JAMARI NATIONAL FOREST ABOVEGROUND BIOMASS DYNAMICS MONITORING THROUGH REPEATED LIDAR SURVEYS

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ABSTRACT

The study was carried out in the Flona Jamari, to assess the effect of logging in the annual production units (UPA), through repeated LiDAR flights to answer how logging impacted the forest and how forest recovered in the first twelve ten years after logging. Aboveground (AGB) was estimate through a LiDAR regression model adjusted with the permanent sample plots established in the UPA. The main results were: i. the LiDAR AGB regression model produced to the study area presented a proportion of explained variance (R^2_{adj}=0.7) and low RMSE (40.6); ii. Logging produced a significant reduction of mean AGB in the UPA from 214.9 ± 56.8 Mg. ha^{-1} to 192.4 ± 51. 0 Mg. ha^{-1} (22.5 Mg. ha^{-1}); iii. five years after logging AGB was still significantly below the observed in the UPA before logging (209.2 ± 56.8 Mg. ha^{-1}), but significantly higher than the observed one year after logging.

Key words — Amazon, forest management, permanent sample plots, tropical forest, logging.

1. INTRODUCTION

Long-term studies on forest growth dynamics thought the use of permanent sample plots (PSP), are recognized as the best way to understand forest responses to natural and anthropogenic disturbances [1]. In the past two decades, the use of Light Detection and Range (LiDAR) data has becoming consolidated as a tool to upscale forest structural parameters estimates from plot (PSP) to landscape level [2]. Scaling estimates through models provides a census of the covered forest area eliminating the chance of the PSP fail to accurately capture the variation of forest structure parameters throughout the landscape due to low sampling intensity or distribution [3].

Tropical forest management (TFM), through the use of reduced-impact logging (RIL) practices, produces relatively low impact in the forest structure [4] and TFM is generally accepted as an activity that allows economic development, biodiversity conservation and environmental services [5]. In the Brazilian Amazon the Brazilian Forest Service (SFB) initiated in 2007 a forest management program to be implemented in National Forests (Flona) through the establishment of forest concessions contracts with private forest companies. The program is monitored by SFB and, since it started, 1.174.324,44 ha in eigth Flona have been managed in concession regime.

The study was carried out in in the Flona Jamari in the southwestern Brazilian Amazon, the oldest Flona concession in the Brazilian Amazon. Since the beginning, the forest monitoring of the annual production units (UPA), has been done through the combination of PSP and LiDAR data. We study the effect of logging in the UPA of the forest from 2011 to 2021. Our objective was to answer three research questions: i. what was the mean AGB before logging; ii. what was the mean AGB loss after logging and iii. what was the mean AGB recover in the first ten years after logging.

2. MATERIAL AND METHODS

2.1. Site description

The Jamari Nacional Forest (Flona) is located in the Itapuã do Oeste municipality, Rondônia State, southwestern Amazon. The Flona Jamari has 223.000 ha and has been designated to be managed in a concession regime since 2008. The study areas are the UPA (annual production units of the UMF 1 (Forest Management Unit) of the Flona Jamari [6]. The UMF 1 has 17,176 ha and was divided into 30 UPA (Figure 1). The forest management system applied to the area

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follows RIL guidelines and logging has been carried out since 2010, with a logging intensity of 13.8 m^3. ha^{-1}. The Flona Jamari is administered by the Brazilian Forest Service (SFB) and has been monitored through permanent sample plots (PSP) and LiDAR flights. The predominant climate according to Köppen classification is Aw, with an average annual temperature of 24ºC and rainfall of 2000 mm. $year^{-1}$ [7]. The relief is flat and slightly undulating. The vegetation is predominantly covered by open ombrophilous forest, with transitions to dense forest forming a canopy with approximately 40 m height [8].

