Evaluating Forest Disturbance Detection Methods based on Satellite Image Time Series for Amazon Deforestation Alerts

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Abstract

This study explores automated detection methods of forest disturbances using satellite image time series for Amazon deforestation alerts. The research focuses on two municipalities in southern Amazonas, Brazil, known for high numbers of deforestation alerts. Five methods—BFAST Monitor, CCDC, COLD, SCCD, and LSTM—were applied to Landsat image time series from 2017 to 2020 to identify forest disturbances and their effectiveness were evaluated, by comparing their results with alerts from the Brazilian Real-time Deforestation Detection System (DETER). The results demonstrate that the COLD and SCCD methods achieved the highest concordance rates with DETER alerts, at 82% and 85%, respectively, indicating their superior performance in disturbance detection. The LSTM method also performed well, with an 83% concordance rate, showcasing the potential of deep learning techniques in satellite image time series. The CCDC method followed with a 75% concordance rate, and the BFAST method had a concordance rate of 72%. This study highlights the importance of utilizing advanced modeling techniques and multi-spectral analysis for effective forest disturbance detection. The results underscore the need for continued refinement and calibration of these methods to enhance their precision and reliability.

1. Introduction

Forest disturbance events significantly impact ecosystems and are directly related to global climate change, greenhouse gas emissions, and biodiversity conservation (Cohen et al., 2016). Therefore, it is essential to systematically detect and monitoring forest disturbances, enabling an early warning and effective management to prevent further loss of forested land (Rogan and Mietkiewicz, 2015).

Earth Observation (EO) satellite data offers consistent measurements to monitor forest disturbances. In Brazil, there are two important initiatives to detect forest disturbances associated to deforestation from EO data: Satellite Monitoring Project of Deforestation in Legal Amazonia (PRODES) and the Real-Time Deforestation Detection System (DETER), managed by National Institute for Space Research (INPE) (Diniz et al., 2015). To support these applications based on EO data, the evolution of software technologies has improved data storage, processing, and analysis capabilities, crucial for handling large EO datasets and utilizing image time series to detect land use and cover changes (Gomes et al., 2020).

The advancement in remote sensing technologies enhances the accuracy of disturbance detection through image time series analysis, facilitating near real-time ecosystem monitoring and the development of automatic detection methods for Satellite Image Time Series (SITS) (Woodcock et al., 2020). To support SITS analysis, big EO satellite data has been organized as multidimensional data cubes. These data cubes, which compile time series of images for spatially aligned pixels, provide Analysis-Ready Data (ARD) that allow for immediate and interoperable analysis with minimal effort from the user (Simoes et al., 2021).

The Brazil Data Cube (BDC) project, managed by INPE, are producing, integrating, and processing EO data cubes for Brazil (Ferreira et al., 2020). This initiative involves the development of a comprehensive computational platform, including software applications and web services, to facilitate the access, integration, and processing of large volumes of EO data. The BDC project leverages advanced methodologies and machine learning techniques to produce detailed land use and cover maps, aiming to provide valuable insights for environmental monitoring and sustainable land management across Brazil (Simoes et al., 2021).

Forest disturbances are defined as discret events that disrupt the integrity and funcionality of the ecossystems by modifying their physical environment, reducing forest productivity (Fitts et al., 2022). According to (Frolking et al., 2009), forest disturbances substantially impact the biomass and canopy structure of trees, which can include fires, windstorms, logging, shifting agriculture, land conversion, floods, landslides, and avalanches.

Deforestation poses significant threats to the Amazon, one of the most biodiverse regions on Earth. The large-scale removal of trees disrupts the intricate balance of the ecosystem, leading to habitat loss and a decline in biodiversity as numerous plant and animal species are driven to extinction. This degradation also affects the livelihoods of indigenous communities who depend on the forest for their cultural and economic well-being (Vieira et al., 2012).

Deforestation contributes to climate change by releasing substantial amounts of stored carbon dioxide into the atmosphere, exacerbating global warming. The loss of forest cover further destabilizes regional weather patterns, potentially altering rainfall distribution and leading to more frequent and severe droughts. These changes not only impact local agriculture and water supplies but also have far-reaching consequences for the global climate system, emphasizing the urgent need for effective monitoring and conservation strategies to protect the

Amazon (Carrero et al., 2020).

