INTEGRATION OF RADAR AND OPTICAL DATA FOR IDENTIFYING TROPICAL FOREST DISTURBANCES

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ABSTRACT

This work integrates optical and radar data cubes to detect forest disturbances in tropical regions. Our method identifies initial degradation and selective logging, often precursors to deforestation, demonstrating its utility in early-warning systems. These results emphasizes the crucial role of integrating optical and radar data to improve the precision and dependability of monitoring systems, essential for sustainable forest management. These findings highlight the value of integrating multi-source data cubes to enhance precision in monitoring forest disturbances, thereby supporting more responsive and reliable environmental management.

Key words – Forest Disturbances, Multi-source Integration, Earth Observation Data Cubes, Satellite Image Time Series.

1. INTRODUCTION

Protecting tropical forests plays a critical role in controlling global carbon levels and preserving biodiversity on both a global and local scale [1]. Tropical forests contribute to maintaining water cycles, soil preservation, and promoting socio-economic benefits [2]. Having up-to-date data on deforestation is crucial for properly managing and preserving natural resources. Monitoring deforestation in near real-time (NRT) can help governments and communities enhance forest management and quickly respond to illegal deforestation [1].

The Brazilian National Institute for Space Research (INPE) operates the Real-Time Deforestation Detection System (DETER) for continuous monitoring of deforestation and forest degradation [3] using near-real-time satellite images. DETER is a global reference system for detecting forest disturbances. DETER's primary purpose is to provide data on where vegetation changes are happening and how extensive they are and assist in enforcement operations and regulations targeting deforestation.

DETER faces two major limitations. The first issue relates to optical sensor images, which can be affected by atmospheric disturbances like clouds, cloud shadows, and cirrus. Furthermore, experts identify changes in land cover through visual interpretation. Every scene needs to be analyzed by an expert, which requires a lot of human resources.

As an alternative, researchers are developing automated and semi-automated methods for detecting tropical forest disturbances [4–7]. Hoekman et al. [5] and Doblas et al. [7] propose using Sentinel-1 radar time series for detecting forest disturbances. Reiche et al. [8] develop Bayesian methods for combining Landsat and ALOS PALSAR. Hirschmugl et al. [6] use empirical thresholds for detecting disturbances on radar and optical images. These results show that it is feasible to use radar and optical imagery to identify disturbances in tropical forests. Doblas et al. [9] argue that combining optical and radar imagery improves detection capabilities for forest disturbances. Optical images offer specific target details, while radar images remain unaffected by cloud cover.

This work uses a multi-source integration of optical and radar data cubes to identify forest disturbances. We conducted an experiment in Rondonia using CBERS-4 and CBERS-4A WFI and Sentinel-1 satellite data, implementing the Bayesian approach introduced by Reiche et al. [4]. Our results compare favourably with the results from DETER and show that multi-satellite automatic event detection is a viable alternative to visual interpretation.

2. METHODS

Reiche et al. [8] propose the BayTS approach to combine optical and radar time series images using Bayesian statistics. Using a Gaussian distribution, the algorithm calculates the conditional probabilities for each time series for the Forest and Non-Forest classes. For a selected observation time t, all Non-Forest probabilities greater than 0.5 are labelled as likely deforestation areas. For each labelled series, a Bayesian method recalculates the conditional probability of Non-Forest. This is done using an iterative Bayesian update, taking the previous time $(t-1)$, the given time (t), and new observations that have arrived after the labelling procedure$(t+i)$. After the Bayesian update, each observation is either confirmed or rejected as a disturbance event in the time series of each satellite sensor.

This work uses the BayTS approach to process image time series extracted from a multi-source Earth observation data cube (see Figure 1). Probabilities of Forest and Non-Forest are calculated for each time series in the data cube. Based on a threshold, these probabilities determine whether a time series is classified as a Forest. The result is a vector map with the dates when disturbances were identified.

Earth Observation Data Cubes (hereafter referred to as data cubes) are multidimensional data structures with three or more dimensions (e.g., space, time, spectral bands), facilitating the extraction of insights from Big Earth Observation Datasets. Using a data cube, researchers and specialists explore the dynamics of the Earth over the years. A data cube

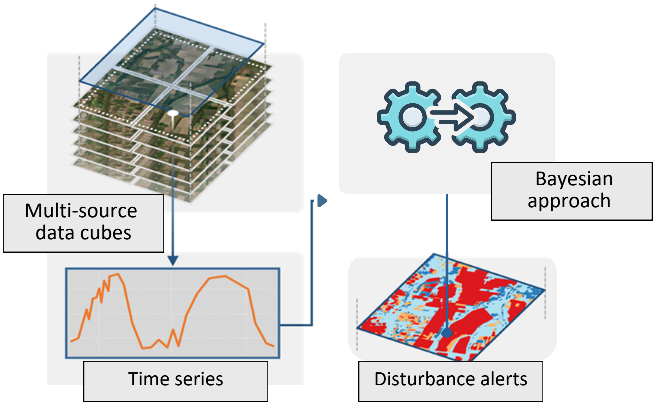

Figure 1: Overview of processing chain for disturbance detection.

comprises Analysis-Ready Data (ARD), defined according to the Committee on Earth Observation Satellites (CEOS) standards. Thanks to its valuable properties, several initiatives are building data cubes at the national level, such as the Swiss Data Cube [10], Australia Data Cube [11] and Brazil Data Cube [12].

