**University of São Paulo**
**"Luiz de Queiroz" College of Agriculture**

# Use of airborne laser scanning to improve selective logging and to assess size-frequency distribution of forest gaps in the Brazilian Amazon

Cristiano Rodrigues Reis

Thesis presented to obtain the degree of Doctor in Science. Area: Forest Resources. Option in: Silviculture and Forest Management

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**Cristiano Rodrigues Reis**
**Forestry Engineer**

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Advisor:
Prof. Dr. LUIZ CARLOS ESTRAVIZ RODRIGUEZ

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# SUMÁRIO

RESUMO.....8

ABSTRACT……..……. 9

1. INTRODUCTION……... 11

References……14

2. QUALIFYING THE INFORMATION DETECTED FROM AIRBORNE LASER SCANNING TO SUPPORT TROPICAL FOREST MANAGEMENT OPERATIONAL PLANNING……. 19

Resumo……19

Abstract.....19

2.1 Introduction……20

2.2 Development……... 23

2.2.1 Methodology……..……...23

2.2.2 Results…….....…….29

2.2.3 Discussion……...……...34

2.3 Conclusion…...……35

References.....36

Appendix.....46

3. FOREST STRUCTURE AND DEGRADATION DRIVE CANOPY GAP SIZES ACROSS THE BRAZILIAN AMAZON…….....59

Resumo……..59

Abstract.....59

3.1 Introduction……60

3.2 Development……... 64

3.2.1 Methodology…….....……...64

3.2.2 Results……...……71

3.2.3 Discussion……...……...74

3.3 Conclusions……81

References…….....81

Appendix……...90

4. GENERAL CONCLUSION……99

# RESUMO


## Uso de escaneamento laser aerotransportado para melhorar a colheita seletiva e para avaliar a distribuição de frequência e tamanho de clareiras florestais na Amazônia Brasileira

O escaneamento laser aerotransportado (ALS) pode apoiar o manejo de florestas naturais complexas. A tese apresenta dois estudos, o primeiro engloba uma avaliação em pequena escala onde o ALS foi usado para qualificar árvores emergentes e para avaliar quantas árvores comerciais podem ser encontradas para melhorar os planos operacionais de manejo florestal. O segundo estudo demonstra a utilidade de uma amostragem em larga escala usando ALS para avaliar a distribuição de clareiras na região amazônica no Brasil. No primeiro estudo (capítulo 1) usando o modelo de dossel emergente do ALS-Lidar 66 indivíduos foram classificados como tendo potencial para comércio, dos quais 58 indivíduos apresentaram as melhores qualidades de fuste para exploração, o que representou mais de sete árvores comerciais de alta qualidade por hectare. Os resultados permitiram propor que o planejamento operacional com dados ALS pode ser usado para direcionar de forma mais eficiente os trabalhos de campo sem a necessidade de um censo completo, o que reduziria o esforço em campo nos estágios iniciais de gestão. No capítulo 2, nós mapeamos a variação do coeficiente de escala (α) da função *power-law*, amplamente utilizada para descrever a distribuição de clareiras em diversas florestas. Observamos assim, um padrão de grande escala na variação dos α de Noroeste a Sudeste (maior proporção de grandes clareiras no Sudeste), o que se alinha com trabalhos recentes sobre taxas de mortalidade de árvores. Também explicamos a relação dessas clareiras do dossel com a estrutura da floresta e variáveis ambientais. A proporção de grandes clareiras no dossel florestal variou substancialmente na Amazônia brasileira como resultado da estrutura do dossel e das taxas de perturbação. Cenários de mudanças climáticas são um ponto de preocupação, pois o aumento de eventos climáticos extremos pode, portanto, aumentar a proporção de grandes clareiras em florestas atualmente intactas, fazendo com que elas se assemelhem a florestas modificadas pelo homem.


Palavras-chave: Árvores emergentes, Clareiras, Colheita seletiva, Dinâmica florestal, Florestas tropicais, LiDAR, Manejo florestal sustentável

# ABSTRACT


## Use of airborne laser scanning to improve selective logging and to assess size-frequency distribution of forest gaps in the Brazilian Amazon

Airborne laser scanning (ALS) can support the management of complex natural forests. The thesis presents two studies, one focuses on a small scale ALS assessment that was used to qualify emergent trees and to assess how many commercial trees can be found in order to improve forest management operational plans. The second study demonstrates the usefulness of a large-scale ALS sampling assessment to evaluate the distribution of canopy gaps across the Amazonian region in Brazil. In the first study (chapter 1) by using the emergent canopy model from ALS-Lidar we classified 66 individuals as having potential for commerce, from which 58 individuals presented the best stem quality for logging, which represented more than seven high quality commercial trees per hectare. We propose that ALS operational planning can be used to more efficiently direct field surveys without the need for a full census that would reduce field work in the initial stages of management. In the chapter 2, we mapped the variation of the power-law scale coefficient (α) function, widely used to describe the gap size-frequency distribution in different forests around the world. We observed a large-scale Northwest to Southeast pattern in α (higher proportion of large gaps in the Southeast), which aligns with recent work on tree mortality rates. We also explained the relationship of these canopy gaps with forest structure and environmental variables. The proportion of large gaps in the forest canopy varied substantially over the Brazilian Amazon as a result of canopy structure and disturbance rates. Scenarios of climate change is a point of concern since increasing extreme weather events may therefore increase the proportion of large gaps in currently intact forests, causing them to resemble human modified forests.


Keywords: Emergent crowns, Forest dynamic, Gap size distribution, LiDAR, Selective logging, Sustainable forest management, Tropical rainforest

# 1. INTRODUCTION

Tropical forests host high biodiversity, comprised by many hotspots filled with endemic species. It also maintains a large aboveground carbon (AGC) stock (Baccini et al. 2012, Saatchi et al. 2011), revealing an important role in the regulation of global climate system (Giardina et al. 2018, Malhi et al. 2008). More than half of all surviving tropical forests occurs in the Amazon Basin, which is being seriously altered by large-scale agriculture, industrial logging, proliferating roads, and oil and gas development (Laurance et al. 2011).

Natural or anthropic disturbance processes, such as mortality, fire, and deforestation contribute to increasing carbon emissions (Baccini et al. 2012, Houghton, Byers, Nassikas 2015, Sist et al. 2014). A large-scale deforestation and agricultural expansion in the Americas has been reported over the years showing significantly more vulnerability to climate and land-use change than other tropical forests (Saatchi et al. 2021). Not only the $CO_2$ emission is a source of concern, but the rapid loss and fragmentation of old-growth forests are among the greatest threats to tropical biodiversity (Laurance et al. 2011). Changes in climate conditions and the increase of human activities are changing the natural dynamics of the forests, such as gaps formation and species colonization. Many species in Amazonian forests are rare or patchily distributed and many of them may be absent from fragments not because their populations have vanished, but because they were simply not present at the time of fragment creation or gap colonization (Saatchi et al. 2021).

High biodiversity, wood supply and reducing $CO_2$ emission from deforestation and degradation (Saatchi et al. 2011, Medjibe, Putz 2012, Leitold et al. 2015, Longo et al. 2016) put rainforests in the global spotlight. Using the forest and still maintain its resources to the future generations is a topic that leads to a wide-range of discussion. Therefore, studies have

been conducted to understand how forest ecosystems respond to different anthropogenic activities. This knowledge enables to plan, manage and monitoring the forests aiming the sustainable development of tropical regions, such as the Brazilian Amazon (Costa et al. 2015). Sustainable forest management driven by selective logging is an important method to use the resources from natural forests and still keep its capacity to maintain biodiversity. Long-term analyses have shown that selective logging in areas with absence of other disturbances, such as fire and illegal logging, do not heavily affect biodiversity, and the effects on ecosystem processes are moderated (Costa et al. 2015). Conversely, illegal and/or conventional logging is a key point of concern, since it threatens biodiversity conservation by deforestation (Silva et al. 2014, Vidal et al. 2016).

The Brazilian Amazon has an area around 5.2 x $10^6$ $km^2$ (Martha Júnior, Contini, Navarro 2011). It is predominantly covered by dense, open and seasonal forests (Almeida et al. 2017), and also presents a large variation in soil, climate, and vegetation. To monitor this ecosystem, a wide network of inventory plots is an important source of information for biomass and carbon estimates (Longo et al. 2016), forest dynamic studies (Dalagnol et al. 2021), sustainable forest management evaluation (Vidal et al. 2016), among other important researches that often are used to implement environmental policies or to show future scenarios (Saatchi et al. 2021) that should be globally discussed to minimize the effects of human actions on the forests and avoid irreversible situations in the future.

Although the forest inventory should be performed on areas that contemplate all possible variations within the forest (Longo et al. 2016), measurements are time consuming and expensive, due to the plot size and area extent, turning it difficult to study the complete variation in large forests, such as in the Amazon (Goetz et al. 2015). Remote sensing data has been used to overcome this challenge by combining plot data with RS data. This technology makes possible the achievement of estimates on a large scale (Asner et al. 2005, Baccini et al.

2012, Longo et al. 2016, Saatchi et al. 2011). The airborne laser scanning (ALS) performed with a LiDAR sensor has excelled in comparison to other technologies on forest applications.

LiDAR measures distances from target to the sensor (Næsset 1997, Lefsky et al. 2002), and provides a 3D representation of returns from the terrain and objects above the terrain (Silva et al. 2015, Gorgens et al., 2016). Matching high penetrability and high spatial resolution, ALS-LiDAR generates detailed information even for layers under the canopy (Coops et al., 2007; Gorgens et al., 2016). Many returns relative to terrain are collected by the sensor allowing the construction of high-resolution terrain model (Andrade et al. 2018). Additionally, ALS metrics combined or calibrated with field plot variables, improve AGB estimates consistently because of the canopy heights precision (Asner, Mascaro 2014; Figueiredo et al. 2016, Longo et al. 2016, de Almeida et al. 2019). Many other studies have been conducted using ALS data to understand forest characteristics (de Almeida Papa et al. 2020, Gorgens et al. 2016), gaps dynamics (Dalagnol et al. 2021), vegetation structure (de Almeida et. Al 2019, Wedeux and Coomes 2015), coarse woody debris (Lefsky et al. 1999), tree life stage (Bater et al. 2007), diameter distribution (Stark et al. 2015, Suárez et al. 2005), and others.

In this thesis we used ALS data to basically create a canopy height model (CHM) to work in two different scales. In the first chapter we used the CHM to find emergent trees in the amazon forest using a sub product generated from the CHM – the emergent canopy model - in an area located in Manaus, Amazonas state. In this chapter we show and discuss the possibility of orientating field work aiming to qualify the emergent trees and see, within these emergent trees, how many commercial trees can be find in order to improve the forest management operational plan.

The second chapter covered a large-scale objective and is a good example of how ALS data is suitable to understand large-scale patterns that are not comprised by even the extensive

field plot network we have available in the Brazilian Amazon. In this chapter we used the CHM from ALS to find openings in the 650 LiDAR transects over the Amazon. These openings, also known as canopy gaps, are a key aspect of forest structure and dynamics, marking the balance between disturbance and regeneration in dense tropical forests. This study provides a new understanding of the variation in canopy gaps across the Brazilian Amazon.

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## 2. QUALIFYING THE INFORMATION DETECTED FROM AIRBORNE LASER SCANNING TO SUPPORT TROPICAL FOREST MANAGEMENT OPERATIONAL PLANNING[1]


### Resumo

Manejo florestal sustentável (MFS) é um método que visa antecipar o que ocorreria naturalmente nas florestas por meio do corte de árvores maduras, cuja queda poderia danificar as árvores circunvizinhas. A coleta de todas as informações necessárias para o planejamento da colheita na Amazônia Brasileira é, atualmente, uma tarefa difícil que demanda muito tempo e cara. As informações necessárias podem ser obtidas de forma mais rápida se produtos do escaneamento laser aerotransportado (ALS) são incluídos no planejamento operacional. Nuvem de pontos ALS foram processadas para isolar as copas emergentes das árvores a partir do modelo de altura do dossel. Na sequência, foi realizado trabalho de campo para validar a existências das árvores, cujas copas foram previamente isoladas, e para verificar quantas árvores comerciais (diâmetro ≥ 50 cm) foram possíveis de serem localizadas a partir do modelo de copas emergentes. Foram detectadas no modelo 184 (54.5%) árvores entre as 338 árvores medidas nas 20 parcelas de campo (total de 8 ha). Das árvores detectadas, 66 indivíduos foram classificados como potenciais para comercialização. Contudo, 58 indivíduos apresentaram as melhores qualidades de fuste exigidas para a colheita, o que representou mais de sete árvores comerciais por ha com elevada qualidade para o comércio. A regressão logística mostrou que os efeitos que afetam positivamente a formação de copas emergentes estão presentes nas árvores comerciais. O uso do ALS pode melhorar o planejamento do MFS por meio da redução do trabalho de campo nas etapas iniciais do planejamento. Portanto, nós propomos o adiamento do trabalho de campo para que seja realizado a partir dos resultados obtidos com o ALS no planejamento operacional e evitar a realização do censo.


Palavras-Chave: LiDAR, colheita seletiva, copas emergentes, floresta tropical, manejo florestal sustentável.


### Abstract

**Background:** Forests throughout the world are managed to fulfil a range of commercial and ecosystem services. The same applies to managed areas of the Amazon forest. We explore a method of sustainable forest management (SFM) which anticipates the result of processes of natural mortality of large, mature trees that could fall and damage their neighbors. Collecting all the information required for planning logging in the Brazilian Amazon is, currently, a hard, time-consuming and expensive task. **Methods:** This information can be obtained more quickly, accurately and objectively by including airborne laser scanning (ALS) products in the operational plan. We used ALS point clouds to isolate emergent crowns from the canopy height model. Then, we performed field work to validate the existence of these trees, and to understand how many commercial trees (tree diameter ≥ 50 cm) we identified by orienting the trees search through the emergent canopy model. **Results:** We


[1] Reis, C.R.; Gorgens, E.B; de Almeida, D.R.A.; Celes, C.H.S.; F.; Rosette, J.; Lima, A.; Higuchi, N.; Ometto, J.; Santana, R.C.; Rodriguez, L.C.E. Qualifying the information detected from airborne laser scanning to support tropical forest management operational planning. Forests 2021, 12, 1724. http://doi.org/10.3390/f12121724".

were able to detect 184 (54.4%) trees from 338 field-recorded individuals in 20 plots (totaling 8 ha). Of the detected trees, 66 individuals were classified as having potential for commerce. Furthermore, 58 individuals presented the best stem quality for logging, which represents more than seven high quality commercial trees per hectare. The logistic regression showed that the effects that positively influence the emergent crown formation are strongly presented in the commercial species. **Conclusions:** Using airborne laser scanning can improve the SFM planning in a structurally complex, dense and mixed composition tropical forest by reducing field work in the initial stages of management. Therefore, we propose that ALS operational planning can be used to more efficiently direct field surveys without the need for a full census.

Keywords: LiDAR; tropical rainforest; sustainable forest management; selective logging; emergent crowns.

## 2.1 Introduction

Forest management planning demands several types of information related to the forest resources and their context. From the perspective of the forest resources, these comprise extent, quantity, composition, and resource condition [1]. Regarding the context, information on logging equipment characteristics, road layout, growing stock, silvicultural activities, terrain description, streamflow network is required. Forest management effectiveness depends on spatially explicit, accurate, and time-effective information.

Sustainable forest management (SFM) demands: (i) delineating relatively homogenous units based on characteristics such as tree species composition and stand structure [2], (ii) determining the best route to logging extraction to minimize soil and forest impacts [3] and (iii) reaching the easily derived indicators to monitor forest management activities [4,5]. SFM organizes actions that allow the ordering of production, implementing the selective logging practices [6,7]. In addition, an SFM plan must guarantee the forest production's continuity, avoid waste of wood, and certify the forest products resulting from the exploitation [8,9]. The accuracy and level of detail of the information has special limitations when forest management plans are implemented in areas that are not easily accessible [3].

Currently, an SFM plan relies on extensive and laborious forest inventory procedures, which contributes to increasing the business risk and cost [3,10]. The Brazilian law, for example, demands an extensive field data collection before any authorization is granted to cut a tree. Two main data collections are necessary. First, the forest inventory based on sample plots is implemented to support information to propose the SFM plan. After the approval of the SFM, it is necessary to get, annually, the approval to implement the operational activities. For that, a second field data collection is performed, recording all the trees (commercial and non-commercial) with diameter at breast height (DBH) greater than 50 cm presented in the annual production unit (also known as census). The census is the most important step for the operational planning since it not only quantifies the volume but also geolocates the trees, quantifies the commercial trees and records additional information such as stem quality, natural direction for tree falls, occurrence of stream flows, existence of gaps, presence of vines, and slope variation, among others.

Long-term analyses have shown that selective logging in areas with absence of other disturbances, such as fire and illegal logging, do not heavily affect biodiversity, and the effects on ecosystem processes are moderated [11]. Conversely, illegal and/or conventional logging is a key point of concern, since it threatens biodiversity conservation by deforestation [9,12]. Thus, individual tree information, including location and characterization, is fundamental to supporting the implementation of any SFM plan. Mapping those trees based on field work is a hard task in forests with large extent and sometimes under extreme conditions found in tropical forests (e.g., humidity, temperature, mosquitoes, etc.) [13].

To overcome those difficulties, a sequence of recent studies [3,10,14–16] has shown that high-resolution products provided by airborne LiDAR (a.k.a. Airborne Laser Scanning - ALS) could be used to improve the SFM and operational planning. ALS generates data sets on large scales [17,18], from which it is possible to detect and segment trees [19,20]. For

instance, the linkage between spatial resolution (pixel size) and the concomitant objects that can be characterized (trees, stands) is well understood, with high spatial resolution data enabling single tree detection and analysis, and lower-spatial-resolution data sources enabling coarser stand-level (or broader) analyses [19,21]. Some individual tree detection and segmentation algorithms give the estimated position, size and shape of crowns [21]. This method preferentially detects trees that reach or grow above the mean forest canopy, i.e., the emergent crowns [19,22]. However, an important limitation to ALS consolidation as a resource for tropical forest planning is the qualitative comprehension of what ALS is capable of seeing regarding the forest.

