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LETTER

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 0.7–4.0 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 6000 harvested trees, and drone RGB images covering over 6000 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 (relative root mean squared error (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 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 (Dupuis *et al* 2024 (available at: 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.

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, 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, 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, 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 (Tritsch *et al* 2020, FSC 2022).

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%–11%, observed using uninhabited aerial vehicle (UAV) and satellite imagery (Ngueguim *et al* 2009, Medjibe, *et al* 2013, Dupuis *et al* 2023). The extent of ground damage varies depending on the type of logging operations: felling gaps range in size from 218 to 578 m^2 (Doucet *et al* 2009, Medjibe *et al* 2011), 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 (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 (Sist and Nguyen-Thé 2002, Peña-Claros *et al* 2008, Gourlet-Fleury *et al* 2013). Logging intensity has a direct impact on the amount of damages caused to the forest (Durrieu de Madron *et al* 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 ha 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). 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 $Mg \cdot ha^{-1}$), basal area (BA, in $m^2 \cdot ha^{-1}$), 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?

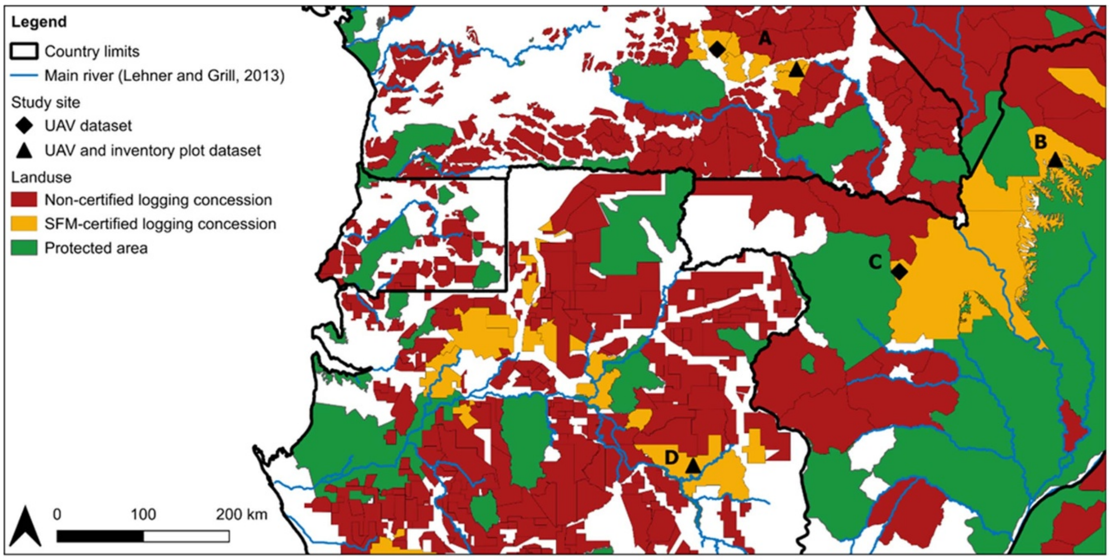
2. Material and methods

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 (figures 1(a) 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, Loubota *et al* 2018). 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 *et al* 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.

2.2. Inventory plots and harvested trees

Forest inventory plots were installed before any logging activities in sites A (1 × 4 ha), B (2 × 9 ha) and D (4 × 4 ha) (figures 1 and 2(a)), 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



	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.

to logging, all trees with a diameter at breast height (DBH) $\geqslant$ 10 cm were identified by field botanists, measured and recorded (figure 2(a)). Each tree was geolocated using the x and y coordinates within the 20 $\times$ 20 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 2(a)). In addition, in the UAV covered areas, we recorded the location and the DBH of all harvested trees (6503 trees in total, figure 2(b)). 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 (Takasu and Yasuda 2009, Cledat *et al* 2020). 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

