LIDAR-based estimation of bole biomass for precision management of an Amazonian forest: Comparisons of ground-based and remotely sensed estimates

Evandro Orfanó Figueiredo [a], Marcus Vinicio Neves d'Oliveira [b], Evaldo Muñoz Braz [c], Daniel de Almeida Papa [d], Philip Martin Fearnside [e,f,*]

[a] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056 Rio Branco, Acre, Brazil
[b] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056 Rio Branco, Acre, Brazil
[c] Embrapa Florestas, Estrada da Ribeira Km 111, CP 319, CEP 83411-000 Colombo, Paraná, Brazil
[d] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056 Rio Branco, Acre, Brazil
[e] Instituto Nacional de Pesquisas da Amazônia (INPA), Av. André Araújo, 2936, Petrópolis, CEP: 69067-375 Manaus, Amazonas, Brazil
[f] Brazilian Research Network on Climate Change (RedeClima), Brazil

ARTICLE INFO

ABSTRACT

Based on airborne LIDAR data on canopy morphology and height of Amazon forest trees, we developed allometric models to estimate dry biomass stored in the boles of dominant and co-dominant individuals and compared these results with those from equations based on traditional variables such as diameter at breast height (DBH). The database consisted of 142 trees of interest for logging in a forest under management for timber in Brazil's state of Acre. The trees chosen for study were selected through proportional sampling by diameter class (ranging from 45 to 165 cm DBH) in order to properly represent the dominant and co-dominant tree populations with diameters appropriate for harvest. Subsequent to LIDAR profiling of these trees, they were felled, subjected to a battery of dimensional measurements and sampled for wood-density determination. A set of models was generated, followed by model selection and identity testing in order to compare groups of basic wood density (low, medium and high). The morphometric variables of the crown had high explanatory power for bole biomass independent of whether the allometric equations included DBH. When calculating bole biomass with equations that include basic wood density, the best estimate is obtained using variables for both DBH and crown morphology. To obtain an allometric equation that encompasses species in all three classes of basic density, one should either use only independent variables representing crown dimensions or complement these with variables for basic density (BD) and total height (Ht). The study demonstrates the feasibility of using ground-based measurements to calibrate biomass models that include only LIDAR-based variables, allowing much larger areas to be surveyed with reasonable accuracy. The present study is designed to produce data needed for forest management, but the methods developed here can be adapted to studies aimed at reducing the uncertainty in biomass estimates of whole forests (not just harvestable trees) for use in quantifying carbon emissions from forest loss and degradation.

© 2016 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

1. Introduction

In recent years great advances have been made in the planning and implementation of forest-management operations in Brazil's Amazon region using precision management techniques (Figueiredo et al., 2007). Precision management integrates the use of geographical positioning system (GPS) and geographical information system (GIS)

technology. Airborne LIDAR (Light Detection And Ranging) technology has recently been shown to have wide application in precision management of tropical forests, allowing information on relief and hydrographic structure to be obtained with sub-meter accuracy over large tracts of forest (d'Oliveira et al., 2012). Dubayah et al. (2010), Stark et al. (2012), Sullivan et al. (2014) and Palace et al. (2015) have described LIDAR's potential in modeling forest carbon stocks, while Hunter et al. (2013) proposed corrective measures to improve estimates of forest biometric parameters using LIDAR. Use of laser profiling improves the quality of planning for infrastructure (such as the network of roads, storage yards and skid trails in the monitoring of forest operations) and in estimating the volume and biomass of managed forests.

* Corresponding author.
E-mail addresses: evandro.figueiredo@embrapa.br (E.O. Figueiredo), marcus.oliveira@embrapa.br (M.V.N. d'Oliveira), evaldo.braz@embrapa.br (E.M. Braz), daniel.papa@embrapa.br (D. de Almeida Papa), pmfearn@inpa.gov.br (P.M. Fearnside).

Despite technological advances in optical physics, remote sensing, GIS and computing (Hudak et al., 2012; Lim and Treitz, 2004; Næsset and Gobakken, 2008; Simbaña et al., 2016), it is still necessary to further develop basic knowledge of forest components, such as the understanding of plant biomass. Biomass estimates are considered to be empirical since the models used to describe a response variable do not identify the causes or explain the phenomena that affect the behavior of this variable (Clark and Clark, 2000; Scolforo et al., 2004, 2008; Vanclay, 1994; Whittaker and Woodwell, 1971). Allometric equations used to estimate volume, biomass and carbon stocks in forests have usually been prepared based on destructive plots, correlating measurements of whole trees with two variables that are possible to measure in the field: height and diameter at breast height measured 1.3 m above the ground or above any buttresses (DBH) (da Silva, 2007; Higuchi et al., 1998).

Morphometric variables of the crown have high correlations with dendrometric parameters of the bole such as DBH and height (Durlo and Denardi, 1998; Orellana and Koehler, 2008; Wink et al., 2012). However, estimating the values of these variables by measuring individual trees in tropical forests is a major challenge. Even for measuring diameter and height, the dense understory, crooked trunks and the presence of roots in strut or tabular form are obstacles to making precise measurements. Especially for variables that cannot be measured directly in the field (i.e., height) the gain produced by inclusion of the variable in the model should not be smaller than the error associated with its measurement in the field (d'Oliveira et al., 2012). In this environment, it is difficult, from a practical standpoint, to obtain morphometric variables for the canopy in conventional forest inventories (Ferraz et al., 2015; Wulder et al., 2012). However, LIDAR data allow measurements of total height and morphological variables for the canopies of co-dominant and dominant trees to be obtained with great precision.

The aim of the present study is to develop allometric equations for estimating stem biomass of dominant and co-dominant trees under precision forest management. A combination of field-based measurements and LIDAR-derived estimates of canopy geometry was used to estimate bole biomass. The equations are based on morphometric variables for the canopy obtained from LIDAR, together with traditionally employed variables such as DBH, total height (Ht), and the apparent density (AD) and basic density (BD) of the wood. Identity was also assessed for groups of models of wood density.

2. Materials and methods

2.1. Study site

The studies were conducted in a 315-ha area of forest management in the Antimary State Forest (68° 01′ to 68° 23′W; 9° 13′ to 9° 31′S) under SmartWood Certification No. SW-FM/COC-1670 and Environment Institute of Acre (IMAC) Operating License No. 530/2008 (renewal). This protected area is located in the municipalities of Bujari and Sena Madureira, Acre state, Brazil (Fig. 1).

The area encompassing the Antimary State Forest has an average annual rainfall of 2000 mm and average temperature of 25 °C (Acre, 2000). A dry season from June to September is the period when the logging is performed. The forest consists of three main types: dense, open, and open with bamboo. These three forest types occur intermittently in the study area. The predominant soils are dystrophic and yellow latosols
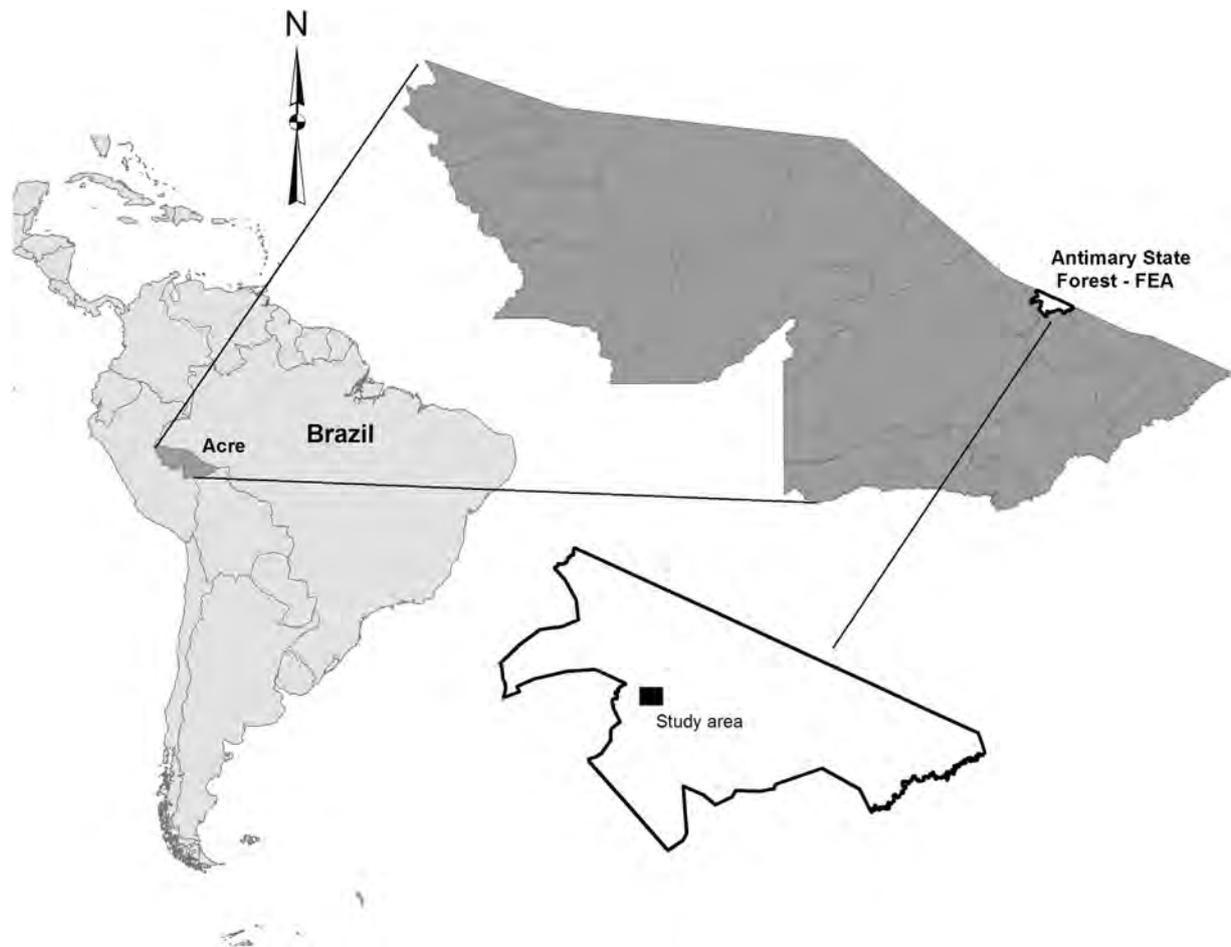
Fig. 1. Location map of Antimary State Forest, Acre, Brazil.

(Oxisols) with gently rolling topography and a maximum elevation of around 300 m (Acre, 2000).

2.2. Forest inventory

In 2009 an inventory census was conducted in order to plan the logging in the 4000-ha 2010 annual-production unit (APU). The survey was conducted considering all commercial timber species with DBH above 30 cm. The location of trees and the planning techniques were performed according to the procedures recommended for precision management (Figueiredo et al., 2007). Thus, for each tree the geographical coordinates and a barometric point were determined using a high-sensitivity GPS. The botanical specimens of the species in the sample were deposited for identification in the herbarium of the Federal University of Acre Zoobotanical Park (UFAC/PZ), Rio Branco, Acre, Brazil.

2.3. LIDAR data

High density (25 pulses m^{-2}) discrete-return LIDAR data were collected before logging between 29 May and 3 June 2010, covering a total of 1000 ha inside the 2010 APU. The Optech ALTM 3100 (Aerial Laser Terrain Mapper) system was used, carried on a twin-engine Piper Seneca II aircraft, model Neiva/Embraer 810C. The flight was conducted at an average speed of 210 km h^{-1} at a height of 300 m; the LIDAR system had a beam diameter of 20 cm, beam divergence of 0.3 mrad, scanning angle of 15°, and scanning frequency of 58.7 Hz. (D'Oliveira et al., 2012).

