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Methodological Approach for Assessing Impacts and Recovery of Selectively Logged Forests in Tropical Forests

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Abstract

Ecosystem structure and function depends on the local and regional species pools, climate, geology, and type and frequency of disturbances. Tropical rain forests have long been growing in relatively stable climatic conditions and little disturbances until recent decades, when large-scale of land conversion into croplands and forest impacts by selective logging activities and forest fires have been more frequently observed. Selective logging causes forest degradation, which requires a rigorous monitoring system to control and mitigate forest impacts and recovery. Overtime forest disturbances and recovery can be estimated by using vegetation indices derived from remotely sensed data that enable us to distinguish disturbed from undisturbed forests and estimate the degree of those disturbances. This study aimed to assess the suitability of the Modified Soil Adjusted Vegetation Index (MSAVI) to detect selectively logged forests and estimate the forest recovery structure in a study site in the state of Pará, Eastern Amazon region. We retrieved the MSAVI from Landsat imagery to assess forest impacts by selective logging before and after logging. The estimated MSAVI index before and after logging activities were significantly different and enabled us to distinguish forest recovery structures after selective logging in the study site. Our methodological approach can be used to monitor selective logging activities and support planning of Sustainable Forest Management in tropical regions.

Keywords: Brazilian Amazon, Landsat, MSAVI, Remote sensing, Spatial and time-Series, Google Earth Engine

1. Introduction

Tropical forests provide a range of ecosystem services such as provisioning (bio-diversity richness, forest production), supporting (biomass production, oxygen, water flow regulation), and cultural (cultural diversity, ecotourism) (Carvalho et al., 2019; Foley et al., 2005; Hansen et al., 2013). Tropical forests are a critical component of the climate system and guarantee the mitigation of planetary environmental problems, such as climate change (Bustamante et al., 2016). The rapidly increasing demand of forest products and agricultural land, coupled with land speculation has led to deforestation and forest degradation, causing several social, economic, and environmental impacts in tropical regions (Matricardi et al., 2010; Tavani et al., 2009). For example, more than 400 M ha of native forests within permanent forest estates have been selectively logged by 2010 in tropical regions (Blaser et al., 2011). Matricardi et al.

(2020) estimated that approximately 120 M hectares of tropical forests were selectively logged between 1992 and 2014 in the Brazilian Amazon. A total of 11.6 million m^3 of roundwood production from tropical forests in 2018 have been reported by (IBGE, 2019).

Deforestation in the Brazilian Amazon has directly impacted an average of 19,625 km^2 $year^{-1}$ between 1996 and 2005, an average of 10,660 km2 year-1 between 2006 to 2012 (INPE, 2019). Recently, there is an increasing trend of deforestation in 2021 (13,235 km2) compared to 2019 (10,129 km^2) (PRODES, 2021). Most timber produced (2.7 M m^3 in 2020) in the state of Pará, Brazil, is selectively logged from previously approved permanent forest estates in the state of Pará (PARÁ, 2019). However, illegal logging is prevalent in that State and 31% of legal selective logging reported between 2015 and 2016 showed technical inconsistencies (Cardoso & Souza Jr., 2017).

Initiatives of monitoring forest degradation in the Brazilian Amazon includes the Brazilian National Institute for Space Research (INPE), which has been applying CBERS and LANDSAT imagery and spectral mixture analysis to monitor forest degradation by logging and fires in the Amazon region. There were DETEX project (Detection of Selective Logging) and the DEGRAD project (Forest Degradation Mapping in the Brazilian Amazon), both have been discontinued in 2016. Monitoring overall forest degradation types has been included in the deforestation detection system using a near time real detection approach to estimate forest cover change and deforestation DETER-B (Diniz et al., 2015).

A few studies based on remote sensing to assess the structure recovery caused by selective logging in forest management areas have been developed and applied. Land-sat images have been used to quantify forest disturbances by selective logging activities and fires at a resolution of 30 m (Matricardi et al., 2010, 2013, 2020), as well as to detect and track the various types of logging activities (Asner et al., 2002; Tritsch et al., 2016). Methodological approaches based on satellite images to detect selective logging include the Carnegie Landsat Analysis System (CLAS) (Asner et al., 2005, 2009), texture analysis (Matricardi et al., 2010) and spectral mixture analysis (Souza et al., 2005). The study developed by (Souza et al., 2005) was based on the Normalized Difference Fraction Index (NDFI) retrieved from spectral mixture analysis to map canopy damage from selective logging and forest fires.