Advanced remote sensing techniques have proven essential for detecting and understanding these disturbances. A study by (Hamunyela et al., 2016) demonstrated the use of spatial context to improve early detection of deforestation from Landsat time series. By incorporating spatial and temporal analysis, their methodology enhanced the accuracy of identifying early-stage deforestation events, which is crucial for timely intervention and conservation efforts.

Another research by (Dutrieux et al., 2016) focused on reconstructing land use history in Brazil using Landsat time series data. Their study utilized a combination of spectral and temporal data to track the dynamics of swidden agriculture systems. This approach allowed for a detailed understanding of land use changes over time, highlighting the potential for remote sensing to inform sustainable land management practices.

(Campanharo et al., 2023) explored the use of the BFAST Monitor algorithm to detect forest disturbances in Maranhão, Brazil. Their research highlighted the utility of NDVI (Normalized Difference Vegetation Index) time series in identifying areas of forest degradation, emphasizing the importance of continuous monitoring to capture subtle changes in forest health. The study found that a significant portion of the monitored areas showed trends of disturbance, demonstrating the effectiveness of time series analysis in forest management.

In a study by (Souza et al., 2021), a data-driven approach was applied to detect disturbances in the Brazilian savannas using time series of vegetation indices. The research underscored the challenges posed by phenological variations and the necessity of developing robust algorithms to differentiate between natural and anthropogenic disturbances. Their findings support the ongoing refinement of remote sensing techniques to improve the accuracy of disturbance detection in diverse ecosystems.

The analysis conducted by (Berveglieri et al., 2021) examined the trends and changes in the successional trajectories of tropical forests using the Landsat NDVI time series. This study linked the structural variability of forest canopies to successional stages, providing insights into the ecological processes driving forest recovery and degradation. The integration of NDVI trajectories with 3D photogrammetric information allowed for a nuanced understanding of forest dynamics over time.

These studies collectively highlight the advancements in remote sensing methodologies for forest disturbance detection. They underscore the critical need for continuous monitoring and the development of sophisticated algorithms to accurately capture the dynamic nature of forest ecosystems.

Building upon these advancements, this study evaluate the BFAST Monitor (Verbesselt et al., 2012), CCDC (Zhu and Woodcock, 2014), COLD (Zhu et al., 2020), SCCD (Ye et al., 2021), and LSTM (Kong et al., 2018) methods to identify disturbance events in forest area by monitoring time series from 2017 to 2020, in a pixel basis, with Landsat image data cube for two case studies in the southern Amazon.

2. Methods

The methodology utilized in this study involves process that can be divided into several key steps, as illustrated in the Figure 1. The first step involves acquiring satellite image time series data from the selected study area, utilizing the Brazil Data Cube (BDC) project. Once the satellite image time series data is retrieved, it undergoes a preprocessing phase. This step includes tasks such as filtering to remove pixels with high cloud cover, linear interpolation to fill missing values, and selection of relevant spectral bands. The preprocessed data is then analyzed using various disturbance detection methods. The final step involves evaluating the results of the disturbance detection methods by using clear cut data from DETER database for 2020.

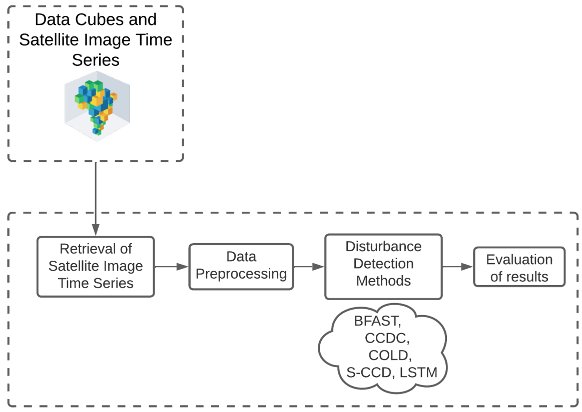

Figure 1. Flowchart illustrating the methodology employed in the study for automated detection of forest disturbances using satellite image time series analysis.

2.1 Study Area

The study area, illustrated in Figure 2, encompassed part of Apuí and Novo Aripuanã, located in the Amazonas state. We selected these areas due to the significant increase in deforested areas in 2020, with Apuí experiencing an increment of 259.63 km² and Novo Aripuanã 110.33 km².

