A STATISTICAL METHOD FOR NEAR REAL-TIME DEFORESTATION MONITORING USING TIME SERIES OF SENTINEL-1 IMAGES

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ABSTRACT

In this paper, we propose an unsupervised statistical approach for near real-time monitoring of forest loss, leveraging Bayesian inference. We address the identification of forest loss as a change-point detection problem within non-filtered Sentinel-1 single polarization time series data. Each new observation contributes to the probability of deforestation occurrence, utilizing prior knowledge and a data model. Our method offers the advantage of detecting small-scale deforestation without resorting to spatial filtering techniques, thus preserving the native spatial resolution of the Sentinel-1 measurements. To assess its effectiveness, we conducted comparative evaluations against existing operational deforestation monitoring systems. The validation campaign revealed that our method exhibits enhanced detection performance with low false alarm rates with respect to existing systems across diverse landscapes, including dense forest regions such as the Brazilian Amazon, as well as seasonality-dependent areas like the Cerrado, which is strongly under-monitored by existing technology. This robustness stems from the sequential adaptive process inherent in our approach, which enables effective monitoring even in the presence of backscatter variations.

Index Terms**—** Forest Loss, Change Detection, Bayesian Inference, Sentinel-1, Time series

1. INTRODUCTION

Over recent decades, 17% of tropical forests vanished due to deforestation [1], urging the need for efficient tools to monitor and preserve them. Earth observation data offer a solution to monitor forests, granting access to vast, previously inaccessible regions. Consequently, numerous Near Real-Time (NRT) forest disturbance detection systems were developed in the recent years. The forefront technology, the Global Land Analysis and Discovery system (GLAD-L, [2]), is a system relying on optical Landsat imagery that faces the challenge of cloud coverage. Consequently, research has shifted in exploring SAR products which are cloud-insensitive and ensure denser time series. JAXA developed the pioneering JJ-FAST system, utilizing L-Band ALOS/PALSAR-2 SAR time series [3]. Furthermore, ESA's Sentinel-1 mission led to the development of several SAR-based systems with enhanced NRT capabilities. For instance, INPE's DETER-R in the Brazilian Amazon employs the adaptive linear threshold algorithm (ALT) to flag low-backscatter pixels [4]. Another system, TropiSCO by CESBIO and CNES, identifies deforestation events through shadow detection at forest-deforested patch edges [5, 6].

Tropical forest ecosystems encompass rainforests, dry forests, savannas, and grasslands. Deforestation within these forests stems from diverse practices: small-scale agriculture, large-scale agriculture, gold mining, and selective logging. SAR backscatter time series over forests inherently consist of seasonality (periodic variations due to climate), trend (gradual changes from long-term environmental shifts), and abrupt changes (e.g., deforestation, fires, etc.) [7]. Within this framework, direct approaches applying thresholds to SAR backscatter for deforestation monitoring [3, 5, 4], lack consideration for the complex nature of the problem at hand. The aforementioned NRT systems perform well only in dense forest regions, seeking enhanced results via threshold adjustments and spatial filtering to reduce speckle. Filtering notably reduces the spatial resolution of the measurements leading to potential inaccuracies such as overestimation of deforestation and challenges in detecting small-scale practices.

To address uncertainty and enhance flexibility in deforestation detection, Bayesian approaches use probability to assess belief in specific events based on available evidence. The RAdar for Detecting Deforestation (RADD) alerts, developed by Wageningen University and Research (WUR) [8], employ a Bayesian update theory-based algorithm. Like other SAR-based NRT systems, RADD uses data stack preprocessing with filtering for speckle suppression, implicitly reducing spatial resolution. Furthermore, RADD divides land cover in discrete categories (i.e., Forest and Non-forest) and requires a multitude of training data to characterize the class-specific distributions.

This study introduces a non-supervised Bayesian inference-based deforestation monitoring technique with NRT capabilities, adaptable to multiple data sources. Starting from the Bayesian Online Change Point Detection algorithm [9], we tailored it for use with Sentinel-1 SAR data through a conjugate Bayesian analysis. Additionally, we extended its functionality to consider spatial context when detecting deforestation events. The method's ability to maintain the original spatial resolution of Sentinel-1 data, enabled the detection of small-scale deforested areas within the Brazilian Amazon. Moreover, the sequential estimation employed in our method, which ensures adaptation to changing conditions, enabled the detection of deforestation even in the presence of seasonal effects within the Cerrado savanna, significantly under-monitored by the existing systems. The obtained results have been compared with the ones produced by other operational systems for NRT deforestation monitoring.

