 2.2). We calculated the area of each 30 m pixel in geographic coordinates using the equations from Tyukavina et al. (2025b); Appendix D).

We estimated the sample-based area of each forest disturbance type for the years 2023 and 2024, and its associated uncertainty, using equal probability sampling equations from Tyukavina et al. (2025b); Appendix A). For the area estimation, we considered the percentage of each disturbance type interpreted within the sampled pixel.

Due to the differences in disturbance definitions between the analyzed forest monitoring products, different spatial resolution of the source satellite data (Landsat and Planet), and potential geolocation mismatch between satellite data sources, accuracy metrics, such as user's and producer's accuracies (Stehman and Czaplewski, 1998), were not suitable for product evaluation. Instead, we evaluated the portion of the reference area of each disturbance type mapped by each product. We also assessed the sensitivity and precision of disturbance mapping by comparing maps and reference data within sampled pixels that were selected to minimize the effects of differences in disturbance definitions, spatial resolution, and spatial registration between products and reference data.

To evaluate the portion of the reference disturbance area mapped by each monitoring product, we implemented sample-based area estimation using only sampled pixels within the extent of mapped disturbances for each product. To simplify the analysis, we aggregated reference disturbance types (Table 3) into the following three categories: "deforestation," "other stand-replacement disturbances" (which include other mechanical tree removal, high-severity fires, and other high-severity natural disturbances), and "low-severity disturbances". Using sampled pixels selected within the annual disturbance map, we estimated the area of each disturbance category that was detected by the respective monitoring product. We subsequently calculated the detected area percentage of the total reference disturbance area for each disturbance category.

We defined the forest disturbance detection sensitivity as the percentage of the reference disturbance area that was correctly

TABLE 4 Map-based area of Brazilian humid tropical primary forests and their annual disturbance, based on analyzed forest monitoring products (ha×1,000).

Variable	2023	2024
Primary forest extent (beginning of the year)	313,362	312,225
MBA deforestation	356	300
TCL non-fire related	768	702
TCL fire-related*	370	2,124
TMF deforestation	841	617
TMF degradation	603	2,936

*Includes TCL, that overlap with any of the two fire-related tree cover loss products, Tyukavina et al. (2022) and Sims et al. (2025).

mapped. To evaluate detection sensitivity, we used only sampled pixels with a 100% reference disturbance percentage. We considered that sampled pixels with partial reference disturbance may represent a geolocation mismatch between the Landsat-based maps and Planet imagery, which may affect product evaluation. The analysis was performed independently for each product, each year, and each of the two reference disturbance categories: (i) deforestation, and (ii) stand-replacement disturbances, which included all mechanical tree removal and high-severity disturbance types.

To adjust our analysis to the specifics of each product, we applied several additional data adjustments for the sensitivity analysis. For the MBA product, we used the 30-m map that considered at least 25% coverage from a deforestation polygon as an indication of mapped forest disturbance (Section 2.2). For the TMF product, we integrated deforestation and degradation categories and excluded samples that were not mapped as forest in the preceding year (Section 2.1.3). For all three products, for the year 2023 analysis, we aggregated the mapped forest disturbances from 2023 to 2024 for each product. This way, we reduce the effect of delayed disturbance detection (e.g., if the reference disturbance was observed in December 2023, but was mapped by a forest monitoring product in 2024). We could not implement this approach in 2024 because the 2025 monitoring products were not yet available.

We defined forest disturbance mapping precision as the percentage of the mapped forest disturbance area that was confirmed by the reference data. For this analysis, we considered sampled pixels with any reference percentage or type of disturbance as correctly mapped. This way, we minimized the difference in disturbance definitions between monitoring products, potential errors in the visual interpretation of disturbance types, and potential geolocation mismatch between satellite imagery from different sensors.

Our reference data were also suitable to evaluate the TCL attribution to fire by Tyukavina et al. (2022) and Sims et al. (2025). To do this, we estimated the percentage of the reference fire-related forest disturbance area within the fire-related and other TCL areas mapped by each of the evaluated products.

3 Results

3.1 Map-based forest disturbance area

The annual area of forest disturbance mapped by each product represents a small fraction (0.4%–1%) of the total primary forest

area (Table 4). Between 2023 and 2024, MBA and TMF products indicate a reduction in annual deforestation, and TCL indicates a reduction in non-fire-related disturbances. In contrast, fire-related TCL increased 5.7-fold between 2023 and 2024. Similarly, the TMF product shows a fivefold increase in forest degradation. According to the product definition, most forest fires are mapped as the TMF degradation class (Vancutsem et al., 2021). We therefore conclude that the observed increase in TMF degradation area reflects the change in burned forest area between 2023 and 2024.

All three monitoring products largely agree with each other within regions where deforestation for agriculture dominates the forest disturbance dynamics (Figure 1). However, fires and natural disturbances are mapped differently due to the difference in disturbance definitions between these products.

