Beyond Alerts: spatiotemporal Trade-offs in near-real-time Detection Systems for Forest Disturbance in the Brazilian Amazon

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Abstract

The Amazon rainforest faces threats from anthropogenic disturbances, which also increase greenhouse gas emissions and contribute to global climate change. In 2004, a system to detect disturbance for the Brazilian Legal Amazon (BLA) was created to mitigate forest loss. The system, Detection of Deforestation in Real Time (Deter), from the National Institute for Space Research (INPE), alerts to seven types of anthropogenic forest disturbances through the visual interpretation of optical satellite imagery from CBERS-4, CBERS-4A and Amazônia-1. Many near-real-time systems currently generate alerts using automated algorithms, primarily leveraging SAR sensors to compensate for the absence of cloud-free images over tropical forests. Deter uses spatial patterns to identify types of disturbances, minimising commission errors, while most algorithms prioritise the temporal dimension for early-stage detections. Discrepancies in space and time across systems and disturbance types, such as omissions, delays, and mismatches, are linked to the selection of sensor technologies, forest masks, and algorithm strategies. Forest disturbances detected between 2020 and 2024 for the entire Brazilian Amazon Biome were extracted from the systems: Deter, Prodes, MapBiomas, SAD, RADD, GLAD, LUCA and TropiSCO. Based on this dataset, we conducted an exploratory analysis revealing agreement and disagreement between detection systems regarding five classes of disturbances (clear-cut, selective logging degradation, fire scars, mining and windthrow). The results emphasise the importance of systems that consider the trade-off between spatial and temporal context to detect different disturbance types, similar to Deter, but using automated near-real-time alert approaches.

1. Introduction

Deforestation and forest degradation significantly impact the Amazon ecosystems, which are directly linked to greenhouse gas emissions and global climate change (Lapola et al., 2023). The Amazon forest is crucial for preserving biodiversity and regulating processes such as carbon sequestration and precipitation patterns. Nevertheless, the biome is threatened by climate change and tree loss caused by anthropogenic disturbances. The Brazilian government has a commitment to reach zero deforestation and degradation in the Amazon by 2030. The degradation primarily comes from disturbances such as edge effects, selective logging, timber extraction, fires, mining and extreme droughts exacerbated climate change (Lapola et al., 2023).

In 2004, a dedicated near-real-time (NRT) system was established to detect disturbances and mitigate forest loss in the Brazilian Legal Amazon (BLA). This system, called Detection of Deforestation in Real Time (Deter), was developed by the National Institute for Space Research (INPE) and utilises the optical satellites Amazônia-1, CBERS-4, and CBERS-4A (Diniz et al., 2015). Deter relies on visual interpretation to classify seven types of anthropic disturbances. Many NRT detection systems currently operate in the Amazon, generating disturbance alerts through automated algorithms (Stahl et al., 2023; Hansen et al., 2016). Recently, the use of SAR images, such as Sentinel-1, has increased to overcome the challenge of obtaining cloud-free optical images during certain periods over tropical forests (Prieto et al., 2023; Mullissa et al., 2024).

The satellite choice determines the sensor technology (SAR or optical) and both temporal and spatial resolutions, impacting the ability to detect disturbances in their early stages, reducing latency (Bottani et al., 2025). For automated algorithms, the model choice determines the time window of detection and the minimal size of the event by counterbalancing spatial and temporal information. For instance, while Deter utilises only spatial patterns to identify types of disturbances, most automated NRT algorithms focus on the temporal dimension for early-stage detections without differentiating between anthropogenic and natural events (Reiche et al., 2021).

Sophisticated algorithms cannot ensure high-performance detection without a clear understanding of forest disturbance dynamics. Knowledge from specialists with decades of experience in visual interpretation in the Amazon, along with feedback from agencies that address illegal deforestation on-site, is essential for developing an algorithm that produces commission errors as low as those of the Deter system. The performance assessment from most of the alert systems available for Amazon can provide essential insights into its detection capacity across different disturbance classes, considering the model and sensor choices (Prieto et al., 2023; Bottani et al., 2025).

For this analysis, we extracted all alerts between 2020 and 2024 from the automated NRT systems Global Land Analysis & Discovery (GLAD Landsat and Sentinel-2), RAdar for Detecting Deforestation (RADD), Global Forest Watch (GFW Integrated Alerts), Land Use Change Alert (LUCA) and TropiSCO (Bouvet et al., 2018; Reiche et al., 2021; Mullissa et al., 2024;

Hansen et al., 2016). The spatial and temporal agreement against Deter per classes of disturbance is then assessed. We also analysed the disturbances reported by Prodes, MapBiomas and Deforestation Alert System (SAD) systems against Deter.

