

# Prediction of Biomass in Dry Tropical Forests: an Approach on the Importance of Total Height in the Development of Local and Pan-Tropical Models

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## Research

**Keywords:** Caatinga domain, Forest management, Allometry, Statistical models

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1 **Prediction of biomass in dry tropical forests: an approach on the importance of total**  
2 **height in the development of local and pan-tropical models**

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25 **Abstract**

26 **Background:** Dry tropical forests in arid lands cover large areas in Brazil, but few studies  
27 report the total biomass stock showing the importance of height measurements, in  
28 addition to applying and comparing local and pan-tropical models of biomass prediction  
29 for the domain of trees and shrubs found in that environment. Here, we use a biomass  
30 data set of 500 trees and shrubs, covering 15 species harvested in a management plan in  
31 the state of Pernambuco, in Brazil. We seek to develop local models and compare them  
32 with the equations traditionally applied to dry forests - showing the importance of tree  
33 height measurements. Due to the non-linear relationships with the independent variables  
34 of the tree, we used a nonlinear least squares modeling technique when adjusting models,  
35 we adopted the cross-validation procedure. The selection of the models was based on the  
36 likelihood measures (AIC), total explained variation (R<sup>2</sup>) and forecast error (RSE, RMSE  
37 and Bias).

38 **Results:** In summary, our above-ground biomass data set is best represented by the  
39 Schumacher-Hall equation:  $\exp [3.5336 + 1.9126 \times \log (D) + 1.2438 \times \log (Ht)]$ , which  
40 shows that height measurements are essential to estimate accurately biomass. The biggest  
41 prediction errors observed when testing pan-tropical models in our data demonstrated the  
42 importance of developing new local models and indicated that careful considerations  
43 should be made if generic “pantropical” models without height measurements are planned  
44 for application in dry forests in Brazil.

45 **Conclusions:** Thus, local equations can be used for carbon accounting in REDD + and  
46 sustainable incentive projects that initiate the development of dry forests and assess  
47 ecosystem services.

48

49 **Keywords:** Caatinga domain, Forest management, Allometry, Statistical models

## 50 **Background**

51 Dry tropical forests are a large reservoir of above-ground living biomass which play a  
52 key role in the global carbon cycle and are widely recognized as one of the main  
53 ecosystems that serve as a barrier to desertification (Salinas-Melgoza et al. 2018; Abich  
54 et al. 2018; Guha et al. 2019). Current efforts to quantify the global above-ground biomass  
55 and carbon stocks in these forests comprise dynamics and productivity (e.g., Avitabile et  
56 al. 2016; Wagner et al. 2016; Althoff et al. 2018), assess the conservation potential to  
57 mitigate climate change (e.g., Salis et al. 2006; Bastin et al. 2017) and examine the  
58 ecosystem function relationships of biodiversity (Chave et al. 2005a, 2014; Hiltner et al.  
59 2018). All of these cases almost exclusively depend on robust estimates of aboveground  
60 carbon and biomass (AGB) storage.

61 Much effort has recently been made by several researchers using remote sensing  
62 techniques to estimate biomass in tropical forests (Baccini and Asner 2013; Avitabile et  
63 al. 2016; Jucker et al. 2017; Kachamba et al. 2017; Gonzalez de Tanago et al. 2018;  
64 Bouvet et al. 2018), although AGB is still common to be estimated at local and pan-  
65 tropical levels by allometric models from soil-based inventory graphs (Sampaio et al.  
66 2010; Chave et al. 2014; Sullivan et al. 2018).

67 It is therefore correct to state that obtaining biomass using allometric models is  
68 substantially important in forest inventories (e.g., Avitabile and Camia 2018; Gonzalez  
69 de Tanago et al. 2018), especially for deforested dry forest areas, because in addition to  
70 supporting estimates of local carbon dynamics (Althoff et al. 2018), it provides  
71 information for understanding concentrations at different continental scales (Chave et al.  
72 2014).

73 However, allometric models which only relate biomass to tree diameter in dry  
74 tropical forests can perform poorly in biomass predictions (Návar et al. 2013; Chaturvedi

75 and Raghubanshi 2015), especially when compared with models that include tree height  
76 and/or basic wood density (Ali and Mattsson 2018) and are parameterized at local,  
77 regional or continental scales (Chave et al. 2014; Abich et al. 2018).

78 Thus, tree height is an important component of this allometric relationship as tree  
79 biomass is partly a function of tree volume, which is a function of tree height, trunk basal  
80 area and trunk taper (Chave et al. 2005; Sullivan et al. 2018). Although obtaining tree  
81 height in forest inventories is not an easy task (see Larjavaara and Muller-Landau 2013  
82 for discussions), the incorporation of a height parameter is known to markedly improve  
83 the estimates of individual tree biomass scales (e.g., Sampaio and Silva 2005; Sampaio et  
84 al. 2010; Lima et al. 2017), and this has a substantial effect on pan-tropical scales as well  
85 (Feldpausch et al. 2012; Sullivan et al. 2018). As a result, in practice this can lead to  
86 incorporating tree height in REDD + carbon monitoring (Pelletier et al. 2017; Sullivan et  
87 al. 2018).