As a fixed benchmark on the ground the RBMC INBO 93911 reference was adopted from the Brazilian Network for Continuous Monitoring of Systems (GNSS). The data were processed in the Universal Transverse Mercator (UTM) coordinate system (Zone 19 South) and the SIRGAS 2000 reference system. Two pairs of Trimble 5700 GPSs with L1/L2 carriers were used. The average intensity of profiling was 43.03 dots m^{-2}.

The LIDAR reflection data were initially placed in a single structured file forming a 315-ha mosaic with approximately 130 million pulses. Files were processed on a three-dimensional basis using Quick Terrain Modeler software, which is specific for this purpose.

2.4. Quantification of bole volume

The sample structure of the dominant and co-dominant trees of interest for logging under forestry-management conditions was measured considering a proportional sampling by diameter class (Table 1). The sampled trees were cut and cubic scaling was performed using the Smalian method. After cutting the trees, the stumps were geo-referenced using a high-sensitivity L1 GPS receiver. The reference point for post-processing was the same as the ground benchmark used for the collection and processing the LIDAR point cloud.

Because the study focuses on trees of commercial interest for timber management, individuals with hollow or crooked stems were not cut and were not included in our sample. Criteria for logging were observed that are standardized by law for rare species, seed trees, maintenance of

Table 1
Proportional-sampling data base stratified by diameter class of the dominant and co-dominant trees with volumes measured for use in fitting allometric models.

Diameter Class	Diameter interval (cm)	Number individuals in the inventoried population	%	Number individuals for fitting the volume models	%
I	45–74.9	1294	61.9	86	60.6%
II	75–104.9	570	27.3	39	27.5%
III	105–134.9	174	8.3	12	8.5%
IV	135–164.9	53	2.5	5	3.5%
Total		2091	100.0	142	100.0%

permanent preservation areas and the geographical location stipulated in the license for the management plan.

2.5. Quantification of biomass

After cutting each tree in the sample, wedges were removed with an average length of 30 cm and thickness of 10 cm. The wood samples (including bark and sapwood) were taken from the first and last log of each tree, using a chainsaw.

To obtain the apparent density (green weight/green volume in g cm^{-3}), the samples were immersed in water to achieve constant weight, as recommended for the hydrostatic balance method (ABNT, 2003). An electronic balance was used with 25 kg capacity and a sensitivity of 2 g. Subsequently, the dry weight of the sample for calculating basic density (dry weight/green volume) was obtained after the samples reached constant weight at 105 °C (± 2 °C). Using the data on the density of the samples from each tree of interest, we calculated the dry biomasses from the volume obtained by rigorous cubic scaling.

2.6. Processing the LIDAR point cloud to obtain canopy morphometric variables

Each sampled tree was georeferenced in the field and the canopy of each tree was subsequently identified in the LIDAR point cloud. The advantage of working with dominant and co-dominant trees is that individual tree crowns can be pulled out of the LIDAR data even in a structurally complex forest because these tree crowns are at the same level or above the main canopy height (Detto et al., 2015; Hunter et al., 2015; Tochon et al., 2015). Physiognomic characteristics of the environment we studied (open forest and open forest with bamboo) were also of fundamental importance for isolating dominant and co-dominant trees in the point cloud.

We interpreted the LIDAR data manually to calculate morphometric variables with Quick Terrain Modeler ×64 software using the following procedure:

a) Point clouds are processed with a hue filter, which allows processing with all of the data on height and on the texture of the target surface;
b) The reflection of the point cloud is controlled using the Voxel Autosize method, in which the points projected on the surface are processed to assign different sizes to each point based on its position in relation to the plane of visualization; the points that are close to the plane appear larger, while the points that are away from the plane appear smaller (Applied Imagery, 2010). Thus, points on the boundary of the profiled structure are highlighted, providing a contrast with the second and third points present within the structure. This process facilitates drawing the outline of the dominant and co-dominant trees and, hence, the process of isolating the trees (Fig. 2), and
c) Sample trees are separated from the LIDAR point cloud by making a three-dimensional polygon surrounding the canopy. Initially, a region that includes the area of the canopy projection of the tree of interest and the understory beneath this canopy was cut out of the point cloud. Next, the tree crown and the projection of the stem were isolated by editing the polygons and by successive cuttings.

2.7. Independent variables

A total of 18 independent variables were used, considering stem data, apparent density (AD), basic density (BD) of the wood, the altitude of the site (As) (elevation above mean sea level of the ground at the location of the tree) and morphometric variables of the crown. The variables for the bole were diameter at breast height measured at 1.3 m above the ground or above any buttresses (DBH, in cm) and height of insertion of the crown (Hic in m), also known as the "commercial height."

Fig. 2. Trees isolated from the understory vegetation using LIDAR data: a) *Dipteryx odorata* Wild ("cumaru-ferro"), b) *Ceiba pentandra* (L.) Gaertn. ("samaúma"), c) *Apuleia leiocarpa* (Vogel) J.F. Macbr. ("cumaru-cetim"), Antimary State Forest (FEA), Acre, Brazil.

The following variables adapted from Burger (1939) were obtained from the LIDAR point cloud to describe the morphometry of the canopy (Fig. 3): length of the crown (Lc, in m), length of the branches (Lb in m), mean crown diameter (CD in m), total height of the tree (Ht in m), percentage of canopy (PC = LC/Ht, in %), degree of slenderness (Ds = Ht/DBH), index of protuberance (IP = CD/DBH), index of enclosure (IE), form of the crown (Fc = CD/Lc), volume of the crown (Vc in m^3) from the solid of rotation that best models the crown, index of living space (ILS = $(CD/DBH)^2$), crown projection area (CPA in m^2) representing the area under the canopy, and mantle of the crown (MC in m^2) representing the area of the surface enclosing the crown. The DBH of each tree was measured in the field during the forest inventory. The one-year time difference between the forest inventory and the LIDAR flight do not significantly affect the use of LIDAR-derived variables and DBH to develop the biomass estimation models.

Of all the variables evaluated, only the data for Vc, CPA and MC were obtained during the processing of the LIDAR point cloud, verification in the field not being possible. This was due to the difficulty of measuring this information in the forest, as already reported by Chambers et al. (2007) and Ferraz et al. (2016).

2.8. Allometric equations for bole biomass

Initially we evaluated the intensity of the linear relationship between the dependent variables – dry biomass (Bd) and green biomass (Bg) – and the independent variables. This step assists in the initial indication of the most significant variables for model building (Statgraphics, 2006).

Only independent variables with correlation coefficient values less than −0.65 or >0.65 were selected for the routine that checks all possible models (Ryan, 2011). The inclusion of independent variables in allometric models was limited to a maximum of three, which allows models with up to four parameters (β_s), including the intercept (β_0).

In order to reduce the number of models initially indicated by the selection routine, additional criteria were incorporated into the screening process: the equations could have no multicolinearity and were required to have normally distributed residuals that are independent and homoscedastic. The following statistics were calculated for this additional screening: multicolinearity array, standardized error distribution, Durbin-Watson (DW) test and Hartley F-maximum (SAS Institute, 1990; Statgraphics, 2006).

Equations for estimating biomass were obtained for the models proposed by the selection routine. The statistical significance of each independent variable was examined using the Fisher test (F test). Variables with significance levels <0.15 were removed to simplify the polynomial.

For each allometric equation we performed an analysis of the influence of the independent observations. An observation was only considered to be influential when it produced substantial changes in the calculated statistical values with and without the observation in accord with the following measures of atypical status: elements in the principal diagonal of the H matrix, DFFITS and Cook's distance (Chatterjee and Hadi, 1986; Figueiredo, 2005; Souza, 1998; Statgraphics, 2006). Selection of the best equation was based on a graphical analysis of the residuals expressed as percentages, standard error expressed in absolute and in percentage terms (S_{yx} and $S_{yx}\%$), the Press_p criterion and the adjusted coefficient of determination ($R^2aj\%$) (SAS Institute, 1990; Souza, 1998).

2.9. Identity of models by density group

After selecting the best allometric equation for dry biomass, we performed an identity test of the models. Because only linear models were involved, we used the procedure described by Graybill (1976) to assess the need for fits made either individually or by basic-density group for three classes of basic density (BD): Low (BDlo: BD < 0.5), medium (BDmd: BD ≥ 0.5 < 0.7) and high (BDhi: DB ≥ 0.7) (do Vale et al., 2005; Nogueira et al., 2005). The procedure consists of minimizing the sum of squares. For linear models, the identity test allows the F test to be used to assess the significance of the difference between the total sum of squares of the regressions fitted for each basic-density group considered by itself (full model: Ω) and the sum of squares of the regressions fitted for all three basic-density groups (reduced model: w) (Figueiredo, 2005; SAS Institute, 1990; Statgraphics, 2006). Table 2 presents the analysis of variance for testing the identity of the linear regression models.

Three hypotheses were tested for the wood-density groups. The first group (a) is for the fit of the original database composed of species in all three basic-density classes (low, medium and high); the second group (b) is composed of species with low and medium basic density, and the third and last group (c) is composed of species with medium and high basic density.

3. Results

The sample structure studied was classified as having 17.6% species with low basic density (BD < 0.5), 40.8% moderately hard (0.5 ≥
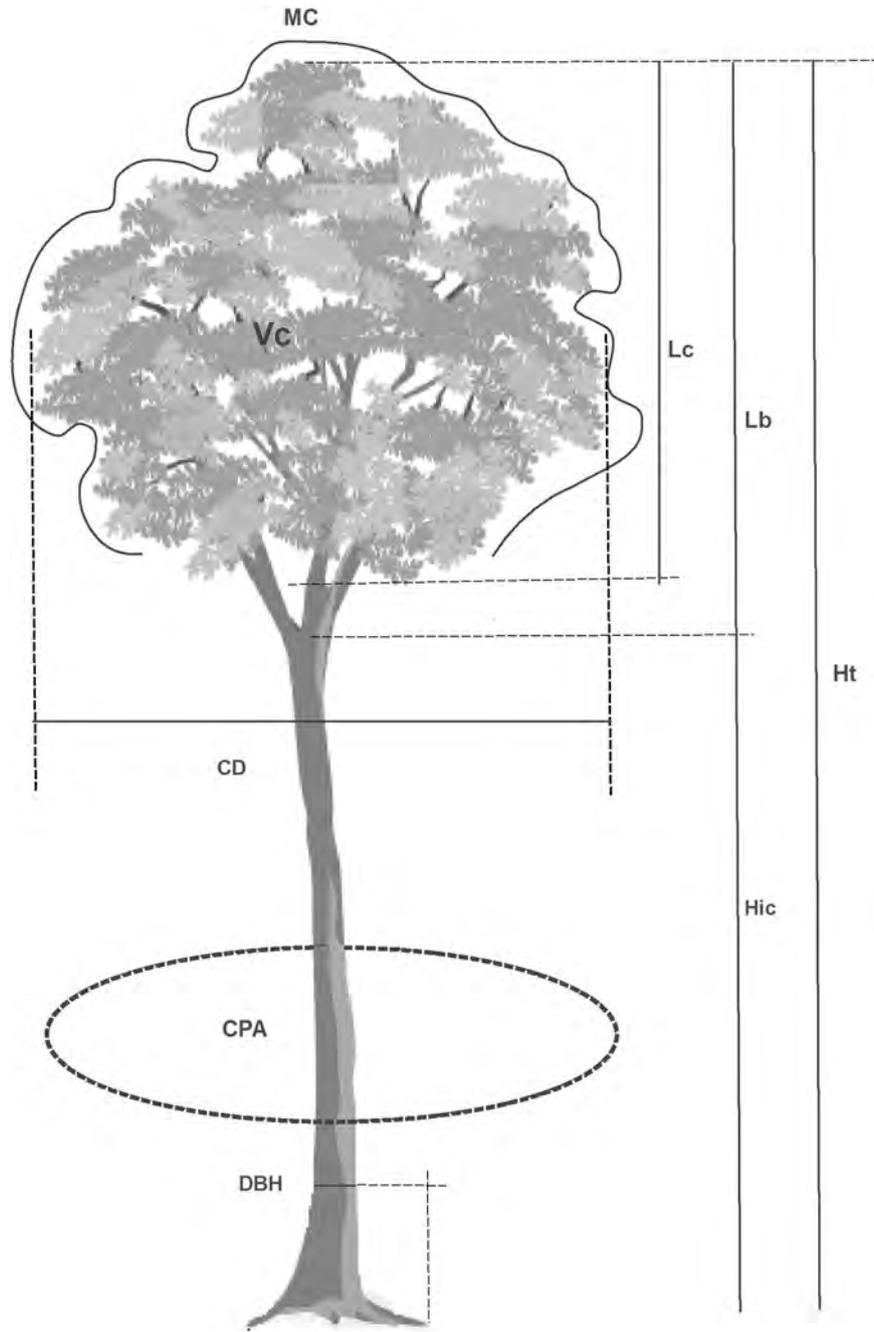
Fig. 3. Tree morphometric variables using LIDAR data and DBH. Adapted from Burger (1939). Vc = volume of the crown from the solid of rotation that best models the crown (m³); MC = mantle of the crown (surface area of the solid of rotation in m²); CPA = crown projection area (m²); DC = diameter of the crown (mean in m); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); Lc = length of the crown (m); Ht = total height of the tree (m); Lb = length of the branches (m); Hic = height of insertion of the crown [height above the ground of the first living branch].