Forest monitoring using satellite images conducted by governmental programs in Brazil (e.g., DETEX and PRODES) have shown some limitations because they mostly detect forest degradation and deforestation. However, few studies have been conducted to assess the impacts of forest structure and forest recovery following logging activities in the Amazon region, as was conducted in our study.

For this work we posed the following research question: How does the identification of logged and unlogged areas by multi-date analysis of the MSAVI index obtained from Landsat multispectral imagery allow monitoring of selective logging in Amazonian forests? In this analysis, we applied, and tested a methodological approach to characterization of logged and non-logged forest and estimate forest recovery following selectively logging activities by applying the MSAVI vegetation index (Qi et al., 1994) retrieved from Landsat imagery and applied multivariate statistical techniques (cluster analyses and Principal Component analyses), to separate different areas of selective logging and their recovery in a permanent forest estate located in the Paragominas municipality, state of Para, Brazil.

2. Method

2.1 Study Site

Our study site was a Permanent Forest Estate (PFE), encompassing a total of 121,000 hectares, spatially located within the Rio Capim ranch, which encompasses a total of 140,658 hectares, southwestern Paragominas municipality, state of Pará, Brazil, 217 km from the capital city of Belém (Figure 1). The PFE has been under a forest concession granted to a logging company named Cikel Brasil Verde Madeiras Ltda. This PFE has been certified by the Forest Stewardship Council (FSC) since 2001 (Sist and Ferreira, 2007), a partner of the Tropical-managed Forests Observatory (TmFO) scientific network, with permanent forest plot data available for monitoring, technical inspection, and validation (TmFO, 2024).

The study site is mostly covered by dense Ombrophylous Submontane Forest (IBGE, 2012). The regional climate is characterized as tropical hot and humid with an annual average precipitation of 1,800 mm, with a well-defined dry season that occurs from May to October every year, annual average temperature of 26 ºC and relative humidity of 81% (Alvares et al., 2013). The soils are mainly Yellow Latosols and Yellow Argisols, and Plintosols. Geisols and Neossols are sparsely observed in the study site (Rodrigues et al., 2003).

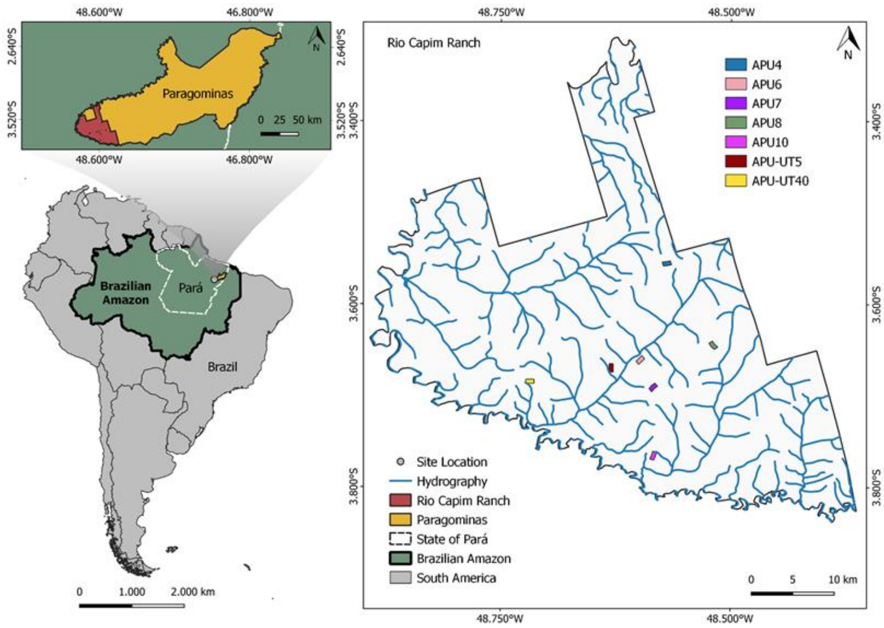

Figure 1. Spatial location of the study site, a Permanent Forest Estate encompassing 121,000 hectares, within the rio Capim ranch, in Paragominas municipality, state of Pará, Brazil. The Annual Production Units (APU) 4, 6, 7, 10, and 13 at Working Unit (WU) 5 were selectively logged in 2000, 2003, 2004, 2007, and 2011, respectively. The APU 13 WU 40 had been selectively logged twice, in 1997 and 2011

2.2 Data Sources and Processing

Our study included seven forest sites, corresponding to different APUs (4, 6, 7, 10, 13WU5 and 13WU40), selectively logged in 2000, 2003, 2004, 2007 and 1997 and 2011, respectively (Table 1). APU 8 was not selectively logged. The pre-selective logging date was chosen before pre-exploration activities were initiated; and the post-exploration date was chosen in 2015 to identify recovery on the different dates when selective logging was conducted. We selected a work unit (WU) within each APU. In each WU eight logging patios of 6.25 ha each were selected, corresponding to a total sampling area of 50 ha per APU/WU. A total of 30 m3/ha logging intensity was adopted by the logging company in the study area. The vegetation index was retrieved from the Landsat-5 TM (Thematic Mapper) and Landsat 8 OLI (Operational Land Imager) images, and the vegetation index average was estimated for each WU.