88 Several pan-tropical models were therefore developed to estimate biomass in dry  
89 tropical forests using models which only relate biomass to diameter (Návar 2015); basic  
90 wood diameter and density (Chave et al. 2005 - Type II.1 and Type II.3); diameter, height  
91 and basic wood density (Chave et al. 2005 - Type I.1 and Type I.5). However, these  
92 relationships can be expected to vary at various environmental and spatial scales (Ubuy  
93 et al. 2018), suggesting that even these developed pan-tropical or local models lack the  
94 sophistication required for many applications (Rutishauser et al. 2013).

95 In addition, it would be very useful to generally understand how tree height affects  
96 the reliability of local scale models in Brazilian dry tropical forests. In particular,  
97 ecologists and professionals with the aim of generating better accuracy of forest biomass  
98 estimates would benefit from knowledge that locally derived models consistently

99 outperform existing regional and pan-tropical models, especially when the importance is  
100 verified in measuring tree height.

101 In this paper, we address these challenges by assembling a data set where 507  
102 trees were sampled for biomass and total height measurement and examined to quantify  
103 how well the locally derived models predict the tree's biomass. A cross-validation  
104 approach was performed to enable testing the performance of different allometric models  
105 with and without height on data which are independent of those used for model fitting.  
106 The specific objectives were: (1) to examine how models with and without height derived  
107 from the site affect forecasting errors; and (2) to test different pan-tropical models with  
108 and without height to local data to verify the improvement in biomass prediction when a  
109 local model is not available for areas with and without change in its structure.

110

## 111 **Results**

112 Among the local equations, those obtained by the Schumacher-Hall and Chave et al.  
113 (2005) logarithmic models - Model I (5 and 6), showed better performance. Both  
114 equations produced similar values for RMSE, RSE, Bias and CV, but the best forecasts  
115 indicate a slight superiority of the Schumacher-Hall model, explaining more than 90% of  
116 the total variance and lower AIC value (Table 4). We noticed that the parameter related  
117 to basic density in the Chave et al. (2005) - Model I equation does not necessarily indicate  
118 statistical significance in biomass forecasts. In addition, with the exception of the  
119 Koperzky-Gehrhardt and Chave et al. (2005) equations - Model II, the other adjusted  
120 models presented significant parameters ( $p < 0.05$ ) with valid confidence intervals ( $P >$   
121  $0.05$ ).

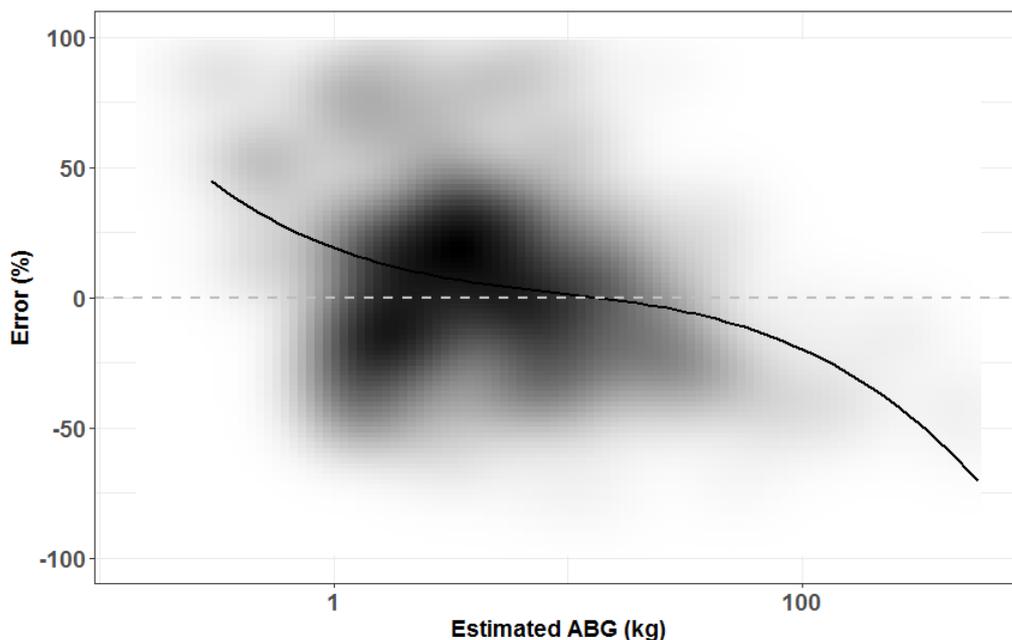
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**Table 4** Estimates of parameters and indexes of adequacy of allometric models for forecasting biomass in tropical dry forest, Northeast Brazil.

