

Article

Using DAP-RPA Point Cloud-Derived Metrics to Monitor Restored Tropical Forests in Brazil

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Abstract

Monitoring forest structure, diversity, and biomass in restoration areas is both expensive and time-consuming. Metrics derived from digital aerial photogrammetry (DAP) may offer a cost-effective and efficient alternative for monitoring forest restoration. The main objective of this study was to use metrics derived from digital aerial photogrammetry (DAP) point clouds obtained by remotely piloted aircraft (RPA) to estimate aboveground biomass (AGB), species diversity, and structural variables for monitoring restored secondary tropical forest areas. The study was conducted in three active and one passive forest restoration systems located in a secondary forest in Sergipe state, Brazil. A total of 2507 tree individuals from 36 plots (0.0625 ha each) were identified, and their total height (ht) and diameter at breast height (dbh) were measured in the field. Concomitantly with the field inventory, the plots were mapped using an RPA, and traditional height-based point cloud metrics and Fourier transform-derived metrics were extracted for each plot. Regression models were developed to calculate AGB, Shannon diversity index (H'), ht, dbh, and basal area (ba). Furthermore, multivariate statistical analyses were used to characterize AGB and H' in the different restoration systems. All fitted models selected Fourier transform-based metrics. The AGB estimates showed satisfactory accuracy ($R^2 = 0.88$; RMSE = 31.2%). The models for H' and ba also performed well, with R^2 values of 0.90 and 0.67 and RMSEs of 24.8% and 20.1%, respectively. Estimates of structural variables (dbh and ht) showed high accuracy, with RMSE values close to 10%. Metrics derived from the Fourier transform were essential for estimating AGB, species diversity, and forest structure. The DAP-RPA-derived metrics used in this study demonstrate potential for monitoring and characterizing AGB and species richness in restored tropical forest systems.

Keywords: DRONE; ecosystem and environmental services; secondary forest; Fourier; Atlantic Forest; UAV; UAS; PCA



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1. Introduction

Climate change affects biophysical systems and human well-being on a global scale, requiring coordinated actions to mitigate its impacts [1]. In this context, the Paris Agreement, in force since 2016, established the commitment to limit the increase in global temperature to 2 °C above pre-industrial levels, with efforts to restrict it to 1.5 °C. As part of its Nationally Determined Contributions (NDC), Brazil assumed the goal of reforesting 12 million hectares by 2030, highlighting the importance of forest restoration in sustainable development, biodiversity maintenance, and the generation of ecosystem services [1].

Forest restoration is one of the principles of sustainable rural development in Brazil and must consider multiple purposes, from the maintenance of biodiversity and ecosystem services to social conservation and economic progress [1]. The planning, execution, and monitoring of restoration efforts depend heavily on the context and diagnostics of the area in relation to reference ecosystems (e.g., forests, savannas, grasslands, and wetlands) [1].

Traditionally, ecosystem monitoring is performed through field measurements of sample plots [2]. For example, tree trunk diameter, height, and density are measured over time in forest inventory campaigns to estimate the forest biomass. However, only a small part of the area can be inventoried through this laborious and costly approach, and there are serious limitations to the extrapolation of the plot data to represent extensive and heterogeneous areas [2].

As the demand for and scale of forest restoration are increasing globally, monitoring its effectiveness remains a challenge. For forest restoration, structural complexity is a recognized indicator of biodiversity [3]. Traditional methods of measuring structural complexity are costly and time-consuming, resulting in a discrepancy between the scales of “available” and “needed” information. Together with advances in both sensors and platforms, there is an unprecedented opportunity for monitoring effectiveness at the landscape level using remote sensing [3].

The application of new remote sensing technologies for data analysis, storage, and processing can address several important challenges when the goal is to monitor extensive areas of forest restoration more quickly and with greater efficiency [2]. Specifically, these technologies can subsidize the following: (1) the selection of areas to be restored; (2) the definition between forest restoration practices in the landscape (e.g., agroforests, natural regeneration areas, plantings of native tree species) when not known or for verification; and (3) the assessment of indicators of structure, function, and diversity of vegetation [2].

Available remote sensing technologies, such as Light Detection and Ranging (LiDAR), which uses laser pulses to determine distances between structures, as well as spectral imaging (hyperspectral and multispectral), demonstrated potential value for ecological applications and in monitoring restored areas [2,4,5]. LiDAR data can accurately measure height, allowing for estimation of aboveground biomass and carbon stock, but plant diversity remains a challenge [2,4,6].

Alternatively, overlapping oblique photographs taken by a digital camera carried by a Remotely Piloted Aircraft (RPA) can also generate dense point clouds. However, limited by the relatively small penetration capacity of natural light, photographs captured by the digital camera of an RPA are more suitable for obtaining point cloud data from relatively open forests or from forest restorations [7,8].

When performing a cost–benefit analysis between the use of DAP-RPA and traditional forest inventory to estimate aboveground biomass in forest restorations and secondary forests in mangroves in Australia, ref. [9] found that the use of DAP-RPA is cheaper and faster and with the same accuracy as traditional inventory. Ref. [10] measured vegetation height for 30 plots in forest restoration sites by natural regeneration after earthquakes in the

boreal forest of Canada. A total cost was calculated, including field staff, of approximately EUR 9300 for RPA-Lidar and EUR 6800 for DAP-RPA.

Ref. [11] performed a cost and efficiency analysis comparing the acquisition of height, diameter, and basal area data for secondary forests in the Brazilian Atlantic Forest from point clouds obtained by Lidar and DAP-RPA. The results demonstrate that RPA photogrammetry metrics can be used to estimate height, diameter, and basal area of arboreal vegetation with equal accuracy to that obtained by LiDAR. They also had the lowest cost; the estimates derived from DAP-RPA made possible the classification of successional stages in the secondary forest areas analyzed.

In another study, ref. [7] used metrics extracted from DAP-RPA point clouds to estimate information from a secondary forest in Brazil, and the best model for AGB explained 93% ($R^2 = 0.93$, RMSE = 22.5%) of the variation in biomass at the plot level; adjusted models for tree density, diameter at breast height, height, and basal area with R^2 values above 0.90 were observed.

Despite the good results, there are still few studies that used metrics derived from DAP-RPA point clouds to monitor AGB, richness, and structure in areas of restored secondary tropical forest in the Brazilian Atlantic Forest [3]. Although there are examples of the application of such technologies in forestry and conservation ecology, there are few reports of remote sensing to monitor the efficiency of forest restoration actions in reversing land degradation [3]. Such monitoring needs baseline data for the restoration site, as well as a comparative analysis of the restoration trajectory in relation to the structural complexity of a reference system [3].

Therefore, the objective of this study was to estimate the values of above-ground biomass (AGB), Shannon diversity index (H'), basal area (ba), total height (ht), and diameter at breast height (dbh) of restored secondary tropical forests in Brazil with metrics derived from DAP-RPA point clouds.

2. Materials and Methods

2.1. Study Area

The work was carried out in four different restoration systems (three active and one passive) in secondary tropical forests located in the state of Sergipe, Brazil (Figure 1). The active systems are located at the approximate coordinates of 11°06'30" South latitude and 37°19'60" West longitude, in the municipality of Itaporanga D'Ajuda, SE. The predominant soil is classified as Red-Yellow Argisol [12], and the relief is gentle. The passive system is located at the approximate central coordinate of 10°55' South latitude and 37°11' West longitude, in the municipality of São Cristóvão. The predominant soil is classified as Red-Yellow Argisol [12], and the relief is gentle, with altitude values ranging from 14 to 57 m and an average slope of 6% [7].