BD < 0.7), and 41.6% hard (BD ≥ 0.7). When basic densities of wood samples collected from the base of the trunk (first log) were compared with those from the upper end (last log) using the *t*-test, a statistical difference was observed (t = 2.15, α = 0.05, p = 0.03). The basic density of the first log (mean ± standard deviation = 0.69 ± 0.03, n = 142) was 7.3% higher than the density of the last log (0.65 ± 0.03, n = 142).

Table 2
Analysis of variance for identity testing of linear models.

Source of variation	df	Sum of squares.	Mean square	F
Full model	(A × p)	SS Reg.(Ω)		
Reduced model	p	SS Reg. (w)		
Difference for hypothesis testing	(A − 1)p	SS Reg.(Ω)-SS Reg. (w)	$SS_{(difference)}/(A-1)p$	$MS_{(difference)}/MS_{(residual)}$
Residual	N−(A × p)	SS Total(Ω)-SS Reg.(Ω)	$SS_{(residual)}/N-(A \times p)$	
Total	N	SS Total (Ω)		

df = degrees of freedom; SS = sum of squares; MS = mean square; F = F test statistic; A = number of density classes; p = number of parameters in the reduced model (*w*); N = number of observations in the full model (Ω).

The overall mean basic density based on the samples from the first and last logs was 0.67 (n = 142) with a coefficient of variation (CV) of 24.4%.

The apparent density (AD) resulting from the wood sample composition of the first and last log was 0.96 and the CV was 11.1%. Comparing the apparent densities of the first and last logs, there was no statistical difference between the two groups (t = 1.54, α = 0.05, p = 0.12). The mean AD of the base of the tree was 0.97 ± 0.02 (n = 142) and the mean AD of the last log was 0.95 ± 0.02 (n = 142). The mean moisture content of the first log was 0.34 ± 0.09 (n = 142), and for the last log it was 0.34 ± 0.10 (n = 142).

In the tested equations where the independent variables were restricted to those for canopy morphometry, 14.1% of sampled trees were identified as atypical points. When DBH was included as an independent variable in the model this percentage dropped to 6.3%, and when both DBH and Ht were included it dropped to 4.9%.

The descriptive results for the main independent variables are shown in Table 3.

Evaluation of the linear correlation between the independent and dependent variables provides an important tool for the initial selection of independent variables, especially when considering a large number of possible variables of interest. Table 4 describes the results of linear correlation of eighteen variables of interest, including crown morphometric variables, environmental variables and bole variables, with the dependent variable being either green or dry bole biomass.

Correlation analysis between crown morphometric variables and the main dendrometric characters of the bole (Table 5) helps in understanding the importance that the crown data have for representing bole variables and, consequently, the volume and biomass present in the trunks of the trees.

The results of the selection procedure for all possible models were divided into two categories. The first group (Equations 1 to 5 in Table 6) is for estimation of dry biomass of the bole, while the second group (Equations of 6 to 11 in Table 6) is for green biomass.

Figs. 4 and 5 present the standard error percentage graphs for the best equations considering the inclusion or the exclusion DBH, and Figs. S1 and S2 (Supplementary material) present, real and estimated values. The plots of residuals in Fig. 4 are for estimates of dry biomass (Bd) and in Fig. 5 for green biomass (Bg).

All of the selected equations and the equations originating from the combination of subsets for identity testing of the models had Durbin-Watson values between 1.897 and 2.262 (p = 0.409 and 0.926); since the p-value is >0.05, there is no indication of serial autocorrelation in the residuals for the selected models. The assumption of homoscedasticity (Hartley F-max) was also confirmed in the different diameter classes of the sample. Kolmogorov-Smirnov tests of the frequency of the residuals for all selected equations do not allow rejection of the hypothesis of a normal distribution with 95% confidence.

The main purpose of the identity test of model is to evaluate whether the allometric equations fit using the datasets for the three wood-density classes (low, medium and high) have similar characteristics, or whether fits should be made individually for each density class or for groupings of two density classes. Table 7 presents the results for the identity test of models for estimating the dry biomass of the bole and Table 8 the results for models that estimate green biomass.

4. Discussion

Allometric equations should seek to reduce possible sources of variation, avoiding generalizations based on models derived from specific data from case studies (Baker et al., 2004; Bohlman and O'Brien, 2006; Crow and Schlaegel, 1988; Ferraz et al., 2016; Scolforo et al., 2008.). Because of this, allometric equations generated from a given forest structure are not sufficient for general use in the field of forest management. Models must be fitted to reflect the characteristics of each region and interest.

Because the present study is focused on the bole biomass of trees intended for the timber industry that are cut as part of forest management, sampling is for trees with DBH ≥ 45 cm. The sample composition therefore differs from that in studies intended to estimate total tree biomass and the composition of the whole forest, such as Higuchi et al. (1998), da Silva (2007) and Nogueira et al. (2007). In most studies for estimating the biomass of native forests, a sample is taken that begins with the smaller diameter classes (e.g., DBH ≥ 5 cm), and generally has <10% of the sampled individuals with DBH ≥ 50 cm. This change in sample composition directly impacts biomass estimates, mainly due to changes in diameter structure, species and density. These results are therefore not necessarily applicable in other situations.

The statistically significant difference in the density of samples from the first and last logs corroborates the results obtained by Scolforo et al. (2004), Nogueira et al. (2005, 2007) and Silveira et al. (2013). Thus, if basic density is included in estimating the biomass of a species group, a compound sample should be collected along the bole because using samples taken from a single position on the bole was found to misrepresent basic density by an average of 7.28%. The same behavior was not observed when using apparent density, which does not differ significantly between the base and the top of the bole. This variable was not chosen by the routine checking all possible models (Ryan, 2011).

The mean moisture content of the wood of the bole was about 8% lower than the moisture contents of around 41% reported by Fearnside (1997), Higuchi et al. (1998) and Nogueira et al. (2007). This difference is due to the difference in the sample composition explained earlier, i.e., the present study contains a greater proportion of species with medium and high basic density; these species have lower moisture content than trees with low density.

Analysis of influence is a procedure that helps in understanding the composition of linear models and in decisions on whether or not to exclude an atypical observation. When bole-biomass models were fitted that only use variables for the crown as independent variables, over 14% of the observations were simultaneously influential in three

Table 3
Descriptive results for the main independent variables and the bole volumes of dominant and codominant trees, Antimary State Forest, Acre, Brazil.

Description	Units	n	Mean	Standard deviation	Coefficient of variation	Minimum	Maximum
CPA	(m^2)	142	354.1	235.2	66.4%	106.8	1,713.8
Lc	(m)	142	10.3	3.9	37.9%	4.1	24.9
Lb	(m)	142	15.4	4.2	27.5%	6.1	25.0
DBH	(cm)	142	77.9	23.1	29.7%	44.5	164.5
DC	(m)	142	21.8	6.5	29.8%	12.0	49.1
Hic	(m)	142	23.7	4.5	19.2%	12.2	36.1
Ht	(m)	142	39.1	4.9	12.6%	26.4	53.7
MC	(m^2)	142	420.7	290.7	69.1%	112.6	2,001.7
Vc	(m^3)	142	2,495.9	2,449.1	98.1%	235.2	14,998.1
Vol	(m^3)	142	8.3	6.9	82.7%	1.5	55.9

Vc = volume of the crown from the solid of rotation that best models the crown (m^3); MC = mantle of the crown (surface area of the solid of rotation in m^2); CPA = crown projection area (m^2); DC = diameter of the crown (mean in m); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); Lc = length of the crown (m); Ht = total height of the tree (m); Lb = length of the branches (m); Hic = height of insertion of the crown [height above the ground of the first living branch]; Vol = volume of the bole from rigorous cubic scaling (m^3).

Table 4
Results of the correlation between the independent variables and the green and dry biomasses of trees cut under forest management, Antimary State Forest, Acre, Brazil.

Correlation with green biomass of the bole (Bg)				Correlation with dry biomass of the bole (Bd)			
Order	Independent variable	Sample size	Correlation (r)	Order	Independent variable	Sample size	Correlation (r)
1	DBH	142	0.92	1	DBH	142	0.83
2	MC	142	0.79	2	Vc	142	0.72
3	CPA	142	0.77	3	MC	142	0.70
4	Vc	142	0.77	4	CPA	142	0.70
5	DC	142	0.72	5	DC	142	0.66
6	IE	142	0.56	6	Ht	142	0.60
7	Ht	142	0.54	7	Lc	142	0.51
8	Lc	142	0.51	8	IE	142	0.47
9	PC	142	0.38	9	Lb	142	0.42
10	Lb	142	0.36	10	PC	142	0.36
11	Hic	142	0.26	11	Hic	142	0.28
12	Fc	142	0.12	12	BD	142	0.14
13	As	142	0.01	13	Fc	142	0.11
14	AD	142	-0.08	14	AD	142	0.08
15	BD	142	-0.12	15	As	142	0.03
16	IP	142	-0.13	16	IP	142	-0.12
17	ILS	142	-0.15	17	ILS	142	-0.13
18	Ds	142	-0.65	18	DA	142	-0.57

Vc = volume of the crown from the solid of rotation that best models the crown (m^3); MC = mantle of the crown (surface area of the solid of rotation in m^2); CPA = crown projection area (m^2); DC = diameter of the crown (mean in m); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); IE = index of enclosure = DC/Ht; Lc = length of the crown (m); Ht = total height of the tree (m); PC = percentage of crown = (Lc/Ht) × 100 (%); Lb = length of the branches (m); IP = index of protuberance = DC/DBH; ILS = Index of living space = $(DC/DBH)^2$; Hic = height of insertion of the crown [height above the ground of the first living branch]; Fc = form of the crown = DC/Lc; Ds = degree of slenderness = Ht/DBH; As = altitude of the site = elevation of the ground above mean sea level as measured with LIDAR; DB = basic density of the wood; AD = apparent density of the wood.

statistics in the analysis; this atypical feature is explained by the existence of trees with broken crowns. The data were best modeled when canopy morphometric variables and traditionally used bole variables (DBH, Ht and BD) were incorporated into a single model. Even so, only approximately 5% of the observations were influential.

Although trees with broken crowns are easily identified when the LIDAR point cloud is interpreted, the models cannot represent them. These trees were therefore excluded as atypical observations. In a forest management strategy the trees with broken crowns should be prioritized for harvest due to their lower reproductive capacities, their lower yields and because felling them causes the least impact due to

Table 5
Results of the correlation between the independent variables for crown morphometry and the independent variables traditionally employed in dendrometric models, Antimary State Forest, Acre, Brazil.