We selected and subset each Landsat imagery for the 50 ha- WUs (Figure 1) of selectively logged forests in different years (Table 1). The MSAVI developed by Qi et al. (1994) was retrieved from Landsat 5 (TM) and Landsat 8 (OLI), surface reflectance images, available on the Google Earth Engine (GEE) platform, using the following equations (Equation 1 and 2) on Google Earth Engine platform:

$$\mathrm{MSAVI} = \frac{\mathrm{nir-red}}{\mathrm{nir+red+L}} * (1 + \mathrm{L}) \tag{1}$$

where: nir = surface reflectance at near infrared band, red = surface reflectance at red band,

$$\mathrm{L} = [(\mathrm{nir} - \mathrm{red}) * \mathrm{s} + 1 + \mathrm{nir} + \mathrm{red}]^2 - 8.0 * s * (nir - red) \tag{2}$$

where: s = 1.2 (applied to maximize reduction of soil effects on the vegetation signal).

2.3 Statistical Analyses

All statistical analyses were carried out using R software version 4.0.1. (R Core Team, 2018). A statistical test was applied using mean values of MSAVI corresponding to each WU used in this analysis. Based on the ANOVA results, post-hoc analysis using Tukey's HSD (Honest Significant Difference) test to identify significant differences between those selectively logged and non-logged WUs. Additionally, we used two multi-variate statistical analyses: the first method cluster analysis, once we have the similarity between objects, we group them into clusters. Clusters are formed by partitioning of the dendrogram, by cutting it at a fixed height and considering each of the resulting subtrees as a cluster. To assess similarity among the WUs: Second used the Principal Components Analysis (PCA) were performed using the vegan package (Oksanen et al., 2019) and the factoextra package (Kassambara et al., 2016). By applying the Bray-Curtis distance coefficient, a metric coefficient commonly used for binary data (Dufrêne and Legendre, 1997) and the Dissimilarity index based Euclidean distance, we selected the best agglomerative hierarchical classification among WPGMA, simple linkage, complete linkage, Ward grouping, and UPGMA. As suggested by Borcard et al. (2018), we applied the dissimilarity dendrogram for every pair of points to identify the best clustering model for the distance matrix in our analysis.

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To detect which variables are most related to the gradual changes in MSAVI across the 168 samples on the three dates, and to identify the recovery of areas under selective cutting through the mean and standard deviation values of the vegetation index, multivariate ordination procedures were applied assuming that there were underlying gradients within the dataset. Gradient differences in MSAVI were estimated using a multidimensional ordination space using similarity relations. The ordination was used to reduce the number of variables as representatively as possible. An unconstrained linear PCA was applied in our analysis. An ordination analysis was displayed as two-dimensional scatter plot of samples where the explanatory variables are displayed as arrows in which the point from the origin of ordinates in the direction where samples with above average values of a variable are located. The length of the arrows represents the relevance of each variable.

Table 1. Acquisition dates of Landsat images used in this analysis

APU	Image acquisition date		
	Before logging	Selectively logged	After logging
4	2000	2001	2015
6	2000	2003	2015
7	2002	2004	2015
8	2002	2004*	2015
10	2006	2007	2015
13 - WU5	2009	2011	2015
13 - WU40	1995	1997 and 2011	2015

* The APU 8 has not been selectively logged; The UT 40 had been selectively logged in 1997 and 2011.

3. Results

We estimated the mean value of MSAVI index for each sample unit. Complementarily, an eye inspection was carried out using the remotely sensed imagery to observe some characteristics of selective logging techniques adopted in the study area, such as allocation of primary and secondary roads, forest trails, and logging patios. Patios and main forest roads were easily identified in the study area by observing those spatial patterns of logging techniques enforced by the logging company in the study area (Figure 2, 3, and 4).

