Quantifying selective logging intensity through airborne LiDAR data in an Amazon rainforest: study case at Jamari National Forest

Daniel Braga[1,2], Luiz E. O. C. Aragão[3,4], Liana O. Anderson[5], Débora J. Dutra[5], Beatriz F. Cabral[5], Ricardo Dalagnol[2,6,7]

[1]Geosciences Department – Federal University of Santa Catarina (UFSC)
88040-900 - Florianópolis - SC - Brazil

[2]CTrees - 91105 - Pasadena - CA - USA

[3]Earth Observation and Geoinformatics Division – National Institute for Space Research (INPE) 12227-010 - São José dos Campos - SP - Brazil

[4]Geography, College of Life and Environmental Sciences - University of Exeter
EX4 4RJ - Exeter - UK

[5]National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN)
12247-016 - São José dos Campos - SP - Brazil

[6]Center for Tropical Research, Institute of the Environment and Sustainability - University of California (UCLA) 90095 - Los Angeles - CA - USA

[7]NASA, Jet Propulsion Laboratory - California Institute of Technology
91109 - Pasadena - CA - USA

{danielalvezbraga, liana.anderson, ddutra.ambiental, beatriz.figueiredocabral}@gmail.com,
luiz.aragao@inpe.br,ricds@hotmail.com

Abstract. *Airborne LiDAR data represents one of the most accurate ways to estimate forest structure and carbon nowadays. This study aimed to estimate the intensity of selective logging activities in terms of density and volume of logged trees based on airborne LiDAR data in comparison to ground measurements on a forest concession area in the Brazilian Amazon, the Jamari National Forest. The results show a significant relationship between logging intensity and LiDAR height difference, indicating that LiDAR can reliably estimate logging intensity. This constitutes an important step towards monitoring selective logging in the Amazon and areas under forest concession.*

1. Introduction

The occupation of the northern region of Brazil has intensely increased the rates of deforestation and forest degradation in the Amazon (FEARNSIDE, 2005), which has also completely changed the fire regime, since these processes are closely connected (COPERTINO et al., 2019). Also, deforestation and forest degradation are processes that characterize the Amazon as a biodiversity hotspot under threat (LAPOLA et al.,

2023) and its effects consists in the second largest anthropogenic sources of CO2 emissions into the atmosphere (KUCK et al. 2021). Regarding to forest degradation, it is estimated that it will affect the Amazon forest vegetation even more than deforestation in the long term (MATRICARDI et al., 2020), causing carbon loss and impacting forest biodiversity (FEARNSIDE, 2005). It is clear that forest degradation processes should still be a top priority for Brazilian conservation public policy (GANDOUR et al., 2021).

Forest degradation in the Amazon is mainly driven by timber extraction, forest fragmentation, fires, and drought (LAPOLA et al., 2023), with selective logging being one of the main vectors. It is important to emphasize that selective logging begins with the opening of roads in the forest, allowing the occupation and emergence of enterprises related to the timber industry (FERREIRA et al., 2005). On the other hand, legalized selective logging, which takes place in areas of forest concession, is not properly monitored, as well as its quantification is not widely disclosed for public consultation, which generates uncertainties about the amount of wood extracted by the companies responsible for forest management. The certainty is that persistent and recurrent logging in the Amazon is responsible for carbon emissions, ecosystem services reduction and biodiversity loss (MONTIBELLER et al., 2020). Moreover, degradation can also have feedback loop effects, such as fire being enhanced by selective logging due to the opening of the canopy and microclimatic changes, increasing the forest's susceptibility to fire (FEARNSIDE, 2005). In addition, carbon emissions are still not properly measured and reported in national inventories of Amazonian countries (SILVA JUNIOR et al., 2021), which brings the need for new methods and tools to assess the impacts of forest degradation and its drivers.

Aiming at alternatives to quantify selective logging intensity, high-resolution LiDAR (Light Detection and Ranging) airborne data are shown to be effective in accurately delineating the forest structure and estimating the impacts of logging at the level of individual trees to stands (DALAGNOL et al., 2019; DALAGNOL et al., 2021; LOCKS; MATRICARDI, 2019). Several initiatives have successfully used LiDAR data to detect phenomena, such as: estimating the selective logging in the Amazon (LOCKS; MATRICARDI, 2019); temporal analysis of logging effects (PINAGE et al., 2015); and tree canopy loss and gap recovery quantification in tropical forests under low-intensity logging (DALAGNOL et al., 2019).

In this study, the goal was to estimate selective logging intensity in the forest based on airborne LiDAR data in comparison to ground data of logged trees acquired in previous initiatives by Brazilian Forest Service (SFB). The intensity was proxied by the estimation of “density” and “volume” variables. The data were obtained from the Annual Operating Plans (POA) report and shapefiles containing data related to the trees that were harvested as part of forest management activities within certain Annual Production Units (UPA) in Forest Management Units (UMF). This research is part of a larger project to develop a global monitoring system of forest degradation for tropical forests (DALAGNOL et al., 2023).

2. Materials and Methods

2.1 Study area

The study area is located in the north of Rondônia state, between the municipalities of Cujubim and Itapuã do Oeste. The Jamari National Forest belongs to the Legal Amazon and its forest cover consists of 2,200 km² of open, dryland plain vegetation, with tree species of high commercial value (DALAGNOL et al., 2019). This area was selected because it has three fundamental elements for quantifying the selective logging intensity: (1) LiDAR transects in areas of confirmed logging; (2) shapefiles of the UPAs' harvested trees with information such as logging date, height, density, and volume of the trees; and (3) POAs available for some UPAs (Figure 1).