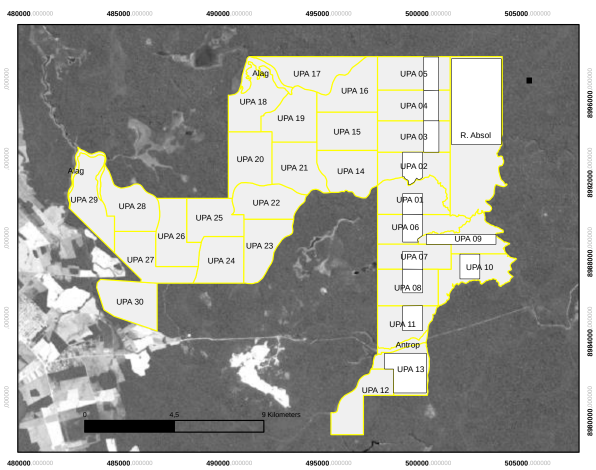


Figure 1. Jamari National forest management unit 1 (UMF) annual production units (yellow polygons). White polygons are areas covered by LiDAR flights between 2011 and 2024.

2.2. Permanent sample plots (PSP)

The permanent sample plots (PSP) were systematically allocated within the UPA prior to logging and remeasured one and five years after (Figure 1), following the Redeflor protocol [9]. All trees with DBH ≥ 10 cm were measured and targeted. Above-ground dry biomass (AGB – Mg. ha^{-1}, DBH ≥ 10cm) was calculated, for individual trees, by the formula AGB = $(DBH^{2.671*0,064})/1000$ [10]. To this study 43 ¼ ha (50x50) PSP were precisely georeferenced through a GNSS, Sanding brand, model Aqua T5. For each vertex the average collection time was 10 minutes, with horizontal accuracy ≤ 1 meter.

2.3. LiDAR data

The Lidar flights were carried out between 2011 and 2024, with Cessna 206 aircraft carrying a Optech-ALTM 3100 LiDAR sensor, flying 850 m above sea level, 500-600 km. h^{-1}, side overlap of 70%. Producing a point cloud with a points density around 10. m^2, with horizontal and vertical precision of ± 0.15 cm and ± 0.20 cm respectively. The flights were georeferenced RTK base station. LiDAR flights covered areas are in figure 1.

2.3.1. LiDAR data processing and aboveground biomass modeling

Processing and regression modeling of aboveground biomass (AGB) was performed using the FUSION package [11], using the same methodology described by [12].

2.4. Statistical analyses

The AGB value for the fixed effect forest condition (unlogged, one year and 5 years after logging and forest absolute reserve) and random effect annual production unit (UPA) were estimated through the RSPL (Residual/Normal Pseudo Maximum Likelihood) procedure. The PROC GLIMMIX procedure (SAS 9.4) was used. Means for fixed effects were compared using the LSMEANS procedure, adjusted by Tukey (SAS 9.4). The mixed model estimated by GLiMMIX is described below:

$$E[Y/\gamma]=g^{(-1)}(X\beta+Z\gamma)$$

Where: $g^{(-1)}$ = inverse of the differentiated monotonic link function; X = incidence matrix for the fixed effect; β = fixed effect; Z = incidence matrix for the random effects within the UPA and y = vector of the random effects of repetitions.

3. RESULTS

3.1. LiDAR data regression modeling

The mean elevation above ground of all lidar returns (AGB = 19.288 * Elev_mean – 186.71, N=57, R^2_{adj}=0.70, RMSE 40.6, F=129.9 p<0.0001) provided robust univariate regression model, with the best overall fit based on proportion of explained variance and root-mean-square error (Figure 2).