The original vegetation of both areas corresponds to the semideciduous seasonal forest (Atlantic Forest). The local climate is humid to subhumid and megathermal, with medium rainfall (~800 mm) in autumn and winter (July and August) and drier months (December to February) in summer [13]. The average annual air temperature is approximately 24.8 °C, with a low thermal amplitude (around 3.4 °C).

2.2. Restoration Systems

The study considered three active restoration systems implemented in areas originally cultivated with *Eucalyptus urophylla* plantations, all managed and planted in 2013, with a 10-year implementation time (Figure 1). In one of the systems, called C100% + P, 100% of the eucalyptus species were removed (C), and native tree species were planted (P) at a spacing of 4 × 4 m. In the C50% + P system, 50% of the eucalyptus was selectively

harvested, and native tree species were planted at a spacing of 4×4 m. Among others, the following native species of the Atlantic Forest biome were planted: *Inga uruguensis*, *Protium heptaphyllum*, *Pseudobombax grandiflorum*, *Cecropia pachystachya*, and *Byrsonima crassifolia* (Figure 1).

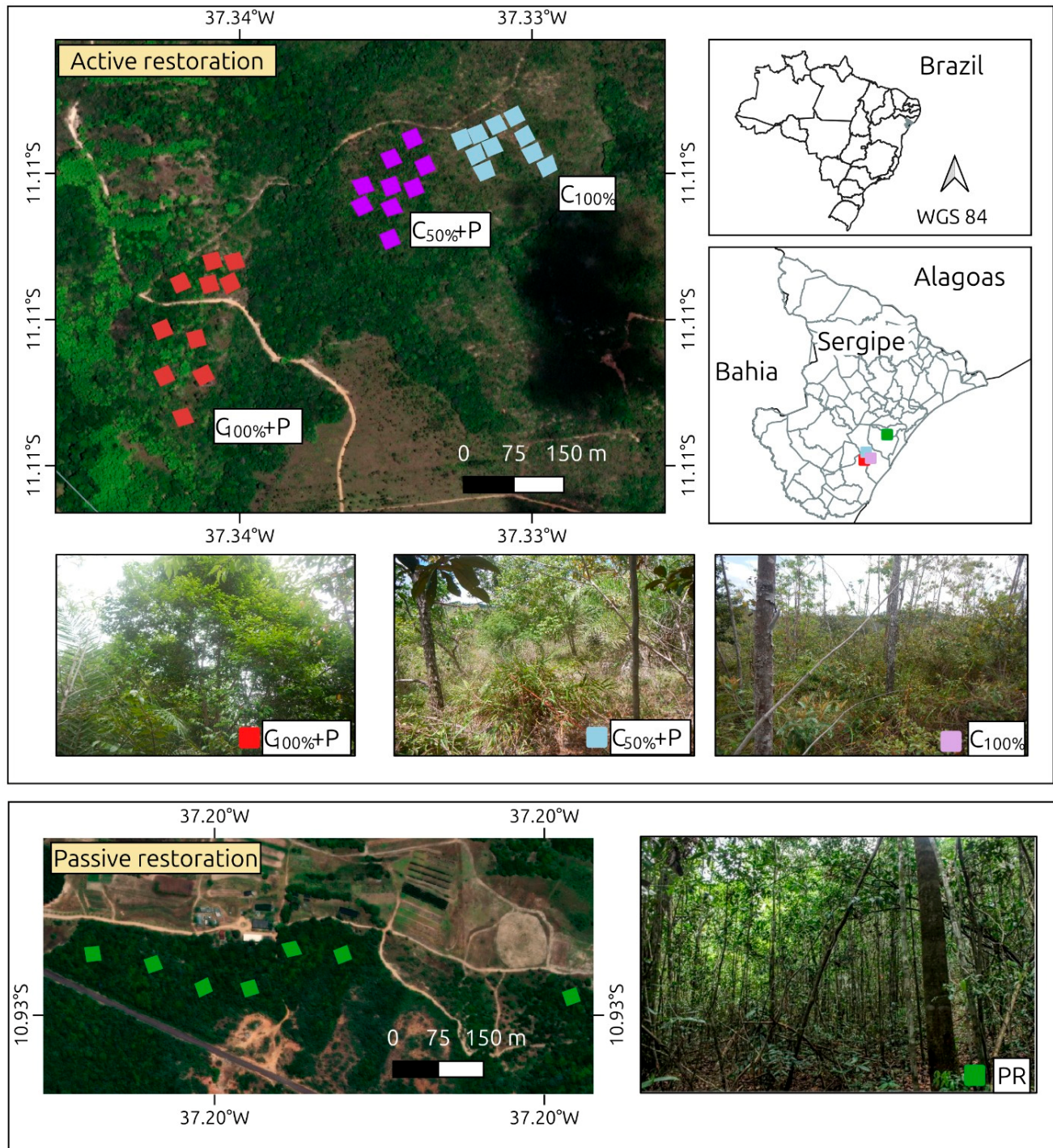


Figure 1. Study areas. The pictures above illustrate the four restoration systems, where C100% + P corresponds to the active system with the removal of all trees of the genus *Eucalyptus* with the enrichment of native forest species; C50% + P corresponds to the active system with the removal of 50% of the trees of the genus *Eucalyptus* with the enrichment of native forest species; C100% corresponds to the active system where all species of the genus *Eucalyptus* were removed and the area fenced; and PR corresponds to the passive restoration system.

In the third active system (C100%), 100% of the eucalyptus individuals were clear-cut, followed by a natural regeneration process with fencing of the area. The passive restoration system (PR) consists of a secondary tropical forest undergoing a natural regeneration process for approximately 20 years, since 2002. The main tree species found are *Cordia trichotoma*, *Cupania vernalis* Cambess, *Byrsonima verbascifolia*, *Himatanthus obovatus*, and *Protium heptaphyllum* (Figure 1).

2.3. Forest Inventory

2.3.1. Sampling

The field inventory was carried out from December 2021 to June 2022, using systematic sampling of fixed area plots. Thirty-six permanent square plots measuring approximately 25 m × 25 m (~0.0625 ha) were allocated, 29 in the active system and 7 in the passive system (Figure 1). In active systems, the average distance between plots was 13 m. In passive systems, the average distance between plots was 70 m. Of the 29 plots in the active system, 10 plots were sampled in the C100% + P system with an area of 0.625 ha. In the C50% + P system, nine plots were sampled with an area of 0.562 ha. In the C100% system, 10 plots were sampled with an area of 0.625 ha. In the passive system, the seven sampled plots totaled an area of 0.437 ha. The sampling intensity was 12%, and an area of 2.25 ha was sampled in relation to a total area of 18.64 ha. Therefore, the sampling units were representative of the population.

2.3.2. Georeferencing of Parcels

The four vertices of the active system plots were georeferenced using a Trimble RTK R6 GNSS receiver manufactured by Trimble Navigation Limited, Westminster, CO, USA (www.trimble.com) under the UTM Zone 24S coordinate system and referenced to the SIRGAS 2000 datum. This procedure resulted in an average horizontal positional error (X and Y) of 0.02 m. Most vertices of the passive system plots were georeferenced using a FOIF A60 GNSS RTK receiver manufactured by Trimble Navigation Limited, Westminster, CO, USA (www.foif.com), with an average horizontal error of 0.92 m. In passive plots where RTK mode was not feasible, vertex coordinates were acquired using GNSS in post-processed differential mode, with a collection duration of 5 min per vertex to ensure positional accuracy.