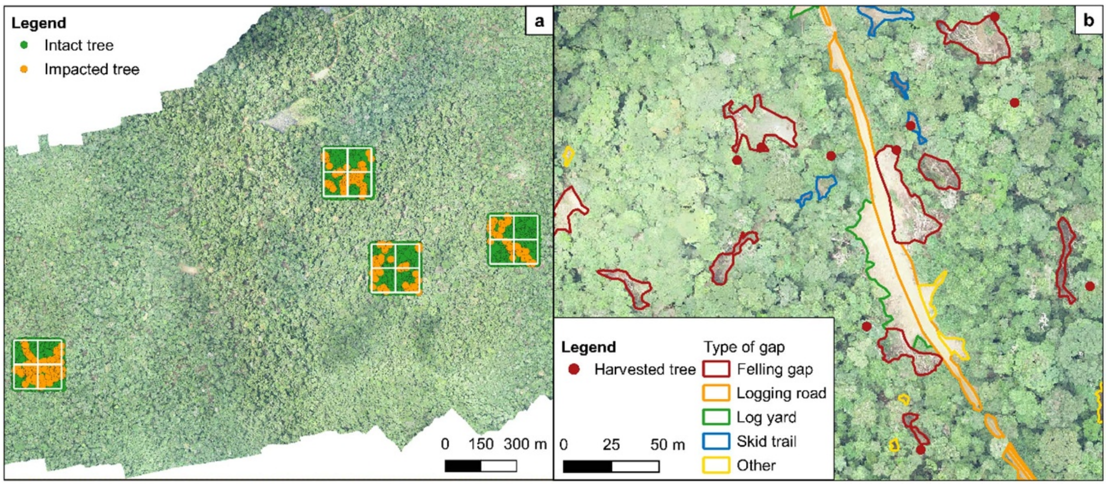


Figure 2. Example of plot data (a) and UAV images (b) used to assess the impact of logging on forest structure from site D. Example of 4 ha plots and inventoried trees are shown in (a). Impacted trees correspond to all trees that are not intact after logging activities. Locations of harvested trees provided 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.

trails, log yards and others when the cause was not clearly identifiable (figures 2(b) and 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 (Dupuis *et al* 2024). 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 RMSE to the mean (rRMSE).

2.4. Biomass and volume estimates at the tree level

The 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 (Molto *et al* 2013, Fayolle *et al* 2016). 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 1 ha-subplot level computing for example AGB (in $t \cdot ha^{-1}$), BA (in $m^2 \cdot ha^{-1}$), and NHA (in number of $trees \cdot ha^{-1}$). 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 $harvested \cdot ha^{-1}$) and commercial timber volume (V harvested in $m^3 \cdot ha^{-1}$) 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 1 ha-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 modeled 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 *et al* 2000, Guitet *et al* 2012). Logging impact was modeled using an exponential growth model including canopy opening as an explanatory variable (equation (2)), indicating that