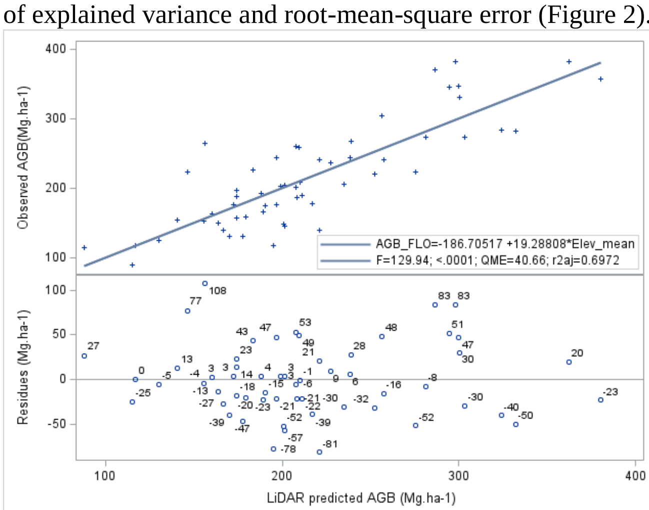


Figure 2. Predicted versus observed ground plot values for above ground biomass for model that use Elev_mean lidar explanatory variables.

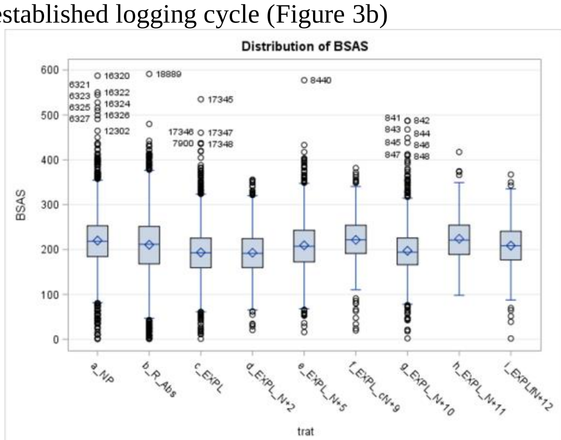
3.2. LiDAR AGB estimates

LiDAR model AGB estimates were 219.9 ± Mg. ha^{-1}, 193.4 ± 51.0 Mg. ha^{-1} and 209.4 ± 56.8 Mg. ha^{-1} respectively to the forest before, one and five years after logging (Figure 3). AGB predict to two years after logging (192.7) was very close to the prediction to one year after logging. Logging produced a significant reduction of mean AGB in the UPA (22.5 Mg. ha^{-1}). Five years after logging AGB was still significantly below the observed in the UPA before logging, but similar to the absolute forest reserve (210.3 ± 71.8 Mg. ha^{-1}) and significantly higher than the observed one and two years after logging. The AGB estimate from ten to twelve years varied from 197.1 to 223.9 Mg. ha^{-1}. This variation can be attributed to the differences observed in the original AGB (e.g. UPA 5 202.8 Mg. ha^{-1} before logging). The relatively low AGB of the absolute forest reserve can be explained by the fact that it is crossed by a stream where flooded areas of considerable size can be observed (Figure 3a).

3.3. Forest AGB increment dynamics prediction model

This model was adjusted from the intersection of eight repeated LiDAR flights over UPA1 from 2011 to 2022. The model presented low R^2_{adj} and relatively low RMSE of 59 Mg. ha^{-1}. The low R^2_{adj} is due to the high number of repetitions along time, but the adjusted linear model is highly significant. The predicted forests increment (≈1.9 Mg. ha^{-1}) suggests that AGB will be fully recovered before the end of the established logging cycle (Figure 3b)

A)



B)