The municipalities of Apuí and Novo Aripuanã, located in the southern part of the Amazonas state in Brazil, are significant regions that have experienced substantial changes in land use and cover, primarily due to the expansion of agricultural activities and deforestation. The region's climate is characterized by an equatorial humid climate with distinct wet and dry seasons, and the dominant vegetation is dense tropical rainforest. Apuí is largely influenced by the Transamazon Highway (BR-230) and has a population heavily reliant on cattle ranching and agriculture. The region has been a hotspot for deforestation, driven by economic activities and shifts in policy that have affected land use practices (Vidal and Neto, 2023).

Novo Aripuanã, similarly, is part of the broader dynamics affecting the southern Amazonas, where infrastructure developments such as road constructions have facilitated increased access and agricultural expansion. The interplay between these environmental conditions and human activities has led to significant ecological impacts, including biodiversity loss and changes in forest cover. These transformations highlight the need for integrated policies to manage land use and protect the remaining forest areas in both municipalities (Yanai et al., 2022).

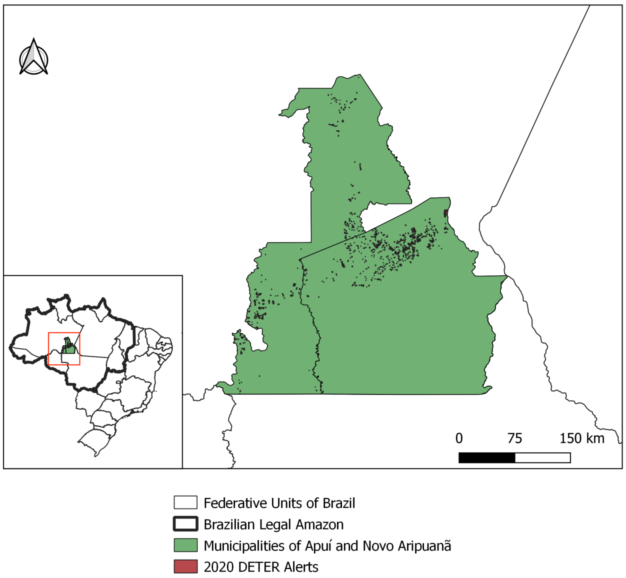

Figure 2. Map showing the study area located in the municipalities of Apuí and Novo Aripuanã, Amazonas, Brazil. The selected areas are highlighted due to significant increases in deforested areas in 2020.

2.2 Disturbance Detection Methods

Various methodologies have been developed and refined to enhance the precision and reliability of disturbance detection using satellite imagery. This section outlines the key detection methods employed in this study, describing their approaches.

Continuous Change Detection and Classification (CCDC) is designed for the continuous monitoring of land disturbances using Landsat time series data. It identifies various land cover and land use changes by detecting breaks in the time series that deviate from predicted statistical intervals. While CCDC is highly effective at detecting disturbances causing significant spectral changes, it may sometimes flag non-disturbance-related changes, reducing its accuracy. Nevertheless, CCDC remains a valuable tool for long-term disturbance monitoring as it continuously updates its model with new observations (Zhu and Woodcock, 2014).

The COntinuous monitoring of Land Disturbance (COLD) algorithm builds upon CCDC by incorporating a broader range of spectral bands and indices, along with advanced statistical methods for outlier removal and model initialization. COLD identifies potential land disturbances by comparing model predictions with new Landsat observations and flagging significant deviations as disturbances. This approach ensures high accuracy in detecting various disturbance types, including those with subtle spectral changes, making COLD a comprehensive tool for large-scale and continuous land disturbance monitoring (Zhu et al., 2020).

Stochastic Continuous Change Detection (SCCD) improves upon COLD by using a state space model, which treats trends and seasonality as stochastic processes. This allows for better modeling of temporal dynamics and more accurate real-time disturbance detection. The SCCD method reduces omission errors and provides faster disturbance alerts compared to COLD, making it highly suitable for operational monitoring of forest health. It demonstrates high computational efficiency and accuracy in detecting both abrupt and subtle forest disturbances using dense Landsat data (Ye et al., 2021).