3.2 Sample-based forest disturbance area

The sample-based area estimates indicate a dramatic (3.8 times) increase in the total area of forest disturbances between 2023 and 2024 (Table 5). The area of high-severity (stand-replacement) fires increased by 3.5 times, from 0.4 Mha/year to 1.5 Mha/year. Meanwhile, the area deforested for agriculture was reduced by 13%, from 0.47 to 0.41 Mha/year, and the area of deforestation due to mining remained relatively stable. We observed a reduction in other mechanical tree removal (including selective logging and shifting cultivation clearing) and non-fire natural high-severity disturbances between 2023 and 2024. The area of low-severity forest disturbance, primarily from surface fires, increased eightfold (from 0.5 to 3.9 Mha/year).

3.3 Evaluation of the mapped disturbance area

By comparing the sample-based deforestation area within the MBA map with the total reference deforestation area within Brazilian primary forests, we showed that MBA captured 64% and 65% of the total reference deforestation area in 2023 and 2024, respectively (Figure 2). MBA, which is designed to map only deforestation events, mapped a negligible percentage of other types of forest disturbances.

The TCL product mapped the highest percentage of reference deforestation (82% and 94% in 2023 and 2024, respectively) and other stand-replacement disturbances (65% and 61%, respectively)

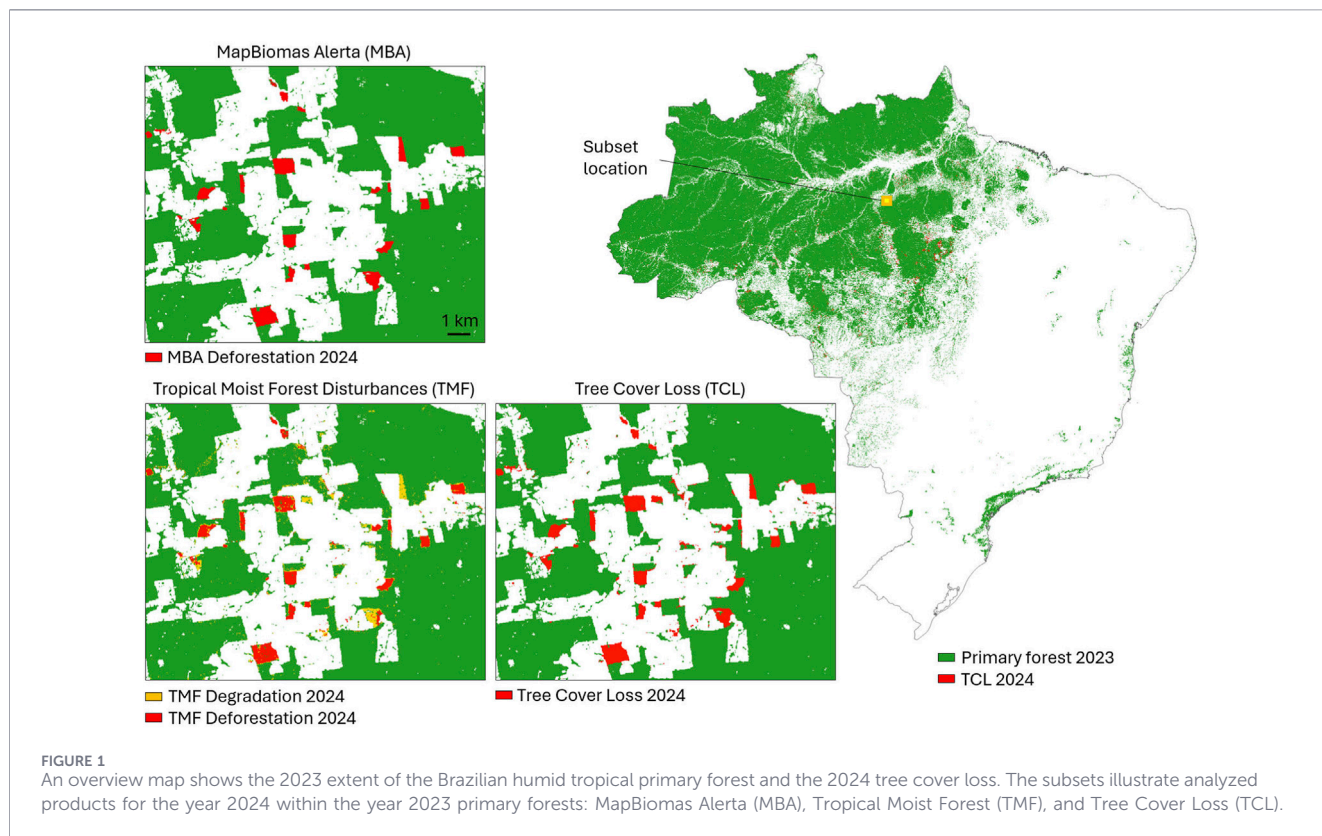


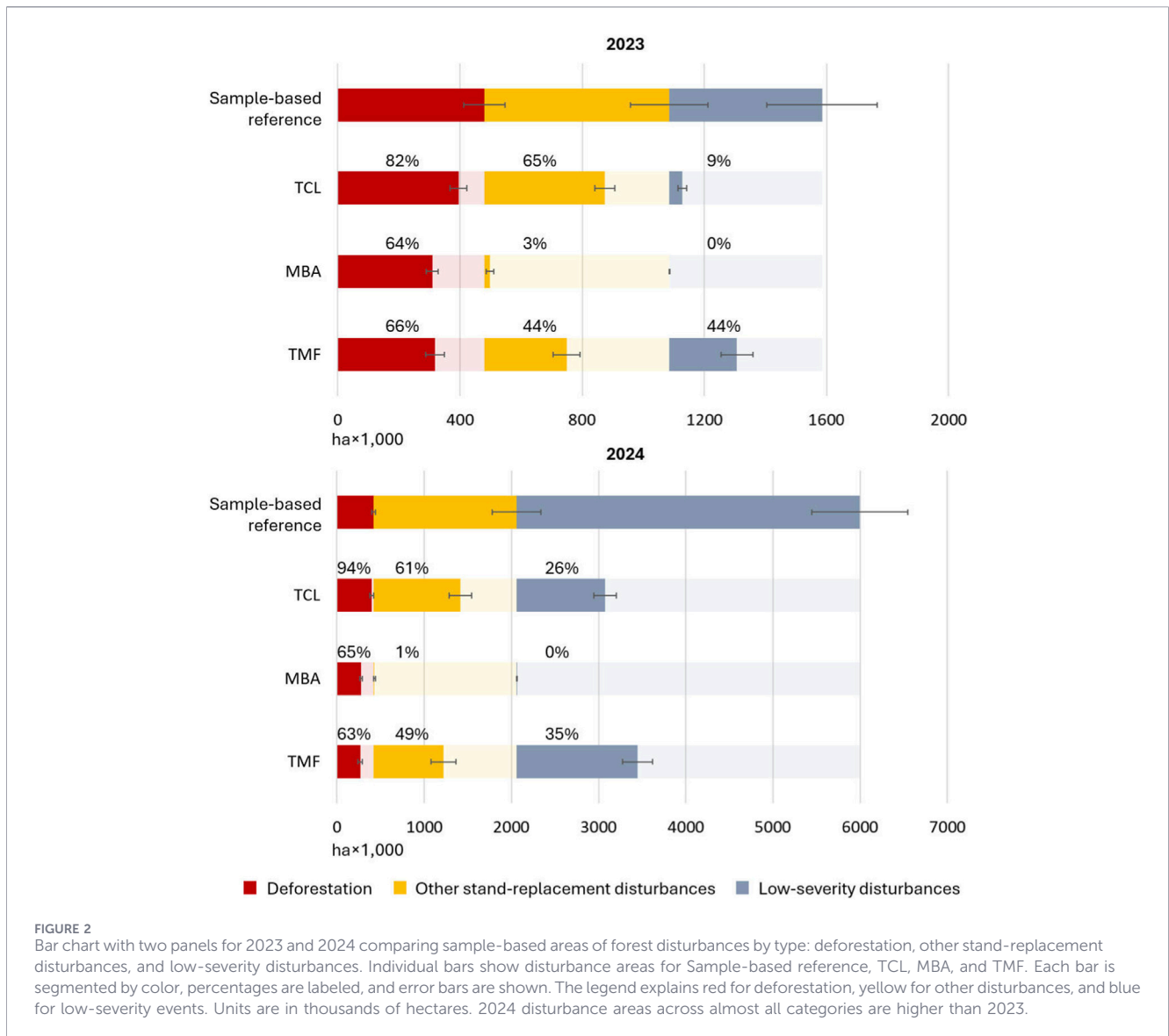
TABLE 5 Sample-based area of 2023 and 2024 primary forest disturbance by type (ha×1,000). Standard errors of the disturbance area are shown in parentheses. Forest disturbance type definitions are provided in **Table 3**.