This study reviews trade-offs in NRT detection systems by linking spatial and temporal discrepancies in detection to factors including sensor technologies, forest masks, algorithms, and the methods used for training and validation. The emphasis here is not on evaluating a new algorithm's accuracy against a benchmark system or a limited set of labelled disturbances sampled from a few specific locations over a short timeframe. While many studies have compared detection systems in Amazon, this research novelty relies on evaluating different disturbance classes and examining the spatiotemporal trade-offs from different methods.

Research questions to be addressed:

1. What are the impacts of satellite and methodology choices in the spatiotemporal detection accuracy and discrimination of different disturbance classes?
2. To what extent is it necessary to consider both temporal and spatial context in an automated NRT system to detect all current disturbance types alerted by Deter?

2. Methods

The method involves a series of raster and vector operations to prepare a comprehensive dataset of forest disturbances to be used in this study. The preprocessing and harmonisation of several forest disturbance alert systems available for the entire Legal Brazilian Amazon were required to guarantee temporal and spatial comparison. Using this dataset and the Deter classification of disturbance types, this study applied exploratory analyses to understand detection trade-offs imposed by the use or lack of spatiotemporal context implicit in their methodology.

2.1 Study Area

The Legal Brazilian Amazon covers 59% of the country's territory, spanning 5 million km^2. This region maintains approximately 80% of its area as native vegetation, distributed across nine Federal States. The study area was limited to the primary forest preserved until 2020, according to Prodes system. The assessment period extends from 2020 to 2024, capturing both intra- and interannual seasonal variations in vegetation phenology and climate, including the historical flood of 2021 and the most extreme droughts recorded in 2023.

2.2 Disturbance Types

The targeted disturbances were deforestation or degradation, defined as the suppression of primary forests due to human activities. Wildfire disturbances are not included, but land use changes due to fire scars are. We focused on four anthropogenic categories summarised from the seven Deter classes that indicate areas of complete deforestation, such as clear-cut disturbances with exposed soil or under vegetation, as well as regions undergoing degradation by selective logging (geometric or non-geometric), fire scars and mining activities (Figure 1). We also include windthrow to represent a natural forest disturbance not registered by Deter.

The disturbance distribution across the Amazon biome classified by Deter (Figure 2) was subdivided into 5540 tiles according to the grid used for the visual interpretation when detecting

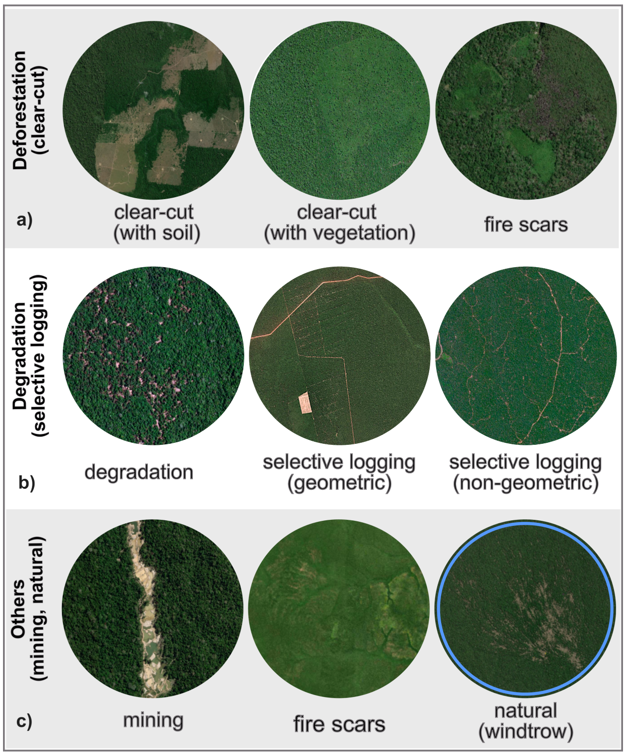

Figure 1. Classes of disturbances selected. (a) Deforestation events related to clear cuts classified by Deter as three different types; (b) Degradation events related to selective logging classified as three types by Deter; and (c) other events classified as mining and fire scars by Deter and a natural windthrow not reported by Deter.

events using CBERS-4A or Amazônia-1 images. Every five days, all biome is covered by the Deter team. Most of the disturbance is concentrated in the so-called deforestation arc (red areas in the map), where multiple classes can occur per tile.