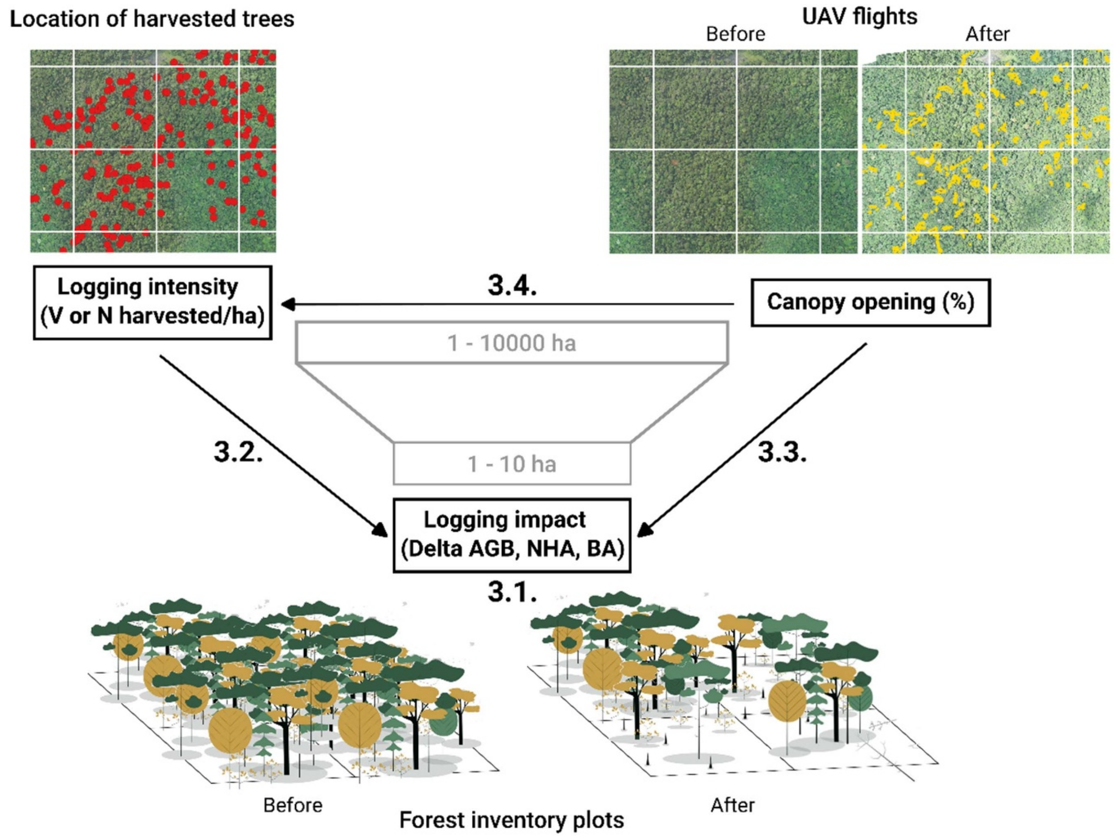


Figure 3. Forest structural attributes measured at different scales, from the inventory plots (paragraph 3.1) to the UAV flights level, and relationships established between these attributes (paragraphs 3.2, 3.3 and 3.4).

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 (equations (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)–(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)–(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 × 2000 m separated by 200 m. Equal numbers of points were randomly selected in each fold during cross-validation,

$$y = 1 - \exp\left((b+\beta)x\right) + \varepsilon_{ij} \quad (1)$$

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

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

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

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

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

3. Results

3.1. Impact of logging on forest structure

Before logging, the mean estimated average AGB was 435.4 t·ha^{-1}, with 381.7 trees·ha^{-1} and a BA of 32.8 m^2·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).

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 ($t \cdot ha^{-1}$)	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 m^3 harvested)	/	0.6	0.3	1.2	2.1
NHA (# $trees \cdot ha^{-1}$)	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 m^3 harvested)	/	0.72	0.56	0.06	1.34
BA ($m^2 \cdot ha^{-1}$)	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 (m^2 per m^3 harvested)	/	0.04	0.03	0.08	0.15

For an average logging intensity of 1.1 trees harvested per hectare corresponding to an exploitable volume of 18.4 $m^3 \cdot ha^{-1}$, AGB, NHA and BA were respectively reduced by an average of 8.8%, 6.5% and 8.5% (table 1). 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).

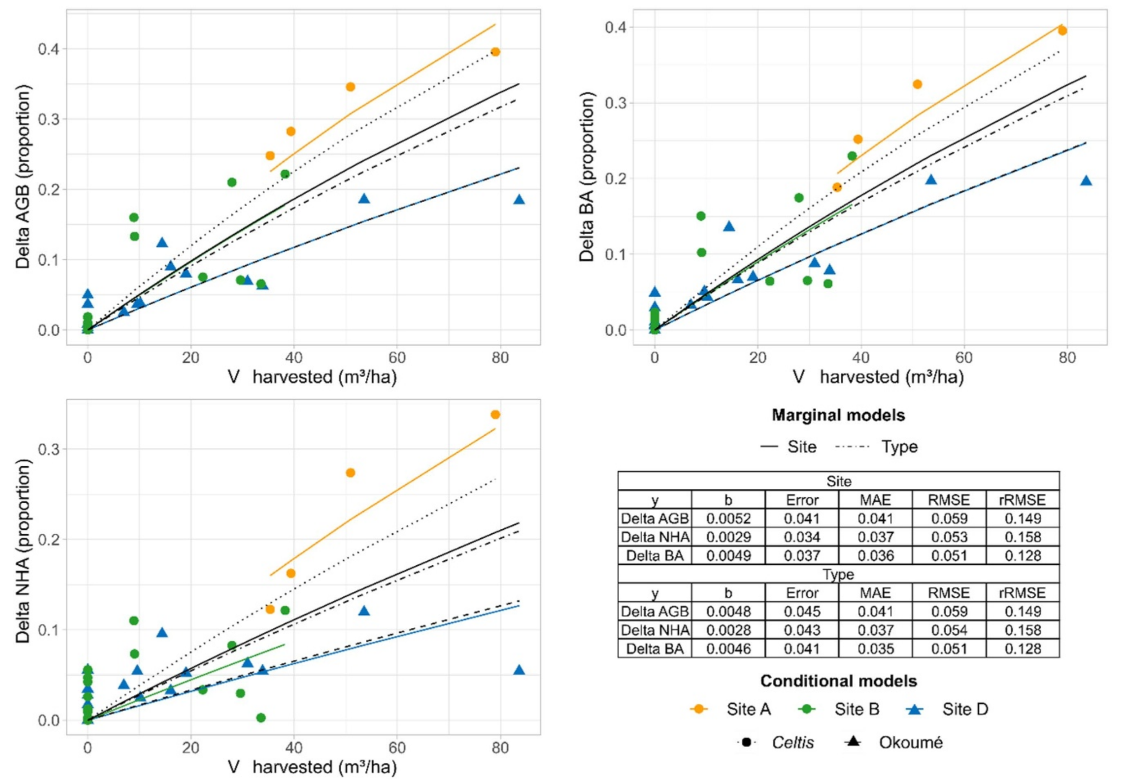
Over the 5937 ha covered by the UAV flights, 4.4% of the canopy area was impacted by logging activities. Felling gaps had a mean area of 577.7 m^2 (median = 448.2 m^2, sd = 531.1 m^2, N = 2443) (figure S6) corresponding to 217 m^2 of gap per harvested tree. Felling gaps were the most important disturbance 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 1 ha-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 (figures 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 (figures 4 and S8).