Rather than supplanting existing approaches, ALS data can be integrated into current forest management processes [23] by providing information about the vertical structure that can be linked with the horizontal structure from field plots [19,24]. Studies have shown that ALS data can already provide information about the terrain characteristics [25], drainage network [26], forest characteristics [24,27], gaps dynamics [28,29], vegetation structure [30–32], coarse woody debris [33], tree life stage [34], diameter distribution [35,36], and others. However, ALS can only provide limited information related to forest composition, i.e., tree species [37].

In this paper, we used single tree locations detected by processing the ALS data, to run an inventory aiming to find and characterize the trees quantitatively and qualitatively in the field. To our knowledge, this is the first attempt to first qualify the information extracted by ALS data from a tropical forest.

Three goals are defined for this paper: (1) quantify and qualify (e.g., species, commercial interest, crown luminosity, stem quality and size) the detected/non-detected trees based on ALS processing; (2) from the detected trees, quantify the percentage of trees that

match legal criteria for logging; (3) identify characteristics that influence detection/non-detection of the individual trees' characteristics.

## 2.2 Development

### 2.2.1 Methodology

The study was conducted at the Experimental Station for Tropical Silviculture (ZF2, Figure 1), at the National Institute of Amazon Research (INPA), located in Manaus (AM, Brazil). The area is located between the coordinates 02°33'43" S to 02°40'23" S and 60°07'15" W to 60°13'31" W and is composed of dense tropical forest of "terra-firme" with two main toposequences: valleys and plateaus [38]. The plateau is formed mainly of Yellow Oxisols, while valleys are formed by Hydromorphic Sandy [39]. The elevation above sea level ranges from 44 to 112 m (Figure 1A). The climate is classified as Af, according to Köppen, and is characterized by high temperature, precipitation and humidity year-round [40]. Temperatures vary between 23 °C and 31 °C and mean annual precipitation can reach 2078 mm [39]. The site where the study was conducted has mean canopy height of 30 m, and the emergent trees can grow over 44 m tall [39] (Figure 1B).

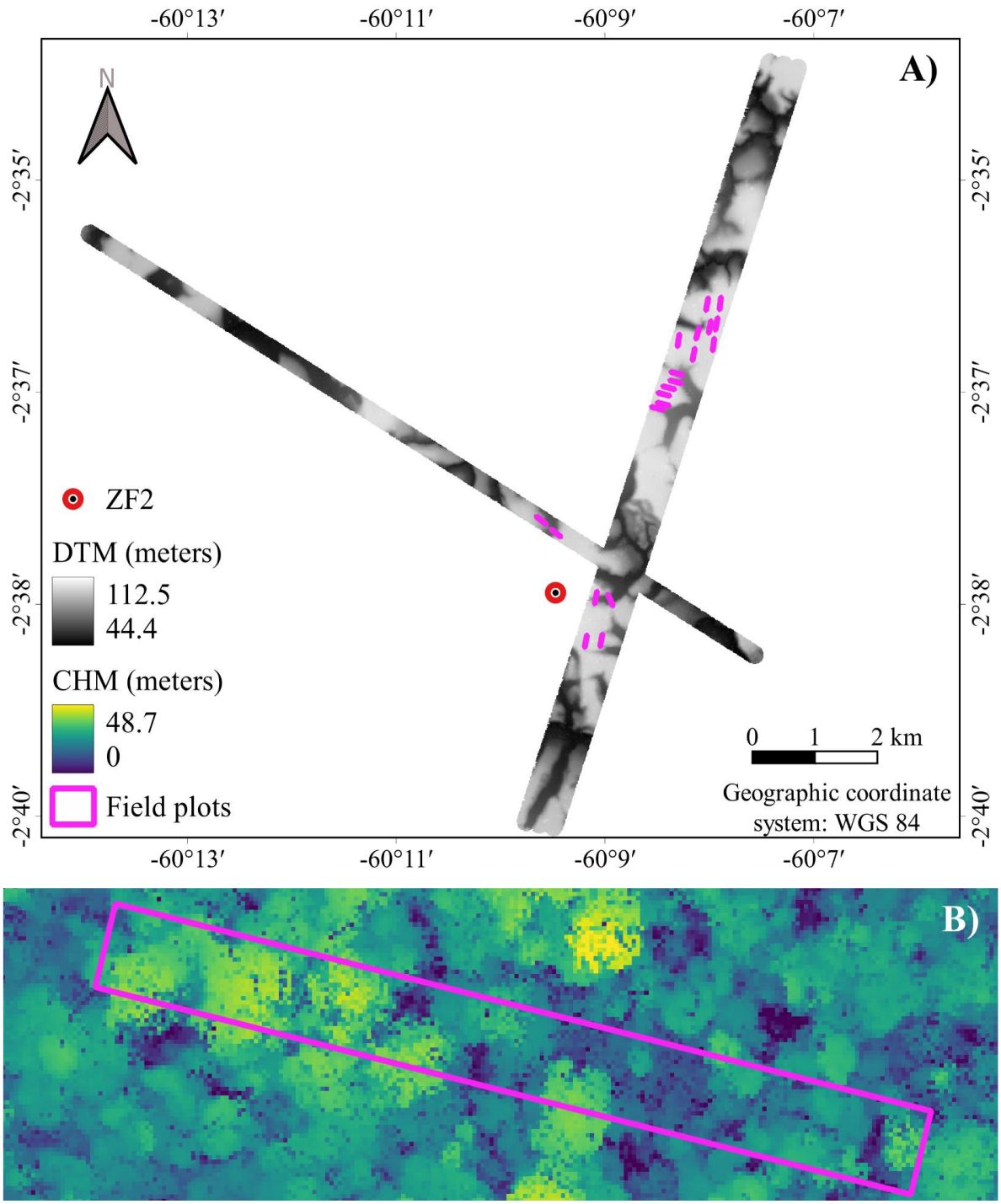


**Figure 1.** Study area is located at Experimental Station for Tropical Silviculture (ZF2), in Manaus, Amazonas State. (A) Digital terrain model (DTM) overlapped with the 20 field plots measured during the field work. (B) 20 x 200 m field plot and the canopy height model (CHM**).**

We launched 20 field plots (20 x 200 m²) in areas covered by four airborne laser scanning transects collected by the "Improving Biomass Estimation Methods for the Amazon" project [41] between 2016 and 2018. Within the area mapped by the transects, as criteria we selected four experimental sites, accessible by internal road and having previously been surveyed. Inside each site, the plots were randomly selected. The ALS campaign produced a point cloud using the LiDAR Harrier 68i sensor parameterized to allow a minimum density of 4 points.$m^{-2}$. The horizontal and vertical accuracy was ± 1.0 m and ± 0.5, respectively. Each transect covers 375 ha (12.5 x 0.3 km²) [42–45].

The ALS data were processed in the FUSION software version 3.80 [46] by removing outliers, homogenizing point cloud density, classifying the ground returns, creating the digital terrain model, normalizing the cloud, producing the canopy height model, and filtering the emergent canopy (>35 m). The outliers were removed by applying a search window of 20 m and considering as outliers all points outside the mean elevation ± 3 standard deviation of returns within the window. Points were then classified as ground by the Kraus and Pfeifer algorithm [47,48] considering a window size of 8 m [25] and the standard parameter of FUSION [46]. We interpolated the ground points to create a digital terrain model (DTM) with 1-m pixel resolution. The canopy height model was created by interpolating the highest above ground points which are normalized with respect to the DTM [49]. The emergent canopy model was produced by applying a lower threshold of 35 m to the CHM. Then, we used the raster to vector function from QGIS to automatically create the crown polygons. Finally, to support the field campaign, we uploaded the vectorized crowns into the GNSS receiver.

During the field campaign we measured all trees with DBH ≥ 50 cm in the 20 plots of 20 m x 200 m. The DBH was defined based on the threshold imposed by the Brazilian law on a SFM plan as the minimum allowable diameter size for logging [50]. For each tree, we recorded the following attributes: DBH, species, stem quality, canopy illumination,

geographic coordinates, commercial interest and the correspondence to an ALS crown polygon. We identified the species based on previous botanical works developed in neighboring areas, and using the expertise of staff at INPA ZF-2 [51–53]. The commercial interest was based on the list provided by the Brazilian Forest Service (available in http://snif.florestal.gov.br/pt-br/especies-florestais, accessed on 22 May 2019). Stem quality is divided into three levels according to percentage of commercial volume potential (straightness, defects, and bifurcations) [54]. The canopy illumination was defined visually as follows: if the canopy reached the highest layer in the forest and receives direct sunlight, it was classified as illuminated; the canopies presented in the mean canopy layer but with incidence of sunlight, they were classified as partially illuminated; lastly, trees under the mean canopy height were classified as shaded [54].

We used a regular navigation GNSS (Garmim 76Cx), which is commonly used by the Brazilian foresters. The intention behind this decision is to see how common devices currently used to support forest management are able to detect the ALS extracted information. The GNSS collected coordinates combining two satellite systems (GPS and GLONASS) to reduce the geolocation error [55,56]. We also classified the DTM by applying the Hill-Climbing clustering algorithm with two clusters to split the data into valleys (floodplain) and plateaus [57].

We defined the trees' sociological position according to [58], from which the author classified the species into 10 different groups. From these 10 groups, one represents the pioneer species (group 7), one represents the emergent/climax species (group 8), and the remaining groups comprised the intermediary species. The field plots were processed to obtain the frequency and dominance, stem density and the importance value for each species

(IVI = frequency, density and dominance combined). The field data were processed using the *forestmangr* package, developed for R [59].

Based on the correspondence to ALS-derived crown polygon (actual class) and to the crown illumination from the field emergent trees (detected class), we built a confusion matrix considering: class II- when a tree stem location matched an emergent canopy polygon (inside polygon) and had its canopy classified as totally or partially illuminated; class IS - when a tree stem matched an emergent canopy polygon (inside polygon) and had its canopy classified as shaded; class OI - when a tree did not match any emergent canopy polygon (outside polygon) and had its canopy classified as totally or partially illuminated; class OS - when a tree did not match any emergent canopy polygon (outside polygon) and had its canopy classified as shaded. The process steps are described in Figure 2.

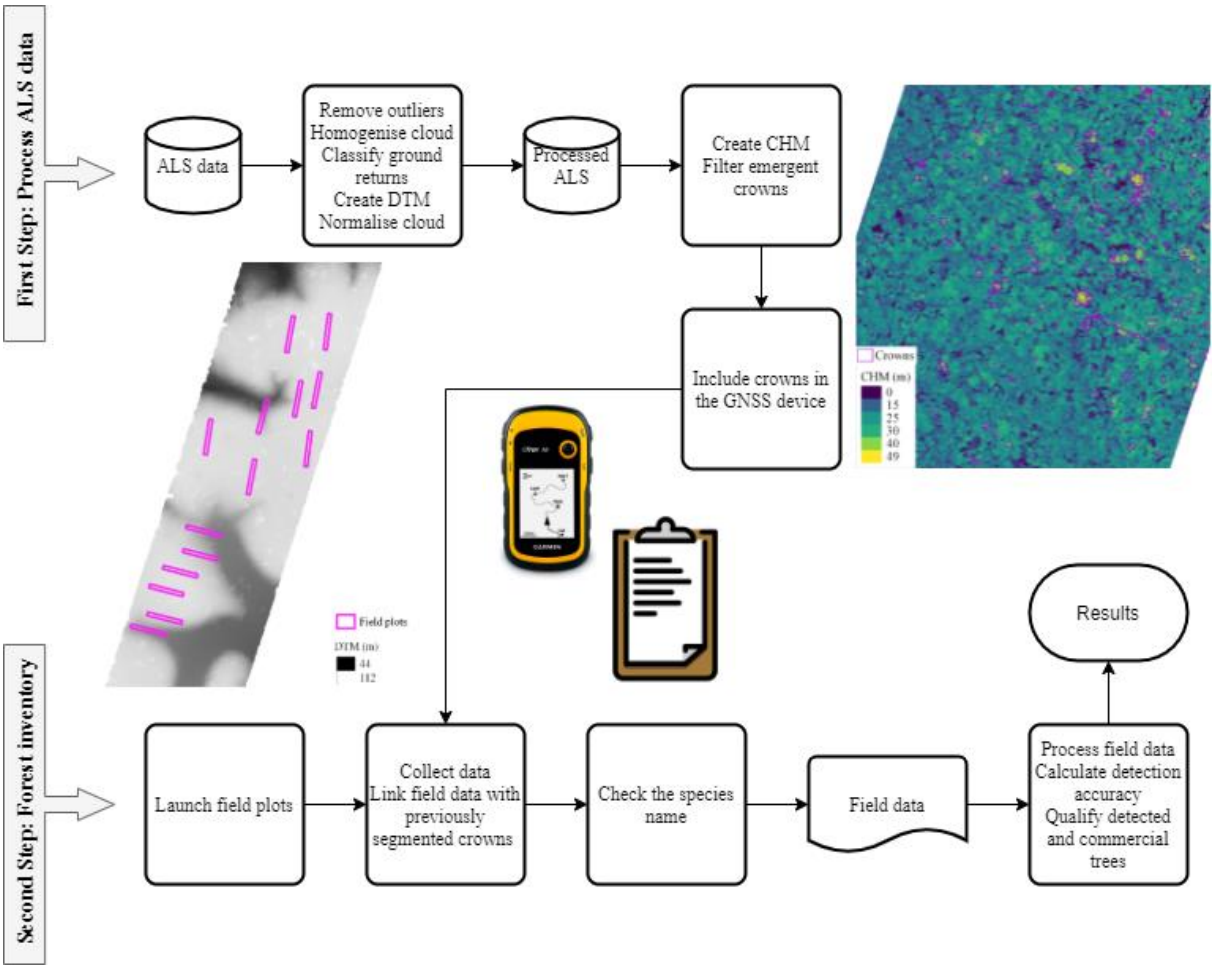


**Figure 2.** Methodological flowchart describing the methodology steps.

Considering the confusion matrix, we calculated for each plot the detection rate (recall, *r*, Equation (1)) and the correct detection of the trees (precision, *p*, Equation (2)). These two indices were used to obtain the *F-score* (Equation (3)), which is the overall accuracy taking into account both commission and omission errors [60].

$$r = \frac{II}{(II+IS)} \tag{1}$$

$$p = \frac{II}{(II+OI)} \tag{2}$$

$$F - score = 2\ x\ \frac{r\ x\ p}{(r+p)} \tag{3}$$

To qualify what has been detected from ALS, we analyzed the characteristics that influence tree detection. The binomial logistic regression (Equation (4)) was used to evaluate the significance of factors in the detection performance by the ALS. We created a binary variable considering the detected and non-detected trees as 0 and 1, respectively. In sequence, we fitted a generalized linear model with a logistic link using the binary variables as a function of tree characteristics (stem quality - *cif*, commercial - *com*, and sociological position - *sp*) and toposequence (*topo*). We chose the model based on the significance of the parameters (p-valor ≤ 0.05) and the Akaike Information Criteria (AIC).

$$log_e\left[\frac{P}{1-P}\right] = logit(P) = \beta_0 + \beta_1 cif + \beta_2 com + \beta_4 sp + \beta_5 topo \qquad (4)$$

where logit (p) is the odds ratio, p is the probability of finding a tree, $\beta_0$~$\beta_5$ are the logistic regression coefficients, *cif* is the stem quality, *com* is the commercial species, *sp* is the sociological position and *topo* is the toposequence.

### 2.2.2 Results

2.2.2.1. Qualification and quantification of inventory trees

We recorded a total of 338 trees with DBH above 50 cm, distributed in 26 botanical families and 93 species. The most representative families were Fabaceae (67 individuals), Lecythidaceae (47 individuals), Sapotaceae (42 individuals), Apocynaceae (30 individuals) and Vochysiaceae (22 individuals). The most frequent species are *Pouteria minima* T.D.Penn. (26 individuals), *Goupia glabra* Aubl. (18 individuals), *Aspidosperma marcgravianum* Woodson (14 individuals), *Piptadenia suaveolens* Miq. (13 individuals), *Qualea paraensis* Ducke (13 individuals) and *Geissospermum argenteum* Woodson (10 individuals). The structural analysis showed that the species with highest importance values were: *Pouteria minima* (IVI = 6.52), *Goupia glabra* (5.15), *Qualea paraensis* (3.95), *Piptadenia suaveolens*

(3.90), and *Aspidosperma marcgravianum* (3.89). Additional information is provided in Supplementary Tables S1 and S2.

The emergent crowns (height > 35 m) from the ALS canopy height model were linked to 54.44% of the trees greater than 50 cm of DBH, recorded in the field. Trees from the climax and intermediary groups were much more predominant among the emergent crowns than trees from the pioneer group: 74% of intermediary trees and 21% of climax trees were included in the emergent crowns, while only 3% were pioneer trees. The remaining 2% of emergent crowns were related to trees not included in any group (Table 1).

2.2.2.2. Quantification of trees with potential for logging

Of the 338 trees recorded in the field plots, 28% (94 individuals) are included in the commercial interest list (Table 2). *Goupia glabra* and *Piptadenia suaveolens* were the commercial species with a greater number of individuals (13 and 12 trees, respectively). Of the commercial trees, 70% (66 individuals within 17 species) were present in the ALS canopy height model. Of the detected trees with commercial interest, 88% had stems classified in the good (i.e., straight, cylindrical and undamaged) or medium quality (slightly tortuous) class (Table 2).