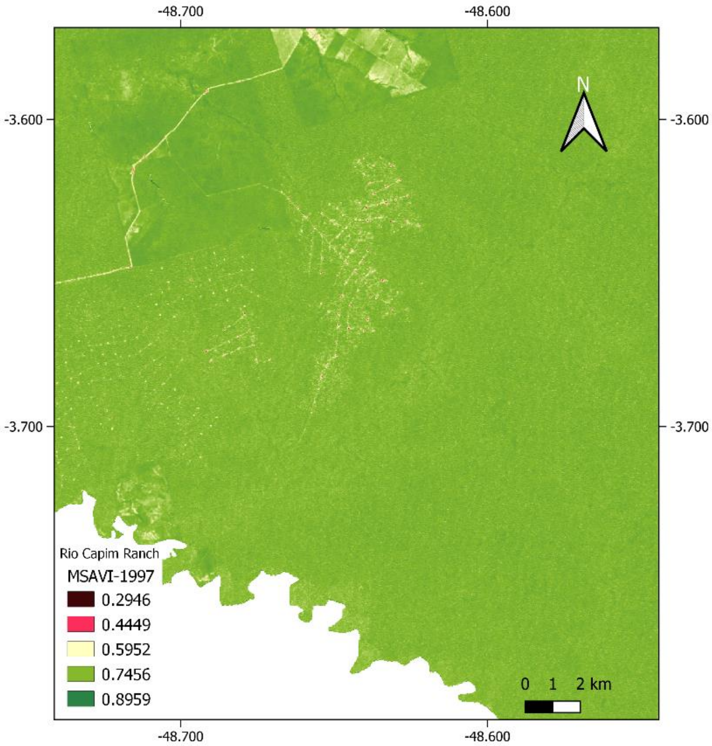

Figure 2. The MSAVI retrieved from Landsat TM of selectively logged forests in a Permanent Forest Estate within the rio Capim ranch in 1997

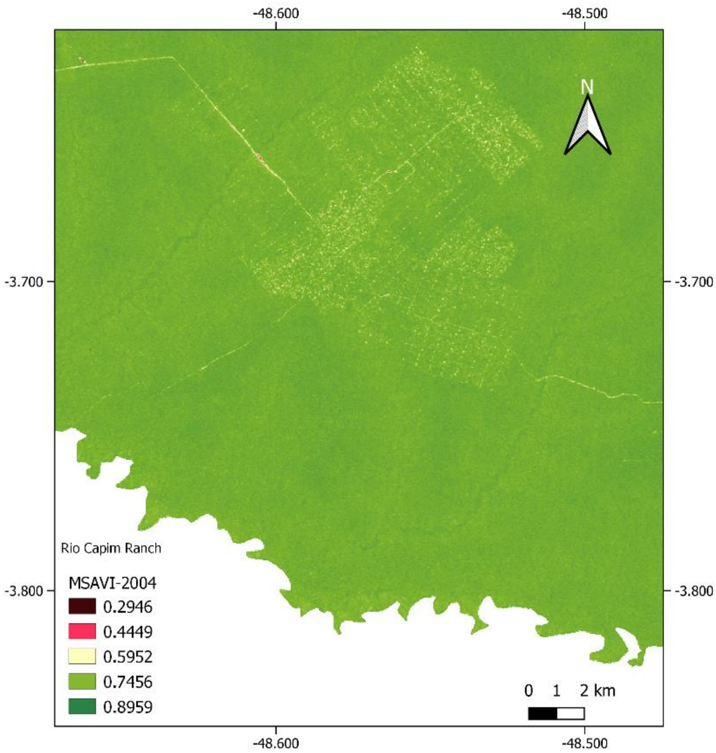

Figure 3. The MSAVI retrieved from Landsat TM of selectively logged forests in a Permanent Forest Estate within the rio Capim ranch in 2004

