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Indicators for monitoring reduced impact logging in the Brazilian amazon derived from airborne laser scanning technology

Quétila Souza Barros [a,*], Marcus Vinicio Neves d' Oliveira [b], Evandro Ferreira da Silva [c], Eric Bastos Görgens [d], Adriano Ribeiro de Mendonça [e], Gilson Fernandes da Silva [e], Cristiano Rodrigues Reis [f], Leilson Ferreira Gomes [g], Anelena Lima de Carvalho [h], Erica Karolina Barros de Oliveira [i], Nívea Maria Mafra Rodrigues [e], Quinny Soares Rocha [j]

[a] *National Institute of Amazonian Research (INPA), Acre Research Nucleus, Street Dias Martins, 3868, 69.917-560, Rio Branco, AC, Brazil*
[b] *Brazilian Agricultural Research Corporation (EMBRAPA-Acre), Rodovia BR-364, km 14, 69900-970, Rio Branco, AC, Brazil*
[c] *Federal University of Pará (UFPA), University Campus of Altamira, Street Cel. José Porfírio, 2515, São Sebastião, 68372-040, Altamira, PA, Brazil*
[d] *Federal University of Jequitinhonha and Mucuri Valleys (UFJM), Department of Forest Engineering, 39447-790 Diamantina, MG, Brazil*
[e] *Federal University of Espirito Santo (UFES), Department of Forestry and Wood Science, Avenue Governor Lindemberg, 316, 29550-000, Jeronimo Monteiro, ES, Brazil*
[f] *School of Agricultural Sciences, São Paulo State University, Fazenda Experimental Lageado, 18610-034 – Botucatu, SP, Brazil*
[g] *University of Brasília, Graduate Program in Applied Geosciences and Geodynamic - Institute of Geosciences, Brasília, Brazil*
[h] *Federal University of Acre, UFAC, Forest Campus Multidisciplinary Center, Forest Campus Road Canela Fina, 69980000 Cruzeiro do Sul, AC, Brazil*
[i] *Federal University of Acre (UFAC), 69905-859 Rio Branco, AC, Brazil*
[j] *São Paulo State University (Unesp), School of Agriculture, Botucatu, Brazil*

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ABSTRACT

Monitoring reduced impact logging (RIL) activities in sustainably managed forest areas in the Amazon is a costly and complex, yet crucial endeavor. One viable monitoring option is the use of airborne laser scanning (LiDAR), which enables estimating forest structure parameters over large areas in a reduced timeframe with high accuracy. In this study, we propose and assess the applicability of five monitoring indicators for RIL based on Light Detection and Ranging (LiDAR) data acquisition in areas under forest concession. Five Annual Production Units (APUs) were investigated within the Forest Management Unit (FMU) III of the Jamari National Forest, located in the Southwest of the Brazilian Amazon. These sites were surveyed by LiDAR in 2014 and 2015 (one year after the exploration). Digital Terrain Models (DTMs), Surface Models (DSMs), and Canopy Height Models (CHMs) were generated for each APU. The proposed indicators were: i. Detection and identification of crown removal in dominant and co-dominant trees above 30 m; ii. Gap detection in the forest canopy; iii. Impacts of Reduced Impact Logging on the Understory; iv. Changes in the vertical canopy profile; and v. Affected areas within Permanent Preservation Areas (PPAs) and restricted areas. There was a 3.95% reduction in the occurrence of taller canopies after RIL, and a higher occurrence of small gaps ($\lambda > 1$), with λ values (2.34) being higher in the area with the oldest logging history (APU 1). Gini coefficient values in all APUs were below 0.5, indicating a low intensity of disturbances in the forest canopy. The shape (γ) and scale (β) parameters of the understory and canopy were not significantly correlated with variables related to selective logging. Restricted areas were considered for the allocation of roads, trails, log landings, and places with slopes equal to or >15%, and the indices of areas affected by RIL in PPAs and restricted areas were <2%. The proposed indicators using LiDAR data show great potential for monitoring managed areas in the Amazon and can be utilized by concession companies and government oversight.

* Corresponding author.
E-mail addresses: quetilabarros@gmail.com (Q.S. Barros), marcus.oliveira@embrapa.br (M.V.N. d' Oliveira), evandrofs@ufpa.br (E.F. da Silva), eric.gorgens@ufvjm.edu.br (E.B. Görgens), adriano.mendonca@ufes.br (A.R. de Mendonça), cristiano.reis@unesp.br (C.R. Reis).

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1. Introduction

Approximately 4.8 million km^2 of tropical forest can be found in the Brazilian Amazon Forest (Costa et al., 2024), from which 1.6 million ha have been designated to Forest Concession (Sist et al., 2021). The Forest Concession mechanism was implemented in Brazil to make possible the management of public forests where the targets are improving resource management, ensuring compliance with forestry product regulations, generating income, and combating illegality (Brazil, 2006). Currently, this policy has been implemented in seven National Forests, distributed across three states, granting over 1.2 million hectares of public forests divided into 22 forest management units (FMUs) and assigned to 11 private companies. The accumulated wood production from 2011 to 2021 has exceeded 1.69 million m^3, with an income of over 26.2 million dollars (2010–2021) (Brazilian Forest Service- SFB, 2023). All of these concessions are located in National Forests, which are protected areas designated for sustainable use, allowing human activities while strategies of biodiversity conservation are also employed (Rylands and Brandon, 2005).

Access to forest resources in concession areas occurs through Sustainable Forest Management (SFM). Brazilian legislation establishes the legal instruments that allow the SFM in the concession areas, and defines the objectives of natural resource exploitation, ensuring the sustainability of ecosystems in environmental, social, and economic dimensions (Brazil, 2006). In the SFM, selective logging is the predominant system for wood exploitation in the Brazilian Amazon. This system contributes to approximately 15% of the global wood production (Condé et al., 2022). Additionally, the SFM implies the use of a method known as Reduced Impact Logging (RIL) which aims to reduce environmental damages, increase activity efficiency based on detailed planning and precise execution of low-impact logging (Capanema et al., 2022). RIL involves meticulous planning based on census forest inventories of trees with a diameter at breast height (DBH) >40 cm, hydrography mapping, previously removing the lianas, defining the tree's falling direction, opening forest roads, log landings, skid trails, and protecting against fires. Some other RIL principles that are also legal requirements comprise the cutting cycle intervals, the intensity of extraction in m^3/ha (maximum of 30 m^3/ha), and minimum DBH size of 50 cm for cutting (Brazil, 2006; de Avila et al., 2017; Dionisio et al., 2018). These practices enable the development of sustainable management plans (Vizcarra et al., 2021), however, reconciling logging activities with the preservation of ecosystem services remains a significant challenge for forest managers and policymakers (Piponiot et al., 2019).

Among these challenges, there is the need to better understand the capacity of forest concessions to sustain wood production over successive cycles (Sist et al., 2021). Considering an estimated potential for forest concession close to 35 million ha across the Brazilian Amazon Forest (Sist et al., 2021), we must take into account more variables to determine whether the SFM is being effective or not. For instance, the rules and regulations for logging in the Brazilian Amazon were established by federal law, without considering the different characteristics of Amazonian forest physiognomies, which vary widely in different regions in this tropical forest. This uniform approach has raised questions about the sustainability and applicability of the adopted legal criteria (Capanema et al., 2022; Condé et al., 2022; David et al., 2019; Dionisio et al., 2022).

In this context, monitoring logging activities in the Amazon is essential to ensure compliance with logging plans, mainly in terms of wood production and the impact generated, as well as the speed of ecosystem recovery (d'Oliveira et al., 2020; Reis et al., 2021). However, field data collection is limited due to the need to cover extensive and hard-to-access areas, often restricted to seasonal regional conditions (d'Oliveira et al., 2012; Ferreira et al., 2021). This calls for more efficient and cost-effective means of obtaining such information, such as remote sensing approaches. The use of remote sensing technologies, such as airborne laser scanning (LiDAR), has proven to be a viable alternative for collecting spatial data and improving information related to logging activities (Gorgens et al., 2020). Previous studies have already established the use of LiDAR for estimating variables related to canopy structure (de Carvalho et al., 2017; Pascual et al., 2022; Reis et al., 2022), understory (Melo et al., 2020), and logging impacts (d'Oliveira et al., 2012; d'Oliveira et al., 2021; Ellis et al., 2016), as well as forest changes before and after selective logging (Papa et al., 2020; Meyer et al., 2018). However, these studies often focus on a single forest parameter extracted from LiDAR data due to the difficulties in obtaining such technology, especially in remote areas of developing countries (Melendy et al., 2018; Ota et al., 2019). However, accurate and available data on the ecosystem's structure are necessary for more precise modeling of forest parameters with high spatial resolution (Dubayah et al., 2020).

The Brazilian Forest Service (SFB, 2008) is the agency responsible for managing Concession Forests in the Amazon, and requires collecting a series of indicators in forest management areas, but without a clear definition or suggestion of how they should be monitored. Given these considerations, the question guiding our research was: can a methodology based only on variables extracted from a high-resolution LiDAR point cloud provide enough information for monitoring logging activity in the Amazon Forest? The aim of this article was to propose and evaluate the applicability of five indicators for monitoring Reduced Impact Logging (RIL) systems in forest concession areas at different stages of management practices in the southwestern region of the Amazon. This is the first time this set of LiDAR variables is used together to test the adherence between logging activity and the recovery of the remaining forest in order to assess the effectiveness of sustainable management practices.

2. Material and methods

The methodology used for conducting the analyses in this study is presented below (Fig. 1).