**Table 1.** Discrimination of each sociological position regarding the number of individuals by ecological group, presence in the emergent canopy and commercial interest.

| Ecological groups | Detected trees | Not detected trees | Trees with commercial interest | Main species (# individuals) |
|---|---|---|---|---|
| Clímax | 39 | 22 | 24 | *Goupia glabra* (18)<br>*Aspidosperma marcgravianum* (14)<br>*Sacoglottis guianensis* (6)<br>*Ladenbergia amazonensis* (5)<br>*Cariniana micrantha* (4)<br>*Hymenolobium sericeum* (4) |
| Intermediary | 136 | 118 | 66 | *Pouteria minima* (26)<br>*Qualea paraensis* (13)<br>*Piptadenia suaveolens* (13)<br>*Geissospermum argenteum* (11)<br>*Couratari stellata* (9) |
| Pioneer | 5 | 9 | 1 | *Trattinnickia peruviana* (8)<br>*Dipteryx magnifica* (2)<br>*Inga gracilifolia* (2)<br>*Eriotheca longipedicellata* (1)<br>*Jacaranda copaia* (1) |
| Not classified | 4 | 5 | 3 | *Maquira sclerophylla* (2)<br>*Apeiba echinata* (1)<br>*Chornelia tenuiflora* (1)<br>*Glycydendron amazonicum* (1)<br>*Lacmellea gracilis* (1)<br>*Duckesia verrucosa* (1)<br>*Vantanea parviflora* (1)<br>*Vantanea sp.* (1) |
| **Total** | **184** | **154** | **94** | |

**Table 2.** Discrimination of the commercial trees recorded in the field plots.

| | **Individuals** | **Stem quality** | **Canopy illumination** | **Main species (# individuals)** |
|---|---|---|---|---|
| Detected | 66 | Good: 37<br>Medium: 21<br>Low: 8 | Illuminated: 61<br>Partially: 4<br>Shaded: 1 | *Goupia glabra* (13)<br>*Piptadenia suaveolens* (12)<br>*Qualea paraensis* (8)<br>*Couratari stellata* (6)<br>*Dinizia excelsa* (5) |
| Not detected | 28 | Good: 10<br>Medium: 9<br>Low: 9 | Illuminated: 20<br>Partially: 7<br>Shaded: 1 | *Goupia glabra* (5)<br>*Qualea paraensis* (5)<br>*Clarisia racemosa* (3)<br>*Couratari stellata* (3)<br>*Ocotea fragrantissima* (3) |

2.2.2.3. Characteristics influencing the trees detection rate from ALS emergent crowns

We observed a high detection rate in our study (*r*, Table 3), indicating that emergent ALS-derived crown polygons are commonly associated with trees having DBH above 50 cm. In all plots, the detection rate was above 80%. The precision values (*p*, Table 3) indicate the amount of trees having a DBH greater than 50 cm that are linked to an emergent crown polygon. We found precision rates ranging from 0.27 to 0.81, with 0.55 on average. Approximately half of trees with DBH above 50 cm in the forest were not associated with any emergent crowns. The f-score (*f-sc*) follows the higher variation observed in the *p*, ranging from 0.40 to 0.92, and an average of 0.70 (Table 3).

**Table 3.** Tree detection rate (r), precision (p) and accuracy (fsc) for each inventory plot. II = tree found inside ALS-derived polygon and the canopy partially or totally illuminated, OI = tree outside ALS polygon and canopy partially or totally illuminated and IS = tree inside ALS polygon and shaded canopy.

| Plots | II | OI | IS | *r* | *p* | *f-sc* |
|---|---|---|---|---|---|---|
| 1 | 6 | 6 | 0 | 1.00 | 0.46 | 0.63 |
| 3 | 4 | 11 | 0 | 1.00 | 0.25 | 0.40 |
| 7 | 11 | 2 | 0 | 1.00 | 0.85 | 0.92 |
| 8 | 6 | 3 | 0 | 1.00 | 0.67 | 0.80 |
| 10 | 10 | 6 | 0 | 1.00 | 0.63 | 0.77 |
| 11 | 4 | 9 | 0 | 1.00 | 0.31 | 0.47 |
| 14 | 13 | 4 | 1 | 0.93 | 0.76 | 0.84 |
| 15 | 5 | 19 | 0 | 1.00 | 0.21 | 0.34 |
| 16 | 16 | 1 | 2 | 0.89 | 0.94 | 0.91 |
| 17 | 10 | 6 | 0 | 1.00 | 0.63 | 0.77 |
| 18 | 11 | 7 | 0 | 1.00 | 0.61 | 0.76 |
| 19 | 13 | 5 | 2 | 0.87 | 0.72 | 0.79 |
| 23 | 6 | 12 | 0 | 1.00 | 0.33 | 0.50 |
| 25 | 10 | 10 | 1 | 0.91 | 0.50 | 0.65 |
| 26 | 10 | 7 | 0 | 1.00 | 0.59 | 0.74 |
| 27 | 6 | 12 | 0 | 1.00 | 0.33 | 0.50 |
| 28 | 13 | 3 | 0 | 1.00 | 0.81 | 0.90 |
| 29 | 8 | 5 | 0 | 1.00 | 0.61 | 0.76 |
| 30 | 9 | 6 | 1 | 0.90 | 0.60 | 0.72 |
| 31 | 6 | 7 | 0 | 1.00 | 0.46 | 0.63 |
| **General** | **177** | **143** | **7** | **0.96** | **0.55** | **0.70** |

The full model (Equation (4) - AIC = 303.5) had the predictor variables sp and topo nonsignificant (*p*-value ≥ 0.05). Therefore, we ran the model only for the remaining significant variables (*cif* and *com*, AIC = 302.1), which had the coefficients with *p*-values < 0.001 (***) for stem quality (*cif*) and <0.01 (**) for species with commercial interest (*com*). The bracket numbers in model 5 are the standard error.

Probability of detecting trees = $1.1026^{***}_{(\pm 0.3325))} - 0.7107^{***}_{(\pm 0.1751)} cif + 1.0337^{**}_{(\pm 0.3227)} com$ (5)

A tree with stem quality classified as good (straight, cylindrical and undamaged) and with commercial interest had a greater probability of being identified in the emergent crown model. The sociological position and the toposequence (valleys and plateaus) did not

influence (p-value > 0.05) the odds of trees having a detectable emergent crown in the ALS-CHM.

### 2.2.3 Discussion

Our results showed that in an area of 8 ha, 28% of the trees greater than 50 cm (in DBH) had commercial interest, and 70% of these were detected and could therefore be classified in the emergent ALS canopy height model. The number of commercial trees detected in the canopy height model correlated to more than seven trees per hectare, which is sufficient to build an SFM plan around [16]. In comparison, [5] analyzed an inventory in the 100% (census) of 1253 ha and arrived at a density of 10.21 commercial trees per hectare with DBH ranging from 50 to 248 cm.

Our study indicated some factors that influence the odds of a tree being part of the emergent canopy. Characteristics like stem quality and species with commercial interest positively increase the odds. The sociological position and the toposequence (valleys and plateaus) did not significantly influence emergent crowns detection. Desired characteristics for logging among commercial species (cylindrical stems, straight or with a slight tortuosity and undamaged) positively influence their possession of an emergent crown (and therefore potential for detection using ALS). Competition for the resources that permit growth is a key factor in allowing trees to emerge from the mean canopy [44]. Our results highlight that good-quality stems reflect more highly competitive individuals which have crucial characteristics enabling them to surpass the others in height growth.

Basing the operational planning on ALS data can reduce costs, accelerate evaluation and approval by the authorities, and increase transparency and governance. However, we clearly show that field data are still needed. Therefore, we propose the use of ALS detected emergent trees to more efficiently target the field work. Before the necessity of sending field

surveyors into the forest, using ALS, in addition to detecting the target trees, it would be possible to optimize the extraction route, avoid steep terrain and costly topographic regions [3,25,61]. Instead of doing a census to record all the trees greater than 50 cm DBH, the field collection will be oriented on the information extracted from ALS data.

Other authors have shown ALS data to enable forest stratification which led to a reduction of 41% in the required sampling intensity [24]. This significant reduction in sampling units (from 46 to 27—1 ha plots) saved US $28,500.00 by reducing the field work, which paid for the ALS data collection (US $26,400.00) [24]. We believe that following the approach that reduces sampling intensity [24] with the approach proposed in this paper could be a future object of study. We also encourage similar studies to ours in different areas to enable the f-score comparison.

The ALS data can support the operational plan with much more information than an operational plan based only on field data. Previous work has shown that ALS can be used to monitor logging impact activities [10,15,16,29] and to estimate biomass and carbon changes [18,62]. To avoid expensive multitemporal ALS to monitor and inspect how forests recover after being submitted to logging, this could be combined with a cheaper remote sensing system, such as 3D UAV photogrammetry [63]. Another product that has been widely used is the detection and segmentation of trees [22]; however, it still presents some difficulties, such as species identification [37] and individual crown isolation in dense tropical forests [22], which still makes field work mandatory to obtain this information. With the advances of remote sensing techniques, such as combining ALS with hyperspectral data can help to better segment and detect trees, and maybe enable species identification.

### 2.3 Conclusion

Using airborne laser scanning can improve SFM planning, reducing field work in the initial stages of planning and additionally adding value to later operational implementation

stages. There is no doubt that SFM could benefit from new technologies to make forest management more efficient and less costly, increasing its sustainability. In this paper, we showed that inclusion of emergent trees detected by ALS can be an alternative to the necessity of conducting a full census, resulting in a sufficient number of trees to integrate into an SFM plan, adding transparency, consistency and confidence.

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# Appendix

## Supplementary material

**Table S1.** Family and species list recorded in the Experimental Station for Tropical Silviculture.

| | Number of individuals | Ecological group | Mean DBH |
|---|---|---|---|
| **Anacardiaceae** | | | |
| *Anacardium spruceanum* Benth ex Engl. | 2 | 2 | 60.3 |
| *Astronium* sp. | 1 | 2 | 97.0 |
| **Apocynaceae** | | | |
| *Aspidosperma desmanthum* Benth. ex Müll.Arg. | 4 | 2 | 61.7 |
| *Aspidosperma marcgravianum* Woodson | 14 | 1 | 68.0 |
| *Geissospermum argenteum* Woodson | 11 | 2 | 59.0 |
| *Lacmellea gracilis* (Müll.Arg.) Markgr. | 1 | NA | 52.5 |
| **Bignoniaceae** | | | |
| *Jacaranda copaia* (Aubl.) D.Don | 1 | 3 | 48.5 |
| *Tabebuia* sp. | 1 | 2 | 50.0 |
| **Bombacaceae** | | | |
| *Eriotheca longipedicellata* (Ducke) A. Robyns | 1 | 3 | 66.0 |
| **Burseraceae** | | | |
| *Trattinnickia peruviana* Loes. | 8 | 3 | 63.3 |
| **Caryocaraceae** | | | |
| *Caryocar glabrum* (Aubl.) Pers. | 2 | 1 | 85.0 |

| | | | |
|---|---|---|---|
| *Caryocar villosum* | 5 | 2 | 86.8 |
| **Chrysobalanaceae** | | | |
| *Licania micrantha* Miq. subsp. Micrantha | 3 | 2 | 61.3 |
| *Licania* sp. | 3 | 2 | 46.3 |
| **Combretaceae** | | | |
| *Buchenavia grandis* Ducke | 1 | 1 | 73.0 |
| *Buchenavia* sp. | 6 | 2 | 62.0 |
| **Duckeodendraceae** | | | |
| *Duckeodendron cestroides* Kuhlm. | 6 | 2 | 99.5 |
| **Elaeocarpaceae** | | | |
| *Sloanea pubescens* (Poepp.& Endl.) Benth. | 2 | 2 | 57.5 |
| **Euphorbiaceae** | | | |
| *Drypetes variabilis* Uittien | 1 | 2 | 65.0 |
| *Glycydendron amazonicum* Ducke | 1 | NA | 52.5 |
| *Micranda siphonoides* Benth. | 4 | 2 | 53.8 |
| *Micrandropsis scleroxylon* W.Rodr. | 1 | 2 | 63.0 |
| **Fabaceae** | | | |
| *Bowdichia nitida* Spruce ex Benth. | 2 | 1 | 73.0 |
| *Dinizia excelsa* Ducke | 5 | 2 | 95.0 |
| *Dipteryx magnifica* (Ducke) Ducke | 2 | 3 | 69.5 |
| *Dipteryx polyphylla* Huber | 2 | 2 | 70.0 |
| *Dipteryx* sp. | 1 | 2 | 74.0 |
| *Enterolobium schomburgkii* (Benth.) Benth. | 1 | 2 | 57.0 |

| | | | |
|---|---|---|---|
| *Hymenaea courbaril* L. var. stilbocarpa (Hayne) Lee et Lang | 3 | 2 | 68.8 |
| *Hymenolobium sericeum* Ducke | 4 | 1 | 66.5 |
| *Inga gracilifolia* Ducke | 2 | 3 | 82.5 |
| *Inga* sp. | 3 | 2 | 61.8 |
| *Parkia multijuga* Benth. | 1 | 2 | 60.0 |
| *Parkia pendula* (Willd.) Benth. ex Walp. | 2 | 2 | 90.0 |
| *Peltogyne excelsa* Ducke | 3 | 2 | 65.3 |
| *Piptadenia suaveolens* Miq. | 13 | 2 | 64.2 |
| *Pterocarpus rohrii* Vahl | 1 | 2 | 45.0 |
| *Schizolobium amazonicum* Huber ex Ducke | 8 | 2 | 76.0 |
| *Swartzia schomburgkii* Benth. | 2 | 2 | 65.0 |
| *Tachigali myrmecophila* Ducke | 8 | 2 | 57.6 |
| *Vatairea paraensis* Ducke | 1 | 1 | 52.0 |
| *Vatairea sericea* Ducke | 1 | 1 | 50.0 |
| *Zygia racemosa* (Ducke) Barneby & J.W.Grimes | 2 | 2 | 58.0 |
| **Flacourtiaceae** | | | |
| *Laetia procera* (Poepp.) Eichler | 1 | 2 | 53.0 |
| **Goupiaceae** | | | |
| *Goupia glabra* Aubl. | 18 | 1 | 66.8 |
| **Humiriaceae** | | | |
| *Duckesia verrucosa* (Ducke) Cuatrec. | 1 | NA | 70.0 |
| *Endopleura uchi* (Huber) Cuatrec. | 1 | 2 | 50.2 |

| | | | |
|---|---|---|---|
| *Sacoglottis guianensis* Benth. | 6 | 1 | 58.6 |
| *Vantanea parviflora* Lam. | 1 | NA | 71.0 |
| *Vantanea* sp. | 1 | NA | 64.0 |
| **Lauraceae** | | | |
| *Aniba panurensis* (Meisn.) Mez | 3 | 2 | 64.0 |
| *Ocotea argyrophylla* Ducke | 3 | 2 | 59.0 |
| *Ocotea fragrantissima* Ducke | 7 | 2 | 63.7 |
| *Sextonia rubra* (Mez) van der Werff | 1 | 1 | 80.0 |
| **Lecythidaceae** | | | |
| *Cariniana micrantha* Ducke | 4 | 1 | 112.1 |
| *Corythophora rimosa* W.A.Rodrigues | 2 | 2 | 57.0 |
| *Couratari stellata* A.C.Sm. | 9 | 2 | 61.6 |
| *Eschweilera atropetiolata* S.A.Mori | 1 | 2 | 71.0 |
| *Eschweilera carinata* S.A. Mor | 5 | 2 | 55.7 |
| *Eschweilera collina* Eyma | 4 | 2 | 54.6 |
| *Eschweilera coriacea* (DC.) S.A. Mori | 3 | 2 | 57.3 |
| *Eschweilera romeu-cardosoi* S.A.Mori | 8 | 2 | 61.0 |
| *Eschweilera* sp. | 2 | 2 | 60.0 |
| *Lecythis prancei* S.A. Mor | 3 | 2 | 59.8 |
| *Lecythis zabucajo* Aubl. | 6 | 2 | 66.6 |
| **Malvaceae** | | | |
| *Apeiba echinata* Gaertn. | 1 | NA | 66.0 |
| *Scleronema micranthum* (Ducke) Ducke | 4 | 2 | 55.3 |

| | | | |
|---|---|---|---|
| *Sterculia excelsa* Mart. | 1 | 2 | 50.5 |
| **Melastomataceae** | | | |
| *Mouriri callocarpa* Ducke | 1 | 2 | 64.0 |
| **Moraceae** | | | |
| *Brosimum potabile* Ducke | 1 | 1 | 89.5 |
| *Brosimum rubescens* Taub. | 5 | 2 | 59.7 |
| *Clarisia racemosa* Ruiz & Pav. | 7 | 2 | 64.9 |
| *Maquira sclerophylla* (Ducke) C.C. Berg | 2 | NA | 55.0 |
| **Myristicaceae** | | | |
| *Virola* sp. | 4 | 2 | 72.3 |
| **Olacaceae** | | | |
| *Minquartia guianensis* Aubl. | 3 | 2 | 65.7 |
| **Rubiaceae** | | | |
| *Amaioua* sp. | 1 | 2 | 80.0 |
| *Chornelia tenuiflora* Benth. | 1 | NA | 87.0 |
| *Ladenbergia amazonensis* Ducke | 5 | 1 | 68.8 |
| **Sapotaceae** | | | |
| *Ecclinusa guianensis* Eyma | 3 | 2 | 60.7 |
| *Manilkara cavalcantei* Pires & W.A.Rodrigues | 1 | 2 | 59.0 |
| *Micropholis guyanensis* (A.DC.) Pierre spp. duckeana (Baehni) T.D.Penn. | 1 | 2 | 54.0 |
| *Micropholis* sp. | 1 | 2 | 78.0 |
| *Pouteria ambelaniifolia* (Sandwith) T.D.Penn | 1 | 2 | 53.0 |

| | | | |
|---|---|---|---|
| *Pouteria anomala* (Pires) T.D.Penn. | 2 | 2 | 60.0 |
| *Pouteria caimito* (Ruiz & Pav.) Radlk. | 4 | 2 | 65.4 |
| *Pouteria minima* T.D.Penn. | 26 | 2 | 59.6 |
| *Pouteria oblanceolata* Pires | 1 | 2 | 58.5 |
| *Pouteria venosa* (Mart.) Baehni ssp. amazonica T.D. Penn. | 2 | 2 | 51.5 |
| **Simaroubaceae** | | | |
| *Simarouba amara* Aubl. | 2 | 2 | 56.8 |
| **Vochysiaceae** | | | |
| *Erisma bicolor* Ducke | 7 | 2 | 65.0 |
| *Qualea acuminata* Aubl. | 1 | 2 | 59.0 |
| *Qualea albiflora* Warm | 1 | 1 | 52.0 |
| *Qualea paraensis* Ducke | 13 | 2 | 70.2 |
| **Total** | **338** | | |