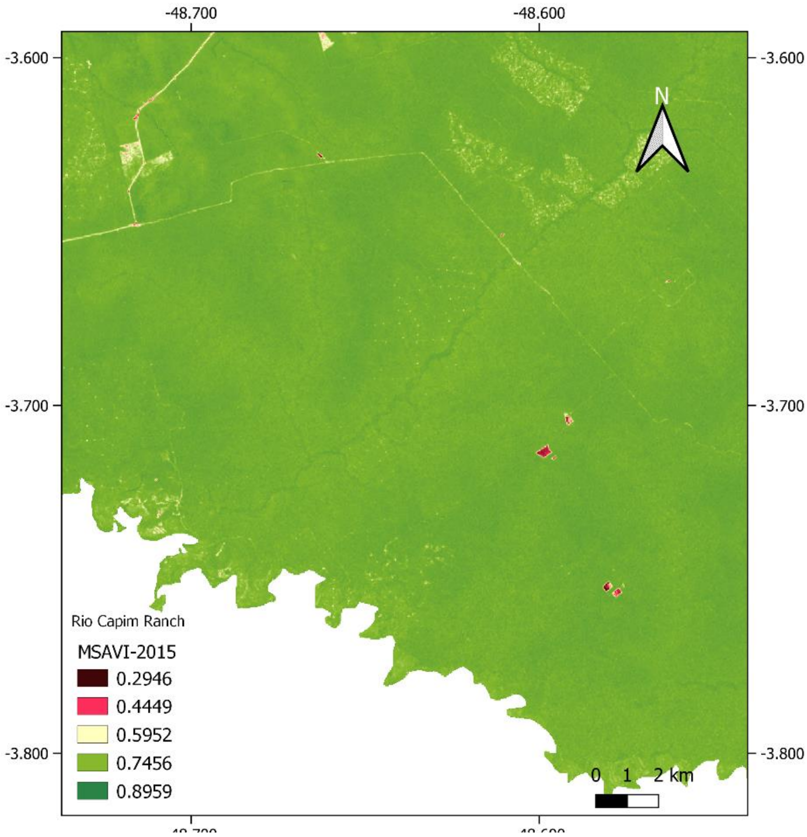

Figure 4. The MSAVI retrieved from Landsat OLI imagery of selectively logged forests in a Permanent Forest Estate within the rio Capim ranch in 2015

Selectively logged forests showed a different pattern of canopy disturbances. Those canopy changes decreased MSAVI values of all sample units, except for UPA8, which had not been selectively logged. The UPA8 showed low average variation of MSAVI values during the period of analysis because it has not been affected by logging activities. Previously to selective logging activities, the MSAVI values showed statistical differences likely due to variations observed in dense rainforest microhabitats (figure 5a). Figure 5b indicates that those selectively logged forests tend to increase variance and average of vegetation indices, as it occurs a strong forest regrowth on those dam-aged forests plots in the years following logging activities. In this case, the vegetation averages may be like undisturbed forests, although the variation will be higher for disturbed forests. We also observed that the dynamics of forest recovery of selectively logged forest are significantly different among the UPAs.

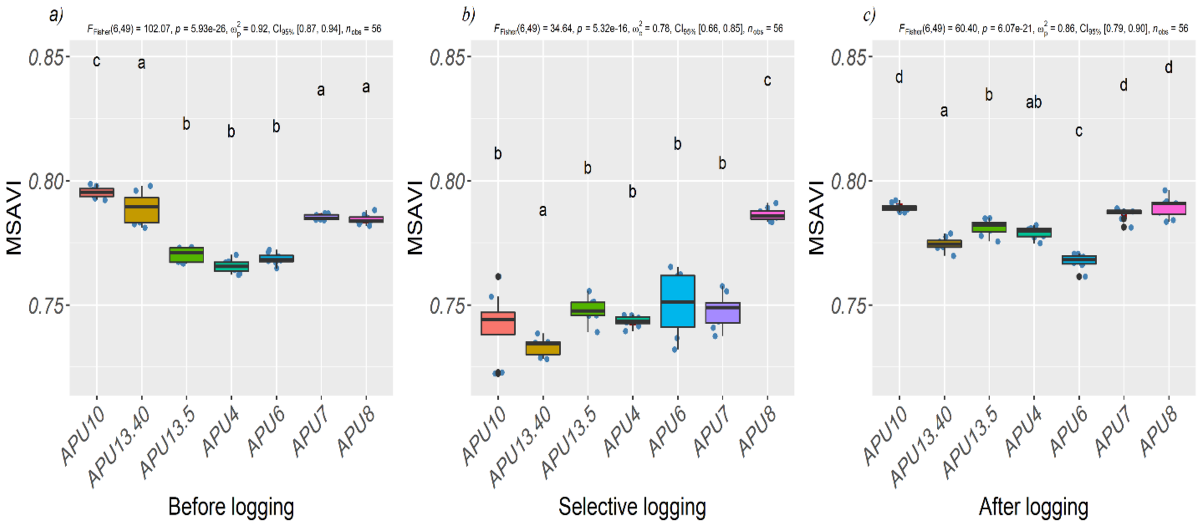

Figure 5. Statistical analysis (box plot) of MSAVI variation by Work Unit for each year of analysis (before, during, and after logging). a) MSAVI variation before selective logging activities, b) MSAVI variation just following selective logging activities and, c) MSAVI variation years after selective logging activities; the boxplots show the mean ± SD. P-values were calculated using one-way ANOVA using Tukeys's comparison test

We observed in the similarity analysis of the MSAVI estimated for all years of our study period that the sampling units of the selectively logged sites formed four groups: G1(UPA6), G2(APU4 and APU 13.2), G3(APU13.1), G4(APU10 and APU 7). The G4 showed high dissimilarity of the sampling units of group five G5 (APU8), which is the undisturbed forest site (Figure 6).

