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Scaling up the assessment of logging's impact on forest structure in Central Africa using field and UAV data

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Abstract:

A third of the forest area in Central Africa has been granted to logging companies. Logging is highly selective in the region, with an average of 0.7 to 4.0 trees harvested per ha, but its direct impact on forest structure and the spatial variation of this impact remain understudied. .

Here, we investigated the direct impact of logging on forest structure, we related this impact to logging intensity and canopy opening. We compiled unique datasets collecting field measurements and aerial observations in four FSC certified concessions. Our data includes pre- and post-logging inventory of forest plots covering 38 ha, records of over 6,000 harvested trees, and drone RGB images covering over 6,000 ha.

In average, logging activities reduced forest above-ground biomass by 8.8%, stem density by 6.5%, basal-area by 8.5% and canopy cover by 4.4%. Strong relationships were found between the reduction in biomass, stem density, or basal area with logging intensity, canopy opening and the number and volume of harvested trees (rRMSE between 0.128 and 0.164). Additionally, we demonstrated that canopy opening can be a good indicator to monitor and upscale logging intensity (rRMSE between 0.0005 and 0.0022).

This study is the first covering extensive inventory plots and UAV (uninhabited aerial vehicle) images before and after logging in different locations in Central Africa, providing a valuable reference to evaluate the impact of logging on forest structure. It demonstrates how canopy opening can be used to estimate measurements usually collected in the field and provides to the remote sensing community a unique dataset that will help improving monitoring systems (https://hdl.handle.net/2268/323683). These findings also have significant implications to control and manage logging activities, especially for certification standards, forest administrations, and European regulations.

Keywords: selective logging, Central Africa, forest structure, canopy opening, logging intensity, forest disturbance, upscaling

1. Introduction

In recent years (2015-2019), tropical forests degradation has increased by 38% while annual deforestation has decreased by 5% (Vancutsem et al. 2021). Degradation, defined as “a disturbance in the tree cover canopy that is visible from space over a short time period, leading to a loss of biodiversity and/or carbon storage”(Vancutsem et al., 2021), is attributed to human activities such as agriculture, logging, fires, road construction, mining, and wood fuel collection (Vancutsem et al. 2021; Laso Bayas et al. 2022; Tyukavina et al. 2018). In Central Africa, small-scale agriculture is the primary driver of forest loss measured on Landsat imagery (84%), followed by industrial logging activities (9.5%) (Tyukavina et al. 2018). Industrial logging in the region covers one-third of the forest area (Eba’a Atyi et al. 2022) and is highly selective, targeting a limited number of high-value tree species and harvesting a restricted number of trees (0.7–4.0 trees.ha^{-1}) every 20–35 years (BAD 2018; Vincent P. Medjibe et al. 2011). In Central Africa, logging companies must produce Forest Management Plans, which address various environmental and social issues including Reduced Impact Logging (BAD 2018; Vincent P. Medjibe et al. 2011). About 10% of production forests are certified by the Forest Stewardship Council ensuring that Forest Management Plans are adopted and implemented by these companies (FSC 2022; Tritsch et al. 2020).

Logging activities impact forest structure, leading to a direct loss of aboveground biomass (AGB) ranging from 7.1% to 13.4%, as measured on inventory plots, and a canopy opening of 4% to 11%, observed using UAV and satellite imagery (Dupuis et al. 2023; Ngueguim et al. 2009; V. P. Medjibe, Putz, and Romero 2013). The extent of ground damage varies depending on the type of logging operations: felling gaps range in size from 218 to 578 m^2 (Vincent P. Medjibe et al. 2011; Doucet et al. 2009), while log yards are approximately 1200 m^2 (Durrieu de Madron et al., 2000). Additionally, skid trails have a mean width of 4.1 m (Vincent P. Medjibe et al. 2011), narrower than secondary (width = 24.8 m) and primary roads (width = 39.3 m) (Hirsh et al. 2013). Earlier studies have demonstrated that the AGB rapidly recovers after logging, as illustrated in the M'Baïki experiment in the Central African Republic (Gourlet-Fleury et al. 2013). It has also been shown that canopy opening for logging roads construction does not persist (Kleinschroth et al. 2019). This rapid recovery is attributed to the growth stimulation of remaining trees and the recruitment of new trees, often including fast-growing pioneer species (Gourlet-Fleury et al. 2013; Sist and Nguyen-Thé 2002; Peña-Claros et al. 2008). Logging intensity has a direct impact on the amount of damages caused to the forest (Durrieu de Madron, Fontez, and Dipapoundji 2000) and its capacity to recover (Gourlet-Fleury et al. 2013; Rutishauser et al. 2015; Maurent et al. 2023).

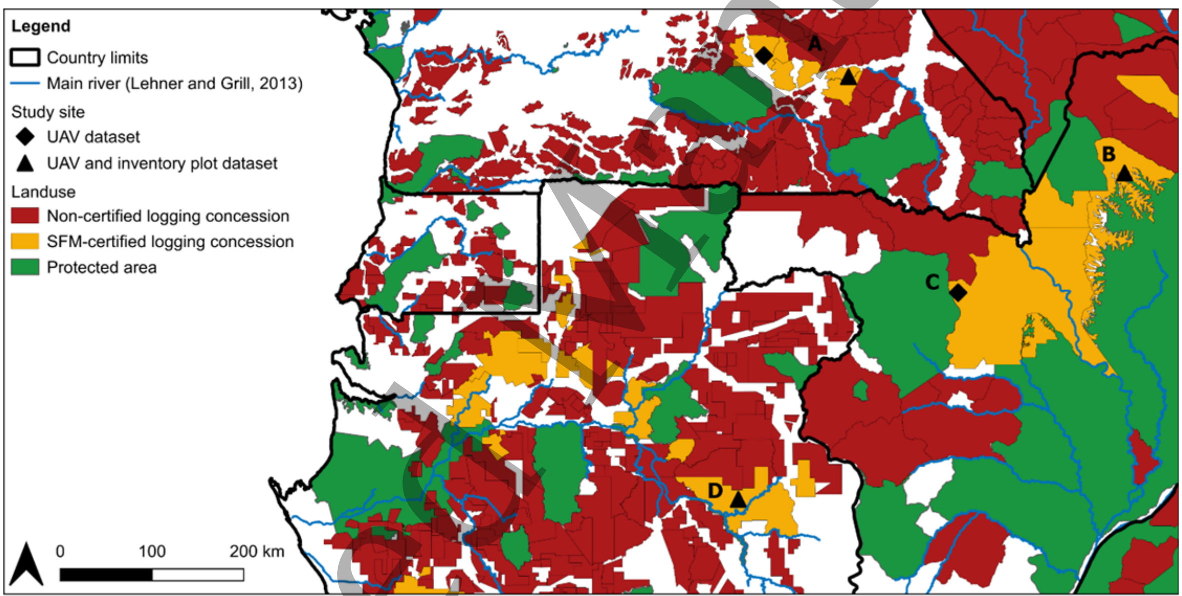
Logging activities are currently monitored on various scales. On a local level, research inventory plots ranging from 1 to 10 hectares provide accurate data, e.g. to study forest recovery after logging (Gourlet-Fleury et al., 2013). However, these plots may not fully represent the entire surface impacted by logging activities. On a broader scale, logging companies gather field data, recording the location of harvested trees along with their diameter and species to plan their activities (BAD 2018). Remote sensing tools on a larger scale have revolutionized the study of tropical forests that are difficult to access by enabling faster and more comprehensive data collection (Sanchez-Azofeifa et al. 2017). While satellite-based systems allow systematic monitoring, they cannot detect small disturbances (Dupuis et al. 2023). Uninhabited Aerial Vehicle (UAV) RGB data has been identified as a potential bridge between satellite and field-collected data but remains poorly explored (Bourgoin et al. 2020; Dupuis et al. 2020). Canopy opening is a frequently measured indicator using remote sensing tools and has great potential for integrating remote sensing and field data for large-scale monitoring but it has not been thoroughly explored yet (Dupuis et al. 2020).