**Table S2.** Horizontal structural analysis performed for the species recorded in the Experimental Station for Tropical Silviculture. AF = absolute frequency, RF = relative frequency (%), AD = absolute density, RD = relative density (%), ADo = Absolute dominance, RDo = relative dominance (%), CVI = cover value index, IVI = importance value index, com = commercial interest.

| Species | AF | RF | AD | DR | ADo | RDo | IVC | IVI | com |
|---|---|---|---|---|---|---|---|---|---|
| *Pouteria minima* T.D.Penn. | 80 | 5.654 | 3.25 | 7.692 | 0.937 | 6.223 | 6.958 | 6.523 | No |
| *Goupia glabra* Aubl. | 65 | 4.594 | 2.25 | 5.325 | 0.834 | 5.54 | 5.433 | 5.153 | Yes |
| *Qualea paraensis* Ducke | 50 | 3.534 | 1.625 | 3.846 | 0.675 | 4.484 | 4.165 | 3.955 | Yes |
| *Piptadenia suaveolens* Miq. | 60 | 4.24 | 1.625 | 3.846 | 0.544 | 3.611 | 3.728 | 3.899 | Yes |
| *Aspidosperma marcgravianum* Woodson | 45 | 3.18 | 1.75 | 4.142 | 0.655 | 4.346 | 4.244 | 3.889 | No |
| *Geissospermum argenteum* Woodson | 35 | 2.474 | 1.375 | 3.254 | 0.383 | 2.544 | 2.899 | 2.757 | No |
| *Duckeodendron cestroides* Kuhlm. | 30 | 2.12 | 0.75 | 1.775 | 0.6 | 3.986 | 2.881 | 2.627 | No |
| *Schizolobium amazonicum* Huber ex Ducke | 25 | 1.767 | 1 | 2.367 | 0.479 | 3.178 | 2.773 | 2.437 | No |
| *Couratari stellata* A.C.Sm. | 30 | 2.12 | 1.125 | 2.663 | 0.359 | 2.382 | 2.522 | 2.388 | Yes |
| *Trattinnickia peruviana* Loes. | 35 | 2.474 | 1 | 2.367 | 0.323 | 2.141 | 2.254 | 2.327 | No |
| *Eschweilera romeu-cardosoi* S.A.Mori | 35 | 2.474 | 1 | 2.367 | 0.302 | 2.004 | 2.185 | 2.281 | No |
| *Erisma bicolor* Ducke | 35 | 2.474 | 0.875 | 2.071 | 0.301 | 1.997 | 2.034 | 2.181 | No |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Ocotea fragrantissima* Ducke | 35 | 2.474 | 0.875 | 2.071 | 0.294 | 1.953 | 2.012 | 2.166 | Yes |
| *Tachigali myrmecophila* Ducke | 30 | 2.12 | 1 | 2.367 | 0.262 | 1.737 | 2.052 | 2.075 | No |
| *Clarisia racemosa* Ruiz & Pav. | 30 | 2.12 | 0.875 | 2.071 | 0.294 | 1.95 | 2.011 | 2.047 | Yes |
| *Cariniana micrantha* Ducke | 20 | 1.413 | 0.5 | 1.183 | 0.507 | 3.364 | 2.274 | 1.987 | No |
| *Dinizia excelsa* Ducke | 20 | 1.413 | 0.625 | 1.479 | 0.453 | 3.006 | 2.243 | 1.966 | Yes |
| *Caryocar villosum* | 20 | 1.413 | 0.625 | 1.479 | 0.398 | 2.645 | 2.062 | 1.846 | No |
| *Buchenavia* sp. | 30 | 2.12 | 0.75 | 1.775 | 0.229 | 1.519 | 1.647 | 1.805 | No |
| *Lecythis zabucajo* Aubl. | 25 | 1.767 | 0.75 | 1.775 | 0.278 | 1.843 | 1.809 | 1.795 | No |
| *Ladenbergia amazonensis* Ducke | 25 | 1.767 | 0.625 | 1.479 | 0.248 | 1.647 | 1.563 | 1.631 | No |
| *Sacoglottis guianensis* Benth. | 20 | 1.413 | 0.75 | 1.775 | 0.21 | 1.396 | 1.586 | 1.528 | No |
| *Eschweilera carinata* S.A. Mor | 25 | 1.767 | 0.625 | 1.479 | 0.154 | 1.02 | 1.25 | 1.422 | No |
| *Brosimum rubescens* Taub. | 20 | 1.413 | 0.625 | 1.479 | 0.177 | 1.173 | 1.326 | 1.355 | No |
| *Pouteria caimito* (Ruiz & Pav.) Radlk. | 20 | 1.413 | 0.5 | 1.183 | 0.171 | 1.133 | 1.158 | 1.243 | No |
| *Virola* sp. | 15 | 1.06 | 0.5 | 1.183 | 0.212 | 1.41 | 1.297 | 1.218 | No |
| *Aspidosperma desmanthum* Benth. ex Müll.Arg. | 20 | 1.413 | 0.5 | 1.183 | 0.15 | 0.998 | 1.09 | 1.198 | No |
| *Eschweilera collina* Eyma | 20 | 1.413 | 0.5 | 1.183 | 0.119 | 0.788 | 0.986 | 1.128 | No |
| *Hymenolobium sericeum* Ducke | 10 | 0.707 | 0.5 | 1.183 | 0.181 | 1.199 | 1.191 | 1.03 | No |
| *Scleronema micranthum* (Ducke) Ducke | 15 | 1.06 | 0.5 | 1.183 | 0.121 | 0.803 | 0.993 | 1.015 | No |

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|---|---|---|---|---|---|---|---|---|---|
| *Hymenaea courbaril* L. *var. stilbocarpa* (Hayne) Lee et Lang | 15 | 1.06 | 0.375 | 0.888 | 0.149 | 0.987 | 0.938 | 0.978 | Yes |
| *Minquartia guianensis* Aubl. | 15 | 1.06 | 0.375 | 0.888 | 0.131 | 0.873 | 0.88 | 0.94 | No |
| *Peltogyne excelsa* Ducke | 15 | 1.06 | 0.375 | 0.888 | 0.13 | 0.864 | 0.876 | 0.937 | No |
| *Aniba panurensis* (Meisn.) Mez | 15 | 1.06 | 0.375 | 0.888 | 0.122 | 0.808 | 0.848 | 0.918 | No |
| *Ecclinusa guianensis* Eyma | 15 | 1.06 | 0.375 | 0.888 | 0.109 | 0.726 | 0.807 | 0.891 | No |
| *Micranda siphonoides* Benth. | 10 | 0.707 | 0.5 | 1.183 | 0.115 | 0.765 | 0.974 | 0.885 | No |
| *Ocotea argyrophylla* Ducke | 15 | 1.06 | 0.375 | 0.888 | 0.106 | 0.704 | 0.796 | 0.884 | No |
| *Eschweilera coriacea* (DC.) S.A. Mori | 15 | 1.06 | 0.375 | 0.888 | 0.098 | 0.65 | 0.769 | 0.866 | No |
| *Parkia pendula* (Willd.) Benth. ex Walp. | 10 | 0.707 | 0.25 | 0.592 | 0.167 | 1.108 | 0.85 | 0.802 | No |
| *Licania* sp. | 15 | 1.06 | 0.375 | 0.888 | 0.064 | 0.425 | 0.656 | 0.791 | No |
| *Licania micrantha* Miq. subsp. *micrantha* | 10 | 0.707 | 0.375 | 0.888 | 0.116 | 0.77 | 0.829 | 0.788 | No |
| *Inga* sp. | 10 | 0.707 | 0.375 | 0.888 | 0.113 | 0.747 | 0.817 | 0.78 | No |
| *Lecythis prancei* S.A. Mor | 10 | 0.707 | 0.375 | 0.888 | 0.105 | 0.7 | 0.794 | 0.765 | No |
| *Caryocar glabrum* (Aubl.) Pers. | 10 | 0.707 | 0.25 | 0.592 | 0.142 | 0.945 | 0.768 | 0.748 | Yes |
| *Inga gracilifolia* Ducke | 10 | 0.707 | 0.25 | 0.592 | 0.134 | 0.888 | 0.74 | 0.729 | No |
| *Bowdichia nitida* Spruce ex Benth. | 10 | 0.707 | 0.25 | 0.592 | 0.106 | 0.701 | 0.646 | 0.666 | Yes |
| *Dipteryx polyphylla* Huber | 10 | 0.707 | 0.25 | 0.592 | 0.104 | 0.691 | 0.641 | 0.663 | No |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Dipteryx polyphylla* Huber | 10 | 0.707 | 0.25 | 0.592 | 0.104 | 0.691 | 0.641 | 0.663 | Yes |
| *Dipteryx magnifica* (Ducke) Ducke | 10 | 0.707 | 0.25 | 0.592 | 0.097 | 0.644 | 0.618 | 0.647 | No |
| *Swartzia schomburgkii* Benth. | 10 | 0.707 | 0.25 | 0.592 | 0.087 | 0.58 | 0.586 | 0.626 | No |
| *Anacardium spruceanum* Benth ex Engl. | 10 | 0.707 | 0.25 | 0.592 | 0.073 | 0.486 | 0.539 | 0.595 | No |
| *Eschweilera* sp. | 10 | 0.707 | 0.25 | 0.592 | 0.071 | 0.47 | 0.531 | 0.589 | No |
| *Pouteria anomala* (Pires) T.D.Penn. | 10 | 0.707 | 0.25 | 0.592 | 0.071 | 0.469 | 0.53 | 0.589 | No |
| *Zygia racemosa* (Ducke) Barneby & J.W.Grimes | 10 | 0.707 | 0.25 | 0.592 | 0.066 | 0.439 | 0.515 | 0.579 | No |
| *Sloanea pubescens* (Poepp.& Endl.) Benth. | 10 | 0.707 | 0.25 | 0.592 | 0.066 | 0.438 | 0.515 | 0.579 | No |
| *Simarouba amara* Aubl. | 10 | 0.707 | 0.25 | 0.592 | 0.063 | 0.42 | 0.506 | 0.573 | Yes |
| *Maquira sclerophylla* (Ducke) C.C. Berg | 10 | 0.707 | 0.25 | 0.592 | 0.059 | 0.394 | 0.493 | 0.564 | Yes |
| *Pouteria venosa* (Mart.) Baehni ssp. *amazonica* T.D. Penn. | 10 | 0.707 | 0.25 | 0.592 | 0.053 | 0.353 | 0.472 | 0.55 | No |
| *Corythophora rimosa* W.A.Rodrigues | 5 | 0.353 | 0.25 | 0.592 | 0.064 | 0.425 | 0.508 | 0.457 | No |
| *Astronium* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.092 | 0.613 | 0.455 | 0.421 | No |
| *Brosimum potabile* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.079 | 0.522 | 0.409 | 0.39 | Yes |
| *Chornelia tenuiflora* Benth. | 5 | 0.353 | 0.125 | 0.296 | 0.074 | 0.493 | 0.395 | 0.381 | No |
| *Amaioua* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.063 | 0.417 | 0.356 | 0.355 | Yes |
| *Sextonia rubra* (Mez) van der Werff | 5 | 0.353 | 0.125 | 0.296 | 0.063 | 0.417 | 0.356 | 0.355 | No |
| *Micropholis* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.06 | 0.397 | 0.346 | 0.349 | No |

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|---|---|---|---|---|---|---|---|---|---|
| *Dipteryx* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.054 | 0.357 | 0.326 | 0.335 | Yes |
| *Buchenavia grandis* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.052 | 0.347 | 0.322 | 0.332 | Yes |
| *Eschweilera atropetiolata* S.A.Mori | 5 | 0.353 | 0.125 | 0.296 | 0.049 | 0.329 | 0.312 | 0.326 | Yes |
| *Vantanea parviflora* Lam. | 5 | 0.353 | 0.125 | 0.296 | 0.049 | 0.329 | 0.312 | 0.326 | No |
| *Duckesia verrucosa* (Ducke) Cuatrec. | 5 | 0.353 | 0.125 | 0.296 | 0.048 | 0.319 | 0.308 | 0.323 | No |
| *Apeiba echinata* Gaertn. | 5 | 0.353 | 0.125 | 0.296 | 0.043 | 0.284 | 0.29 | 0.311 | Yes |
| *Eriotheca longipedicellata* (Ducke) A. Robyns | 5 | 0.353 | 0.125 | 0.296 | 0.043 | 0.284 | 0.29 | 0.311 | Yes |
| *Drypetes variabilis* Uittien | 5 | 0.353 | 0.125 | 0.296 | 0.041 | 0.275 | 0.286 | 0.308 | No |
| *Mouriri callocarpa* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.04 | 0.267 | 0.281 | 0.305 | No |
| *Vantanea* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.04 | 0.267 | 0.281 | 0.305 | No |
| *Micrandropsis scleroxylon* W.Rodr. | 5 | 0.353 | 0.125 | 0.296 | 0.039 | 0.259 | 0.277 | 0.303 | No |
| *Parkia multijuga* Benth. | 5 | 0.353 | 0.125 | 0.296 | 0.035 | 0.235 | 0.265 | 0.295 | Yes |
| *Manilkara cavalcantei* Pires & W.A.Rodrigues | 5 | 0.353 | 0.125 | 0.296 | 0.034 | 0.227 | 0.261 | 0.292 | No |
| *Qualea acuminata* Aubl. | 5 | 0.353 | 0.125 | 0.296 | 0.034 | 0.227 | 0.261 | 0.292 | No |
| *Pouteria oblanceolata* Pires | 5 | 0.353 | 0.125 | 0.296 | 0.034 | 0.223 | 0.259 | 0.291 | No |
| *Enterolobium schomburgkii* (Benth.) Benth. | 5 | 0.353 | 0.125 | 0.296 | 0.032 | 0.212 | 0.254 | 0.287 | Yes |
| *Micropholis guyanensis* (A.DC.) Pierre spp. *duckeana* (Baehni) T.D.Penn. | 5 | 0.353 | 0.125 | 0.296 | 0.029 | 0.19 | 0.243 | 0.28 | No |

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|---|---|---|---|---|---|---|---|---|---|
| *Laetia procera* (Poepp.) Eichler | 5 | 0.353 | 0.125 | 0.296 | 0.028 | 0.183 | 0.239 | 0.277 | No |
| *Pouteria ambelaniifolia* (Sandwith) T.D.Penn | 5 | 0.353 | 0.125 | 0.296 | 0.028 | 0.183 | 0.239 | 0.277 | No |
| *Glycydendron amazonicum* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.027 | 0.18 | 0.238 | 0.276 | No |
| *Lacmellea gracilis* (Müll.Arg.) Markgr. | 5 | 0.353 | 0.125 | 0.296 | 0.027 | 0.18 | 0.238 | 0.276 | No |
| *Qualea albiflora* Warm | 5 | 0.353 | 0.125 | 0.296 | 0.027 | 0.176 | 0.236 | 0.275 | No |
| *Vatairea paraensis* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.027 | 0.176 | 0.236 | 0.275 | No |
| *Sterculia excelsa* Mart. | 5 | 0.353 | 0.125 | 0.296 | 0.025 | 0.166 | 0.231 | 0.272 | No |
| *Endopleura uchi* (Huber) Cuatrec. | 5 | 0.353 | 0.125 | 0.296 | 0.025 | 0.164 | 0.23 | 0.271 | No |
| *Tabebuia* sp. | 5 | 0.353 | 0.125 | 0.296 | 0.025 | 0.163 | 0.229 | 0.271 | No |
| *Vatairea sericea* Ducke | 5 | 0.353 | 0.125 | 0.296 | 0.025 | 0.163 | 0.229 | 0.271 | No |
| *Jacaranda copaia* (Aubl.) D.Don | 5 | 0.353 | 0.125 | 0.296 | 0.023 | 0.153 | 0.225 | 0.268 | No |
| *Pterocarpus rohrii* Vahl | 5 | 0.353 | 0.125 | 0.296 | 0.02 | 0.132 | 0.214 | 0.26 | Yes |

# 3. FOREST STRUCTURE AND DEGRADATION DRIVE CANOPY GAP SIZES ACROSS THE BRAZILIAN AMAZON[2]


## Resumo

Clareiras são aberturas no dossel da floresta que ocorrem devido à queda de galhos e mortalidade das árvores. Com isso, a luz atinge as camadas inferiores da copa através dessas clareiras, permitindo que as árvores presentes no sub-bosque possam crescer e, consequentemente, manter a heterogeneidade e a biodiversidade em florestas tropicais. A distribuição do tamanho e frequência das clareiras segue a distribuição "power-law", e a inclinação da reta da função "power-law" (α) é um indicador da estrutura e da dinâmica florestal. Neste trabalho foram detectadas clareiras a partir de um conjunto de dados LiDAR que consistem de 650 transectos aleatoriamente distribuídos pela Amazônia brasileira. Estes dados fornecem uma perspectiva sem precedentes sobre a variação estrutural em mais de 2500 km² de floresta. Portanto, foi possível investigar como o coeficiente α da função "power-law" variou em relação à estrutura florestal, elevação, fertilidade do solo, déficit hídrico, velocidade do vento e intensidade de queda de raios. Os resultados mostraram que florestas sob algum tipo de efeito antropogênico apresentaram clareiras maiores que em florestas classificadas como intactas. Dentro das florestas intactas, foi observado um padrão de variação de α na direção Noroeste-Sudeste na Amazônia brasileira (clareiras maiores no Sudeste). Esse resultado está em concordância com taxas de mortalidade encontradas em estudos recentes. As variáveis mais importantes na explicação dessa variação foram a altura média do dossel e a altura das árvores maiores, com efeitos opostos na predição de α. Florestas com a altura do dossel maior contém menos e menores clareiras, por outro lado a presença de árvores muito grandes resultam em clareiras maiores. As variáveis ambientais com menos importância, mas significativas no modelo, mostraram que clareiras maiores ocorreram em florestas sob déficit hídrico acentuado e com solos mais férteis, sob rajadas de vento e maior intensidade de queda de raios. A distribuição de clareiras maiores no dossel variou substancialmente na Amazônia brasileira como um resultado da estrutura do dossel e taxas de mortalidade. Nós mapeamos essa variação e encontramos mais e maiores clareiras em florestas modificadas pelo homem, florestas sobre solos mais férteis e expostas a maior velocidade de vento, queda de raios e estresse hídrico. O aumento de eventos extremos no clima devido às mudanças climáticas pode, portanto, aumentar o número e a frequência na ocorrência de clareiras nas florestas que, atualmente, são consideradas intactas.


