

QUANTIFYING CARBON LOSS AT FORESTS DEGRADED BY LOGGING WITH REPEATED AIRBORNE LIDAR DATA IN THE BRAZILIAN AMAZON

Ricardo Dalagnol^{1,2}, Daniel Braga^{3,4}, Celso Silva-Júnior^{1,2}, Fabien Wagner^{1,2}, Le Bienfaiteur Sagang^{1,2}, Samuel Favrichon², Jean Ometto⁴, Sassan Saatchi^{1,2}

¹ Institute of the Environment and Sustainability, University of California Los Angeles (UCLA), Los Angeles, CA, dalagnol@ucla.edu, celsohlsj@ucla.edu; fhwagner@ucla.edu; sagangb@ucla.edu; ² NASA-Jet Propulsion Laboratory, Pasadena, CA, samuel.favrichon@jpl.nasa.gov; sasan.s.saatchi@jpl.nasa.gov; ³ Federal University of Juiz de Fora, MG, daniel.braga@ich.ufff.br; ⁴ National Institute for Space Research (INPE), São José dos Campos, SP, jean.ometto@inpe.br

ABSTRACT

Forest degradation is a major issue and a key component of tropical forests and carbon emissions. In this study, we use repeated Airborne Laser Scanning (ALS) data to quantify carbon losses in degraded forests due to logging at the Mato Grosso state rainforests. We identified logged areas using Planet Norway's International Climate and Forests Initiative (NICFI) satellite imagery and estimated aboveground carbon density (ACD) and changes (Δ ACD) using canopy structure derived from ALS data acquired before and after the logging. Logging caused carbon losses between 16-35% of the original ACD, but also as high as 89% in heavily disturbed areas. Our findings bring estimates to limited sites, so we recommend caution on using them for estimates of carbon loss elsewhere. Spatialized and continuous estimates should be explored in future studies connecting ALS estimates with other optical and SAR remote sensing datasets.

Key words — forest degradation, LiDAR, carbon.

1. INTRODUCTION

Forest degradation is a major threat to tropical ecosystems, even surpassing deforestation in affected areas [1]. Moreover, it consists of a key factor in accurately estimating carbon emissions in tropical regions. To reach these estimates, two main components are required: (1) accurate maps of forest degradation dynamics and type of disturbance that caused the degradation; and (2) estimates of the associated carbon losses according to disturbance type. In the Brazilian Amazon, the main drivers of forest degradation are logging and fire. There are satellite-based forest disturbance and burned area data products that can help tackle degradation mapping, such as the Global Forest Change [2], Tropical Moist Forests [3], MCD64 [4], MapBiomass Fire [5]. However, the carbon estimates have only a handful of studies [6, 7], mainly due to the lack of high-resolution data to solve the problem.

The main goal of this study was to examine carbon losses due to logging at dense rainforests of the Brazilian state of Mato Grosso using repeated ALS data.

2. MATERIAL AND METHODS

We studied three sites of dense rainforest in the Brazilian state of Mato Grosso (Figure 1). Repeated small-footprint ALS data (point density 4 pts/m²) were acquired using a Trimble HARRIER 68i laser scanning system onboard an airplane before and after logging (Table 1), by the *Estimativa de Biomassa na Amazônia* (EBA) project from the National Institute for Space Research (INPE). The point cloud data were used to calculate canopy height models (CHM), considering the maximum observed height on 1-m grid cells using *LAStools* software [8] and procedures described in [9].

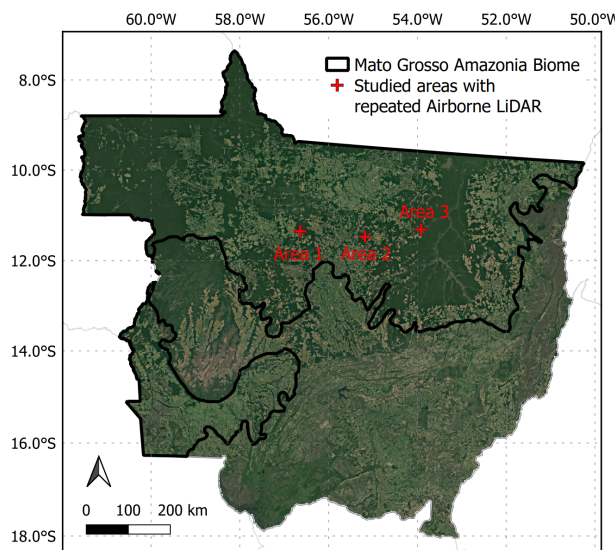


Figure 1. Study areas in Mato Grosso state. The background is a true-color composite from Google Satellite in QGIS software.