This study aims to assess the direct impact of selective logging on forest structure, and investigate how logging damages are affected by logging intensity. Field and UAV measurements will be integrated to spatially extent this information in Central Africa. The following questions are addressed. (1) What is the impact of logging on forest structure, specifically on AGB (in Mg.ha^{-1}), basal area (BA, in m^2.ha^{-1}), stem density (N, ha^{-1}) and canopy cover (proportion of canopy opening), using inventory plots? (2) How logging intensity (harvested volume and number of trees) and canopy opening (proportion) can be used to estimate the impact of logging on forest structure? (3) How can canopy opening be used to predict logging intensity using a dataset combining UAV data with harvested trees on a larger scale?

2. Material and methods

2.1. Study sites

Field inventory campaigns were conducted in four FSC-certified logging companies, incorporating the installation of forest plots and UAV flights both before and after logging, where industrial and mechanized operations are employed (Figure 1a and S1). The sites encompassed various types of tropical moist forests (Fayolle et al. 2014; Réjou-Méchain et al. 2021). Sites A and B corresponded to dense, mature semi-deciduous forests dominated by *Celtis* spp. These forests feature a stratified canopy, with deciduous trees allowing more light penetration during the dry season, promoting moderate understorey growth (Fayolle et al. 2014). Site C, by contrast, is characterized by a highly open canopy, with widely spaced trees and a dense herbaceous understorey dominated by *Marantaceae* species, a typical feature of post-disturbance environments that promote herbaceous layer development (Gillet 2013). Finally, site D is dominated by *Aucoumea klaineana* (Okoumé) (Van Hoef, Doucet, and Fayolle 2019), the most important timber species in Gabon. The site underwent its first logging cycle prior to our study, which focuses on the second harvesting rotation.



	Site	Site A		Site B	Site C	Site D
	Forest type	*Celtis* spp.	*Celtis* spp.	*Celtis* spp.	*Marantaceae* spp.	Okoumé
Field	Plot design	1 x 4 ha	/	2 x 9 ha	/	4 x 4 ha
Field	Inventory before logging	July 2019	/	2018	/	2019
Field	Inventory after logging	October 2019	/	2019	/	2020
Field	Number of trees recorded	1877	/	6510	/	6117
Field	Number of trees with height measurement	438	/	1054	/	106
UAV flights	UAV flights area	504 ha	964 ha	528 ha	3312 ha	629 ha
UAV flights	Flight before logging	/	/	June 2018	February 2019	June 2020
UAV flights	Flight after logging	July 2019	August 2021	January 2019	September 2019	September 2020

Figure 1. Location of the study sites across Central Africa and information about the field and UAV data collected in each site. The map shows protected areas (in green), non-certified (in red) and sustainable forest management (SFM) in certified logging concessions (in yellow). Country limits are shown in black and main rivers are in blue.

2.2. Inventory plots and harvested trees

Forest inventory plots were installed before any logging activities in sites A (1 x 4ha), B (2 x 9ha) and D (4 x 4ha) (Figure 1; Figure 2a), following the protocol for the installation of permanent sampling plots proposed by Picard and Gourlet-Fleury (2008). Each plot was geolocated using a Garmin GPS for sites B and D, and a GPS with RTK/PPK corrections for site A. Prior to logging, all trees with a diameter at breast height (DBH) ≥ 10 cm were identified by field botanists, measured and recorded (Figure 2a). Each tree was geolocated using the x and y coordinates within the 20x20 m quadrats (see Picard and Gourlet-Fleury 2008, p 81), then calibrated against UAV images based on the emerging tree crowns to minimize geolocation errors. DBH was measured using a tape at a height of 1.3 m for regular stems, or 30 cm above the top of the buttresses, and then converted to DBH using a taper model for irregular stems (Bauwens et al. 2021). In most 1 ha subplots (Figure 1), at least 50 trees including the 10 largest trees and 10 trees randomly selected in 10-cm-wide diameter classes to cover the diameter range, were selected for height measurement (Sullivan et al. 2018). The total height of these trees (H in m) was measured using a VERTEX Haglöf ultrasonic meter or a Nikon Forestry laser rangefinder. The social status (understory, canopy or emergent) was observed in the field for all trees in sites A and D. After logging, each tree was revisited and categorized into one of four damage categories based on the impact of logging activities: alive, when it was intact; damaged, when the tree was impacted by logging but could still live (i.e., debranched, broken, barked, leaning tree); harvested, when it was cut by the logging company; dead, when it was dead or had no chance to survive because of logging activities (i.e., uprooted tree or lying on the ground). The general category 'impacted' gathers all trees that are damaged, harvested or dead (Figure 2a). In addition, in the UAV covered areas, we recorded the location and the DBH of all harvested trees (6,503 trees in total, Figure 2b). The recorded DBH corresponded to the midpoint of the diameter class estimated by operators in site A, and to the DBH measured with a tape in sites B, C and D.

