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Assessing ALOS-2/PALSAR-2 Data's Potential in Detecting Forest Volume Losses from Selective Logging in a Section of Tapajós National Forest †

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Abstract: This study assesses ALOS-2/PALSAR-2 (ALOS2) polarimetric images for detecting forest volume losses due to selective logging in a region in the Brazilian Amazon. Two logging-intensive areas APU 2016 and APU 2017, were studied. ALOS2 imagery atributes, including backscatter and phase data, were analyzed for differences between logged and unlogged regions using Wilcoxon's nonparametric test at a 95% confidence level. The Radar Normalized Difference Vegetation Index proved effective in detecting selective logging-induced forest volume losses, with consistent results (p-value 0.003 for APU 2016 and 0.037 for APU 2017). These findings provide insights for monitoring and mitigating ecological impacts from logging in complex forest ecosystems.

Keywords: ALOS-2/PALSAR-2; Brazilian Amazon Rainforest; Selective Logging; Forest Volume Losses

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1. Introduction

Selective logging consists of removing timber selected trees species and usually takes place in limited areas and over short periods [1,2]. This process can lead to a deterioration of the canopy density and structure [3], causing a reduction in aerial biomass [4] and photosynthesis [5]). It can also harm the canopy floristic composition [6] and increase the risk of local extinction of native species [7].

Increased canopy openness due to selective logging can contribute to enhancing microclimatic changes which, in turn, influence the proliferation of exotic species [8]. The sum of these changes can contribute to increasing the mortality rate of trees [6]. The recovery time of areas affected by selective logging is often determined by the pre-perturbation conditions of the biophysical structure and the intensity of the disturbance [9].

According to Curtis et al. [10], selective logging stands out as a prominent contributor to tropical forest degradation. This degradation phenomenon has notably gained momentum across most tropical forests, driven primarily by the escalating demand for timber products [11]. Research Barros et al. [12] underscores this trend, specifically in the Amazon region. Their findings emphasize the frequent occurrence of selective logging, particularly targeting timber species of high commercial value. The upsurge in this activity can be attributed to the burgeoning domestic timber market and concurrent enhancements in road infrastructure.

Selective logging, when executed without adherence to sustainable forest management practices, leads to the formation of heterogeneous forest landscape with remnants of logging infrastructure, and degraded forests [13]. This type of degradation increases the forest's susceptibility to events such as fire and drought [14] and can also be a precursor to deforestation [15]. Consequently, it does not ensure the preservation of the forest cover, its structure and diversity, as well as the regional ecology of the forest ecosystem [16].

Studies on the impacts caused by forest degradation due to selective logging processes are of fundamental importance. Monitoring and quantifying biomass losses caused by forest degradation due to selective logging, using remote sensing products, is still a major challenge, especially since changes in forest cover are very subtle and punctual. In this sense, this study focuses on evaluating the capabilities of ALOS-2/PALSAR-2 polarimetric images for detecting forest volume losses resulting from the selective logging process in Tapajós National Forest, situated in the Brazilian Amazon rainforest.

2. Materials and Methods

2.1. Study Area

The study area is composed of two Annual Production Units (APU) – APU 2016 and APU 2017, inserted in the Tapajós National Forest (TNF), near the BR-163 highway (Cuiabá/Santarém highway), in the Pará state, Brazil.

Despite the APU are areas with high timber exploration (between 27 m^3 ha^{-1} and 29 m^3 ha^{-1}) [17], the timber management in these areas is carried out sustainably. Together the APU 2016 and APU 2017, cover an area of approximately 10.7 km^2. The main species selected for selective logging were: maçaranduba (*Manilkara huberi*), tauari (*Couratari guianensis*), jarana (*Lecythis lurida*), and goiabão (*Pouteria bilocularis*), with only those with a diameter greater than or equal to 50 cm being considered.

2.2. Field Data

The sample set consists of selective logging points obtained from the Cooperativa Mista da Floresta Nacional do Tapajós (Coomflona). For each sample point, representative geographic coordinates (latitude and longitude), using a Global Positioning System (GPS) receiver (Garmin 60CSx and 64s models), were gathered.