	Area 1	Area 2	Area 3
ALS Pre-logging	T-0103 21 May 2016	T-0301 29 Mar 2016	T-0303 30 Mar 2016
ALS Post-logging	T-0738 05 Nov 2017	T-0820 08 Nov 2017	T-0822 05 Nov 2017
Logging date	Jun-Nov 2017	Jun-Nov 2016	Jun-Nov 2016
Area (ha)	106.50	103.25	57.75

Table 1. ALS data acquisition and logging dates.

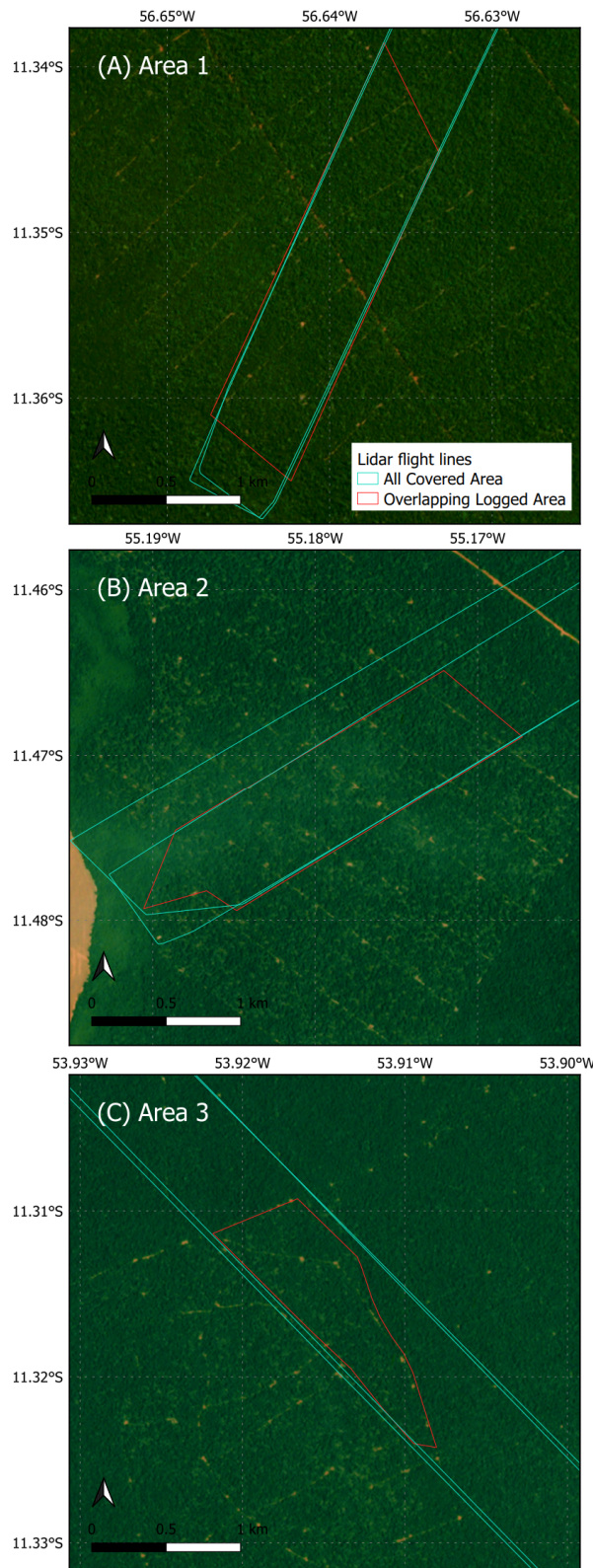


Figure 2. Airborne LiDAR flight lines overlaid on top of true-color composites from post-logging Planet NICFI imagery for the three studied areas (A-C). Panel A Planet NICFI background is from Jun-2017, B and C are from Jun-2016.

The date of logging and the areas involved were characterized from visual interpretation of high-resolution (4.77-m) Planet NICFI data [10] (Table 1). The spatial patterns related to logging activities namely logging trails, logging decks, and felling gaps (Figure 2) were digitalized within the ALS coverage. The remaining analysis considered only the areas identified as degraded by logging. We do not expect the time since disturbance to affect much the results, because post-logging ALS data were acquired at most 1-year after the activities. The legality of each logging activity was checked using the SIMEX dataset [11], indicating that Area 1 and 2 were legal, and Area 3 was illegal logging.

