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Supplement of

Canopy area of large trees explains aboveground biomass variations across neotropical forest landscapes

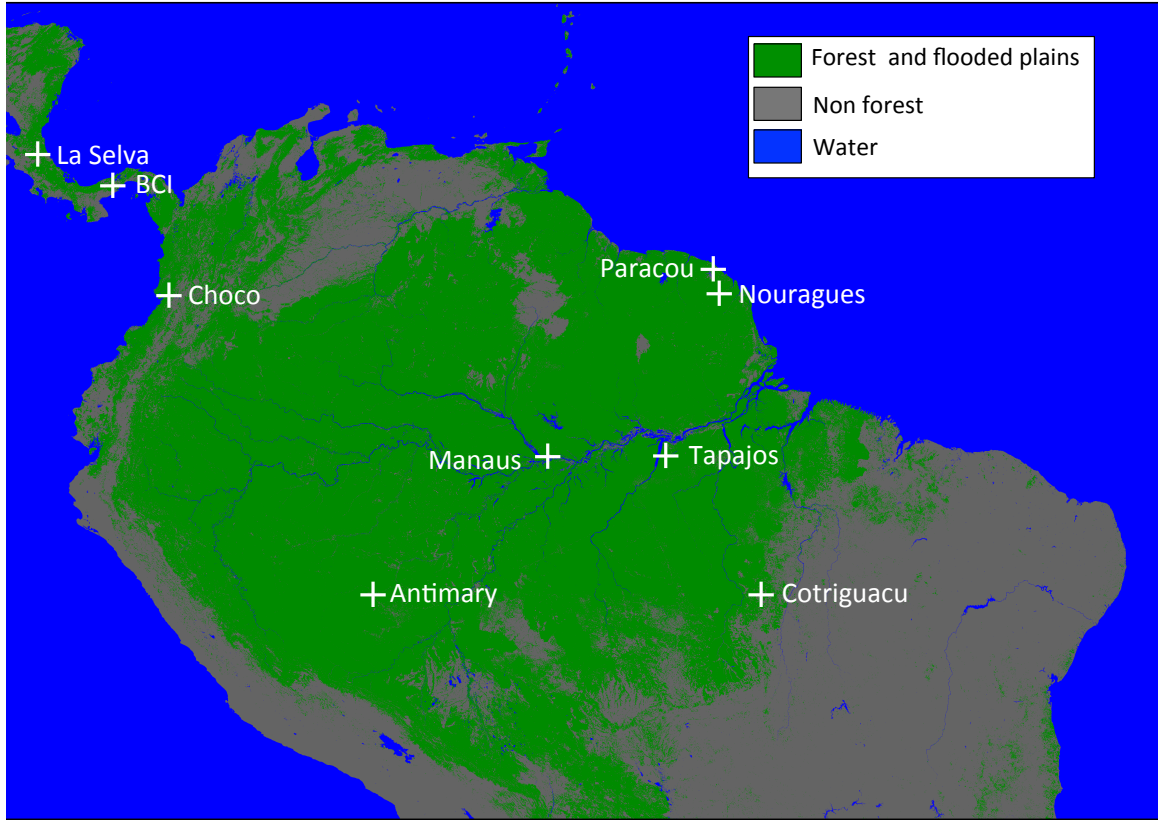
Victoria Meyer et al.

Correspondence to: Victoria Meyer (victoria.meyer@jpl.nasa.com)