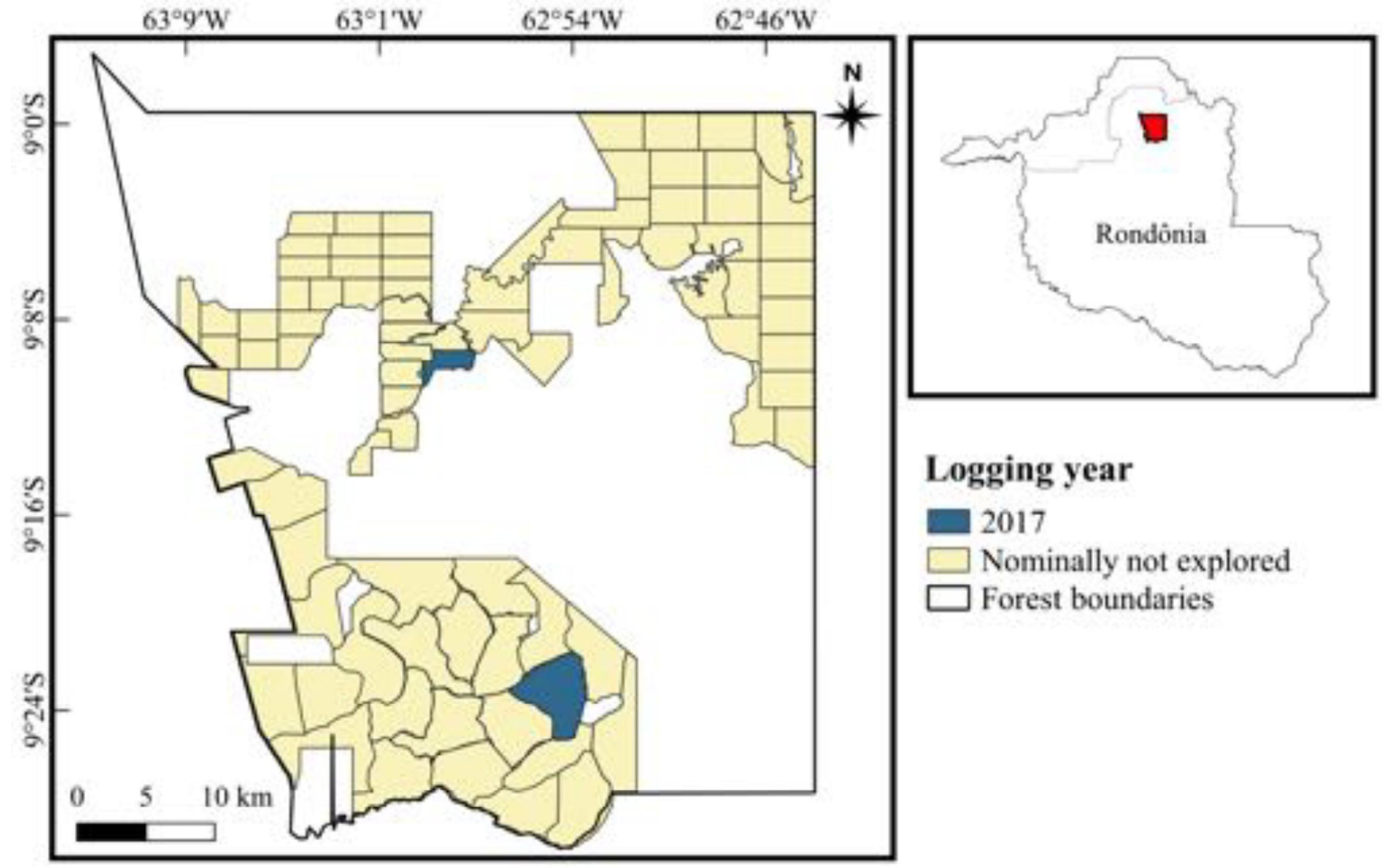

Figure 1. UPAs of Jamari National Forest.

As the first national forest to be submitted to the forestry concession process (2008), selective logging in the region follows the rules of the Public Forest Management Law, nº 11.284 of 2006 (SFB, 2022), which guarantees the private sector the right to explore territories demarcated in national forests according to the principles of public forest management (CHULES, 2018). The forest concession and the premise of sustainable forest management are necessarily planned, since the logging process in a concession area is foreseen and organized in a cyclical manner, which would provide the necessary regeneration time for each portion of the operated forest (25 to 30 years) (SFB, 2022). Monitoring areas under forest concession represents a challenge for remote sensing researchers, especially due to the lack of ground data, which makes it difficult to validate remote observations.

2.2 LiDAR data acquisition and pre-processing

Four airborne LiDAR flight lines were obtained in LAS (LASer, LiDAR point cloud data) and Canopy Height Model (CHM) point cloud formats with 1 × 1 m cell size (Table 1). The CHM rasters were loaded into QGIS for visualization and later into RStudio for quantitative analysis and the height difference was calculated from before (1) and after (2) logging CHMs.

Table 1. Logging date and LiDAR data acquisition

UMF - UPA	Logging date	LiDAR date 1	LiDAR date 2
I - 10	May - 2017	April - 2017	July - 2018
III - 14	April - 2017 to January - 2018	April - 2017	July - 2018

To prepare the table, it was necessary to gather information on the logged date of the trees in the Jamari UPAs, through the POA and/or the harvested tree shapefile, containing points as vectors that represents the logged trees location in the UPA territory and valuable information such as the logged trees volume.