Local models	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	AIC	RSE	$R^2_{aj}$	RMSE	Bias	CV (%)
1	-2.5851*	2.3599*	-	-	-	702.52	0.4819	0.8715	19.9242	0.2718	3.77
2	-0.5999 <sup>ns</sup>	0.6376 <sup>ns</sup>	-	-	-	765.89	0.513	0.8543	65.0296	0.323	4.01
3	-2.1445*	1.8207*	0.1499*	-	-	697.72	0.4791	0.8729	13.5859	0.2705	3.74
4	-3.3722*	1.0053*	-	-	-	577.34	0.4259	0.8996	18.2462	0.2034	3.33
<b>5</b>	<b>-3.5336*</b>	<b>1.9126*</b>	<b>1.2438*</b>	-	-	<b>573.77</b>	<b>0.4240</b>	<b>0.9005</b>	<b>18.285</b>	<b>0.2018</b>	<b>3.31</b>
6	-3.5466*	1.9180*	1.2399*	-0.0406 <sup>ns</sup>	-	575.49	0.4243	0.9003	17.658	0.2010	3.32
7	-3.1093*	3.5856*	-0.8313 <sup>ns</sup>	0.1681	0.0083 <sup>ns</sup>	697.59	0.4777	0.8737	16.532	0.2670	3.73
8	-2.8154*	0.9325*	-	-	-	728.41	0.4943	0.8647	32.304	0.2762	3.86

123 Note: Values in italics are not significant ( $p \geq 0.05$ ) and the best model is in bold. \*  
 124 significant at 0.05.

125 The Schumacher-Hall equation selected for biomass prediction in local dry forest  
 126 predicts that the logarithmic transformation of diameter and height for a given tree weight  
 127 decreases the bias in the estimate. These results support the decision to use regression  
 128 methods to build models and estimate their parameters, therefore suggesting that it is  
 129 more parsimonious to maintain an allometric double entry model, in this case the  
 130 Schumacher-Hall model obtained for the area (Fig. 3).



132 **Fig. 3** Dispersion of percentage residues for the Schumacher-Hall equation developed to  
 133 predict biomass in dry tropical forest, northeastern Brazil.

134

135 The residual dispersion graph of the models indicates a trend line in the highest  
 136 expected values of biomass with the presence of few outliers in the lowest values.  
 137 However, it should be considered that the outliers suggest a curvature possibly caused by  
 138 model errors rather than the data selected for the fit (trees which are unusually tall or short  
 139 for their diameter).

140 Although much of the variation in biomass for pan-tropical models was explained  
 141 by only diameter, the improvement was relatively significant when basic height and  
 142 density were included (see Table 5). When analyzing the predictions of local and pan-  
 143 tropical models, the variation in biomass estimated for small diameter trees is in fact  
 144 smaller, being similarly predicted by models which include height or height and basic  
 145 wood density. However, there is a great divergence for different diameter classes when  
 146 height is not included in the prediction, which results in significantly higher percentage  
 147 biases of those models that include height (Fig. 4).

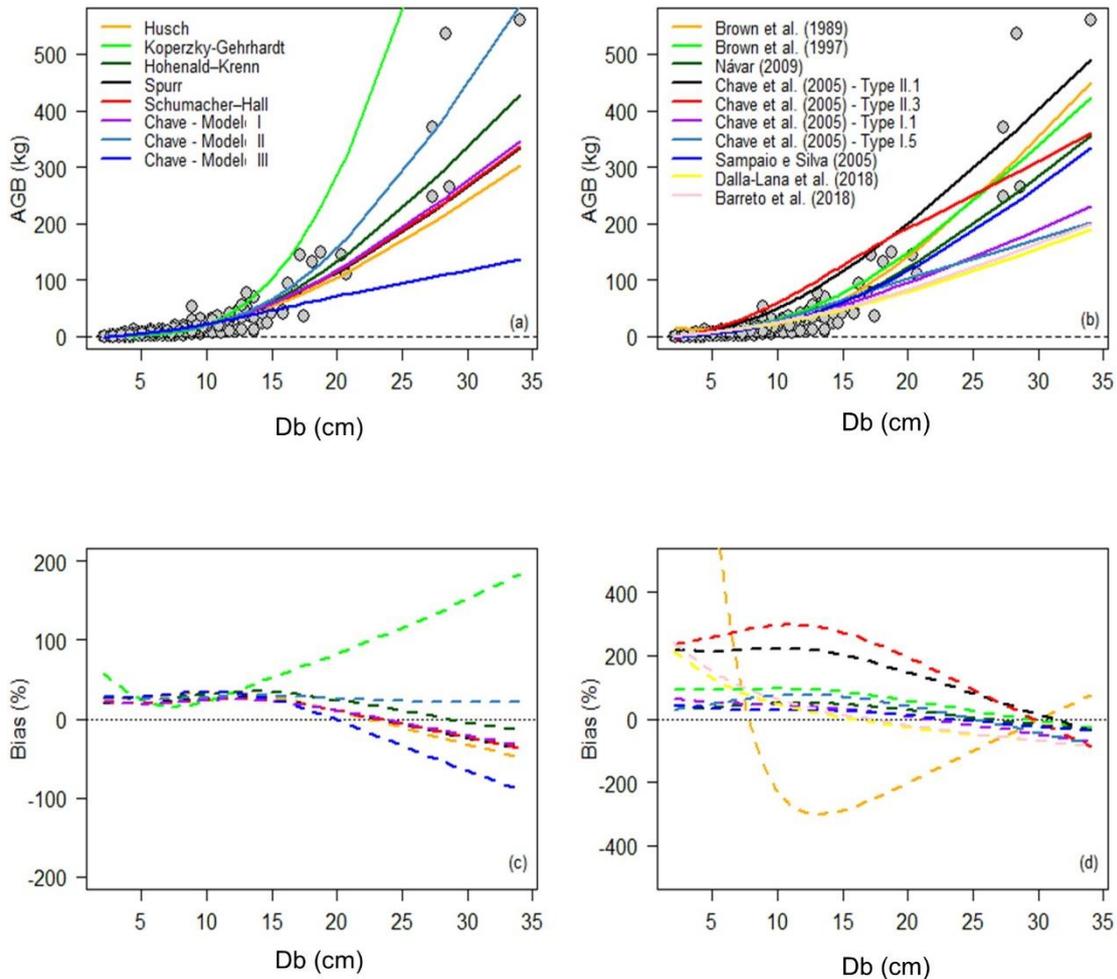
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**Table 5** Accuracy and bias for biomass prediction from pan-tropical models with dry  
 tropical forest, northeastern Brazil.