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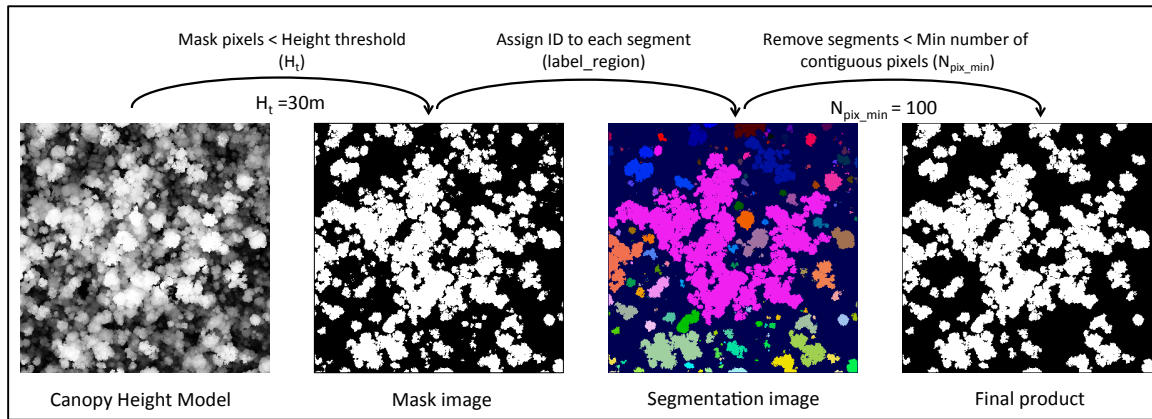
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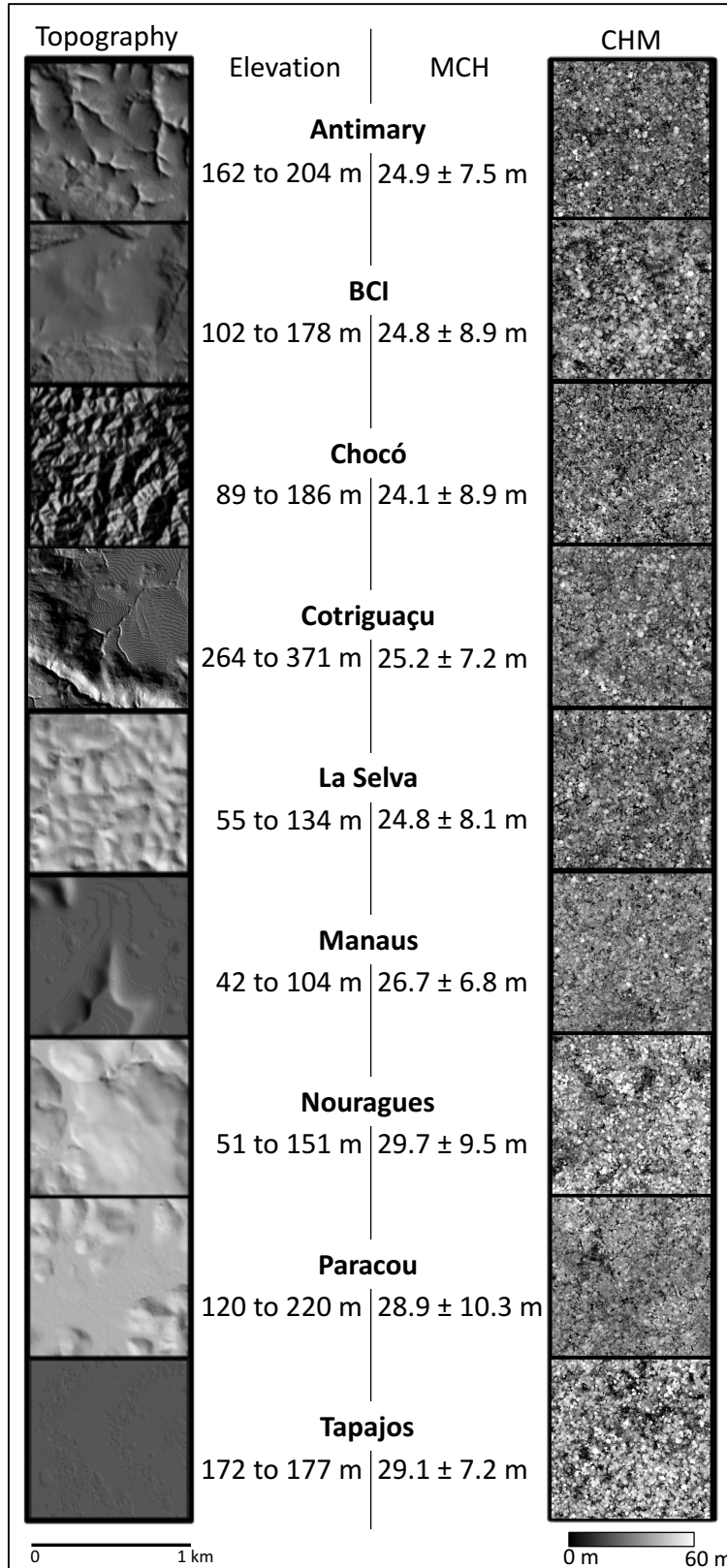
Figure S1. Location of the nine study sites (GlobeCover). All sites are located in old growth tropical forests.