In the existing POAs of each UPA, the logging date was obtained from the “Exploratory Activities" section, also involving processes such as opening roads, dragging and transporting. In tree shapefiles, the logging date was identified from the column with the same name in the attribute table of each layer. This process of compiling information on the logging date was quite laborious, as the official SFB website on Jamari suffers from the lack of complete information, which limits the accuracy of the information and the monitoring of areas under forest concession.

2.3 Selective logging density and volume

The density and volume of logged trees were calculated using RStudio v. 4.2.2 by filtering the attributes table of vector files compiled in the database. The “logging date” field, along with tree locations represented as points and their respective volumes, played a crucial role in generating density and volume rasters. As an initial parameter, each group of trees was separated in shapefile format with logged date information. Only 2 UPAs at Jamari had the necessary data to validate the intensity estimate through the use of LiDAR CHMs: UPA 10 from UMF I; and UPA 14 from UMF III. This suitability is due to the presence of selective logging confirmed by the SFB with the logging date (by the POA or the tree shapefile) and by the spatial intersection of the UPA perimeter with the LiDAR transects on the 2 flight dates.

The vector data of logged trees was converted to a raster surface of 100 × 100 cell resolution using the rasterize function from the R raster package (HIJMANS et al., 2023). A raster of density for each UPA that has a shapefile of trees was generated and loaded in QGIS for visual inspection. Descriptive statistics were calculated to characterize the intensity of logging. We calculated the density and volume of logged trees per hectare, such as mean, standard deviation, maximum, and total number of trees.

2.4 Density and volume and its relation to height difference (LiDAR)

The selective logging density and volume metrics were overlaid with the height difference obtained from LiDAR data, considering the period before and after logging activities in each UPA (Figure 2). In UPA 10 of UMF I, logging activities were confirmed by the SFB in May 2017, with the date sourced from the tree shapefile, alongside the LiDAR rasters captured in April 2017 (flight 1) and June 2018 (flight 2). Similarly, in UPA 14 of UMF III, logging was verified between April 2017 and January 2018, as confirmed by multiple sources, including the POA, tree shapefile and the LiDAR data, which were also collected from April 2017 (flight 1) and June 2018 (flight 2).

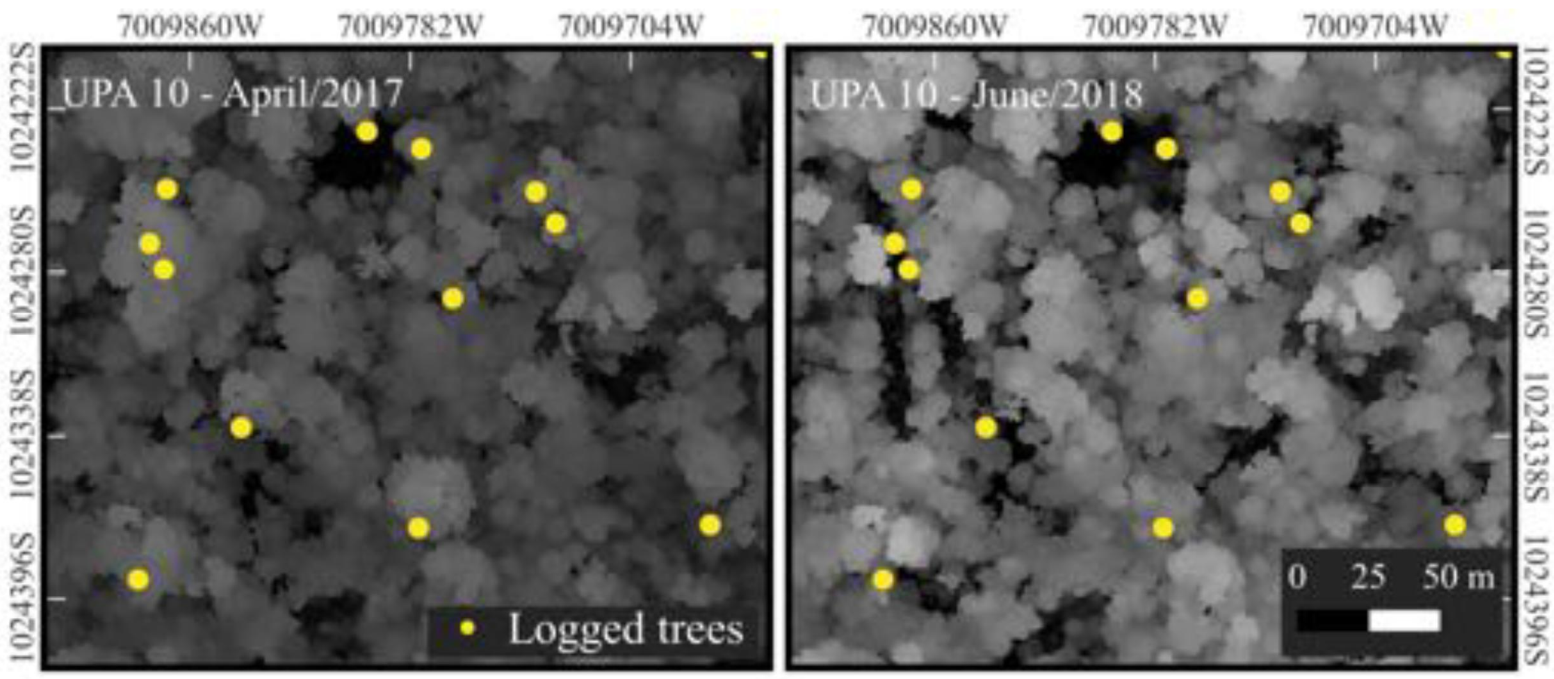

Figure 2. Height difference obtained from LiDAR flights in comparison to tree location.