Independent variables used for crown morphometry	Independent variables traditionally used in dendrometric models				
	DBH	Dmax	Dmin	Hic	Ht
Ds	− 0.8301*	− 0.8294*	− 0.8011*	0.0798	− 0.0167
ILS	− 0.2621	− 0.2604	− 0.2150	− 0.2665	0.0902
IP	− 0.2476	− 0.2457	− 0.1988	− 0.2429	0.1268
Fc	0.1331	0.1346	0.1956	0.1158	− 0.1695
Lb	0.3299	0.3358	0.2699	− 0.3465	0.5634
PC	0.3797	0.3741	0.3490	− 0.2317	0.3797
Lc	0.4800	0.4717	0.4257	0.0086	0.6457
IE	0.5826	0.5843	0.6046	− 0.2262	0.1622
DC	0.7053*	0.7027*	0.6899	0.0410	0.5266
Vc	0.7238*	0.7143*	0.6874	0.0540	0.5258
CPA	0.7307*	0.7265*	0.7170*	0.0323	0.4681
MC	0.7557*	0.7531*	0.7343*	0.0461	0.4588

Vc = volume of the crown from the solid of rotation that best models the crown (m^3); MC = mantle of the crown (surface area of the solid of rotation in m^2); CPA = crown projection area (m^2); DC = diameter of the crown (mean in m); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); IE = index of enclosure = DC/Ht; Lc = length of the crown (m); Ht = total height of the tree (m); PC = percentage of crown = (Lc/Ht) × 100 (%); Lb = length of the branches (m); Ds = degree of slenderness = Ht/DBH; ILS = index of living space = $(DC/DBH)^2$; Hic = height of insertion of the crown [height above the ground of the first living branch]; Fc = form of the crown = DC/Lc; Ds = degree of slenderness = Ht/DBH; Dmax = diameter at the thick end of the bole (m), Dmin = diameter at the thin end of the bole (m; * = correlation that explains information with values equal to or >50%.

their reduced canopies. However, they should be measured in the field, since the models are unable to generate reliable estimates. The CPA, MC and Vc variables were the independent variables that were most influenced by the existence of broken crowns. The largest variation was seen in the volume of the crown (Vc) because the consequences of a partial loss of the crown are strongly reflected in the three-dimensional volume results.

The results of a linear correlation between all independent variables and the modeled independent variable indicate that DBH, MC, CPA, Vc and CD have strong linear correlations with dry biomass (Bd) (Table 4). This information is important for fitting linear models or for assessing the explanatory power of a given type of information. This is especially evident for the four morphometric variables for the crown (MC, Vc, CPA and CD), which have strong explanatory power with correlation-coefficient values above 0.7. The MC and Vc variables obtained exclusively by the processing the LIDAR point cloud explain >50% of the variation in data for estimating biomass stored in the stems of dominant and co-dominant trees. This corroborates the findings of Schneider and Schneider (2008), who emphasize the importance of understanding the horizontal space of the forest, i.e., the individuals with the largest crowns have the greatest capacity for storing biomass and represent the potential of the forest site. A number of authors have developed and studied methods for estimating tree biomass from canopy morphometry, eliminating field measurements (Balzotti et al., 2016; Bouvier et al., 2015; Ferraz et al., 2016; Shugart et al., 2015; Zolkos et al., 2013).

Analyzing the correlation between the data on the bole (DBH, Dmax, Dmin, Hic and Ht) and morphometric information on the crown can help better understand the importance of each independent variable derived from the crown (Table 5). The mantle of the crown (MC) and the crown projection area (CPA), in addition to providing good predictions of DBH and Dmax, also exhibit strong correlations with the Dmin. The diameter of the thin end of the bole, or Dmin, provides information relevant to the yield obtained by the forest industry and is also important for the estimating biomass stored in the trunk. Therefore, trees with large crown structures have greater DBH and Dmin values, and, consequently, greater stocks of biomass, corroborating the results obtained by Duncanson et al. (2015) and Balzotti et al. (2016).

The tallest trees were not necessarily those with the largest diameters (DBH, Dmax and Dmin). This shows the low hypsometric relation

Table 6
Allometric equations fitted to estimate the dry biomass and green biomass of the bole (tons) and accuracy statistics for dominant and codominant trees, Antimary State Forest, Acre, Brazil.

Nº.	Fitted equation	$R^2_{\%}$	$R^2_{aj.\%}$	$S_{yx}(ton)$	$S_{yx}(\%)$	$PRESS_p$	Data source
1	$Bd = -10.7967 + 0.125589 \times DHB + 0.00000188112 \times CPA^2 + 8.98374 \times BD$	87.01	86.71	±1.251	23.74	225.71	LIDAR and field
2	$Bd = -11.8835 + 0.143744 \times DHB + 9.00693 \times BD - 16.3341 \times (Vc)^{-1}$	85.55	85.22	±1.320	25.17	255.38	LIDAR and field
3	$Bd = -14.1089 + 0.131683 \times DHB + 7.91695 \times BD + 0.09971 \times Ht$	87.06	86.76	±1.249	23.82	228.36	LIDAR and field
4	$Bd = -11.669 + 0.142277 \times DHB + 9.01489 \times BD - 31.8948 \times (MC)^{-1}$	85.62	85.29	±1.317	25.10	251.6	LIDAR and field
5	$Bd = -3.35215 + 0.00000611781 \times CPA^2 + 2.92418 \times BD + 0.00360727 \times Ht^2$	81.05	80.57	±1.400	27.41	253.33	LIDAR and field
6	$Bd = -2.70687 + 0.00000555826 \times CPA^2 + 0.304461 \times FC + 0.00405378 \times Ht^2$	79.35	78.82	±1.456	28.29	270.98	LIDAR
7	$Bd = -8.508 + 0.00000570871 \times CPA^2 + 0.034357 \times As + 0.00407486 \times Ht^2$	80.19	79.68	±1.426	27.71	262.79	LIDAR
8	$Bd = -1.83062 + 0.00000567638 \times CPA^2 + 0.0039187 \times Ht^2$	78.86	78.51	±1.467	28.50	268.96	LIDAR
9	$Bg = -6.93355 + 0.00000317129 \times CPA^2 + 0.000889017 \times DHB^2 + 0.218007 \times Ht$	93.24	93.08	±1.496	19.00	372.69	LIDAR and field
10	$Bg = -7.21209 + 0.00000312968 \times CPA^2 + 0.00104766 \times DHB^2 + 7.99746 \times AD$	92.05	91.86	±1.622	20.60	382.25	LIDAR and field
11	$Bg = -11.1972 + 0.00112925 \times DHB^2 + 5.39896 \times AD + 0.167327 \times Ht$	92.80	92.64	±1.545	19.76	379.67	LIDAR and field
12	$Bg = -7.29007 + 0.00106939 \times DHB^2 + 0.210261 \times Ht$	92.00	91.87	±1.619	20.75	412.08	LIDAR and field
13	$Bg = -8.0981 + 0.00122105 \times DHB^2 + 8.31836 \times AD$	91.12	90.98	±1.707	21.68	429.90	LIDAR and field
14	$Bg = 0.282158 + 0.00116885 \times DHB^2$	89.69	89.61	±1.837	23.13	475.75	LIDAR and field
15	$Bg = -5.75185 + 0.0000116474 \times CPA^2 + 0.00593658 \times Ht^2 + 1.15658 \times FC$	84.38	83.95	±2.321	27.73	655.25	LIDAR
16	$Bg = -12.6105 + 0.0000122488 \times CPA^2 + 0.0528847 \times As + 0.00554453 \times Ht^2$	82.76	82.31	±2.428	29.75	752.07	LIDAR
17	$Bg = -2.53575 + 0.0000130776 \times CPA^2 - 0.207888 \times Lb + 0.00664606 \times Ht^2$	82.60	82.16	±2.416	30.10	782.18	LIDAR
18	$Bg = -1.50343 + 0.0000130013 \times CPA^2 + 0.00594433 \times Ht^2 - 7.98952 \times PC$	82.51	82.07	±2.423	30.18	779.52	LIDAR

Vc = volume of the crown from the solid of rotation that best models the crown (m^3); MC = mantle of the crown (surface area of the solid of rotation in m^2); CPA = crown projection area (m^2); Lb = length of the branches (m); Lc = length of the crown (m); Ht = total height of the tree (m); PC = percentage of crown = (Lc/Ht) × 100 (%); Fc = form of the crown = DC/LC; DB = basic density of the wood, AD = apparent density of the wood; As = Altitude of the site = elevation of the ground above mean sea level as measured with LIDAR; Bd = dry biomass of the bole (tons); Bg = green biomass of the bole (tons), $R^2_{\%}$ = coefficient of determination, $R^2_{aj.\%}$ = adjusted coefficient of determination, S_{yx} = residual standard error (±tons), $S_{yx\%}$ = residual standard error as a percentage; $\bar{e}_i$ = mean of the error estimate; $PRESS_p$ = error of prediction statistic (ton^2).

of the population we studied. Allometric equations based on simple input variables such as DBH may not adequately represent the variations in Amazonian forest. This is reinforced by the findings of Crow and Schlaegel (1988), Santos (1996), Fearnside (1997, 2007), Clark and Clark (2000) and Duncanson et al. (2015). This increases the importance of including the independent variable Ht (total height); this variable was present in 66% of the equations selected for estimating green and dry biomass. The total height of the tree (Ht) is discarded as a variable in most regression models due to the difficulty of measurement in the field. According to Overman et al. (1994), Brown et al. (1995), Higuchi et al. (1998) and da Silva (2007), inclusion of tree height in allometric models contributes little to improving results and is subject to inaccuracy due to the difficulty of obtaining measurements. However, in large pan-tropical data sets, height data can significantly improve allometric estimates (Asner and Mascaro, 2014; Banin et al., 2012; Chave et al., 2014; Duncanson et al., 2015; Feldpausch et al., 2011, 2012).

When airborne LIDAR is employed, the total height (Ht) variable gains importance and is more practical to collect because the problems of data collection and of imprecision for total height (Ht) are technologically overcome. The height variable should be incorporated into allometric models whenever possible because it is both logically related to biomass and is the variable that is most easily obtained by processing the LIDAR point cloud. However, before obtaining the heights of the trees from the LIDAR point cloud, one should normalize the heights and delete the set of floating points above the forest canopy. These points represent flocks of birds that are detected during profiling with airborne LIDAR. Neglecting this step in the processing can result in overestimation of the total height (Ht).

Another important aspect that shows the importance of including the height variable was described by Brown (2002). This is that equations that only consider diameter and that represent large areas of forest with variations in forest type tend not to adequately reflect the true biomass of trees at any given location. Moreover, the height of the dominant trees has always been seen as reflecting the quality of a forest ecosystem. The height variable is linked to the ecosystem's capacity to stock biomass (Balzotti et al., 2016; Cassol, 1982; Duncanson et al., 2015; Ferraz et al., 2016; Figueiredo, 2005; Scolforo, 1998; Stansfield et al., 1992).

Eight equations were selected to estimate the dry biomass of the bole (Bd) (Table 6); the best results were achieved by Equations 1, 3, 4, and 2. In the four best models the variables DBH and basic density were always included. Equation 1 resulted in the best statistical

precision and the lowest validation value ($Press_p$). In Equations 2 and 4, crown morphometric variables were incorporated: crown projection area (CPA), volume of the crown (Vc) and mantle of the crown (MC), i.e., the three independent variables of the crown with the highest correlations with bole biomass. Equation 3 represents the models traditionally used to estimate dry biomass. These models include the variables DBH, BD and Ht, and the statistical results are similar to those of equations that include canopy variables. Equations fit with better statistical results are possible; however, these apply to simpler forest structures, as in temperate forests (Cao et al., 2016; Gregoire et al., 2016).

Equations with simple inputs for Bd were not selected by the statistical routine. This was because they failed to adequately represent the largest variations in the dendrometric characters of the sampled trees.