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8 **Figure S2.** Description of steps taken from the original Lidar canopy height model to the final LCA product. This
9 example is a 400 m by 400 m area in BCI, with a height threshold of 30 m and the minimum number of contiguous
10 pixels set to 100.



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Figure S3. Lidar derived images: shaded relief of topography and canopy height model (CHM), at 1 m resolution. Mean canopy height (MCH), standard deviation of canopy height and elevation range are reported.

15 **S.1 Estimating aboveground biomass from forest inventories.**

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17 For trees with no height measurement, a site specific DBH height model was used to infer tree
18 height in each site, as described in previous studies (Feldpausch et al., 2012; Meyer et al., 2013).
19 Wood density (WD) was extracted from the global wood density database for tropical trees
20 (Chave et al., 2009; Zanne et al., 2009) for each tree, based on its level of botanical identification
21 (species, genus, family). Trees with no botanical identification were assigned the average WD of
22 the plot. Average WD of each site was calculated as the unweighted average of all trees within a
23 site, or was taken from a previous study in the case of Cotriguaçu (Fearnside, 1997).
24 Average WD of large trees was calculated as the unweighted average of trees with $DBH \geq 50$ cm
25 in each site. Tree level AGB was aggregated at the plot level using a commonly used allometric
26 regression model for moist tropical forests (Eq. (S1), Chave et al., 2005), except for La Selva and
27 Chocó, for which a model for wet tropical forest (Eq. (S2), Chave et al., 2005) and a local
28 allometric model (Eq. (S3), Duque et al., 2017) were used, respectively.

$$29 \quad AGB_{moist} = 0.0509 \times WD \times DBH^2 \times H \quad (S1)$$

$$30 \quad AGB_{wet} = 0.0776 \times (WD \times DBH^2 \times H)^{0.940} \quad (S2)$$

$$31 \quad AGB_{Chocó} = 0.089 \times (WD \times DBH^2 \times H)^{0.951} \quad (S3)$$

32 where trunk diameter (DBH in cm) is measured during the inventory, tree height (H , in m) is
33 either measured in the field or estimated from a local DBH – H model, and specific gravity or
34 wood density (WD in $g\ cm^{-3}$) is known for each tree. AGB (in kg of dry biomass) of individual
35 trees estimated using the former equations was used to calculate plot level AGB density ($Mg\ ha^{-1}$)
36 ¹) by summing over the biomass of all stems within each plot. Ground estimated AGB density is
37 henceforth referred to as AGB_{inv} . Estimating AGB with these allometric models has been
38 reported to have a standard error of 12.5 % when using height as a parameter, against 19.5 %

39 when height is not available (Chave et al., 2005).

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41 **S.2 Local estimates of AGB using MCH**

42 We estimated AGB locally for each of the nine sites in order to find the best height threshold for
43 LCA in all sites, in addition to the information provided by the four calibration sites (see Fig. 3).
44 Mean canopy height (MCH) is a good predictor of AGB provided that the regression model is
45 calibrated locally. It was calculated by averaging all the canopy height model pixels falling in an
46 area of interest. Here, we calculated a locally calibrated AGB map of each site from MCH using
47 the following model form (Eq. (3), Asner and Mascaro, 2014).