The Breaks For Additive Season and Trend (BFAST) method decomposes time series data into seasonal, trend, and remainder components to monitor changes continuously. By modeling these components, BFAST can identify structural changes that indicate disturbances. This method is particularly useful in environments with strong seasonal variations, as it can distinguish between normal seasonal fluctuations and actual disturbances. The use of trigonometric functions to model seasonality enhances BFAST's ability to detect subtle changes in vegetation cover, providing robust disturbance detection (Verbesselt et al., 2012).

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, can be employed for disturbance detection by analyzing satellite image time series (SITS). In the referenced work, LSTM models were trained with historical SITS data to predict new time series data. Disturbances were then detected by identifying significant deviations between the predicted and actual data. This method effectively captures temporal dependencies in data, making it well-suited for real-time disturbance detection across diverse ecosystems due to its ability to adapt to non-seasonal patterns (Kong et al., 2018).

2.3 Data

For our analysis, we utilized image time series from 2017 to 2020 extracted from the 16-day temporal composite Landsat data cube of the Brazil Data Cube (BDC) project. We used image times series of NDVI, of the spectral bands Red, Green, Blue, Near Infrared (NIR), Shortwave Infrared 1 (SWIR1), Shortwave Infrared 2 (SWIR2), and of the Pixel Quality Assessment Band (QA_PIXEL).

The Landsat data cube, used in this work, is composed of 16-day temporal composites, where the most recent cloud-free pixel within each 16-day window is selected. These images are then aggregated into multidimensional data cubes and distributed using the BDC Grid System (V2), specifically in the Medium (MD) grid, which consists of 211200m x 211200m tiles. This hierarchical tiling system ensures efficient data management and retrieval, allowing for scalable processing and analysis of large volumes of Landsat-8/OLI data.

Moreover, the polygons of alerts for Clear Cut in 2020 from the DETER system, collected via TerraBrasilis, were used to delimit the areas to be analyzed. The DETER system continuously maps forest suppression and degradation in the Legal Amazon as well as areas with suppression of primary vegetation in the savanna and forest formations of the Cerrado biome.

DETER methodology considers clear-cutting as the complete removal of forest cover, in an abrupt manner, regardless of the intended use for the deforested area. In DETER, clear-cutting refers to the deforestation feature observed with exposed soil in the image used for its detection.

Until 2015, DETER used MODIS and WFI sensors with a 250-meter resolution, mapping deforestation in areas of 25 hectares without distinguishing between deforestation and degradation (Shimabukuro et al., 2006). From 2015, it adopted WFI sensors from CBERS-4, 4A, and Amazonia-1/INPE satellites. This allowed differentiation between detected deforestation and degradation and reduced the minimum alert area to 3 hectares (Diniz et al., 2015).

To address the potential edge effects caused by the differences in resolution between the data used, a negative buffer process was applied to the polygons from the DETER alerts. The DETER system employs satellites with resolutions between 56 and 64 meters, while the Landsat data used in this study has a finer resolution of 30 meters. This discrepancy can lead to inaccuracies at the edges of detected disturbances. Applying a 60-meter negative buffer is a potential approach to mitigate these issues, ensuring that the analysis focuses on the core areas of deforestation and degradation detected by the Landsat imagery that has 30 meters of spatial resolution, which is the main objective of an alert system.

After selecting the spectral bands, we used these buffered polygons from the 2020 DETER alerts to select pixels inside these polygons and to extract image time series from these pixels. The methods applied, including CCDC, COLD, and SCCD, utilized time series of the spectral bands Red, Green, Blue, NIR, SWIR1, SWIR2, and QA. In contrast, the BFAST and LSTM methods used only time series of NDVI.

Initially, the NDVI data underwent a filtering process to exclude pixels with more than 60% cloud cover, corresponding to 55 records. Subsequently, the data for the remaining pixels were subjected to linear interpolation to fill in missing values. Notably, the CCDC, COLD, and SCCD methods do not require this interpolation, as they use the cloud mask from the QA pixel band to internally select clean observations.

Finally, we employed Python-based libraries to detect disturbances in the dataset. Specifically, the `BFASTMonitor` function from the `bfast` library, `detect` from the `pyccd` library, and `cold_detect` and `sccd_detect` from the `pycold` library were used. Additionally, to configure the LSTM, we utilized the `tensorflow` library. Unlike the other methods, there is no dedicated library for applying LSTM in the context of disturbance detection, thus requiring the use of `tensorflow` to implement this neural network approach.