Equations 5, 6, 7 and 8 can be used when one chooses only variables obtained with LIDAR, whether or not they are associated with wood-density variables. However, the precision of the results is lower than that of equations that include DBH. In the equations using only LIDAR variables (Equations 5, 6, 7 and 8; Fig. 4), there was a tendency to overestimate the bole biomass for trees with diameters between 45 and 60 cm. The models' difficulty in representing this diameter range is due to the fact that it contains the greatest number of species of commercial interest in forest management. For diameter intervals representing larger trees, the number of species decreases and the sources of variation therefore also decrease.

The distributions of the residuals (expressed as percentages) for the first four equations are all similar (Fig. 4). All of these equations include DBH and BD as variables. When these four equations are graphed we observe substantial heterogeneity in the residuals in the smaller diameter classes, but this did not represent an impediment to meeting the assumptions for regression because the distribution of errors showed no trends and converged to zero.

Equations 9 and 13 (for green biomass) had the highest accuracy and the lowest validation values ($Press_p$). The distributions of percentage residuals for the two equations (Fig. 4) show similarities, with little scattering of percentage errors and a lack of tendencies to over- or underestimate biomass. For estimates of green biomass, the traditionally used linear models with directly measured explanatory variables (DBH, Ht and AD) have good predictive capacity, and incorporation of morphometric variables of the crown contributes little to improving accuracy. It was even possible to fit models with a single input (DBH – Equation 14), corroborating the results of Higuchi et al. (1998).
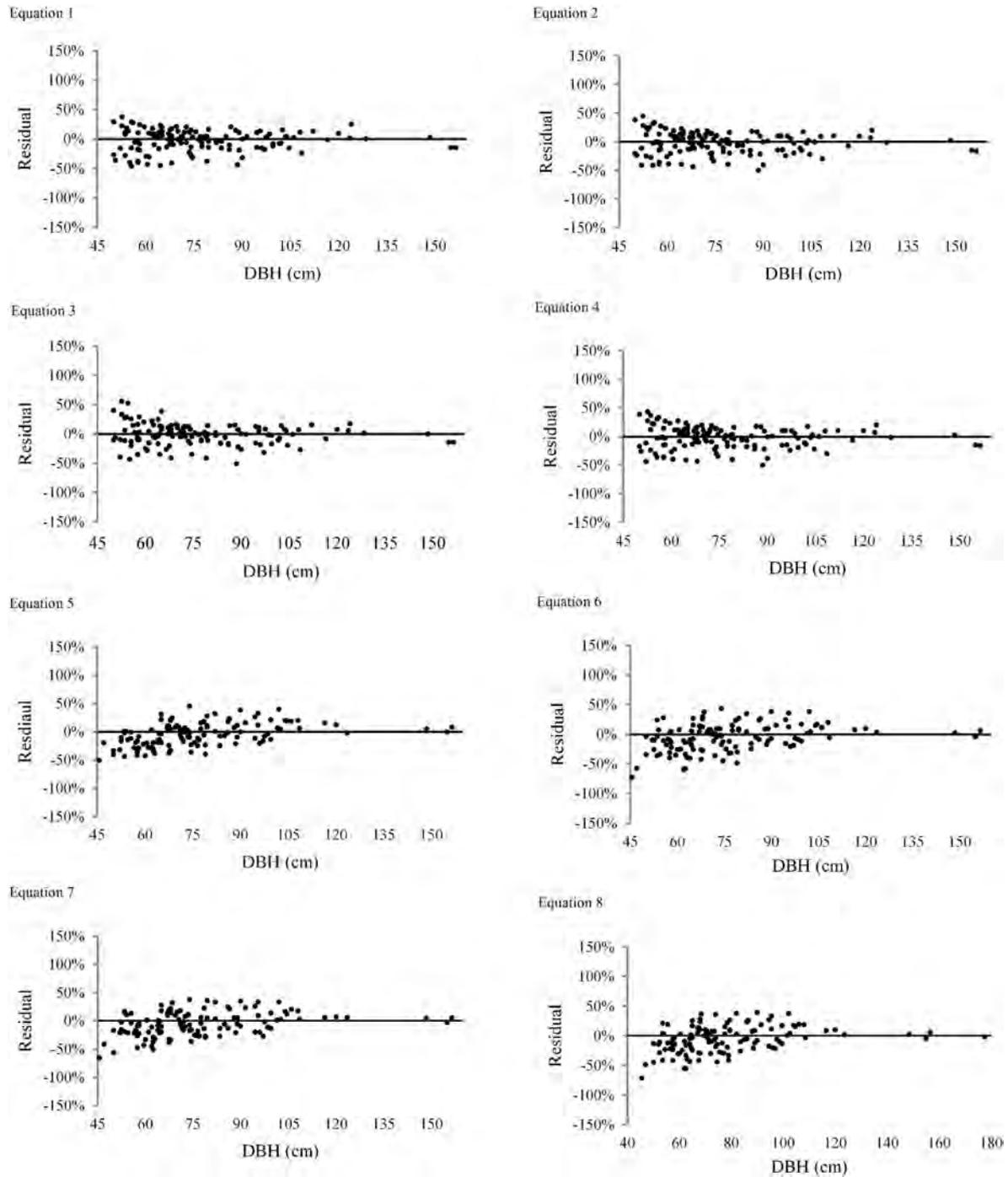
Fig. 4. Distribution of residuals (expressed as percentages) for the best equations for estimating dry biomass, with DBH and without DBH.

However, when opting to use only DBH as an explanatory variable, it is clear that the dispersion of residuals is greater in all diameter ranges. The green biomass Equations 15, 16, 17 and 18, which only use variables obtained from processing the LIDAR point cloud, had lower statistical accuracy than models that include DBH. This was also the case for the equations for dry biomass, where the inclusion of DBH as an explanatory variable decreased the dispersion of residuals for the smaller diameter classes.

Identity testing of models seeks to assess whether it is better to fit models that consider a single data group with species in all three categories of basic wood density (low, medium and high), or whether the data should be divided into subgroups (Graybill, 1976). Equations 1, 2 and 4, which estimate dry biomass using DBH as the independent variable, show significant differences as indicated by the F test (Table 7). Better results are obtained when models are fitted separately for each density group. The only equation that considers DBH as an independent variable and that allows the formation of a single database with all densities is Equation 3. This equation is traditionally used, and considers as independent variables DBH, AD and Ht.

Equations 6, 7 and 8 only use variables that are obtained with airborne LIDAR, especially CPA, Ht, FC and As. These variables can be fitted to the data for datasets for the different wood basic density groups. This
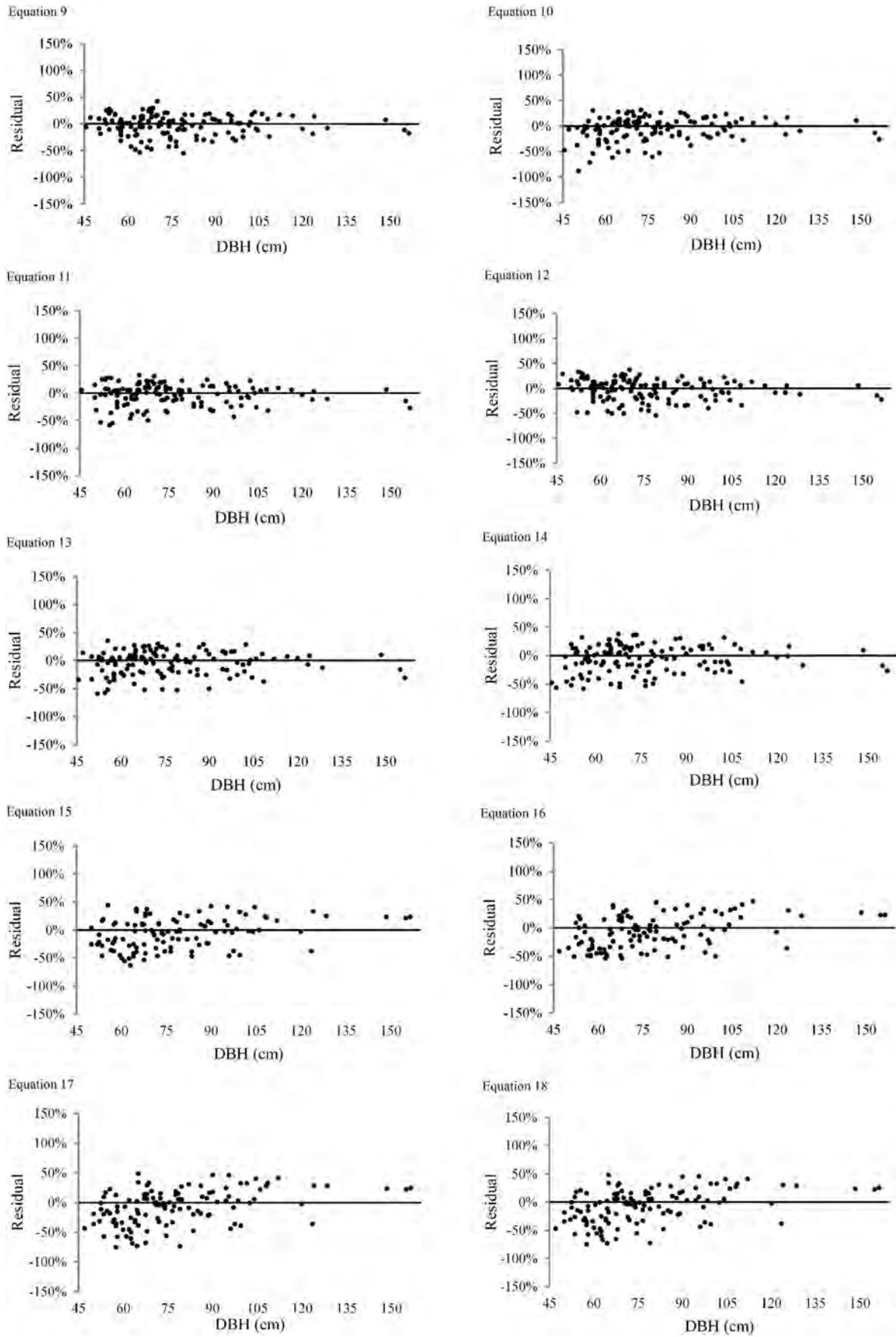
Fig. 5. Distribution of residuals (expressed as percentages) for the best equations for estimating green biomass, with DBH and without DBH.

Table 7
Dry biomass equations: results of the model identity tests (using the F test) using three different combinations of species sets classified by wood density, Antimary State Forest, Acre, Brazil.