2.3. Canopy gap identification on UAV images

RGB images, where each pixel is defined by the amount of red, green, and blue color, were obtained from UAV flights performed before and after logging, except for site A for which flights were performed only after logging (Figure 1). Technical information can be found in Table S1. GPS data with RTK/PPK corrections were processed using RTKLIB to ensure accurate georeferencing of the images (Cledat et al. 2020; Takasu and Yasuda, 2009). Orthomosaic and Digital Surface Model (DSM) at 10 cm resolution were generated using photogrammetry in *Metashape* software (Lisein et al. 2013). Using before and after orthomosaic and DSM canopy gaps caused by logging activities were photo-interpreted, manually digitalized in QGIS and categorized into felling gaps, roads, skid trails, log yards and others when the cause was not clearly identifiable (Figure 2b, Figure S1). In site A, where only post-logging images were available, errors in photointerpretation were minimized by utilizing the locations of harvested trees and by recognizing the clear distinctions between natural gaps and logging gaps, characterized by the absence of logs and associated damages (Figure S2). This dataset is available at https://hdl.handle.net/2268/323683. In site A, the length of 41 felling gaps were measured in the field using a VERTEX Haglöf ultrasonic meter. The length from the stump to the outer edge of the crown within each gap was recorded in the field, accounting for damage delineated under the canopy, as well as assessed on UAV images to capture damages occurring within the canopy (Figure S3). The difference between field and UAV measurements was assessed by calculating the mean absolute error (MAE), the root mean squared error (RMSE) and the relative root mean squared error to the mean (rRMSE).

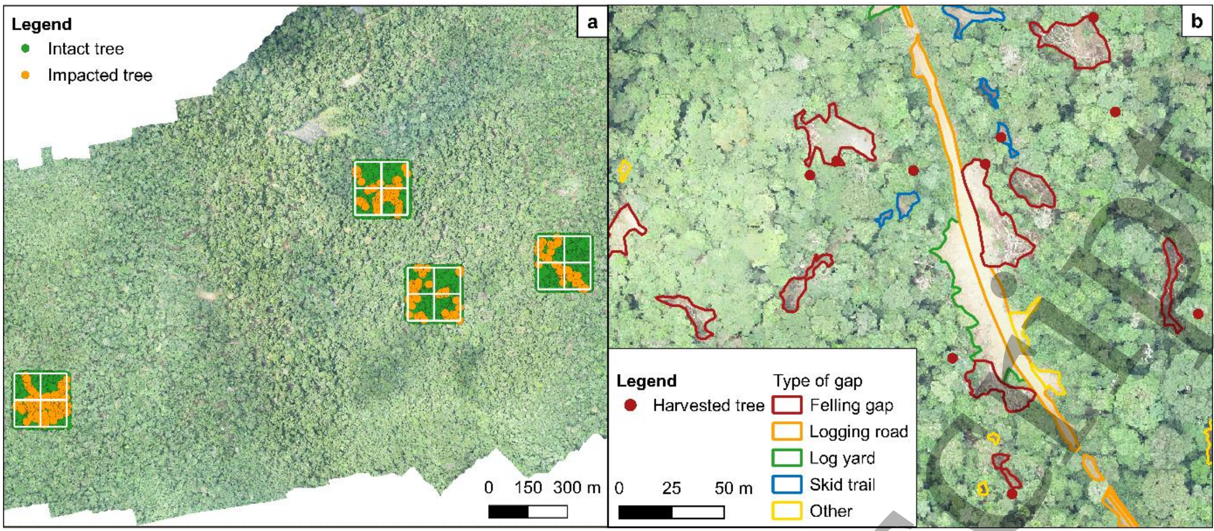


Figure 2. Example of plot data (a) and UAV images (b) used to assess the impact of logging on forest structure from site D. Example of 4-ha plots and inventoried trees are shown in a. Impacted trees correspond to all trees that are not intact after logging activities. Locations of harvested trees provided by logging companies, UAV images taken after logging and canopy openings categorized in different types of gaps are shown in b. 'Others' refers to gaps where the cause of damage was not clearly identifiable.

2.4. Biomass and volume estimates at the tree level

The aboveground biomass (AGB in kg) of all trees in the inventory plots was calculated using the pantropical allometric equation of Chave et al. (2014) that was earlier validated for Central Africa (Fayolle et al. 2018). Site-specific height-diameter allometric equations were first developed to estimate the height of all trees in the plots fitting non-linear Michaelis-Menten model as recommended (Fayolle et al. 2016; Molto, Rossi, and Blanc 2013). The BIOMASS package in R (Réjou-Méchain et al. 2017) was used to extract wood density values (species average) and to compute AGB estimates (results shown in tons). The commercial timber volume (in m^3), i.e, the over-bark volume, of all harvested trees was estimated using DBH measurements and species-specific allometric equations (Table S4) compiled from Gourlet-Fleury et al. (2013), Henry et al. (2013) and Ligot et al. (2019).

2.5. Data analyses

Forest structural attributes were firstly assessed at the 1ha-subplot level computing for example AGB (in $t.ha^{-1}$), BA (in $m^2.ha^{-1}$), and NHA (in number of $trees.ha^{-1}$). The choice of 1 ha subplots is recommended for upscaling field data to larger areas (Réjou-Méchain et al. 2019), and allows for covering a gradient of logging intensity within the study sites. The reduction in these attributes (delta AGB, BA and NHA), called logging impact (3.1. in Figure 3), was assessed computing the metrics by damage categories ("intact" or "impacted" trees) and social status (understory, canopy, emergent) before and after logging inventories. Logging intensity was quantified as the number (N $harvested.ha^{-1}$) and commercial timber volume (V harvested in $m^3.ha^{-1}$) of harvested trees per hectare, both using the inventory plots and the harvested trees (Figure 3, Paragraph 2.2). At the UAV-flight level and using gap photo-interpretation, canopy opening was evaluated according to different types of logging operations (felling gaps, logging roads, log yards, skid trails, others).

At the 1ha-subplot level, we explored the relationships between logging impact, logging intensity and canopy opening (3.2. and 3.3. in Figure 3). Logging impact was modelled using an exponential decay model including logging intensity as an explanatory variable (Equation 1). As intensity increases, damages tend to overlap, resulting in a decrease in damage per tree (Durrieu de Madron, Fontez, and Dipapoundji 2000; Guitet et al. 2012). Logging impact was modelled using an exponential growth model including canopy opening as an explanatory variable (Equation 2), indicating that larger openings result in a greater impact on forest structure.