We used DETER data to evaluate the consistency between the disturbances detected by these methods and the alerts detected by the monitoring system. Our validation approach focused on the concordance between the pixels identified as disturbed by each method and the areas delineated by the DETER alert polygons for the year 2020. It is important to note that this evaluation is partial, as it assesses the alerts generated by DETER rather than the deforestation identified by each algorithm. This analysis does not measure the accuracy of the detection methods but rather their agreement with the DETER alerts.

3. Results

The concordance analysis results, detailed in Table 1, demonstrate notable variations in the effectiveness of the different methods. Overall, methods that utilize time series analysis of multiple spectral bands, such as COLD and SCCD, achieved the best performance. Specifically, the COLD method had a concordance rate of 82%, while the SCCD method showed the highest performance with an 85% concordance rate. The LSTM method, which leverages deep learning for time series analysis, also performed well, achieving a concordance rate of 83%. The CCDC method followed with a 75% concordance rate, and the BFAST method, which only utilizes the NDVI time series, had a concordance rate of 72%. These findings align with the observations reported in (Ye et al., 2021), which highlight superior outcomes of methods that analyze multiple spectral bands and employ advanced modeling techniques for detecting forest disturbances accurately.

Method	Concordance
BFAST	72%
CCDC	75%
COLD	82%
SCCD	85%
LSTM	83%

Table 1. Percentage of agreement between the disturbances identified by the methods and the DETER alerts.

Figure 3 illustrates the comparison within a selected small area. The top image (a) shows the buffered DETER polygon, marking an alert issued on May 21, 2020. The images below display the results from the BFAST (b), CCDC (c), LSTM (d), COLD (e), and SCCD (F) methods, respectively.

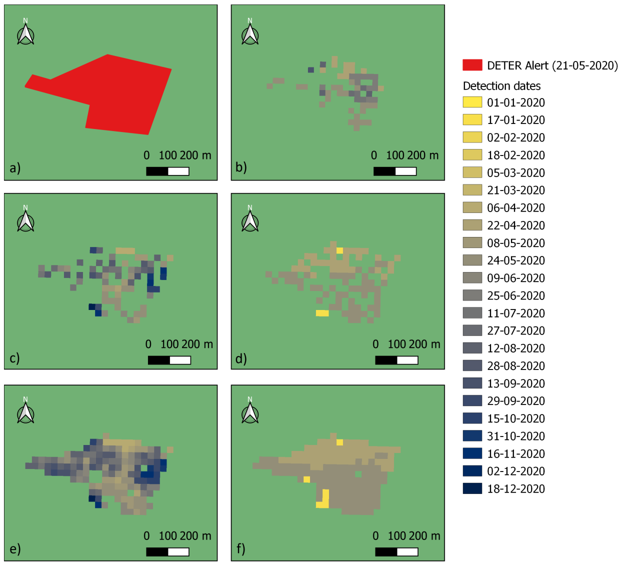

Figure 3. Results of the disturbance detection methods within the buffered DETER polygon alert issued on May 21, 2020 (a): BFAST (b), CCDC (c), LSTM (d), COLD (e), and SCCD (f).

Analyzing the image, it becomes evident that BFAST (b) captures fewer pixels within the target area compared to other methods, a point already noted in the concordance. Notably, the detection dates are clustered around the alert date, specifically between April and June. Moreover, BFAST maintains a homogeneous distribution of detection dates among neighboring pixels, which indicates consistency in temporal detection within the affected area.

The CCDC (c) method, on the other hand, captures a larger number of pixels. However, the majority of these detections occur after the alert date, starting from June and extending to October. This delay in detection is similar to what is observed with the COLD method (e), which also identifies a broader area but with detection dates largely following the alert. Additionally, CCDC's results reveal significant variability in detection dates among neighboring pixels, indicating less temporal coherence.

COLD (e) shows an ability to detect a larger area of disturbance, similar to CCDC, but it also shares the characteristic of post-alert detection dates. This suggests that while COLD is effective in spatial coverage, its temporal detection lags behind

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the actual disturbance events. The method also exhibits less homogeneity in detection dates among neighboring pixels.