$$48 \quad AGB_{Local} = aMCH^b + \epsilon \quad (S4)$$

49 where AGB_{Local} is the aboveground biomass estimation derived from Lidar data, a is a scaling
50 constant, which is expected to depend significantly on forest type and stand level WD, b is a
51 power law exponent and $\epsilon \sim N(0, \sigma^2)$ represents the uncertainty in measurements. All
52 coefficients are presented in Table S1. We inferred the model parameters directly for the sites
53 where AGB_{inv} of 1 ha plots was available (La Selva, BCI, Paracou and Nouragues). For Chocó
54 and Antimary, we developed models based on 0.25 ha plots and 50 m x 50 m pixels of Lidar data
55 and after estimating AGB_{Local} , aggregated the image to 1 ha or 100 m pixels. For the remaining
56 sites of the Central Amazon (Cotriguaçu, Manaus and Tapajós), we developed a model based on
57 existing data in Manaus and Tapajós from a previous study, derived from airborne and
58 spaceborne Lidar (see Lefsky et al., 2007). This model may have larger uncertainty in estimating
59 biomass compared to our site specific model, but we here assume that all 1 ha scale AGB_{Local}
60 estimates have approximately similar uncertainties.

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67 **Table S1.** Coefficients, R^2 and RMSE for the local models used to estimate AGB from MCH in the different sites,
 68 based on available ground data.

Site	a	b	R^2	RMSE	plot size
Antimary	0.1687	2.2544	0.62	45.30	0.25
BCI	2.3257	1.4336	0.68	28.14	1
Chocó	10.7328	1.0509	0.66	33.34	0.25
Cotriguacu	3.0249	1.3895	-	-	-
La Selva	2.1241	1.3889	0.84	11.45	1
Manaus	3.0249	1.3895	0.59	43.73	0.25
Nouragues	5.7963	1.242	0.46	59.19	1
Paracou	5.707	1.239	0.58	40.49	1
Tapajos	3.0249	1.3895	0.59	43.73	0.25

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72 **Table S2.** Matrices of canopy height thresholds (20 m to 50 m, presented with a 5 m increment for readability
73 purposes) and crown area thresholds (50 to 200 pixels or m²), represented respectively by the minimum height
74 considered for segmentation and by the minimum number of contiguous 1m pixels in a segment. Values are given in
75 percentage of coverage of the 1km² subsets.

Site	Number of pixels	20 m threshold	25 m threshold	30 m threshold	35 m threshold	40 m threshold	45 m threshold	50 m threshold
Antimary	50	75.30	48.32	22.19	8.23	2.12	0.46	0.06
	100	75.03	47.40	20.92	7.64	1.92	0.43	0.05
	150	74.84	46.55	19.82	7.03	1.75	0.41	0.04
	200	74.81	45.89	18.93	6.33	1.60	0.34	0.04
BCI	50	70.06	51.53	29.19	11.66	2.51	0.25	0.05
	100	69.79	50.92	28.21	11.08	2.30	0.21	0.05
	150	69.48	50.38	27.44	10.52	2.06	0.17	0.05
	200	69.35	49.96	26.67	10.06	1.95	0.16	0.05
Chocó	50	70.48	48.64	23.22	7.72	1.88	0.24	0.02
	100	70.20	47.58	21.31	6.45	1.53	0.18	0.00
	150	69.97	46.81	19.83	5.52	1.17	0.09	0.00
	200	69.84	46.05	18.19	4.83	0.94	0.06	0.00
Cotriguaçu	50	80.07	53.85	25.93	8.12	1.65	0.24	0.02
	100	79.91	52.87	24.70	7.33	1.43	0.21	0.02
	150	79.85	52.08	23.23	6.48	1.26	0.18	0.02
	200	79.84	51.71	21.92	5.70	1.12	0.18	0.02
La Selva	50	74.32	50.22	24.00	7.88	1.95	0.27	0.06
	100	74.15	49.30	22.71	7.17	1.70	0.25	0.05
	150	74.05	48.69	21.57	6.55	1.47	0.21	0.05
	200	74.01	48.03	20.57	6.01	1.22	0.11	0.03
Manaus	50	86.07	66.42	33.69	9.02	1.63	0.41	0.08
	100	86.04	65.99	32.72	7.91	1.48	0.38	0.07
	150	86.03	65.69	31.20	6.99	1.17	0.34	0.03
	200	86.00	65.51	29.87	6.08	1.05	0.32	0.03
Nouragues	50	85.14	69.77	48.77	28.82	13.34	4.05	0.79
	100	85.05	69.37	47.86	27.73	12.45	3.56	0.60
	150	84.93	69.16	47.23	26.67	11.41	3.02	0.44
	200	84.89	68.87	46.62	25.73	10.30	2.51	0.29
Paracou	50	84.56	63.40	31.82	9.56	1.83	0.17	0.00
	100	84.50	62.90	30.18	8.47	1.46	0.10	0.00
	150	84.46	62.43	28.64	7.36	1.10	0.05	0.00
	200	84.42	62.18	27.61	6.30	0.82	0.23	0.00
Tapajós	50	79.61	66.61	51.61	33.46	15.15	4.06	0.60
	100	79.46	66.24	51.37	32.89	14.42	3.56	0.48
	150	79.35	65.98	45.89	31.80	13.51	3.19	0.35
	200	79.34	65.69	50.18	30.92	12.64	2.67	0.26