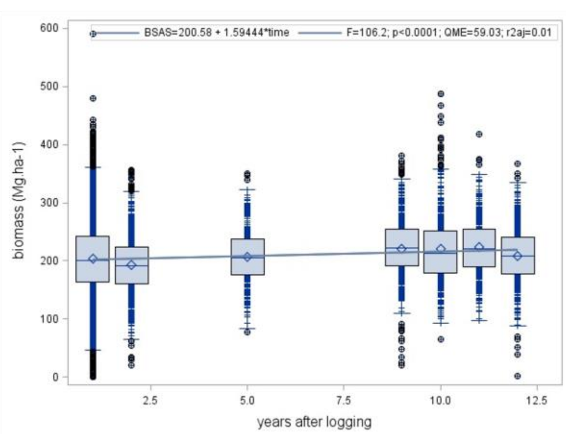


Figure 3. A) Boxplots of the LiDAR regression model AGB prediction for the Jamari UPA before (NP), one (EXPL), two (EXPL_N+2), five (EXPL_N+5), nine (EXPL_N+9), ten (EXPL_N+10), eleven(EXPL_N+11) and (EXPL_N+11) years after logging, and the absolute forest reserve (R_Abs), means followed by different letters are significantly different (Tukey test, p<0,05) and B) the linear tendency to AGB increment predicted for the forest in the first 12 years after logging.

4. DISCUSSION

The main concerns about tropical forest management are the forest AGB and commercial timber recover along the logging cycles. Usually, low intensity logging leads to a fast AGB recovery [13] but the commercial timber logged volume demands longer cycles [14]. In this study we focused in the post logging AGB recover through the combination of LiDAR and PSP data. Repeated LiDAR measures have been used to spatially monitoring AGB and carbon changes produced by logging or natural causes [15, 16], overcoming the limitations of ground plots on properly capture the variation of forest structure parameters throughout the landscape [3]. Our AGB stock prediction was produced through an adjusted univariate LiDAR regression model, which used mean height as independent variable. Mean height is recognized as been highly correlated with AGB and carbon density and dynamics [17] and our model presented a R^2_{adj} and RMSE similar to other reported LiDAR models developed to tropical forests [17, 18, 19]. As expected [20], the results indicate that logging operations significantly reduced AGB. However, five years after, although still below the original forest, AGB was already significantly higher than one year after logging and equal to the absolute forest reserve (AR). The studied forest although structurally similar presented pre-logging differences in AGB stocks of the UPA, which also were submitted to different silvicultural interventions (e.g. differences in logging intensity and damage to residual trees). The predicted UPA AGB annual increment, considering the estimates to one to 12 years after logging (1.9 Mg. ha^{-1}. yr^{-1}.), was similar to the means obtained to other forests in the region [21], and was a consequence of the low logging intensities (≈ 14 m^3. ha^{-1}) applied to the UPA and the observance of RIL guidelines during the logging operations [6]. The results allowed to estimate both AGB loss by logging and gain by forest growth and confirmed the expected fast AGB recover in the first ten years after logging.

5. CONCLUSIONS

Repeat LiDAR surveys are a powerful tool to accurately quantify biomass dynamics in tropical forests. The methodology we used was efficient to identify AGB gain, loose and increment in the logged UPA of Flona Jamari and can be replicate to all Brazilian National forest's concessions administered by the SFB which have similar LiDAR cover and PSP data.

6. REFERENCES

[1] K. J. Anderson-Teixeira et al. Carbon dynamics of mature and regrowth tropical forests derived from a pantropical database (TropForC-db). *Global Change Biology*, v. 22: pp. 1690-1709, 2016. https://doi.org/10.1111/gcb.13226

[2] M. Réjou-Méchain et al. Using repeated small-footprint LiDAR acquisitions to infer spatial and temporal variations of a high-biomass Neotropical forest. *Remote Sensing of Environment*, v. 169: pp. 93-101, 2015. https://doi.org/10.1016/j.rse.2015.08.001

[3] F. D. B. Espírito-Santo et al. Size and frequency of natural forest disturbances and the Amazon forest carbon balance. *Nature Communications*, v. 5: pp. 1-6, 2014.