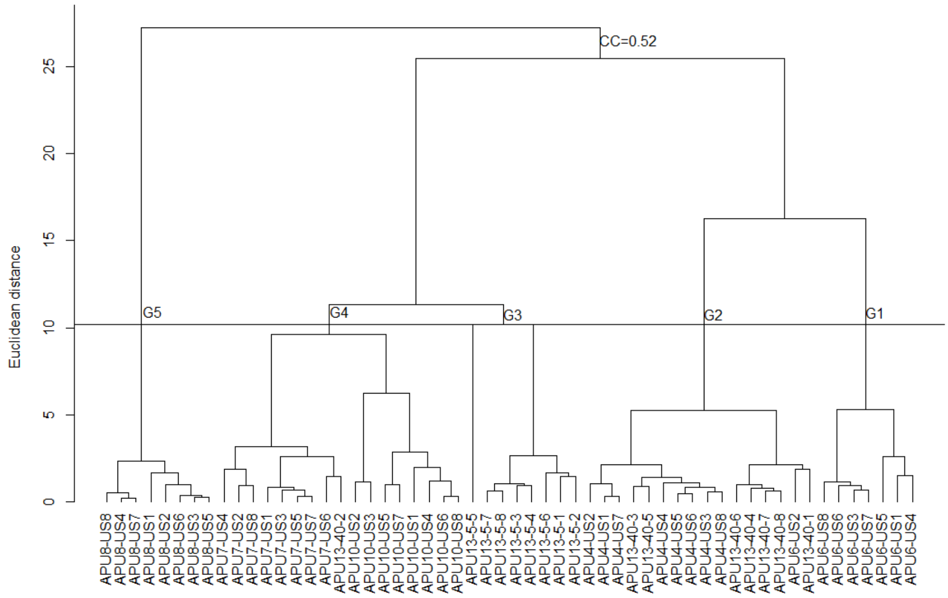

Figure 6. Cluster analysis using the Ward.D2 linkage method and Euclidean similarity coefficient, to compare sampling units from different study sites and MSAVI of years of analysis. Cophenetic Correlation Coefficient = 0.52

Both Principal Component Analysis (PCA) and Ward's hierarchical clustering method showed cluster similarities of selectively logged forests based on the MSAVI results. The PCA results of the mean and standard errors between selectively logged sites and the control area (undisturbed forests) in the study area are described in figure 7. The variations explained by axes one and two were 35.5% and 28%, respectively.

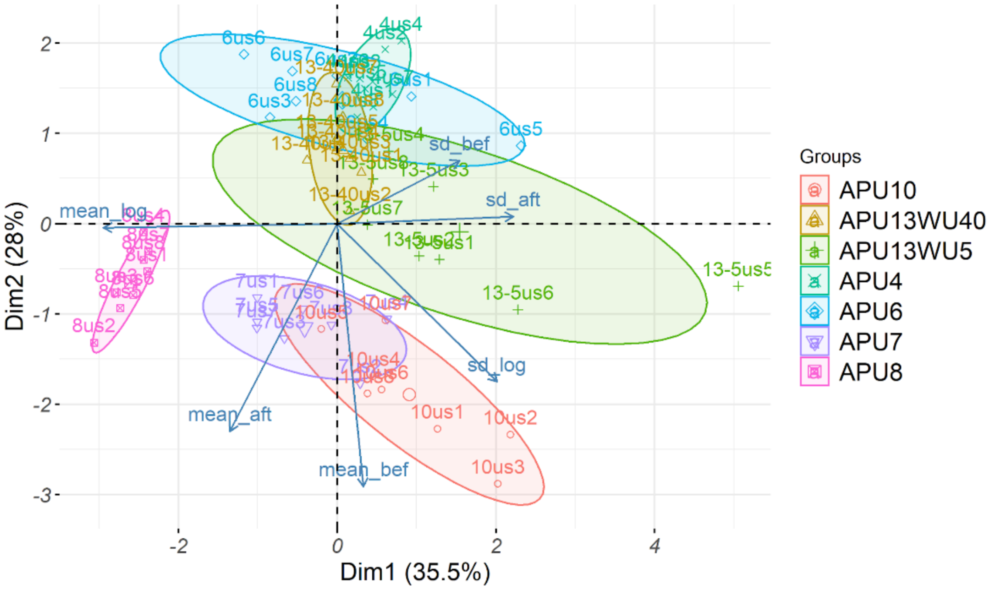

Figure 7. Two-axis decomposition of mean and standard deviation variation of MSAVI estimated for different sampling units (APUs). One and two axis variations were of 35.5% and 28%, respectively