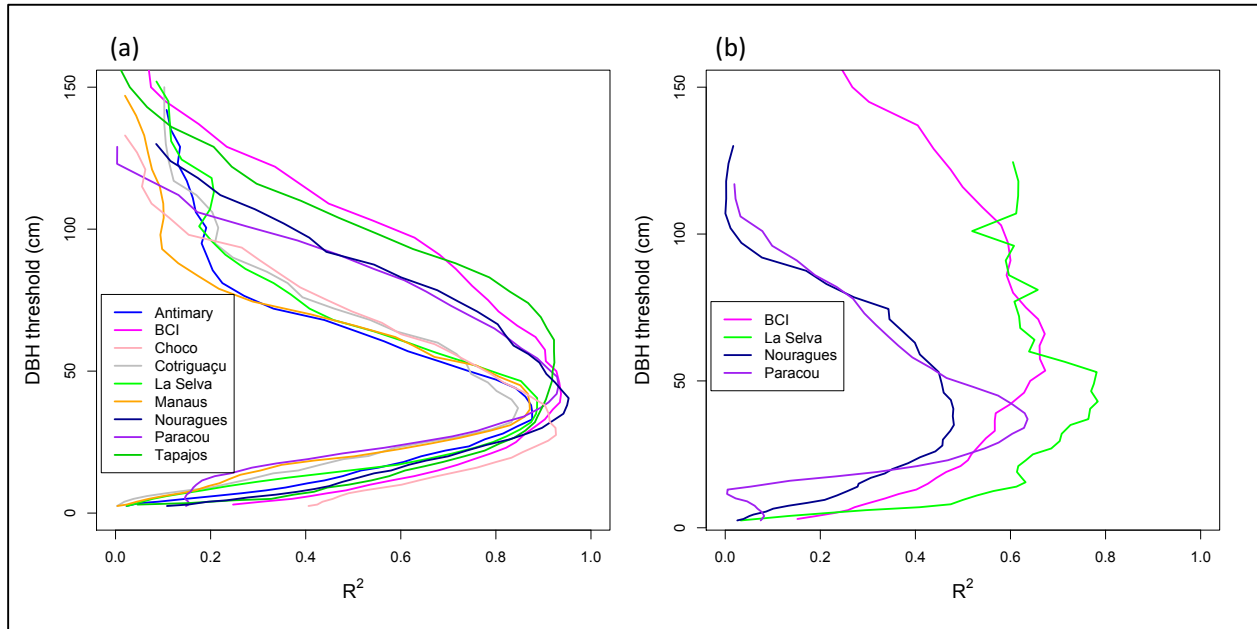
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78 **Table S3.** Coefficients, R^2 , RMSE and bias for the models used to estimate AGB from MCH without and with wood
 79 density (WD) as a weighting factor

Model	Equation	a	b	R^2	RMSE	Bias	R^2 cross-val	RMSE cross-val	Bias cross-val
m_MCH	AGB = aMCH ^b	0.91	1.77	0.68	54.76	-0.30	0.67	55.38	-0.54
m_MCH_wd	AGB = aWDxMCH ^b	4.16	1.44	0.80	42.52	-0.13	0.80	43.49	-0.21