Equations	scale	variable	Pseudo-R <sup>2</sup>	RMSE	Bias	CV%
Brown et al. (1989)	Pan-tropical	Db	0,9023	16,0791	7,5796	297,99
Brown et al. (1997)	Pan-tropical	Db	0,8982	14,7558	0,9086	301,47
Návar (2015)	Pan-tropical	Db	0,9049	16,6454	0,3744	251,12
Chave et al. (2005) - Type II.1	Pan-tropical	Db/WD	0,8254	23,4906	2,1383	378,07
Chave et al. (2005)- Type II.3	Pan-tropical	Db/WD	0,6070	32,9759	2,5968	350,73
Chave et al. (2005) - Type I.1	Pan-tropical	Db/Ht/WD	0,8080	25,1675	0,5028	181,96
Chave et al. (2005) - Type I.5	Pan-tropical	Db/Ht/WD	0,6434	28,3263	0,4917	191,58
Sampaio and Silva (2005)	Local	Db/Ht	0,8662	18,8651	0,3236	242,37
Dalla-Lana et al. (2018)	Local	Db/Ht	0,8222	28,0706	1,1956	146,38
Barreto et al. (2018)	Local	Db/Ht	0,8185	27,3953	1,3992	154,21

149

150



151

152 **Fig. 4** Biomass prediction from the equations developed for the site (a) and from other  
 153 local and pan-tropical equations (b); and percentage difference (bias) of biomass  
 154 predictions at tree level by diameter class for local equations (c) and other local and pan-  
 155 tropical equations (d).

156

157 When compared with the equations developed in this study, the average errors  
 158 (RMSE and Bias) of the biomass estimate of the pan-tropical equations validated at the  
 159 tree level did not reveal substantially visible differences, with the exception of the local  
 160 Koperzky-Gehrhardt equation (Table 4) and the pan-tropical equation by Brown et al.  
 161 (1989) (Table 5) who use only the diameter as a predictor variable. The highest mean  
 162  $CV_{(i)}$  in all comparisons was 378% for the equation that uses wood density and diameter  
 163 (Chave et al. 2005 - Type II.1) despite the Brown et al. (1989) reported a greater absolute

164 error at the tree level (bias = 7.57 kg). The mean lower bias was 0.32 kg for the Sampaio  
165 and Silva (2005) equation, which presents the same structure as the model developed  
166 locally.

167 For pan-tropical equations, these results reflect not only absolute values, but also  
168 a large percentage variation, especially when wood density is included along with  
169 diameter and height in biomass forecasts. Interestingly, however, in these equations the  
170 RMSE values practically double when compared to the equations of other tropical regions  
171 that use only the diameter or diameter and basic density.

172 The local equations developed tend to predict the AGB values in a more  
173 homogeneous manner and with a smaller amplitude of error for trees of smaller diameter,  
174 with a slight divergence for trees with  $Db > 15$  cm (bias > 30%, Fig. 4c). Pan-tropical and  
175 local equations from other regions suggest greater differences by class of diameter, being  
176 substantially more visible in smaller trees mainly by the equation of Brown et al. (1989)  
177 (Fig. 4d). With the exception of the equations of Brown et al. (1989) and Barreto et al.  
178 (2018), the average biomass measured in the field does not report visible differences  
179 between the best local equations developed and the local equations of Dalla-Lana and  
180 pantropical of Navar (2015).