At the UAV flight level, logging intensity was modeled using grids of various sizes, ranging from 1 ha to 100 ha (see example in white grid lines in Figure 3 with a grid size of 500 m). A linear model was used to estimate logging intensity, with canopy opening as the explanatory variable (3.4. in Figure 3, Equation 3). By varying grid sizes, we aimed to identify the scale at which these attributes could be most reliably estimated. The data were collected from various sites and forest types, leading to inherent clusters within the dataset, and thus non-independent data. Non-linear (Equation 1 and 2) and linear (Equation 3) mixed models were used to address this issue as they can accommodate the dataset structural complexity. These models include random effects to account for sites and forest types (α and β in Equations 1, 2 and 3) but these models can be used to predict new observations considering only the fixed effects (marginal model with $\alpha=0$ and $\beta = 0$ in Equations 1, 2 and 3). Due to the limited size of the dataset (38 ha), the MAE, RMSE, and rRMSE of the marginal models for equations 1 and 2 were calculated on the entire dataset. For equation 3, as the dataset was bigger (6000 ha of UAV flights), a k-fold cross-validation with k=5 was performed. Each site corresponds to a fold and site C was divided into two folds representing areas of 6500 x 2000 m separated by 200m. Equal numbers of points were randomly selected in each fold during cross-validation.

$$y = 1 - exp\ ((b + \beta)x) + \varepsilon_{ij} \text{ (Equation 1)}$$

where y = Delta AGB, BA or NHA, x = V or N harvested

$$y = \left(\frac{1}{1-x}\right)^{1/(b+\beta)} - 1 + \varepsilon_{ij} \text{ (Equation 2)}$$

where y = Delta AGB, BA or NHA, x = canopy opening

$$y = (a + \alpha) + bx + \varepsilon_{ij} \text{ (Equation 3)}$$

where y = V or N harvested, x = canopy opening

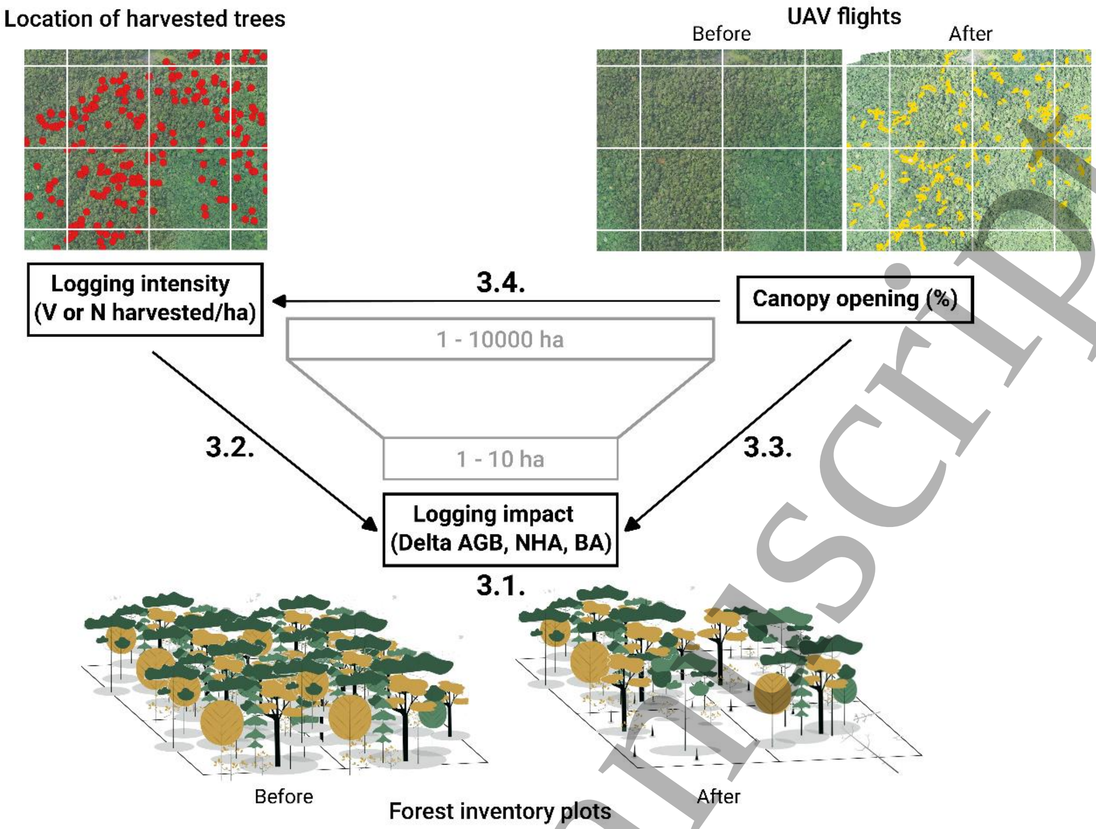


Figure 3. Forest structural attributes measured at different scales, from the inventory plots (paragraph 3.1.) to the UAV flights level, and relationships established between these attributes (paragraphs 3.2., 3.3., and 3.4.).

3. Results

3.1. Impact of logging on forest structure

Before logging, the mean estimated average AGB was 435.4 tons.ha^{-1}, with 381.7 trees.ha^{-1} and a BA of 32.8 m².ha^{-1} (Table 1). Only slight variations across sites were observed with lower AGB and BA in Okoumé forests than in *Celtis* forests (Figure S4). Understory trees were more abundant (75% of NHA) and emergent/canopy trees stored a greater proportion of biomass (75% AGB and 78% BA, Table 1). For an average logging intensity of 1.1 trees harvested per hectare corresponding to an exploitable volume of 18.4 m³.ha^{-1}, AGB, NHA and BA were respectively reduced by an average of 8.8%, 6.5% and 8.5% (Table 2). Most impacted trees were understory trees (77.8% of NHA), but canopy trees (14.9%) and emergent trees (7.2%) were also impacted. The DBH of harvested trees ranged between 80 and 200 cm, resulting in a significant reduction in AGB at the 1-ha subplot level (Table 1, Figure S5). In Okoumé forests (site D), 71% of the harvested trees were *Aucoumea klaineana* trees, while in *Celtis* forests (site A and B) *Entandrophragma cylindricum* and *Erythrophleum suaveolens* accounted for 75% of the harvested trees (Table S3).