Disturbance category	Disturbance sub-category	Disturbance area (SE)	
		2023	2024
Mechanical tree removal	Deforestation for agriculture	467.5 (67.3)	407 (25.7)
	Deforestation by mining	12.8 (7.6)	11.9 (10.5)
	Other mechanical tree removal	125.2 (24.5)	97.3 (41.3)
High-severity disturbances	High-severity fires	437.5 (125.1)	1539.1 (278.8)
	Other high-severity natural disturbances	42.1 (20.6)	5.3 (3.4)
Low-severity disturbances		500.5 (180.7)	3934.6 (549)

of all evaluated products (Figure 2). For the TCL product, to better understand performance across disturbance types, we estimated separately the percentage of correctly mapped high-severity fires and other stand-replacement disturbances. The latter category includes shifting cultivation, mechanical clearing of non-primary forests, and windfalls, but excludes deforestation. We found that TCL successfully detected 93%–91% (in 2023 and 2024, respectively) of non-fire-related stand-replacement disturbance area, while it detected only 58%–59% (respectively) of high-severity fire area. TCL mapped only 9% and 26% (in 2023 and 2024, respectively) of low-severity disturbances. This is partly explained by the TCL forest disturbance definition, which requires at least 50% tree cover removal within the Landsat pixel (Hansen et al., 2013). Thus, TCL is highly sensitive to disturbances that cause substantial canopy loss

but is less likely to map disturbances that result in partial canopy removal, including low-severity disturbances and disturbances that affect a small percentage of tree canopy cover within the Landsat pixel.