2.1. Characterization of the study area

The study was conducted in the Forest Management Unit III (FMU III), located in the Southwest of the Jamari National Forest (JNF) in Brazil. The FMU III covers an area of approximately 46.2 thousand hectares. The FMU III has been under a forest concession regime for certified timber forest management by the Forest Stewardship Council System (FSC) since 2010. Additionally, the FMU was splitted in 25 annual production units (APU) where the logging activities planned for a given year should be executed. The monitoring indicators we tested in this paper were obtained from APU 1, 2, 3, 4 and 5 (Fig. 2). The studied area is predominantly classified as Dense Tropical Forest, with some open Ombrophilous Forest areas and the presence of palms or lianas. The JNF region experiences a tropical rainy climate (Aw) according to the Köppen climate classification (Brazilian Forest Service - SFB, 2019).

2.2. Logging intensity and methods

The logging planning in APUs 1, 2, 3, and 4 followed the conventional method with mapping using false coordinate techniques (X-Y system of field markings). The Digital Exploration Model (Modeflora) was implemented in APU 5 as a new approach that aims to reduce the impact for logging by including detailed spatial information in the planning. The Modeflora system is a set of tools which increase the precision of management by optimizing logging planning, defining better transportation routes, identifying trees near watercourses and, also, slopes >45°. Areas close to rivers and watercourses as well as areas with slope >45° must be designated as Permanent Preservation Areas (PPA), according to the Brazilian law (IBAMA, 2006).

The forest inventory was performed to identify all trees with diameter at breast height (DBH) equal or >40 cm in all the APU. From the

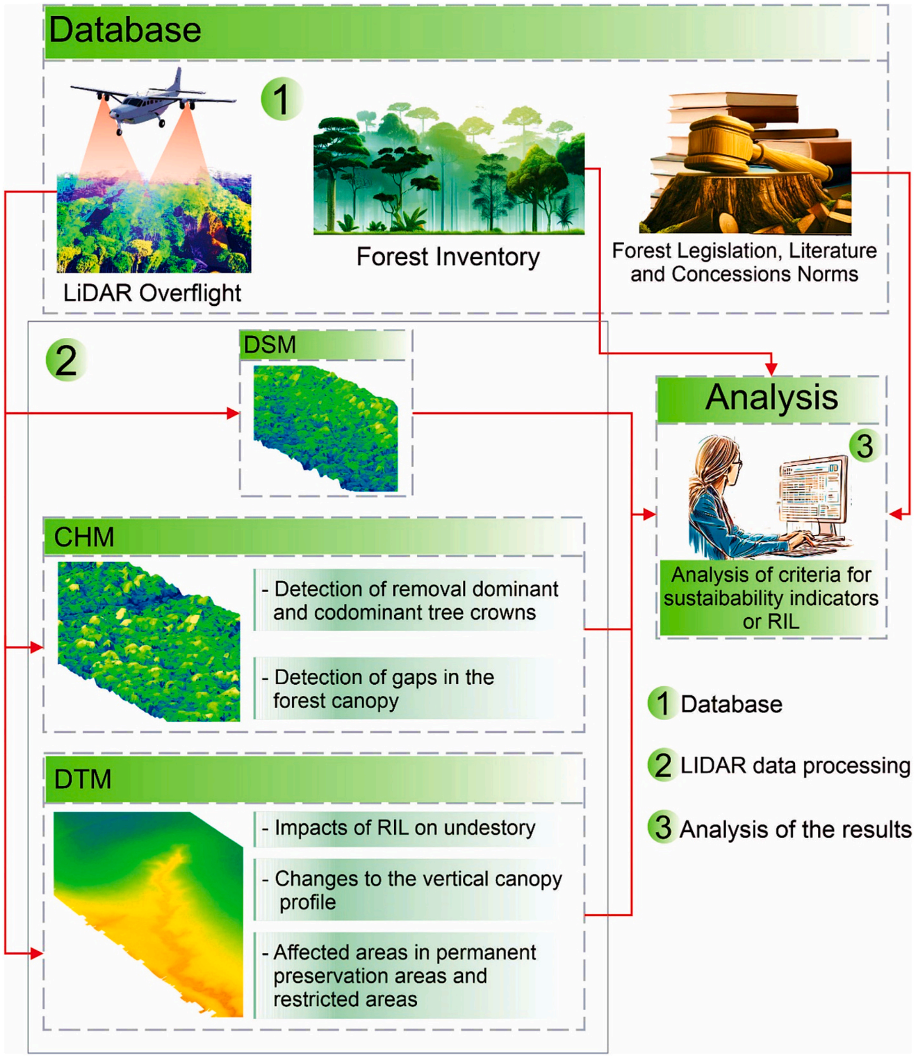

Fig. 1. Methodological flowchart with procedures for determining and evaluating RIL indicators collected with LiDAR in the Jamari National Forest between 2014 and 2015.

inventory variables collection the trees can be selected for harvesting. Field data is georeferenced using GNSS receivers, and detailed maps are created based on this georeferencing for planning and executing harvesting operations (Figueiredo et al., 2007).

In this concession area, the silvicultural system adopted in the APUs is known as polycyclic, which means cutting cycles of 25 years with a maximum allowed logging intensity of 21.50 $m^3.ha^{-1}$. Both the cutting cycle and logging intensity values are within of those used as reference in the brazilian regulation, such as a maximum logging intensity of 30 m^3/ha allowed by Brazilian legislation, a minimum cutting diameter (MCD) of 50 cm, and the cutting cycle varying from 25 to 35 years (Brazil, 2006). The calculation of logging intensity (m^3/ha) was based on work units (WUs) which considered the legal parameters of maintaining either 10% of the number of trees per species or a minimum of 3 individuals per species per 100 ha. The final selection of trees for cutting was based on the preservation of seed trees and non-commercial species in the forest. The numbers of harvested species, logging intensities, and other information about logging in the five APUs studied are presented in Table 1.

2.3. LiDAR data acquisition and processing

The discrete-return airborne LiDAR data was collected in October 2014 as part of the Sustainable Landscapes Project (The Brazilian Agricultural Research Corporation - Embrapa, 2014). The surveyed APUs were APU 1, APU 2, APU 3, APU 4, and APU 5 (Fig. 2; Table 2). Three flights were conducted at an altitude of 500 m using a Trimble Harrier 68i LiDAR sensor with a scanning frequency of 400 kHz, a viewing angle of 15°, 65% swath overlap, and an average point density of 50.55 pts.m^2, covering an area of 895.22 ha. Only APU 5 was scanned again in October 2015, providing \\a consistent perspective of the logging effects right after the exploitation, mainly for monitoring the forest concession contracts. The flights for APU 5 in 2015 were conducted at an altitude of 750 m using an OPTECH/ALTM 3100/05SEN171 LiDAR sensor with a scanning frequency of 40 kHz, a viewing angle of 15°, 70% swath overlap, and an average point density of 66.36 pts.m^2.

We used the FUSION LiDAR package (USDA Forest Service) for LiDAR data processing (McGaughey, 2018). Outliers in the point clouds were removed using a three-standard deviation threshold considering a 50-m scanning window. The following layers were produced with a spatial resolution of 1 × 1 m: digital terrain model (DTM), generated from ground points using the weighted least squares (WLS) linear interpolation algorithm (Kraus and Pfeifer, 2001); digital surface model (DSM); and canopy height model (CHM). The CHM was calculated by subtracting the DSM from DTM (d'Oliveira et al., 2012).

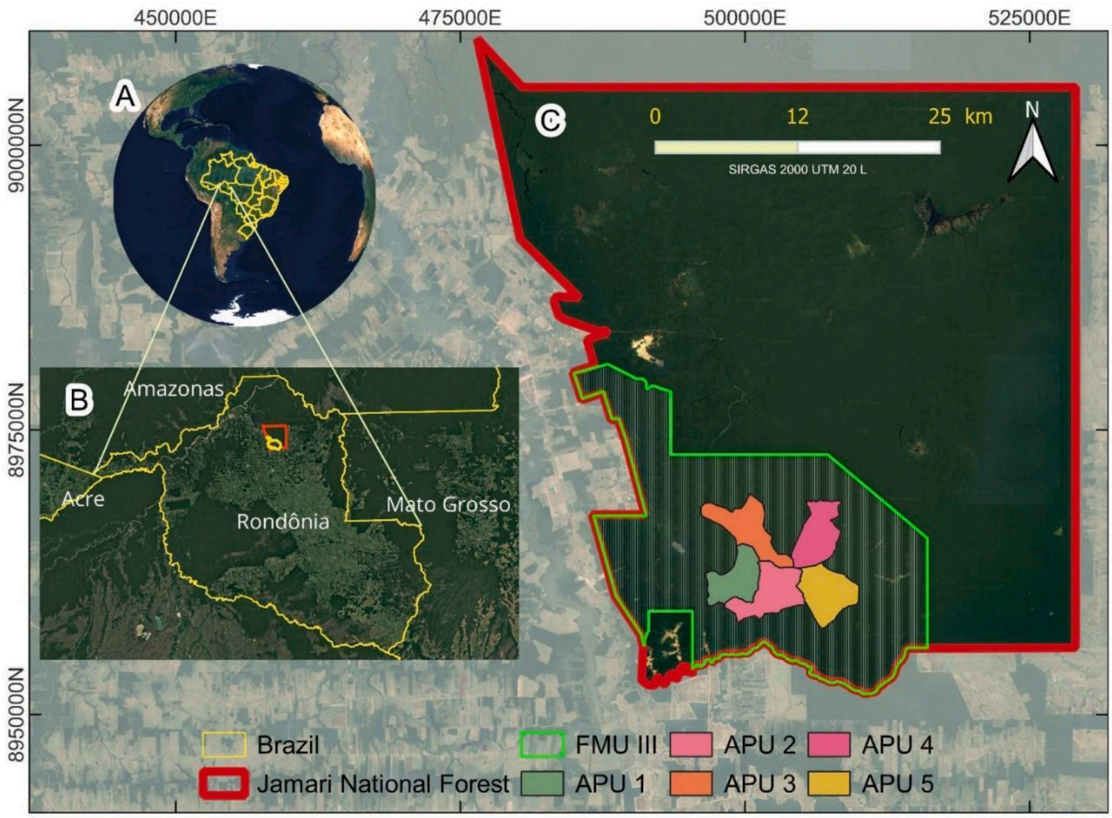

Fig. 2. Location of the Study Area. (A) Location of the state of Rondônia and the Jamari National Forest in Brazil. (B) Location of the Jamari National Forest (red polygon) within the state of Rondônia (green polygon). (C) Delimitation of the Jamari National Forest (Red Polygon), Forest Management Unit 3 (FMU 3) (Green Polygon), and the studied Annual Production Units (APUs). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Production results of forest management in selectively logged APUs in FMU III of the Jamari National Forest in the years 2014 and 2015.