The height difference between the two LiDAR flight dates for both UPAs (UPA 10 and 14) was calculated in RStudio by loading the LiDAR rasters and cropping them to the overlapping areas within each UPA. A linear model was fitted to estimate the intensity and volume of logged trees measured on the ground based on the airborne LiDAR height difference. From this model, statistical metrics were extracted with the "summary" function, explaining the variability of the logging intensity (R^2) and the significant relationship between the presence of selective logging and the loss of height (p-value).

3. Results

3.1 Selective logging density and volume

The two rasters generated for each UPA, one for density (Figure 3) and other for volume (Figure 4), considered the non logged trees, which were assigned a value of 0 during the process. The density rasters unveil the spatial distribution of logged trees across the UPAs, enabling a more accurate estimation of logging concentration in the areas. The volume rasters illustrate the amount of tree volume being harvested within the UPAs.

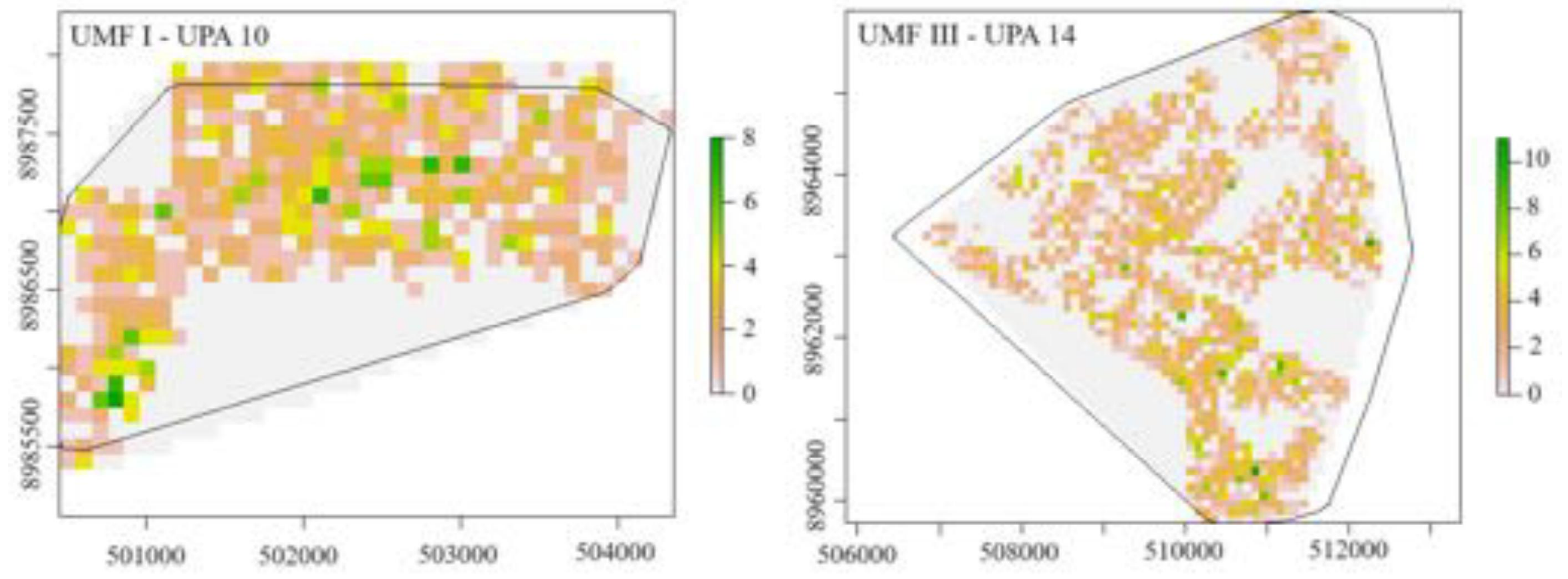

Figure 3. Logging density per hectare (logged trees/ha).