The TMF product mapped a smaller percentage of reference deforestation (66% and 63% in 2023 and 2024, respectively) and other stand-replacement disturbances (44% and 49%, respectively) compared to TCL. However, the TMF product captured the highest percentage of low-severity disturbances (44% and 35% in 2023 and 2024, respectively) compared to other monitoring products (Figure 2). The primary reason for the lower percentage of mapped disturbances is the difference in the analysis extent. The TMF algorithm only detects disturbances within the forest mask of the preceding year and does not



consider forest disturbances occurring outside this extent. Although the TMF forest mask was only 3% smaller than the primary forest extent used for our analysis in both 2023 and 2024, a substantial share of reference disturbance samples fell outside this mask. Specifically, only 52% (in 2023) and 44% (for 2024) of samples interpreted as deforestation events were located within the TMF forest mask. The rest of the samples were classified in TMF as “deforested lands” or “other land cover” categories and were therefore excluded from the TMF disturbance detection. Detailed visual inspection of these samples using high-resolution Planet and Google Earth imagery confirmed that all these samples had dense, tall tree cover in the year preceding deforestation. However, we observed that some were either located near older disturbances, were affected by selective tree removal, or recovered from historic disturbances. We concluded that the lower detection of deforestation and stand-replacement disturbances by TMF compared to TCL was primarily due to the differences in the forest mask used to define the area of analysis.

3.4 Evaluation of forest disturbance mapping sensitivity and precision

We evaluated forest disturbance mapping sensitivity by estimating the percentage of the reference area of deforestation and stand-replacement disturbances that were correctly mapped by each product, based on sampled pixels with a 100% reference disturbance percentage. Our analysis indicated that both TCL and TMF products have high sensitivity for mapping stand-replacing disturbances. TCL had the highest percentage of correctly mapped deforestation (99.2% and 94.6% in 2023 and 2024, respectively), while the TMF had the highest sensitivity to all stand-replacement disturbances (84.5% and 76.7%, respectively) of all evaluated products (Table 6).

For the MBA product sensitivity analysis, we used a specially prepared rasterized MBA map in which a 30 m pixel was assigned to the disturbance class if at least 25% of its area fell within a deforestation polygon, reducing omission of small polygon fragments that did not capture pixel centroids. The MBA

TABLE 6 Forest disturbance detection sensitivity, presented as the percentage of the reference disturbance area that was correctly mapped by each forest monitoring product. Only sampled pixels with 100% reference disturbance area are considered for this analysis. The TMF analysis was done using only sampled pixels within the preceding year's forest extent.

Year	Product	Percentage of reference disturbance area mapped by each monitoring product	
		Stand-replacement disturbances	Deforestation
2023	MBA	37.1 (5.6)	84.9 (4)
	TCL	84.4 (11.3)	99.2 (0.5)
	TMF	84.5 (3.9)	92.7 (4.4)
2024	MBA	16.5 (2.5)	72.4 (3.3)
	TCL	74.4 (9.3)	94.6 (0.8)
	TMF	76.7 (10.8)	88.5 (4.1)

TABLE 7 Forest disturbance mapping precision, presented as the percentage of forest disturbance areas mapped by each forest monitoring product that were confirmed by the reference data. We considered the presence of any type and proportion of reference disturbances as confirmation of the correct change detection. Standard errors of the estimated percentages are shown in parentheses.

Year	Product	Percentage of disturbance area mapped by each monitoring product confirmed with reference data
2023	MBA	100 (0)
	TCL	98.1 (0.9)
	TMF	69.6 (4.3)
2024	MBA	99.6 (0.4)
	TCL	97.5 (1.4)
	TMF	80.2 (4)

TABLE 8 Percentage of the reference fire-related disturbance area within the area of mapped TCL due to fire and other TCL provided by two TCL driver attribution products and their aggregation (when we consider the TCL event as fire-related if it was mapped as such by either of the two products). Standard errors of the estimations are shown in parentheses.

TCL driver attribution product	Year	Percentage of the reference fire-related disturbance area within each mapped class	
		TCL due to fire	Other TCL
Tree cover loss due to fire (Tyukavina et al., 2022)	2023	89.9 (3.4)	16.4 (2.6)
	2024	97.4 (2.2)	42.6 (2.4)
Drivers of forest loss at 1 km resolution (Sims et al., 2025)	2023	94.8 (3.3)	17.3 (2.8)
	2024	96.7 (1.3)	52.9 (5.8)
Aggregation of both products (Tyukavina et al., 2022; Sims et al., 2025)	2023	88.2 (3.6)	10.5 (2.4)
	2024	95.2 (2.1)	24.6 (3.1)

deforestation mapping sensitivity varied between the years; the product detected 84.9% deforestation during low-fire 2023, but only 72.4% deforestation during high-fire 2024. MBA had the lowest mapping sensitivity to stand-replacement disturbances (37.1% and 16.5% in 2023 and 2024, respectively) because this product was not designed to map forest disturbances other than deforestation.