Palavras-Chave: Altura da copa, dinâmica florestal, distribuição do tamanho de clareiras, ecologia de paisagem, floresta tropical, gradientes ambientais, modelagem, power-law.


## Abstract

Canopy gaps are openings in the forest canopy resulting from branch fall and tree mortality events. Light reaches the lower layers of the canopy through these gaps, enabling understory trees to grow and maintaining the high heterogeneity and biodiversity of tropical forests. The size distribution of canopy gaps follows a power-law distribution, and the slope of this power-law (α) is a key indicator of forest structure and dynamics. Low values of α (usually defined as $\alpha < 2$) correspond to forests with a higher proportion of large gaps. We


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detected canopy gaps using a unique LiDAR data set consisting of 650 transects randomly distributed across the Brazilian Amazon Forest providing an unprecedented perspective on forest structural variation over 2500 $km^2$ of forest. We found that human modified forests had a higher proportion of large gaps than intact forests. We observed a large-scale Northwest to Southeast pattern in α (higher proportion of large gaps in the Southeast), which aligns with recent work on tree mortality rates. Forests containing very tall trees were associated with a higher proportion of large gaps. We also found a higher proportion of large gaps occurring in drier forests, forests with high soil fertility, strong wind gust speeds, and high lightning intensity. Synthesis: The proportion of large gaps in the forest canopy varies substantially over the Brazilian Amazon as a result of canopy structure and disturbance rates. We mapped this variation and found a higher proportion of large gaps in human modified forests, forests on fertile soils and those exposed to higher wind, lightning and drought stress. Increasing extreme weather events due to climate change may therefore increase the proportion of large gaps in currently intact forests, causing them to resemble human modified forests.

Keywords: Canopy height, environmental gradients, forest dynamic, gap size distribution, landscape ecology, modeling, power-law, tropical forest.

## 3.1 Introduction

Gaps in tropical forest canopies arise from tree mortality and play an important role in forest regeneration processes and forest biodiversity by creating habitat heterogeneity for forest dwelling organisms (Grubb 1977, Brokaw 1985, Yamamoto 1992, Muscolo et al. 2014). Many understory plants survive in a low-light environment and depend upon these occasional gaps to capture light and grow (Marthews et al. 2008). Small gaps favour species which are shade-tolerant, while large gaps favour light-demanding pioneer species (Brokaw 1985, Yamamoto 1992). Gap colonization is driven by the nature of soil, plants and animals in the surrounding forest (Grubb 1977). The size of gaps is also linked to the mode of death - with broken/uprooted trees leaving larger gaps than standing dead trees (Esquivel-Muelbert et al. 2020. In this study we map the size distributions of canopy gaps across the Brazilian Amazon and show how they are related to canopy height and environmental variables.

Remote sensing technologies make it possible to map canopy gaps over large areas of tropical forests (Lobo & Dalling 2013, Asner et al. 2013, Espírito-Santo et al. 2014, Kent et al. 2015, Wedeux & Coomes 2015, Dalagnol et al. 2021). Several studies using airborne lidar

datasets have found that gap size distributions follow a simple power-law function ($f(x) = cx^{-\alpha}$) in which small gaps heavily outnumber large gaps in all forest environments (Kellner & Asner 2009, Asner et al. 2013, Lobo & Dalling 2013, Espírito-Santo 2014, Silva et al. 2019). Identifying power-law distributions for ecological features such as canopy gaps provides insight into the nature of gap formation processes such as tree mortality (Goodbody et al. 2020). The power-law scaling coefficient α has been associated with the type and degree of disturbance in forested areas at the landscape and regional scales (Yamamoto 1992), and can vary from less intense disturbance events (lower proportion of large gaps) to mortality of large trees or damage at the stand level (higher proportion of large gaps) (Asner et al. 2013, Silva et al. 2019). Extremely large gaps are very rare and they are mainly caused by wind storms (Espírito-Santo et al. 2014, Negron-Juarez et al. 2018), fire and logging events (Broadbent et al. 2008). Conversely, canopy openings due to tree mortality and branch falls result in small gaps (<0.1 ha) and are far more common (Asner et al. 2013, Espírito-Santo et al. 2014), and account for an estimated 1.28 Pg of gross carbon losses per year over the entire Amazon region - a proportion of 98.6 % of the total carbon losses due to gap formation (Espírito-Santo et al. 2014).

The size distribution of canopy gaps is also related to the history of anthropogenic disturbance (Kent et al. 2015). Forest recovery after a disturbance event depends on the severity of disturbance, the time since it occurred, and local environmental factors (Kent et al. 2015, Cole et al. 2014), as well as anthropogenic actions such as deforestation, logging and fires (Aragão et al. 2014). In Gola rainforest park in Sierra Leone, Kent et al. (2015) found a higher gap fraction in logged blocks (3 - 6.3%) than in old-growth forest blocks (1 - 2.3%). In a peat swamp forest in Indonesia Wedeux and Coomes (2015) showed that, even eight years after becoming protected for conservation, logged plots had a higher gap fraction and a higher proportion of large gaps (lower α) in comparison with an old-growth forest. Popatov et al.

(2008) provide a map of ‘intact forest landscapes’ across the Brazilian Amazon which we use in this study. They define intact forests as “an unbroken expanse of natural ecosystems within the zone of current forest extent, showing no signs of significant human activity, and large enough that all native biodiversity, including viable populations of wide-ranging species, could be maintained”.

The scaling coefficient α will vary along environmental gradients, since forest dynamics is controlled by environmental variables (Phillips et al. 2004, Quesada, Phillips, Schwarz, et al. 2012). Dalagnol et al. (2021) found that gap fraction across the Brazilian Amazon was positively correlated with soil nutrients ($r$ = 0.46), water deficit ($r$ = 0.42), dry season length ($r$ = 0.41), wind speed ($r$ = 0.21), and floodplains fraction ($r$ = 0.27); and negatively correlated with distance to the forest edge ($r$ = -0.43) and precipitation ($r$ = -0.38). Gap size distribution in primary forests has been linked to broad-scale patterns such as climate, topography and soils (Goulamoussène et al. 2017, Goodbody et al. 2020), as well as wind and lightning. Mortality and turnover rates in the Amazon mainly vary along an east-west gradient coinciding with a soil fertility gradient, with higher tree mortality and turnover in the rich soils of western Amazon (Phillips et al. 2004, Quesada, Phillips, Schwarz, et al. 2012, Esquivel-Muelbert et al. 2020). A large proportion of Amazonian forests have also experienced water stress by intense droughts (Marengo et al. 2018), which has increased rates of tree mortality and biomass loss (Phillips et al. 2009, Phillips et al. 2010). Wind has also been linked to higher tree mortality (Rifai et al. 2016, Negron-Juarez et al. 2018), with forests in the northwest Amazon more vulnerable to windthrows and higher tree mortality than central Amazonian forests (Negron-Juarez et al. 2018). Recent work has shown that large trees are more likely to be directly struck by lightning in tropical forests with strong influences on forest structure and dynamics (Gora, Muller-Landau, Burchfield et al. 2020).

Dalagnol et al. (2021) focused on scaling-up tree mortality estimates and did not explore the gap size distribution and its relationship with environmental factors.

Local canopy height also influences the number and size distribution of canopy gaps (Wedeux & Coomes 2015). This relationship depends on the definition of a canopy gap, i.e. whether the cutoff height is defined as a relative number to local canopy height or as a fixed value (Dalagnol et al. 2021). Therefore, interpreting environmental effects on gap properties across heterogeneous forests can be challenging. For example, a treefall event creates a much smaller gap in a forest with a substantial understory layer, as compared to the same event in sparser forest (Leitold et al. 2018, Dalagnol et al. 2021). Furthermore, the time it takes for a gap to close depends on the surrounding canopy height (Grubb 1977, Muscolo et al. 2014) and the size of the gap (Dalagnol et al. 2019). Canopy height is related to environmental factors, and a recent study in the Brazilian Amazon showed that the presence of very large trees is explained by wind, soil, precipitation, temperature and light availability (Gorgens et al. 2020). Therefore, we expect both canopy height and environmental factors interacting to control the size distribution of canopy gaps, however little is known about these interactions in Amazonian forests.

In this study, we use a large tropical forest LiDAR data set to explore the relationship between gap size distribution with environmental factors, anthropogenic disturbance and canopy height. This data set, which was collected by the “Improving Biomass Estimation Methods for the Amazon” project, provides an unprecedented perspective on forest structural variation over 2500 km2 of forest. We formulated four hypotheses:

H1. Human modified forests contain a higher proportion of large gaps (lower $\alpha$) than intact forest.

H2. Forests with a higher maximum tree size will contain a higher proportion of large gaps (lower $\alpha$ in taller forests) because big trees produce large gaps when they die.

H3. Higher water availability and soil fertility will be associated with a lower proportion of large gaps because gaps will recover more quickly.

H4. Higher wind speeds and lightning intensity will be associated with a higher proportion of large gaps (lower α) due to an increased rate of disturbance. Therefore, in a region with high disturbance rates may resemble human modified forests.

## 3.2 Development

### 3.2.1 Methodology

#### 3.2.1.1 LiDAR data collection and processing

The "Improving Biomass Estimation Methods for the Amazon" project (Ometto et al. 2021) collected >650 LiDAR transects of 375 ha (12.5 x 0.3 km) each between 2016 and 2018 (Almeida et al. 2019, Tejada et al. 2019). The transects were allocated in forested areas by using mask layers for primary (PRODES, Inpe, 2016) and secondary forests (TerraClass, Inpe, 2014). Within these classes the transects were randomly located, except for a small number of transects which intentionally overlapped with existing field plots. The flights were performed at approximately 600 m height using a LiDAR Harrier 68i sensor. The survey produced a point cloud with a minimum density of 4 points.m$^{-2}$ (Andrade et al. 2018), based on a field of view of 45° and footprint diameter between 15 and 30 cm. The data had horizontal and vertical accuracy of ±1.0 m and ±0.5, respectively (Almeida et al. 2019, Gorgens et al. 2019, Tejada et al. 2019, Gorgens et al. 2020).

We reclassified all LiDAR points into ground, vegetation and noise, excluding noise points from further analyses. The classification of the points in LiDAR data is important to provide reliable digital terrain models (DTM) and consequent height values used to estimate forest attributes, such as volume or biomass (Leitold et al. 2015; Longo et al. 2016). Points corresponding to terrain (ground points) were isolated and interpolated by the triangulation

irregular network method (TIN), generating a 1-m spatial resolution DTM. In addition, we subtracted the elevation for each vegetation point by its corresponding DTM to obtain the height (Popescu & Wynne 2004). Lastly, we applied the pit-free algorithm to create the canopy height model (CHM, Khosravipour et al. 2014) using the one highest return per grid cell and triangulated them in order to obtain a 1-m spatial resolution CHM (Figure 1). The LiDAR transects were processed using LAStools software (v. 190404, Isenburg 2019).

#### 3.2.1.2 Extracting gaps and characterizing their size distributions

As in other studies, we defined canopy gaps as contiguous areas of low canopy height which meet a number of thresholds. The first threshold (A) is that the canopy height must be below a cutoff height. We chose to use a 10 m cutoff height following (Silva et al. 2019) since this is commonly found in LiDAR data but low enough to be the result of a disturbance event. The second threshold (B) is that the area of low canopy height must be larger than 20 m², this is to focus on larger gaps which are more likely the results of disturbance events and to filter out noise and small gaps between tree crowns. The third threshold (C) was that the gap must be smaller than 10,000 m² (1 ha) to avoid permanent features, such as roads or rivers, being classified as gaps. We then filtered out erroneous gaps (D) which were usually found along the transect edges (Figure 1a). We achieved this by calculating topographic position index, which depends on the values of neighbouring pixels, and excluded all polygons with missing values (Figure 1b). We filtered out transects where the median canopy height (Hmed, see “Characterizing forest structure” section) was under 15 m since we could not reliably detect gaps in these cases. This reduced the number of transects in our models to 487.

These thresholds are somewhat arbitrary and different studies choose different values (Brokaw 1985, Marthews et al. 2008, Wedeux & Coomes 2015). We conducted a sensitivity

analysis and found that our results were not highly sensitive to the choices in B, C or D (Figures S3 and S4). Our results were sensitive to the choice of cutoff height (A) (Figure S2). We found that a cutoff height of 5 m or 10 m produced similar results, but that a 2 m cutoff height resulted in far fewer gaps, particularly the large gaps we are interested in here. We were also concerned that the 2 m cutoff height would be more sensitive to errors in the ground detection algorithm used to create the canopy height model. We therefore decided to use the 10 m cutoff height for our analysis, but models for the 2 m and 5 m cutoff heights are provided in the supplementary materials (Figure S2). We used the ForestGapR package (Silva et al. 2019) to extract all polygons within the established parameters and the spatialEco package (Evans 2020) to calculate the topographical position index.

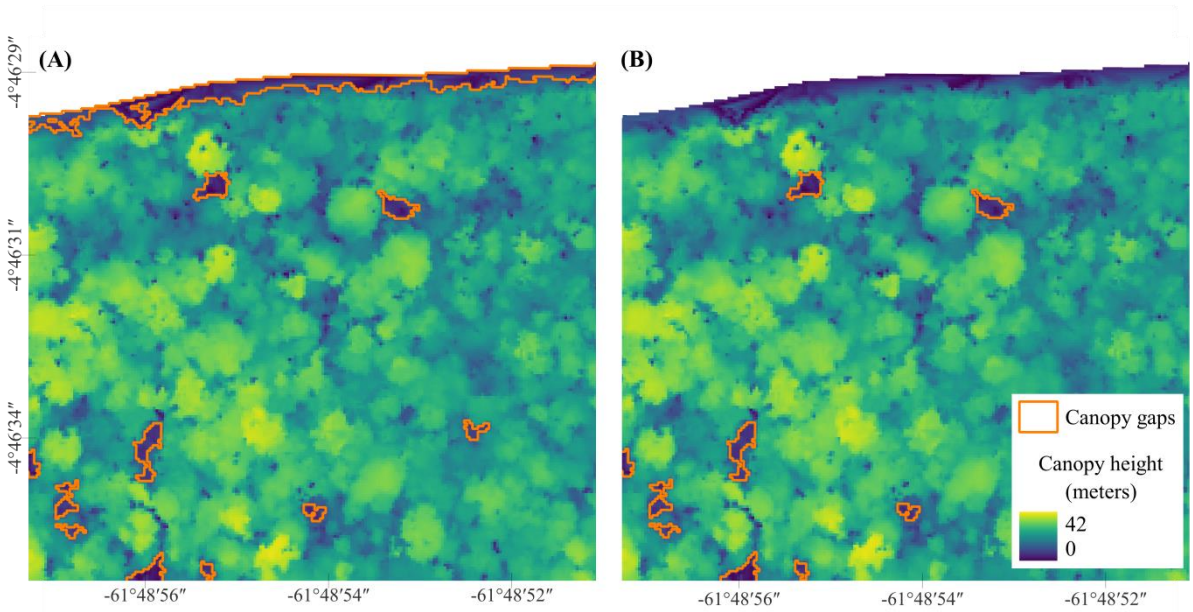


Figure 1. Gap filters applied in the dataset: example of gap delineation in a transect with the lowest proportion of large gaps (α = 2.50) before (A) and after (B) applying the topographical position index filters.

We calculated the area of each gap to have their size and then be able to fit a simple power-law function (Equation 1):

$$f(x) = cx^{-\alpha} \quad (1)$$

where c is a normalization term, x is the gap size (m²), and the scaling parameter α quantifies the disturbance level. As a rule of thumb, higher values of α (> 2) are found in forests dominated by small gaps and with less intense disturbance events, whereas lower α values (< 2) indicate a higher proportion of large gaps (Asner et al. 2013, Silva et al. 2019). Deviation from the power-law pattern has also been reported at large gap sizes, but the interpretation of the scaling coefficient remains the same (Wedeux & Coomes 2015). Using the poweRlaw package (Gillespie 2015) we looked for the scaling coefficients (α) of each one of the transects. We set 20 m² as a minimum gap size (setXmin function) and then we estimated the power-law parameters. Finally, we plotted the α scaling coefficient to understand how α varies across the Brazilian Amazon biome.

#### 3.2.1.3 Characterizing forest structure

Following previous studies (Feldpausch et al. 2011), we split the Amazon into four regions (North, West, South-East, Central-East). We tested for statistical differences among mean α's by region, on which we applied the post hoc Tukey's test at 95% of confidence level.

To classify intact forests, we used the intact forest landscapes (IFL) map (Potapov et al. 2008), which delineates contiguous areas of natural ecosystems, showing no signs of significant human activity, and large enough that all native biodiversity could be maintained. The IFL map (scale 1:1,000,000) for 2016 was applied to divide the dataset into two categories of forests - intact and human modified forests. This product was created through expert-based visual mapping of fragmented and altered forest areas using medium spatial resolution images from Landsat TM circa year 1990 and ETM+ circa year 2000 as the primary data source for year 2000 IFL mapping. The IFL map updates, such as the one

available for 2016, were based on the same data sources and methodology as the year 2000 mapping to ensure consistency (see details in https://intactforests.org/). We included IFL as a factor in our linear model to test whether land-use is related to gap size distribution (H1).

We extracted median canopy height (Hmed) and 99th percentile of canopy height (Hmax) from the CHM. These canopy height metrics will soon be available at a global scale from the Global Ecosystem Dynamics Inventory project (Duncanson et al. 2020) which may allow future studies to extend our predictions. The Hmed was used to filter transects where the median height was below 15 m, to avoid the inclusion of erroneous gaps in the analysis. The Hmax variable was used as predictor variable to test the hypothesis H2.