Table 1. Impact of logging on the aboveground biomass (AGB), the number of trees (NHA) and the basal area (BA) for trees with DBH > 10 cm, categorized by damage status and social position of the trees

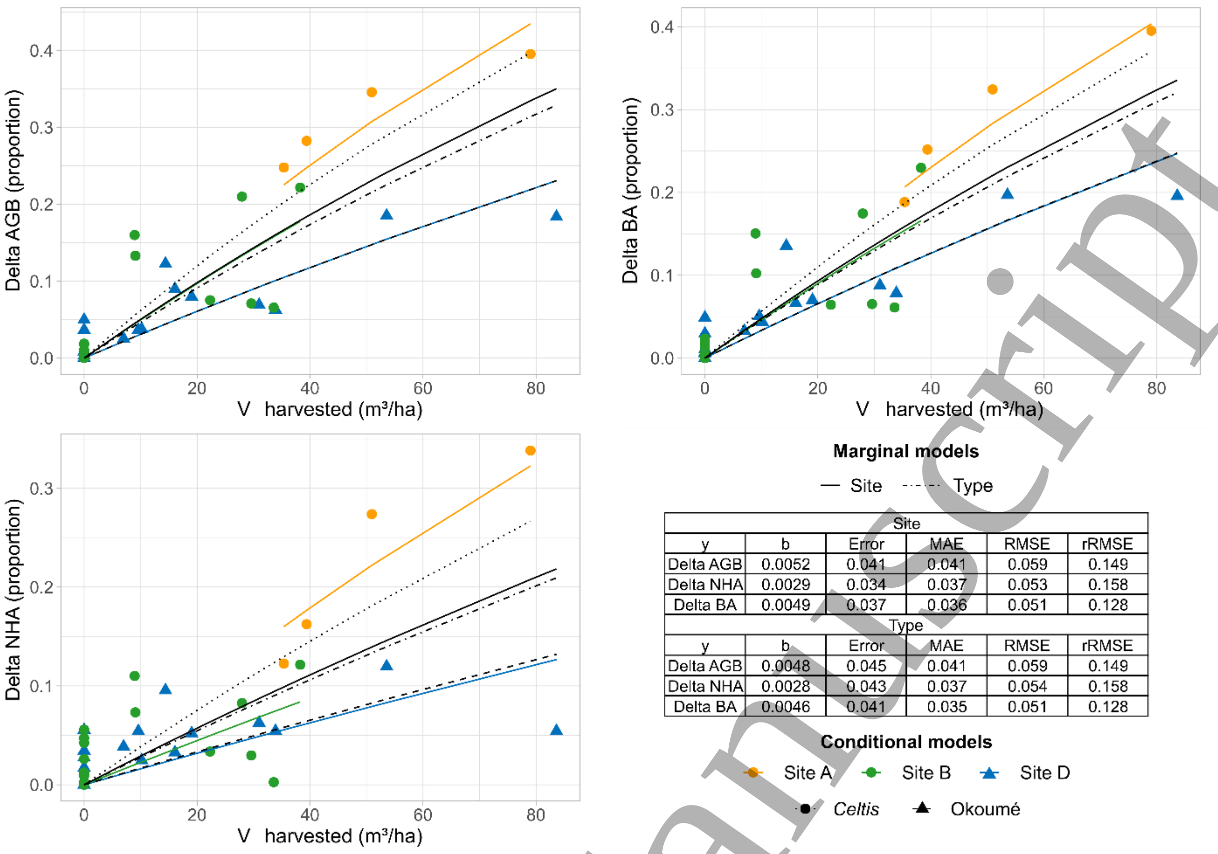
Structural attribute	Before logging	After logging			
		Damaged	Dead	Harvested	All impacted trees
AGB (t.ha^{-1})	435.4 sd = 83.9	10.3 sd = 31.9	5.9 sd = 12.1	22.0 sd = 28.1	38.2 (-8.8%) sd = 49.8

% in emergent	39.5	37.5	13.5	90.4	68.1
% in canopy	35.3	38.2	29.0	9.6	19.2
% in understory	25.2	24.3	57.5	0.0	12.7
AGB (t per m³ harvested)	/	0.6	0.3	1.2	2.1
NHA (# trees.ha^{-1})	381.7 sd = 42.1	13.3 sd = 47.6	10.3 sd = 9.5	1.1 sd = 1.2	24.7 (-6.5%) sd = 33.9
% in emergent	5.9	3.7	1.5	91.4	7.3
% in canopy	18.9	20.1	7.9	8.6	14.9
% in understory	75.3	76.2	90.5	0.0	77.8
NHA (# trees per m³ harvested)	/	0.72	0.56	0.06	1.34
BA (m².ha^{-1})	32.8 sd = 4.86	0.8 sd = 2.33	0.5 sd = 0.76	1.5 sd = 1.87	2.8 (-8.5%) sd = 3.44
% in emergent	33.4	26.3	9.9	91.3	62.6
% in canopy	34.6	37.4	25.4	8.7	18.8
% in understory	32.0	36.3	64.8	0.0	18.6
BA (m² per m³ harvested)	/	0.04	0.03	0.08	0.15

Over the 5,937ha covered by the UAV flights, 4.4% of the canopy area was impacted by logging activities. Felling gaps had a mean area of 577.7 m² (median = 448.2 m², sd = 531.1 m², N = 2,443) (Figure S6) corresponding to 217 m² of gap per harvested tree. Felling gaps were the most important disturbance accounting for 56% of the impacted area, followed by logging roads (23%), skid trails (10%), the category “others” (8%) and log yards (3%), with only slight differences between sites (Table S2). For site A, the lengths of felling gaps measured on UAV images (mean = 37.8 m, sd = 8.2 m) were smaller than those measured on the ground (mean = 43.2 m, sd = 5.7 m), with a MAE of 6.2 m and a RMSE of 7.6 m (Figure S7).

3.2. Relationships between logging impact and logging intensity at 1-ha level

Relationships were identified to predict logging impact (delta AGB, NHA, BA) based on logging intensity expressed in harvested volume (V harvested, Figure 4) and number of harvested trees (N harvested, Figure S8) at the 1ha-subplot level. V harvested was a better explanatory variable of logging impact than N harvested, and a different response was observed depending on the forest type. For the same logging intensity, the logging impact was more severe in *Celtis* forests than in Okoumé forests (Figure 4 and S8). Random effect values associated with different sites and types of forest for conditional models are presented in Table S5. Marginal models were nearly identical between types and sites, with a rRMSE ranging between 0.128 and 0.164 across variables (Figure 4, Figure S8).