Parameters	Unit.	APU 01	APU 02	APU 03	APU 04	APU 05
Total area of the APU	ha	1587	1946	1944	1781	1927
Effective management area	ha	1360	1743	1633	1489	1597
Harvested volume	m^3	19.544	27.82	16.7	19.015	23.897
Harvest density	m^3. ha^{-1}	14	16	10	13	15
Number of trees harvested	Unit	7.09	5.994	4.167	4.507	3.043
Harvest intensity	num. Tree. ha^{-1}	2	2	1	2	2
Number of species harvested	Unit	40	40	24	28	35
Volume in relation to the approved	%	67%	75%	49%	61%	71%

2.4. *Indicators of reduced impact logging*

Five variables extracted from LiDAR data were studied as potential indicators for monitoring changes as result of the reduced impact logging (RIL) operation and also to evaluate the forest recovery over the years. These variables were: the detection of dominant and co-dominant trees' crown removal; the detection of canopy gaps; the impacts of RIL on the understory vegetation; changes in the vertical canopy profile; and the magnitude of possible effects in areas mapped as restricted or as for permanent preservation (PPA). Previous research had already considered some verifiers for evaluating environmental impacts on forests under concession (Table 3). Verifiers are data or information sets that highlight the level of specificity or evaluation of an indicator and provide more detailed information (CIFOR, 1999). They were used to assess compliance with principles and criteria established by forest certification based on Brazilian forest legislation (Brazil, 2012) and forest concession rules (SFB, 2008).

2.4.1. *Crown removal detection from dominant and co-dominant trees*

We performed a reclassification in the GIS environment of each canopy height model (CHM) generated. In this process, we excluded all canopies with a height lower than 30 m. We then created a raster file containing only tree crowns with a height above 30 m, following the adapted methodology by Andersen et al. (2014). Thereafter, we converted these raster files into vector files and then we calculated the area occupied by the crowns of dominant and co-dominant trees in hectares for each Annual Production Unit (APU). These two forest canopy occupation classes can be considered very important in the context of our study due to the economic interest and high wood volumes usually found in large trees. Specifically for APU 5, we subtracted the dominant and co-dominant layers generated from the LiDAR data collected in 2015 (after logging) and in 2014 (before logging) to quantify the canopy coverage loss above 30 m in height. Their difference provided a measure of the canopy coverage loss resulting from the logging activity.

2.4.2. *Detection of canopy gaps in the forest*

The ForestGapR package (Silva et al., 2019) was used in R version 4.1 program (R Core Team, 2021) to detect canopy gaps in the forest. We defined gaps as contiguous opening areas containing low canopy height

Table 2
Description of LiDAR samples from FMU III in the Jamari National Forest in 2014 and 2015.

APU	Total area (ha)	LiDAR coverage (ha)	Final exploration date	Harvest density ($m^3.ha^{-1}$)	LiDAR flyby date	Time elapsed from exploration to overflight (years)
1	1587	207.76	oct/11	14	oct/14	3
2	1946	205.93	dec/12	16	oct/14	2.4
3	1944	105.60	oct/13	10	oct/14	1
4	1781	188.94	sep/14	13	oct/14	0
5	1927	186.99	sep/15	15	oct/14	–
					oct/15	0

Table 3
Proposed indicators of Reduced Impact Logging using LiDAR data for FMU III in the Jamari National Forest.

Principle	Criterion	Indicator	Verifier
Environmental Impact, Monitoring and, Evaluation (FSC, 2001)	Monitoring the environmental impact (Brazil, 2006; SFB, 2008).	Detection of the removed dominants and codominants crowns trees	12% reduction in the highest canopy (locks; matricardi, 2019).
		Detection of gaps in the forest canopy (Frequency and distribution of gaps)	Changes in Lambda parameters (>1) and Gini coefficient (G < 0.5) (Silva et al. (2019) and the percentage of area occupied by gaps must not exceed 10% of the APU area (SFB, 2008)
		Impacts of selective logging on the understory	The area impacted by secondary roads, skid trails and log landings will be a maximum of 8% (8 %) of the APU area and the percentage of areas occupied by gaps of 10% (SFB, 2008).
		Changes in the vertical profile of the canopy	Significant correlation at 0.05 in the parameters γ and β at the canopy and understory level, in relation to the parameters of selective logging.
		Affected areas in Permanent Preservation Areas (PPA) and restricted areas.	Vestiges of logging in PPAs and restricted areas must not exceed 2% of the total area[*].

[*] This value was arbitrarily determined based on technical knowledge as no reference was found in the literature or legislation regarding it.

with vegetation greater than or equal to 5 m (Zhang, 2008) and a minimum size of 10 m^2 (Hunter et al., 2015; Stark et al., 2012). In this step, we quantified the frequency distribution of gap sizes in the forest canopy. This methodological approach followed the description by Hanel et al. (2017) and was applied as described by Silva et al. (2019). The frequency distribution of gap sizes in the forest canopy was determined using the Zeta power-law distribution (Asner et al., 2013). A lambda value (λ) close to 1 indicates the presence of large canopy gaps and, on the other hand areas dominated by small gaps would present higher λ values (Fisher et al., 2008; Goulamoussène et al., 2017).

We calculated relevant statistics such as area, maximum height, minimum height, average height, standard deviation, Gini coefficient, and height range of the canopy gaps. These statistics are essential for understanding the structure and dynamics of the forest canopy, as well as for evaluating the degree of disturbance or disruption in the environment. The Gini coefficient (Eq. 1) was used to measure the inequality in the distribution of gap heights, allowing us to understand the uniformity or inequality of the forest canopy:

$$GC = 1 - 2\int_0^1 L(X)dX \tag{1}$$

Where:

$L(X)$ is the expected value of X. In the case of LiDAR metrics, the variable X is the height of LiDAR returns (Valbuena et al., 2012).

We followed the approach of Silva et al. (2019), which adopted the Gini coefficient (GC) to predict canopy irregularity caused by logging. Therefore, the interpretation for the GC is: < 0.5 represents the low occurrence of canopy disturbances, GC $= 0.5$ represents irregular canopy, GC > 0.5 indicates a canopy area with high irregularity, and GC $= 1$ represents maximum irregularity in the canopy (adapted from Adhikari et al., 2020).

Canopy gaps occur naturally as a result of the forest dynamic (Zhang et al., 2023). Due to this, we used the multitemporal LiDAR data from APU 5, collected before and after RIL, to make it possible to differentiate those gaps created by natural dynamics and those resulting from RIL activities. During the analysis of the identified gaps, which we converted into vector files in polygon format, we distinguished between canopy gaps resulting from road and log landing construction and natural gaps. Additionally, we performed an intersection among the vector files of canopy gaps and the constructed infrastructures using GIS.

2.4.3. *Impacts of reduced impact logging on the forest understory*

We followed the method proposed by d'Oliveira et al. (2012) to calculate the areas directly impacted by selective logging, which involves creating a relative density model (RDM) from data collected by LiDAR sensors. The RDM calculation creates a model that represents the relative density of vegetation in a given area. The RDM is a raster layer of the relative percentage of LiDAR point return heights within a specified ground height stratum enabling the identification and quantification of different vertical vegetation layers. We used LiDAR datasets from APUs 1, 2, 3, 4, and 5, with a spatial resolution of 1 m, and processed this data in the Fusion version 3.8 program (McGaughey, 2018), as described in previous studies (Andersen et al., 2014; Ellis et al., 2016; de Carvalho et al., 2017; Pinagé et al., 2019).

To create this layer we divided the number of LiDAR point returns within the height interval corresponding to the RDM by the total number of returns below the upper limit of the RDM in order to calculate the RDM values. We used the standard RDM limits with a lower limit of 1 m and an upper limit of 5 m. These limits were selected because the study areas have similar environmental characteristics to the areas where the method was developed by d'Oliveira et al. (2012). Then, we calculated the percentage value for each RDM by dividing the number of returns within the 1 to 5-m height range above the ground by the total number of returns below 5 m, multiplied by 100. Pixels in the generated model with a relative vegetation density value of zero in the selected layer represent areas without vegetation.