The LSTM (d) and SCCD (f) methods demonstrate a higher degree of temporal homogeneity and spatial coverage in their detection of disturbances. These methods successfully capture a majority of the disturbances close to the alert date, showing a robust ability to detect changes promptly. Furthermore, they indicate that the deforestation process in the top of example area (Figure 3) might have commenced prior to the DETER alert.

The results obtained with BFAST might be influenced by the preprocessing step that involved removing time series with more than 60% cloud cover. Since the analyzed region is a tropical rainforest characterized by high cloud cover, this preprocessing step significantly impacts the method's performance. BFAST does not have built-in strategies to handle data gaps caused by clouds, which leads to fewer detected disturbances in areas with persistent cloud coverage.

The issue caused by cloud cover is addressed by the CCDC, COLD, and SCCD methods, as they internally manage the lack of available observations by utilizing the pixel quality band. CCDC employs a systematic approach to exclude cloud-contaminated pixels, ensuring that only clear observations are used for disturbance detection. Building on this, the COLD method enhances this capability by incorporating additional statistical methods, allowing for more accurate identification of cloud-free observations. SCCD further improves upon these strategies by using a state-space model that treats trends and seasonality as stochastic processes, providing better handling of data gaps caused by clouds. These robust strategies enable COLD and SCCD to perform more effectively in regions with high cloud cover, ensuring reliable disturbance detection even in challenging conditions.

The results obtained with the LSTM method are very similar to those achieved with the SCCD method, as both utilize advanced temporal analysis strategies. LSTM leverages the capabilities of recurrent neural networks to capture short-term and long-term temporal dependencies in satellite image time series data. On the other hand, SCCD employs a state space model that treats trends and seasonality as stochastic processes. This similarity in approach allows both methods to effectively detect changes in forest cover with high accuracy, demonstrating their robustness in analyzing complex temporal patterns in the data.

It is worth noting that using LSTM in this scenario requires a greater effort in configuring the network compared to other models. While all non-machine learning models used default parameters, the LSTM had to undergo a process of determining the best configurations for the number of layers, learning rate, epochs, and optimizer. This configuration effort is necessary to achieve good results, but the same network configuration may not be suitable for other areas. This implies that while LSTM can yield effective results, the effort involved in configuration can be a limiting factor, especially for systems intended to serve as near-real-time alert emitters.

Additionally, it is important to note that the alerts issued by DETER do not distinguish between the time of occurrence and the time of detection. The process of deforestation can occur gradually, but its identification as clear-cutting or degraded area happens only when it is captured by the satellite sensor. Therefore, the date provided by the polygons is directly related to the detection time and may not necessarily indicate when the change initially began.

The results obtained from BFAST, SCCD, and LSTM methods in Figure 3 suggest that the deforestation process in the area likely began at the top at the end of April and progressed downward throughout May, being detected by DETER only in the images from May 21.

To illustrate the forest disturbance detection methods used in this study, two high-resolution images from the Sentinel-2 satellite, with low cloud cover, were selected. The first image (Figure 4), dated June 17, 2019, was captured before the forest disturbance, while the second image (Figure 5), from June 16, 2020, was recorded after the occurrence of the disturbance. Both images highlight, in red, the buffered DETER polygon used in the study, allowing for a clear visual comparison of changes in forest cover over time. This choice is crucial to demonstrate the methods' capability to accurately identify and monitor deforested areas.

In the images, it is observed that the area within the buffered polygon shows a significant difference between the two years, indicating an extensive removal of forest cover between 2019 and 2020. The 2020 image reveals a clear area, contrasting with the dense vegetation seen in the 2019 image. This visual contrast is an evidence of the effectiveness of the detection methods employed, which correctly identified changes in forest cover. These images are representative of the results obtained and emphasize the importance of using high-resolution images and advanced temporal analysis methods to efficiently and accurately monitor and validate forest disturbances.