The elevation was computed based on the third version of the Shuttle Radar Topography Mission (SRTM in m) provided by NASA JPL with a spatial resolution of 30 m (Farr et al. 2007; Liu et al. 2014). The SRTM mission occurred in February 2000 and collected data during ten days of operations. The digital elevation model (DEM) is available from 60° north latitude and 56° south latitude, covering 80% of Earth's land surface. SRTM mission employed two synthetic aperture radars: a C band system (5.6 cm wavelength) and an X band system (3.1 cm).

#### 3.2.1.4 Environmental data

To test our hypotheses (H3 and H4) we downloaded spatial data on water deficit, soil cation concentration, wind gust speed and lightning frequency for the entire Amazon.

The water deficit (DEF in mm) was provided by the TerraClimate dataset, a global monthly climate and water balance for terrestrial surfaces spanning 1958–2015. With a spatial resolution of ~5 km, this layer combined high-spatial resolution climatological normals from WorldClim with Climate Research Unit (CRU) Ts4.0 and the Japanese 55-year Reanalysis

(JRA-55) data. DEF is a derived variable calculated from the difference between reference evapotranspiration and actual evapotranspiration. The reference evapotranspiration was calculated using the Penman-Monteith approach (Abatzoglou et al., 2018).

The soil cation concentration (SCC in cmol(+).kg-1) is a result of compiling soil data and adding indicator species to derive soil information for locations that have been sampled for plants but not soils. This approach increased the number of points to be used in soil mapping. A raster map of estimated SCC values covering all Amazonia was obtained by inverse distance weighting interpolation at the spatial resolution of 6 arcmin (~11 km). The raster values are in log-transformed scale and represent the soil fertility gradient across the Amazon (Zuquim et al. 2019).

We used the instantaneous 10m wind gust (WG in m.s-1), which represents the maximum wind gust averaged over 3 second intervals, at a height of 10 meters above the surface of the Earth. This layer has a spatial resolution of ~25 km. This variable came from the fifth major global reanalysis (ERA5) produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). The reanalysis combined model data with observations from across the world into a globally complete and consistent dataset (Olauson 2018).

The lightning frequency layer (LGT) was provided by the Lightning Imaging Sensor (LIS) with a spatial resolution of ~11 km. The sensor collected data onboard the Tropical Rainfall Measuring Mission provided by NASA Earth Observing System Data and Information System (EOSDIS) from January 1998 to December 2013. The lightning flash rates provided the basis to detect the distribution and variability of total lightning occurring in the Earth's tropical and subtropical regions (Albrecht et al., 2016).

We resampled all the layers above to a spatial resolution of 500 m applying the bilinear interpolation method, cropped them to the Amazon biome extension (Figure S5), and calculated the transects median values to correlate them with their respective level of

disturbance represented by α. We used the raster package (Hijmans & Etten 2012) to work with these layers.

#### 3.2.1.5 Statistical modeling

During the exploratory analysis, we performed the Pearson correlation (r) among α and environmental variables and forest structure metrics. The resulting covariance matrix guided us during selection of predictor variables that should be included in the model, avoiding the strongly correlated metrics (Figure S6). The r among variables were below 0.6 and we kept all variables in the models.

We standardized all predictor variables rescaling them to have a mean of zero and a standard deviation of one. Thereafter, we fitted linear regression models to capture the variance explanation of environmental variables and forest structure metrics (Equation 3):

$$\alpha_{ij} = \beta_0 + \beta_j X_{ij} + \varepsilon_{ij} \quad (3)$$

where $\alpha_i$ is the power-law scaling coefficient for transect *i*, $\beta_0$ is the intercept, $\beta_j$ is the regression coefficient for each predictor variable $X_{ij}$, and $\varepsilon_{ij}$ is the residual error. Here, *j* is the index of the predictor variable.

To assess the goodness of fit we performed a graphical analysis, calculated the Akaike Information Criterion (AIC) and the adjusted coefficient of determination (Adj. $R^2$). We also evaluated the variance inflation factor (VIF) to see how strong was the collinearity among predictors. The final model was built with the variables that most contributed to understanding α variation across the Brazilian Amazon.

### 3.2.2 Results

#### 3.2.2.1 Gap distributions across the Brazilian Amazon biome

We analyzed 487 transects of LiDAR data randomly distributed over the Brazilian Amazon to test whether the size distribution of canopy gaps varies systematically. Figure 2a shows patterns of gap size distributions across the Amazon from Northwest to Southeast. The South-east region had the highest proportion of large gaps (mean α ± 95% confidence interval: 1.9422±0.0223). The North (2.0066±0.0283) and West (2.0162±0.0361) regions contained a similar distribution of gaps while the Central-east (2.0928±0.0199) region had the lowest proportion of large gaps (Figure 2c).

#### 3.2.2.2 Human modified forests

We tested whether human modified forests contained a higher proportion of large gaps (lower α) than intact forest (H1). The range of α values for human modified forest (1.75 - 2.31, n = 119) was significantly lower than that found for intact forest (1.66 - 2.50, n = 368, Wilcoxon p-value < 0.001), although the two distributions overlapped. The mean α for intact forest areas of 2.04±0.0156 and 1.95±0.0231 for human modified forests. This result supports H1 that human modified forests contain a higher proportion of large gaps than intact forests (Figure 2b). This is also demonstrated by the fact that intact forests status significant increased predicted α in all our multiple linear regression models (Table 1).

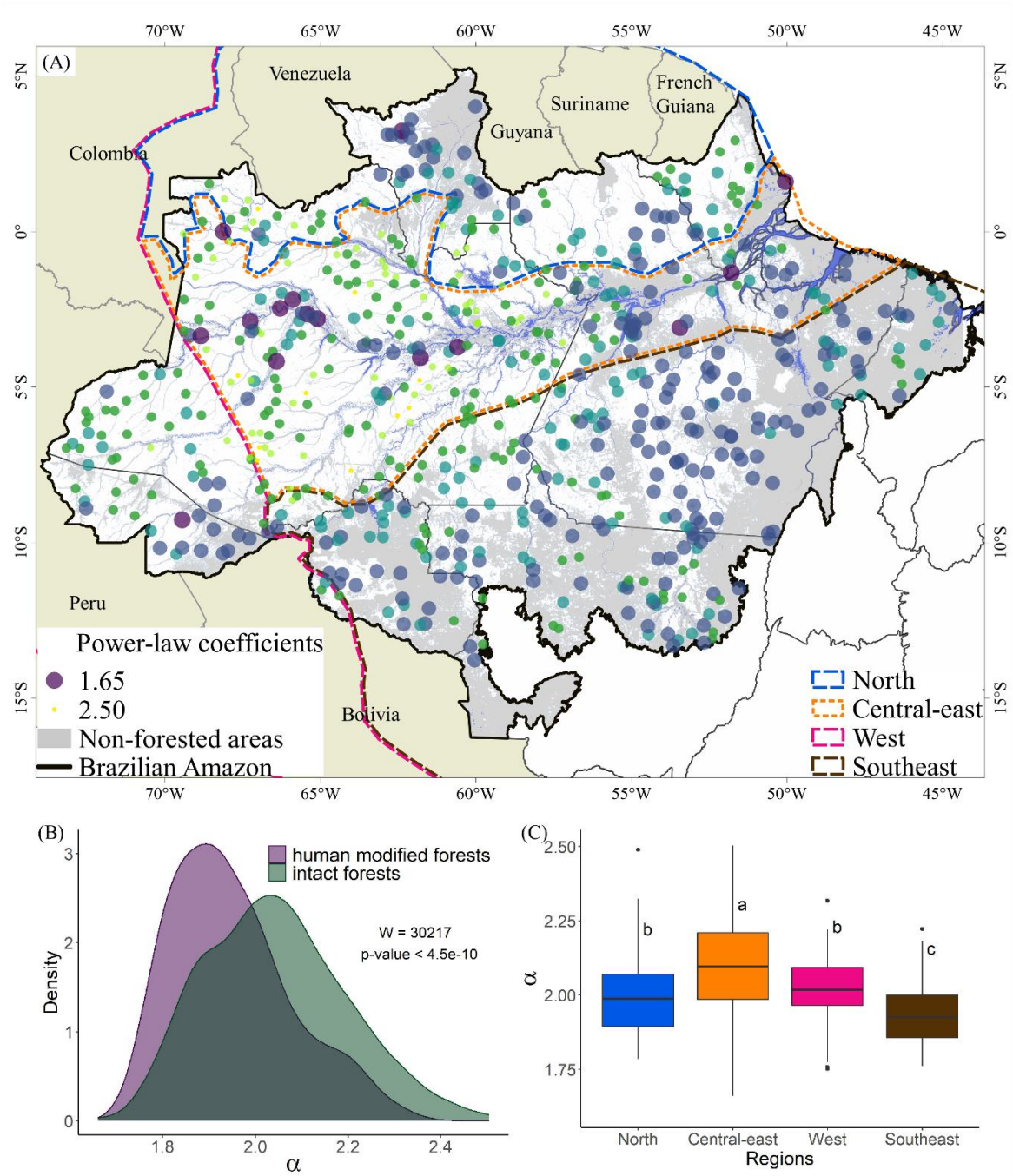


Figure 2. Canopy gap size distribution across the Brazilian Amazon derived from airborne lidar transects (n = 487). (A) Each point represents a LiDAR transect and the size represents the estimated α for both intact forested areas and human modified forests. Dashed lines represent the regions' division obtained from Feldpausch et al. (2011); (B) distribution of α for intact forests (green) and human modified forest (purple) (significantly different according to Wilcoxon test, p<0.001); (C) Boxplot showing the α values in each region considering

intact forests only. Letters show the results from post hoc Tukey's tests comparing the mean α values among the different regions within the Amazon biome.

#### 3.2.2.3 Modelling the size distribution of canopy gaps

We used multiple linear regression to understand how the environmental variables and canopy height jointly explain the observed variation in gap size distribution. We present three separate models, all of which contained intact forest status as a factor (Table 1). We also test the models with interaction terms but the results did not contribute much to explain the α variation (Table S7). The first model additionally contained maximum canopy height. The second model excluded maximum canopy height and contained all significant environmental variables (water deficit, soil cation content, wind gust speed and lightning intensity). The third model contained all significant variables.

Our second hypothesis (H2) was that forests with taller trees will contain a higher proportion of large gaps because big trees produce large gaps when they die. We found that maximum tree height was negatively associated with α in both model 1 and model 3, meaning that the presence of very tall trees was associated with a higher proportion of large gaps (supporting H2).

Our third hypothesis (H3) was that higher water availability and soil fertility will be associated with a lower proportion of large gaps because gaps will recover more quickly. We found that water deficit and soil cation content were negatively associated with α in both model 2 and 3. This means that a higher proportion of large gaps is associated with drier forests (contrary to H3) and those with more fertile soils (supporting H3).

Our final hypothesis (H4) was that higher wind speeds and lightning intensity will be associated with a higher proportion of large gaps due to an increased rate of storm disturbance. Both model 2 and 3 found a significant negative effect of wind gust speed on α,

which supports H4. However, lightning intensity was insignificant in model 2 and marginally significant in model 3, providing weak support for this part of H4.

Table 1. Power-law α coefficient fitted as function of environmental and ALS canopy height metric (H). Estimate = model's coefficients and Std error = standard error. The predictor variables were: IFL = intact forest landscapes used to split data into intact (1) and human modified forests (0); Hmax = 99$^{th}$ percentile from ALS transects; DEF = water deficit (mm); SCC = soil cation concentration (cmol(+)/kg); WG = instantaneous 10m wind gust (m/s) and; LGT = Lightning density; Adj. $R^2$ =adjusted coefficient of determination; AIC = Akaike information criteria; VIF = variance inflation factor.

| | **Model 1 (α ~ H)** | | | **Model 2 (α ~ environment)** | | | **Model 3 (α ~ H + environment)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | Estimate | Std error | VIF | Estimate | Std error | VIF | Estimate | Std error | VIF |
| **Intercept** | 1.943 *** | 0.012 | | 1.981*** | 0.012 | | 1.978 *** | 0.012 | |
| **IFL (1 / 0)** | 0.103 *** | 0.015 | 1.003 | 0.057 *** | 0.013 | 1.122 | 0.057 *** | 0.013 | 1.158 |
| **$H_{max}$** | -0.051 *** | 0.006 | 1.003 | - | - | - | -0.023 *** | 0.006 | 1.388 |
| **DEF** | - | - | - | -0.042 *** | 0.006 | 1.362 | -0.038 ** | 0.007 | 1.523 |
| **SCC** | - | - | - | -0.052 *** | 0.006 | 1.142 | -0.045 *** | 0.006 | 1.271 |
| **WG** | - | - | - | -0.019 ** | 0.006 | 1.173 | -0.019 ** | 0.007 | 1.855 |
| **LGT** | - | - | | - | - | - | -0.014 * | 0.007 | 1.594 |
| **Adj. $R^2$** | **0.185** | | | **0.374** | | | **0.392** | | |
| **AIC** | **-546** | | | **-673** | | | **-685** | | |

### 3.2.3 Discussion

#### 3.2.3.1 Human modified forests contain a higher proportion of large gaps

Our findings show that human modified forests are characterized by a higher proportion of large gaps with α values smaller than 2 in 85 transects out of 119 (71%).

Conversely, 58% of transects (215 out of 368) with α values larger than 2 were intact forests. The low α values we found in human modified forests likely indicates particularly high rates of disturbance in these areas.

All our models saturated at approximately α = 2.23 (Figure 5), which represents the maximum value predicted by our model. This indicates that these intact forests with very low proportions of large gaps are difficult to distinguish from each other. We suggest further work to address this knowledge gap, perhaps focused on stem density, species composition or soil properties (ter Steege et al. 2006, Quesada, Lloyd, Schwarz et al. 2010, Quesada, Phillips, Schwarz, et al. 2012), for which we have particularly little data in this region.

#### 3.2.3.2 Tall trees leave large canopy gaps when they fall

We found that α was negatively correlated with the local maximum canopy height. This effect supports our hypothesis (H2) that forests containing the tallest trees also contain a higher proportion of large gaps. This is likely because large trees leave large canopy gaps when they fall, as hypothesized by Grubb (1977).

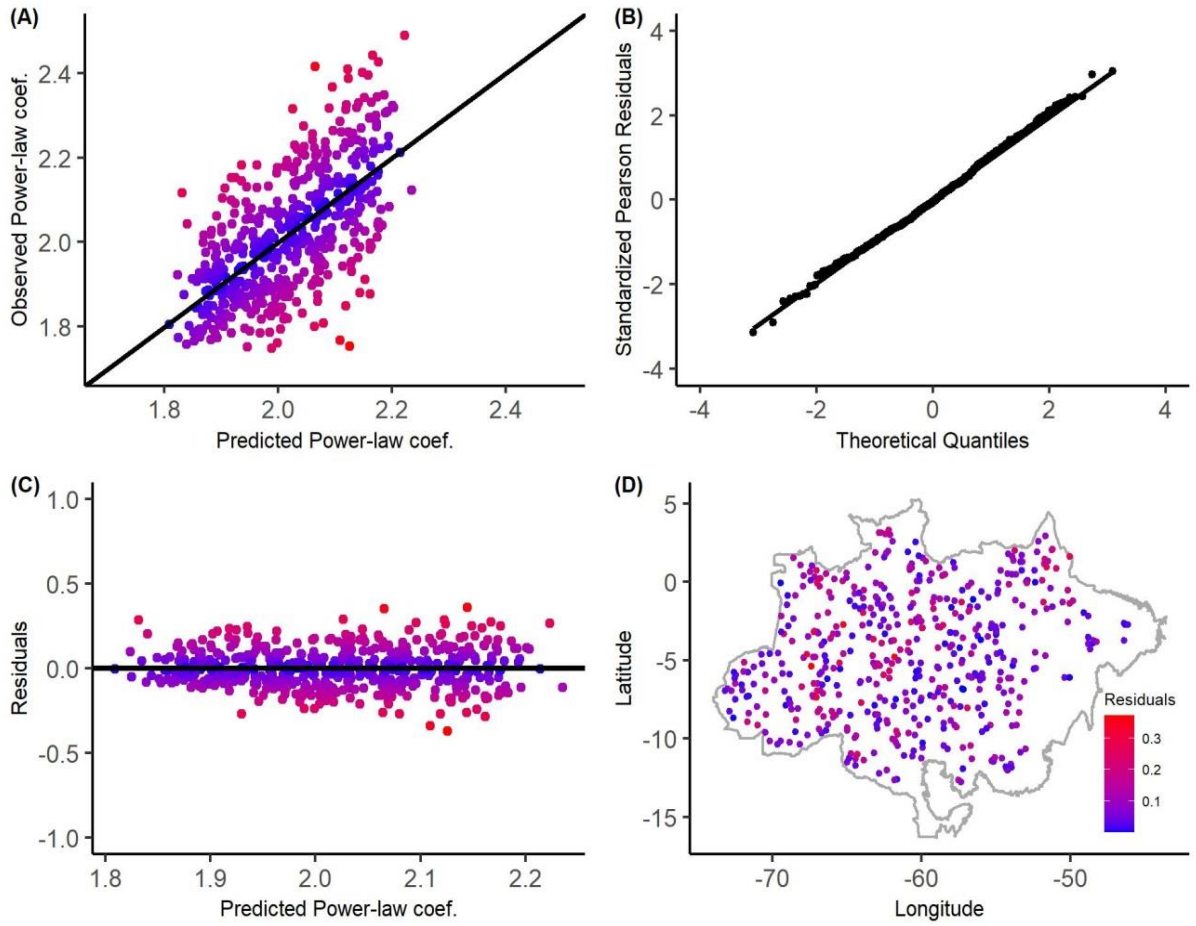


Figure 5. Goodness-of-fit of the final model: (A) predicted vs observed α values from the power-law function; (B) normal quantile-quantile plot for the standardized Pearson residuals; (C) scatter plot of residuals; and (D) the residuals distribution for all ALS transects across the Brazilian Amazon.