Using the RDM as reference, we digitized, manually, all the main and secondary roads, log landing sites, skid trails, and harvested tree gaps in the studied APUs using GIS in order to identify areas directly impacted by forest harvesting operations. We created buffers around the infrastructures and harvested tree gaps, as suggested by d'Oliveira et al. (2012) for Amazonian forests. For example, we added 6-m buffers to the digitized centerlines of main and secondary roads, 4-m buffers for skid trails, 20-m buffers to the central points of log landings, and 25-m buffers for harvested tree gaps. These buffers were converted into rasters with a resolution of 5 m, resulting in maps of the impacted areas.

Finally, we compared the points collected with GNSS and the infrastructure measurements conducted by the concessionaire company in the field to verify the accuracy of the disturbed areas identified in the RDM models compared to field surveys.

2.4.4. *Changes in the vertical canopy profile*

We quantified the vertical profile of the forest canopy using normalized LiDAR point cloud returns. This profile represents the vertical distribution of LiDAR points in height intervals based on empirical distributions or probabilistic functions. We utilized the Density Metrics tool in the Fusion version 3.8 program (McGaughey, 2018), which provides a series of statistical metrics related to the vertical distribution of LiDAR returns (Gelabert et al., 2020) to calculate the metrics of the vertical canopy profile (VCP) with pixel sizes of 50 × 50 m^2 and 1-m height intervals. This step results in a CSV file output containing raster layers representing the total number of returns for each one of the 1 m height intervals above the ground.

Next, we fitted a two-parameter Weibull density function to describe the canopy height distributions. This function is widely used for modeling the VCP based on LiDAR data due to its adaptability and flexibility in characterizing various forest attributes (Liu et al., 2018; Palace et al., 2015; Zhang et al., 2017). The Weibull function parameters were estimated using the Maximum Likelihood method in the R version 4.1 program through the Fitdistrplus package version 1.1 (Delignette-Muller and Dutang, 2015) (Eq. 2).

$$L(Z) = 1 - \left[e^{-\left(\frac{1 - \frac{Z}{H}}{\alpha} \right)^{\beta}} \right] \tag{2}$$

where: α and β are adjusted parameters, where α determines the basic shape of a vertical distribution and β represents the increase or decrease in the distribution amplitude; z is a function of height, and H is the maximum canopy height (i.e. the tallest return) (Coops et al., 2007; Liu et al., 2018).

A two-parameter Weibull function was fitted for the upper stratum (trees with heights above 15 m) and the lower stratum (trees with heights up to 15 m) of the forest in each APU. We considered these height thresholds as half of the average canopy height, which was approximately 30 m.

Other studies have found strong correlations between scale and shape parameters and forest attributes (Coops et al., 2007; Silva et al., 2015). We conducted correlation analyses to investigate the relationships between the vertical canopy profile structure and factors related to selective logging. We used variables from the vertical profile (γ = shape parameter; β = scale parameter of the Weibull function) and variables related to selective logging, such as time (years), harvesting intensity ($m^3.ha^{-1}$), sampled area (ha), and impacts on the sub-canopy (ha) for each correlation analysis. We used the Pearson's coefficient to assess the correlations.

All analyses were performed in the R environment considering a significance level of 5%. This methodology allows us to understand the relationship between the vertical canopy structure and factors related to selective logging (RIL).

2.4.5. *Affected areas in permanent preservation areas (PPA) and restricted areas*

According to Brazilian forest legislation (Law No. 12,651/2012, Brazil, 2012), the PPA are protected primarily for preserving natural resources, holding strategic importance for conservation. They include river and lake margins, hilltops, slopes, areas around springs, coastal dunes, mangroves, and high-altitude areas. PPA in this study were considered under the following categories: (i) springs, which should have a buffer zone of at least 50 m; (ii) vegetation along watercourses, with a buffer zone determined by the width of the river; and (iii) steep areas where the slope is >45°.

The concessionaire company provided the vectorized PPA they measured in the field then we could ensure accurate delineation of PPA using LiDAR. This approach will be considered from now on as Approach 1, where we applied two methodologies: The first methodology for Approach 1 consists in delineating PPA in APU 1 by placing signs such as red ribbons around them at intervals of 10 m along their entire length, with a distance of 30 m from the watercourse on both sides. The minimum distance of 50 m required by law was used for measuring springs. The second method used to map PPA was done by theModeflora system (Figueiredo et al., 2007), in which PPA areas were obtained by mapping watercourses in the field with GNSS receivers. Since the Modeflora method seeks for high precision in the logging operation planning, even areas difficult to access are visited in the field making it possible to map all branches of the existing drainage network in the APU. Thus, PPA were calculated by summing the areas of watercourse PPAs, springs, and slopes (BRASIL, 2012). All processing of this information was performed in a GIS environment.

On the other hand, the high-resolution terrain products from LiDAR were used in Approach 2. Here we mapped the hydrography using the models generated from the LiDAR point cloud only, following the methodology proposed by d' Oliveira et al. (2014). To perform this analysis spurious depressions (imperfections) in the DTM raster file were removed, the water flow direction was defined, and the accumulation basin of the flow network was delimited. Minimum values for the accumulation basin were set in the raster calculator, and the order of the watercourses was determined. The resulting image of the watercourse order was converted into a vector file. Buffers were created around rivers and streams using the hydrography mapping generated earlier as input. The width of the riverbank used for buffer creation was 30 m, as required by law for watercourses with widths <10 m, which was the case for all analyzed APU. When springs were identified, their corresponding points were created, and then buffers of 50 m around them were delineated. In addition, the watercourse and spring PPA files were merged to define the final PPA related to hydrography by combining the attributes of each file. In our study area, no areas with slopes >45° were found (Brazil, 2012).

In the forest environment, restricted or limited-use areas are locations that can be exploited, but with certain restrictions mostly because of equipment limitation and access difficulties. It is essential to avoid the construction of management infrastructure such as roads, log landings, and skid trails in these areas (d' Oliveira et al., 2014). We considered restricted areas for the allocation of roads, skid trails, log landings, and locations with slopes equal to or >15% (d' Oliveira et al., 2014; Figueiredo et al., 2007). Following this recommendation, we reclassified the Digital Terrain Model (DTM) of each APU into two slope classes in a GIS environment: the class 1 ranging from 0% to 14.9% (suitable for infrastructure construction and heavy machine traffic); and class 2, with a slope equal to or >15% (restricted areas). We divided the calculated area of PPAs and restricted areas in each APU by the corresponding total area and obtained the percentage of the area occupied by PPAs and restricted-use locations for each location.

Lastly, we checked for possible indications of selective logging impacts in the PPA and restricted areas by performing an intersection in a GIS environment among them and the selective logging impact found in the APU. Therefore, we calculated the amount of area that was in fact damaged during RIL activity in each APU.

3. Results

3.1. Removal detection of dominant and co-dominant tree crowns

The proportion of canopy height exceeding 30 m in the five APU evaluated was >30%. The scanning performed before logging in the APU 5 and in the APU 1 (three years after logging) indicated the highest emergent canopy cover percentages showing 37.85% and 34.53%, respectively. Both APUs where the LiDAR data was collected one year (APU 4) and two years (APU 2) after logging showed the lowest emergent canopy cover percentages of 32.57% and 32.86%, respectively (Fig. 3).

When we look to the the proportion of canopy area occupied by the dominant and co-dominant canopy in APU 5 immediately after logging in 2015, with a cutting intensity of 15 $m^3.ha^{-1}$, we found a decreasing in this proportion from 37.85% to 33.90%. This represents a reduction of 3.95% in the occurrence of canopy cover above 30 m. This value is below that established threshold of 12%, indicating the sustainability of selective logging based on this indicator.

3.2. Indicator: detection of canopy gaps

We observed through the distribution of canopy gaps in the forest (Fig. 4) that there was higher canopy closure in APU 1 (which was logged three years before the LiDAR survey) compared to the other APUs where selective logging was conducted closer to the LiDAR survey dates. A total of 3605 canopy gaps were identified through the areas surveyed in 2014. Then, there was an increase of 486 canopy gaps through 2015 after logging in APU 5, totaling 4091 gaps in the surveys conducted for the two years.

The frequency of canopy gaps (Fig. 5) in all APUs followed a power-law distribution ($\lambda > 1$) with an average value of 2.02, considering the first flight of APU5 performed in 2014. Overall, the values of $\lambda > 2$ indicated a forest dominated by smaller gaps in these areas. As expected, the mean λ value decreases when we replace the data from 2014 to 2015 (after logging) reaching the λ value of 1.96. Taking into account only the values of λ in APU 5 before logging (2014) and in APU 1, with the oldest history of selective logging, were higher than 2. The value of λ decreased to 1.79 after RIL activities in APU 5.