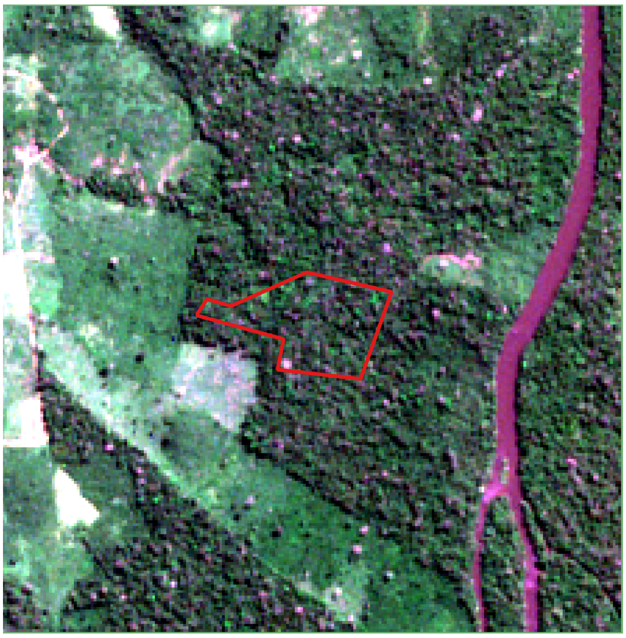

Figure 4. Sentinel-2 image of the study area taken on June 17, 2019, before the occurrence of forest disturbance. The red polygon indicates the buffered DETER alert area used in the analysis.

It is worth noting that the non-detection of the clear cut area by the DETER system in the Figure 5 can be attributed to several causes. First, cloud cover frequently obscures satellite imagery, and DETER's reliance on lower-resolution sensors (64 meters) may miss smaller or partial deforestation events visible

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Figure 5. Sentinel-2 image of the study area taken on June 16, 2020, after the forest disturbance. The red polygon indicates the buffered DETER alert area used in the analysis.

in higher-resolution Sentinel-2 images (10 meters). Additionally, the time between satellite revisits could delay detection if deforestation occurs rapidly. The system may also struggle with gradual or subtle changes in forest cover, which advanced methods like COLD and SCCD can detect more sensitively. Lastly, DETER prioritizes large-scale deforestation for immediate enforcement, potentially overlooking smaller areas that do not meet its alert thresholds.

An important aspect of forest disturbance detection methods is their ability to quantify the magnitude of the detected disturbances. Methods such as BFAST, COLD, and SCCD not only identify the occurrence of disturbances but also provide detailed information on the extent and severity of these events.

The statistical analysis of the COLD method’s results provides insightful data on the magnitudes of disturbances detected across various spectral bands. Among these bands, the Near Infrared (NIR) band stands out with the highest standard deviation (0.00318) and the widest range of values, from -0.34610 to 0.31698. This indicates that the NIR band is the most sensitive to changes in forest cover, likely due to its ability to capture variations in vegetation health and biomass. High magnitudes of change in the NIR band suggest significant alterations in vegetation structure, typical of clear-cutting events where large areas of forest are removed, drastically altering the reflectance properties captured by the NIR sensor.

Conversely, the visible bands (Blue, Green, Red) show lower standard deviations and narrower ranges of values, with the Red band having a slightly higher standard deviation (0.00122) compared to Blue and Green. While these bands are also important for detecting disturbances, their lower sensitivity compared to the NIR band might indicate that they capture less abrupt changes in forest cover, such as gradual deforestation or degradation.

The Shortwave Infrared bands (SWIR1 and SWIR2) also exhibit significant standard deviations (0.00240 and 0.00227, respectively), and a notable range of values, suggesting their effectiveness in identifying changes in moisture content and structural components of the forest. These bands are particularly useful in detecting changes in soil and vegetation moisture levels, which are also indicative of deforestation activities.

The statistical analysis of the SCCD method’s results also provides valuable insights into the magnitudes of disturbances detected across different spectral bands. Similar to the COLD method, the SCCD evaluates changes in the Blue, Green, Red, NIR, SWIR1, and SWIR2 bands, each one showing distinct characteristics in terms of mean values, standard deviations, and ranges of values, which are crucial for interpreting the severity of forest disturbances such as clear-cutting.

Among these bands, the Shortwave Infrared 1 (SWIR1) band stands out with the highest standard deviation (0.00325) and a substantial range of values from -0.08230 to 0.20824. This indicates that the SWIR1 band is highly sensitive to changes in forest cover, particularly in detecting variations in moisture content and structural components of the forest. High magnitudes of change in the SWIR1 band suggest significant alterations, such as clear-cutting, which drastically impacts soil and vegetation moisture levels.

The Near Infrared (NIR) band also shows a considerable standard deviation (0.00237) and a wide range of values from -0.25275096 to 0.20369, highlighting its effectiveness in capturing variations in vegetation health and biomass. Similar to the COLD method, the NIR band’s sensitivity makes it an essential indicator of substantial forest disturbances.