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 1 ha-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	0.0052	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

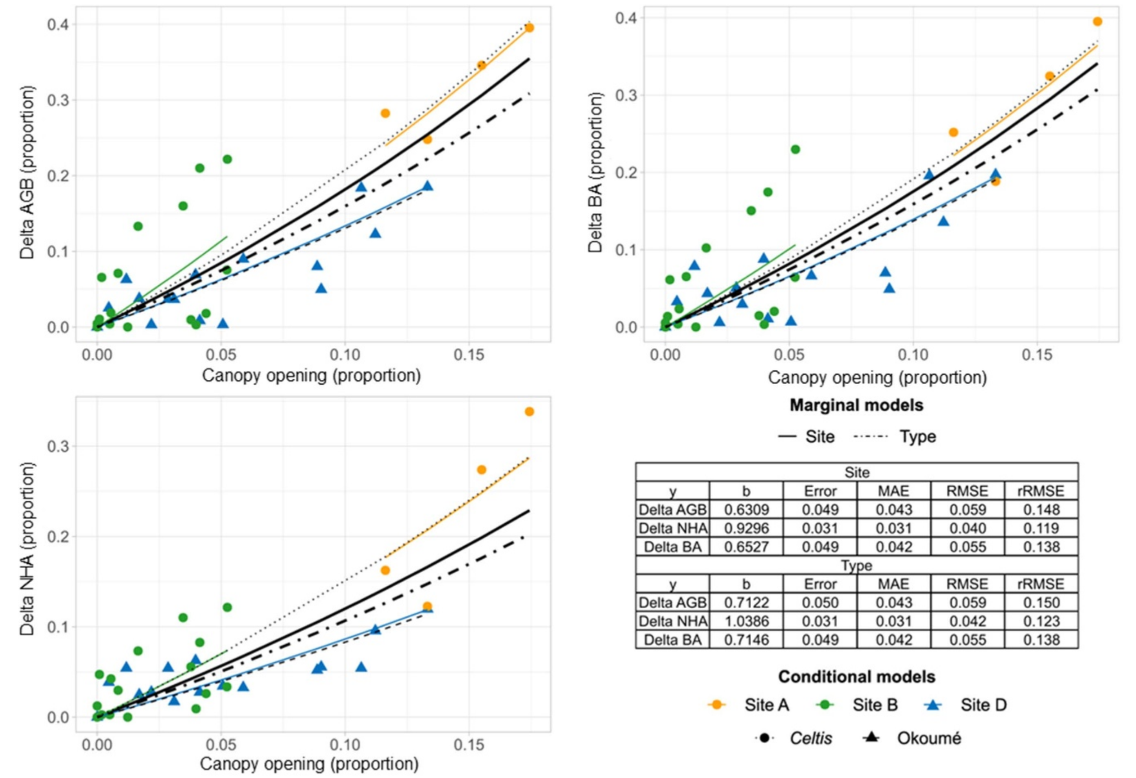
Figure 4. Prediction of logging impact based on logging intensity in terms of volume (V) harvested per hectare within 1 ha-subplots ($n = 38$), according to the different sites and types of forest. Marginal and conditional models for each site and type of forests are shown on the graphs. The table contains 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.

3.4. 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 500×500 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 500×500 m.