2.3.3. Tree Measurement Methods

The circumference of the stem (trunk) of each tree in the plot was acquired with a tape measure at a height of 1.30 m above ground level and then converted to diameter at breast height (dbh). In the plots, all individuals ≥ 15 cm in circumference were measured. Few individuals with a circumference < 15 cm were observed in the systems analyzed in our study. Although important for species richness, these smaller individuals contribute little to the total biomass values per plot and the other structural variables analyzed. Therefore, these individuals were not measured. The total height (ht) values of the trees were collected with a 10 m graduated (telescopic) pole. The ht of trees taller than 10 m was estimated using a digital hypsometer Haglof. Then, the mean ht and dbh values of each plot were calculated. The basal area (ba) values of each tree were calculated based on the dbh values and totaled for the plot area. Finally, ten plots were randomly selected, and the ht and dbh values of ten random trees were estimated again by the same observer. The repeated estimates of the same tree were used to estimate the inventory measurement error, as described in the next section.

To identify the species, botanical collections were made, which were later identified through literature, in addition to the assistance of a para-botanist. Species not identified in the field were identified by comparison in the herbarium of the Federal University of Sergipe. Once the species had been identified, the wood density values (ρ) were obtained from the database of [14] at the genus or family level. A total of 2507 trees were measured. On average, 45 individuals were measured per plot, 36 (588 trees per ha) in passive systems and 70 (1030 trees per ha) in active systems.

2.4. Measurement Uncertainties

Using duplicate measurements of dbh and ht collected during the forest inventory, measurement errors were characterized in terms of total, systematic, and random components. The standard deviation values for wood density (ρ) were obtained from the study [15]. Total measurement error was quantified using the root-mean-square error (RMSE), while systematic and random errors were assessed based on the bias and the standard deviation (SD) of the measurement differences (e_i), respectively:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (e_i)^2} \text{ with } e_i = (m1_i - m2_i) \quad (1)$$

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n e_i \quad (2)$$

$$\text{SD} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (e_i - \text{Mean})^2} \quad (3)$$

where “n” is the number of pairs of repeated measurements for dbh and ht; $e_i = (m1_i - m2_i)$; $m1_i$ = the first measurement of dbh and ht; $m2_i$ = the second measurement of dbh and ht.

2.5. Estimation of AGB and Associated Uncertainties

The quantification of the aboveground biomass (AGB) of each tree (kg) in the plot was performed using the allometric equation adjusted for tropical forests [15] (Equation (4), Tables 1 and 2). This model has already been tested and successfully used in this same type of secondary forest in Brazil [7,11]. Furthermore, there are no reliable allometric models in the literature for estimating AGB adjusted for the different restoration systems analyzed in our study.

Table 1. Allometric equations used to estimate the AGB of each tree and to estimate the model selection uncertainty (σ_S).

Equations		References
$B_{\text{tree}} = \exp[-2.997 + \log(\rho \times \text{dbh}^2 \times h)]$	(4)	
$B_{\text{tree}2} = \exp(-2.134 + 2.53 \ln(\text{dbh}))$	(5)	[16]
$B_{\text{tree}3} = \rho \exp(-1.499 + 2.148 \ln(\text{dbh}) + 0.207 \ln(\text{dbh})^2 - 0.0281 \ln(\text{dbh})^3)$	(6)	[14]
$B_{\text{tree}4} = \exp(-0.37 + 0.333 \ln(\text{dbh}) + 0.933 \ln(\text{dbh})^2 - 0.122 \ln(\text{dbh})^3)$	(7)	[17]
$B_{\text{tree}5} = \exp(-3.1141 + 0.9719 \ln(\text{dbh}^2 h))$	(8)	[18]

Above-ground biomass (AGB) per hectare (Mg ha^{-1}) was calculated by summing the biomass of all individual trees within each plot and dividing by the respective plot area. Associated uncertainties were quantified and propagated through the regression models following the approach described by [19]. Measurement uncertainties (σ_M) were considered for tree height, diameter at breast height, and wood density. Uncertainties related to the allometric model (Equation (4)) were also incorporated, specifically model selection uncertainty (σ_S) and residual error (σ_A). Model selection uncertainty was estimated as the

standard deviation of biomass values obtained from the selected allometric equation in comparison with alternative models listed in Table 1. For further methodological details, see ref. [19].

Table 2. Parameters and statistics of the adjusted models for estimating aerial biomass in forest restorations.

Equations	β_0	β_1	β_2	β_3	RSE	R ²	AIC	R ² _{aj}	MSE	SE
Btree	−2.997	----	----	----	0.316	0.989	972	----	----	15.63
Btree2	−2.134	2.53	----	----	0.310	0.961	----	0.970	----	10.6
Btree3	−1.499	2.148	0.207	0.0281	0.356	0.996	1869			19.48
Btree4	−0.37	0.333	0.933	0.122				0.973	0.297	----
Btree5	−3.1141	0.9719	----	----	0.341	----	----	0.970	0.1161	----

RSE, relative standard error; R², coefficient of determination; AIC, Akaike's information criterion; R²_{aj}, adjusted R-squared; MSE, mean squared error; SE, standard error.

All uncertainty components were initially estimated at the tree level. These values were then aggregated and squared to compute plot-level uncertainty. Finally, all uncertainty components were combined in quadrature to derive the total uncertainty (σ_{AGB}) at the plot level. This total uncertainty was used as a weighting factor during regression model fitting.

2.6. Shannon Diversity Index (H')

Based on the floristic composition data collected from the forest inventory, the Shannon diversity index (H') was calculated for each area using the following expression [20]:

$$H' = -\sum_{i=1}^S p_i \cdot \ln(p_i) \quad (9)$$

where H' represents the Shannon index and p_i the proportion of individuals belonging to species i .

2.7. Digital Aerial Photogrammetry (DAP)

2.7.1. Obtaining Images

Aerial imagery (~0.04 m) was acquired using a 1'' CMOS sensor (20 megapixels) mounted on a DJI Phantom 4 PRO multirotor platform (SZ DJI Technology Co., Ltd., Shenzhen, China). Image acquisition was conducted during the forest inventory, around 12:00 p.m. local time, under clear sky conditions and wind speeds below 10 m s^{−1}, as recommended in [21]. Flights were performed at an altitude of 120 m above ground level, with 75% frontal and 70% lateral image overlap. Two flights were conducted: one (i) on 13 June 2022, over the passive restoration (PR) system, and another (ii) on 14 June 2022, covering the remaining restoration systems. A total of 252 images (JPEG format) were captured in the PR area, and 170 images in the other restored areas. All flights were conducted under visual line of sight (VLOS) conditions, in compliance with current Brazilian aviation regulations (<https://www.anac.gov.br>) (accessed 10 January 2025).

2.7.2. Aerial Photogrammetric Processing

Image processing was conducted independently for each flight using Agisoft Metashape Professional Edition 1.1.0 software [22,23]. This software uses an algorithm to detect and match keypoints, such as corners, boards, and textures. These points are matched between multiple images, finding the same features seen from different angles. From the keypoint correspondence, the Structure from Motion (SfM) algorithm calculates the relative position of the cameras and reconstructs the 3D geometry of the scene. The

result is a sparse point cloud, which represents the basic structure of the area. With the camera positions defined, Matching Dense is applied to generate the dense point cloud. During the photo alignment process, 20 ground control points (GCPs) and 10 checkpoints were employed for the flight covering the active restoration systems, while 10 GCPs and 5 checkpoints were used for the passive restoration flight. These points were physically marked in the field using red plastic templates with a diameter of 0.40 m. The points were randomly distributed within each study area, following the two predefined flight polygons. All 45 points were surveyed using a Trimble RTK R6 GNSS receiver (www.trimble.com), yielding an average horizontal positional error (X and Y) of 0.01 m across both study areas. Upon completion of image processing, the root-mean-square error (RMSE) values for the check points were 0.04 m (horizontal) and 0.11 m (vertical) in the active system area, and 0.08 m (horizontal) and 0.25 m (vertical) in the passive system area.