3. RESULTS AND DISCUSSIONS

To test our proposed method, we performed a case study in an area in the north of Rondonia (RO) in the Brazilian Amazon (Figure 2), in tile 003003 (BDC Large tile system). Rondonia is characterised by its complex environmental dynamics and significant ecological importance. Rondonia has experienced extensive land-use changes over the past few decades, primarily due to agricultural expansion, cattle ranching, and logging activities. Significant human occupation began in the 1970s, driven by settlement projects promoted by Brazil's then-military government [13]. Small- and large-scale cattle ranching now occupies most of the deforested areas. Deforestation in Rondonia is highly fragmented, partly due to the initial settlement by small farmers. This fragmentation presents considerable challenges for automated methods attempting to distinguish between clear-cut and highly degraded areas. While visual interpreters can draw on experience and field knowledge, researchers must meticulously train automated methods to achieve the same level of distinction.

This study uses two data cubes from the study area, created based on CEOS-ARD definitions. The first contains a Sentinel-1 C band with VH polarisation. The second contains EVI data from CBERS-4 and CBERS-4A WFI produced by the BDC project. The cubes were created using temporal aggregation of eight days. We consider the dates of both data cubes from January 2023 to December 2023. We use a Bayesian approach to integrate these two data cubes for forest disturbance detection in a Rondonia region.

We compared our results with the DETER polygons from 2023 to evaluate the proposed method. The identification results are made pixel by pixel. Several BayTS detections may exist with different dates in a single DETER polygon. Thus, to compare the results, we initially calculated the average of the BayTS detection dates in each DETER polygon.

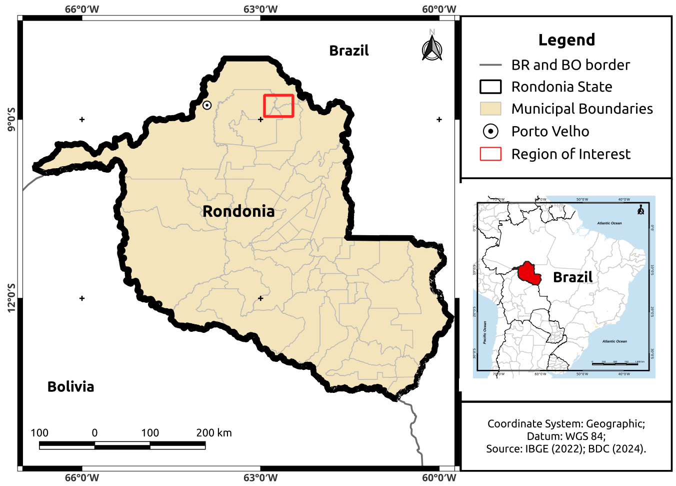

Figure 2: Region of interest in Rondonia.

Then, we calculated the difference between DETER dates and the average date. The resulting data were then grouped by DETER deforestation classes: Burn Scar, Disordered Selective Logging, Geometric Selective Logging, Degradation, Clear-Cutting Deforestation, and Vegetation Clearance.

The temporal difference in days between our methodology and the DETER polygons is presented in Table 1. The average difference in days may be either negative or positive: negative values indicate points identified before DETER, while positive values denote identification occurring after. All of our detections were made before DETER, with a minimum difference of 16 days and a maximum of 183 days.

DETER classification	Mean detection difference (in days $\pm$)
Burn Scar	-87.8
Disordered Selective Logging	-183.
Geometric Selective Logging	-142.
Degradation	-89.4
Clear-Cutting Deforestation	-16.6
Vegetation Clearance	-61.1

Table 1: Mean detection time differences between DETER and BayTS.

The most significant differences occur in degraded areas, such as Disordered Selective Logging and Geometric Selective. This is due to the low atmospheric interference in radar images, which enabled a higher frequency of observations at the onset of selective logging events. However, clear-cut areas showed minor differences since complete vegetation removal occurs briefly.

The Burn Scar areas had a average difference of 87 days. This difference does not imply a delay in DETER's detection. A possible explanation is that other events, such as Clear-Cutting Deforestation, occurred before the burn, shortening the detection period. Another explanation could be the widespread cloud coverage in the Amazon region, which increases the detection time using optical data.

Table 2 compares the areas (in hectares) of each DETER class with those produced by BayTS. Selective logging classes show a high discrepancy between areas where only part of the vegetation is removed. This difference arises from the fact that DETER polygons are created by specialists who classify the entire region as selectively logged. In contrast, our automated method identifies only the pixels where selective logging occurred. Event-related classes such as Clear-Cutting Deforestation and Burn Scar have larger areas in BayTS than in DETER. This difference is due to the higher level of detail captured by radar imagery, which allowed for more precise delineation of the events detected.