2. DATASET AND STUDY AREA

This work utilizes Copernicus Sentinel-1 Interferometric Wide Swath (IW), Radiometrically Terrain Corrected (RTC) acquisitions, processed by the European Space Agency (ESA). Any pre-processing, notably spatial filtering, has been omitted to demonstrate the capabilities of the proposed method to preserve the spatial resolution of the data and better perform in the detection of small-scale deforestation.

The study areas selected for this research and depicted in Figure 1 are the Brazilian Amazon rainforest, and the Cerrado woodland savanna. The choice of the study area is motivated by the availability of reliable reference data, as well as the willingness to test our method in presence of various types of vegetation, and implicitly, different signal behaviors. For validation purposes, we made use of the MapBiomas Alerta dataset [10] of year 2020, containing manually validated deforestation polygons over Brazil. For performance evaluation, our algorithm has also been compared with the deforestation alerts of year 2020 produced by two forest loss monitoring systems: GLAD-L ([2], optical system operational over both Amazonia and Cerrado), and RADD ([8], SAR systems operational only over Amazonia).

3. PROPOSED METHOD

The method developed in this work, and named BOCD in the following, starts from the algorithm Bayesian Online Change Point Detection [9]. The method is based on Bayesian inference which provides a posterior probability of an event as a consequence of a prior probability, and a likelihood function extrapolated from the data. Assuming the time series under examination comprises a single-pixel, single-polarization Sentinel-1 SAR backscatter ($x_{1:t}$) time series segmented by change points, the algorithm probabilistically partitions the time series into segments, each representing a different state of the forest. This segmentation is achieved by tracking the posterior distribution over the most recent change point, thereby inferring the current segment's run length, r_t.

$$p(r_t|\mathbf{x}_{1:t}) = \frac{p(r_t, \mathbf{x}_{1:t})}{\sum_{r_t=0}^{t} p(r_t, \mathbf{x}_{1:t})} \tag{1}$$

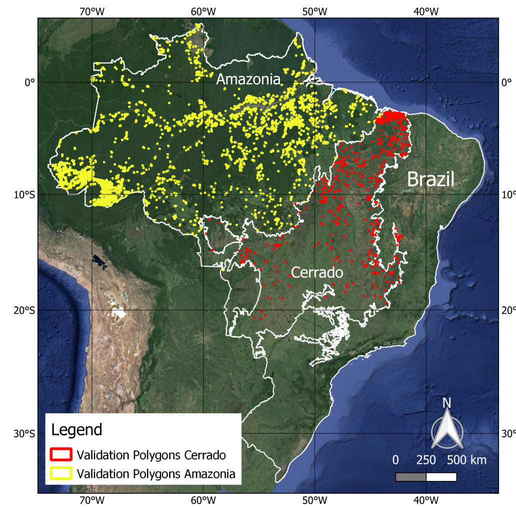

Fig. 1. Study area depicting the MapBiomas Alerta validation polygons for Amazonia and the Cerrado. Optical background image from Google Earth (©2023 Google).

We assume that the data in each segment are independent identically distributed samples from p_θ using a parameter prior, $\theta \sim \pi(\theta)$, and a data model, $x_t|\theta \sim p_\theta(x_t)$. Additionally, considering that the probability of deforestation increases with proximity to previous deforestation, we introduce a conditional prior on the run length, $r_t|r_{t-1} \sim H(r_t|r_{t-1})$, designed to incorporate spatial coherence. This prior influences the assessment of the run length posterior probability which is tractable only if the joint distribution is tractable:

$$p(r_t, \mathbf{x}_{1:t}) = \sum_{r_{t-1}=0}^{t-1} p(x_t|\mathbf{x}_{t-1}^{(r_t)}) \cdot H(r_t|r_{t-1}) \cdot p(r_{t-1}, \mathbf{x}_{1:t-1}) \tag{2}$$

In this context, $\mathbf{x}_{t-1}^{(r_t)}$ represents a segment of length r_t, while $p(x_t|\mathbf{x}_{t-1}^{(r_t)})$ denotes the posterior predictive distribution:

$$p(x_t|\mathbf{x}_{t-1}^{(r_t)}) = \int_{\Theta} p_\theta(x_t) \cdot \pi(\theta|\mathbf{x}_{t-1}^{(r_t)}) d\theta \tag{3}$$

In equation (3), the integral is solvable only when there is conjugacy between the data likelihood and the prior. This results in the Bayes posterior, $\pi(\theta|\mathbf{x}_{t-1}^{(r_t)})$, having the same functional form as the prior, allowing a straightforward derivation of the posterior predictive distribution. Through a conjugate Bayesian analysis we approximated the likelihood of the log-scale Sentinel-1 backscatter data with a Normal distribution (Normal-Gamma prior) and derived a Student's t posterior predictive [11].