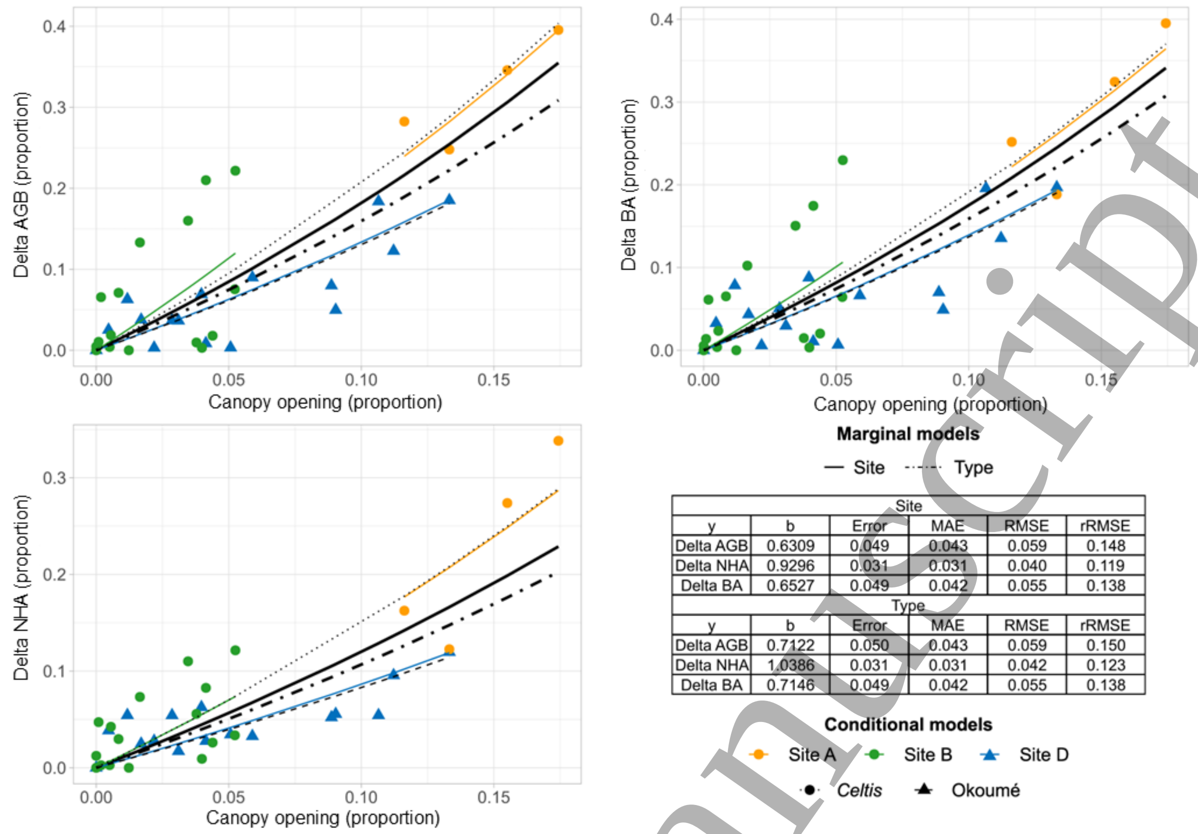


y	b	Error	MAE	RMSE	rRMSE
Site					
Delta AGB	0.0052	0.041	0.041	0.059	0.149
Delta NHA	0.0029	0.034	0.037	0.053	0.158
Delta BA	0.0049	0.037	0.036	0.051	0.128
Type					
y	b	Error	MAE	RMSE	rRMSE
Delta AGB	0.0048	0.045	0.041	0.059	0.149
Delta NHA	0.0028	0.043	0.037	0.054	0.158
Delta BA	0.0046	0.041	0.035	0.051	0.128

Figure 4. Prediction of logging impact based on logging intensity in terms of volume (V) harvested per hectare within 1ha-subplots (n=38), according to the different sites and types of forest. Marginal and conditional models for each site and type of forests are shown on the graphs. The table contains the mean absolute error (MAE), the root mean squared error (RMSE) and the relative root mean squared error (rRMSE) for the marginal models, as well as the fixed effects (b) and the standard deviations of the mixed model residuals (Error) for equation 1. Values of random effects for the conditional models are in Table S5.

3.3. Relationships between logging impact and canopy opening on the 1-ha scale

Relationships were identified for the prediction of logging impact (delta AGB, NHA, BA) based on canopy opening, with a rRMSE ranging between 0.119 and 0.150 for marginal models (Figure 5). Three 1ha-subplots in site B showed a reduction in AGB and BA with not much canopy opening because of skid trails under the canopy that are not visible on UAV images.