#### 3.2.3.3 Large gaps are more common in productive forests

We hypothesized (H3) more productive forests with recover from disturbance more quickly, and therefore contain a lower proportion of large gaps. In support of this hypothesis, we found that drier forests were associated with a higher proportion of large gaps (lower α), particularly in the Southeast fringes with frequent prolonged moisture deficits (Phillips et al. 2009). This follows similar regional patterns previously described for mortality rates (Phillips et al. 2004, Phillips et al. 2009, Quesada, Phillips, Schwarz, et al. 2012, Zuquim et al. 2019).

However, higher soil nutrient availability was associated with a higher proportion of large gaps. For example, Acre state has fertile soils (Quesada, Phillips, Schwarz, et al. 2012, Zuquim et al. 2019) and high productivity which results in high turnover rates (Phillips et al. 2004) and a high proportion of large gaps. The Southeast region also contains fertile soils (Zuquim et al. 2019), which are strongly associated with a number of important forest attributes, particularly species occurrence (ter Steege et al. 2006, Figueiredo et al. 2018, Tuomisto et al. 2019). Conversely, the poor nutrient soils found in the centre of the biome, mostly Amazonas state (Figueiredo et al. 2018), was associated with a lower proportion of large gaps. This suggests that these areas of higher soil fertility have a high disturbance rate, and therefore a large number of gaps despite their presumably quicker recovery rates.

These two results suggest a complex relationship between forest productivity, disturbance rates and recovery. Combining this with our findings on H2, that tall trees are associated with a higher proportion of large gaps, suggests that high disturbance rates are often found in highly productive forests.

#### 3.2.3.4 Wind and lightning are associated with a higher proportion of large gaps

Increased wind gust speeds and lightning frequency were associated with a higher proportion of large canopy gaps (lower α) suggesting that these large gaps are caused by disturbance (H4).

In extreme cases, wind disturbance can cause extensive damage (gaps >10 ha) to the forest canopy (Negron-Juarez et al. 2018, Espírito-Santo et al. 2014), but the frequency of smaller scale wind disturbance is more difficult to study. Wind may be the direct cause of death for some individual trees and will also cause damaged / dead trees to snap or uproot, increasing the size of canopy gaps (Esquivel-Muelbert et al. 2020). Individual trees acclimate to their local wind environment (Bonnesouer et al 2016) so when they are exposed to

increased wind loading, for example due the creation of a nearby canopy gap, they are more likely to be damaged (Mitchell et al. 2013, Aleixo et al. 2019, Kamimura et al. 2019). This leads to a gap 'contagion' effect where large gaps may grow over time (Wedeux & Coomes 2015).

We also found that increased lightning frequency was associated with a higher proportion of large gaps. Lightning is often underestimated as a driver of tree mortality, partly because it can take many years for a tree to die (Yanoviak et al 2020) and the proximate cause of death may be mislabeled (e.g. as wind damage). Recent studies show that a single lightning strike can kill multiple trees, that it predominantly affects taller trees, and that lightning could be responsible for approximately 40% of the mortality of tall trees in lowland tropical forests (Yanoviak et al 2020; Gora, Burchfield, Muller-Landau et al., 2020).

#### 3.2.3.5 Large-scale trends in gap size distributions across the amazon

Overall, we found a northwest to southeast pattern in α across the intact forests of the Brazilian Amazon. The Central-east Amazon, which is characterized by slower forest dynamics (Phillips et al. 2004, Esquivel-Muelbert et al. 2020), exhibited a lower proportion of large gaps. This contradicts our hypothesis (H3) that higher turnover leads to a lower proportion of large gaps due to faster recovery rates. However, the Northern region, which also has slow dynamics (Phillips et al. 2004, Esquivel-Muelbert et al. 2020), had a higher proportion of large gaps with a mean α statistically indistinguishable from that of the Western Amazon. Phillips et al. (2004) found that the Western and Southern regions had nearly double the turnover rate (median value 2.60 % yr-1) compared to the Eastern and Central regions (1.35 % yr-1).

In addition to turnover rates, canopy gaps are also related to tree mortality rates. Tree mortality rates vary across the Amazon with a higher mortality in Western and Southern regions than in the less-dynamic Northern and Central-east regions (Esquivel-Muelbert et al. 2020). Johnson et al. (2016) found the lowest rate of stem mortality in the Central-east Amazon, followed by the Northern, Western and Southeastern regions using a network of field plots (Table 2). Dalagnol et al. (2021) predicted mortality rates using gap fraction and found a similar pattern, although with lower absolute values of mortality (Table 2). We found a higher proportion of large gaps in the Southeastern region (mean α ± 95% confidence interval: 1.9422±0.0223) which aligns with previous studies and supports the relationship between canopy gaps and tree mortality. However, we found a mean α for the North (2.0066±0.0283) with no statistical difference from the West (2.0162±0.0361) and substantially lower than the Central-east region (2.0928±0.0199). This is surprising because the Northern region has previously been shown to have lower mortality rates, similar to the Central-east. We therefore conclude that these large-scale observations present a complicated picture of the relationship between canopy gaps and both turnover rates and or mortality.

Table 2. Mean α coefficients found in each Amazon region (Feldpausch et al. 2011) in comparison with mortality studies.

| | Central-east | North | West | South-east |
|---|---|---|---|---|
| Johnson et al. (2016) Mortality %yr$^{-1}$ ± SE | 1.38 ± 0.08 | 1.66 ± 0.16 | 2.62 ± 0.12 | 3.19 ± 0.38 |
| Esquivel-Muelbert et al. (2020) Mortality %yr$^{-1}$ (95% CI) | 1.4 (1.2–1.6) | 1.3 (1.2–1.4) | 2.2 (2.0–2.3) | 2.8 (2.4–3.4) |
| Dalagnol et al. (2021) Mortality %yr$^{-1}$ ± SD | 0.66 ± 0.28 | 0.65 ± 0.17 | 0.8 ± 0.28 | 0.89 ± 0.2 |
| This study α ± 95% CI | 2.058 ± 0.02 | 1.990 ± 0.03 | 1.998 ± 0.04 | 1.912 ± 0.02 |

One important caveat in the comparisons between studies described above is that the regions used were designed to be allometrically distinct (Feldpausch et al. 2011), rather than being directly related to mortality. We use them to facilitate comparison with other studies (Johnson et al. 2016, Esquivel-Muelbert et al. 2020, Dalagnol et al. 2021) but our data set does not sample them evenly. In particular, the Northern and Western regions are not fully covered by our LiDAR data set (Figure 2a). Also, the North Brazilian Amazon contains a higher proportion of large gaps close to the savanna of Roraima, which display a different pattern of vegetation and canopy structure (Barbosa & Campos, 2007) from the rest of the Amazon.

It is important to consider the different time-scales of the main processes determining α. Water and nutrient gradients have long-term effects on forest structure and species composition (ter Steege et al., 2006). The immediate effects of disturbance are short-lived in the tropics since canopy gaps will close after 3-6 years due to natural regeneration (Brokaw 1985). Repeated disturbance can have long-term impacts on forest structure, but these are more difficult to predict and poorly represented by our wind layer. For instance, decades of high deforestation rates left behind a legacy of fragmentation, increased forest edges, and degraded forests (Aragão et al. 2014). The chronic effects of wind (Ennos 1997) and lightning (Gora, Burchfield, Muller-Landau et al., 2020) necessarily influence forest structure in the long term. For example, recent work found that low wind speeds were a key factor in determining the presence of ‘giant’ trees in the Amazon (Gorgens et al. 2020). This will have knock-on effects on the presence of large gaps as suggested by H2.

### 3.3 Conclusions

Canopy gaps are a key aspect of forest structure and dynamics, marking the balance between disturbance and regeneration in dense tropical forests. This study provides a new understanding of the variation in canopy gap size distributions across the Brazilian Amazon.

We found a Northwest to Southeast gradient in gaps size distributions, which aligns with recent mortality studies. As expected, human modified forests contained a higher proportion of large gaps than intact forests. The presence of very tall trees was also associated with a higher proportion of large gaps, presumably because large trees leave large gaps when they die.

We also found that higher soil fertility, water deficit, wind speed, lightning intensity were associated with a higher proportion of large gaps. We suggest further work to address this knowledge gap, perhaps focused on stem density, species composition or soil properties. This suggests that disturbance events are more common in fertile soils and that stressors such as drought, wind and lightning significantly increase these disturbance rates. Together, these findings show that increasing extreme weather events may increase the proportion of large gaps in currently intact forests across the Brazilian amazon, causing them to resemble human modified forests.

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# Appendix

## Supplementary material

## Map of flightlines

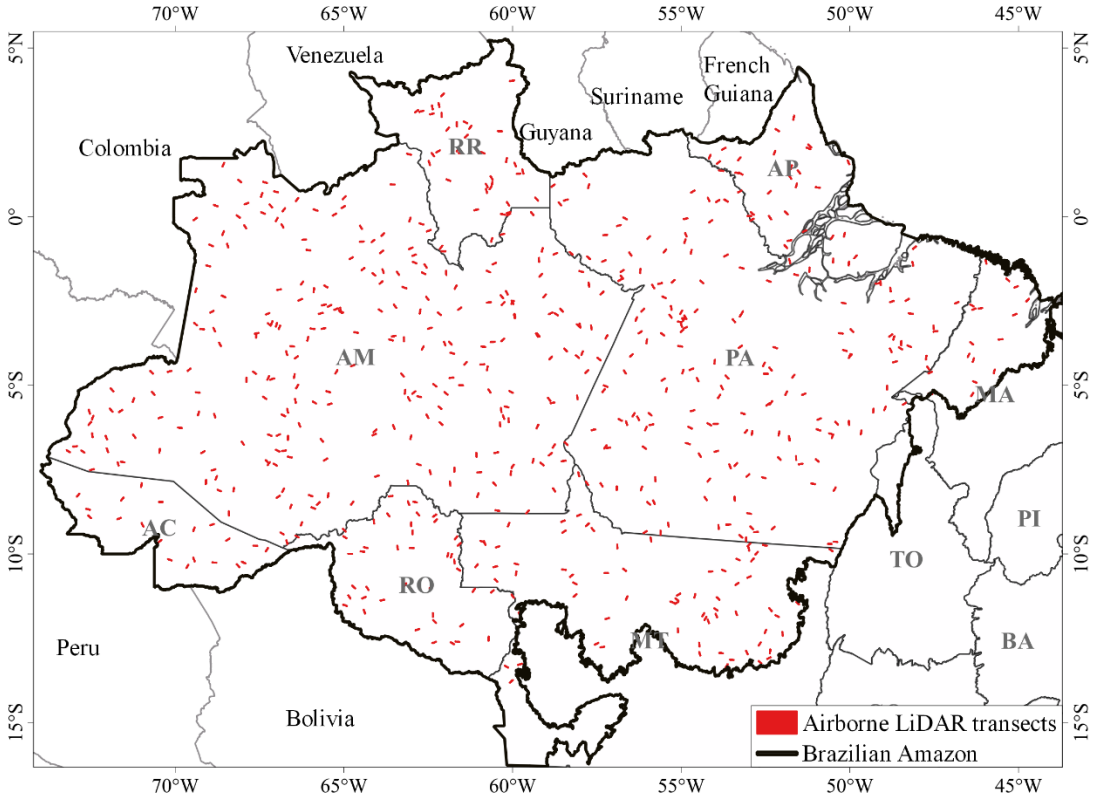


Figure S1. Map of the 650 airborne laser scanning transects collected between 2016 and 2018 and initially used in our canopy gap analysis.

**Sensitivity to gap definitions and filtering decisions**

We defined canopy gaps as contiguous areas of low canopy height which meet a number of thresholds. In this section we test the sensitivity of our results to our choice of thresholds. In particular, we test how the full multiple linear regression model would change if we changed the threshold, within reasonable limits. The first threshold (A) is that the canopy height must below a cutoff height, set as10 m in our analysis (Figure S2).

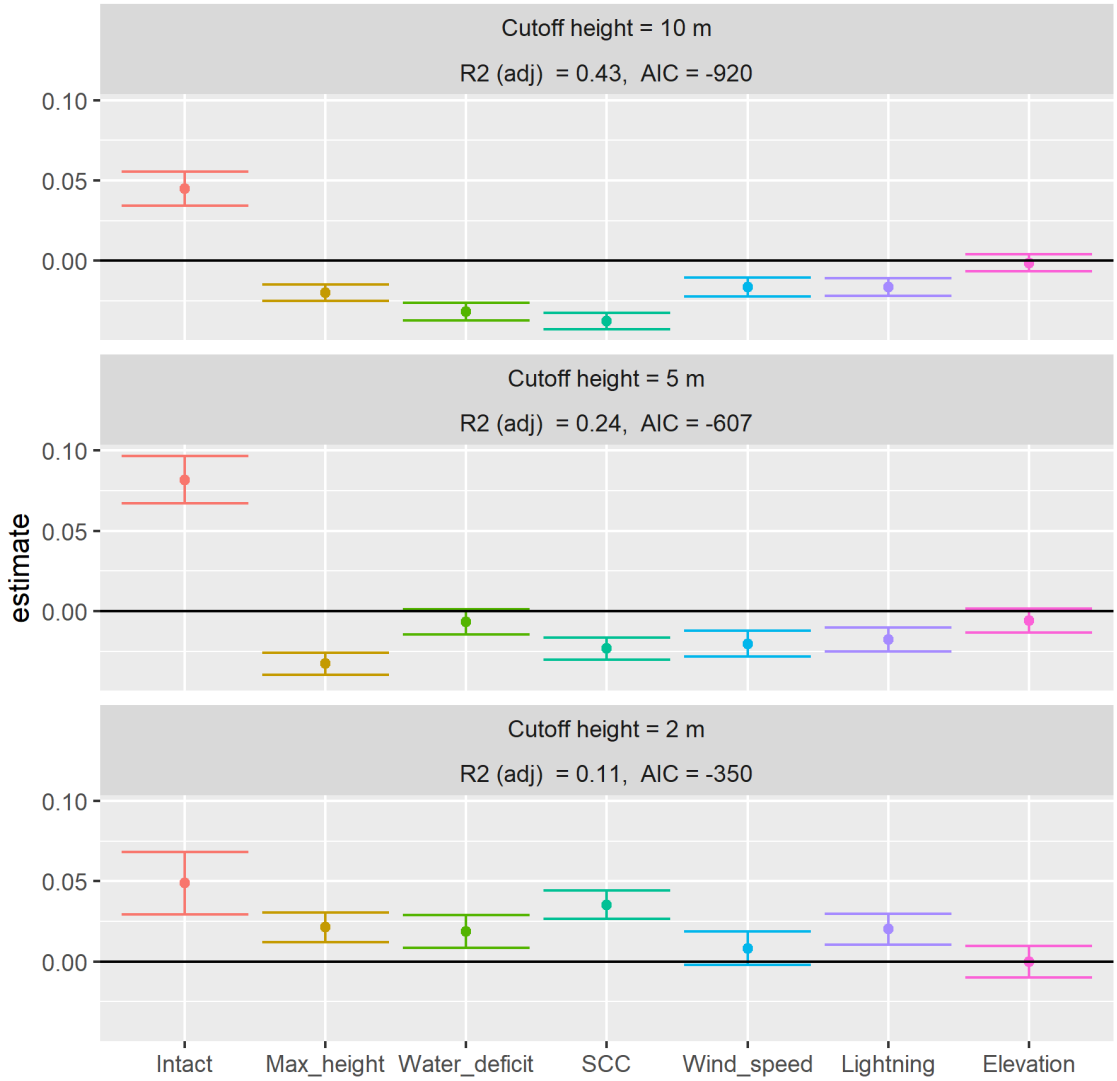


Figure S2. Sensitivity of multiple linear regression model to choice of cutoff height. The model was run with all other thresholds set at the values used in the main text (i.e. minimum area = 20 $m^2$, maximum area = 1 ha, erroneous gaps filtered out, only transects with median height > 15 m included).

The second threshold (B) is that the gap must be larger than 20 $m^2$ to focus on larger gaps which are more likely the results of disturbance events, and to filter out noise and small gaps between tree crowns. We found the model to be relatively insensitive to this choice of threshold (Figure S3).

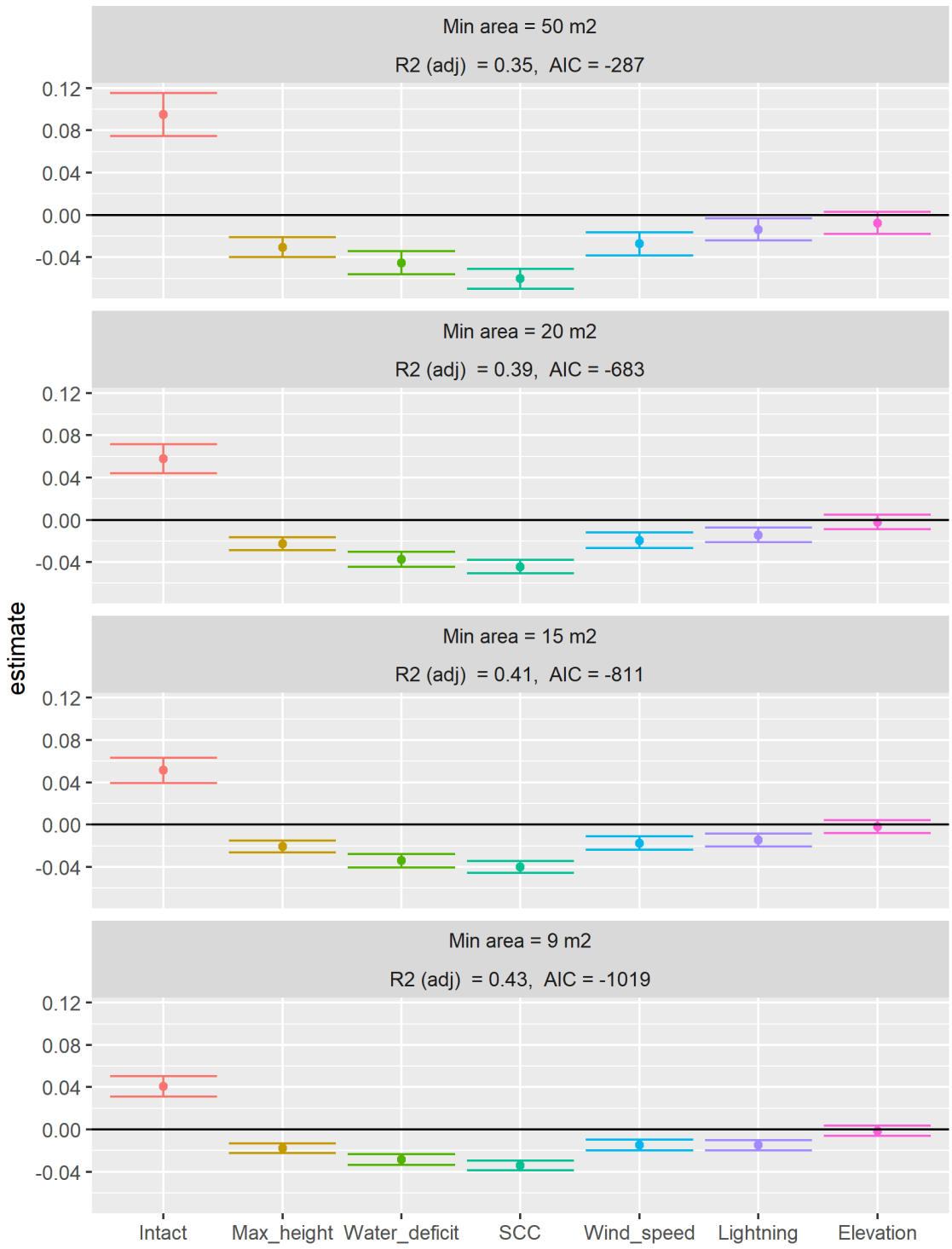


Figure S3 Sensitivity of multiple linear regression model to choice of minimum area threshold. The model was run with all other thresholds set at the values used in the main text (i.e. maximum area = 1 ha, cutoff height = 10 m, erroneous gaps filtered out, only transects with median height > 15 m included).