There was a 37.42% increase in the average gap area in APU 5 after logging in 2015, with a higher variation compared to the previous year. Before logging, 94.61% of the gaps had areas smaller than 150 m^2, with the maximum observed dimension being 775 m^2. All gaps larger than 150 m^2 were located in infrastructure areas composed of primary and

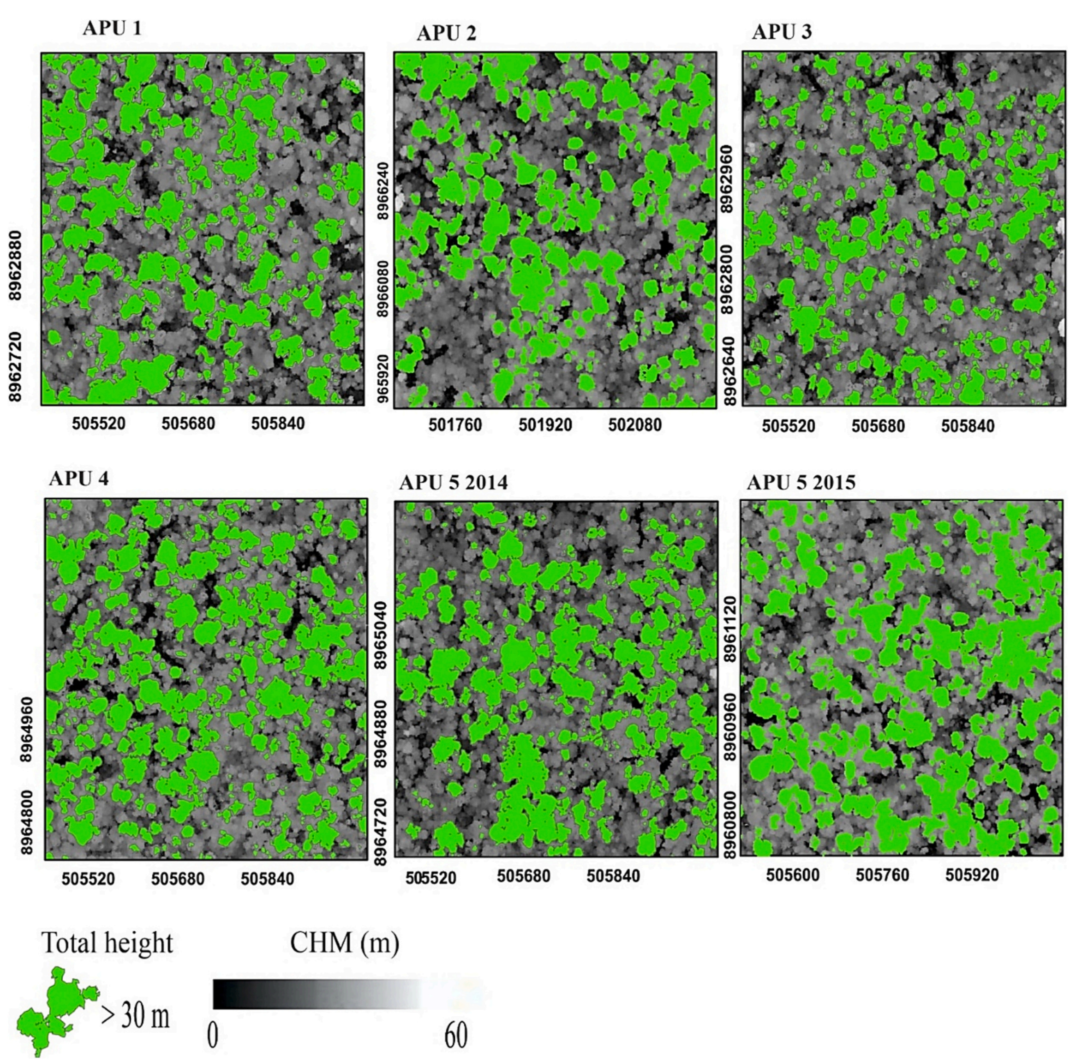

Fig. 3. Representation of the canopy distribution above 30 m in the Canopy Height Model (CHM) for the studied APUs of APU 3 in the Jamari National Forest in the years 2014 and 2015.

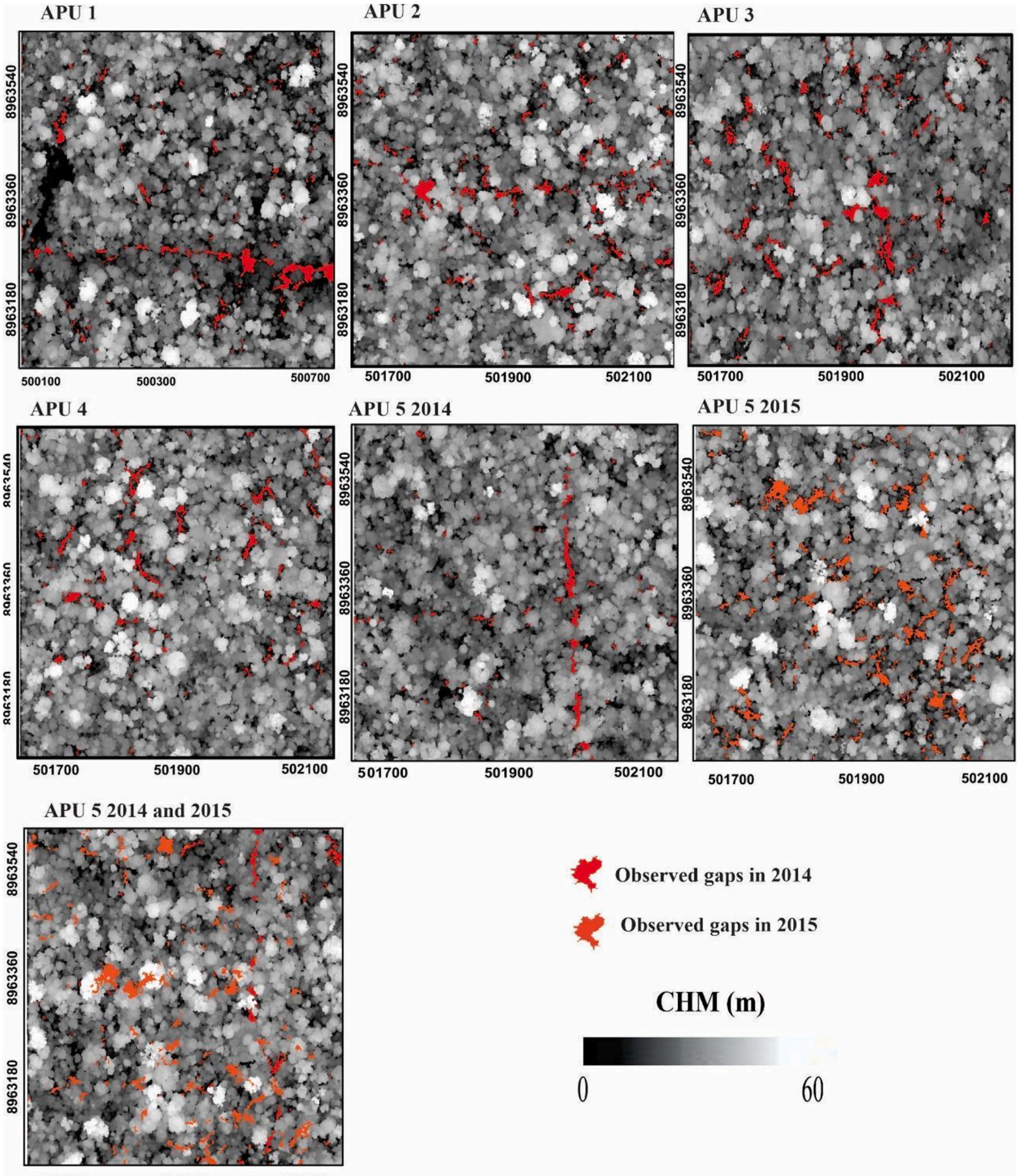

Fig. 4. Canopy Height Model derived from Airborne Laser Scanning (CHM; 1 m grid cell) and forest canopy gaps (red and orange polygons) detected at 5 m intervals in the studied APUs of FMU III in Floresta Nacional do Jamari for the years 2014 and 2015. Canopy gaps with multitemporal surveys in APU 5 for the corresponding year (2014) are shown in red, and the increment of gaps related to the previous airborne laser scanning coverage (2015) is shown in orange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

secondary roads and log landings. Which means that gaps greater than this size should be not usually naturally found in a preserved forest. A total of 23% of the total gaps surveyed were in these locations, mainly associated with secondary roads. The largest gap observed in areas without built infrastructure was 108 m^2 (Table 4).

The percentages of the total area occupied by canopy gaps were much lower the allowed limit in managed areas of 10%, even in places where the survey occurred simultaneously with logging activities (APU 4 with 3.08% and APU 5 with 3.44%). The Gini coefficient, which expresses the canopy alteration level caused by logging in 2014, varied from 0.19 in APU 1 to 0.40 in APU 4 (Table 4). The coefficient remained below 0.5 in all locations, with higher values in APUs 4 and 5, where the survey was conducted close to the logging activities (Table 4). After logging in 2015, APU 5 showed a 50.15% (486) increase in the total number of gaps compared to the survey from the previous year (483). This resulted in a 20.33% increase in the percentage of the total area with gaps and an average Gini coefficient increase of 9.67%.

3.3. Indicator: impacts of reduced-impact logging (RIL) on the forest understory

The area directly impacted by logging activities detected by LiDAR varied from 9.08% to 17.10% in the APUs 1 in 2014 and 5 in 2015, respectively (Table 5). The highest disturbance percentage identified in areas with up to two years elapsed between logging and LiDAR assessment (APU 1 and 2) was caused by felled tree gaps (4.51% to 6.69%). Conversely, skid trails caused more significant disturbances in the understory (5.77% to 6.92%) in FMUs 3, 4, and 5 with more recent selective cutting.