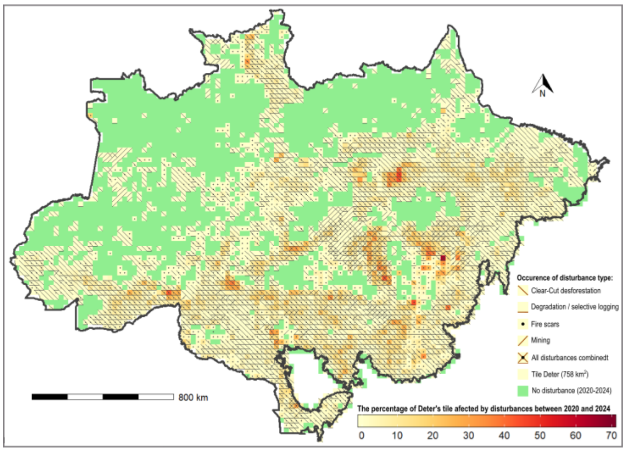

Figure 2. Distribution of Deter alerts per disturbance type and density in relation to the tile area.

2.3 Comparisons between Alert Systems

Deter tiles will be used to compare alert systems regarding their spatial and temporal agreement between 2020 and 2024 across different types of disturbances. Therefore, disturbance alerts were also extracted from the systems RADD, GLAD (Landsat and Sentinel-2), GWF, LUCA, TropiSCO, SAD and MapBiomas (table 1) for each tile of the grid (Mullissa et al., 2024; Diniz et al., 2015; Hansen et al., 2016; Reiche et al., 2021). For the MapBiomas system, which integrates many systems (including Prodes, SAD and GLAD), alerts that Deter was the exclusive source were excluded before comparing both systems. The alerts released as raster were transformed into polygons, and the overlapping area per tile was extracted to facilitate comparison.

Symmetrical differences and intersections of all systems against Deter were extracted to assess the level of agreement and disagreement, generating maps showing the density of disturbance occurrence in the Amazon region. Tiles that epitomise five disturbance classes (three each) were selected to explore in more depth these differences in space and time. For these samples, areas where all systems agree or where none of the systems agrees with Deter were identified to understand omissions, commissions and spatiotemporal mismatching. We have assessed the latency and the temporal dynamics until a certain disturbance was fully detected for the case of degradation. Selective logging is a gradual process spread over years, which may lead to a lack of a clear alert when this degradation occurs.

Systems	Area (km^2) per year				
	2020	2021	2022	2023	2024
Deter	20635	13494	16726	12877	38150
Prodes	10723	12631	13704	8973	8078
MapBiomas	12372	13958	15277	10185	7307
SAD	16584	12605	19853	10179	40331
GLAD-L	29848	25840	29110	25329	42214
GLAD-S2	27614	16798	20041	12721	39774
RADD	8681	9644	11342	9704	13185
TropiSCO	11508	9318	12719	9498	12772
LUCA	29292	21547	24500	16665	21433

Table 1. Area (km^2) alerted between 2020 and 2024 per source.

This exploratory analysis of agreement and disagreement between alert systems per disturbance types will be used to select later a comprehensive set of labelled samples from biotic, abiotic, and anthropogenic events. This dataset will be used to better understand the spatial and temporal trade-offs among algorithms and sensor choices. Around 300 labelled areas will be used in the following works to train and validate algorithms for detecting disturbances. The samples represent the main types of disturbances (Figure 1) in a varied and representative set of sizes, shapes, locations, and years, while selecting detection failures (omissions and commissions), delays, and disagreements among alert systems. Locations with natural disturbances (e.g. windthrow), natural non-forest areas outside of the mask and undisturbed areas will be collected to balance the dataset, evaluating non-anthropogenic events, the effect of climate-induced variations and inherent vegetation phenology.

3. Results

3.1 General Comparison of Detection Systems

According to the official forest loss inventory system (i.e. Prodes), the annual deforestation achieved the highest value at 2022 with an area of 13,704 km^2. However, this figure dropped by almost half in 2024 (see Table 1). The MapBiomas platform reports slightly higher values, but exhibits a similar trend to Prodes. Conversely, most NRT systems record the largest areas of deforestation in 2024. According to Deter, it is caused mainly by fire scars (82.9%) that are events with a large extent of degradation and not classified as deforestation by Prodes nor MapBiomas. This occurs because most of the fire scars are derived from wildfire induced by weather conditions, differing from illegal deforestation surveillance and law enforcement targets by both systems.

As Deter is designed to present very low commission errors to minimise unsuccessful operations that aim to suppress illegal activities, most tiles show a significantly higher area detected (red) by other alert systems (Figure 3). Nevertheless, there are some regions where Deter detects bigger areas of disturbance if compared with other systems (blue). This difference is partially explained by the fact that blue areas coincide with more degraded areas by selective logging. Degradation are not easily detected and most of the case, alerts are only highlighted by automated systems at the spots where the timber was extracted (clearing), while Deter delimits the entire area explored.