Image alignment was performed with high accuracy settings, including the selection of a reference pair. The maximum number of key points was set to 40,000, and tie points to 4000. For dense point cloud generation, the processing was carried out using medium-quality and mild depth filtering settings. Digital Terrain Models (DTMs) were derived from the 3D point clouds using the Adaptive Triangulated Irregular Network (TIN) algorithm developed by [24] and implemented within Agisoft Metashape. The dense point cloud was exported in LAZ format (".laz"), while the DTM was exported as a raster file (".tif") with a spatial resolution of 0.50 m.

2.7.3. DAP-RPA Metrics

The DAP-RPA dense cloud was cropped for each plot in the LidR package [25] of the R software Version 4.5.1 [26], using as a mask the polygon file generated by the four RTK vertices collected in the field. Traditional height-based metrics and canopy cover metrics were derived for each plot from the normalized dense point cloud (Table 3). When the point cloud is normalized (i.e., the height of each point is relative to the DTM), these metrics directly represent the vertical structure of the analyzed vegetation. These metrics are statistics derived from the distribution of heights in the dense point cloud. These metrics are statistics derived from the distribution of heights of the dense point cloud. Canopy height metrics included basic statistical descriptors (e.g., mean, mode, variance, maximum, and percentiles) as well as the proportion of points exceeding the specified height threshold relative to the total number of points. All metrics were extracted using the função cloudMetrics do FUSION/LDV software, version 4.61 [27]. This software was created to analyze and visualize point clouds obtained by LiDAR. A height threshold of 1.5 m was applied to distinguish ground and understory vegetation from canopy elements corresponding to trees.

In addition to the traditional structural metrics, frequency-domain metrics based on the Fourier transformation were also calculated, following the approach described by [26]. For each plot, vertical vegetation profiles were decomposed into 30 frequency components, ranging from 0.01 to 0.30 cycles per meter, with an interval of 0.01 cycles/m. This process yielded 30 metrics corresponding to the amplitude of the complex numbers associated with each frequency (e.g., amp. 01, amp. 02, ..., amp. 30). Fourier Transform-based metrics allow capturing spatial patterns of vegetation structure at different spatial frequencies, which is particularly useful for characterizing heterogeneity and periodicity in the spatial arrangement of canopy elements. All Fourier-based metrics were computed using the R programming environment [25].

Table 3. Traditional metrics extracted from normalized height values derived from digital aerial photogrammetry (DAP).

Metric Type	Variable
Height	Minimum ($H_{\min}$)
	Max ($H_{\max}$)
	Mean (H_{mean})
	Mode (H_{mode})
	Coefficient of variation (H_{cv})
	Standard deviation (H_{SD})
	Variance (H_v)
	Interquartile (H_{IQ})
	Asymmetry (H_{skew})
	Kurtosis (H_{curt})
	Percentiles ($P_{01}, P_{05}, P_{10}, P_{20}, P_{25}, P_{30}, P_{40}, P_{50}, P_{60}, P_{70}, P_{75}, P_{80}, P_{90}, P_{95}, P_{99}$)
	Generalized square root mean ($H_{\text{SQRTmeanSQ}}$)
	Generalized cubic root mean ($H_{\text{CURTmeanCUBE}}$)
	Mean absolute deviation (H_{AAD})
	Median absolute deviation from median height ($H_{\text{MAD}}_{\text{Median}}$)
	Median absolute height mode deviation ($H_{\text{MAD}}_{\text{Mode}}$)
	Linear moments (HL_1, HL_2, HL_3, HL_4)
	Linear moment asymmetry height (HL_{skew})
	Coefficient of variation of linear moments (HL_{cv})
	Canopy Relief Ratio (HCRR) ($(H_{\text{mean}} - H_{\text{min}})/(H_{\text{max}} - H_{\text{min}})$)
Canopy cover	Total all returns (CCH)
	All returns above the mean height (CCHmean)
	All returns above the height mode value (CCHmode)
	Percentage of all returns > average height in relation to the total number of points (CC%Hmean)
	Percentage of all returns > mode height relative to total number of points (CC%Hmode)
Fourier	Amplitudes (amp. 01, amp. 02, amp. 03, ..., amp. 30)

2.7.4. Photogrammetry Evaluation

The accuracy of the generated Digital Terrain Models (DTMs) was assessed using two approaches. First, DTM-derived elevation values were directly compared with field-measured elevations obtained using a Trimble RTK R6 GNSS receiver (www.trimble.com). For this comparison, elevation data from selected vertices of the forest inventory plots were used, totaling 50 points in the active restoration systems and 25 points in the passive system. Second, dominant tree height values estimated in the field were compared with the 99th percentile height values derived from the normalized DAP-RPA point clouds for each plot. Dominant tree height was calculated as the average total height of the 15 tallest trees per plot. Systematic error was evaluated using the bias, while total error was estimated using the root mean square error (RMSE), both reported in absolute terms and as percentages. All statistical analyses were performed using the R programming language [25].

2.8. Adjustment of Regression Models

Multiple linear regression models were used to estimate the AGB, the Shannon diversity index (H'), and the analyzed structural parameters (ht, dbh, and ba), with the metrics derived from the DAP-RPA point cloud as explanatory variables. Before fitting the linear regression models, we tested the strength and direction of the relationship (correlation coefficient) between the DAP-RPA metrics and the transformed values of the vegetation variables estimated in our study for logarithmic, square root, exponential scale, by its inverse value and its raised value in quadrature. The R Core

Team programming language and the package leaps [28] were used in this phase of the research.

The final model was selected based on the absence of multicollinearity among predictor variables and the lowest root mean square error (RMSE) observed in both model fitting and cross-validation (RMSECV). Model predictive performance was evaluated using a repeated random subsampling cross-validation procedure, consisting of 1000 iterations. In each iteration, 80% of the data were randomly assigned to model calibration and 20% to validation. Multicollinearity was assessed using the variance inflation factor (VIF), and models with any predictor variable showing a VIF value greater than 10 were excluded. Cross-validation was performed independently, with 1000 repetitions using 20% of the sample in each run to ensure robustness. The selected model was further evaluated using diagnostic plots, coefficient interpretation, and statistical tests for residual analysis, including the Shapiro–Wilk test for normality and Bartlett’s test for homoscedasticity. It is important to note that during model calibration, plot-level AGB uncertainties (σ AGB) were incorporated as weights, as detailed in the section on AGB estimation and associated uncertainties.

2.9. Principal Component Analysis

The characterization of the AGB and H' of each of the restoration systems was performed based on multivariate statistics, using principal component analysis (PCA). Some metrics selected in the adjustment of the regression models were considered in the PCA. Initially, the metrics were normalized, the covariance matrix was estimated, and the matrix eigenvectors were estimated. Then, the dimensionality of the data was reduced, concentrating the most significant information in the first two estimated components. Next, the variables with the greatest influence on the formation of each component were determined. All PCA analysis was performed on the R platform using the FactoMineR package [29]. The biplot graphs were generated with the factoextra package [30].

3. Results

3.1. Photogrammetry Assessment

Figure 2 shows the values, estimated in the field and by DAP-RPA, of terrain altitude (Figure 2A) and dominant tree height (Figure 2B).

Consequently, with the overestimation of terrain altitude values, an underestimation of the dominant height values of the trees was observed (Figure 2B), with bias values of 1.0 m (11.7%) and an RMSE of 25.8%, that is, approximately 2.3 m. A low/medium correlation ($R^2 = 0.45$) can be noted between the dominant height values estimated in the field and the 99th percentile values of the height of the normalized point cloud.