Combinations	MS (difference)	MS (residual)	F (calculated)	F 5% (table)	Significance
Equation 1 - $Bd = \beta_0 + \beta_1 DBH + \beta_2 CPA^2 + \beta_3 BD$					
BDlo/BDmd/BDhi	6.42	1.18	5.46	2.02	S
BDlo/BDmd	2.68	1.07	2.52	2.51	S
BDmd/BDhi	5.46	1.21	4.52	2.46	S
Equation 2 - $Bd = \beta_0 + \beta_1 DBH + \beta_2 BD - \beta_3 Vc^{-1}$					
BDlo/BDmd/BDhi	5.02	1.33	3.77	2.02	S
BDlo/BDmd	1.09	1.36	0.80	2.51	NS
BDmd/BDhi	5.72	1.19	4.82	2.46	S
Equation 3 - $Bd = \beta_0 + \beta_1 DBH + \beta_2 BD + \beta_3 Ht$					
BDlo/BDmd/BDhi	1.87	1.50	1.25	2.02	NS
BDlo/BDmd	0.70	1.75	0.40	2.51	NS
BDmd/BDhi	1.76	1.25	1.41	2.46	NS
Equation 4 - $Bd = \beta_0 + \beta_1 DBH + \beta_2 BD - \beta_3 MC^{-1}$					
BDlo/BDmd/BDhi	4.84	1.38	3.51	2.02	S
BDlo/BDmd	1.24	1.45	0.86	2.51	NS
BDmd/BDhi	4.39	1.27	3.47	2.46	S
Equation 5 - $Bd = \beta_0 + \beta_1 APC^2 + \beta_2 BD + \beta_3 Ht^2$					
BDlo/BDmd/BDhi	0.69	2.07	0.34	2.03	NS
BDlo/BDmd	1.16	1.84	0.63	2.51	NS
BDmd/BDhi	1.11	2.16	0.51	2.47	NS
Equation 6 - $Bd = \beta_0 + \beta_1 APC^2 + \beta_2 FC + \beta_3 Ht^2$					
BDlo/BDmd/BDhi	1.57	2.09	0.75	2.03	NS
BDlo/BDmd	3.24	1.92	1.68	2.52	NS
BDmd/BDhi	0.25	2.17	0.12	2.47	NS
Equation 7 - $Bd = \beta_0 + \beta_1 APC^2 + \beta_2 HSolo + \beta_3 Ht^2$					
BDlo/BDmd/BDhi	0.90	2.04	0.44	2.03	NS
BDlo/BDmd	2.50	1.77	1.41	2.52	NS
BDmd/BDhi	0.43	2.13	0.20	2.47	NS
Equation 8 - $Bd = \beta_0 + \beta_1 APC^2 + \beta_2 Ht^2$					
BDlo/BDmd/BDhi	1.54	2.12	0.73	2.18	NS
BDlo/BDmd	4.37	1.87	2.34	2.74	NS
BDmd/BDhi	0,96	2,22	0,43	2,70	NS

Vc = volume of the crown from the solid of rotation that best models the crown (m³); MC = mantle of the crown (surface area of the solid of rotation in m²); CPA = crown projection area (m²); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); Ht = total height of the tree (m); Fc = form of the crown = DC/Lc; Bd = dry biomass of the bole (tons); As = altitude of the site = elevation of the ground above mean sea level as measured with LIDAR; BDlo = set of species with low basic density (BD < 0.5); BDmd = set of species with medium basic density (0.5 ≥ BD < 0.7); BDhi = set of species with high basic density (BD ≥ 0.7); MS = mean square; $F_{(calculated)}$ = value of the Fisher F test calculated for the data set of interest; F5% $_{(table)}$ = table value of the F test statistic; S = significant; NS = not significant; β_i = parameters to be estimated.

Table 8
Green biomass equations: results of the model identity tests (using the F test) using three different combinations of species sets classified by wood density, Antimary State Forest, Acre, Brazil.

Combinations	MS (difference)	MS (residual)	F (calculated)	F 5% (table)	Significance
Equation 9 - $Bg = \beta_0 + \beta_1 CPA^2 + \beta_2 DBH^2 + \beta_3 Ht$					
DBlo/DBmd/DBal	17.82	1.94	9.18	2.02	S
DBlo/DBmd	42.28	2.17	19.53	2.51	S
DBmd/DBal	8.82	1.82	4.85	2.46	S
Equation 10 - $Bg = \beta_0 + \beta_1 CPA^2 + \beta_2 DBH^2 + \beta_3 AD$					
DBlo/DBmd/DBal	18.24	2.40	7.60	2.02	S
DBlo/DBmd	41.35	2.86	14.48	2.51	S
DBmd/DBal	9.78	2.05	4.78	2.46	S
Equation 11 - $Bg = \beta_0 + \beta_1 DBH^2 + \beta_2 AD + \beta_3 Ht$					
BDlo/BDmd/BDhi	23.74	2.33	10.18	2.02	S
BDlo/BDmd	37.36	3.08	12.15	2.51	S
BDmd/BDhi	2.23	1.74	1.28	2.46	NS
Equation 12 - $Bg = \beta_0 + \beta_1 DBH^2 + \beta_2 Ht$					
BDlo/BDmd/BDhi	30.28	2.55	11.86	2.17	S
BDlo/BDmd	53.72	3.23	16.65	2.74	S
BDmd/BDhi	6.78	1.97	3.44	2.69	S
Equation 13 - $Bg = \beta_0 + \beta_1 DBH^2 + \beta_2 AD$					
BDlo/BDmd/BDhi	39.47	2.97	13.31	2.18	S
BDlo/BDmd	31.29	4.02	7.78	2.74	S
BDmd/BDhi	3.15	2.30	1.37	2.69	NS
Equation 14 - $Bg = \beta_0 + \beta_1 DBH^2$					
BDlo/BDmd/BDhi	76.24	3.12	24.47	2.45	S
BDlo/BDmd	131.43	4.13	31.82	3.14	S
BDmd/BDhi	14.37	2.51	5.72	3.08	S
Equation 15 - $Bg = \beta_0 + \beta_1 CPA^2 + \beta_2 Ht^2 + \beta_3 Fc$					
BDlo/BDmd/BDhi	18.00	4.44	4.06	2.03	S
BDlo/BDmd	57.32	4.19	13.70	2.54	S
BDmd/BDhi	10.44	4.13	2.53	2.48	S
Equation 16 - $Bg = \beta_0 + \beta_1 CPA^2 + \beta_2 As + \beta_3 Ht^2$					
BDlo/BDmd/BDhi	4.44	5.33	0.83	2.03	NS
BDlo/BDmd	22.26	4.08	5.46	2.53	S
BDmd/BDhi	2.54	5.21	0.49	2.48	NS
Equation 17 - $Bg = \beta_0 + \beta_1 CPA^2 - \beta_2 Cc + \beta_3 Ht^2$					
BDlo/BDmd/BDhi	4.11	5.13	0.80	2.03	NS
BDlo/BDmd	28.49	4.31	6.61	2.52	S
BDmd/BDhi	12.09	5.00	2.42	2.47	NS
Equation 18 - $Bg = \beta_0 + \beta_1 CPA^2 + \beta_2 Ht^2 + \beta_3 PC$					
BDlo/BDmd/BDhi	4.10	5.16	0.79	2.03	NS
BDlo/BDmd	28.50	4.30	6.63	2.52	S
BDmd/BDhi	12.01	5.04	2.38	2.47	NS

Bg = green biomass of the bole (tons); Lc = length of the crown (m); PC = percentage of crown = (Lc/Ht) × 100 (%); CPA = crown projection area (m²); DBH = diameter at breast height measured in the field 1.3 m above the ground or above any buttresses (m); Ht = total height of the tree (m); Fc = form of the crown = DC/Lc; DB = basic density of the wood; AD = apparent density of the wood; As = altitude of the site = elevation of the ground above mean sea level as measured with LIDAR; BDlo = set of species with low basic density (BD < 0.5); BDmd = set of species with medium basic density (0.5 ≥ BD < 0.7); BDhi = set of species with high basic density (BD ≥ 0.7); MS = mean square; $F_{(calculated)}$ = value of the Fisher F test calculated for the data set of interest; F5% $_{(table)}$ = table value of the F test statistic; S = significant; NS = not significant; β_i = parameters to be estimated.

allows for greater ease in fitting and in using the equations for estimating the biomass of dominant and co-dominant trees in forest-management areas.

The equations for dry biomass that have been developed with variables representing the canopy (CPA and FC), together with Ht or altitude of the site (As), were better able to represent the set of information on the sampled forest population, regardless of the density of the wood. If one chooses not to use models that consider the canopy variables, models should either be fitted separately for each group of basic wood density or they should include the basic density (BD) as an independent variable so that species of all densities can be fitted in a single model.

The great advantage of using a model without independent variables that are measured in the field (DBH and density), such as Equations 5, 6, 7 and 8, is that the equation can make estimates for dominant and co-dominant trees as soon as one has a model that has been fitted and validated for a given location. This optimizes the work in annual operational planning in forest management.

5. Conclusion

The study shows the viability of measuring crown morphological variables and total height in Amazonian forest based on airborne LIDAR data alone. These variables are sufficient to obtain useful estimates of forest biomass, and especially the biomasses of large commercially valuable trees that are of interest for forest management. On-the-ground measurements of traditional variables such as diameter at breast height and wood density are needed to calibrate the remotely sensed variables to biomass in each general location, but once this is done, remotely sensed data can be gathered and the estimates extended

to much wider areas than would be practical to assess with traditional forest inventories.

The variables with the highest linear correlations with the dry biomass of the bole are: diameter at breast height (DBH), basic wood density (BD), mantle of the crown (MC), crown projection area (CPA), volume of the crown (Vc) and crown diameter (CD). In estimating dry biomass, the best results for accuracy and distribution of residuals are always achieved when both crown morphometric variables and traditional variables for the bole (DBH, total height and basic density) are used. When opting to include wood density as an explanatory variable, one must determine basic density from samples collected along the length of the bole. Trees with broken crowns (about 14%) can be identified as outliers by analysis of influence and should not be modeled by equations that use crown morphology variables. The mantle of the crown (MC) and the crown projection area (CPA) are strongly correlated with the diameter of the thin end of the bole (Dmin) and are important independent variables for forest yield and for the biomass stored in the trunk.

The equations for estimating dry biomass (Bd) that only include crown morphometry variables and/or the altitude of the site (As) provide lower accuracy as compared to models with DBH. However, they have good performance in estimating the biomass of dominant and co-dominant trees, regardless of the basic wood density group, and may be used based only on data obtained by processing the point cloud from airborne LIDAR.

The application of LIDAR on a wide scale in Amazonian forest can potentially make significant contributions to improving estimates of forest biomass (thus reducing uncertainty in estimates of greenhouse-gas emissions from deforestation). These estimates can also contribute to detecting and monitoring forest degradation, and to assuring the sustainability of forest management.

Acknowledgments

Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.rse.2016.10.026.

References

ABNT (Associação Brasileira de Normas Técnicas), 2003. NBR 11941: Madeira – Determinação da Densidade Básica. ABNT, Rio de Janeiro, Brazil (6 pp).

Acre, 2000. Zoneamento Ecológico-Econômico: Recursos Naturais e Meio Ambiente. Governo do Estado do Acre, Programa Estadual de Zoneamento Ecológico-Econômico do Estado do Acre. SECTMA, Rio Branco, Acre, Brazil (116 pp).

Applied Imagery, 2010. Quick Terrain Modeler – LIDAR Exploitation Software, Version 7. User's Manual. Applied Imagery, Silver Springs, Maryland, U.S.A. (232 pp).

Asner, G., Mascaro, J., 2014. Mapping tropical forest carbon: calibrating plot estimates to a simple LiDAR metric. Remote Sens. Environ. 140, 614–624. http://dx.doi.org/10.1016/j.rse.2013.09.023.

Baker, T.R., et al., 2004. Variation in wood density determines spatial patterns in Amazonian forest biomass. Glob. Chang. Biol. 10, 545–562.

Balzotti, C.S., Asner, G.P., Taylor, P.G., Cole, R., Osborne, B.B., Cleveland, C.C., Porder, S., Townsend, A.R., 2016. Topographic distributions of emergent trees in tropical forests of the Osa Peninsula, Costa Rica. Ecography 39, 1–11.

Banin, L., et al., 2012. Cross-continental comparisons of maximum tree height and allometry: Testing environmental, structural and floristic drivers. Glob. Ecol. Biogeogr. 21, 1179–1190.

Bohlman, S., O'Brien, S., 2006. Allometry, adult stature and regeneration requirement of 65 tree species on Barro Colorado Island, Panama. J. Trop. Ecol. 22 (2), 123–136. http://dx.doi.org/10.1017/S0266467405003019.

Bouvier, M., Durrieu, S., Fournier, R.A., Renaud, J.P., 2015. Generalizing predictive models of forest inventory attributes using an area-based approach with airborne LiDAR data. Remote Sens. Environ. 156, 322–334.

Brown, S., 2002. Measuring carbon in forests: Current status and future challenges. Environ. Pollut. 116, 363–372.