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85 **Figure S4.** Distribution of R^2 between DBH thresholds and AGB_{Local} in 1 ha subareas (a) and AGB_{inv} in 1 ha inventory
86 plots (b). DBH was calculated from tree height using Chave's E factor model (Chave et al., 2014)
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89 **S.3 LCA and ground data**

90 We looked at the relation between LCA and other stand level metrics: AGB_{inv} of large trees,
91 stand basal area, Lorey's height (H_L), and the number of large trees. Lorey's height is defined by

92 $H_L = \frac{\sum_{i=1}^N BA_i H_i}{\sum_{i=1}^N BA_i}$ where H_i is the height of stem i , and BA_i is the basal area of stem i . Weighting

93 tree height with basal area increases the relative importance of large trees in a stand (Lefsky,
94 2010).

95 There was a significant correlation between LCA and AGB_{inv} in all calibration sites ($R^2_{max} = 0.77$,

96 in La Selva), and even more so between LCA and AGB_{inv} of large trees ($R^2_{max} = 0.83$ in La

97 Selva) (Table S4). LCA correlated with Lorey's height, especially at La Selva but less so at

98 Nouragues ($R^2_{LaSelva} = 0.86$, $R^2_{Nouragues} = 0.21$). We also found that LCA and total basal area are

99 correlated. The relationship between LCA and the number of large trees is significant in all sites,

100 but it is lower than other structural metrics in Paracou ($R^2 = 0.32$). Among study sites, La Selva

101 and BCI show higher correlations between LCA and ground derived metrics. The strong

102 correlation of LCA with plot level AGB_{inv} as well as with AGB_{inv} of large trees suggested that a

103 model based on LCA can be used as an estimator of AGB.

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105 **Table S4.** Coefficients of correlation (R^2) between LCA and ground data derived metrics : AGB_{inv} , AGB_{inv} of trees \geq
 106 50 cm DBH, basal area, Lorey's height and number of large trees in BCI, La Selva, Nouragues and Paracou.

	BCI	La Selva	Nouragues	Paracou
AGB_{inv}	0.64	0.77	0.48	0.64
AGB_{50}	0.68	0.83	0.47	0.69
BA	0.63	0.53	0.41	0.43
LH	0.57	0.86	0.21	0.63
N_{70}	0.64	0.76	0.46	0.32

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109 **S.4 Contribution of Large Trees to AGB_{inv}**