In Figure 3, we can observe the synthesized vertical profile of the vegetation height values of a plot of each of the forest restoration systems analyzed. Despite the underestimation of the height values of the dominant trees (Figure 2B), we can see that the DAP-RPA was able to characterize the vertical structure of each of the systems. The C100% + P system (Figure 3A) exhibits fewer individuals in the upper canopy strata compared to the C50% + P system (Figure 3B). In the C100% system (Figure 3C), tree individuals are predominantly concentrated in the lower stratum. In contrast, the reference system (Figure 3D) displays a vertical structure characteristic of a secondary tropical forest in a mid-successional stage, with individuals distributed across all vertical strata.

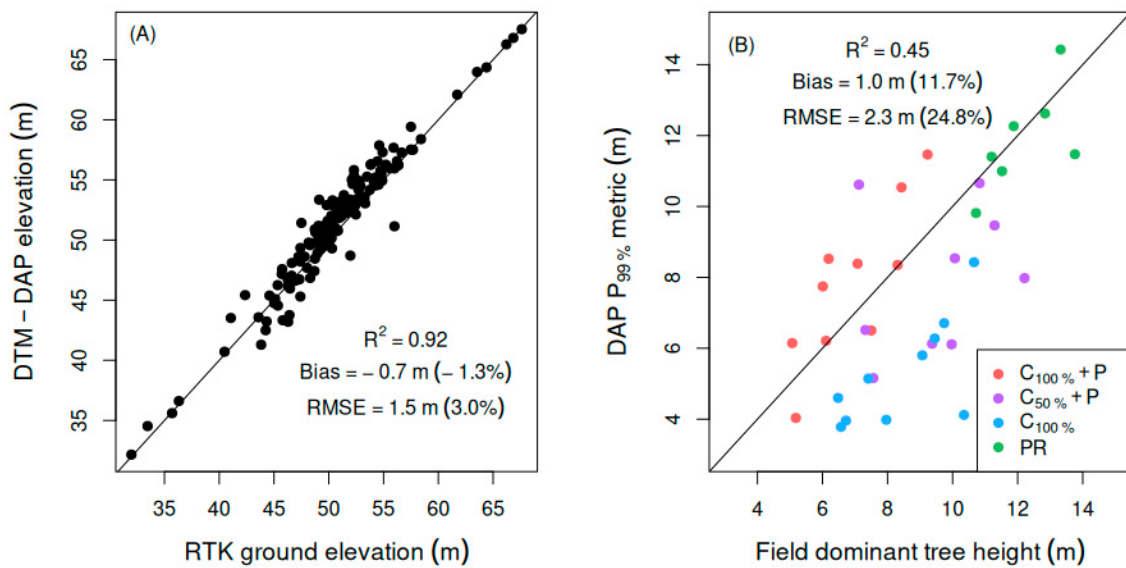


Figure 2. The scatterplot in (A) shows DTM elevations vs. the elevations collected in the field with RTK for 50 checkpoints (filled circles), while (B) shows the dominant tree heights measured in field plots (empty polygons) vs. the height values derived with the P99% metric in the same locations. C_{100%} + P: clear-cutting (C) of 100% of the species of the Eucalyptus genus and planting (P) of native tree species.

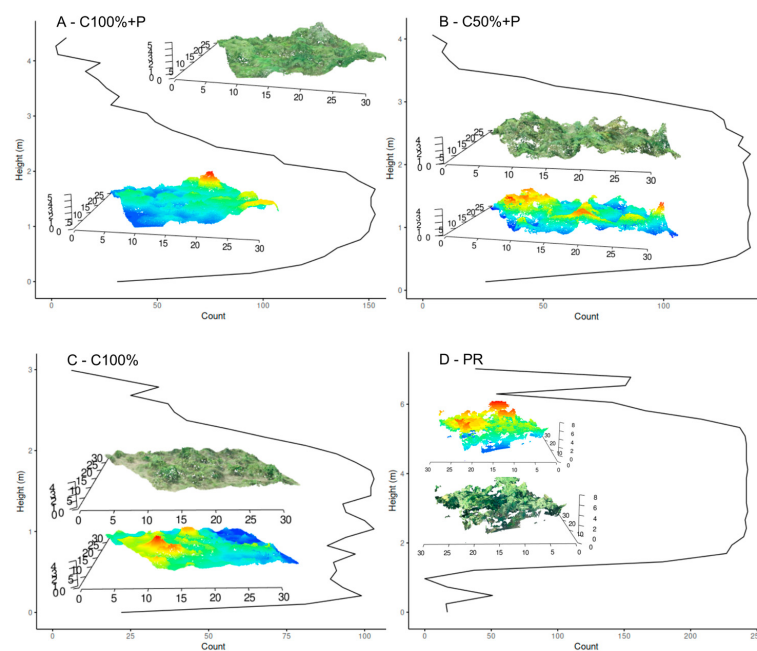


Figure 3. Vertical profiles extracted from DAP-RPA point clouds of each of the restoration systems analyzed. In the C_{100%} + P system, 100% of the eucalyptus was selectively harvested, and native tree species were planted. In the C_{50%} + P system, 50% of the eucalyptus was selectively harvested, and native tree species were planted. In the C_{100%} system, 100% of the eucalyptus individuals were clear-cut, followed by a natural regeneration process with fencing of the area. The passive restoration (PR) system consists of a secondary tropical forest.

3.2. Forest Inventory Errors and Uncertainties Associated with AGB

The differences (errors) estimated for diameter breast height (dbh) and tree total height (ht) are presented in Table 4. As in other studies [7,9], the largest differences (RMSE = 11.71%) were observed in tree height values. No tendencies of overestimation or underestimation (Bias ~0.0%) of dbh and ht values were observed.

Table 4. Measurement errors estimated with the remeasurement of X trees in two restoration systems. Statistics include total error (RMSD), systematic error (Bias), and random error (SD), in absolute and relative terms.

Variable	Range	RMSD	Bias	SD
dbh (cm)	15–87	1.28 (4.25%)	−0.1125 (−0.373506%)	1.28 (4.25%)
ht (m)	3–15	1.031 (11.71%)	−0.077 (−0.88%)	−0.077 (−0.88%)

Table 5 shows the uncertainties associated with the AGB estimation. An error in the AGB estimation at the tree level of approximately 15% was observed, of which 4.25% came from the error in estimating the diameter and 11.71% from the height of the trees. However, when estimated at the plot level, this error was reduced to an average value of 5.85% (Table 5). The errors in the model selection and its residual were, on average, approximately 3.0%. The average total uncertainty in the AGB estimates made at the plot level was approximately 10%, with minimum and maximum values of 2.98 and 39.02%, respectively.

Table 5. Plot-level uncertainty for estimating AGB of restoration systems in Brazil.

Source of Error	Error: Medium	Minimum	Maximum
		%	
Measurement (σ_M)	5.85	3.08	11.88
Allometric (model selection, σ_S)	3.1	1.79	6.89
Allometric (model residual, σ_A)	3.5	1.68	6.26
Total (σ_{AGB})	9.92	2.98	39.02

3.3. Statistical Models

Applying the exhaustive search algorithm, an accurate model with five independent variables was obtained to estimate AGB, and a model with three variables to estimate ht. We noticed that there was no improvement in the relationship between the transformed values of vegetation information and the DAP-RPA metrics. Regarding dbh, four variables were part of the model; for ba and H' , the model presents three variables. Table 6 shows the best selected models, the statistics of R^2 , RMSE, adjustment bias, and cross-validation to evaluate the performance of the models in estimating AGB, ht, dbh, ba, and H' of forest restorations.