Brown, I.F., Martinelli, L.A., Thomas, W.W., Moreira, M.Z., Ferreira, C.A.C., Victoria, R.A., 1995. Uncertainty in the biomass of Amazonian forests: an example from Rondônia, Brazil. For. Ecol. Manag. 75, 175–189.

Burger, H., 1939. Baumkrone und zuwachs in zwei hiebsreifen fichtenbeständen. Mitteilungen der Schweizerischen Anstalt für das Forstliche Versuchswesen. 21 pp. 147–176.

Cao, L., Coops, N.C., Innes, J.L., Dai, J., Ruan, H., She, G., 2016. Tree species classification in subtropical forests using small-footprint full-waveform LiDAR data. Int. J. Appl. Earth Obs. Geoinf. 49, 39–51.

Cassol, C.I.A., 1982. Relações entre Características do Solo, Crescimento e Produtividade em Povoamento Implantado de Araucaria angustifolia (Bert.) O·Ktze., em Passo Fundo – RS. Masters Dissertation in Agronomy. Universidade Federal de Santa Maria, Santa Maria, Rio Grande do Sul, Brazil (84 pp).

Chambers, J., Asner, G., Morton, D., Anderson, L., Saatchi, S., Espírito-Santo, F., Palace, M., Souza, J., 2007. Regional ecosystem structure and function: Ecological insights from remote sensing of tropical forests. Trends Ecol. Evol. 22 (8), 414–423. http://dx.doi.org/10.1016/j.tree.2007.05.001.

Chatterjee, S., Hadi, A.S., 1986. Influential observations, high leverage points, and outliers in linear regression. Stat. Sci. 3, 379–416.

Chave, J., et al., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob. Chang. Biol. 20 (10), 3177–3190. http://dx.doi.org/10.1111/gcb.12629.

Clark, D.B., Clark, D.A., 2000. Landscape-scale variation in forest structure and biomass in a tropical rain forest. For. Ecol. Manag. 137 (1–3), 185–198.

Crow, T.R., Schlaegel, B.E., 1988. A guide to using regression equations for estimating tree biomass. North. J. Appl. For. 5 (1), 15–22.

da Silva, R.P., 2007. Alometria, Estoque e Dinâmica da Biomassa de Florestas Primárias e Secundárias na Região de Manaus (AM). Doctoral Thesis. Instituto Nacional de Pesquisas da Amazônia/Fundação Universidade Federal do Amazonas, Manaus, Amazonas, Brazil (152 pp).

Detto, M., Asner, G., Muller-landau, H., Sonnentag, O., 2015. Spatial variability in tropical forest leaf area density from multireturn lidar and modeling. J. Geophys. Res. 120 (2), 294–309. http://dx.doi.org/10.1002/2014JG002774.

do Vale, A.T., Sarmento, T.R., Almeida, A.N., 2005. Caracterização e uso de madeiras de galhos de árvores provenientes da arborização de Brasilia - DF. Ciência Florestal 15 (4), 411–420.

D'Oliveira, M.V.N., Reutebuch, S.E., Mcgaughey, R.J., Andersen, H.E., 2012. Estimating forest biomass and identifying low-intensity logging areas using airborne scanning LIDAR in Antimary state Forest, Acre State, Western Brazilian Amazon. Remote Sens. Environ. 124, 479–491.

Dubayah, R.O., Sheldon, S.L., Clark, D.B., Hofton, M.A., Blair, J.B., Hurtt, G.C., Chazdon, R.L., 2010. Estimation of tropical forest height and biomass dynamics using lidar remote sensing at La Selva, Costa Rica. J. Geophys. Res. Biogeosci. 115 (G2). http://dx.doi.org/10.1029/2009JG000933.

Duncanson, L.I., Dubayah, R.O., Cook, B.D., Rosette, J., Parker, G., 2015. The importance of spatial detail: Assessing the utility of individual crown information and scaling approaches for lidar-based biomass density estimation. Remote Sens. Environ. 168, 102–112.

Durlo, M.A., Denardi, L., 1998. Morfometría de Cabralea canjerana, em mata secundária nativa do Rio Grande do Sul. Ciência Florestal 8, 55–66.

Fearnside, P.M., 1997. Wood density for estimating forest biomass in Brazilian Amazonia. For. Ecol. Manag. 90 (1–3), 59–87.

Fearnside, P.M., 2007. Uso da terra na Amazônia e as mudanças climáticas globais. Braz. J. Ecol. 10, 83–100.

Feldpausch, T.R., et al., 2011. Height-diameter allometry of tropical forest trees. Biogeosciences 8, 1081–1106. http://dx.doi.org/10.5194/bg-8-1081-2011.

Feldpausch, T.R., et al., 2012. Tree height integrated into pan-tropical forest biomass estimates. Biogeosciences 9 (8), 3381–3403. http://dx.doi.org/10.5194/bg-9-1-2012.

Ferraz, A., Mallet, C., Jacquemoud, S., Gonçalves, G.R., Tomé, M., Soares, P., Pereira, L.G., Bretar, F., 2015. Canopy density model: a new ALS-derived product to generate multilayer crown cover maps. Remote Sens. Environ. 168, 102–112. http://dx.doi.org/10.1109/TGRS.2015.2448056.

Ferraz, A., Saatchi, S., Mallet, C., Meyer, V., 2016. Lidar detection of individual tree size in tropical forests. IEEE Trans. Geosci. Remote Sens. 183, 318–333. http://dx.doi.org/10.1016/j.rse.2016.05.028.

Figueiredo, E.O., 2005. Avaliação de povoamentos de teca (Tectona grandis L.f.) na Microrregião do Baixo Rio Acre. Masters Dissertation in Forestry Engineering. Universidade Federal de Lavras, Lavras, Minas Gerais, Brazil.

Figueiredo, E.O., Braz, E.M., d'Oliveira, M.V.N., 2007. Manejo de Precisão em Florestas Tropicais: Modelo Digital de Exploração Florestal. Embrapa Acre, Rio Branco, Acre, Brazil (183 pp).

Graybill, F.A., 1976. Theory and Application of the Linear Model (Duxbury, Belmont Massachusetts, U.S.A). (704 pp).

Gregoire, T.G., Næsset, E., McRoberts, R.E., Ståhl, G., Andersen, H.E., Gobakken, T., Ene, L., Nelson, R., 2016. Statistical rigor in LiDAR-assisted estimation of aboveground forest biomass. Remote Sens. Environ. 173, 98–108.

Higuchi, N., dos Santos, J., Ribeiro, R.J., Minette, L., Biot, Y., 1998. Biomassa da parte aérea da vegetação da floresta tropical úmida de terra-firme da Amazônia brasileira. Acta Amazon. 28, 153–166.

Hudak, A.T., Crookston, N.L., Evans, J.S., Falkowski, M.K., Smith, A.M.S., Gessler, P.E., Morgan, P., 2012. Regression modeling and mapping of coniferous forest basal area

and tree density from discrete-return LIDAR and multispectral data. Can. J. Remote. Sens. 32, 126–138.

Hunter, M.O., Keller, M., Victoria, D., Morton, D.C., 2013. Tree height and tropical forest biomass estimation. Biogeosciences 10 (12), 8385–8399.

Hunter, M.O., Keller, M., Morton, D., Cook, B., Lefsky, M., Ducey, M., Saleska, S., Oliveira, R.C., Schietti, J., 2015. Structural dynamics of tropical moist forest gaps. PLoS One 10 (7), e0132144. http://dx.doi.org/10.1371/journal.pone.0132144.

Lim, K.S., Treitz, P.M., 2004. Estimation of above ground forest biomass from airborne discrete return laser scanner data using canopy-based quantile estimators. Scand. J. For. Res. 19 (6), 558–570.

Næsset, E., Gobakken, T., 2008. Estimation of above and below-ground biomass across regions of the boreal forest zone using airborne laser. Remote Sens. Environ. 112, 3079–3090.

Nogueira, E.M., Nelson, B.W., Fearnside, P.M., 2005. Wood density in dense forest in Central Amazonia, Brazil. For. Ecol. Manag. 208, 261–286.

Nogueira, E.M., Fearnside, P.M., Nelson, B.W., França, M.B., 2007. Wood density in forests of Brazil's 'arc of deforestation': implications for biomass and flux of carbon from land-use change in Amazonia. For. Ecol. Manag. 248, 119–135.

Orellana, E., Koehler, A.B., 2008. Relações morfométricas de *Ocotea odorifera* (Vell.) Rohwer. Ciências Agrárias Ambiental 6, 229–237.

Overman, J.P.M., White, H.J.L., Saldarriaga, J.G., 1994. Evaluation of regression models for above-ground biomass determination in Amazon rainforest. J. Trop. Ecol. 10, 207–218.

Palace, M.W., Sullivan, F.B., Ducey, M.J., Treuhaft, R.N., Herrick, C., Shimbo, J.Z., Mota-E-Silva, J., 2015. Estimating forest structure in a tropical forest using field measurements, a synthetic model and discrete return lidar data. Remote Sens. Environ. 161, 1–11.

Ryan, T.P., 2011. Estatística Moderna para Engenheira. Elsevier, Rio de Janeiro, Brazil (324 pp).

Santos, J., 1996. Análise de Modelos de Regressão para Estimar a Fitomassa da Floresta Tropical Úmida de Terra-Firme da Amazônia Brasileira. Doctoral Thesis. Universidade Federal de Viçosa, Viçosa, Minas Gerais, Brazil (121 pp).

SAS Institute, 1990. SAS User's Guide: Statistics. Release 6.03. SAS Institute, Cary, North Carolina, U.S.A (584 pp).

Schneider, P.R., Schneider, P.R.P., 2008. Introdução ao Manejo Florestal. Universidade Federal de Santa Maria (UFSM), Santa Maria, Rio Grande do Sul, Brazil (566 pp).

Scolforo, J.S.R., 1998. Modelagem do Crescimento e da Produção de Florestas Plantadas e Nativas. Universidade Federal de Lavras (UFLA/FAEPE), Lavras, Minas Gerais, Brazil (451 pp).

Scolforo, J.R.S., Pérez, J.F.M., Mello, J.M., Oliveira, A.D., Camolesi, J.F., Borges, L.F.R., Acerbi Júnior, F.W., 2004. Estimativas de volume, peso seco, peso de óleo e quantidade de mourões para candeia (*Eremanthus erythropappus* (DC.) MacLeish). Cerne 10, 87–102.

Scolforo, J.R.S., Oliveira, A.D., Acerbi Júnior, F.W., 2008. Inventário Florestal de Minas Gerais: Equações de Volume, Peso de Matéria Seca e Carbono para Diferentes Fisionomias da Flora Nativa. Universidade Federal de Lavras (UFLA), Lavras, Minas Gerais, Brazil (216 pp).

Shugart, H.H., Asner, G.P., Fischer, R., Huth, A., Knapp, N., Le Toan, T., Shuman, J.K., 2015. Computer and remote-sensing infrastructure to enhance large-scale testing of individual-based forest models. Front. Ecol. Environ. 13 (9), 503–511.

Silveira, L.H.C., Rezende, A.V., Vale, A.T., 2013. Teor de umidade e densidade básica da madeira de nove espécies comerciais amazônicas. Acta Amazon. 43 (2), 179–184.

Simbaña, P.X.M., Abadía, M.F., Manrique, J.C.O., Diez, L.A.S., Asner, G., Valencia, R., 2016. Spatially-explicit testing of a general aboveground carbon density estimation model in a western Amazonian Forest using airborne LiDAR. Remote Sens. 8 (1), 1–15.

Souza, G.S., 1998. Introdução aos Modelos de Regressão Linear e Não-Linear. Embrapa-SPI/Embrapa-SEA, Brasília, DF, Brazil (505 pp).

Stansfield, W.F., Mctague, J.P., Lacapa, R., 1992. Dominant height and site index equations for Douglas fir and Engelmann spruce in east-Central Arizona. West. J. Appl. For. 7 (2), 40–44.