To evaluate forest disturbance mapping precision, we calculated the percentage of the total forest disturbance area mapped by each product that was confirmed with the reference data, considering any reference percentage or type of disturbance as correctly mapped. We showed that TCL and MBA had very high ($\geq 98\%$) disturbance mapping precision for both years (Table 7). Practically all forest disturbances mapped by MBA were confirmed by the reference data.

The TMF disturbance mapping precision was comparatively lower, 69.6% and 80.2% for 2023 and 2024, respectively. We acknowledge that visual interpretation may miss some ephemeral low-intensity forest degradation events that TMF correctly captures, as our ability to detect change events is limited by the spatial and temporal resolution of Planet monthly mosaics and Landsat 16-day time series.

3.5 Evaluation of the fire-related forest disturbance area

The evaluation of the reference fire-related forest disturbance percentage within fire-related TCL maps by Tyukavina et al. (2022) and Sims et al. (2025) showed that both products mapped burned forests with high precision (Table 8). Of the total mapped fire-related TCL, $\geq 90\%$ (low-fire year 2023) and $\geq 97\%$ (high-fire year 2024) were correctly attributed to fire-related disturbance. The omission of fire-related TCL (which was mapped as “other” TCL) was higher during the intensive fire year 2024 than in 2023. The aggregation of both products, when we consider the TCL event as fire-related if it was mapped as such by either of the two products, resulted in a reduction in the omitted fire-related TCL area.

4 Discussion

4.1 Advantages and limitations of the forest monitoring product evaluation method

Each of the three evaluated operational satellite-based forest monitoring products (MBA, TCL, and TMF) utilizes different forest and forest disturbance definitions, source data, and data analysis methods, making direct comparison challenging. Assessing and comparing the uncertainties reported by the data producers is also difficult because existing validation reports are specific to each product and employ different validation approaches. To enable consistent evaluation of multiple products using the same reference data, we implemented several standardization procedures. First, we limited our analysis to products providing annual data aligned with calendar years. To assess product performance under contrasting fire regimes, we conducted separate analyses for 2023 (low fire activity) and 2024 (high fire activity). Second, we constrained our analysis to Brazilian humid tropical primary forests, a region covered by all three products and where deforestation monitoring is particularly critical for informing conservation policy. For the TMF product, we further reduced the analysis area using the intersection of the primary forest map with the TMF forest extent. Third, all products were resampled to a common pixel grid that served as the sampling framework, which simplifies the collection and analysis of reference data. Fourth, we implemented a sample-based evaluation using a specifically designed protocol that quantifies the proportion of reference disturbance area mapped by each monitoring product, forest disturbance detection sensitivity, and mapping precision. Our data analysis approach allowed us to minimize the confounding effects of differences in

disturbance definitions, spatial resolution between maps and reference satellite data, and geolocation mismatches between satellite data sources.

By conducting the sample analysis following good practice recommendations (Olofsson et al., 2014; Tyukavina et al., 2025a), we ensured that the estimated areas of forest disturbances and disturbance types are accurate and unbiased, and their uncertainty is quantified. Sample-based analysis using reference data collected from high spatial resolution imagery serves as the foundation for disturbance area reporting and performance evaluation of forest monitoring products. To ensure the efficiency of the sample analysis, we implemented a stratified sampling design that targeted mapped classes (forest disturbance presence and type), disagreements between analyzed maps (map intersection), and potential omission errors, following recommendations by Olofsson et al. (2020). The reference sub-pixel disturbance proportion data were essential to estimate the actual disturbance area independent of the map resolution constraints. The disturbance type interpretation allowed us to conduct a detailed analysis of forest disturbance drivers, specifically, to estimate the deforestation area and to evaluate the role of forest fires.

One limitation of our sample analysis approach was the use of 25 samples for strata 1–3, whereas good practice guidelines recommend a minimum of 50 samples per stratum (Tyukavina et al., 2025a). We chose 25 samples for several reasons. First, we reasoned that the forest disturbances in strata 1–3 had already been manually verified by the MBA team during the product generation and therefore represent high-certainty disturbance events. Our results confirmed that assumption. Across all samples in strata 1–3 for 2023 and 2024 (150 samples in total), we found only one sampled pixel that did not represent forest loss. Second, the areas of strata 2 and 3 were very small (Table 2); due to the low stratum weights, their variance did not meaningfully affect the standard error of the total disturbance area (Table 5). Finally, resource constraints required us to use the smallest feasible sample size. The selected sample size allowed us to estimate disturbance detection sensitivity and precision with relatively low standard errors (Tables 6, 7). However, the overall small sample size, and the allocation of only 25 samples to strata 1–3, resulted in relatively high uncertainty of sample-based area estimates for certain disturbance drivers (e.g., deforestation by mining; Table 5). We recommend using a larger sample size in research aimed at sample-based estimation of forest disturbance areas by individual disturbance drivers.