181

## 182 **Discussion**

183 Logarithmic models have constantly been used in the study of biometric relationships,  
184 mainly for developing biomass equations in dry tropical forests (Brown et al. 1989;  
185 Packard and Boardman 2008; Ubuy et al. 2018). These results are also in line with studies  
186 carried out in dry tropical forests in Brazil (Brahma et al. 2018; Roitman et al. 2018) and  
187 another regions tropical dry forest (Návar-Cháidez 2010; Abich et al. 2018).

188           The base diameter and the total height of the tree were generally the best  
189    predictive biometric variables to estimate AGB. All the statistical evaluation criteria  
190    revealed that the double entry equations suggest greater precision of predictions,  
191    especially the equation obtained from the Schumacher-Hall model. These results indicate  
192    the inclusion of the height variable in the biomass estimate, as the simple entry models  
193    assume that trees of different diameters have the same heights, which is not true for dry  
194    tropical forests (Helmer et al. 2010; Salas-Morales et al. 2018). The functional form of  
195    the generated equation is biologically consistent, especially with the inclusion of the  
196    height variable, therefore it is concluded that tree height is an important biomass  
197    predictor, especially when considering data from different species (Abich et al. 2018).

198           Although height measurements are more expensive and time-consuming in forest  
199    inventories, the use of models which relate height and diameter is recommended in  
200    tropical forests (Feldpausch et al. 2011, 2012; Sullivan et al. 2018). Models which include  
201    tree height improve the biomass estimate in many tropical forests and support more  
202    accurate biomass and carbon estimates (Rutishauser et al. 2013).

203           However, it is important to note that the predominant tree forms are represented  
204    among the sample trees used to develop allometric and hypsometric models (Duncanson  
205    et al. 2015). The accuracy of biomass predictions is likely to be improved with appropriate  
206    sample trees and small measurement errors by adding height as an explanatory variable,  
207    despite the uncertainty added using a diameter height model (Larjavaara and Muller-  
208    Landau 2013; Sullivan et al. 2018).

209           The biomass predictions by the best pan-tropical models suggest that its shape  
210    parameters and trunk profile ( $\alpha_1$  and  $\alpha_2$ ) were not substantially different from the  
211    parameter estimates of the best local model. This indicates that biomass does not vary  
212    much on a pan-tropical scale, and that the local model of this study could be applied in

213 other parts of dry forests in the tropics. These results may also explain that there is a  
214 similarity in the type of vegetation with different land use histories, due to bioclimatic  
215 conditions and soil types; or intrinsic characteristics of the tree, such as physiology,  
216 regrowth, adaptive development and trunk bifurcations (multiple stem species) (Chave et  
217 al. 2014).

218         This work seeks to fill the gap on the validity of allometric equations developed  
219 for dry tropical forests, although some research has already suggested the development  
220 of individual equations for species and regions (Chave et al. 2014; Lima et al. 2017). In  
221 addition to the importance of height measurements, the question currently being discussed  
222 in this paper is whether it would be better to use generic equations from other locations  
223 in locations where no generic allometric equation is available, or to develop location-  
224 specific equations.

225         Another important point that must be considered for the development of equations  
226 is related to the intra and interspecific factors of the species, such as variations in the basic  
227 wood density (Henry et al. 2010; Bastin et al. 2015; Ali and Mattsson 2018); the tree  
228 canopy (Duncanson et al. 2010; Gara et al. 2014; Bastin et al. 2014; Salas-Morales et al.  
229 2018), leaf area index and height profiles (Helmer et al. 2010; Greaves et al. 2015;  
230 Wagner et al. 2016; Cushman and Kellner 2019). Considering that such factors may still  
231 be influenced by changes in structural parameters such as richness, density, frequency  
232 and dominance, the development of specific allometric equations for locations and even  
233 more at the species level is fundamental for understanding the concentration of carbon  
234 stocks (Abich et al. 2018).

235         However, the development of allometric models is not a trivial task. The limiting  
236 factor has always been destructive sampling of the trees for adjusting and selecting the  
237 models. Highly accurate volume and biomass estimates of individual trees are

238 increasingly available through Lidar technology (Estornell et al. 2011, 2012; Hildebrandt  
239 and Iost 2012). These estimates do not require destructive sampling of trees and can be  
240 carried out systematically in the field (Duncanson et al. 2017; Duncanson and Dubayah  
241 2018). A system could be developed with proper sampling to sample biometric data in  
242 situ from the tree in environmental gradients, providing a potential solution to the  
243 outstanding problems related to forest biomass and carbon stock.