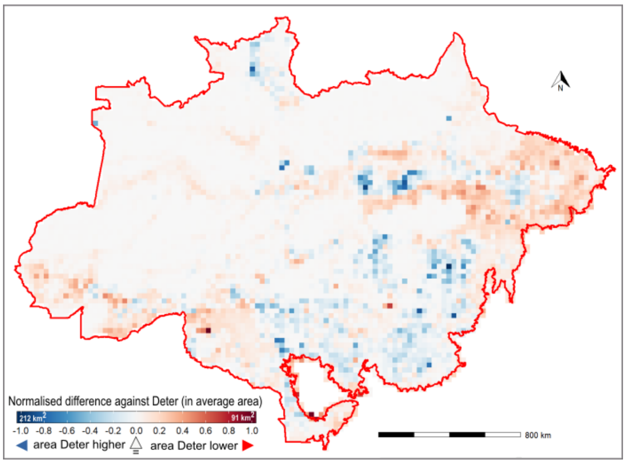

Figure 3. Normalised difference between Deter disturbance area (km2) and the average of the automated NRT systems per tile during 2020-2024 in the Brazilian Amazon.

3.2 Detection by Disturbance Types

The performance to detect clear-cut events (spatially) is very similar for all systems, independently of the method or sensor technology. Figure 4 (b and d) shows clearly that most of the systems agree (orange) with the main area of deforestation provoked by clear cuts. This behaviour is observed in different tiles, demonstrating that the task to detect clear cuts is currently well performed with little margin to improve, mainly in terms of latency.

Deter classifies degradation and two types of selective logging events (geometric and non-geometric). In the case of degradation, there are strong disagreements between Deter and other systems in areas related to selective logging (Figures 4a and 7b). As observed, Deter polygons (yellow) demark all the area under logging, while other automated NRT systems (small orange spots) have only detected the actual forest clearing. The SAD alert also has delimited one degradation area at a certain timestamp, as it is a semi-automated system with visual validation.

While Deter and SAD refer to the total of degradation, the others NRT system alerts only point to the actual area of deforestation. These differences highlight the inability of the current automated NRT systems to distinguish deforestation from degradation. This conceptual spatial difference also restricts the

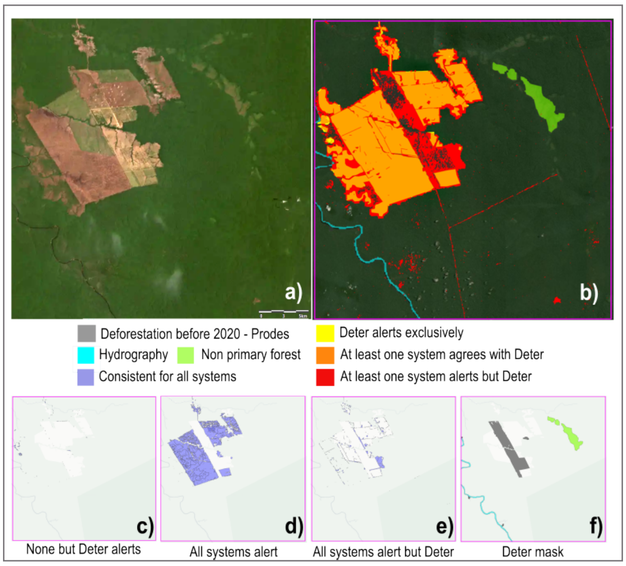

Figure 4. Agreements in detection in a tile with clear-cut deforestation. Planet composition for Fev/2025 (a); agreements and disagreements (b,c,d,e), and mask used by Deter from Prodes (f). Leaflet — Tiles © Esri and © OpenStreetMap.

use of these systems for on-site inspection tasks, as the alert area at a certain period is often smaller than the minimum required to trigger the process.

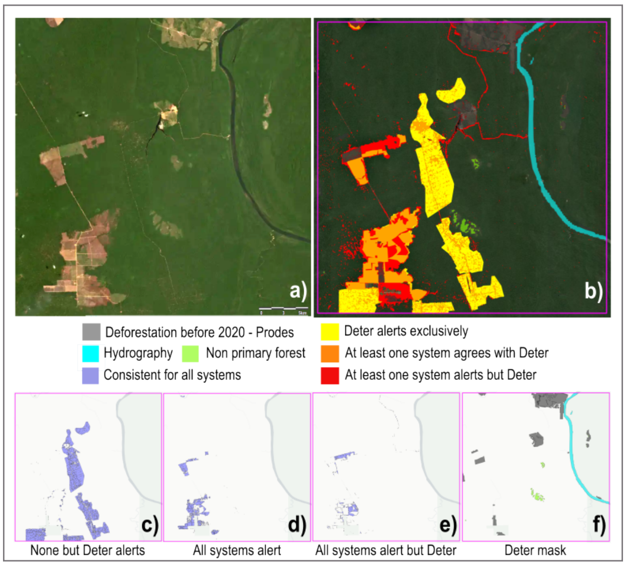

Figure 5. Agreements in detection in a tile degradation events releted to selective logging. Planet composition for Fev/2025 (a); agreements and disagreements (b,c,d,e), and mask used by Deter from Prodes (f). Leaflet — Tiles © Esri and © OpenStreetMap.