The CHM was aggregated from 1-m to 50-m resolution (CHM50) by taking the average height values. To avoid edge effects, we removed the borders of the flight line for the 50-m cells which were not fully covered by original 1-m cells. The equation from Longo et al. [6] (Eq. 1) was used to convert aboveground carbon density (ACD) from the CHM. This equation was developed using ALS data calibrated on inventory plots with an average size of 50 m distributed within undisturbed and degraded areas in the Amazon forests. The parameters in between parentheses were used to calculate the ACD uncertainty [6]. ACD was calculated in kg C/m² and then converted to Mg C/ha.

$$ACD = 0.054 (\pm 0.17) CHM50^{1.76(\pm 1.04)} \quad (1)$$

To estimate the ACD change (ΔACD), we calculated the difference between post-logging and pre-logging ACD. The uncertainty of ΔACD was calculated by the root sum of squares of the ACD from the two dates. We also calculated the relative ΔACD by the ratio of ΔACD and the ACD pre-logging, indicating the percentage of change in carbon caused by logging in relation to the ACD of the pre-disturbed forest.

3. RESULTS

The 1-m CHMs show the damage caused by the logging activities from the first to the second date, with tree felling, opening of logging decks and trails (Figure 3). Those were the same visual patterns observed in the Planet NICFI imagery (Figure 2). The tree height decreased by an average of 2 to 5 meters amongst the three sites (Table 2), that is, from 10 to 20% of the original average heights. Meanwhile, the ΔACD showed values ranging from -16.6 to -41.7 Mg C/ha (Table 2), that is, a relative ΔACD ranging from -16 to -33.6%. The ΔACD greatly varied in between sites, indicated by the high SD values. The uncertainty of ΔACD was higher than the mean ΔACD estimates. The ΔACD map at 50-m spatial resolution shows the diffuse patterns of logging over the forest canopy, where some areas were more heavily affected by the logging than others, reaching up to -89% of ΔACD .

