Towards Semi-automatic Detection of Illegal Logging: Integrating Optical and SAR Satellite Imagery with StanForD Field-Machine Data

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Abstract. Illegal logging is a global issue with severe ecological, economic, and social consequences. In Europe, it often occurs as small-scale, selective harvesting, which, despite its limited footprint, significantly contributes to forest degradation, biodiversity loss, and ecosystem disruption. Detecting illegal logging is essential for assessing its impacts and supporting sustainable forest management. However, its fragmented nature poses significant detection challenges, requiring advanced monitoring solutions. This study presents an exploratory data analysis and preliminary results toward a semi-automatic monitoring framework developed within the EU Horizon SINTETIC project (Single Item Identification for Forest Production, Protection, and Management). The framework integrates high-resolution satellite data from Sentinel-1 (SAR) and Sentinel-2 (multispectral) to analyze time-series trends in optical spectral indices and dual-polarized SAR backscatter, identifying distinctive patterns associated with logging events. An unsupervised sliding-window breakpoint detection algorithm was implemented to detect logging-induced disturbances in satellite time series. The method was validated using georeferenced ground data from legal mechanized logging operations, provided in StanForD 2010 standard format. Two logging scenarios were examined: clear-cutting and selective logging. The exploratory analysis provided valuable insights into forest disturbance patterns, while breakpoint analysis successfully identified the timing of logging events in both scenarios. This system offers a promising approach for detecting illegal logging.

Keywords: illegal logging · selective logging · remote sensing · forest disturbance detection · satellite monitoring

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1 Introduction

Forest disturbances resulting from human-driven land management practices include extensive wildfires, commercial deforestation, mining operations, infrastructure development, small-scale farming, and timber harvesting. Many of these activities are not only environmentally unsustainable but are also frequently carried out illegally, leading to significant ecological consequences [1]. Selective logging of forests – i.e. selectively removing a limited number of targeted trees, which may not be contiguous, while leaving the remaining trees in the stand –, in particular, has now become a dominant harvesting process in Europe. It ensures ecosystem conservation than a more intensive logging system (e.g. clearcutting – i.e. removal of all trees in the targeted area). However, when unregulated or illegal, it wreaks havoc on ecosystems, altering the forest's light regime, microclimate, and nutrient cycling, with long-term impacts on species composition and biodiversity, up to contributing to increased vulnerability to any other type of natural or human-induced disturbance [2]. Yet, uncertainties remain in fully understanding the impacts of selective logging [3], and detecting illegal logging is critical to assessing its effects and ensuring sustainable forest management [1].

With the introduction of new European legislation addressing deforestation-free products, such as Regulation (EU) No 995/2010 (European Union Timber Regulation – EUTR) and its replacement Regulation (EU) 2023/1115 (Regulation on Deforestation-free Products - EUDR), the European Union has taken steps to curb illegal logging practices. However, in Europe, logging standards are not universally regulated, with practices varying significantly between countries and even within regions (e.g., Italy) due to fragmented national and sub-national governance. These inconsistencies complicate efforts to monitor and manage logging effectively.

On a landscape scale, satellite remote sensing holds great promise for detecting active logging and harvesting [4]. Recent advancements in remote sensing technologies, including high-resolution optical and synthetic aperture radar (SAR) imagery, offer new opportunities to monitor forest degradation and disturbances [5]. SAR, in particular, is less impacted by weather conditions, making it an ideal tool for continuous monitoring. However, although SAR data provides valuable insights into structural changes within the forest canopy, its ability to detect low-intensity selective logging is limited due to the small canopy gaps such harvesting practices produce [2, 3].