244

## 245 **Conclusions**

246 The statistical results of the selected models were satisfactory and the evaluations  
247 revealed that the equations which include height in the biomass forecasts are more  
248 accurate than the models without height, and this statement is valid for the pan-tropical  
249 models with height when a local equation is not available. Predictive errors generally  
250 observed when testing and validating local and “pan-tropical” models without height  
251 demonstrated the importance of developing new models including the total height of  
252 trees. The large forecasting errors for “pan-tropical” models without height also indicate  
253 that careful considerations should be made if they are planned to be applied to dry forests  
254 elsewhere in northeastern Brazil. As there are no other appropriate model options, it is  
255 recommended that the model set be generally applied for estimates of large biomass areas  
256 in the region.

257 After fitting and validation, our above-ground biomass data set is best represented  
258 by the Schumacher-Hall equation:  $e^{3.5336+1.9126 \times \log(D)+ 1.2438 \times \log(Ht)}$ . The development  
259 of local allometric equations is appropriate to improve the above-ground biomass (AGB)  
260 estimates in the dry tropical forests of Pernambuco, Brazil. It is a vital step in the  
261 ecosystem assessment of forest resources. This forest is widely recognized as one of the  
262 main ecosystems for carbon sequestration and desertification barriers. They can serve as

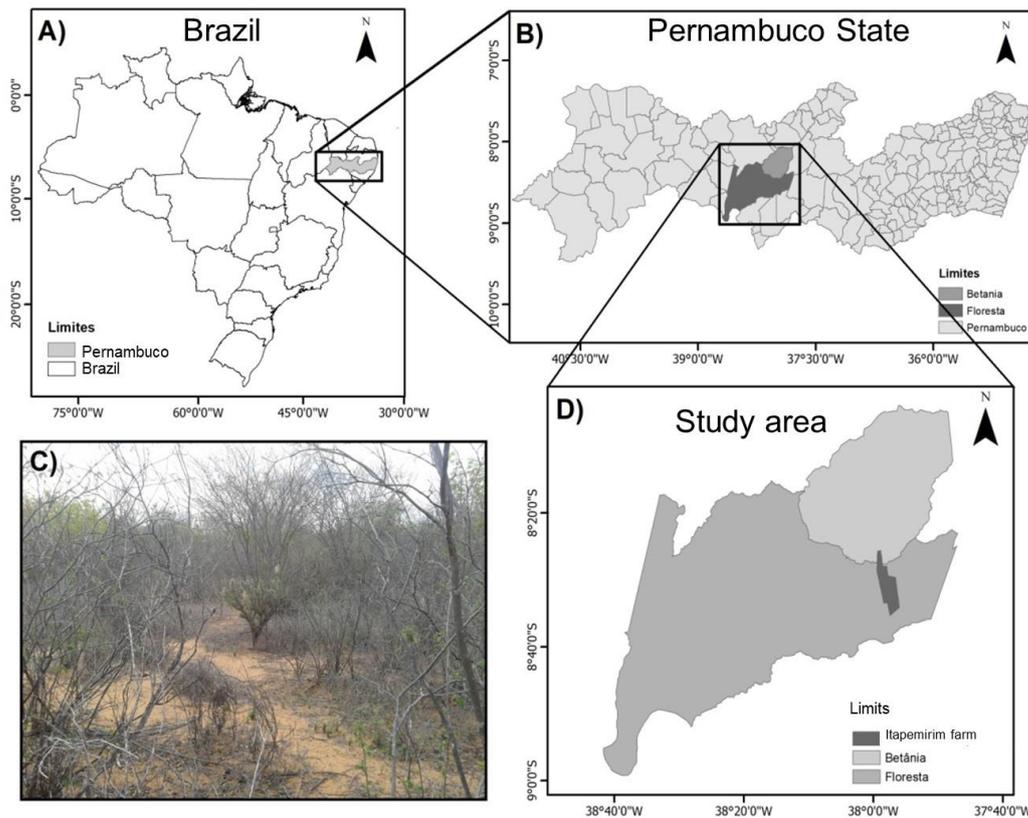
263 important tools for carbon credit and payment for environmental services initiatives. As  
264 revealed in this study, the base diameter and height are the best biomass estimators,  
265 representing more than 90% of the AGB for multi-species data. The comparison of  
266 equations showed that the pan-tropical equation for dry forests developed by Chave et al.  
267 (2005) can be used for the evaluation of forest biomass when the specific equations of the  
268 place and species are absent. Thus, the equations can be used for carbon accounting in  
269 REDD + and appropriate incentive projects which initiate forest development and  
270 evaluate ecosystem services.