Sampled pixel interpretation was conducted using 4.8 m spatial resolution Planet’s monthly basemaps, which provide optimal reference data for visual interpretation of the date, type, and extent of disturbance within each sampled pixel. Planet offers the best combination of spatial resolution and temporal frequency among available datasets (Pickering et al., 2021). While very high-resolution imagery (e.g., WorldView) enables precise identification and characterization of forest disturbances, it lacks the monthly temporal coverage and consistent wall-to-wall acquisition needed for national-scale annual change interpretation. The combination of Planet’s fine spatial resolution and frequent revisit interval ensures high interpretation confidence. However, the prohibitive cost of Planet data access may prevent

routine performance evaluation of forest monitoring products by research institutions and non-governmental environmental organizations.

Despite following good practice recommendations, we identified several sources of potential uncertainty in the reference data and evaluation methodology. The analysis extent (2023/2024 primary forest area) was defined using historical TCL data and, therefore, is not fully independent of the evaluated products. Excluding historical tree cover loss mapped by all products (2019–2022 MBA and 1990–2022 TMF) would reduce the analysis area and may increase disturbance detection sensitivity estimates by removing historical product errors. However, such an approach would prevent evaluation of the product performance within the [Turubanova et al. \(2018\)](#) primary forest extent in the context of WRI forest change reporting ([Goldman et al., 2025](#)), which was the objective of our analysis. The use of a 30-m Landsat pixel as the sampling unit ensured consistency across products; however, this is suboptimal for evaluating MBA, which provides deforestation polygons derived from 3.7-m resolution data. A smaller sampling unit would better support MBA validation but would complicate the evaluation of Landsat-based datasets. Our area of analysis included areas that the TMF product marked as non-forest and excluded from the operational change detection. The difference in the operational monitoring frames between the products may negatively affect the evaluation of the TMF performance. We suggest improving future evaluation methods by using the common operational monitoring frame between all analyzed products. Finally, reference data collected through visual interpretation may contain analyst-driven errors. Despite efforts to engage multiple interpreters and a consensus approach for sampled pixel interpretation, distinguishing between high- and low-severity disturbances (e.g., between stand-replacement and surface fires) may be uncertain due to the limited spatial resolution of Planet imagery. Additionally, spatial inconsistencies between Landsat and Planet data may produce boundary mismatches, causing discrepancies between mapped and reference data that could affect product evaluation.

4.2 MBA deforestation mapping performance

The MBA product detects deforestation, which is a subset of overall forest disturbance. According to MBA definitions, deforestation refers to forest conversion to non-forest land use. MBA forest disturbance mapping relies on expert-driven image interpretation. MBA prioritizes low commission error as it aims to be suitable for use in policy enforcement, legal cases, and compliance studies. Our evaluation shows that the MBA delivers the most accurate delineation of deforestation events among all analyzed products. Almost 100% disturbance mapping precision of the MBA guarantees that every mapped polygon reliably indicates the presence of forest disturbance. The MBA product has very low sensitivity to other stand-replacement disturbances and does not map low-severity disturbances, which is consistent with the product definition. The MBA product cannot be used to monitor all stand-replacement disturbances.

Most forest disturbance events mapped by MBA represent deforestation (87% and 91% in 2023 and 2024, respectively). However, other disturbance types, such as fires, shifting cultivation, selective logging, and secondary vegetation clearing, were occasionally included in the MBA product due to misclassification errors. Observed commission errors primarily reflect expert misclassification of specific disturbance events, which can be difficult to control when multiple experts are involved.

Our analysis showed that MBA detects 64%–65% of the total deforestation area ([Figure 2](#)). We suggest that the primary reasons for deforestation omission are (i) scope of enforcement, compliance, and legal actions that deliberately exclude ambiguous, unconfirmed, or legally fragile events, (ii) forest disturbance omissions by the near-real-time monitoring products used as alert sources that target visual interpretation, and (iii) the visual image interpretation errors. We suggest that the integration with other vegetation disturbance alert products, such as DIST-Alert ([Pickens et al., 2025](#)), may improve the MBA disturbance detection rate in the future.