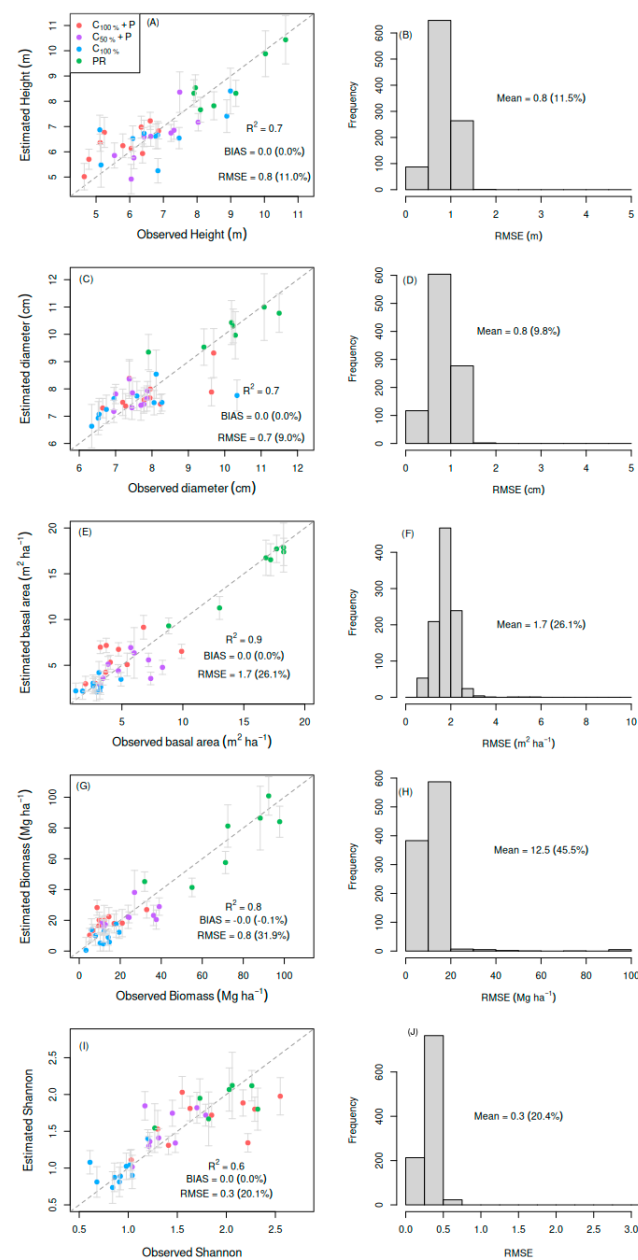
All estimated parameters for the AGB, ht, dbh, ba, and H' equations were considered significant as determined by the student's *t*-test at the 1% probability level. The five models presented a normal distribution, confirmed by the Shapiro–Wilk test ($p = 0.25$). The independent variables of each model also did not present multicollinearity ($IVF < 10$). All DAP-RPA metrics in the models to estimate AGB, ht, dbh, ba, and H' present direct relationships with height and canopy cover.

Among the dependent variables, dbh was the best performing model with the lowest RMSE and BIAS in the adjustment and validation (Table 6). The ht presents an R^2 of 0.72 and an RMSE of 11% (0.8 m), which is considered a good accuracy. In the model selected for dbh, three DAP-RPA variables are of vertical structure (H_{mode} , H_{skew} , and amp . 19) and one of canopy cover (CCH). Regarding ht, two DAP variables are of vertical structure (H_{skew} and amp . 29) and one of mean canopy cover ($CC\%H_{mean}$).

The relationships between AGB, ht, dbh, ba, and H' observed and estimated with the three-dimensional data derived from digital aerial photogrammetry obtained by the RPA were analyzed and presented as scatter plots and residuals (Figure 4). The statistics presented in Table 6 corroborate the RMSE frequency histograms observed in the model validations (Figure 4), presenting average values equal to the RMSE values observed in the adjustment.

Table 6. Result of the statistics of the selected models, adjustment and validation data, for the estimation of AGB, ht, dbh, ba, and H' .

Variable	Model	R^2	RMSE	BIAS	R^2_{CV}	$RMSE_{CV}$
AGB ($Mg\ ha^{-1}$)	$H_{mode} + H_{skew} + P_{01} + CCH_{mode} + amp.$ 23	0.88	8.8 (31.9%)	−0.0 (−0.1%)	0.71	12.5 (45.5%)
ht	$H_{skew} + CC\%H_{mean} + amp.$ 29	0.72	0.8 (11.0%)	0.0 (0.0%)	0.64	0.8 (11.5%)
dbh	$H_{mode} + H_{skew} + CCH + amp.$ 19	0.70	0.7 (9.0%)	0.0 (0.0%)	0.64	0.8 (9.8%)
ba	$H_{mode} + H_{curt} + amp.$ 01	0.90	1.6 (24.8%)	0.0 (0.0%)	0.76	1.7 (26.1%)
H'	$P_{90} + CCH_{mode} + amp.$ 19	0.67	0.3 (20.1%)	0.0 (0.0%)	0.67	0.3 (20.4%)

**Figure 4.** Scatter plots between the estimated and observed ht, dbh, ba, AGB, and H' values and the RMSE frequency histograms in model validation: (A) height scatter diagram, (B) frequency histogram of height RMSE, (C) diameter scatter diagram, (D) frequency histogram of diameter RMSE, (E) basal area scatter diagram, (F) frequency histogram of basal area RMSE, (G) biomass scatter diagram, (H) frequency histogram of biomass RMSE, (I) Shannon scatter diagram, and (J) Shannon histogram of RMSE.

3.4. Principal Component Analysis (PCA)

In the PCA, only the height mode values (Hmode), the 01% (P01) and 90% (P90) height percentiles, the canopy (CCHmode), and the two Fourier amplitudes (amps. 19 and 23) selected in the regression models were used. In addition to the AGB and H' values, the first two components (67.4% of D1 + 18.2% of D2) were able to explain more than 85% (85.6%) of the variation in the values of the DAP-RPA metrics analyzed (Figure 5).