By using vegetation indices retrieved from remote sensing we were able to understand the forest dynamics following selective logging activities that impact forest ecosystems. The MSAVI accurately showed a forest disturbance pattern within the Permanent Forest Estate site associated with logging activities, which varied according to each APU, mostly because of the adopted logging intensity and characteristics of each analysed forest sample. Tropical forest is a mosaic of small habitats with different floristic compositions and interaction between species and the environment.

Also, we observed similarities between MSAVI estimate for selectively logged and undisturbed forest. In this case, we observed there occurred a strong forest regrowth where forest canopy has quickly recovered following logging activities. Consequently, it helped to increase mean values of the vegetation index at similar bases of undisturbed forests.

Moreover, the PCA analysis with the MSAVI accurately showed a forest disturbance pattern within the Permanent Forest Estate site associated with logging activities, which varied according to each APU, mostly because of the adopted logging intensity and characteristics of each analysed forest sample. Also, we observed similarities between MSAVI estimate for selectively logged and undisturbed forest. In this case, we observed there occurred a strong forest regrowth where forest canopy has quickly recovered following logging activities. Consequently, it helped to increase mean values of the vegetation index at similar bases of undisturbed forests.

4. Discussion

Our results indicated that the MSAVI can accurately characterize forest impacts caused by selective logging activities in the study region. However, as opposed to de-forestation that normally consist of a permanent or long-term land use change, selective logging activities are often followed by a faster forest regeneration process (Grecchi et al., 2017; Matricardi et al., 2013, 2020). We observed that forest canopy within selectively logged sites will be like undisturbed forest 1 to 4 years following selective logging activities (Asner et al., 2009; Costa et al., 2019; Matricardi et al., 2013, 2020). However, the carbon stocks and ecological processes in tropical forests can take longer to be fully recovered from selective logging activities (Matricardi et al., 2013, 2020). Kennedy et al., (2010) observed a good performance of using Landsat series to capture different land cover dynamics of forest ecosystems, such as disturbance and regeneration. By using a long-term time series of Landsat images, we were able to accurately differentiate disturbed from undisturbed forests by logging activities in tropical forests.

The MSAVI vegetation index retrieved from remotely sensed data helped to estimate forest impacts by selective logging. We can observe a clear pattern of forest disturbances following selective logging activities in the Permanent Forest Estate site. Based on our results, we observed that those twice selectively logged forests (1997 and 2011) showed forest canopies fully recovered 14 years after logging. That pattern was previously described by (Tritsch et al., 2016), which observed that forest canopies were fully recovered even after subject to various intensities of forest disturbances by illegal logging activities in the municipality of Paragominas, state of Pará, Brazil.

Our results indicated that the MSAVI combined with multivariate statistical analyses is a reliable estimator to assess forest impacts and recovering following logging activities). Costa et al. (2019) observed that impacts by selective logging activities may remain detectable on Landsat images from 1 to 3 years. In addition, the pixel-by-pixel analysis allowed to estimate the vegetation index variability in the three forest measurements, showing different patterns of forest disturbances. Also, it proved to be effective for monitoring and predicting logging intensities and impacts at low-cost estimates (Bourgoin et al., 2018), if there is a qualitative standardization of those selective logging detection classes.

Ecologists have often suggested that the unpredictable regime of tree fall, storms, rainfall, temperature, disease, and other environmental factors in tropical forests usually result in highly heterogeneous plant communities (Mabberley, 1992; Whitmore, 1990). Each UPA used in this analysis showed its own pace of recovery dynamics (figure 5c) in which the forest recovering pattern may vary according to the adopted logging intensity (number of trees and volume) and topographic variations of each study site (Roy et al., 2014; Schmitt et al., 2020). Each UPA used in this analysis showed its own pace of recovery dynamics (figure

5c) in which the forest recovering pattern may vary according to the adopted logging intensity (number of trees and volume) and topographic variations of each study site.