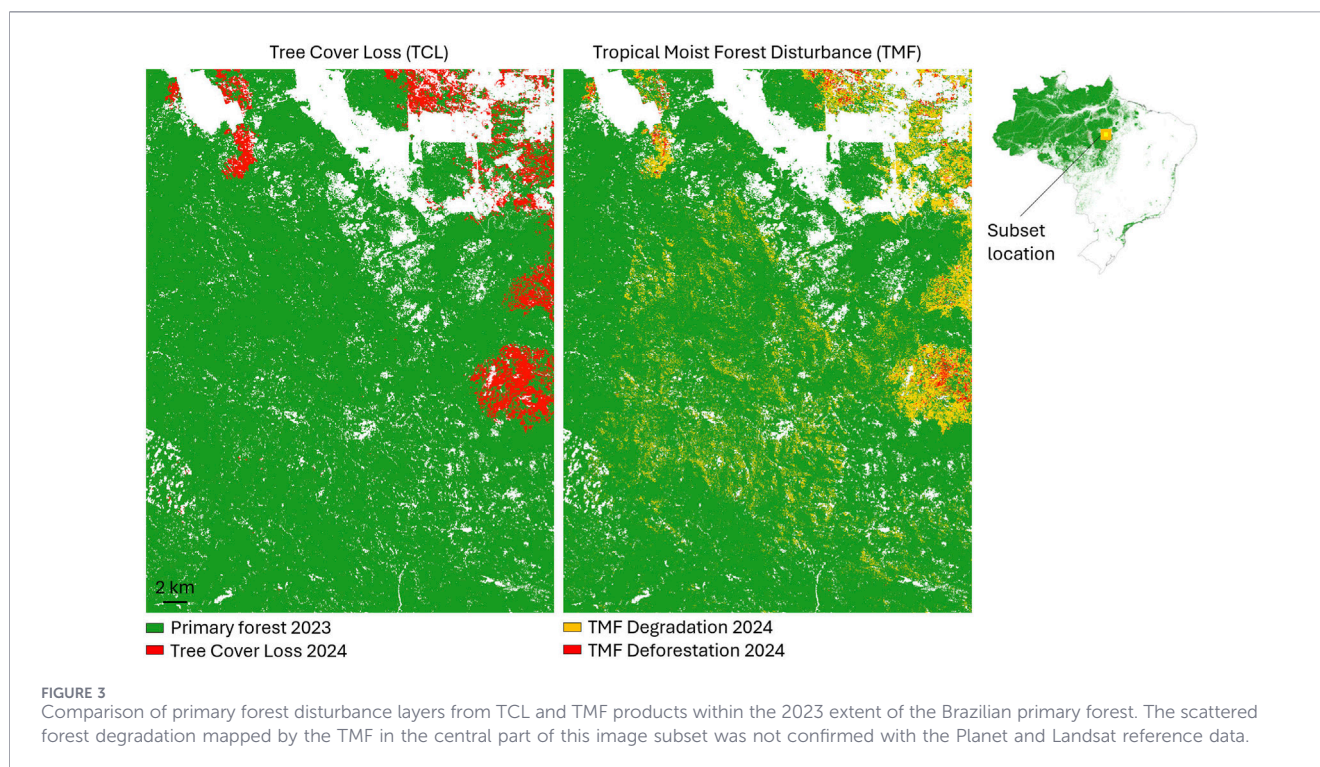
4.3 TCL forest disturbance mapping and driver attribution performance

Unlike MBA, TCL is designed to map all types of stand-replacement disturbances. TCL provides globally consistent forest disturbance data beginning in 2001, making it well-suited for understanding overall forest dynamics and its implications for carbon emissions and biodiversity. The TCL methodology is mostly automated and requires limited post-processing. The latest version of the TCL workflow, which has been implemented since 2023, is expected to have the highest disturbance detection sensitivity due to the incorporation of the DIST-Alert ([Pickens et al., 2025](#)) into the annual mapping workflow.

Our results showed that TCL has the highest sensitivity to deforestation events (it mapped 82% and 94% of the total deforestation area in 2023 and 2024, respectively). The TCL product maintained a high (98%) precision of forest disturbance mapping, with a small proportion of forest disturbance commission.

While TCL showed high sensitivity to all stand-replacement disturbances (84% and 74% in 2023 and 2024, respectively), the product omits a portion of high-severity fires (only 58% and 59% of high-severity fire areas were correctly mapped in 2023 and 2024, respectively). The flood events that we observed in sampled pixels in 2023 were not mapped as disturbances by the TCL. We concluded that while TCL has consistently high sensitivity to mechanical tree removal events, its sensitivity to natural disturbances is lower. TCL has low sensitivity to low-severity disturbance events because the product definition excludes forest disturbance events when less than 50% of a Landsat pixel area is affected by the disturbance.

Our analysis of fire-driven TCL mapping by [Tyukavina et al. \(2022\)](#) and [Sims et al. \(2025\)](#) showed that both products have high precision of fire-related TCL mapping. However, both products omitted a portion of the burned forest area in 2024 ([Table 8](#)). Fire-related disturbance omission may be reduced by integrating both maps, indicating that these products may contain complementary information. The higher omission of burned area mapping in



2024 may be explained by the late fire season, which resulted in insufficient clear-sky Landsat observation availability between the fire event and the end of the calendar year.