However, the main challenge of using remote sensing data to detect low-intensity logging is compounded by the lack of robust field data for comprehensive model training, validation and development. While localized field campaigns have provided valuable insights, a continent-wide standardized approach remains elusive due to the high costs and time demands of such efforts. The integration of detailed, georeferenced ground-based data collected from mechanized logging operations following the StanForD 2010 standard [6] offers a potential breakthrough. A key element of this approach is the integration of detailed ground-based, georeferenced harvesting data, including the number, volume, and location of harvested trees, collected from mechanized legal logging operations. This data might be employed to train and validate advanced classification models, enabling precise correlation between observed forest disturbances and known harvesting activities, leading to more effective monitoring and management of forest ecosystems. In

the framework of Horizon EU project SINTETIC (https://sinteticproject.eu/), an intensive and heterogeneous collecting campaign is programmed from project partners across Europe. In this framework, this study aims to assess the sensitivity of Sentinel-1 and Sentinel-2 data in detecting and mapping logging activities, in particular selective logging, utilizing StanForD 2010 machine-field data as geolocation and position reference. By integrating this data with remote sensing tools, we seek to enhance the detection of forest disturbances and improve our understanding of the impacts of selective logging across Europe.

2 Study Areas

Three areas in different parts of Europe were analyzed (Fig. 1): two in Spain (SPAN - 42°06′55″N, 1°27′45″E; SPAN2 - 43°13′34.9″N 3°11′54.1″W), and a third in Scotland (SCOT - 56°43′09″N, 5°46′28″W). These areas were subjected to two distinct types of forest interventions: for SPAN and SPAN2 area, logging was selective, with 168 and 176 trees respectively, removed from an area of approximately 6500 m^2 and 1150 m^2. The trees were randomly distributed, but their selection for felling was predetermined (selective logging). This method preserved full canopy coverage even after logging. In contrast, in SCOT area, all trees within a 13000 m^2 area were felled (clearcutting).

The topography of the two areas differs significantly. The SCOT and SPAN2 areas are located in a flat region, whereas the SPAN area is situated on a hillside watershed with a slight slope oriented toward the south.

Additionally, both areas are characterized by challenging weather conditions, with a high number of cloudy days, which can significantly impact sky clarity and remote sensing observations.

This experimental setup enabled a comparative analysis of the responses of the S1 and S2 signals under two distinct and highly challenging scenarios.

3 Dataset

3.1 StanForD Field-Based Harvesting Data

During the logging process, multiple data points were recorded to track harvesting activities. Specifically, the number of felled trees and the total geometric volume skidded from the forest were systematically documented. Additionally, the geolocation of the logging machine (forest harvester machine) was recorded throughout all phases of the operation, providing precise spatial information about the harvesting process. This information was stored in StanForD 2010 (Standard for Forest Machine Data and Communication) files, a standardized format developed by Skogforsk [6] for communication with forest machine controllers. StanForD 2010 consists of two main components: i) data standard that defines how information is structured and recorded; ii) an XML-based file structure (HPR files) that stores detailed records of the harvesting process. A unique continuous *StemNumber* is assigned to each felled tree (or stem), which is recorded directly by the harvester's onboard computer to the HPR file. Although this data collection is highly detailed, its frequency and completeness still depend on the discretion of the machine operators.

In this study, we utilized geolocation points of logging machinery (StanForD 2010), provided by logging companies, to ensure precise spatial and temporal tracking of harvesting activities. To facilitate data extraction, a custom Python script was developed to efficiently retrieve and restructure information from HPR files into a more accessible format.

3.2 Sentinel-1 SAR Satellite Data

The S1 dataset consisted of a time series of ground range detected (GRD) images, acquired in interferometric wide (IW) mode, for each of the two available polarizations: co-polarized VV and cross-polarized VH. Google Earth Engine (GEE) was exploited for bulk-downloading of the entire dataset. GEE is a cloud computing platform providing calibrated, ortho-corrected Sentinel-1 scenes that have been processed in the following steps using the Sentinel-1 Toolbox [7]: i) thermal noise removal; ii) radiometric calibration; iii) geometric terrain correction (i.e. geocoding) using the Shuttle Radar Topography Mission (SRTM) 30 m digital elevation model (DEM); iv) decibels (dB) backscatter conversion. The pixel spectral resolution was 10 m.

A time series was necessary since Sentinel-1 single image is not enough to differentiate logging activities with reasonable precision [3]. It covered a period of just over two years before and just over one year after the logging event (196 images, SPAN; 269 images, SPAN2; 155 images, SCOT).