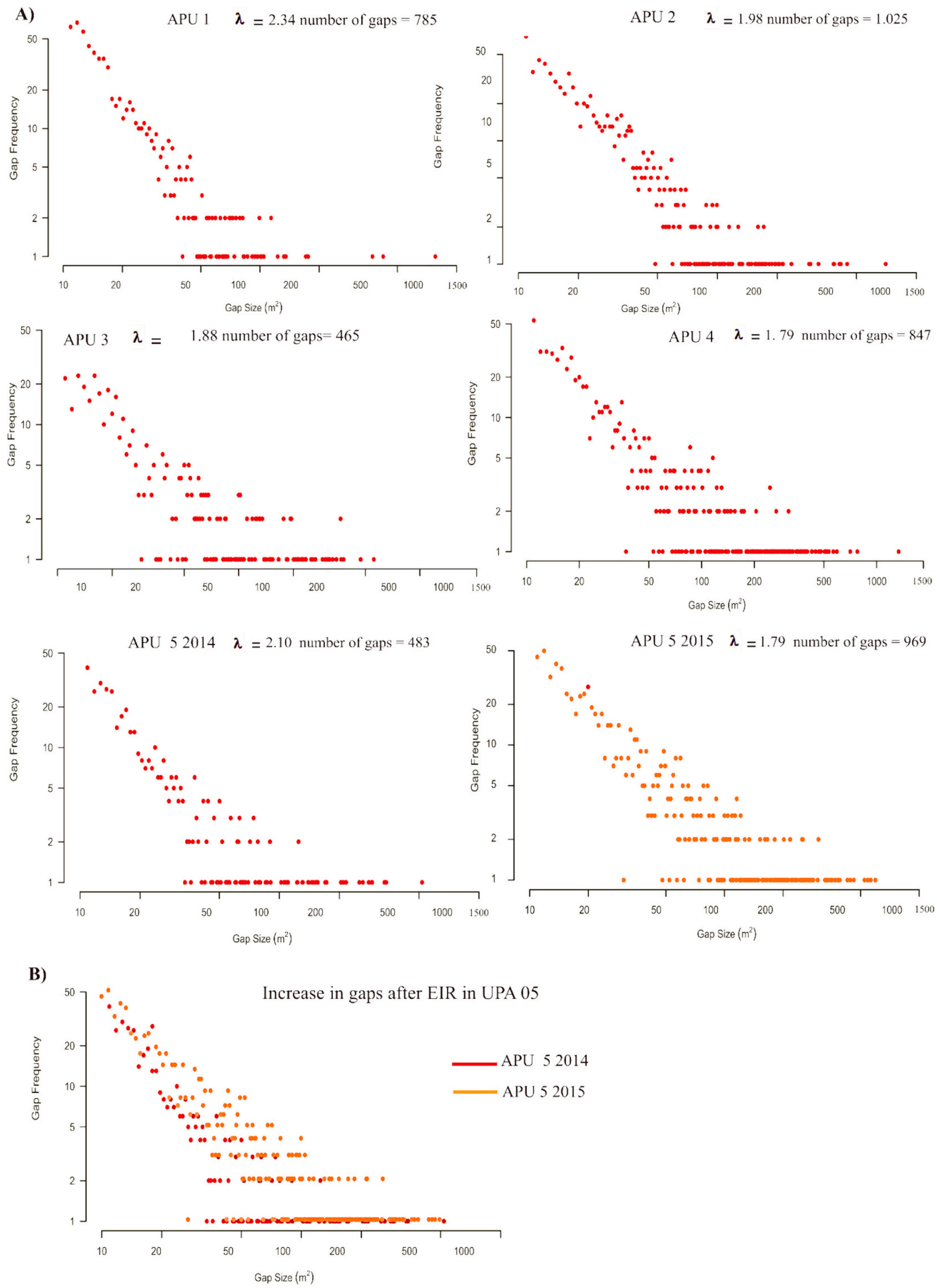

Fig. 5. A) Frequency distribution of canopy gap sizes (distribution of power-law exponents λ) in the studied APUs of FMU III in Floresta Nacional do Jamari for the years 2014 and 2015. B) Increase in gaps after EIR in UPA 05.

3.4. Indicator: changes in the vertical canopy profile

Regarding the distribution of the Weibull function parameters for the vertical canopy profile in the understory (h $\leq$ 15 m), the shape parameter (γ) showed the highest value in APU 5 in 2014 before logging (γ = 2.41) and the lowest in APU 3 (γ = 1.81). The largest variations of γ were detected (CV = 19.97% and 18.79%, respectively) in APUs 4 and 5, where the LiDAR flyover was conducted at the end of logging, and the smallest variations were in APUs 1 (CV = 13.24%) and 2 in 2014 (CV = 15.24%).

The highest scale parameter (β) values were observed in APUs 4 and 5 in 2014. The smallest variations were observed in APUs 1 and 5 in 2014 (CV = 12.84% and 15.55% respectively), while the lowest parameter values and the highest variations were observed in APUs 4 in 2014 (CV = 25.91%) and 5 in 2015 (CV = 23.93%).

The correlations obtained between the γ and β parameters and the factors related to logging activities (years since logging; harvest intensity in $m^3.ha^{-1}$; impacts in hectares) and the studied area presented

Table 4
Descriptive statistics of canopy gaps in the APUs surveyed by LiDAR in FMU III of Floresta Nacional do Jamari for the years 2014 and 2015.

LiDAR overflight year	Place	Situation	Number of gaps	Average area of gaps ± standard deviation (m^2)	Minimum area (m^2)	Maximum area (m^2)	Percentage of total area of gaps (%)	Gini coefficient(Mean ± standard deviation)
2014	APU 1	After logging	785	30.29 ± 61.98	10	1337	1.14	0.19 ± 0.12
	APU 2	AL	1025	43.86 ± 69.34	10	1072	2.18	0.22 ± 0.12
	APU 3	AL	465	53.14 ± 72.11	10	557	2.34	0.29 ± 0.12
	APU 4	AL	847	68.58 ± 108.10	10	1337	3.08	0.40 ± 0.21
	APU 5	BL	483	41.58 ± 70.30	10	775	1.07	0.31 ± 0.21
2015	APU 5	AL	969	66.45 ± 100.30	10	810	3.44	0.42 ± 0.18
Total				47.50 ± 80.35	10		1.92* 2.41**	0.28 ± 0.18* 0.31 ± 0.19**

*Number of gaps identified in 2014. **Number of gaps identified in 2015, added to the values of UPAs that had been logged until 2014.

Table 5
Areas directly impacted by logging in the forest understory of the FMUs studied in the Jamari National Forest within the years 2014 and 2015.

Year	Place	Situation	Gaps of trees (%)	Skid trail (%)	Secondary roads (%)	Primary roads (%)	Log landings (%)
2014	APU1	After logging	6.69	1.28	0.59	0.23	0.29
	APU2	After logging	4.51	3.75	0.88	0.19	0.53
	APU3	After logging	4.69	5.77	1,10	–	0.76
	APU 4	After logging	5.73	6.54	2.29	0.16	1.01
	APU 5	After logging			2.34	1.41	0.30
2015	APU 5	Before logging	6.65	6.92	2.23	0.78	0.52

non-significant coefficients ($p > 0.05$), implying the absence of an association between the parameters and the factors (Table 6). We must clarify that this correlation was performed with a small amount of data, considering the mean values for each APU, and we suggest that a more robust analysis should be carried out to disprove the existence of such correlation.

Considering the distribution of shape (γ) and scale (β) parameters of the Weibull function for the vertical canopy profile for trees with a total height greater than or equal to 15 m, the highest shape parameter values were observed in APUs 3 and 4 ($\gamma = 11.95$ and 11.64, respectively), while the lowest values occurred in APUs 2 and 4 ($\gamma = 2.23$ and 2.46, respectively). The largest variations were detected in the shape parameter (CV = 21.14% and 19.57%, respectively) in APUs 4 and 5 in 2014. The highest scale parameter values at the canopy level were observed in APUs 2 in 2014 and 5 in 2015 ($\beta = 42.28$ and 40.42, respectively), and the lowest in APUs 1 and 4 ($\beta = 17.87$ and 18.23). The coefficient of variation ranged from a maximum of 10.03% to a minimum of 9.83%. The correlations between the shape (γ) and scale (β) parameters at the canopy level and the logging factors (years since logging, related to the Gini coefficient and λ, and sampled area in hectares), as well as at the understory level, were not significant (Table 7).

Table 6
Correlation coefficients between the shape (γ) and scale (β) parameters of the understory and the logging parameters of the APUs studied in FMU III of the Jamari National Forest in the years 2014 and 2015.

Factors	Parameters			
	γ		β	
	r	P	r	P
Time (years)	−0.64	0.25	−0.43	0.47
Intensity (m^3 ha^{-1})	0.30	0.63	−0.31	0.61
Sampled area (ha)	−0.098	0.87	−0.13	0.83
Impact (ha)	0.47	0.42	0.27	0.66

Table 7
Correlation coefficients between the shape (γ) and scale (β) parameters of the canopy and the logging and canopy parameters of the APUs studied in FMU III of the Jamari National Forest in the years 2014 and 2015.

Factors	Parameters			
	γ		β	
	r	P	r	P
Time (years)	−0.02	0.98	0.05	0.93
Intensity (m^3 ha^{-1})	0.41	0.50	−0.18	0.78
Sampled area (ha)	−0.32	0.60	−0.21	0.73
GC	0.15	0.81	−0.27	0.66
λ	0.21	0.73	−0.20	0.75

3.5. *Indicator: affected areas in permanent preservation areas (PPA) and restricted areas*

Overall, the vectorization method of permanent preservation areas (PPAs) using LiDAR showed high percentage accuracy compared to field measurements, with a precision of 87.26%. The percentages of total PPA areas with evidence of logging impact were low in the intersection between PPAs and restricted areas affected by selective logging. We found values ranging from 0.06% to 1.15% in Approach 1, where field measurements were made and used for validation, and from 0.03 to 0.37% in Approach 2 that was performed using only LiDAR information. The total percentage of restricted areas with traces of impacts was only 0.52% (Table 8).