Stark, S.C., Leitold, V., Wu, J.L., Hunter, M.O., de Castilho, C.V., Costa, F.R., McMahon, S.M., Parker, G.G., Shimabukuro, M.T., Lefsky, M.A., Keller, M., 2012. Amazon forest carbon dynamics predicted by profiles of canopy leaf area and light environment. Ecol. Lett. 15 (12), 1406–1414.

Statgraphics, 2006. Statgraphics Centurion XV: User's Guide. StatPoint, Inc., Warrenton, Virginia, U.S.A. (299 pp).

Sullivan, F.B., Palace, M., Ducey, M., 2014. Multivariate statistical analysis of asynchronous lidar data and vegetation models in a neotropical forest. Remote Sens. Environ. 154, 368–377.

Tochon, G., Féret, J.B., Valero, S., Martin, R.E., Knapp, D.E., Salembier, P., Chanussot, J., Asner, G.P., 2015. On the use of binary partition trees for the tree crown segmentation of tropical rainforest hyperspectral images. Remote Sens. Environ. 159, 318–331. http://dx.doi.org/10.1016/j.rse.2014.12.020.

Vanclay, J.K., 1994. Modelling Forest Growth and Yield: Applications to Mixed Tropical Forests. CAB International, Wallingford, UK (312 pp).

Whittaker, R.H., Woodwell, G.E., 1971. Measurement of net primary production of forests. In: Duvigneaud, P. (Ed.), Productivity of Forest Ecosystems: Proceedings of the Brussels Symposium on Ecology and Conservation 4. UNESCO, Paris, France, pp. 159–175.

Wink, C., Monteiro, J.S., Reinert, D.J., Liberalesso, E., 2012. Parâmetros da copa e a sua relação com o diâmetro e altura das árvores de eucalipto em diferentes idades. Scientia Forestalis 40 (93), 57–67.

Wulder, M.A., White, J.C., Nelson, R.F., Næsset, E., Ørka, H.O., Coops, N.C., Bater, C.W., Gobakken, T., 2012. Lidar sampling for large-area forest characterization: a review. Remote Sens. Environ. 121, 196–209. http://dx.doi.org/10.1016/j.rse.2012.02.001.

Zolkos, S.G., Goetz, S.J., Dubayah, R., 2013. A meta-analysis of terrestrial aboveground biomass estimation using lidar remote sensing. Remote Sens. Environ. 128, 289–298. http://dx.doi.org/10.1016/j.rse.2012.10.017.

SUPPLEMENTARY MATERIAL

LIDAR-based estimation of bole biomass for precision management of an Amazonian forest: Comparisons of ground-based and remotely sensed estimates

Evandro Orfanó Figueiredo[1], Marcus Vinicio Neves d´Oliveira[2], Evaldo Muñoz Braz[3], Daniel de Almeida Papa[4,] Philip Martin Fearnside[5*]

[1] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056, Rio Branco, Acre, Brazil, evandro.figueiredo@embrapa.br
[2] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056, Rio Branco, Acre, Brazil, marcus.oliveira@embrapa.br
[3] Embrapa Florestas, Estrada da Ribeira Km 111, CP 319, CEP 83411-000, Colombo, Paraná, Brazil, evaldo.braz@embrapa.br
[4] Embrapa Acre, Rodovia BR-364, km 14, CEP 69900-056, Rio Branco, Acre, Brazil, daniel.papa@embrapa.br
[5] Instituto Nacional de Pesquisas da Amazônia (INPA), Av. André Araújo, 2936 - Petrópolis, CEP: 69067-375, Manaus, Amazonas, Brazil, pmfearn@inpa.gov.br

*Corresponding author.

Figure S1 - Distribution of real and estimated values for the best equations for estimating dry biomass, with DBH and without DBH.

Figure S2 - Distribution of real and estimated values for the best equations for estimating green biomass, with DBH and without DBH.

Equation 1

Equation 2

Equation 3

Equation 4

Equation 5

Equation 6

Equation 7
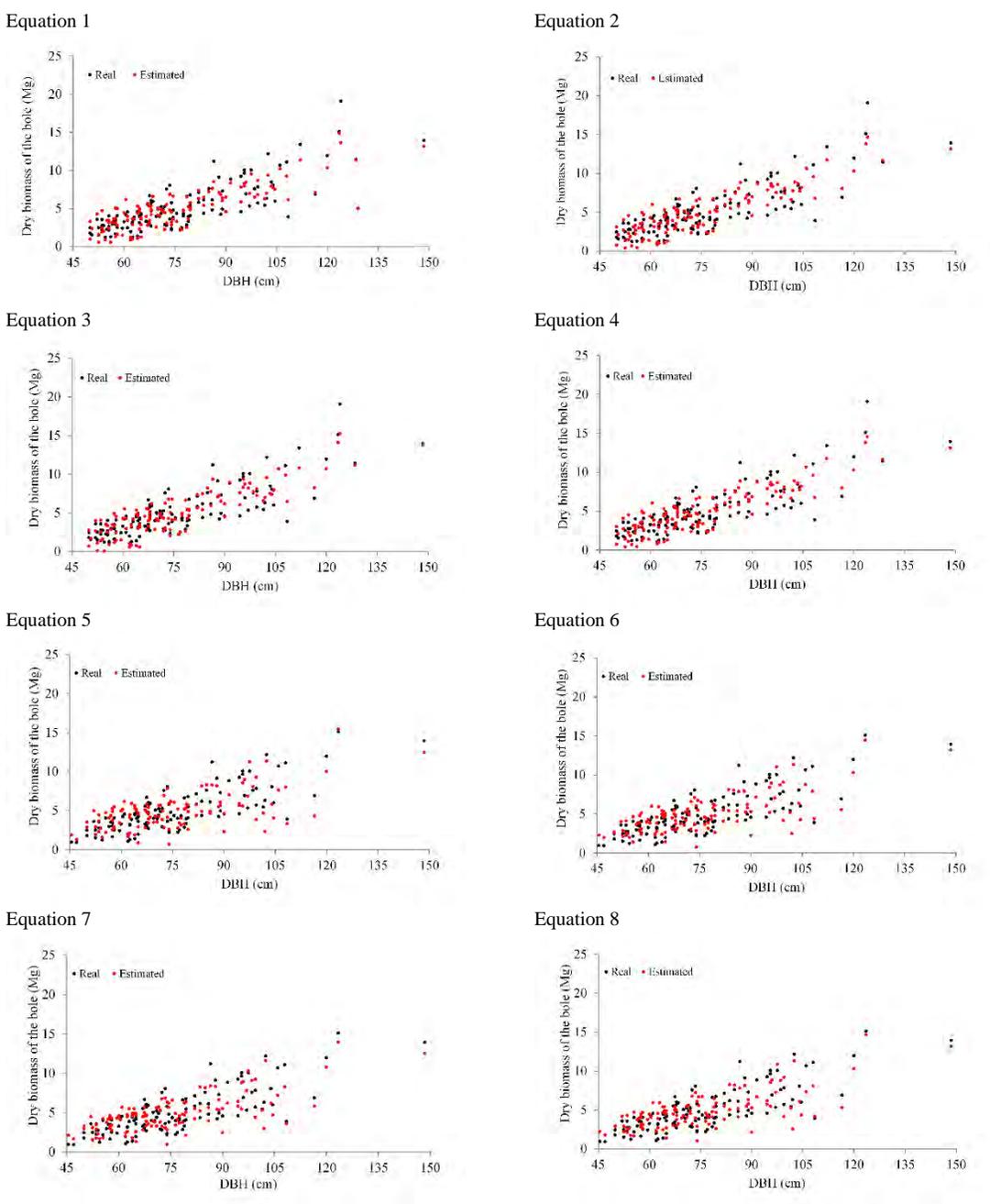
Equation 8

Figure S1 - Distribution of real and estimated values for the best equations for estimating dry biomass, with DBH and without DBH.
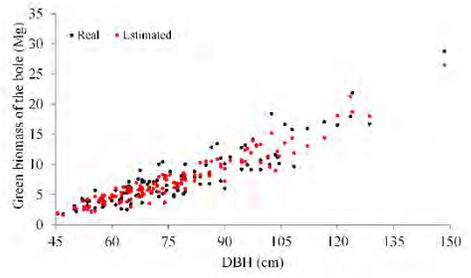
Equation 9

Equation 10
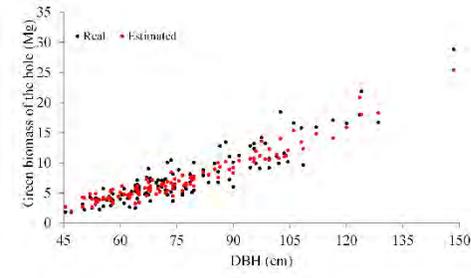
Equation 11
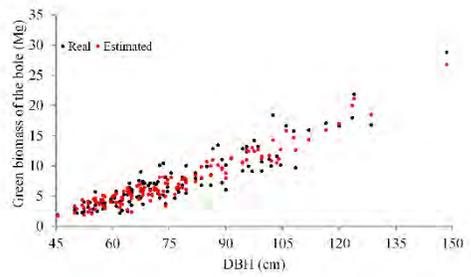
Equation 12
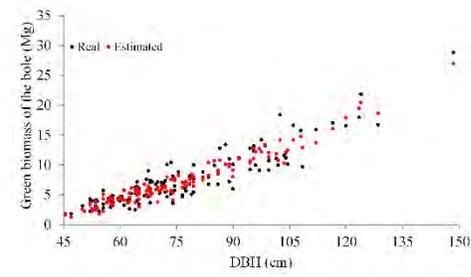
Equation 13
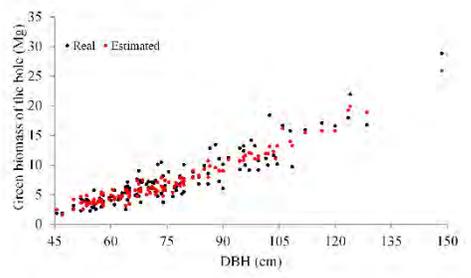
Equation 14
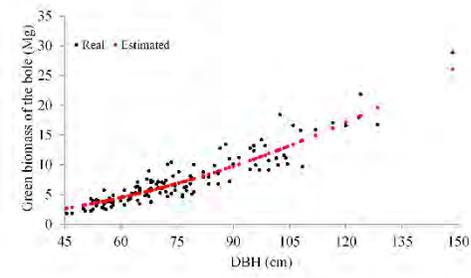
Equation 15
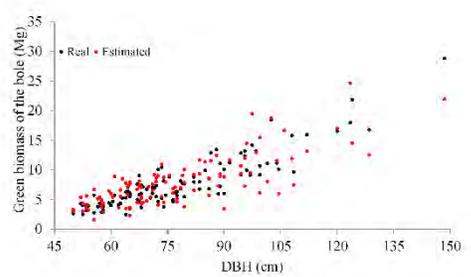
Equation 16
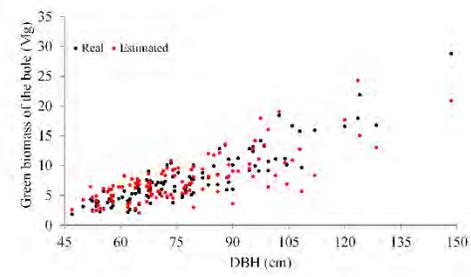
Equation 17
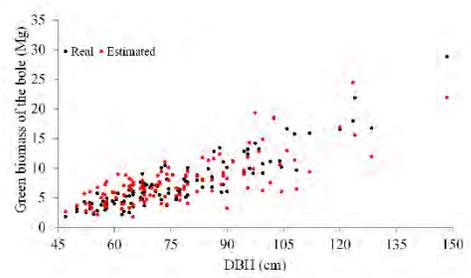
Equation 18

Figure S2 - Distribution of real and estimated values for the best equations for estimating green biomass, with DBH and without DBH.