3.3 Spatial and Temporal Dynamics

These spatial inconsistencies between visual interpretation and automated NRT algorithms when detecting progressive degradation caused by selective logging are provoked by the lack of spatial context. Figure 6 shows a zoom on the selective logging area presented in Figure 5, where the colour range represents the date when the event has been detected by Deter (6c) or by the automated systems (6b,d). The sequential plot (6e) also shows the temporal sequence of the event(s), but separately for Deter (vertical dashed lines) and the combination of automated NRT SAR systems (RADD, LUCA and TropiSCO) or an optical based on Sentinel-2 (GLAD S2).

In both cases, it is noticeable that Deter alerts disturbances at a few timestamps between 2020 and 2024, but delimiting and classifying big areas. In contrast, automated NRT systems detect small areas spread across the five years on several different dates. In the upper part of the zoomed area (Figure 6d), it is noticeable that the tracks coming upwards were detected between 2020-2021 (blue), followed by logging over perpendicular lines close to the track between 2022-2023 (light green) and later further up and both sides of the track in 2023-2024 (yellow).

Although latency is important in the NRT forest disturbance system, the emphasis on the temporal context at the detriment of the spatial patterns (or clusters with a particular shape) can generate alerts fragmented in time and space. This fragmentation can be mistakenly taken as false positive alarms (salt and pepper effect) or simply ignored by the agency responsible for prioritising the events to check on-site because of a filter of minimum total area.

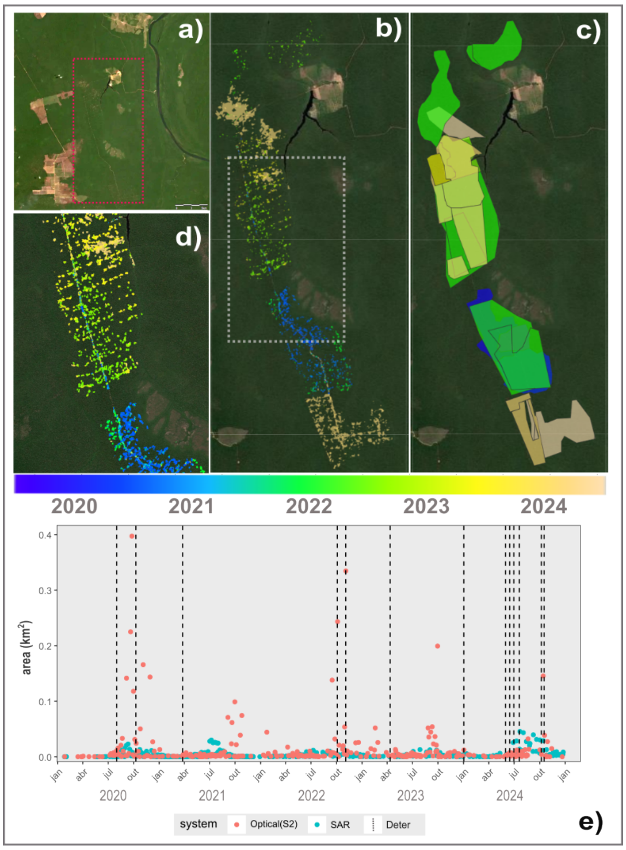

Figure 6. Temporal fragmentation of selective logging detection. Tile with the area of selective logging dashed (a). Combination of all automated alerts (b), Deter alerts (c), close zoom of the image b (d) and sequential plot alerts of optical and SAR alert systems and Deter (dashed lines) per date between 2020 and 2024 (e). Leaflet — Tiles © Esri.

The spatial context is not only important for the detection of gradual and spread degradations, but also to differentiate mining, fire scars and natural hazards such as windthrows and landslides. For instance, windthrow events as the two observed in the Figure 7e (blue), are not alerted by Deter (but collected for research applications). Automated NRT systems have detected their heart as shown (in red), but the detection will be displayed together with all kinds of anthropogenic alerts that later need to be filtered to avoid field operation. Although patterns of windthrow and degradation are similar to a certain extent, they can be distinguished by their peculiar recurrent spatial distribution. Also, while degradation occurs across months or even years, windthrow occurs in a fraction of a second, being the combination of spatial and temporal patterns more than sufficient to classify it. Similar logic can be applied to mining and fire scars (Figure 7c,d).