Ultimately, the BOCD algorithm outputs a triangular matrix containing the run length posterior probabilities for each observed acquisition. Significant drops in probability mass within this matrix indicate deforestation events. Additional details regarding the algorithm's operational process are reported in Figure 2.

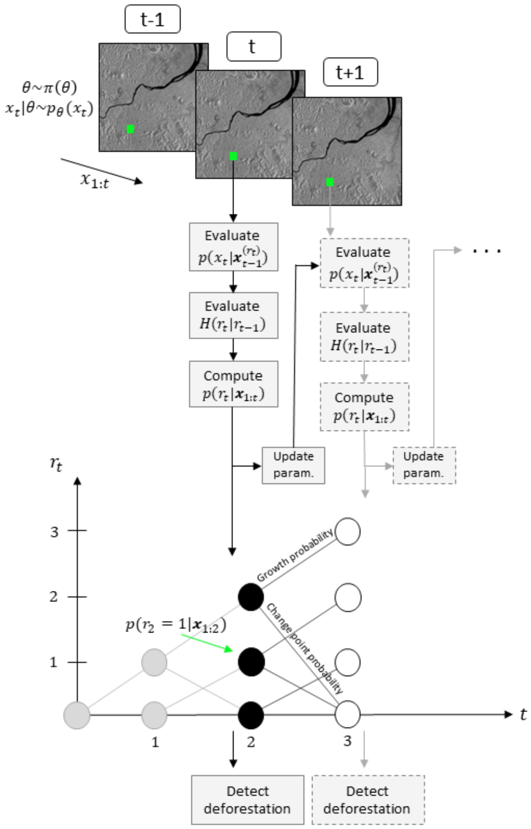

Fig. 2. BOCD working principle: r_t represents the output triangular matrix. The circles indicate probability values for each possible run length, while the colors differentiate past (gray), present (black), and future (white) acquisitions. A significant drop in probability indicates a deforestation event.

4. RESULTS

This section discusses deforestation detection results obtained using the BOCD algorithm in the 2020 monitoring year across two Brazilian biomes, and compares them them with the NRT monitoring systems GLAD-L (Amazonia and Cerrado) and RADD (Amazonia). Results were evaluated against the MapBiomas Alerta dataset used as reference. The BOCD's ability to detect small-scale deforestation was validated focusing on reference polygons smaller than 1ha, totaling 629 polygons in the Cerrado and 3590 in Amazonia. Moreover, the choice of these two validation areas emphasizes the algorithm's adaptability to changing conditions. The Amazon, with its nearly piece-wise constant reflectivity, is extensively monitored by existing NRT systems. Conversely, the Cerrado, the world's most biodiverse woodland savanna, exhibits a backscatter influenced by seasonal effects and is significantly under-monitored by the existing systems.

Considering that within the MapBiomas dataset deforestation flagging occurs in the hypothesis of previous forest, a non-rigorous confusion matrix was constructed for performance evaluation. Specifically, a true positive (TP) is a substantial portion of a polygon detected by the BOCD algorithm that aligns with the MapBiomas dataset for the year 2020. A false negative (FN) represents a significant portion of a polygon missed by BOCD but present in MapBiomas 2020. A false positive (FP) denotes a significant portion of a polygon detected by BOCD in 2019, aligning with MapBiomas 2020. Lastly, a true negative (TN) signifies a substantial portion of a polygon correctly identified as non-deforested by BOCD in 2019, aligning with MapBiomas 2020. The "evaluation threshold" (Thr) indicates the variability in the percentage of a detected polygon needed to consider the entire area as deforested. The confusion matrices regarding Amazonia and the Cerrado are shown respectively in Table 1, and Table 2. We focus on reporting TP and FP, as FN and TN can be easily derived from the former, as well as the F1-score offering a balance metric between precision (p) and sensitivity (s), $F1 = (2 \cdot p \cdot s)/(p + s)$.

Table 1. Confusion Matrix and F1-score for Amazonia. RADD alerts unavailable for year 2019.

	True Positive [%]			**False Positive [%]**		**F1-Score [%]**	
Thr	BOCD	GLAD-L	RADD	BOCD	GLAD-L	BOCD	GLAD-L
75%	**53.34**	49.16	37.60	**0**	0.58	**69.57**	65.66
50%	**74.82**	68.11	64.93	**0**	1.34	**85.60**	80.39
30%	**84.62**	79.22	77.49	**0**	3.45	**91.67**	86.73
10%	**87.24**	86.21	85.79	**1.09**	10.03	**92.65**	87.86

Table 2. Confusion Matrix and F1-score for the Cerrado.