The visible bands (Blue, Green, Red) exhibit lower standard deviations and narrower ranges of values compared to the NIR and SWIR bands. Among the visible bands, the Red band has the highest standard deviation (0.00135) and a range of values from -0.04029 to 0.10750. While these bands are also important for detecting disturbances, their lower sensitivity compared to the NIR and SWIR1 bands might indicate they are more effective for identifying less abrupt changes in forest cover.

The Shortwave Infrared 2 (SWIR2) band shows significant standard deviation (0.00252) and a notable range of values, suggesting its usefulness in detecting changes related to forest disturbances. The SWIR2 band’s ability to capture variations in vegetation and soil properties makes it a critical component of the SCCD method.

The BFAST method, unlike COLD and SCCD, provides results solely for the NDVI, as it is the only input data it receives. The statistical analysis reveals that the mean NDVI change is -0.00043, with a standard deviation of 0.0097. The NDVI values range from -0.58 to 0.28, indicating significant variability in the detected disturbances. The negative mean value suggests a general trend of vegetation loss. The minimum NDVI value of -0.58 points to areas with substantial vegetation loss, while the maximum value of 0.28 may indicate areas of regrowth or less severe disturbances. Additionally, the median and percentiles (10th, 25th, 50th, 75th, 90th) being zero indicate that many changes detected are minor or that there are numerous instances with no significant change. This highlights that BFAST is sensitive to both large-scale and smaller-scale disturbances, underscoring the need for complementary methods like COLD and SCCD for a more comprehensive analysis.

In summary, the BFAST method’s reliance on NDVI offers a focused view of vegetation health and changes. The statistical results suggest that BFAST is effective at detecting both large-scale disturbances with significant vegetation loss and smaller-scale changes. However, its sensitivity to a wide range of disturbance magnitudes underscores the importance of using additional spectral bands and complementary methods, like COLD and SCCD, for a more comprehensive analysis of forest disturbances.

4. Conclusions and Future Work

This study evaluated the performance of several automated disturbance detection methods—BFAST Monitor, CCDC, COLD, SCCD, and LSTM—using satellite image time series to monitor forest disturbances in two municipalities in southern Amazonas, Brazil. The results demonstrated varying levels of concordance between the automated methods and the DETER alerts, with the COLD and SCCD methods showing the highest concordance rates of 82% and 85%, respectively. The superior performance of these methods highlights the importance of using a wide range of spectral bands and advanced modeling techniques for effective disturbance detection.

Challenges such as high cloud cover in tropical rainforests continue to affect the accuracy of methods like BFAST, which lack integrated strategies to handle data gaps. However, other methods, such as COLD and SCCD, have shown remarkable resilience to these challenges by effectively utilizing multi-spectral data to improve detection.

Future research should focus on further exploring the current methods in terms of refinement and calibration to improve detection accuracy and reduce errors, particularly in regions with high cloud cover. Strategies involving deep learning techniques appear promising but require significant effort in parameterization. Additionally, the evolution of validation methods should include working with expert-analyzed samples of time series to accurately assess the temporal detection precision of disturbances. Longitudinal studies are also essential to evaluate the evolution of forest disturbances over time and to assess the effectiveness of conservation policies.

Expanding the application of these methods to other regions of the Amazon and different biomes will help validate the generalizability and robustness of these approaches. Additionally, integrating data from multiple satellite sensors, such as Sentinel-2 and RADAR, could improve the temporal and spatial resolution of disturbance detection.

One of the possibilities to advance forest disturbance detection and address the issue of non-detection observed in DETER images and polygons is to use a mask that indicates forest areas, such as the one generated by PRODES. This approach could help refine the analysis by focusing on regions where forest cover is expected, thereby improving the accuracy of disturbance detection and reducing the likelihood of missing smaller or gradual changes in the forest cover. Integrating high-resolution images from Sentinel-2 with such masks could enhance the system’s ability to detect and monitor deforestation events more effectively.

Developing operational tools based on these methods can significantly enhance the existing systems used by INPE, providing indications to guide the work already being conducted by the institute’s teams. This integration can facilitate more precise real-time decision-making and improve the overall efficiency of forest monitoring and conservation efforts.

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