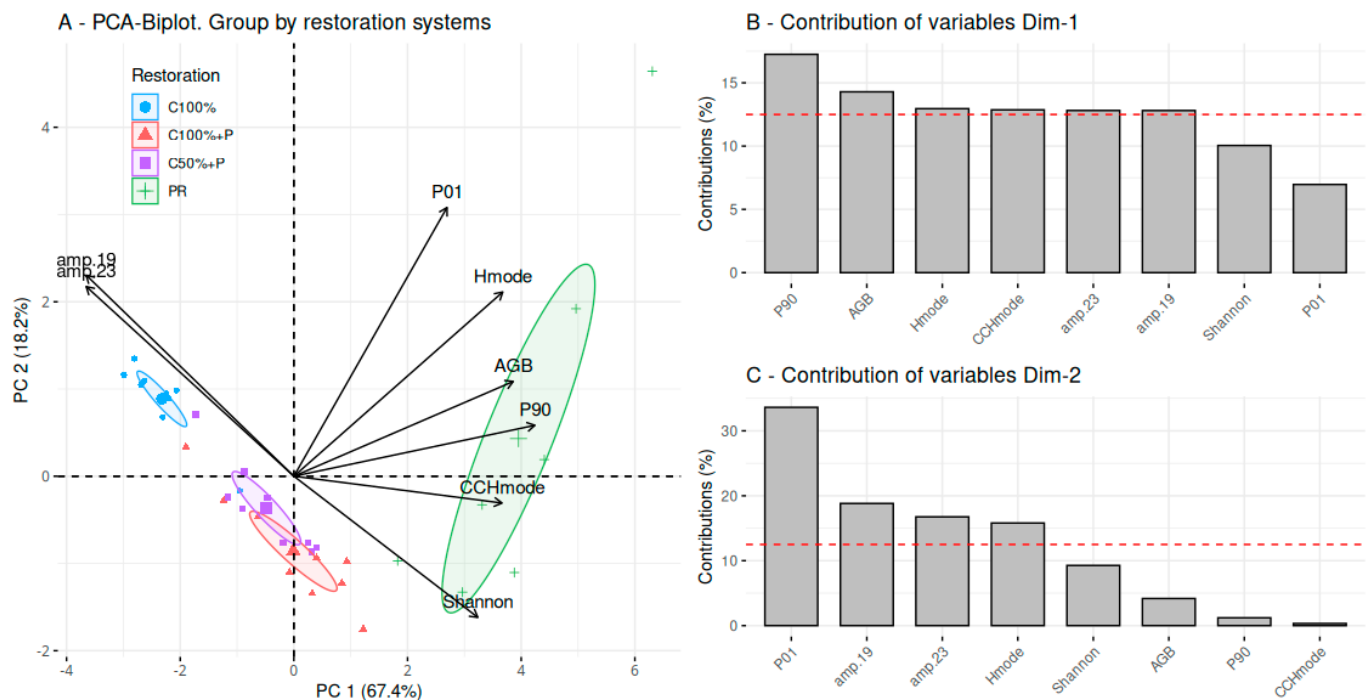


Figure 5. ACP biplot ordering the metrics derived from the height and vegetation cover obtained from the DAP-RPA point cloud and grouping the different forest restoration systems and the reference area analyzed in the study.

The variables derived from DAP-RPA that best explain the first component are related to P90, Hmode, CCHmode, amp. 19, and amp. 23, all positively correlated with this component. Two variables related to height, the 90th percentile (P90) and the height mode (Hmode). One variable related to canopy cover (CCHmode) is correlated with the first component, the metric that represents the number of points above the mode height (CCHmode) (Figure 5B). There were also two variables related to the Fourier amplitude, amp. 19 and amp. 23 (Figure 5B).

The variables that best explain the second component are P01, amp. 19, amp. 23, and Hmode (Figure 5), with two variables related to height, the 01st percentile of height (P01) and the height mode (Hmode). The variables amp. 19 and amp. 23 are related to the Fourier amplitudes (Figure 5C).

Figure 5 shows the biplot of the principal component analysis, ordering the metrics derived from the height and vegetation cover obtained from the DAP-RPA point cloud and grouping the different restoration systems and the reference area analyzed in the study. It can be seen that the reference plots were grouped together, being further away from the restoration areas (Figure 5A). The restoration plots were grouped together, with C100% + P being closer to C50% + P (similar systems, in terms of DAP-RPA variables). The C100% forest restoration differed from the other forest restorations and PR; it was not similar to any of the forest restorations (Figure 5A).

4. Discussion

As observed in other studies that used DAP-RPA in areas with secondary tropical forest in Brazil [7,11], a slight overestimation (bias of -0.7 m, 1.3%) of the terrain altitude can be observed (Figure 2A), with a total error of 3% (1.5 m). This result was expected, since DAP-RPA typically overestimates terrain altitude values because it cannot penetrate the forest canopy [31,32], which is a disadvantage when compared to data collected by LiDAR. It is also worth noting that the overestimation of altitudes may be related to the method of classifying representative points on the terrain in the 3D point cloud.

In addition to the low correlation, the performance was also lower than that observed in other studies with vegetation similar to that analyzed in this study [7]. Using DAP-RPA, ref. [11] observed an RMSE of 1.8 m (15%) in the estimation of the dominant height of plots with secondary tropical forests located in the north of Espírito Santo state, Brazil.

It is worth noting that the underestimation of the dominant height was concentrated in the C50% + P and C100% restoration systems (Figure 2B), with good performance for the C100% + P system and the reference plots (PR). Possibly, the better performance may be related to the occurrence of local roads near and around these areas and the presence of larger clearings in contrast to areas with a more closed canopy. The underestimation of the dominant heights in these two systems may also be related to the method of classifying representative points on the ground in the 3D point cloud.

In the system with the removal of all eucalyptus species and the planting of native forest species (C100% + P) (Figure 3A), a plot with 505 trees ha^{-1} , 13.73 Mg ha^{-1} , and Shannon diversity of 2.90 [33], we noted that most tree individuals are concentrated between heights of 2 and 4 m and the presence of few individuals in the upper stratum (>4 m).

Theoretically, the removal of all eucalyptus individuals and the planting of native forest species in 2013 should have led to the formation of a more complex vertical structure, such as secondary forest (PR). However, the short time since implementation did not allow for a greater diversity of forest species, resulting in a more complex canopy with understory and emergent strata.

In the system with only 50% removal of eucalyptus species (C50% + P) (Figure 3B), a plot with 799 trees ha^{-1} and 32.79 Mg ha^{-1} and Shannon diversity of 1.56 [34], we observed a greater occurrence of individuals in the highest stratum. The permanence of 50% of individuals of eucalyptus species allowed for greater stratification of the vertical structure of the forest restoration, forming an emergent canopy.

While in the C100% system, a plot with 459 trees ha^{-1} and 11.77 Mg ha^{-1} and Shannon diversity of 1.09 [33], we noted the presence of shorter individuals (height < 3 m) and a more heterogeneous distribution along the height profile (Figure 3C). The vertical profile of the passive forest restoration carried out in C100% shows that natural regeneration was slow and poorly developed, generating a taller and more stratified canopy.

In the reference plots (PR), with 1133 trees ha^{-1} and 54.74 Mg ha^{-1} and Shannon diversity of 2.53 [33], we observed a more complex vertical structure, with taller trees (>6 m) and the occurrence of individuals in all height strata (Figure 3D). Thus, it is observed that the vertical profile derived from the DAP-RPA point cloud represents well the structure of the dossel of the canopy of all plots, regardless of tree density [33].

The hypothesis of height variation, in which there is a clarity of the vertical structure of the vegetation (heterogeneity of height) with diversity of tree species [35], was confirmed in the PR. However, the same hypothesis is not observed in C100% + P, despite the greater Shannon diversity among the areas not presenting a canopy with greater height heterogeneity (Figure 3). Our results also show that the presence of dominant eucalyptus species in consortium with native species can provide a canopy with greater height heterogeneity, as observed in C50% + P.

Recent studies [33] recommended that the various uncertainties associated with the AGB estimate performed by allometric equations should be estimated and propagated when adjusting empirical models (i.e., regression models) calibrated with remote sensing data to improve biomass estimation. In addition to these, other uncertainties should be considered, such as the lack of spatial agreement between field and remote sensing data, and the temporal disagreement between the collection dates of these two pieces of information. In the study [19] in the Brazilian Amazon Forest, the authors showed that, when combined, these errors have resulted in uncertainties of up to 30% and should not be neglected. In studies that use remote sensing data to estimate (model) some information about the forest, we must assume that we are making an “estimate” of the “estimate”. Initially, we assume that the data estimated in the inventory (field) is our reference. However, we know that the forest information obtained in the inventory is an estimate and has different sources of uncertainty. Therefore, these uncertainties must be estimated and propagated when adjusting models (in our case, regression) for estimation based on remote sensing observations [19]. In our study, we estimated the measurement uncertainties in the diameter, height, and wood density measurements of the trees and performed their propagation when adjusting the regression model to estimate aboveground biomass. In addition, we estimated and propagated the uncertainties associated with the allometric models for estimating biomass from field data. As a result, we observed a worse statistical performance (RMSE ~ 40%) of the model adjusted for biomass, when compared to other studies. However, we performed a more consistent and reliable modeling, following the protocols established in the literature [33].

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The average total error (~10%) found in our study was similar to that observed in other studies in the same forest typology, the Brazilian Atlantic Forest [7], and was considered when adjusting the regression model, which guarantees us a more reliable estimate of the AGB values.