	True Positive [%]		**False Positive [%]**		**F1-Score [%]**	
Thr	BOCD	GLAD-L	BOCD	GLAD-L	BOCD	GLAD-L
75%	**24.64**	13.35	**0**	0	**39.54**	23.56
50%	**56.28**	31.64	**0**	0.48	**72.02**	47.89
30%	**74.40**	50.40	**0**	0.95	**85.32**	66.60
10%	**85.21**	61.69	**0.48**	4.29	**91.78**	74.33

Figure 3 presents a visual comparison between systems in terms of normalized true positives versus normalized false positives for various evaluation thresholds. The results obtained for the Amazon biome showcase a slight enhancement in BOCD's detection capabilities compared to GLAD-L and RADD, and a considerable reduction of false alarms (FP). Moreover, the outcomes concerning the Cerrado biome demonstrate a consistent improvement over GLAD-L's leading results, both in detections and false alarm rates. Figure 4 shows some examples of detection of various MapBiomas Alerta polygons. The first two examples point out the tendency of existing systems to overestimate deforestation due to the application of spatial filtering reducing measurement resolution, and leading to less precise detections compared to the BOCD method. The last example highlights the detection superiority of BOCD against GLAD-L in the Cerrado.

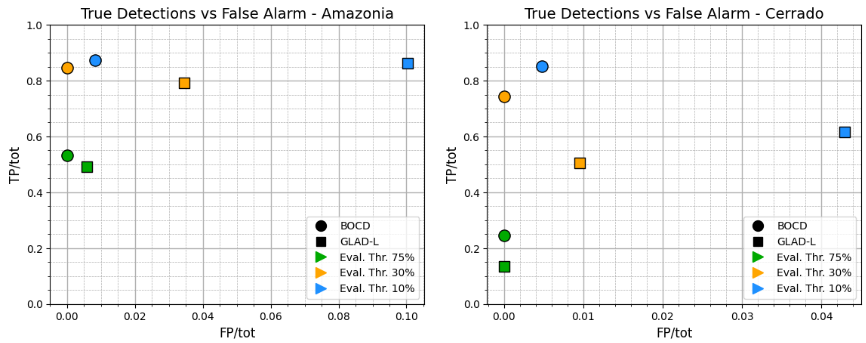

Fig. 3. Normalized true positives versus normalized false positives for different systems and varying evaluation thresholds.

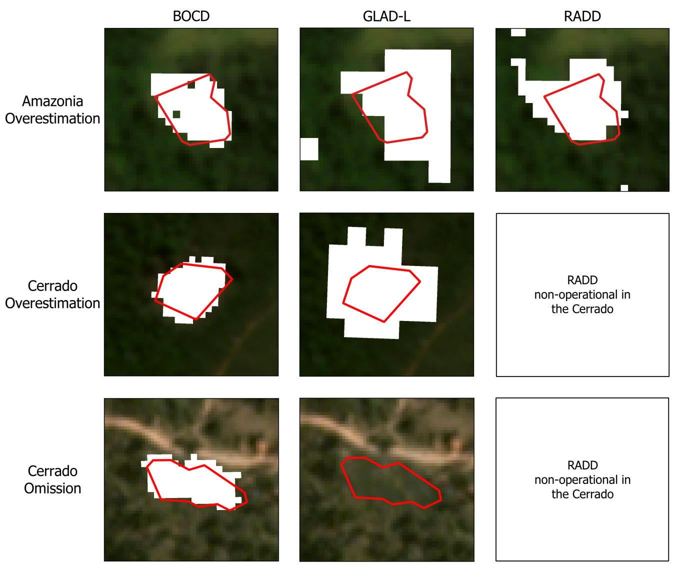

Fig. 4. Example of BOCD, GLAD-L and RADD's detection of MapBiomas Alerta polygons.

5. CONCLUSIONS

This paper introduces a non-supervised near real-time (NRT) forest loss monitoring technique based on Bayesian inference. This work makes several key contributions: (1) The development of a method for NRT forest loss detection that surpasses existing systems in terms of detection accuracy and false alarm reduction. (2) Application of the method in the seasonality-sensitive biome of the Cerrado, demonstrating its adaptability to patterns in the data. (3) A filtering-free approach that maintains spatial resolution and reduces the risk of deforestation overestimation.

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