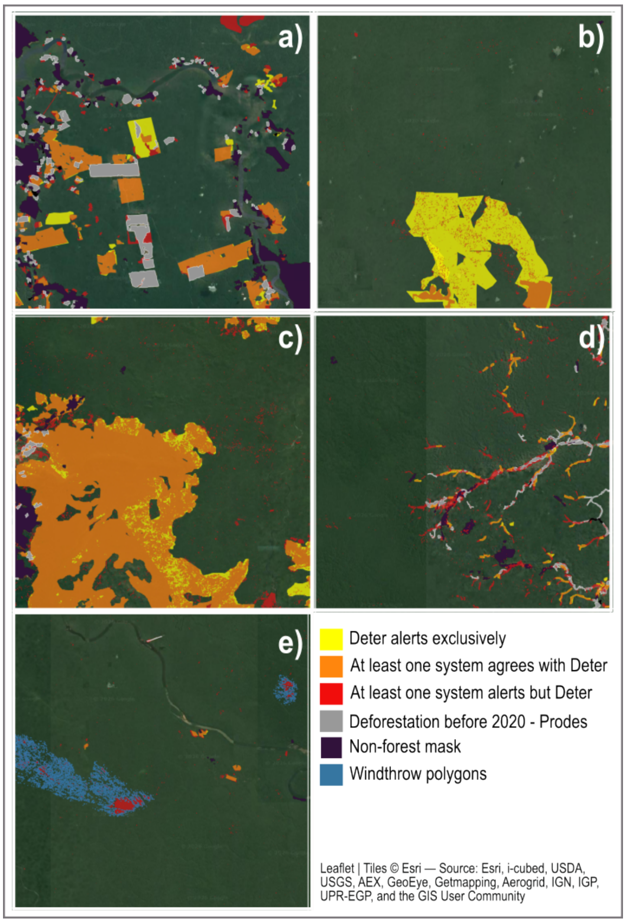

Figure 7. Examples of tiles with detections for the five disturbances analysed in the study. Mainly clear cuts (detected by soil, low vegetation or fire scars) (a), degradation by selective logging (b), fire scars (c), mining (d) and natural disturbance by windthrow (e). Background images by Leaflet — Tiles © Esri.

4. Discussion

In this study, we gathered the most important forest disturbance alert systems available to the Amazon region and analysed their consistency in detecting different types of events. We clearly demonstrated that in the case of clear-cut deforestation, the current available automated NRT systems perform similarly, arriving at results in time and space close to Deter. For this type of disturbance, methods using univariate time series of independent pixels derived from optical or SAR are sufficient to perform the task with reasonably low latency and spatial accuracy. However, disturbances related to degradation, such as selective logging, which are gradual processes and produce sparse small forest clearing, generate alerts that are fragmented and gradually released. This condition may lead to overlooking of the full event when using automated NRT systems. In a recent publication of a novel NRT detection approach, Bottani et al (2025) exclude degradation from selective logging from the study, showing that this type of disturbance is still a current scientific gap. This study also provides valuable insights for post disturbance classification and differentiation by types and agents (anthropogenic and natural) by using the combination of temporal and spatial context.

4.1 Temporal context

For alert systems, the denomination of near-real-time is intrinsically related to the satellite revisit period. However, the temporal context here is more comprehensive and includes: 1) the historical time range used to estimate the distribution parameters (i.e. thresholds) of non-disturbed forest (non-masked); 2) the training period that captures inter- and intra-annual variations in plant phenology and climate; 3) the maximum period from the first detection until the alert confirmation by subsequent images; and 4) the full duration of a disturbance event. The third can greatly vary in the case of an optical sensor, given the possibility of several successive images covered by clouds.

All automated NRT alert systems evaluated use time-series images (Landsat, Sentinel-1 and -2) as independent pixels to detect and confirm the disturbance events. The method changes according to the satellite and detection algorithm, but they are mainly looking for breakpoints or anomalies compared to distribution parameters from the period where the location was still considered a primary forest. The alarm confirmation is also based on temporal context by checking if the anomaly is repeated along the subsequent timestamps when available. Only the temporal context is used to detect and confirm the alerts in the automated NRT algorithms, excluding some rare cases of minimum area configuration in the surroundings of the pixel (a small number of pixels interconnected, between 4 and 8). This procedure works well for clear cuts and other abrupt events that do not require classification by disturbance types or agents.

It is clear that using a pixel-by-pixel algorithm based on independent time series will detect forest clearing even if isolated. However, to what extent the behaviour of these independent time series are distinguishable for different types of disturbance and whether they only depend on the date of the event (breaking point) remains uncertain. To answer these questions, future works will generate functional PCA to identify components that may explain the temporal variations for different disturbance types and also investigate factors that characterise the temporal behaviour of the disturbances by relating them to auxiliary variables and contextual information. These analyses will uncover reasons for the lack of transferability to specific locations or periods, which may be related to model overfitting or non-adaptive thresholds (Rocha et al., 2019).