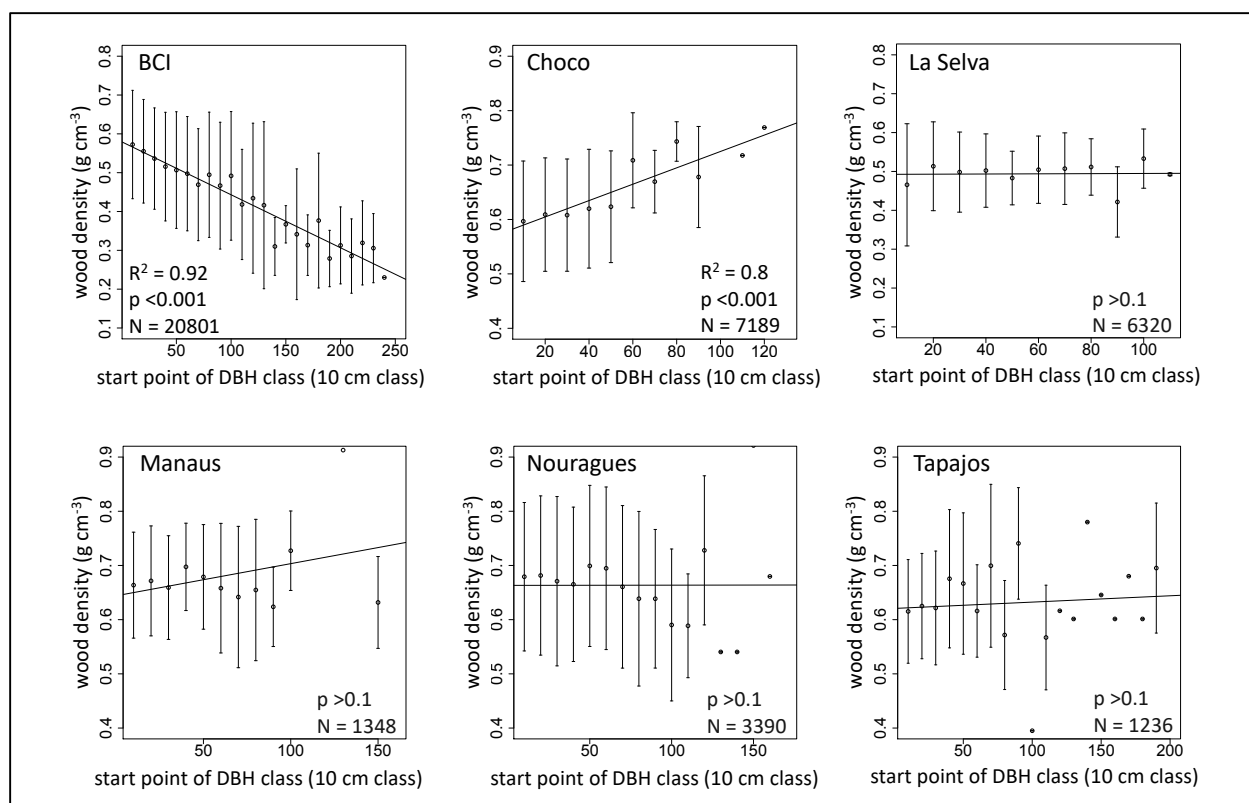
110 First, we explored the role of WD as a key variable in allometric models to scale the tree volume
111 or size to AGB_{inv} (Brown et al., 1989; Chave et al., 2005; Chave et al., 2014, Ngomanda et al.,
112 2014). We examined the variations of WD as a function of DBH classes in all sites and for all
113 trees greater than 10 cm arranged in 10 cm DBH bins.

114 We then assessed the proportion of large trees by examining the DBH frequency distribution of
115 trees at different sites using the field inventory data, and compared it to the distribution of
116 AGB_{inv} for the same DBH ranges, using 1 cm bins to create DBH classes.

117 **Results**

118 DBH and WD: At BCI, mean WD decreased significantly with increasing DBH ($p < 0.001$, $R^2 =$
119 0.92), which is consistent with the results of a previous study (Chave et al., 2004). On the
120 contrary, at Chocó, mean WD increased significantly with increasing DBH ($p < 0.001$, $R^2 = 0.8$).
121 No significant trend was found at the other study sites (Fig. S5). These results show that stand
122 average WD and WD of large trees are not significantly different in four sites and can therefore
123 be used interchangeably in a model using these data. However, using one or the other will have
124 an impact on the results of a model calibrated using data from BCI or Chocó. Mean WD of trees
125 ≥ 50 cm is 0.49 in BCI (vs. stand average WD = 0.54 g cm^{-3}) and 0.66 in Chocó (vs. stand
126 average WD = 0.60 g cm^{-3}).

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128

129 **Figure S5.** Wood density and DBH classes in BCI, Chocó, La Selva, Manaus, Nouragues and Tapajós. The decrease
 130 in mean wood density is significant in BCI ($p < 0.001$, $R^2 = 0.92$). The increase in mean wood density is significant
 131 in Chocó ($p < 0.001$, $R^2 = 0.8$) but there is no significant wood density change across DBH classes in the other sites
 132 ($p > 0.1$). Points with no standard deviation bars mean that only one tree was present in the class.

133

134 We found that using mean WD of trees ≥ 50 cm DBH in our LCA model gives slightly better

135 results than using mean WD (see Eq. (3)), with R^2 of 0.78, RMSE of 45.34 Mg ha⁻¹ and bias of -

136 0.36 Mg ha⁻¹.