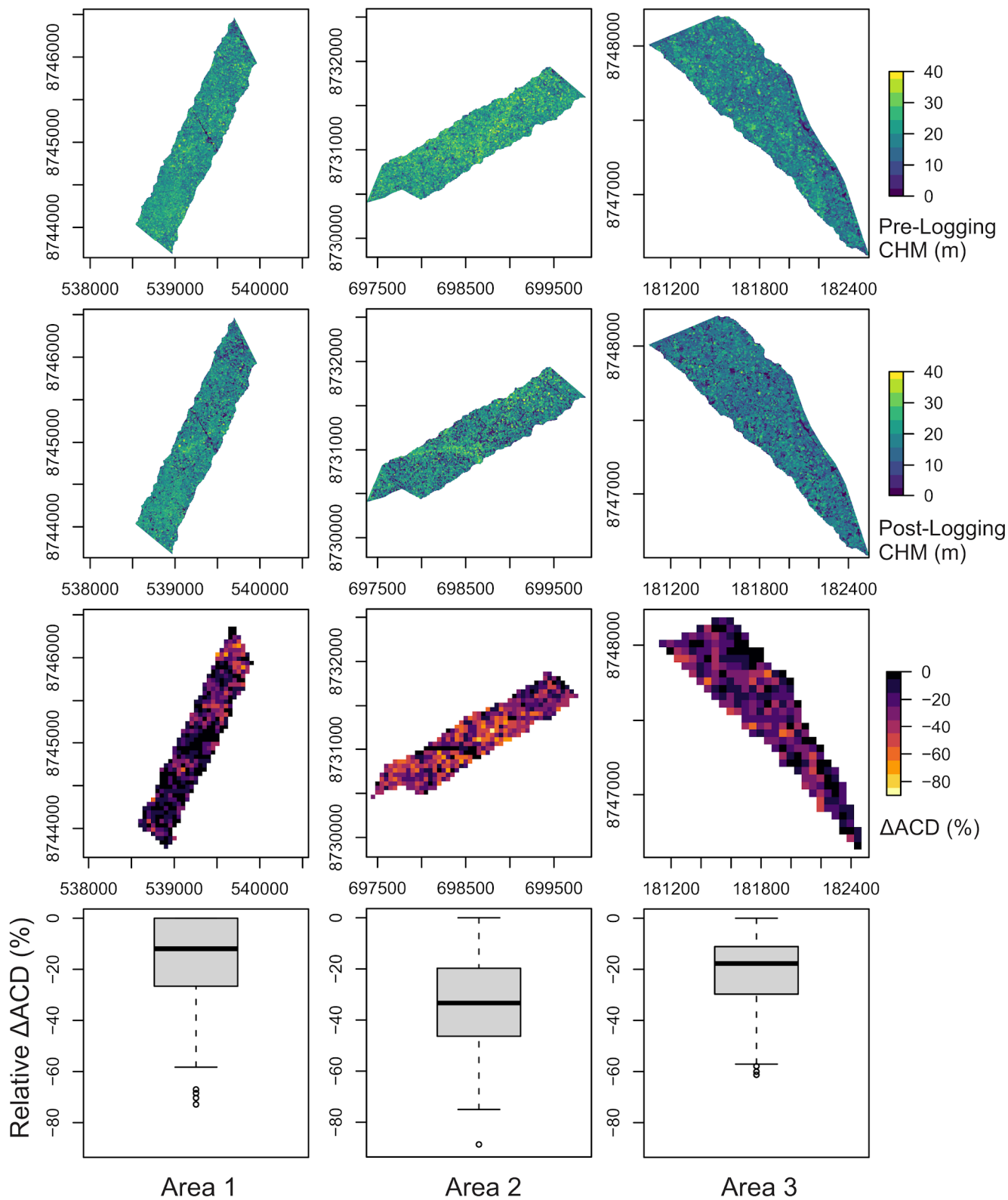


Figure 3. Forest canopy height model (CHM, 1x1m) pre-logging (first row), CHM post-logging (second row) and relative aboveground carbon density change (Δ ACD, 50-m grid, third and fourth rows).

Metrics	Area 1	Area 2	Area 3
CHM _{pre} (m)	20.3 ± 6.3	22.5 ± 6.6	17.1 ± 5.9
CHM _{post} (m)	18.3 ± 7.4	17.7 ± 8.9	14.9 ± 6.6
ACD _{pre} (Mg C/ha)	104.2 ± 18.7	124.1 ± 22.8	77.2 ± 13.6
ACD _{post} (Mg C/ha)	87.6 ± 15.7	82.4 ± 14.8	60.1 ± 10.6
Estimated ΔACD (Mg C/ha)	-16.6 ± 18.0	-41.7 ± 26.7	-17.1 ± 14.8
ΔACD (%)	-16.0	-33.6	-22.2
Uncertainty ΔACD (Mg C/ha)	24.4	55.56	43.45

Table 2. Landscape-average metrics of canopy height model (CHM) and aboveground carbon density (ACD) estimated by repeated airborne ALS (mean ± SD across the landscape).

4. DISCUSSION

Our findings indicate that logging caused significant carbon losses to the analyzed forests causing losses between 16 and 33.6% of the original ACD at the landscape-scale. These estimates are comparable to those from [6], which found logging causing up to 49% carbon losses in several sites in the Brazilian Amazon using a similar methodology.

In our approach, we calculated landscape-scale carbon losses considering the entire boundary of degraded area, and not strictly the pixels of trails, decks, and treefalls. Therefore, it provides average values without the explicit need of an index to estimate the intensity of degradation. We note, however, that this can underestimate the damage over local heavily degraded areas, and overestimate lightly degraded or undisturbed forests. The development of indices degradation intensity could help improve these estimates.

The uncertainty of carbon change estimates was higher than the carbon change estimates. This occurs due to the accumulation and propagation of uncertainty from the individual ACD estimates. Therefore, when we aggregated undisturbed or lightly disturbed forests in our ΔACD estimates, we also added error from these sources. As an experiment, we tested calculating the ΔACD uncertainty considering only pixels that experienced ACD loss greater than 5 Mg/ha to exclude areas that were likely not affected by logging, but merely shown natural mortality. This caused the uncertainty to significantly drop to levels closer to the average estimates. Nevertheless, there is still work to be done to properly account for the uncertainty on calculating high-resolution carbon change estimates.

Although looking at a very limited sampling of logged forests, the legality of logging activities (indicated by the SIMEX dataset) did not seem to affect the intensity of carbon loss. The only illegal logging was Area 3, which presented a higher carbon loss than Area 1, but inferior loss than Area 2.

In future studies, to reach more accurate estimates of forest carbon loss, a few components must be improved: (i)

maps of degradation considering disturbance attribution. This can potentially be solved using convolutional neural networks models for image segmentation to capture the spatial patterns of the disturbance features; (ii) acquisition of additional ALS data to calibrate models of carbon change in high resolution (such as done in this study); and (iii) the development of degradation intensity metrics from continuous optical and SAR remote sensing datasets, connecting with ALS datasets for calibration and validation.

5. CONCLUSIONS

Our study showed that logging caused losses ranging from 16 to 33.6% of the original aboveground carbon density at the studied rainforests over the Mato Grosso state region. These carbon emission estimates are essential to accurately monitor the effect of REDD+ initiatives and estimate carbon emissions at the landscape scale.

6. ACKNOWLEDGEMENTS

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