[4] F. E. Putz et al. Intact forest in selective logging landscapes in the tropics. *Frontiers in Forests and Global Change*, v. 2: pp. 30, 2019. https://doi.org/10.3389/ffgc.2019.00030

[5] D. P. Edwards et al. Selective-logging and oil palm: multitaxon impacts, biodiversity indicators, and trade-offs for conservation planning. *Ecological Applications*, v. 24: pp. 2029-2049, 2014. https://doi.org/10.1890/14-0010.1

[6] SFB. *Sistema de Cadeia de Custódia – SCC*. Brasília, 2024.

[7] IBGE. *Manual técnico da vegetação brasileira*. Rio de Janeiro, 2012.

[8] IBAMA. *Plano de Manejo da Floresta Nacional do Jamari*. Brasília, 2005.

[9] J. N. M. Silva et al. *Diretrizes para instalação e medição de parcelas permanentes em florestas naturais da Amazônia brasileira.* Embrapa Amazônia Oriental, Belém, Pará, 2005.

[10] A. W. F. Melo et al. To improve estimates of neotropical forest carbon stocks more direct measurements are needed: An example from the Southwestern Amazon. *Forest Ecology and Management*, v. 570: pp. 122195, 2024. https://doi.org/10.1016/j.foreco.2024.122195

[11] R. J. McGaughey. FUSION/LDV: software for LIDAR data analysis and visualization. *United States Department of Agriculture, Forest Service*, Washington, DC, 2018. http://forsys.cfr.washington.edu/fusionlatest.html

[12] M. V. N. O. D'Oliveira et al. Estimating forest biomass and identifying low-intensity logging areas using airborne scanning LiDAR in Antimary State Forest, Acre State, Western Brazilian Amazon. *Remote Sensing of Environment*, v. 124: pp. 479-491, 2012. https://doi.org/10.1016/j.rse.2012.05.014

[13] E. Rutishauser et al. Rapid tree carbon stock recovery in managed Amazonian forests. *Current Biology*, v. 25: pp. R787-R788, 2015. https://doi.org/10.1016/j.cub.2015.07.034

[14] P. Sist et al. Sustainability of Brazilian forest concessions. *Forest Ecology and Management*, v. 496: pp. 119440, 2021. https://doi.org/10.1016/j.foreco.2021.119440

[15] B. W. Griscom et al. Reduced-impact logging in Borneo to minimize carbon emissions and impacts on sensitive habitats while maintaining timber yields. *Forest Ecology and Management*, v. 438: pp. 176-185, 2019. https://doi.org/10.1016/j.foreco.2019.02.025

[16] A. T. Hudak et al. Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys. *Remote Sensing of Environment*, v. 123: pp. 25-40, 2012. https://doi.org/10.1016/j.rse.2012.02.023

[17] Y. M. Moura et al. Carbon dynamics in a human-modified tropical forest: a case study using multi-temporal LiDAR data. *Remote Sensing*, v. 12: pp. 430, 2020. https://doi.org/10.3390/rs12030430

[18] M. H. Phua et al. Estimating logged-over lowland rainforest aboveground biomass in Sabah, Malaysia using airborne LiDAR data. *Terrestrial Atmospheric and oceanic Sciences*, v. 27: pp. 481-489, 2016. https://doi.org/10.3319/tao.2016.01.06.02

[19] F. E. Rex et al. Comparison of statistical modelling approaches for estimating tropical forest aboveground biomass stock and reporting their changes in low-intensity logging areas using multi-temporal LiDAR data. *Remote Sensing*, v. 12: pp. 1498, 2020. https://doi.org/10.3390/rs12091498

[20] E. R. Pinagé et al. Long-Term Impacts of Selective Logging on Amazon Forest Dynamics from Multi-Temporal Airborne LiDAR. *Remote Sensing*, v. 11: pp. 709, 2019. https://doi.org/10.3390/rs11060709

[21] C. Piponiot et al. Carbon recovery dynamics following disturbance by selective logging in Amazonian forests. *eLife*, v. 5: pp. e21394, 2016. https://doi.org/10.7554/eLife.21394