3.3 Sentinel-2 Multispectral Satellite Data

The S2 Level-2A (bottom-of-atmosphere) multi-spectral time series was also processed and retrieved from GEE [8]. For this preliminary analysis, two bands were selected: the red band (B3, ~655 nm) and the near-infrared (NIR) band (B8, ~800 nm). These wavelengths were chosen because they are well-established as being highly sensitive to foliar chlorophyll content and are particularly suitable for vegetation monitoring [2]. Additionally, both bands have a fine native pixel spatial resolution of 10 m. The normalized difference vegetation index (NDVI) was then calculated:

$$\mathrm{NDVI} = (\mathrm{Red} - \mathrm{NIR})/(\mathrm{Red} + \mathrm{NIR}) \tag{1}$$

The time series (75 images, SPAN; 104 images, SPAN2; 155 images, SCOT), filtered for cloud coverage (with a threshold of 50%), covered the same period as the S1 dataset (Sect. 3.2). Further cloud filtering was conducted using the QA60 cloud mask band [9].

4 Methods

4.1 Processing

The aim of this study was to analyze the responses of optical and SAR satellite signals in order to identify distinctive patterns or biometry characteristics associated with logging events. This involved two separate steps: *ad-hoc* processing for explorative data analysis, and breakpoint identification.

Exploratory Data Analysis. The Harmonic Analysis of Time Series (HANTS) algorithm was employed in this study for robust smoothing and gap-filling of remotely sensed time-series data. HANTS effectively mitigates common remote sensing challenges, such as persistent cloud cover, atmospheric disturbances, and sensor anomalies, which can obscure true seasonal dynamics. The analysis included NDVI time series derived from multispectral Sentinel-2 imagery, as well as VV and VH backscatter from Sentinel-1 data. To ensure a focused analysis, a location mask was generated using georeferenced logging areas from the StanForD 2010 database, allowing targeted evaluation of both affected pixels and their neighboring areas.

Breakpoint Detection. Abrupt changes (breakpoints) in the temporal evolution of the average pixel value within the location mask—calculated at each time step by averaging all pixels in the mask—were detected following selective logging, serving as indicators of forest disturbance. Window-based change point detection, implemented through the *ruptures* library [10], was used for fast time-series segmentation and breakpoint detection. For a comprehensive technical description of the algorithm, please refer to [11]. The model requires only a few parameters to be set: the window length, which is the number of samples used to estimate a change point within the segment, was set to 2; the squared deviations segmentation model (l2) was adopted; the minimum segment length was set to 2 (default); the jump parameter, defining the interval between consecutive points that are used in the analysis, was set to 2; and the expected number of breakpoints was set to 1. Temporal information from StanForD 2010 was used as the reference timeframe for validating breakpoint detection.

5 Results and Discussions

5.1 StanForD 2010 Field-Machine Data

Besides georeferencing and logging timing, several other pieces of information can be retrieved from the StanForD 2010 field-machine database. For example, Fig. 2 presents the volume and diameter-at-breast-height (DBH) distribution of logged stems in the form of boxplots. The total volume exported was 19.44 m^3 10.78 m^3 and 431.49 m^3 for SPAN, SPAN2 and SCOT areas. These data provide key insights into extracted timber volume, influencing canopy gap formation and serving as critical biophysical indicators for remote sensing-based logging detection.

5.2 Satellite Analysis

The temporal distribution of smoothed Sentinel-2 NDVI exhibits a clear decline following logging, with the effect being most pronounced after clearcutting (Fig. 2, left column). In the case of selective logging (Fig. 2, right column), the overall decrease in NDVI is less evident in terms of mean trend but becomes more pronounced during the subsequent dry season. A key indication of this change is provided by the density bins of the curves, where a darker red gradient signifies a higher frequency of pixels within a specific NDVI range. Notably, shortly after selective logging, a greater proportion of pixels exhibit lower NDVI values, as indicated by the brighter red gradient. A