A set of 1,127 selective logging samples was obtained for UPA 2016. The selective logging period in this area was between December 28, 2016, and January 30, 2017. In turn, for UPA 2017, were obtained a set of 1,103 selective logging samples, and the selective logging period was between November 11, and December 07, 2017. Further details on the acquisition of the field samples can be found in Wiederkehr, 2022 [17].

2.3. Control Group

To create the control group, data from undisturbed and undegraded Tropical Moist Forests mapping (TMF) from 1982 to 2020, freely available on the platform of the European Commission's Joint Research Centre, was used as a reference. To compose the control group, 567 random points were generated in vector format using QGIS v.3.6.10 software, with a minimum distance of 100 m, inserted into a total area of around 664 km^2. These points were overlaid on the undisturbed and undegraded tropical rainforests map, which were in raster format. From this overlay, it was possible to extract the forest sample values for all the random points generated from the map.

2.4. SAR Images and Processing

Four dual polarimetric images, HH and HV, in StripMap-3 mode from ALOS-2/PALSAR-2 satellite (ALOS2), L band (~23.6 cm), with 1.1 processing level (Single Look Complex data) were used. The multitemporal ALOS2 images were acquired on 09/18/2016, 02/05/2017, 11/12/2017, and 05/13/2018. These acquisition dates correspond to the period before and after selective logging exploration. The image pairs used by the field samples and control group associated with each APU are listed in Table 1.

Table 1. ALOS2 image pairs correspond to the period before and after selective extraction in each Annual Production Units (APU).

Image acquisition				
APU	**Before**	**After**	**Nº samples**	**Period of selective logging**
APU 2016	09/18/2016	02/05/2017	1.127	12/28/2016 – 01/30/2017
APU 2017	11/12/2017	05/13/2018	1.103	11/20/2017 – 12/07/2017

The Sentinel Application Platform (SNAP) software was used for the ALOS2 images processing. The multilook processing was carried out with a window size of 1 pixel in range and 2 pixels in azimuth, which resulted in pixel spacing of 5.13 m in the range direction and 3.22 m in the azimuth direction. The BoxCar filter with a 3x3 pixel window was applied to reduce the speckle noise, and afterwards H-α polarimetric decomposition was carried out [18], in order to extract the entropy (H), and alpha angle (α-ALOS2) attributes.

The ALOS2 images were also radiometrically calibrated into backscattering coefficients ($\sigma°$) that allowed generating the Radar Normalized Difference Vegetation Index [19] and the grey level co-occurrence matrix - GLCM [20] in HV polarization. The GLCM attributes considered were Contrast (Con), Energy (Ener), and Maximum Probability (Max). Images were geometrically corrected using a 30 m digital elevation model derived from the Shuttle Radar Topography Mission. The last procedure consisted of the coregistered by the neighbour distance method. After carrying out all the procedures in the processing step, a final pixel size of 8.24 m was obtained for the georeferenced products derived from the ALOS2 images.

2.5. Forest Volume Loss Detection Procedures

The pixel-by-pixel detection approach was used to verify the hypothesis of vegetation volume loss due to degradation by selective logging processes. In this approach, each selective logging sample corresponds to a pixel in the ALOS2 images. In this sense, a pixel with a spatial resolution of 8.24 m corresponds to a total area of 67.90 m^2, which is considered the smallest total area possible to be imaged by the ALOS2/PALSAR2 system. The main assumption is a change in the value of each pixel investigated. Before selective logging, the pixel corresponding to unchanged vegetation has a certain value associated with it. After selective logging, it is expected that the respective pixel will have another associated value since trees have been felled and adjacent logging activities have been carried out.

2.6. Evaluation

To validate the results obtained from the detection of forest volume loss, the non-parametric Wilcoxon test was applied. The Wilcoxon test has the null hypothesis H_0 that the two samples follow the same probability distribution and the alternative hypothesis H_1 that the distributions of the two samples are different. The Wilcoxon test returns a p-value, which is compared to the significance level of 0.05.