DETER classification	DETER Area (ha)	BayTS Area (ha)
Burn Scar	920,52	928,15
Disordered Selective Logging	5985,44	996,14
Geometric Selective Logging	1823,19	73,72
Degradation	1818,41	729,49
Clear-Cutting Deforestation	5920,34	6283,26
Vegetation Clearance	207,07	128,61

Table 2: Comparison between areas measured by DETER and BayTS for each disturbance class.

Figure 3 shows visual examples of areas detected by DETER and the BayTS approach. The differences between how visual interpreters and detection algorithms work are illustrative. Experts tend to delineate closed polygons, which approximate the effect of degradation and disturbance identified in the images. There is a high degree of generalisation resulting from expert knowledge. By contrast, automated methods work pixel-by-pixel and may underestimate the degraded area. These results indicate a possible combination of specialist knowledge and automated processes complementing each other.

4. CONCLUSIONS

This study shows how to combine time series and presents the potential of using optical and radar data cubes to detect forest disturbances. Integrating radar and optical data cubes through the BayTS approach offers significant advantages for monitoring forest disturbances. It reduces noise and enhances spatial consistency. BayTS effectively identifies initial degradation, and selective logging, often precursors to deforestation, demonstrating its utility in early-warning systems. These findings highlight the value of integrating multi-source data cubes to enhance precision in monitoring forest disturbances, thereby supporting more responsive and reliable environmental management.

The results improve on accuracies reported in previous papers [8, 9]. The main difference between our work and prior papers is the choice of EVI time series instead of NDVI data, which was used by Reiche et al. [8]. Also, the intercomparison paper by Doblas et al. [9] only used Sentinel-1 data for the best-performing methods. We also calibrated the BayTS parameters to increase the importance of radar data. Our work indicates that there are substantial grounds for improvement in detecting degradation and disturbance of tropical forests using multi-source data.

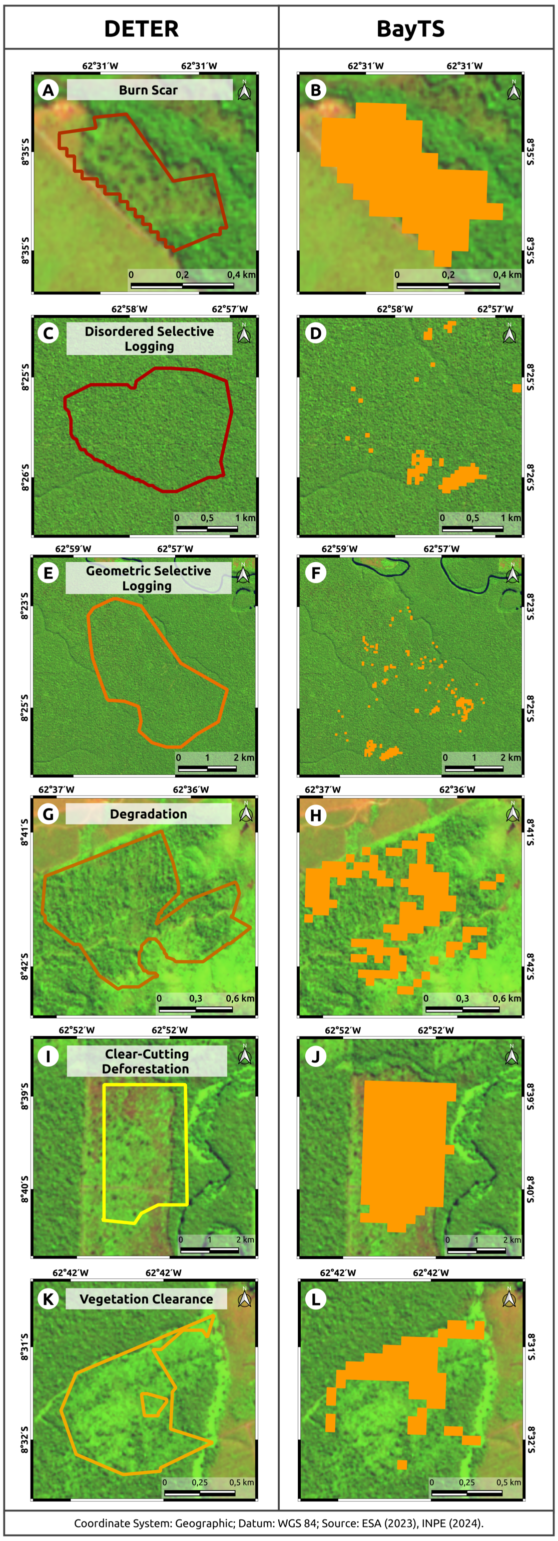

Figure 3: Sampling areas of each DETER classification

CODE AND DATA AVAILABILITY

We implemented a high-performance version of BayTS approach in `sits` [14], an open-source R package for satellite image time series analysis. The code and data used in the experiment presented in this paper are available on GitHub: `https://github.com/OldLipe/bayts-paper-sbsr25`. The study used the open source software SITS, developed in R language and available on the GitHub platform at `https://github.com/e-sensing/sits`. The SITS documentation is available in an online book: `https://e-sensing.github.io/sitsbook/`.

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