4.4 TMF annual forest disturbance mapping performance

The TMF product is designed to map changes within tropical moist forests. Using only sample data collected within the TMF forest extent of the preceding year, we showed that the product has high sensitivity to deforestation and the highest sensitivity to stand-replacement disturbances of all products (Table 6). While all products are influenced by their underlying forest definitions, the TMF approach explicitly constrains disturbance detection to areas classified as forest in the preceding year. As a result, differences in the forest mask, particularly those arising from earlier classification errors, have a stronger influence on the spatial extent of detected changes. TMF omits some changes within our area of analysis, which reduces the proportion of correctly mapped deforestation and other stand-replacement disturbances compared to the sample-based reference data (Figure 2).

While TMF outperformed other products in capturing stand-replacement and low-severity disturbances, it also had the lowest mapping precision (Table 7). Visual inspection of the TMF forest disturbance map (Figure 3) reveals a pattern of commission errors that align spatially with the boundaries of individual Landsat scene footprints. This suggests that the fully automated processing approach used by TMF may occasionally result in false change detection within some Landsat scenes. By contrast, the TCL and MBA products use human analysts to review and remove such false detections. While this manual quality control increases both cost and processing time, it results in higher mapping precision.

5 Conclusion

Our evaluation of the forest disturbance mapping by the MBA, TCL, and TMF confirmed that each operational product provides usable information on disturbance dynamics, while also revealing key differences in their change detection capabilities.

The MBA product provides conservative deforestation estimates, capturing only 64%–65% of the total deforested area. However, it also demonstrated the highest deforestation mapping precision, with negligible false positives within mapped deforestation polygons. MBA data are well-suited for operational enforcement of deforestation prevention policies. The MBA deforestation map may be used as a reference for the mapping precision evaluation of other operational products.

The TCL product achieved the highest detection rates for deforestation (82%–94%) while maintaining a high disturbance detection precision. The fire-related TCL maps show high accuracy in attribution of forest disturbance drivers. TCL has lower sensitivity to small-scale and low-severity disturbances due to the limitation of the spatial resolution of Landsat data. This deficiency may be improved by recalibrating the TCL change detection model using training data collected within forest disturbance omission areas that were highlighted by our analysis. The operational TCL product highlights forest disturbance areas in a globally consistent way, supporting continental and global analyses.

The TMF product, designed to track changes in tropical moist forests, provides unique, consistent, multidecadal time series of tropical forest extent and change. Within the TMF forest mask, the product has high sensitivity to deforestation and the highest sensitivity to all stand-replacement disturbances. The TMF outperformed other products in capturing low-severity disturbances; however, it showed the lowest mapping precision.

The TMF product is not suited to detect disturbances in forest areas outside the TMF forest mask, which may omit certain forest areas due to the historic change detection commission errors and forest recovery omissions. While the TMF product is suited for operational annual primary forest disturbance monitoring within its own forest mask, we consider it less suitable for use within the primary forest extent defined by Turubanova et al. (2018), as used in WRI Forest Pulse reporting (Goldman et al., 2025).

The results presented here underscore the distinct yet potentially complementary nature of the evaluated forest monitoring products. For broad-scale forest disturbance detection and to assess the carbon implications of forest disturbances, TCL offers the most extensive spatial coverage and provides high sensitivity to forest disturbance. Conversely, for precise deforestation mapping, crucial for policy enforcement in Brazil, the MBA provides highly accurate and conservative estimates with negligible commission. The TMF product provides unique long-term forest change data and has the highest sensitivity to both stand-replacement and low-severity disturbances, but has comparatively higher commission errors, and the TMF data should be used only to estimate disturbances within the TMF forest mask of the preceding year. Ultimately, the selection of an appropriate forest monitoring product should be guided by the specific research question, the type of forest change under investigation, and the required level of thematic accuracy and spatial detail.

Our detailed analysis of operational forest disturbance detection accuracies was possible due to the availability of Planet monthly imagery mosaics. We consider Planet imagery as the best reference product for change detection product validation, highlighting the continued need for free and open access to Planet basemaps for tropical forest monitoring, as was made available through Norway's International Climate and Forest Initiative (NICFI)'s Satellite Data Program from 2020 to 2025. Restoring free and open access to these data would increase the feasibility and reliability of deforestation area estimation in tropical countries.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

PP: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review and editing. ST: Conceptualization, Data curation, Formal Analysis, Investigation, Writing – original draft, Writing – review and editing. MR: Conceptualization, Data curation, Formal Analysis, Investigation, Writing – review and editing. LT: Data curation, Formal Analysis, Writing – review and editing. JS: Writing – review and editing. VZ: Writing – review and editing. MS: Writing – review and editing.

RS: Writing – review and editing. AL: Data curation, Writing – review and editing. EG: Writing – review and editing. NH: Resources, Supervision, Writing – review and editing. FS: Resources, Supervision, Writing – review and editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This study was supported by the Bezos Earth Fund. The Planet monthly basemaps access was supported by the GLAD Lab at the University of Maryland.

Acknowledgements

We want to thank Alexandra Tyukavina for editing the early version of the manuscript and suggesting sample analysis methods and tools, and Dr. Frédéric Achard for providing comments regarding the TMF product evaluation.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frsen.2026.1818592/full#supplementary-material>

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