In this sense, to validate that the differences detected in the forest volume of the field samples are significant, at a significance level of 0.05, we expect to reject hypothesis H_0 and accept hypothesis H_1. On the other hand, for the control group, we expect to accept hypothesis H_0 and reject hypothesis H_1, since, theoretically, there was no forest disturbance in the control areas, consequently, the samples follow the same probability distribution.

3. Results and Discussion

3.1. Detecting Forest Volume Losses from the Control Group

The control sample group was employe to evaluate whether the disparities observed in forest volume could be attributed to degradation processes stemming from selective logging or possibly random variations. A total of six attributes extracted from the ALOS2 images were tested.

The SAR attributes tested (RNDVI, Con, Ener, Max, H, and α-ALOS2), and associated with both APUs, 2016 and 2017, in the Wilcoxon test indicated that the distributions of the samples observed before and after the hypothetical selective logging event followed the same distributions, with p-values ranging from 0.055 to 0.807 (Table 2). This suggests that there were no significant differences between the same samples analyzed in different periods.

Table 2. Wilcoxon test results applied to the control group from 2016 and 2017 APUs.

	APU 2016		APU 2017	
Attribute	**p-value**	**conclusion**	**p-value**	**conclusion**
RNDVI	0.276	Accept H_0[1]	0.077	Accept H_0
Con	0.460	Accept H_0	0.055	Accept H_0
Ener	0.511	Accept H_0	0.068	Accept H_0
Max	0.567	Accept H_0	0.230	Accept H_0
H	0.561	Accept H_0	0.807	Accept H_0
α-ALOS2	0.549	Accept H_0	0.622	Accept H_0

[1] Wilcoxon test applied at significance level α = 0.05. Interpretation of the test: accepting the H_o hypothesis indicates that the samples follow the same distribution.

3.2. Detection of Forest Volume Losses from Field Samples

According to the Wilcoxon test results for APUs 2016 and 2017, in Ener and Max, the samples followed the same distributions (Table 3). For 2016 were obtained p-values of 0.776 for Ener and 0.631 for Max. For 2017 p-values of 0.056 for Ener, and 0.756 for Max were obtained. These results suggest that the radar signal did not detect significant variations between the radiometric responses of the samples, denoting the low potential of this attribute.

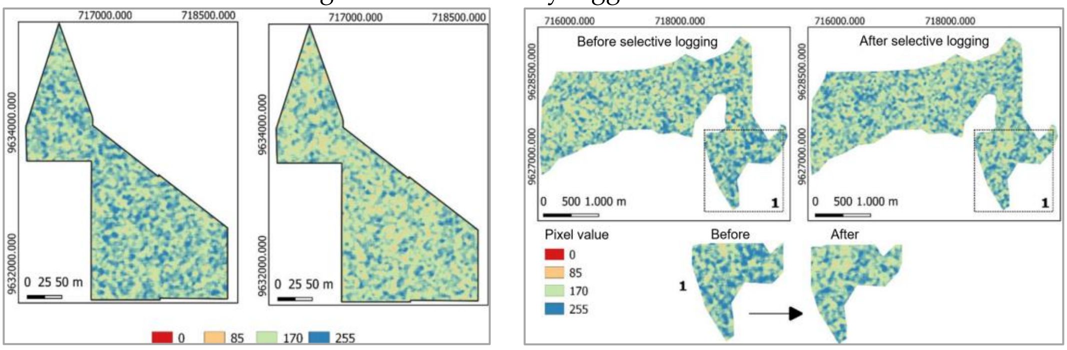
Table 3. Wilcoxon test results applied to the field data sample from 2016 and 2017 APUs.

	APU 2016		APU 2017	
Attribute	**p-value**	**conclusion**	**p-value**	**conclusion**
RNDVI	0.003	Reject H_0[1]	0.037	Reject H_0
Con	0.001	Reject H_0	0.0001	Reject H_0
Ener	0.776	Accept H_0	0.056	Accept H_0
Max	0.631	Accept H_0	0.756	Accept H_0
H	0.0001	Reject H_0	0.501	Accept H_0
α-ALOS2	0.0001	Reject H_0	0.227	Accept H_0

[1] Wilcoxon test applied at significance level α = 0.05. Interpretation of the test: accepting the H_o hypothesis indicates that the samples follow the same distribution; rejecting the H_o hypothesis implies accepting the H_1 hypothesis, which suggests that the sample distributions are different.