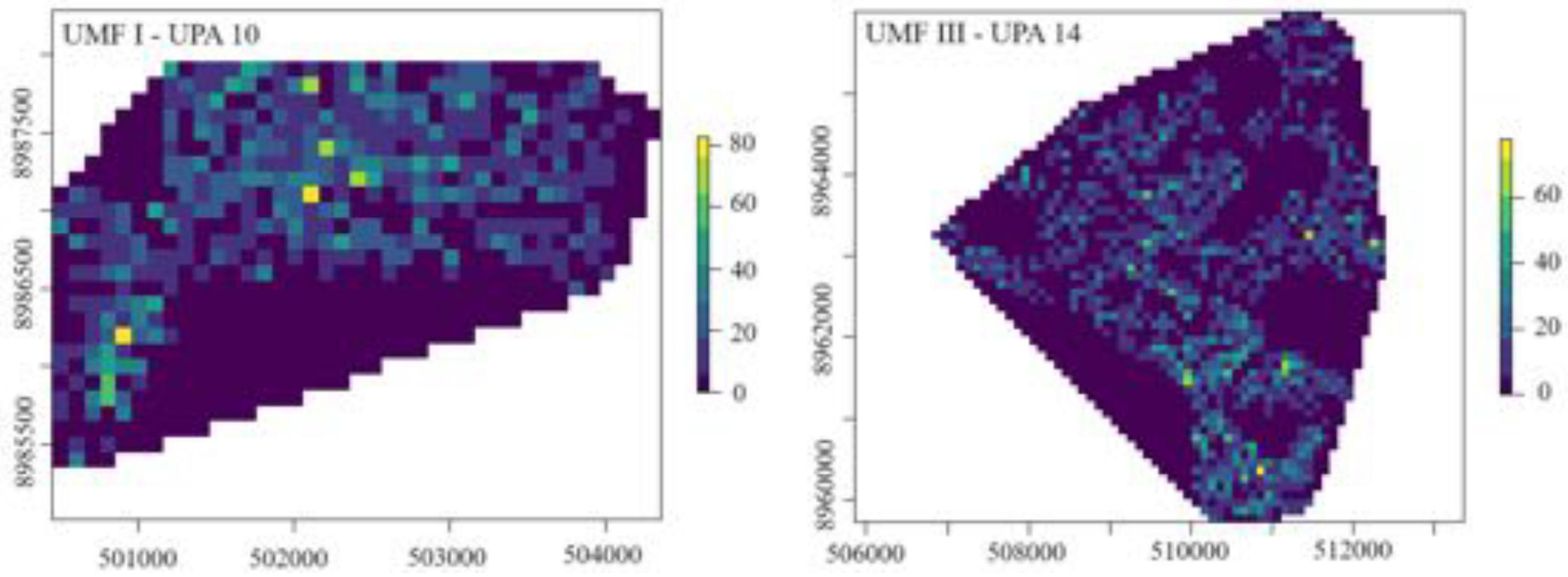

Figure 4. Logging volume per hectare (m^3/ha).

The density maps revealed that logging was distributed throughout the UPAs, with an average of 1.2 logged trees/ha and a maximum of 11 logged trees/ha, providing insights into the intensity of forest management per hectare (Table 2). Moreover, within the UPAs, there were areas where no logging had taken place (value = 0), indicating that not all parts of the forest area had been logged. Regarding the volume of logged trees, it averaged 10.12 and 7.15 m^3/ha for areas I-10 and III-14, respectively. This information allowed us to identify specific regions within the UPA with the highest volume of logged trees, as indicated by the color-coded representations above.

Table 2. Intensity of selective logging measured by density (trees/ha) and volume (m^3/ha) of logged trees in the Jamari Forest.

UMF/UPA (area)	Mean ± SD logging density (tree/ha)	Maximum density (tree/ha)	Mean ± SD Logging Volume (m^3/ha)	Maximum logged volume (m^3/ha)	Total number of logged trees
I - 10	1.2 ± 1.5	8	10.12 ± 13.33	82.88	911
III - 14	1.2 ± 1.6	11	7.15 ± 10.54	78.00	2599

3.2 Height difference in vegetation by LiDAR data

To quantify the height difference in vegetation in Jamari, the essential data were: the tree shapefile for each UPA; and pre-processed CHMs in ".tiff" format. The resulting raster, created by subtraction between LiDAR CHMs, identifies areas where there was a substantial reduction in vegetation height (>10 meters) between 2017 and 2018 (Figure 5). A significant portion of the extracted tree coordinates is in proximity to regions with LiDAR height differences exceeding 10 meters, which could be quantified with a simple spatial analysis between sets of points.