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 (Ngueguim *et al* 2009, Medjibe *et al* 2013). 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 m^2 with N harvested = 2443 and 217 m^2 per harvested trees) was nevertheless smaller than earlier measurements in Gabon (mean = 787 m^2, N harvested = 12) (Medjibe, *et al* 2013), but close to the estimation of Doucet *et al* (2009) in Cameroon, where the average gap area was 265.8 m^2 (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*

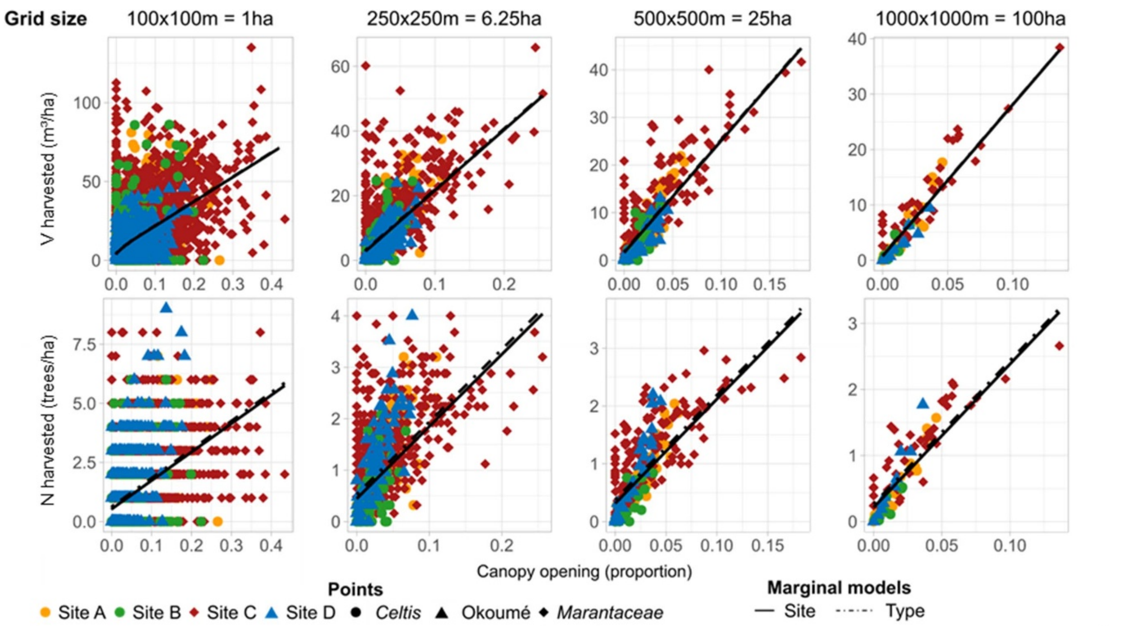


Site					
y	b	Error	MAE	RMSE	rRMSE
Delta AGB	0.6309	0.049	0.043	0.059	0.148
Delta NHA	0.9296	0.031	0.031	0.040	0.119
Delta BA	0.6527	0.049	0.042	0.055	0.138
Type					
y	b	Error	MAE	RMSE	rRMSE
Delta AGB	0.7122	0.050	0.043	0.059	0.150
Delta NHA	1.0386	0.031	0.031	0.042	0.123
Delta BA	0.7146	0.049	0.042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

Figure 5. Prediction of logging impact based on canopy opening within 1 ha-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.

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 (Quentin *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, Eliott *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 *et al* 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



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 100 ha, 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.

(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 ∼6000 ha of UAV flights and >6000 harvested trees, they could be utilized with high confidence, when measured over a grid of 500 × 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 ha. 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 0.7–4.0 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 (Ota *et al* 2019, Réjou-Méchain *et al* 2019, McNicol *et al* 2021). 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 (Chave *et al* 2019, Geo-Trees 2024), 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 × 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.

Data availability statement

The dataset is available at this link: https://hdl.handle.net/2268/323683 (Dupuis *et al* 2024).

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Conflict of interest

The authors declare no conflict of interest.