For RNDVI attribute, the statistical test suggested that the sample distributions were different in both APUs, with a p-value of 0.003 for 2016, and 0.037 for 2017, denoting sensitivity in detecting differences in forest volume due to selective logging events. Those results show that RNDVI was able to detect forest volume losses for both APUs (Figure 1 and b). After selective logging, there was subtle radar signal decay in the RNDVI. This result was expected, as the RNDVI is a biophysical index that is sensitive to the vegetation presence [19]. In this sense, the radar signal decay denotes little or no presence of tree vegetation in the terrain resolution cells investigated, after thinning by selective logging processes.

The Con attributes also showed sensitivity in detecting forest volume losses due to selective logging. The Wilcoxon test indicated that the differences between the sample distributions were significantly different, with p-values ≤ 0.0001 in APU 2016 and 2017. The Con attribute obtained an increase in the intensity of the pixel values after selective logging exploitation. This increase is associated with a greater contrast between the radiometric responses of the vegetation samples. According to Hethcoat et al. [21], the high values in the Contrast measure obtained after selective logging disturbances may be associated with the visual edges of the selectively logged areas.



(**a**) (**b**)

Figure 1. Detection of forest volume losses in APU 2016 (**a**), and APU 2017 (**b**) considering the RNDVI attribute derived from ALOS2 data.

The Wilcoxon test applied to α-ALOS2 attribute indicated that the differences between the sample distributions were significantly different, with p-values between 0.0001 in APU 2016. On the other hand, for APU 2017, the Wilcoxon test indicated that α-ALOS2 tended to follow the same probability distributions, showing p-values of 0.227 (Table 3). In this sense, the α-ALOS2 attribute, when associated with the 2016 APU dataset, showed potential for detecting forest volume losses. There was a decrease in pixel intensity in the samples after selective logging, indicating a decrease in the radar signal due to tree removal. This result was also expected, as the removal of trees leads to greater interaction of electromagnetic waves with the ground surface [22].

Regarding the H attribute, the Wilcoxon test applied for APU 2016, indicated that the differences between the sample distributions were significantly different, with p-values of 0.001. It was observed that there was slight radar signal decay after selective logging exploration. According to Khati et al. [22], this result was expected, because with the removal of trees, there is an absence and/or a reduction in the structural volume of tree vegetation, consequently, there are fewer spreading mechanisms (leaves, branches, stems, trunks) interacting to depolarize the electromagnetic waves, resulting in lower resulting in a lower backscattering intensity in H.

The H attribute for APU 2017, the Wilcoxon test suggests that samples tended to follow the same probability distributions, showing p-values of 0.501 (Table 3). As observed with α-ALOS2, the longer time interval between the acquisition of the ALOS2 image and selective logging exploration may have influenced the results. The initial regeneration of vegetation in areas previously subjected to selective logging could have influenced augmentation of the backscatter signal in the H attribute volume variations within the forest canopy. However, when considering a longer time frame, specifically five months post-selective logging, these same attributes did not show any discernible trends or potential effects.

5. Conclusions

The results obtained by the attributes extracted from dual polarimetric images from ALOS-2/PALSAR-2 showed different performances and capacities for detecting forest volume losses due to high-intensity selective logging (~27-29 m^3 ha-1). The Contrast attribute derived from the GLCM Matrix and the RNDVI biophysical index were particularly sensitive to detecting forest volume losses due to selective logging processes in the two APUs investigated.

Despite technological advances in the detection and monitoring of large-scale selective logging, there are still many uncertainties in assessing the impact of selective logging on the carbon balance, as well as the impact on the forest environment. Therefore, further investigations are warranted, encompassing diverse sensor systems and their combinations, time series analyses, and the development of novel computer algorithms. These efforts are essential to enhance our comprehension of the capabilities of these data in detecting forest degradation attributed to selective logging processes.

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