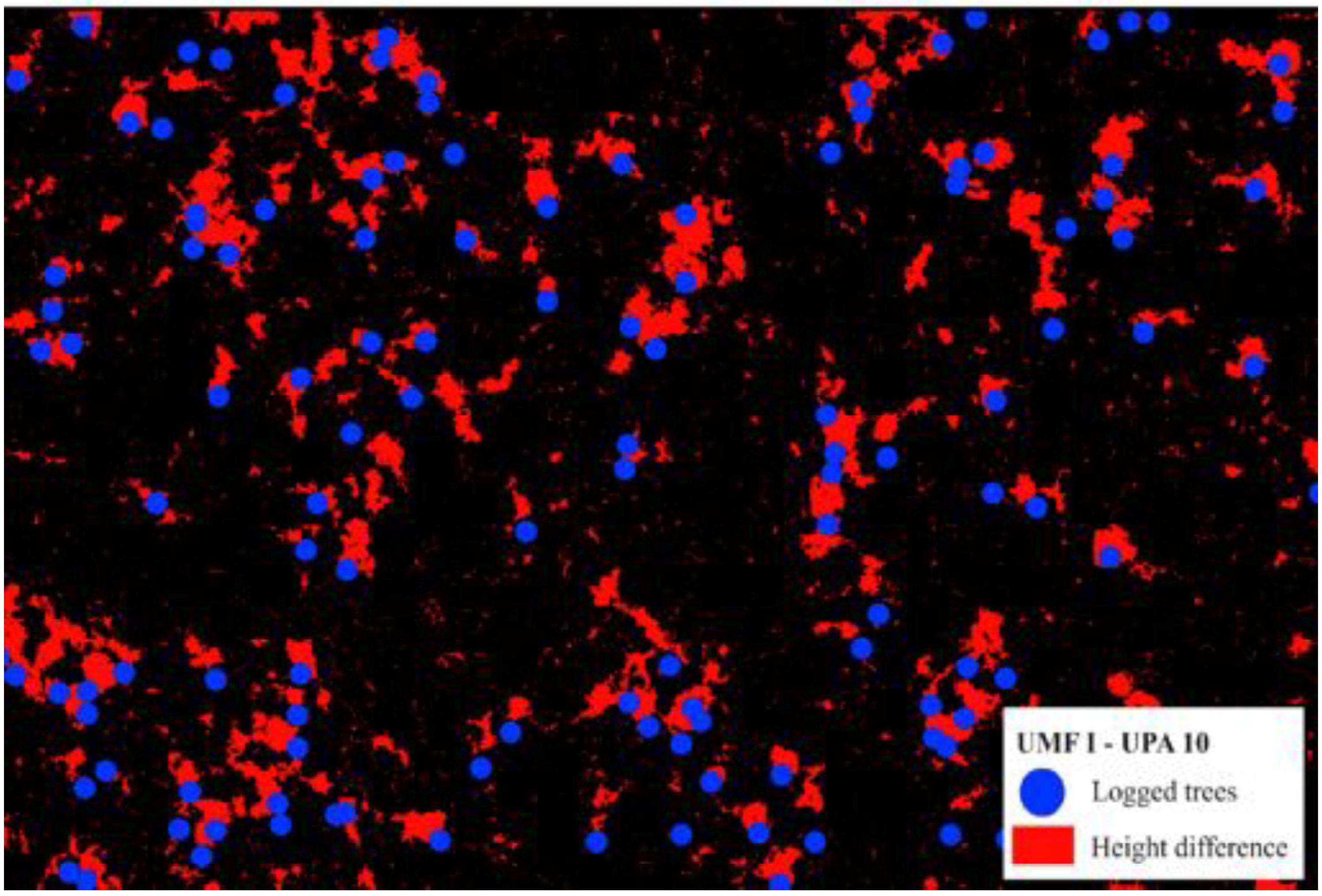

Figure 5. Overlap of logged trees with the height difference for UPA 10 of UMF I.

The linear regression model, which was adjusted between the variable difference height and logging intensity, explained approximately 44% of the variability in logging intensity (R^2=0.4365, refer to Table 6). The p-value less than 1% reveals a significant relationship between the loss of height in the forest structure and the number of logged trees. Similarly, for volume, the same metrics were obtained, with R^2 equal to 0.472 (~47%, refer to Table 6) and the p-value also lower than 1%, proving the significance of the relationship. When analyzing the selective logging in terms of the volume variable, a stronger relationship is observed with the metric extracted from LiDAR data.

Table 6. Statistical metrics for logging intensity and volume of logged trees × height difference.

Coefficients	Estimative	Standard error	t	p-value	
Intercept	0.38131	0.07389	5.16	3.26e-07	DENSITY
Height difference	-0.79016	0.03486	-22.67	<2e-16	
R^2	0.4365	-	-	< 2.2e-16	
Intercept	1.1277	0.5567	2.026	0.0432	VOLUME
Height difference	-6.3942	0.2626	-24.347	<2e-16	
R^2	0.472	-	-	< 2.2e-16	

The relationship observed between height difference × logging intensity (Figure 7) and height difference × volume of logged trees (Figure 8) represented that the greater the loss of height, which indicates the tree removal, the greater the number of trees logged within that hectare.

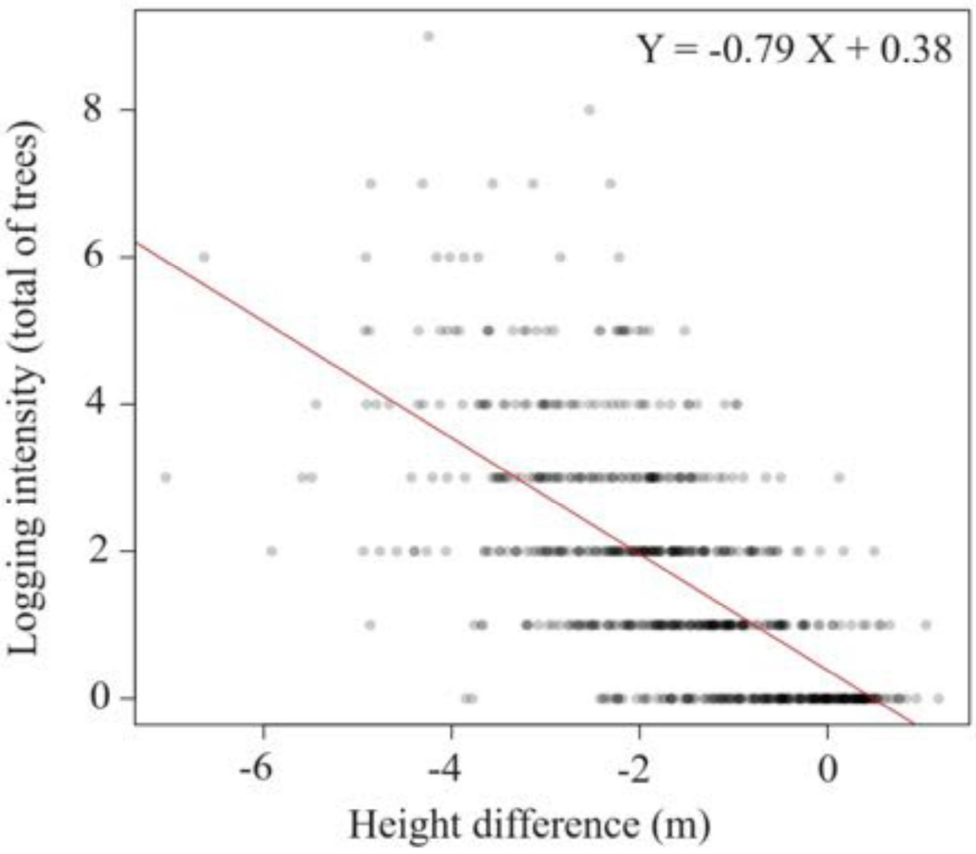

Figure 7. Relationship between selective logging intensity × height difference.