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References

Eba'a Atyi R, Richard F H H, Lescuyer G, Mayaux P, Defourny P, Bayol N, Saracco F, Pokem D, Sufo Kankeu R and Nasi R 2022 The forests of the Congo Basin: state of the forests 2021 *The Forests of the Congo Basin: State of the Forests 2021* (CIFOR) 10.17528/cifor/008700
BAD 2018 Rapport Stratégique Régional—Développement Intégré et Durable de La Filière Bois Dans Le Bassin Du Congo : opportunités, Défis et Recommmandations Opérationnelles *Vision Stratégique et Industrialisation de La Filière Bois En Afrique Centrale* (Hori)
Bastin J F *et al* 2018 Pan-tropical prediction of forest structure from the largest trees *Glob. Ecol. Biogeogr.* **27** 1366–83
Bauwens S, Ploton P, Fayolle A, Ligot G, Loumeto J J, Lejeune P and Gourlet-Fleury S 2021 A 3D approach to model the taper of irregular tree stems: making plots biomass estimates comparable in tropical forests *Ecol. Appl.* **31** 1–12
Bayas L *et al* 2022 Drivers of tropical forest loss between 2008 and 2019 *Sci. Data* **9** 1–8
Bourgoin C *et al* 2020 UAV-based canopy textures assess changes in forest structure from long-term degradation *Ecol. Indic.* **115** 106386
Castillo G V B, de Freitas L J M, Almeida Cordeiro V, Orellana J B P, Reategui-Betancourt J L, Nagy L and Matricardi E A T 2022 Assessment of selective logging impacts using UAV, Landsat, and Sentinel data in the Brazilian Amazon *J. Appl. Remote Sens.* **16** 014526
Chave J *et al* 2014 Improved allometric models to estimate the aboveground biomass of tropical trees *Glob. Change Biol.* **20** 3177–90
Chave J *et al* 2019 Ground data are essential for biomass remote sensing missions *Surv. Geophys.* **40** 863–80
Cledat E, Jospin L V, Cucci D A and Skaloud J 2020 Mapping quality prediction for RTK/PPK-equipped micro-drones operating in complex natural environment *ISPRS J. Photogramm. Remote Sens.* **167** 24–38
de Madron D, Luc B F and Dipapoundji B 2000 Dégats d'exploitation et de Débardage En Fonction de l'intensité d'exploitation En Forêt Dense Humide d'Afrique Centrale *Bois For. Trop.* **264** 57–60
Doucet J L, Lambert Kouadio Y, Monticelli D and Lejeune P 2009 Enrichment of logging gaps with moabi (Baillonella toxisperma Pierre) in a Central African rain forest *For. Ecol. Manage.* **258** 2407–15
Dupuis C *et al* 2024 Scaling up the assessment of logging's impact on forest structure in Central Africa using field and UAV data: dataset (available at: https://hdl.handle.net/2268/323683)
Dupuis C, Fayolle A, François Bastin J, Latte N and Lejeune P 2023 Monitoring selective logging intensities in Central Africa with sentinel-1: a canopy disturbance experiment *Remote Sens. Environ.* **298** 113828
Dupuis C, Lejeune P, Michez A and Fayolle A 2020 How can remote sensing help monitor tropical moist forest degradation?—A systematic review *Remote Sens.* **12** 1087
Eliott M, Hérault B, Piponiot C, Derroire G, Delgado D, Finegan B, Aubry Kientz M, Amani B H K and Ange Ngo Bieng M 2023 A common framework to model recovery in disturbed tropical forests: common model for disturbed forest recovery *Ecol. Modelling* **483** 110418
Fayolle A *et al* 2018 A regional allometry for the Congo Basin forests based on the largest ever destructive sampling *For. Ecol. Manage.* **430** 228–40
Fayolle A, Jopaul Loubota Panzou G, Drouet T, Swaine M D, Bauwens S, Vleminckx J, Biwole A, Lejeune P and Louis Doucet J 2016 Taller trees, denser stands and greater biomass in semi-deciduous than in evergreen lowland Central African forests *For. Ecol. Manage.* **374** 42–50
Fayolle A, Picard N, Louis Doucet J, Swaine M, Bayol N, Bénédet F and Gourlet-Fleury S 2014 A new insight in the structure, composition and functioning of Central African moist forests *For. Ecol. Manage.* **329** 195–205
FSC 2022 Forest stewardship council—Africa (available at: https://africa.fsc.org/)
Geo-Trees 2024 Geo-trees 2024 (available at: https://geo-trees.org/)
Gillet J-F 2013 Les Forets a Marantaceae Au Sein De La Mosaïque Forestiere Du Nord De La Republique Du Congo : origines Et Modalites De Gestion *Communaute Francaise De Belgique Academie Universitaire Wallonie-Europe Universite De Liege*— (*Gembloux Agro-Bio Tech*)
Gourlet-Fleury S, Mortier F, Fayolle A, Baya F, Ouédraogo D, Bénédet F and Picard N 2013 Tropical forest recovery from logging: a 24 year silvicultural experiment from Central Africa *Phil. Trans. R. Soc.* B **368** 1–10
Guitet S, Pithon S, Brunaux O, Jubelin G and Gond V 2012 Impacts of logging on the canopy and the consequences for forest management in French Guiana *For. Ecol. Manage.* **277** 124–31
Heinrich V H A *et al* 2023 The carbon sink of secondary and degraded humid tropical forests *Nature* **615** 436–42
Henry M *et al* 2013 GlobAllomeTree: international platform for tree allometric equations to support volume, biomass and carbon assessment *IForest* **6** 326–30
Hirsh F, Jourget J-G, Feintrenie L, Bayol N and Atyi R E 2013 Projet Pilote REDD+ de La Lukénie (available at: www.cifor.org/publications/pdf_files/WPapers/WP111Atyi.pdf)
Kleinschroth F, Laporte N, Laurance W F, Goetz S J and Ghazoul J 2019 Road expansion and persistence in forests of the Congo Basin *Nat. Sustain.* **2** 628–34
Larjavaara M, Muller-Landau H C and Metcalf J 2013 Measuring tree height: a quantitative comparison of two common field methods in a moist tropical forest *Meth. Ecol. Evol.* **4** 793–801
Ligot G, Dubart N, Tchowo Hapi M, Bauwens S, Doucet J-L and Fayolle A 2019 Réviser Les Tarifs de Cubage Pour Prendre En Compte l'évolution de La Ressource Au Cameroun *Bois For. Trop.* **338** 57
Lisein J, Pierrot-Deseilligny M, Bonnet S and Lejeune P 2013 A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery *Forests* **4** 922–44
McNicol I M, Mitchard E T A, Aquino C, Burt A, Carstairs H, Dassi C, Modinga Dikongo A and Disney M I 2021 To what extent can UAV photogrammetry replicate UAV LiDAR to determine forest structure? A test in two contrasting tropical forests *J. Geophys. Res.* **126** 1–17
Medjibe V P, Putz F E and Romero C 2013 Certified and uncertified logging concessions compared in Gabon: changes in stand structure, tree species, and biomass *Environ. Manage.* **51** 524–40
Medjibe V P, Putz F E, Starkey M P, Ndouna A A and Memiaghe H R 2011 Impacts of selective logging on