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138 DBH and AGB : The relationship between AGB_{inv} and the DBH frequency distribution was

139 similar in BCI, La Selva, Nouragues and Tapajós (Fig. S6). In these sites, more than 50 % of the

140 total AGB_{inv} was contributed by around 5 % (between 3 % and 6 %) of the stems, corresponding

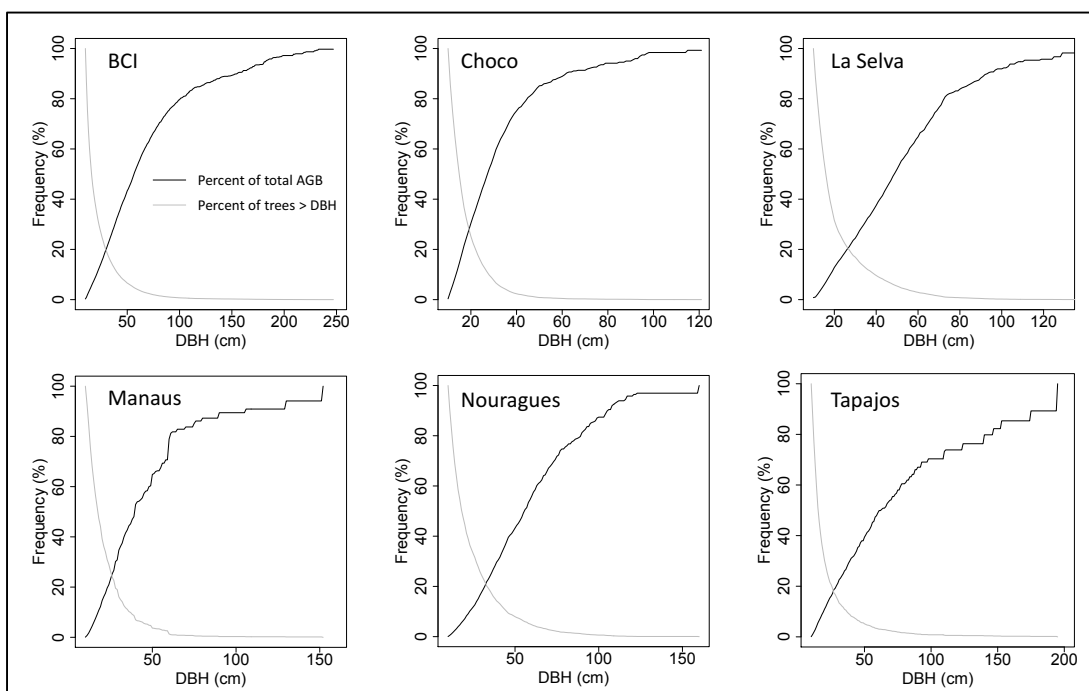
141 to a threshold DBH of 58 cm, 50 cm, 55 cm and 61 cm respectively for the four study sites.

142 Similar results were found in a recent study focusing on the contribution on large trees to AGB

143 in Central Africa (Bastin et al., 2015). Also, 80 % of the AGB stock was in trees with $DBH \geq 30$

144 cm DBH at BCI, 26 cm at La Selva, 32 cm at Nouragues and 29 cm at Tapajós, which echoes

145 results published on BCI (Chave et al., 2001). These represent only 20 % of the total number of
 146 trees in each site (only 15 % in Tapajós). Chocó and Manaus had far less large trees, 50 % of
 147 their total AGB_{inv} being explained by respectively 10 % and 7 % of the total number of trees,
 148 corresponding to a DBH greater than only 28 cm and 40 cm. In these two sites, 80 % of AGB_{inv}
 149 is found in trees above 17 cm and 23 cm, respectively, representing 37 % and 31 % of their total
 150 number of trees. These findings corroborate with previous studies from other sites and suggests
 151 that large trees can explain AGB variations and could potentially be used to estimate biomass
 152 without having to measure all trees in a plot (Bastin et al., 2015; Slik et al., 2013). Note that
 153 some ground data from Manaus and Nouragues were included in Silk et al.'s dataset).



154
 155 **Figure S6.** Cumulation of AGB_{inv} and of number of trees (total number of trees ≥ 10 cm DBH) as a function of DBH
 156 in BCI, Chocó, La Selva, Manaus, Nouragues and Tapajós plots.
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