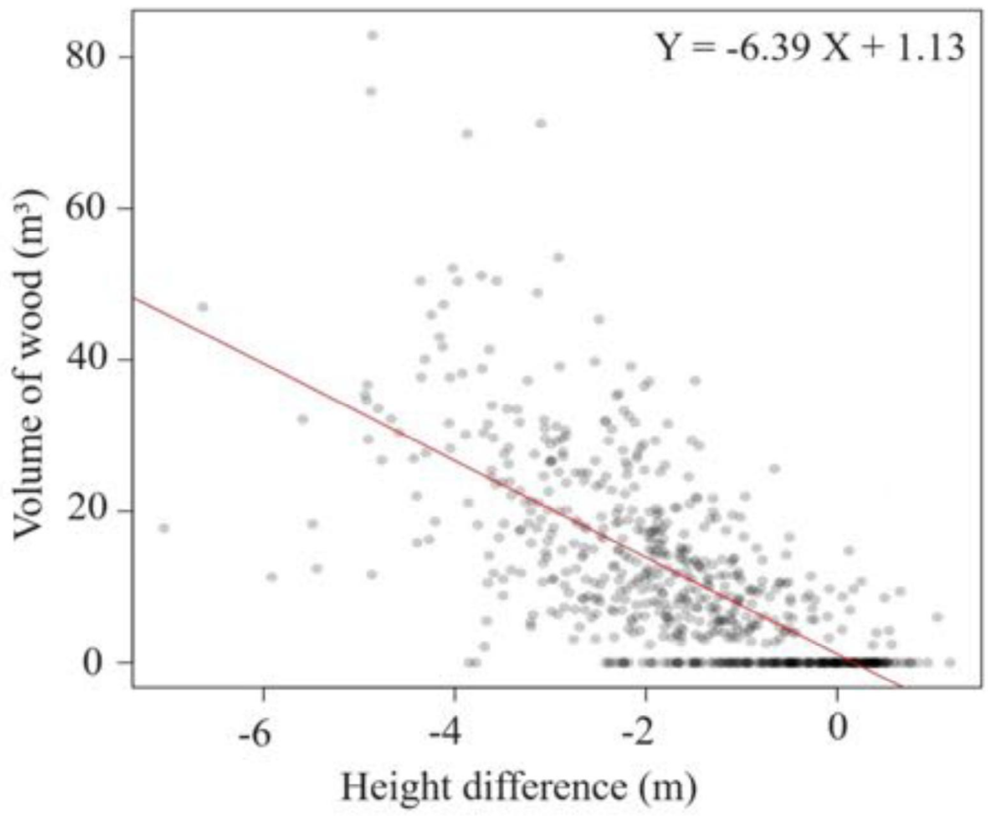

Figure 8. Relationship between volume of logged trees × height difference.

4. Discussion

Our findings revealed a significant relationship between volume of logged trees and density measured in the ground with the observed LiDAR height change ($R^2 > 0.44$). Overlaying the spatial distribution of logged trees with areas exhibiting a reduction in tree height, as confirmed by CHMs subtraction, reveals that there is indeed a correlation between the diminishing in the forest structure height and the number of trees logged. As the height difference approaches zero, the number of logged trees decreases. Some values close to zero in the height difference, yet still indicating logging intensity, may be associated with pre-selective logging extraction activities or even the natural dynamics of the forest. Companies engaged in forest management areas must execute their activities considering the exploration limit of 25.8 m^3/ha over a 25-year selective logging cycle, so the impact does not exceed the contractual agreements (LOCKS, MATRICARDI, 2019). To legally respect this quantity, it is necessary to better understand logging density and volume with the help of remote sensing and high-resolution satellite data to monitor this disturbance.

Limitations of the current logging intensity estimation approach include that the results are subject to factors intrinsic to the forests studied and the data collected, and that further analysis should be carried out considering different logging intensities and forests. The tested forest is a dense canopy forest, therefore results may vary in areas of more open canopy. Also, the time difference between LiDAR acquisitions can influence the observed relationship, as with time passes by the gaps created by the felling of trees may rapidly close (DALAGNOL et al., 2019). The development of robust approaches to estimate intensity of logging needs to tackle these challenges in future developments.

A direct application of this methodology, although highly difficult due to the limited availability of POAs and tree shapefiles on the SFB website, would involve comparing the calculated intensity for the UPA with the values documented in their respective records. Additionally, the acquisition of airborne LiDAR data is expensive, and the availability and dissemination of data are selective, which hinders broad access by the independent academic community. Therefore, these products still require a more detailed analysis when applied to monitoring impacts in tropical forests, such as the Amazon forest (LOCKS, MATRICARDI, 2019). The development of new methodologies for integration between LiDAR and optical data (Landsat, Sentinel-2 or PlanetScope) and/or SAR (Sentinel-1, ALOS PALSAR), would be crucial to estimate and monitor the intensity of selective logging in cost-efficient ways in the future.

5. Final considerations

The overlap with the location of logged trees represents the spatial relationship between height loss in vegetation and selective logging and obtaining LiDAR CHMs in raster format already processed in the aforementioned period allows the analysis of vegetation before and after extraction. In this way, through the LiDAR height difference variable, it is possible to estimate the intensity and volume of logged trees in the forest.