With the advancement of remote sensing technology in the last decade and its accessibility, it is now possible to monitor the dynamics of the landscape and its relationship with anthropic activities using sub-pixel information for the assessment of selective logging with remote sensing imagery. Tyukavina et al. (2017) used the Global Forest Change (GFC) dataset as stratification layer for a study of forest disturbances in the Brazilian Legal Amazon. Matricardi et al. (2020) observed that the total forest degradation by logging, fire, and forest fragmentation in the Brazilian Amazon be-tween 1992 and 2014 was greater than those caused by deforestation (337,427 km^2 and 308,311 km^2, respectively. Selective logging activities may cause severe forest degradation and impact biodiversity and carbon stocks (Montibeller et al., 2020; Morton et al., 2013; Souza et al., 2013) and, therefore, it is important a continuing spatiotemporal monitoring of forest dynamics. Our proposed methodological approach using Landsat imagery to monitor forest recovery in the state of Pará showed to be accurate to monitoring selective logging activities at local and regional scales and can support land decision makers to define strategies of land management and land use policies.

Cluster grouping of MSAVI data accurately characterized a pattern of forest disturbance within the permanent forest farm site associated with the selective logging activities of each APU; primarily due to the intensity of logging adopted and the characteristics of small habitats with different floristic compositions and species-environment interactions.

The spectral recovery of a vegetation index signal is directly related to forest recovery. This is related to an ecological process after a disturbance, referring to the re-establishment or development of forest biomass and canopy structure (Bartels et al. 2016). The applicability of emerging remote sensing technologies for the study of forest recovery patterns has been recognized (Teixeira et al., 2013; Galvão et al., 2015). However, there is a need for further studies to explore the relationship between the recovery of forest structure and biomass with the post-disturbance vegetation index signal. The results obtained show a great potential for the use of this information by regulatory and control agencies of forest management areas that have selective logging areas, being an indirect monitoring methodology of low cost and of great importance to consider these data for the evaluation of second cutting cycle areas.

Our analysis has provided tools for mapping forest degradation and assessing forest impacts and recovery in tropical forests. Our approach can be easily adjusted to other remotely sensed data (e.g., Sentinel-2, CBERS) and study areas. Moreover, our approach is improving selective logging classification accuracy and allowing the integration of expert knowledge into the classification process, as proposed by Platt & Rapoza (2008). The MSAVI data combined with analyses statistical multivariate, focused on forested areas, allowed us to retrieve detailed information from Landsat imagery on the mapping of selective logging, which is an important step when regarding the limitation of the medium spatial resolution of Landsat. Finally, our results allowed us to assess forest disturbances by selective logging activities and forest dynamics overtime in the Brazilian Amazon region.

5. Conclusion

Our methodological approach showed high potential to characterize forest disturbances in tropical forests by applying the MSAVI index. We showed that historical remotely sensed data can be used to create a "baseline" of the natural condition of a landscape of interest, especially those spatially located in permanent forest estates. Forest canopy changes can be distinguished from ephemeral variations in the data by comparing repeated observations to that "baseline". The characterization of forest post-disturbance dynamics can then be used to differentiate forest degradation from deforestation in forest estates. Our approaches can be used to achieve a comprehensive analysis of forest ecosystem dynamics and forest disturbances by selective logging activities. MSAVI values tend to reach similar values of undisturbed forests seven year after forest interventions (disturbances). By combining MSAVI Index with multivariate statistical analysis, we were able to accurately detect and assess forest recovery following selective logging in tropical forests.

Author Contributions: GUIDO V.B. CASTILLO, Dr. LUCAS J.M. FREITAS, Dr. ERALDO A.T. MATRICARDI were responsible for the study design and revising. GUIDO V.B. CASTILLO and Dr. LUCAS J.M. FREITAS were responsible for the data provision and curation. GUIDO V.B. CASTILLO, Dr. LUCAS J.M. FREITAS, JORGE L. R. BETANCOURT, Dr. EDER P. MIGUEL, Dr. OSMAR L.F. CARVALHO, RENATO P. SANTOS, RENATO P. SANTOS, and Dr. ERALDO A.T. MATRICARDI were responsible for investigation, data, and statistical analysis. GUIDO V.B. CASTILLO, Dr. LUCAS J.M. FREITAS, and Dr. ERALDO A.T. MATRICARDI were responsible for writing—preparation of original draft. GUIDO V.B. CASTILLO, Dr. LUCAS J.M. FREITAS, JORGE L. R. BETANCOURT, Dr. Eder P. MIGUEL, Dr. OSMAR A. CARVALHO, RENATO P. SANTOS, and Dr. ERALDO A.T. MATRICARDI were responsible for writing—review and final editing. All authors have read and agreed with the published version of the manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Macrothink Institute.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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