4. Discussion

The average harvest intensity in the areas was 13.6 m^3/ha. Although these values are below the limits allowed by the Brazilian legislation, they fall within the range observed for the Southwest Amazon region of Brazil (11.8 m^3/ha to 14.8 m^3/ha) as reported by Carvalho et al. (2017) and Locks and Matricardi (2019). It's essential to tailor that the

Table 8
Estimates of Permanent Preservation Areas (PPAs) and Restricted Areas with traces of selective cutting in the APUs studied in FMU III of the Jamari National Forest in the years 2014 and 2015.

Place	Approach 1 PPA area (%)	Approach 2 PPA area (%)	Restricted area (%)
APU 1	0.06	0.28	0.16
APU 2	0.12	0.03	0.11
APU 3	1.15	0.21	0.00
APU 4	0.28	0.37	0.21
APU 5 2014	0.00	0.00	0.00
APU 52015	0.10	0.07	0.04
Total %	1.71	0.96	0.52

harvesting intensity should be adapted to the specific characteristics of the managed forest (Dionisio et al., 2018; Sist et al., 2021).

4.1. Removal detection of dominant and co-dominant tree crowns

The results of our research revealed a reduction of 3.95% in the area covered by the tallest canopy trees in UPA 5, compared to the data before the logging activity in 2014 (Fig. 3). This finding is consistent with the study conducted by Andersen et al. (2014), which investigated the impact of selective logging in areas of the Acre State with similar logging intensity to our study area. They observed a reduction of 4.1% in the area covered by the tallest canopies. In contrast, d'Oliveira et al. (2021), also in the Western Amazon, observed a canopy coverage loss (above 30 m) of 22.7% in areas with logging intensity of approximately 10 to 15 m^3/ha. The reduction in the area occupied by dominant and co-dominant canopies is directly linked to selective logging, as these classes encompass the main target trees for Sustainable Forest Management (SFM) (Figueiredo et al., 2007). This result emphasizes the importance of implementing sustainable forest management practices that consider the selective removal of these key trees to avoid significant impacts on the structure and composition of the forest (Poudyal et al., 2018).

The findings of Locks and Matricardi (2019), who assessed the effects of logging on canopy coverage using LiDAR data before and after forest management activities, are consistent with our results. They observed a reduction in canopy coverage of up to 12.8%, indicating Reduced Impact Logging (RIL) practices. Our results corroborate these findings, as the 3.95% reduction in canopy coverage following selective logging is below the value reported by these authors.It is important to note that the logging intensity is directly related to the impact generated in the managed area, with lower intensities favoring less impact. However, the minimal change in canopy coverage indicates that selective logging followed an appropriate cutting intensity for local environmental conditions (Gaui et al., 2019).

In summary, the results of our research highlight the relationship between changes in canopy coverage and the intensity of selective logging. Furthermore, our methodology was effective in detecting this impact. However, while the studied areas met the criteria established by the methodology due to their characteristics, it is important to investigate higher logging intensities and their behavior concerning forest typology and the employed logging structure (Bousfield et al., 2023).

4.2. Indicator: gap detection in the forest canopy

Canopy closure was noticeable in areas with a longer history of logging (Fig. 4). Several studies conducted in the Amazon region have observed that canopy closure begins to occur in the forest within three to five years after logging (Carvalho et al., 2017; Dionisio et al., 2018; Pinagé et al., 2019; Silva et al., 1995; Vatraz et al., 2016). This canopy closure dynamic reflects the forest's ability to regenerate after disturbance, seeking to restore its structure and function (Gorgens et al., 2023). At this stage, differences between logged and unlogged areas become almost imperceptible using remote sensing techniques (Silva et al., 1995). These findings underscore the importance of considering time as a crucial component in assessing the effects of selective logging on forest canopy (Pinagé et al., 2019).

A predominance of small gaps was identified in analyzing the size of gaps in the forest (Fig. 5), which aligns with a study by Kellner and Asner (2009), who found that areas dominated by small gaps tend to recover more rapidly. These gaps are naturally filled through advanced natural regeneration and horizontal growth of vegetation around the gaps (Zhang et al., 2023). This is supported by the λ values observed in the area with the longest history of logging (APU 1), which are higher than those in APUs with more recent logging activities. It's important to note that the λ values in all analyzed locations fall within the range of 1.0 to 3.0, which are values observed in other studies in tropical forests (Asner et al., 2013; Fisher et al., 2008; Goodbody et al., 2020; Goulamoussène et al., 2017; Kellner and Asner, 2009).

A reduction in λ values was observed in APUs 4 in 2014 and 5 in 2015 due to an increase in the occurrence of larger gaps shortly after logging (Table 4). As noted in other studies (Kent et al., 2015; Wedeux and Coomes, 2015). This suggests that the number of gaps in the forest canopy was influenced by the time elapsed since tree cutting. Additionally, APU 5 had a higher λ value before logging compared to APU 1, which was logged three years before the LiDAR survey. This could be explained by the presence of main and secondary roads and log landings already built for the upcoming logging activity. This activity resulted in larger gaps opening in the area, as the λ coefficient has been associated with the type and degree of disturbance in forest areas (Yamamoto, 1992), presenting lower values in areas with less intense disturbance and a lower proportion of large gaps (Asner et al., 2013; Reis et al., 2022).

The Gini coefficient values obtained in the studied APUs indicate that the timber forest management activities had a moderate impact on the forest canopy, as all values remained below 0.5 (Silva et al., 2019; Valbuena et al., 2016). These results are highly desirable for sustainable timber production in tropical forests, as they suggest an appropriate balance between logging intensity and remaining tree stocks (Condé et al., 2022). This indicates that the forest management techniques used in these areas were able to minimize negative impacts on the forest structure and maintain a significant proportion of remaining trees (Gaui et al., 2019).

The percentages of areas occupied by gaps in the studied APUs (Table 4) were lower compared to other studies conducted in locations with and without a history of logging in the western and eastern regions of the Brazilian Amazon. For example, the Fazenda Cauaxi in Pará, reported by da Costa et al. (2020), and the Ducke Forest Reserve in Amazonas and the Tapajós National Forest in Pará, reported by Hunter et al. (2015), showed higher proportions of the area occupied by gaps.

These differences can be attributed to the different logging intensities practiced in the explored areas, which directly influence the proportion of areas occupied by gaps. The average logging intensity in Cauaxi was 17.60 m^3/ha, with some locations reaching maximum intensities exceeding 27 m^3/ha, which is higher than the practices adopted in the JNF.

The low-intensity logging, as practiced in the studied areas, along with other low-impact management practices, has the potential to reduce impacts on the remaining forest by up to 20% to 50% compared to conventional logging (Putz et al., 2008; Sist et al., 2021; Zimmerman and Kormos, 2012). This approach can be effective in promoting the recovery of most forest attributes after forest management (de Avila et al., 2017).

The Brazilian Forest Service (SFB) has established a limit of 10% in its concession guidelines of the total area managed for gap opening. By observing the data in the studied areas, it is evident that these established limits were widely respected (3.08% in APU 4 in 2014 and 3.44% in APU 5 in 2015, areas surveyed at the end of logging). Therefore, accurate quantification of the impact on the remaining vegetation using LiDAR data is feasible and plays an important role in monitoring logging activities in the Brazilian Amazon (d'Oliveira et al., 2021), as it allows verifying if the execution of the Forest Management Plan followed the regulations established by law (Locks and Matricardi, 2019).

4.3. Indicator: Impacts of Reduced-Impact Logging (RIL) on the forest understory

The APUs explored up to one year after the RIL (APUs 3, 4, and 5) (Table 5) showed similar impacts to the percentages observed by d'Oliveira et al. (2012), which were 15.4%. However, the percentages of directly affected areas by logging up to two years after the end of forest management activities (9.08% to 9.86%) were higher than reported in other studies conducted in tropical forests under reduced-impact logging regimes. For example, studies by Arevalo et al. (2016) in Belize, Carvalho et al. (2017) in the Antimary State Forest in Western Amazon, and Pinagé et al. (2019) in Cauaxi in Eastern Amazon, reported affected area percentages not exceeding 8% of the total area. This difference can be attributed to factors such as the adopted management practices and the specific characteristics of the forest in the study areas.

Enhanced forest management practices, exemplified by approaches like Reduced Impact Logging for Climate Change Mitigation (RIL-C), which advocate for operational adjustments including the reduction of wood waste, utilization of narrower transportation roads, and the utilization of lower-impact skidding equipment, hold the potential to decrease carbon emissions by up to 44%, all while maintaining timber production (Ellis et al., 2019).

The study by Arevalo et al. (2016) used field measurements to assess impacts, while Pinagé et al. (2019) employed LiDAR data, but with a height threshold of 0.5 m. Both studies considered the percentage of area occupied by infrastructure to calculate impacts on the understory. Carvalho et al. (2017) also adopted buffer zones but used longer time intervals between logging and aerial surveys (4 and 8 years). They additionally employed lower logging intensities (10.6 to 13.3 m^3/ha) and did not consider the presence of primary roads. In addition to methodological differences such as choice of measurement techniques, the time intervals analyzed, logging intensities, and inclusion of impacts caused by primary roads may explain variations in the percentages of affected areas found in the study area and the mentioned works.

>1.23 million hectares of FLONAs were under the forest concession regime in 2022, and >4.04 million hectares are eligible for management in the 2023 survey of the Forest Outgrant Plan (SFB,2023). In this context, RIL is a combination of adopting logging techniques, qualified labor, and field execution monitoring.