above-ground forest biomass in the Monts de Cristal in Gabon *For. Ecol. Manage.* **262** 1799–806

Molto Q, Rossi V, Blanc L and Freckleton R 2013 Error propagation in biomass estimation in tropical forests *Meth. Ecol. Evol.* **4** 175–83

Ngueguim J R, Gatchui H C, Ayobami S T and Orimoogunje O O 2009 Evaluation of logging impacts on tropical rainforest in Eastern Cameroon using Remote Sensing and GIS techniques *Int. J. Bio. Chem. Sci.* **3** 771–85

Ota T, Ahmed O S, Thu S, Cin T, Mizoue N and Yoshida S 2019 Estimating selective logging impacts on aboveground biomass in tropical forests using digital aerial photography obtained before and after a logging event from an unmanned aerial vehicle *For. Ecol. Manage.* **433** 162–9

Ouédraogo D Y, Beina D, Picard N, Mortier F, Baya F and Gourlet-Fleury S 2011 Thinning after selective logging facilitates floristic composition recovery in a tropical rain forest of Central Africa *For. Ecol. Manage.* **262** 2176–86

Loubota G J, Fayolle A, Feldpausch T R, Ligot G, Doucet J-L, Forni E, Zombo I, Mazengue M, Loumeto J-J and Gourlet-Fleury S 2018 What controls local-scale aboveground biomass variation in Central Africa ? Testing structural, composition and architectural attributes *For. Ecol. Manage.* **429** 570–8

Peña-Claros M *et al* 2008 Beyond reduced-impact logging: silvicultural treatments to increase growth rates of tropical trees *For. Ecol. Manage.* **256** 1458–67

Pérez M R *et al* 2005 Logging in the Congo Basin: a multi-country characterization of timber companies *For. Ecol. Manage.* **214** 221–36