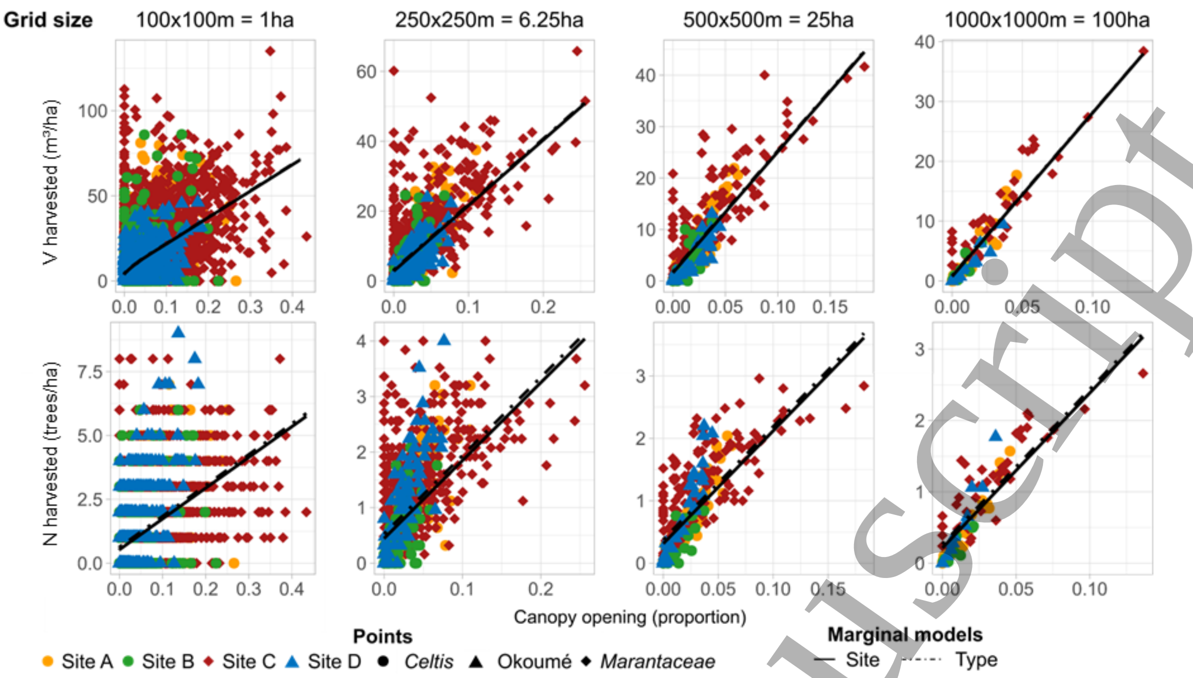


Site					
y	b	Error	MAE	RMSE	rRMSE
Delta AGB	0.6309	0.049	0.043	0.059	0.148
Delta NHA	0.9296	0.031	0.031	0.040	0.119
Delta BA	0.6527	0.049	0.042	0.055	0.138
Type					
y	b	Error	MAE	RMSE	rRMSE
Delta AGB	0.7122	0.050	0.043	0.059	0.150
Delta NHA	1.0386	0.031	0.031	0.042	0.123
Delta BA	0.7146	0.049	0.042	0.055	0.138

Figure 5. Prediction of logging impact based on canopy opening within 1ha-subplots (n=38), according to the different sites and types of forest. Marginal and conditional models for each site and type of forests are shown on the graphs. The table contains the mean absolute error (MAE), the root mean squared error (RMSE) and the relative root mean squared error (rRMSE) for the marginal models, as well as the fixed effects (b) and the standard deviations of the mixed model residuals (Error) for equation 2. Values of random effects for the conditional models are in Table S5.

3.4. Relationships between the logging intensity and canopy opening on different scales

Relationships were identified to predict logging intensity based on canopy opening on different scales ranging between 1 and 100 ha (Figure 6, see example in white grid lines in Figure 3 with a grid size of 500 m). Marginal and conditional models for different sites and types of forest were very similar and provided a good fit to the data, thus only marginal models are presented in Figure 6. The average MAE ranged between 2.4 and 8.1 m^3 for predicting V harvested, and between 0.3 and 0.86 trees for predicting N harvested. However, below the grid size of 500 x 500 m, there was significant noise in the distribution of points, with extreme values of logging intensity. Upon observing the data, this noise is partly explained by the mislocation of harvested trees or by edge effects, which are smoothed from a grid size of 500 x 500 m.



y = V harvested							
Model	Grid size (ha)	a	b	Error	mMAE	mRMSE	mrRMSE
site	1	3.83	155.12	13.061	8.053	11.764	4.98E-03
type	1	4.26	155.35	13.066	8.160	11.800	4.99E-03
site	6.25	2.85	187.53	6.826	4.173	5.777	2.62E-03
type	6.25	3.18	187.70	6.831	4.232	5.825	2.64E-03
site	25	1.59	234.94	4.053	3.643	4.599	2.47E-03
type	25	1.80	234.69	4.055	3.781	4.734	2.54E-03
site	100	0.75	273.46	2.280	2.273	2.677	2.12E-03
type	100	0.89	272.65	2.279	2.367	2.760	2.17E-03

y = N harvested							
Model	Grid size (ha)	a	b	Error	mMAE	mRMSE	mrRMSE
site	1	0.53	12.04	1.156	0.863	1.161	4.91E-04
type	1	0.63	12.08	1.157	0.871	1.156	4.88E-04
site	6.25	0.45	14.03	0.631	0.469	0.607	2.78E-04
type	6.25	0.53	14.09	0.633	0.471	0.603	2.76E-04
site	25	0.31	18.07	0.407	0.472	0.575	2.97E-04
type	25	0.38	18.09	0.409	0.480	0.578	2.99E-04
site	100	0.21	21.72	0.255	0.328	0.408	3.07E-04
type	100	0.27	21.70	0.256	0.329	0.402	3.02E-04

Figure 6. Prediction of logging intensity in terms of V and N harvested (according to the location of 6503 trees harvested) based on canopy opening within grids of size ranging between 1 and 100ha, according to the different sites and types of forest. Marginal models considering sites and types of forest are shown on the graphs. The tables contain the average mean absolute error (mMAE), root mean squared error (mRMSE) and relative root mean squared error (mrRMSE) for the k-fold cross-validation of the marginal models, as well as the fixed effects (a and b) and the standard deviations of the mixed model residuals (Error). Values of random effects for the conditional models are in Table S6.

4. Discussion

Our results show that the selective logging applied in FSC-certified concessions in Central Africa has a small direct impact on the forest structure. On average, logging reduced AGB by 8.8%, NHA by 6.5% and BA by 8.5% which is analogous to previous results (Pinard et al. 1995; Sist 2000). Our estimates align with other studies conducted in Central Africa, estimating direct AGB losses ranging between 7.1% and 13.4% depending on whether concessions are FSC-certified or not (Medjibe, Putz, and Romero 2013; Ngueguim et al. 2009). There is no significant difference in carbon emissions between FSC-certified and non-certified logging concessions. However, Reduced Impact Logging practices can effectively reduce emissions by approximately half without compromising timber yields (Umunay et al., 2019). Felling gaps exhibited the most important impact on the canopy cover, which is consistent with earlier results found in south-east Cameroon (Dupuis et al. 2023) and in French Guiana (Guitet et al. 2012). The mean size of canopy opening (578 m² with N harvested = 2443 and 217 m² per harvested trees) was nevertheless smaller than earlier measurements in Gabon (mean = 787 m², N harvested = 12) (Medjibe, Putz, and Romero 2013), but close to the estimation of Doucet et al. (2009) in Cameroon, where the average gap area was 265.8 m² (N harvested = 174). Concerning canopy opening, our estimates show that low-intensity logging activities (1-2 trees.ha^{-1}) cause an opening of 4.4% of the canopy which is lower than the 11% measured in south-east Cameroon (Ngueguim et al. 2009). This difference can be partly explained by the resolution of images used to measure the canopy opening, i.e., 10 cm for the UAV images (this study) and 30 m for the Landsat images (Ngueguim et al. 2009), suggesting that, depending on data resolution, measurements may be overestimated. In this study, we demonstrated that the impact of logging varies by forest type. One possible explanation is that in forests dominated by a single species, such as Okoumé forests (Guidosse et al. 2022), the average crown size of the harvested trees tends to be smaller compared to the larger crowns of species like *Meliaceae* (e.g., *Entandrophragma cylindricum* in *Celtis* forests, see Table S3). This difference in crown size may lead to less canopy opening in Okoumé forests compared to *Celtis* forests, where larger-crowned trees are harvested. Second, certain exploited species, like Okoumé, tend to be more gregarious (Guidosse et al. 2022), leading to concentrated exploitation in specific areas. This can result in overlapping damages and reduce the need for operators to penetrate deep into the forest to find valuable trees, thereby minimizing the impact caused by roads and skid trails, and leading to reduced canopy opening per harvested tree. Finally, we showed that logging practices in Central Africa have low impact on canopy compared to other continents. In French Guiana, a logging intensity of 3.5 trees.ha^{-1} resulted in a canopy opening of 20% (measured on SPOT images, resolution = 4 – 20 m) (Guitet et al. 2012), whereas forest in Malaysia, a logging intensity of 27 trees.ha^{-1} led to a canopy opening of 21% (measured with fish eye photographs from the ground) (Saiful and Latiff 2019).