Logging planning occurs at the beginning of this production chain, which differs from company to company, and the equalization of logging techniques should be prioritized from a management perspective of this scale. In studying optimized planning of the allocation of logging infrastructure in the Amazon, da Silva et al. (2020) and Aguiar et al. (2020) observed a reduction in logging costs by reducing skidding trails, forest roads, and log landings by applying operational research techniques. This cost reduction implies a reduction in environmental impacts through reduced allocated infrastructure and/or better allocation efficiency considering scenarios that had the same generated impact, but with a lower estimated logging cost.

In this context, monitoring the impacts on the understory using the proposed methodology has the advantage of quantifying the impact of logging, monitoring the execution of the proposed planning, equalizing logging and monitoring techniques among companies, providing data for optimized planning considering various forest typologies and peculiarities of the Amazon, and defining consistent logging parameters for monitoring logging in concessionaire companies (Aguiar et al., 2023; Tritsch et al., 2016).

The gaps resulting from tree cutting were responsible for the highest disturbance levels in the understory up to two years after logging, accounting for over 40% of the assessed impacts. Furthermore, it was observed that opening skidding trails in locations with a shorter interval between logging and aerial survey caused a higher percentage of impacts.

These results corroborate studies conducted in the Central and Eastern Amazon by Lima et al. (2019) and Condé et al. (2022), which used passive sensors and field measurements. These studies identified the gaps resulting from tree cutting as the main cause of impact in the managed areas. However, some studies conducted in tropical forests in Central America and Asia by Arevalo et al. (2016), Melendy et al. (2018), and Pearson et al. (2018) highlighted that skidding trails represent the most significant disturbances in the total impacted area. This difference may be explained by the fact that skidding trails, being temporary structures, may be less noticeable using remote sensing data two to three years after area logging (Carvalho et al., 2017; Ellis et al., 2016), as evidenced in APUs 1 and 2 in this study.

However, it is essential to pay attention to the planning of these logging areas because empirical planning may unnecessarily increase the number of forest roads, log landings, and skid trails (Aguiar et al., 2020; da Silva et al., 2020).

The percentage of impact in APUs 4 and 5 resulting from opening skidding trails, log landings, and forest roads (10% and 10.45%, respectively) exceeded the 8% limit established by the SFB in forest concession notices by about 2% (SFB, 2008). However, a clear recovery of vegetation was observed in areas occupied by skidding trails, forest roads, and log landings in APU 1 evaluated three years after logging compared to other locations. This resulted in impacts from these infrastructures representing only 2.39% in APU 1. These results confirm that damage to the understory is more evident in areas with recent RIL and gradually diminishes over time (Pinagé et al., 2019).

The area impacted by gaps resulting from tree cutting did not exceed the 10% limit established by the Brazilian Forest Service (SFB) in any of the studied areas. This reinforces the importance of using LiDAR for this purpose since both the infrastructure opened for logging and the gaps formed by tree removal could be visually identified in LiDAR data, providing a method to detect fine-scale disturbances in the understory (d'Oliveira et al., 2012). For example, the impacts of logging can be greatly reduced by adopting reduced impact logging (RIL), which has a set of principles designed to maximize efficiency while mitigating undesirable outcomes (Putz et al., 2008; Putz et al., 2012; Santos de Lima et al., 2018).

It is crucial to assess infrastructure within a maximum of one year after the end of management activities to accurately account for RIL impacts. All analyzed parameters were influenced by the time interval, and only the damage caused to the canopy by tree harvesting remained visually perceptible up to three years after the area was logged (d'Oliveira et al., 2021; Ellis et al., 2016; Tavankar et al., 2022).

4.4. Indicator: changes in the vertical canopy profile

Height values equal to or <15 m in the vertical canopy profile result in a decrease in γ values and also greater variation in the γ parameter. The lack of significant correlations between the mean Weibull distribution parameters and factors related to selective logging (Table 6) reinforces the low impact resulting from the applied logging. In the study by Reis (2018) in Cauaxi in Eastern Amazon in which higher logging intensities were applied, both the shape parameter (γ) and the scale parameter (β) for the understory reflected the impacts of logging.

Regarding the distribution of the Weibull function parameters for the upper forest stratum (Table 7), the highest γ values were observed in APUs with lower logging intensities (10 and 13 m^3/ha). The logging intensity in all APUs was generally low (10–16 m^3/ha), indicating a logging intensity that favors forest recovery, as also observed in other parts of the Amazon by Carvalho et al. (2017), Locks and Matricardi (2019), Silva et al. (2019), and Pinagé et al. (2019). The correlations between the mean γ and β parameters of the canopy and factors related to logging showed no significant difference between the areas. These findings are in line with previous studies in the Amazon region, which also showed the positive influence of lower logging intensities on forest recovery (Piponiot et al., 2019) and canopy structure (d'Oliveira et al., 2021).

Therefore, it is important to consider logging intensity as a crucial factor in the management and monitoring of logging activities in the Amazon (d'Oliveira et al., 2021; Hethcoat et al., 2020; Lima et al., 2020; Piponiot et al., 2019). Furthermore, the use of high-resolution LiDAR models, such as the 1-m DTM used in our study, is essential to avoid potential errors in estimating the vertical forest structure parameters (Yu and Jung, 2023), especially in areas where the vertical forest structure is highly complex and poorly understood (Burns et al., 2020; Gonçalves et al., 2023).

4.5. Indicators: affected areas in permanent preservation areas (PPA) and restricted areas

The overlap results of areas impacted by selective logging with PPAs and restricted areas showed few traces of impacts in these areas, with a percentage below 2% for all APUs (Table 8). The Permanent Preservation Areas (PPAs) are protected areas in Brazil, and their correct quantification is decisive for environmental conservation (Pacheco et al., 2018). Visual analysis of inventories of trees conducted before logging ($>$ 40 cm DBH) and trees extracted for logging purposes ($\geq$ 50 cm) confirmed that trees present in these environments were not impacted by RIL. Therefore, the survey of PPAs and restricted areas with ALS technology has a high potential for implementation in areas under forest management in the Amazon due to the high accuracy in estimates and the fact that it can be conducted in large areas (Papa et al., 2020; d'Oliveira et al., 2021).

We confirm that adopting the selective system in forest logging aided PPAs and restricted areas in not being affected by forest management activities. The overlap of areas impacted by selective logging with PPAs and restricted areas confirmed the reduction of logging impacts provided by adopting Reduced Impact Logging (RIL), also resulting in greater conservation of protected areas (DeArmond et al., 2023), since high-resolution ALS data models (1 m), such as those presented in this work, provide more detailed information on hydrography, terrain, and existing infrastructure than SRTM data with coarser models and resolutions of 90 or 30 m (Poppenga et al., 2013). The use of remote sensing images has been a tool of paramount importance for mapping large areas (Ferreira et al., 2021), becoming a viable alternative to streamline monitoring and enforcement of relevant legislation (Eugenio et al., 2017).

Normative Instruction No. 5 (BRAZIL, 2006), which deals with technical procedures for the preparation, presentation, execution, and technical evaluation of Sustainable Forest Management Plans (PMFS) in pristine forests and their successional forms, regulated zoning of Permanent Preservation Areas (PPAs) on properties as mandatory in areas under RIL in the Amazon. Thus, studies on the delimitation of PPAs in managed areas have been limited to this legal requirement in management plans. More recent studies indicate that there has been a shortage of studies in the last decade on the impacts of RIL in PPAs throughout the Brazilian Amazon (DeArmond et al., 2023).

In this context, our approach to surveying areas affected by Reduced Impact Logging (RIL) in Permanent Preservation Areas (PPAs) and restricted areas, along with the arbitrary 2% index, represents a breakthrough for forest management. We suggest adopting this approach in areas with similar environmental characteristics and adapting it to other forest typologies. This specific approach allows considering the particularities of each region, taking into account environmental characteristics and conservation needs LiDAR data can support RIL planning and execution with much more information than just field data collection (d'Oliveira et al., 2021; Reis et al., 2021), contributing to more appropriate and sustainable management of forest resources in the Amazon region.

5. Conclusion

The results demonstrated the adequacy of the forest management practiced in the areas under concession for exploration in the Jamari National Forest to Brazilian forest legislation. We confirmed that logging intensities compatible with the forest structure and combined with the use of geotechnologies in planning logging activities minimized the effects of forest exploitation for our study area. It was also evident that higher logging intensities could jeopardize the sustainability of logging activities, causing a high level of impact on the remaining forest.

We recommend adopting the proposed indicators as a method for monitoring tropical forest management in areas with available LiDAR data. However, it is essential to emphasize the importance of further studies on the impacts of Reduced Impact Logging (RIL) in global tropical forests considering different environments, various logging structures, and forest management practices.

CRediT authorship contribution statement

Quétila Souza Barros: Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization. **Marcus Vinicio Neves d' Oliveira:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Evandro Ferreira da Silva:** Writing – original draft, Validation, Methodology, Conceptualization. **Eric Bastos Görgens:** Writing – original draft, Validation, Methodology, Conceptualization. **Adriano Ribeiro de Mendonça:** Writing – original draft, Validation, Methodology, Conceptualization. **Gilson Fernandes da Silva:** Writing – review & editing, Visualization. **Cristiano Rodrigues Reis:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Leilson Ferreira Gomes:** Writing – review & editing, Writing – original draft, Methodology. **Anelena Lima de Carvalho:** Writing – original draft, Methodology, Conceptualization. **Erica Karolina Barros de Oliveira:** Writing – review & editing, Visualization. **Nívea Maria Mafra Rodrigues:** Writing – review & editing, Visualization. **Quinny Soares Rocha:** Writing – review & editing, Visualization.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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