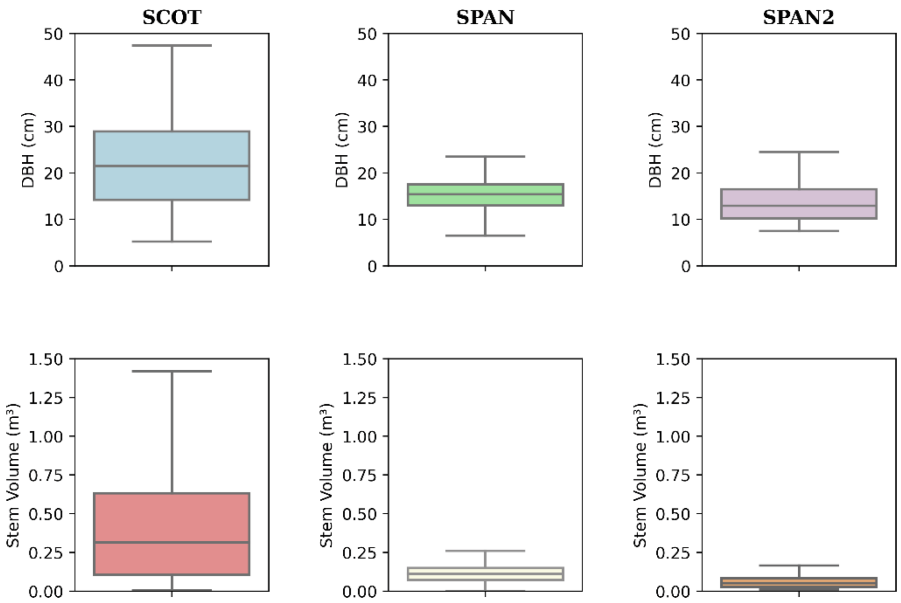

Fig. 1. Boxplot stems volume and diameter at breast height (DBH) distribution.

similar pattern was observed following clearcutting, although weaker. The role of secondary factors potentially influencing NDVI behavior in this specific context—beyond the direct reduction in leaf area due to the removal of targeted trees—should be further investigated. These may include increased shading caused by canopy gaps, the influence of understory vegetation, a more intense dry season affecting vegetation broadly, or a combination of these elements. The preliminary results presented in this study will help guide future analyses in this direction.

The SAR backscatter, on the other hand, seems to not have returned any useful information in this part of the analysis when selective logging was performed (Fig. 2, bottom-right).

5.3 Breakpoint Detection

The algorithm accurately detected breakpoints with high precision and computational efficiency (Fig. 3). The vertical dashed line represents the exact start date of logging, while the blue and red areas in the plots indicate the detected breakpoints. Notably, unlike the previous phase, the SAR backscatter time series used for breakpoint detection was not smoothed. When analyzing the average metric, a discernible shift in the trend cycle is visually apparent. At the time of logging, a distinct—albeit subtle—change in the time series signal is observed. These findings are particularly significant, as SAR data enables continuous monitoring even in regions where persistent cloud cover obstructs optical observations for most of the year.

Both polarizations proved to be potentially useful for logging detection, including selective logging. This supports the notion that the co-polarized channel plays a valuable