The model for *ba* performed well ($R^2 = 0.90$) and had an RMSE of 1.6 (24.8%). Despite having an RMSE of 24.8%, Ref. [7], using DAP-RPA to estimate *ba* in a secondary forest in the same region as the present study, obtained an R^2 of 0.93 and an RMSE of 22.16%. The model presents three DAP-RPA variables of vertical structure (Hmode, HLcurt, and amp. 01) but was not related to any canopy cover metric (Table 5).

In the model adjusted for AGB, DAP-RPA metrics show direct relationships with tree height, given that four of the selected variables represent the vertical structure (Hmode, Hskew, HP01, CCHmode, and amp. 23) and one represents the crown cover mode (CCHmode). As observed in [7], the importance of the two types of metrics (vertical structure and crown cover) obtained by DAP-RPA in the estimation of AGB can be verified.

In the AGB estimation, an R^2 of 0.88 and an RMSE of 31.9% ($8.8 \text{ Mg} \cdot \text{ha}^{-1}$) were obtained, even with an RMSE of 31.9%. Other studies, such as [7], using DAP-RPA to estimate AGB in secondary forest in the same region and forest typology, observed an R^2 of 0.93 and an RMSE of 30.6%. For example, ref. [37] observed an RMSE of 31.51% using DAP-RPA to estimate AGB in the Miombo rainforests of Africa, a result similar to our study.

In a study using DAP-RPA point cloud to assess the height and AGB of forest restorations in the Costa Rican rainforest, ref. [5] observed an R^2 of 0.83 and RMSE of $9.18 \text{ Mg} \cdot \text{ha}^{-1}$ to estimate AGB and an R^2 of 0.87 and RMSE of 1.37 m to estimate height, which are strongly correlated with height and AGB collected in the field. According to the same author, models derived from DAP-RPA metrics that have strong correlations with field-based AGB calculations can be used as a methodology to estimate the carbon accumulation in forest restorations.

This is an important result given the need for more cost-effective ways to sell carbon credits in Brazil, as a way to estimate carbon stock and storage, and the certification and validation of the credits sold. A strength of this methodology is the relative ease with which the rate of biomass and carbon sequestration can be assessed, as long as the data have been calibrated with field-based measurements.

The results showed that the use of DAP-RPA point cloud metrics to estimate Shannon diversity (H') had good accuracy ($R^2 = 0.67$, RMSE = 0.30 m). In a study conducted in a secondary forest in China, ref. [38], working with the combination of Sentinel-2 data and LiDAR point cloud data to estimate Shannon diversity, observed an R^2 of 0.44 and an RMSE of 0.28 m. In another study in the Brazilian Atlantic Forest, ref. [39] managed to estimate Shannon diversity using the spectral variation hypothesis with hyperspectral data collected by an RPA, obtaining an R^2 of 0.76. Despite all the complexities in estimating the species richness and diversity of a forest, the DAP-RPA data allowed estimating and characterizing the richness of the different restoration systems investigated, which is a pioneering step in monitoring secondary tropical forests in Brazil.

In this study, working only with data from the DAP-RPA point cloud, the species diversity was estimated more accurately, which demonstrates the feasibility of using a low-cost RPA for monitoring the species diversity in tropical forest restoration projects. In a study using LiDAR to estimate height, AGB, species diversity metrics, and species composition in different forest restorations in the Brazilian Atlantic Forest, ref. [40] observed that canopy height and vegetation density were good predictors of AGB. However, in this same study, an index based on height and uniformity of the leaf area density profile was weakly related to the Shannon Index of tree species diversity and showed no relationship with species richness or changes in species composition.

The models have been demonstrated to be reliable for estimating AGB, ht, dbh, ba, and H' from the statistical models estimated by regression. One of the few studies in the Brazilian Atlantic Forest carried out by [11] observed that digital aerial photogrammetry obtained by RPA is a reliable estimation method for ht, dbh, and ba.

As observed in other studies [7], we can also highlight the importance of DAP-RPA metrics derived from the Fourier transform, being selected at least once in each of the adjusted models (Table 5). Unlike conventional metrics based on the height of the point cloud, the Fourier transform allows exploring more detailed information on the vertical structure of the vegetation [7,41].

For the AGB model, the selected amplitude (amp. 0.23) presents a spatial frequency of 0.23 cyc/m, which means that the biomass is related to the average height (4.3 m) of the trees, as obtained in the field. A result similar to that observed in [7], estimating AGB with DPA-RPA in a secondary tropical forest in Brazil. The dbh and H' presented a strong

correlation with the upper stratum of the restoration systems, with the spatial frequency of 0.19 cyc/m being selected, which corresponds to 5.2 m of tree height obtained in the field, as well as the ba, presenting a strong correlation with the maximum heights of the point cloud (amp. 01).

The Fourier amplitudes 19 and 23 participated in the explanation of the two components of the biplot. The selection of these metrics suggests that AGB and species diversity in the study site are strongly dependent on variations in forest structure observed at vertical scales [7]. The use of the Fourier transform allows exploring finer details in the vertical structure, which are generally omitted in traditional height-based metrics [26,38].

It can also be seen that the reference plots (PR) are concentrated close to the AGB and Shannon variables, showing that these plots have greater biomass and species diversity. The P90 variable indicates that PR has taller trees. Similarly, PR is more correlated with CCHmode, revealing a more closed canopy.

The biplot in Figure 5 shows that the plots of the C100% forest restoration were grouped according to the influence of the variables, amp. 19 and amp. 23. The C100% + P and C50% + P forest restorations were grouped according to canopy cover (CCHmode) and species diversity (Shannon), demonstrating that they have similar species diversity and canopy cover, but are more closed than C100%. The plots of the C100% + P forest restoration were the ones that most closely resembled PR, mainly related to a greater species diversity (Shannon) and a more closed canopy (CCHmode).

The P90 variable was the one that most correlated with AGB, demonstrating that biomass is more closely related to tree height. Species diversity (Shannon) is more correlated with the CCHmode variable; that is, environments with a more closed canopy present a greater diversity of forest species. We can highlight as a weak point the inability of the height, canopy cover, and density metrics derived from DAP-RPA to correlate with AGB and the diversity of forest restorations.

Despite the good results found in our study, we suggest that analyses should be performed in other forest types, with a more closed canopy and sloping terrain conditions. In addition, the number (>50) and size (0.25 ha) of inventory plots should be increased, which can be considered a limitation of our study ($n = 36$ and ~ 0.0625 ha). With a larger number of plots, other modeling techniques can be tested and thus improving the performance of the estimates.

5. Conclusions

The DAP-RPA-derived metrics used in this study demonstrate potential for monitoring and characterizing AGB, species richness, and forest structure in restored tropical forest systems in Brazil. Being an economically more viable alternative to improve and stagger the estimates made in the field inventory.

The DAP-RPA was able to represent the terrain well, make reliable height estimates, and thus characterize the vertical profile of the vegetation of the analyzed restoration systems.

The uncertainties of AGB estimation must be considered and propagated in estimation models based on DAP-RPA and remote sensing metrics.

Metrics derived from the Fourier transform were essential for estimating AGB, species diversity, and forest structure.

Based on the results obtained, it is recommended that future studies explore the application of metrics derived from DAP-RPA in different biomes and topographic conditions, especially in areas of dense vegetation and terrain with greater slope, where the accuracy of aerial photogrammetry is still little tested. The integration of spectral data (hyperspectral or multispectral) and the use of machine learning algorithms can improve the predictive

capacity of the models, especially for estimates of biodiversity and floristic composition. In addition, continuous temporal monitoring of areas restored with DAP-RPA will allow the evaluation of the successional trajectory and the effectiveness of restoration practices over time. Finally, the potential of the technology as a low-cost tool for measuring carbon and supporting the validation of Payments for Environmental Services (PES) and carbon credits projects is highlighted, as long as it is accompanied by rigorous calibration and field validation protocols.

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