Picard N and Gourlet-Fleury S 2008 Manuel de Référence Pour l'installation de Dispositifs Permanents En Forêt de Production Dans Le Bassin Du Congo (Comifac) p 265 (available at: http://hal.cirad.fr/cirad-00339816/)

Pinard M A, Putz F E, Tay J and Sullivan T E 1995 Guidelines for a reduced-impact logging project in Malaysia *J. For.* **93** 41–45

Quentin G, du Jardin P, White L J T, Lassois L and Louis Doucet J 2022 Gabon's green gold: a bibliographical review of thirty years of research on Okoumé (Aucoumea Klaineana Pierre) *Biotechnol. Agron. Soc. Environ.* **26** 30–42

Reiche J *et al* 2021 Forest disturbance alerts for the Congo Basin using Sentinel-1 *Environ. Res. Lett.* **16** 024005

Réjou-Méchain M *et al* 2019 Upscaling forest biomass from field to satellite measurements: sources of errors and ways to reduce them *Surv. Geophys.* **40** 881–911

Réjou-Méchain M *et al* 2021 Unveiling African rainforest composition and vulnerability to global change *Nature* **593** 90–94

Réjou-Méchain M, Tanguy A, Piponiot C, Chave J and Hérault B 2017 Biomass: an R package for estimating above-ground biomass and its uncertainty in tropical forests *Meth. Ecol. Evolut.* **8** 1163–7

Rutishauser E *et al* 2015 Rapid tree carbon stock recovery in managed Amazonian forests *Curr. Biol.* **25** R787–88

Saiful I and Latiff A 2019 Canopy gap dynamics and effects of selective logging: a study in a primary hill dipterocarp forest in Malaysia *J. Trop. For. Sci.* **31** 175–88

Sanchez-Azofeifa A, Antonio Guzmán J, Campos C A, Castro S, Garcia-Millan V, Nightingale J and Rankine C 2017 Twenty-first century remote sensing technologies are revolutionizing the study of tropical forests *Biotropica* **49** 604–19

Sist P 2000 Reduced-impact logging in the tropics : objectives, principles and impacts *Int. For. Rev.* **2** 3–10

Sist P and Nguyen-Thé N 2002 Logging damage and the subsequent dynamics of a dipterocarp forest in East Kalimantan (1990–1996) *For. Ecol. Manage.* **165** 85–103

Sist P, Piponiot C, Kanashiro M, Pena-Claros M, Putz F E, Schulze M, Verissimo A and Vidal E 2021 Sustainability of Brazilian forest concessions *For. Ecol. Manage.* **496** 119440

Sullivan M J P *et al* 2018 Field methods for sampling tree height for tropical forest biomass estimation *Methods Ecol. Evol.* **9** 1179–89

Takasu T and Yasuda A 2009 Development of the low-cost RTKGPS receiver with an open source program package RTKLIB *Int. Symp. on GPS/GNSS* (*4–6 November*) (International Convention Center)

Tritsch I, Le Velly G, Mertens B, Meyfroidt P, Sannier C, Sylvestre Makak J and Houngbedji K 2020 Do forest-management plans and FSC certification help avoid deforestation in the Congo Basin? *Ecol. Econ.* **175** 106660

Tyukavina A, Hansen M C, Potapov P, Parker D, Okpa C, Stehman S V, Kommareddy I and Turubanova S 2018 Congo Basin forest loss dominated by increasing smallholder clearing *Sci. Adv.* **4** 1–12

Umunay P M, Gregoire T G, Gopalakrishna T, Ellis P W and Putz F E 2019 Selective logging emissions and potential emission reductions from reduced-impact logging in the Congo Basin *For. Ecol. Manage.* **437** 360–71

Van Hoef Y, Doucet J-L and Fayolle A 2019 *Installation d'un Dispositif Permanent de Suivi de La Dynamique Forestière Au Gabon* (Gembloux Agro-Bio Tech, University of Liege)

Vancutsem C, Achard F, Pekel J F, Vieilledent G, Carboni S, Simonetti D, Gallego J, Aragão L E O C and Nasi R 2021 Long-term (1990–2019) monitoring of forest cover changes in the humid tropics *Sci. Adv.* **7** 1–22

Welsink A, Reiche J, de Sy V, Carter S, Slagter B, Suarez D R, Batros B, Peña-Claros M and Herold M 2023 Towards the use of satellite-based tropical forest disturbance alerts to assess selective logging intensities *Environ. Res. Lett.* **18** 054023