Logging impacts primarily depends on logging intensity. The reduction in BA has become a widespread indicator of logging intensity, it was also used in the M'Baïki forest experiment and related to the proportion of pioneer species (Ouédraogo et al. 2011, Gourlet-Fleury et al. 2013). The direct impact of logging on other structural attributes such as AGB and NHA has been proposed to evaluate the sustainability of logging activities (Sist et al. 2021) and used to model forest recovery after logging (Rutishauser et al. 2015; Maurent et al. 2023). Tree information necessary to compute these structural attributes and, consequently, logging impacts is not commonly measured in tropical forests. This process requires inventory plots in the field, which can be expensive and time-consuming. Additionally, some measurements are challenging, such as tree heights, which are needed to calculate AGB (Larjavaara and Muller-Landau 2013). Here, we proposed to use more accessible measurements, i.e., logging intensity (V or N harvested per ha) and canopy opening as a starting point to predict logging impact (delta AGB, BA, NHA). Logging intensity is a commonly used metric (BAD 2018) and is recorded by logging companies for timber trackability, while canopy opening can be measured by remote sensing (Dupuis et al. 2020). For example, logging companies could use their existing inventory data to evaluate the impact of logging on forest structure, enabling them to adapt their practices for improved sustainability. By employing these alternative metrics, we aim to provide a more practical approach for assessing logging impacts and facilitating sustainable practices in tropical forest management. The models used to assess the logging impact based on logging intensity and canopy opening were built using a dataset that covers a total area of 38 ha across 3 sites. Further validation in other locations and forest types should be carried out, such as *Marantaceae* forests. While waiting for these valuable data, the marginal models presented here could provide initial estimates of the logging impact on forest structural attributes. Concerning the models predicting logging intensity based on canopy opening, and using ~6,000ha of UAV flights and >6,000 harvested trees, they could be utilized with high confidence, when measured over a grid of 500 x 500 m at least, due to the extensive dataset covering four sites and three types of forest.

In addition to this information on the direct impact of logging on forest structure, this study also confirms that UAV could act as a bridge between field inventories and satellite-based monitoring techniques. Logging impacts on forest structure are typically measured on a small scale, using inventory plots ranging from 1 to 10 hectares. However, these observations may not be representative of the overall logging intensity due to spatial variations within central African logging concessions, as shown in this study, and higher pressure on smaller concessions (Pérez et al. 2005). Localized intensity can surpass the average of 0.7 to 4.0 trees per hectare, with certain areas experiencing up to 9-10 trees and 180-200 m^3 harvested, along with 85% of canopy opening in 1-ha plots (Dupuis et al., 2023; Welsink et al., 2023). A larger-scale evaluation should be recommended, and using UAV RGB imagery as a bridge offers a cost-effective alternative to LiDAR, and can be repeated affordably to detect and quantify disturbances (McNicol et al. 2021; Ota et al. 2019; Réjou-Méchain et al. 2019). In French Guiana, Bourgoin et al. (2020) used texture indices to reveal disturbances on UAV images, while we propose to use a simpler indicator here in Central Africa, the percentage of canopy opening after logging. Canopy opening is a key indicator of disturbance frequently measured by remote sensing (Dupuis et al. 2020), and can be detected automatically on UAV images using a classification algorithm (Castillo et al. 2022) or manually, as shown in this study. Moreover, canopy opening is a simple metric attributed to the fall of emergent and canopy trees, contributing significantly to the decrease in AGB and BA because large trees shape the structure of tropical moist forests (Bastin et al. 2018). Canopy opening measured on UAV images can help detect small disturbances that are not identifiable using satellite data. This information can be used to accurately assess the extent of disturbances and calibrate satellite-based methods (Castillo et al. 2022; Dupuis et al. 2023; Heinrich et al. 2023), and finally upscale the impact of logging on large scale (Réjou-Méchain et al. 2019). Indeed, current large-scale disturbance detection methods such as the Tropical Moist Forest products (Vancutsem et al. 2021) and the RADD system (Reiche et al. 2021) have limited accuracy as shown in Cameroon (Dupuis et al. 2023). Promising results indicate that it may soon be possible to detect forest disturbance caused by logging on a large scale (Carstairs et al., 2022; Dupuis et al., 2023; Welsink et al., 2023) and the datasets created in this study could certainly contribute to this improvement. Similar to the Geo-Trees project (Geo-Trees 2024; Chave et al. 2019), which was designed for biomass estimation, the protocol used in this study—combining inventory plots and UAV flights—could be replicated in various regions to establish reliable references for calibrating satellite-based methods.

5. Conclusion

This study covers multiple inventory plots and UAV images in Central Africa, improving the representativeness of the results compared to local studies and providing a valuable reference to evaluate logging activities' impact on forest structure. Logging practices in Central Africa have small direct impact on forest structural attributes and on canopy compared to other continents. Logging impact is strongly related to logging intensity and canopy openings, but the models proposed in this study and based on a few plots should be further validated. Logging intensity can be predicted with high confidence based on canopy openings when measured over a grid of 500 x 500 m at least. By using UAV-measured canopy openings as a bridge, we show how field data can be connected to remote sensing measurements for large-scale monitoring of logging impacts on forest structure. These findings have strong implications for forest disturbance monitoring systems, which is particularly important within the context of environmental crises, sustainable forest management, certification standards, and European regulations.

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