271

## 272 **Material and methods**

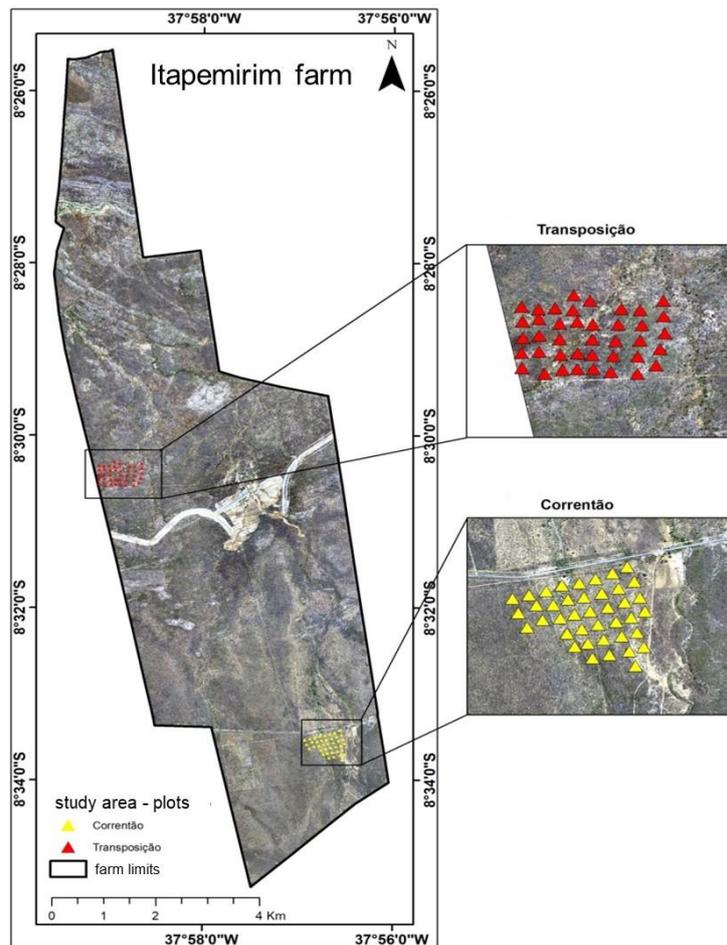
### 273 **Study area and collected data**

274 The data used in the present study were collected from trees harvested from an area  
275 submitted to forest management located in the municipality of Floresta, State of  
276 Pernambuco ( $8^{\circ} 30' 37''$  S and  $37^{\circ} 59' 07''$  W). The vegetation is predominantly Caatinga  
277 (tropical dry forest) characterized by shrub-tree vegetation, with the presence of cacti and  
278 herbaceous strata (IBGE, 2012) (Fig. 1).



279  
 280 **Fig. 1** Coverage of the study area: A, B and D, and profile photo in Floresta C, in the  
 281 hinterland of Pernambuco, Brazil.

282 The two study areas differ from each other in terms of preservation conditions.  
 283 The first to the north is called “transposition” with 40 permanent plots of 400 m<sup>2</sup> (20 x 20  
 284 m), having an extension of approximately 50 ha and is considered preserved (55 years of  
 285 lesser anthropic disorders). The second area further south, also with 40 permanent plots  
 286 of 400 m<sup>2</sup> (20 x 20 m) called “*correntão*”, underwent logging using the *correntão*  
 287 technique in 1987 for planting eucalyptus, but was abandoned and has been undergoing  
 288 regeneration for 29 years (Fig. 2).



289

290 **Fig. 2** Sampling procedure used in the two inventoried areas in the Municipality of  
 291 Floresta, Pernambuco

292 The aboveground biomass (trunk and branches), total and commercial heights and  
 293 base diameter (0.30 cm from ground level) and diameter at breast height (1.30 cm from  
 294 ground level) of 507 trees distributed in 14 species and 2 genera were measured. The trees  
 295 were harvested with a minimum diameter at the base of the stem (Db) of 1.9 cm, up to  
 296 the maximum found in the area, and covered a wide sampling range for diameter and  
 297 heights. Table 1 has a descriptive summary with the means, maximums and minimums  
 298 for the variables of the measured species. We consider the local values of basic wood  
 299 density of the species, and when not available, the global database (Chave et al. 2014)  
 300 available at <https://datadryad.org/handle/10255/dryad.235> was considered. Despite the

301 lack of sufficient data, several studies recommend average wood density at the gender  
 302 level for biomass assessment (Henry et al. 2010; Ubuy et al. 2018).

303 **Table 1** Dendrometric variables of dry tropical forest species, in northeastern Brazil, used  
 304 to develop local biomass equations.