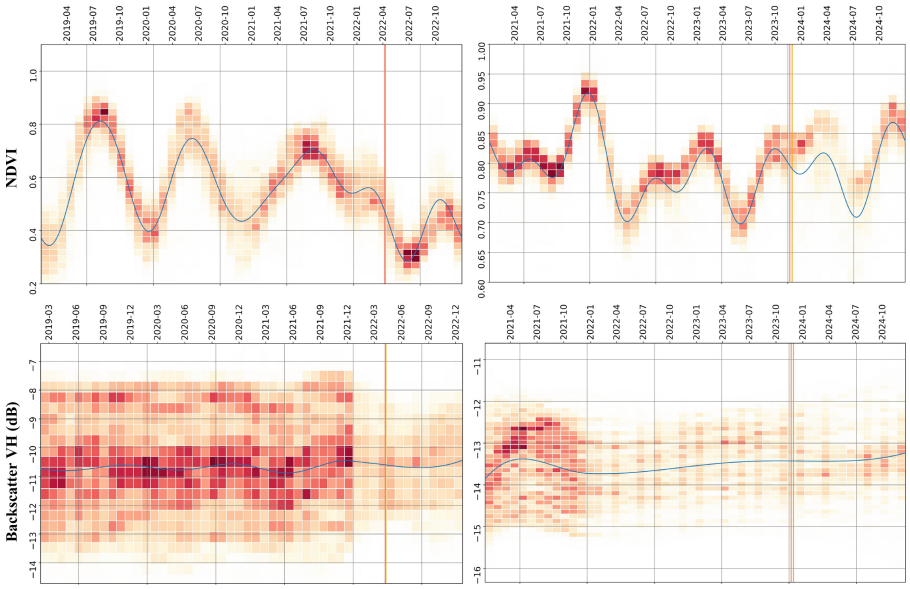

Fig. 2. Temporal distribution of smoothed NDVI (top) and VH (bottom) for SCOT. The blue line represents the mean value while red-gradient bins show the density. The vertical orange and yellow lines indicate the harvesting start and end times respectively.

role and should not be ignored in forest disturbance detection analyses [3], despite cross-polarization being more sensitive to stand volumetric properties and widely recognized in the literature as the most suitable for detecting forest cover changes [12–14]. Hethcoat et al. (2021) [3] observed that VV polarization decreases shortly after selective logging. Additionally, their time-series breakpoint detection approach performed well for logging events exceeding 20 m^3/ha. These findings align with the well-documented physical behavior of SAR backscattering in the C-band, where the disruption or removal of volumetric forest components leads to reduced direct surface scattering and/or diminished volume scattering, resulting in lower backscatter values in both co- and cross-polarization channels [1, 11].

In this study, a slight decrease in backscatter values is observable, with a more pronounced reduction in VH polarization. However, it is important to note that the volumetric removal in the selective logging area of Spain (29.9 m^3/ha) is only slightly above the minimum threshold observed by Hethcoat et al. (2021).

This suggests that Sentinel-1 time series have significant potential for detecting and monitoring selective logging activities, provided the logging intensity remains at this level. However, the data may not be fully suitable for detecting very low-intensity selective logging (<15 m^3/ha) and small felling gaps (<300 m^2) [11].

Predictably, the change in the S1 time series signal was more evident in the clear-cutting areas, as anticipated. This is because higher logging intensities enhance the detection of canopy gaps, making them more detectable from satellite [11].



Fig. 3. Breakpoint detection results. The vertical dashed line represents the exact start date of logging, while the blue and red areas in the plots indicate the detected breakpoints. The continuous blue line represent SAR temporal backscatter. From the top: SPAN2 VH; SPAN VH; SPAN VV; SCOT VH.

Selective logging poses a significant challenge, as undetected disturbances due to remaining trees can lead to omission errors [1]. This issue is especially critical for shorter wavelengths, such as X and C-band SAR [12–14]. Investigating these uncertainties, including small-scale disturbances (e.g., roads, wildfires, windstorms) and radar shadows, will be a crucial step for future research, as they can closely resemble logging backscatter responses.

6 Conclusions

The findings of this study demonstrate the potential of integrating SAR and optical data for detecting logging activities across various scenarios, particularly selective logging. SAR data has proven to be sensitive to medium-to-low intensity timber extractions and represent the unique solution in areas where cloud cover obstructs optical observations. This is crucial for the development of semi-automatic detection methodology that generates maps of forest disturbances, including location, timing, and probability, and filters legal operations to focus on unexpected disturbances, such as those from unauthorized harvesting or natural events. For these purposes, StanForD 2010 machine-field data provides standardized, robust ground data in massive quantities, which is essential for effectively training remote sensing models and optimizing detection accuracy.

The objectives defined within the broader timber traceability ongoing framework developed under the EU Horizon SINTETIC project, which attempts to establish a comprehensive end-to-end monitoring system, from standing trees to the final timber product. By integrating freely available satellite imagery, open-source tools, and advanced data analysis with ancillary datasets to identify potential illegal logging activities, the system significantly enhances proactive forest governance and supports sustainable timber markets within the framework of precision forestry.

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