The third threshold (C) was that the gap must be smaller than 10,000 $m^2$ (1 ha) to avoid permanent features, such as roads or rivers, being classified as gaps. We found the model to be relatively insensitive to this choice of threshold (Figure S4).

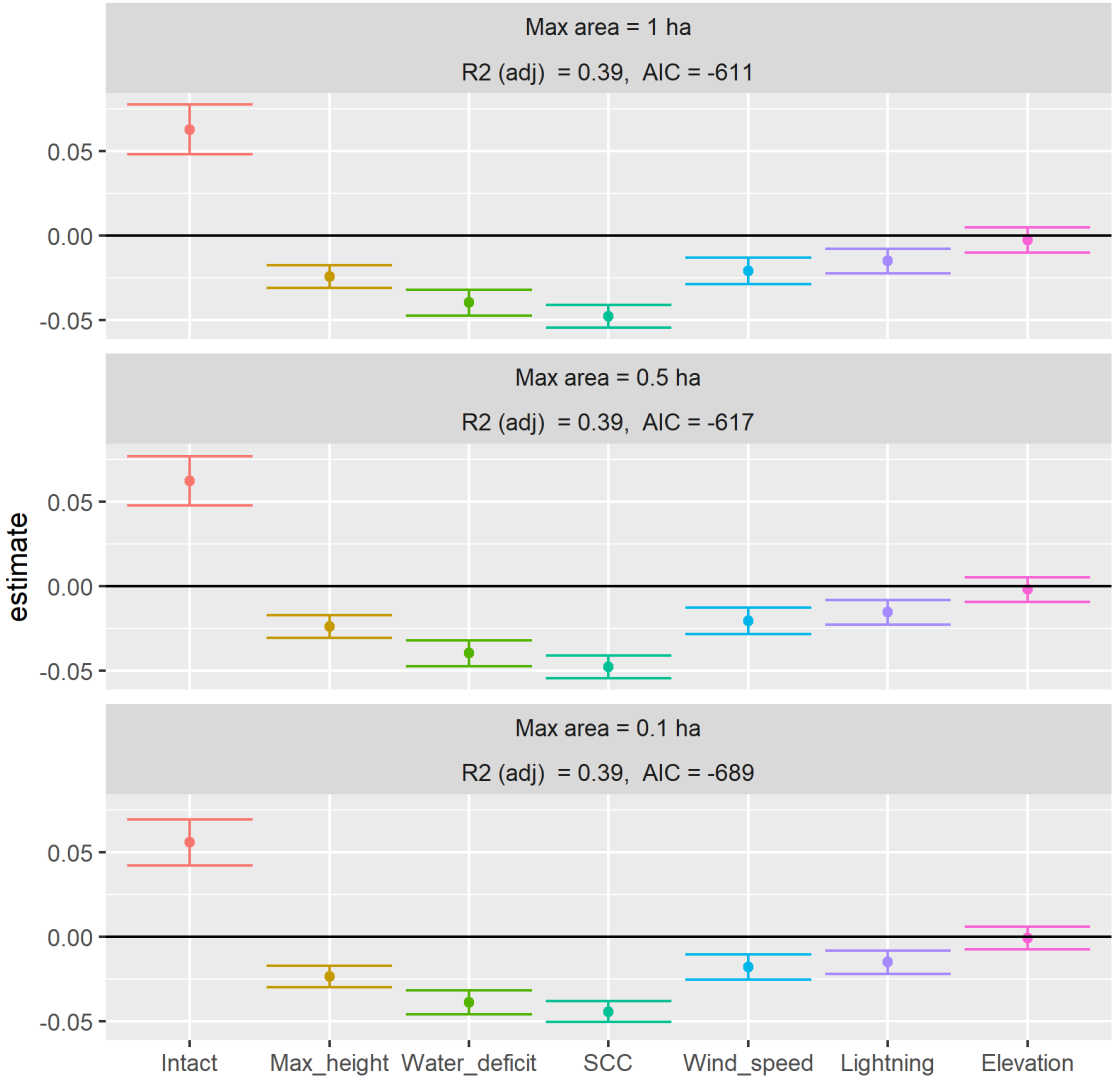


Figure S4 Sensitivity of multiple linear regression model to choice of maximum area threshold. The model was run with all other thresholds set at the values used in the main text (i.e. minimum area = 20 m2, cutoff height = 10 m, erroneous gaps filtered out, only transects with median height > 15 m included).

**Environmental layers used**

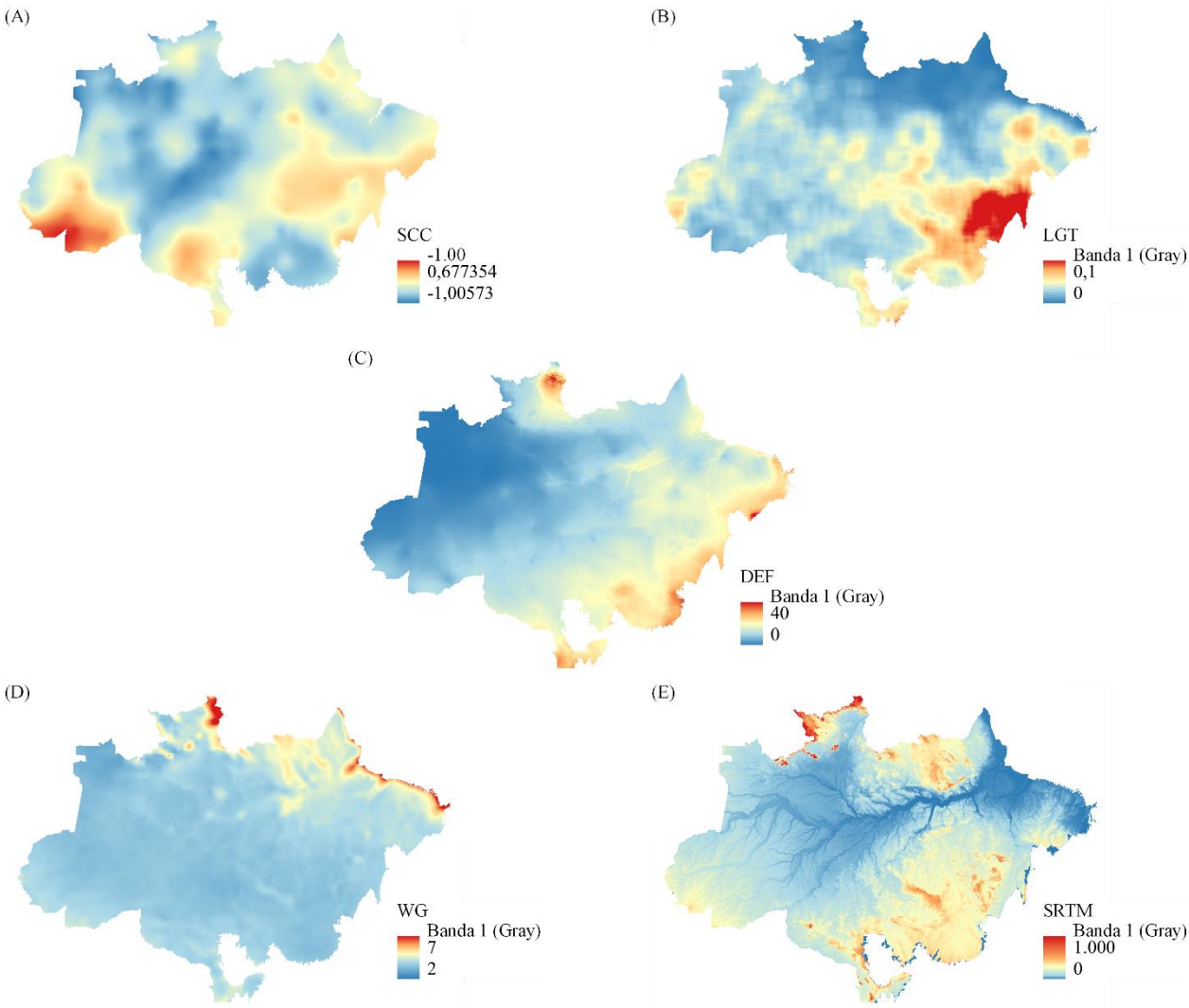


Figure S5. Environmental variables and modeled maximum height maps. (A) Soil concentration cation (cmol(+).kg$^{-1}$) in log scale, (B) lightning intensity, (C) water deficit (mm), (D) instantaneous wind gust (m.s$^{-1}$), and (E) Elevation above sea level (m).

**Correlations of individual variables**

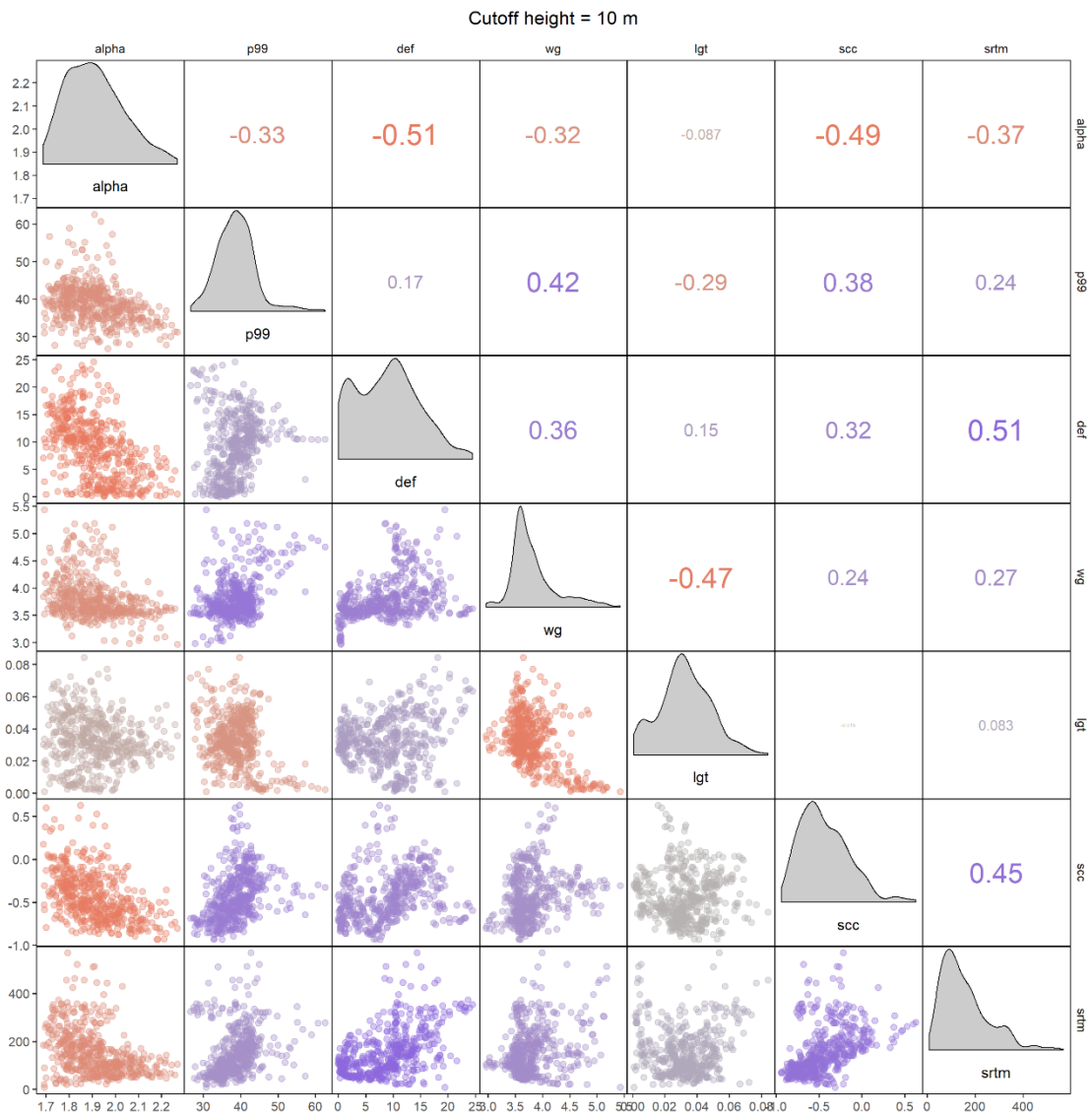


Figure S6. Pearson's correlation (*r*) between LiDAR derived gap information (alpha) and independent variables for human modified forests. alpha = power-law scaling coefficient, def = water deficit (mm), scc = soil cation concentration (cmol(+)/kg), wg = instantaneous 10m wind gust (m/s), lgt = Lightning density rates, srtm = elevation above sea level (m), p99 = maximum height (m).

**Multiple linear regression with interaction terms**

Table S7. Power-law α coefficient fitted as function of environmental and ALS canopy height metric (H) considering interaction terms. Estimate = model's coefficients and Std error = standard error. The predictor variables were: IFL = intact forest landscapes used to split data into intact (1) and human modified forests (0); Hmax = 99th percentile from ALS transects; DEF = water deficit (mm); SCC = soil cation concentration (cmol(+)/kg); WG = instantaneous 10m wind gust (m/s) and; LGT = Lightning density; SRTM: elevation (m); Adj. $R^2$ =adjusted coefficient of determination; AIC = Akaike information criteria; VIF = variance inflation factor.

| | Estimate | Std error | p.value |
|---|---|---|---|
| Intercept | 1.981 | 0.012 | 0.00E+00 |
| IFL | 0.054 | 0.013 | 4.85E-05 |
| $H_{max}$ | -0.037 | 0.008 | 4.09E-06 |
| DEF | -0.036 | 0.007 | 1.00E-06 |
| SCC | -0.047 | 0.007 | 4.25E-11 |
| WG | -0.029 | 0.008 | 1.58E-04 |
| LGT | -0.013 | 0.007 | 5.07E-02 |
| SRTM | 0.013 | 0.009 | 1.52E-01 |
| $H_{max}$: SCC | 0.020 | 0.008 | 9.96E-03 |
| $H_{max}$ : Wind gust speed | 0.018 | 0.005 | 2.24E-04 |
| SCC : LGT | -0.021 | 0.007 | 1.17E-03 |
| SRTM : DEF | -0.034 | 0.009 | 1.06E-04 |
| SRTM : LGT | 0.016 | 0.005 | 8.10E-04 |
| R2 | 0.451 | | |
| AIC | -728 | | |

## 4. GENERAL CONCLUSION

The thesis illustrates in two different ways how airborne laser scanning (ALS) can support the management of complex natural forests, like the Amazonian rainforest. In the first study, a small scale ALS assessment was used to qualify emergent trees and to assess how many commercial trees can be found in order to improve the forest management operational plan. In the second study we demonstrate the usefulness of a large-scale ALS sampling assessments to evaluate the distribution of canopy gaps across the Amazonian region in Brazil.

The use of ALS as an auxiliary tool improves the quality of forest management operational plans by mapping the exact location of the tallest trees, and consequentially locating the most valuable. An ALS canopy height model (ALS-CHM) is the essential tool for that purpose. This procedure might reduce the time and costs of the current operation, which depends on a census of all trees in the area. The use of ALS proves to be of great importance to mitigate negative impacts on forests when selective logging is prescribed as a technique to promote sustainable forest management.

ALS also proved successful to evaluate how natural and human disturbances processes affect important ecological parameters, such as gap formation. It helps on the understanding of the importance of avoiding deforestation to reduce carbon emission and, consequently, climate change. As demonstrated in the second study in this thesis, the proportion of large gaps in the forest canopy varies substantially over the Brazilian Amazon due to canopy structure and mortality rates. However, we showed in the second study that the higher proportion of large gaps we found were caused mainly by human intervention, by variation on soil fertility and by exposition to higher wind, lightning and drought stress. Therefore, increasing extreme weather events due to climate change may therefore increase the proportion of large gaps in currently intact forests, making them as damaging as the clear cuts found in human modified forests.

As future work we recommend studies following the approach that reduces sampling intensity in selective logging with the approach proposed in the first chapter. Also, similar studies, like the one presented in the first chapter, should be encouraged to make it possible to validate the proposed methodology in different areas enabling the f-score comparison. As recommendation to the second chapter, it is important to consider the different time-scales of the main processes determining α. We suggest further work to address this knowledge gap, perhaps focused on stem density, species composition or soil properties. Multitemporal ALS data could provide information to better understand the long-term effects and the immediate effects on forest structure and species composition.