4.2 Spatial context

The spatial context of the disturbance alert system is often restricted to the discussion of whether the sensor’s pixel resolution is fine enough to detect a certain kind of disturbance or to reduce mixed pixels. Our analysis demonstrates that the spatial context is crucial to identify gradual disturbance as degradation or selective logging. In addition, spatial distribution of closeby alerts can support strategies for faster confirmation, classification per type or agent, and to reduce false positives given the shape, cluster formation or context information such as proximity to river, settlement or croplands. The work of Reis et al. (2025) uses the proximity to past disturbances to reduce the commission error in the Deter-RT prototype using Sentinel-1 time series.

The five types of disturbance present in this study show very clear spatial patterns. For instance, fire scars, when not following a previous clear cut, often cover a vast extent and present a more rounded shape (Figure 7c), while the mining scars follow the river path and present a very distinguished, elongated shape. Therefore, the spatial context is fundamental to classify the disturbance in different types and agents, but also can be detrimental for validation, combined with the traditional temporal confirmation. Spatial patterns and shapes can also support the reduction of false positives (communication errors) by identifying wrong alerts derived from cloud cover, and its shadows, or flooded forest, for instance.

While most (if not all) of the automated NRT systems are available as raster, the ones used by Brazilian authorities as alerts or forest inventory are vector-based. The polygonisation of alerts allow to extract more useful statistics and indicators about the total area per year, filtering event by size or further classifying disturbances by type or agent in a certain location. But when converted to polygons, it became clearer the spatial patterns and the temporal fragmentation of the alerts. Also, raster alerts converted to polygons tend to present isolated pixels as alerts (salt and pepper), as well as holes inside big confirmed disturbance areas, which may need some manual adjustments later.

4.3 Spatiotemporal context

Automating certain Deter tasks that have been performed visually over the past 20 years will only be feasible if a trade-off between spatial and temporal patterns is taken into consideration. The timeframe of the study to create an automated NRT system is determined by the sensor timespan and choices of historical baseline of undisturbed pixels and the mask for ignored previous disturbance areas, as well as the period of training and validation until the full operation starts. During this period of development, some disturbance events were in their course, others have started but will not be completed within the study timeframe. The time range (start and end) and the complete extent of a disturbance event are often not clearly definable. Abrupt disturbances such as windthrow require only three images to determine the spatial extent and form, but also the time window for detection (latency, missing opportunity, omission).

In case of a gradual degradation, as shown here, it may start before and will not end during the study period. This scenario leads to question what the event is. Should we define the event as the extraction of a tree (small and independent forest clearing) or the entire degradation area, composed of the combination of tracks and clusters of removed trees? While the first has a clearer definition as an event and may be feasible with the temporal context alone, small isolated alerts cannot fulfil the task performed by Deter to alert illegal activities of wood extraction or forest suppression to the authorities entitled to inspect the area.

It is necessary to capture the spatiotemporal evolution of an event without increasing the latency by waiting for the disturbance to present a clear spatial pattern (e.g. fishbone shape from skid trails, logging decks and treefall gaps). For that, techniques such as Trajectory Analysis could follow the formation of this disturbance in an accumulative way based on individual alerts of clearing forest patches per image using moving windows or fixed tiles. In other words, it would identify fragmented areas of disturbance (clusters of pixels) at each timestamp, applying thresholds (or alerts) to track features across consecutive time steps based on spatial relationships.

Other advantages of this approach is to incorporate spatial forms without losing the timeframe to produce similar outputs as Deter polygons. It also facilitates overlay disturbance areas with high-resolution images to double check the extention of the event before field operations. With these time-series polygons, instead of pixels, statistics can be easily obtained from the vectors generated at each time step, providing vital insights, for instance, for training better AI models (Rocha et al., 2017). Furthermore, knowing how these events are formed (in space and time), the task of classifying them by types of disturbance and likely responsible agents will be enormously facilitated.

4.4 Spectral context

Although not the focus of this study, the spectral dimension (wavelength regions) plays an important role in forest disturbance in areas susceptible to recurrent cloud cover. From the automated NRT alert systems analysed, three of them (RADD, TropiSCO and LUCA) work in the microwave region (i.e. SAR), while two (GLAD-Landsat and GLAD-S2) use different spectral indices from bands of the visible and near infrared from optical images (Reiche et al., 2021; Mullissa et al., 2024). Most of the systems use only one index in an univariate fashion to generate alerts. The GFW combines alerts from the two GLADs and RADD, and the relatively new GLAD-HLS (Harmonised Landsat Sentinel-2) combine optical sensors (Pickens et al., 2025). However it occurs either previous, to run the univariate algorithm, or after, by combining alerts by different methods, rather than being incorporated in the method to generate or confirm alerts.