Future steps in this study involve calculating forest biomass loss and the consequent implication in the carbon balance rates of the logged portion. The long-term objective is to develop a tool for monitoring and inspecting logging activities in forest concession areas. In the case of the Jamari National Forest, the lack of data is still a limiting factor in this monitoring strategy, which depends on the location, volume and date of logged trees for cross-referencing with LiDAR data.

6. Acknowledgments

We thank Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPQ) for financing the PIBIC project carried out in partnership with Instituto Nacional de Pesquisas Espaciais (INPE) between 2022 - 2023, which was essential to elaborate this work. We also thank SFB for providing data on the Jamari National Forest.

References

Chules, E. L. (2018) "Floresta Nacional do Jamari: percepções e expectativas dos atores sobre a concessão florestal". Dissertation (Mestrado - Programa de Pós-Graduação em Desenvolvimento Sustentável). Universidade de Brasília.

Copertino, M., Piedade, M. T. F., Vieira, I. C. G. and Bustamante, M. (2019) "Desmatamento, fogo e clima estão intimamente conectados na Amazônia". In: *Ciência e Cultura*, v. 71, n. 4, pages 4-5.

Dalagnol, R., Phillips, O. L., Gloor, E., Galvão, L. S., Wagner, F. H., Locks, C. J. and Aragão, L. E. O. C. (2019) "Quantifying canopy tree loss and gap recovery in tropical forests under low-intensity logging using VHR satellite imagery and airborne LiDAR". In: *Remote Sensing*, v. 11, n. 7, page 817.

Dalagnol, R., Wagner, F. H., Galvão, L. S., Streher, A. S., Phillips, O. L., Gloor, E., Pugh, T. A. M., Ometto, J. P. H. B. and Aragão, L. E. O. C. (2021) "Large-scale variations in the dynamics of Amazon forest canopy gaps from airborne lidar data and opportunities for tree mortality estimates". In: *Scientific Reports*, v. 11, page 1388.

Dalagnol, R. et al. (2023) "Mapping tropical forest degradation with deep learning and Planet NICFI data". In: *Remote Sensing of Environment*, In Press Publishing.

Ferreira, L. V., Venticinque, E. and Almeida, S. (2005) "O desmatamento na Amazônia e a importância das áreas protegidas". In: *ESTUDOS AVANÇADOS*, v. 19, n. 53, pages 157-166.

Fearnside, P. M. (2005) "Deforestation in Brazilian Amazonia: history, rates, and consequences". In: *Conservation Biology*, v. 19, n. 3, pages 680–688.

Gandour, C., Menezes, D., Vieira, J. P. and Assunção, J. (2021) "Degradação florestal na Amazônia: fenômeno relacionado ao desmatamento precisa ser alvo de política pública". In: *Climate Policy Initiative*.

Hijmans, R. J. et al. (2023) "Raster: geographic data analysis and modeling". Available on: < https://cran.r-project.org/web/packages/raster/index.html>.

Kuck, T. N., Sano, E. E., Bispo, P. d. C., Shiguemori, E. H., Silva Filho, P. F. F. and Matricardi, E. A. T. (2021) "A comparative assessment of machine learning techniques for forest degradation caused by selective logging in an Amazon region using multitemporal X-band SAR images". In: *Remote Sensing*, v. 13, n. 17, page 3341.

Lapola, D. M. et al. (2023) "The drivers and impacts of Amazon forest degradation". In: *Science*, v. 379, n. 6630.

Locks, C. J. and Matricardi, E. A. T. (2019) "Estimativa de impactos da extração seletiva de madeiras na Amazônia utilizando dados LiDAR". In: *Ciência Florestal*, v. 29, n. 2, pages 481-495.

Matricardi, E. T., Skole, D. L., Costa, O. B., Pedlowski, M. A., Samek, J. H. and Miguel, E. P. (2020) "Long-term forest degradation surpasses deforestation in the Brazilian Amazon". In: *Science*, v. 369, n. 6509, pages 1378-1382.

Montibeller, B., Kmoch, A., Virro, H., Mander, Ü. and Uuemaa, E. (2020) "Increasing fragmentation of forest cover in Brazil's Legal Amazon from 2001 to 2017". In: *Sci Rep*, v. 10, page 5803.

Pinagé, E. R., Keller, M., Dos-Santos, M. N., Spinelli-Araujo, L. and Longo, M. (2015) "Avaliação temporal dos efeitos da exploração madeireira usando dados LiDAR". In: *Anais XVII Simpósio Brasileiro de Sensoriamento Remoto - SBSR*, INPE.

Serviço Florestal Brasileiro (SFB). Instituto Chico Mendes de Conservação da Biodiversidade. (2022). Available on: <https://www.gov.br/agricultura/pt-br/assuntos/servico-florestal-brasileiro/concessao-florestal/o-que-e-concessao-florestal>. Acesso em: 23 de Agosto de 2023.

Serviço Florestal Brasileiro (SFB). Ministério da Agricultura, Pecuária e Abastecimento. (2022). Available on:< https://www.gov.br/agricultura/pt-br/assuntos/servico-florestal-brasileiro/concessao-florestal/concessoes-florestais-em-andamento-1/madeflona-industrial-madeireira-execucao-financeira-e-tecnica-da-concessao-jamari-umf-i>. Acesso em: 23 de Agosto de 2023.

Silva Junior, C. H. L. et al. (2021) "Amazonian forest degradation must be incorporated into the COP26 agenda". In: *Nature Geoscience*, v. 14, n. 9, pages 634–635.