Although a combination of sensors at distinct regions of the spectrum could improve detection, given different spatial and temporal resolutions, their use is jeopardised when using methods based on time series of pixels. The combination of different sensors would improve detection in methods that use patches of images as Deep Learning, or to create Embeddings that extract the most important features from them. Like the other two dimensions, spectral information is prone to autocorrelation. Close by wavelength regions (e.g. bands) captured under similar surfaces (forest vs non-forest) can be quite redundant, and the extraction of features should be done carefully (Rocha et al., 2017).

4.5 Disturbance event versus alert

As discussed before, there is a huge difference between alerts and disturbance events. We want to go beyond fragmented alerts in time and space, producing a more refined product that is almost ready to inform the authorities without many previous steps of human manipulation (detection, polygonisation, validation and prioritisation). The significant differences among systems in the number and size of disturbances can arise from various factors due to the particularities of visual interpretation or NRT automated algorithms. For example, whether the event definition considers natural and anthropic disturbances or if there is a minimum area of detection to be published. Raster- or vector-based outputs can also provoke substantial differences. While the first is more prone to have undisturbed islands with small remnant areas covered by trees that are no longer considered primary forest, or because the clearing occurs in a following image and will be alerted again but never confirmed due to the size. On the other hand, polygons will generate gaps and overlaps between two or more polygons created on different dates that need to be adjusted to update the mask, ignoring them in the next steps.

Strategies to confirm the event may also influence system comparisons, as they mainly rely on temporal confirmation (anomaly repeated in the following timestamps). Deter is audited before publication in the maximum period of ten days, while automated systems can confirm a disturbance up to 150 days after assimilation, depending on how many suitable new images repeat the detection. To derive statistics of missed detection (omissions), delays, event duration, spatial mismatching and false positive error (commissions) from alert systems, it is first necessary to define well what a forest disturbance event is. High-resolution image compositions (e.g. Planet) can support these definitions and provide a base for spatial and temporal delimitations, but are very time-consuming and dependent on cloud-free image availability.

A detailed and comprehensive open dataset of forest disturbance labelled by types of event and dates of occurrence, with spatially precise polygon delimitation, is crucial to develop and test properly a new generation of NRT systems able to detect and classify precisely different kinds of events. For this dataset, disturbance polygons need to be refined to accurately represent the entire sequence of a deforestation event, from its initial to its final stage. In addition, a representative alert-validated dataset extracted from systems with different methodologies and sensor technologies to assess the current performance and the remaining challenges will be incorporated. For the selected location, data cubes of images from the CBERS-4, CBERS-4A, Amazônia-1, Landsat, and Sentinel-1 and -2 satellites can be extracted over the entire period using INPE tools like Brazil Data Cube, Integrated Images Catalogue, and TerraCollect platform (Ferreira et al., 2020).

Ancillary datasets, such as elevation, hydrography and flooded forest, could also be used to check the generalisation of the method to different environments that later could be incorporated into detection algorithms or for creating forest disturbance-specific embeddings. The spatiotemporal analysis can guide a deep review of advantages and disadvantages of change detection methods (both operational and in the literature) for each type of forest disturbance. The ultimate goal is to achieve a high accuracy, fully operational automated NRT system for large-scale applications, utilising the state-of-the-art technologies to improve Deter system to guarantee legal reinforcement to preserve the remaining Amazon forest.

5. Conclusion

In this study, we have compared the datasets of distinct automated near-real-time forest disturbance alarm systems available for the Brazilian Amazon using five classes of events caused by anthropogenic and natural agents. We also assessed the agreements of these systems with the detection performed by visually interpreted alerts released by Deter between 2020 and 2024. The exploratory analysis shows that for more abrupt disturbances, such as clear-cut detection, all the systems delivered similar results regarding the spatial and temporal agreement. However, for events related to degradation, the automated systems present fragmented small clearing alerts over time and discontinuous over space, which may deceive the detection when a gradual and dispersed disturbance occurs.

We conclude that a trade-off between the current exclusive temporal approaches used by automated systems and the exclusive use of spatial patterns over time by visual interpretation used by Deter is required to detect and classify multiple types of forest disturbance. This could be achieved by optical, SAR or a combination of time-series path images (e.g. deep learning) instead of pixel-by-pixel approaches, or by analysing the alerts' spatiotemporal trajectory until a clear identifiable pattern formation similar to the human interpretation occurs without losing track of the event's duration. The current availability of ready-to-use image data cubes, high-performance (super) computers and powerful algorithms can lead to a new generation of NRT alert systems that deliver a more refined output able to more autonomously trigger an enforcement of the law, skipping most of the human intermediations until arriving at the final authority destination.

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