Espécies	n	WD			Db			Ht			AGB		
		Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
<i>Anadenanthera colubrina</i>	17	0.79	2.55	8.57	18.78	3.20	5.61	8.00	1.30	44.16	145.00		
<i>Aspidosperma pyrifolium</i>	45	0.74	2.07	4.60	9.55	2.50	3.84	5.40	0.50	7.92	52.00		
<i>Bauhinia cheilanta</i>	19	0.79	1.91	2.25	3.18	2.10	3.11	4.20	0.15	0.77	2.00		
<i>Cnidocolus phyllacanthus</i>	5	0.55	7.32	12.29	17.19	5.80	6.58	7.60	17.00	71.90	132.00		
<i>Commiphora leptophloeos</i>	7	0.39	6.37	17.37	27.37	4.20	6.30	8.30	17.00	215.71	536.00		
<i>Croton spp.</i>	68	0.59	1.91	2.58	6.37	2.00	3.27	5.20	0.25	1.55	11.00		
<i>Jatropha mollissima</i>	5	0.29	2.23	3.18	4.77	2.00	2.82	3.20	0.50	2.18	4.00		
<i>Manihot glaziovii</i>	4	0.38	4.14	7.64	11.78	4.40	5.60	7.80	8.40	19.23	36.50		
<i>Mimosa ophthalmocentra</i>	81	0.71	1.91	3.33	5.09	3.00	3.89	5.40	0.30	3.72	16.00		
<i>Mimosa tenuiflora</i>	22	1.12	2.23	7.22	16.87	3.20	5.43	9.10	1.50	26.90	149.00		
<i>Piptadenia stipulacea</i>	21	0.74	2.07	3.93	7.00	3.40	5.24	8.80	0.50	6.87	23.00		
<i>Poincianella bracteosa</i>	202	0.99	1.91	4.96	14.48	2.10	4.02	6.80	0.50	8.35	45.00		
<i>Erythrostemon calycina</i>	3	1.01	2.23	2.33	2.55	3.40	3.57	3.70	0.50	0.97	1.30		
<i>Sapium lanceolatum</i>	1	0.47	30.88	30.88	30.88	8.90	8.90	8.90	559.50	559.50	559.50		
<i>Thiloa glaucocarpa</i>	7	0.63	1.91	2.36	2.71	2.80	3.43	4.00	0.25	0.89	1.10		

305 where n is number of trees harvested, WD is mean wood basic density of individual trees  
 306 ( $\text{g cm}^{-3}$ ), Db is diameter at stump height (cm), Ht is total tree height (m), AGB is total  
 307 aboveground tree biomass (kg).

308

### 309 **Model fitting and validation**

310 The biometric data were randomly divided into two subsets after measurement for fitting  
 311 and validating the allometric models using the *Hold-out*, cross-validation tool which  
 312 randomly selects a sample  $N1 = 80\%$  to adjust the models and  $N2 = 20\%$  to validate the  
 313 models.

314 Three single-entry allometric models (with only the base diameter as an  
 315 explanatory variable) and five double-entry models were tested, with the explanatory  
 316 variables being Db and total height (later referred to as locally derived models, Table 2).

**Table 2** Allometric models tested to estimate above-ground biomass in a dry tropical forest in the semi-arid region of Pernambuco, Brazil.

Autor	Model	Variables
1. Husch	$1. \text{AGB} = \exp(\beta_0 + \beta_1 \times \text{Ln}(D) + \epsilon_i)$	$\text{AGB} = f(\text{Db})$

2. Koperzky-Gehrhardt	2. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D)^2 + \varepsilon_i)$	AGB=f(Db)
3. Hohenald-Krenn	3. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D) + \beta_2 \times \text{Ln}(D)^2 + \varepsilon_i)$	AGB =f(Db)
4. Spurr	4. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D^2 \times \text{Ht}))$	AGB =f(Db,Ht)
5. Schumacher-Hall (1933)	5. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D) + \beta_2 \times \text{Ln}(\text{Ht}) + \varepsilon_i)$	AGB =f(Db,Ht)
6. Chave et al. (2005) - model I	6. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D) + \beta_2 \times \text{Ln}(\text{Ht}) + \beta_3 \times \text{Ln}(\text{WD}) + \varepsilon_i)$	AGB =f(Db,Ht, WD)
7. Chave et al. (2005) - model II	7. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D) + \beta_2 \times \text{Ln}(D)^2 + \beta_3 \times \text{Ln}(D)^3 + \beta_4 \times \text{Ln}(\text{WD}) + \varepsilon_i)$	AGB =f(Db,WD)
8. Chave et al. (2005) - model III	8. AGB = $\exp(\beta_0 + \beta_1 \times \text{Ln}(D^2 \times \text{Ht} \times \text{WD}) + \varepsilon_i)$	AGB =f(Db,Ht, WD)

317 where  $\beta_i$  = parameters to be estimated;  $\varepsilon_i$  = random error.

318 We estimate model parameters using the Ordinary Least Squares (OLS) method  
319 and we verified the significance using the t test ( $p = 0.05$ ). The parameters were generally  
320 calculated using the total data of the trees measured and are assumed to be the true  
321 parameters which represent allometry. However, samples (20%) were extracted from the  
322 complete data set to assess the influence of predictions and calculate the bias of the  
323 estimates with the adjusted parameters (Hold-out). The purpose of this tool is to estimate  
324 the value of a set of evaluation statistics using cross-validation testing. This type of  
325 estimate is obtained by performing N repetitions of a test cycle, where N is the size of the  
326 data set provided. One of the N observations is left out in each repetition to serve as a test  
327 set, while the remaining N-1 cases are used to obtain the model (James et al. 2013). The  
328 process is repeated N times, setting aside each of the N observations given. The Hold-out  
329 estimates are obtained by the average of the N scores obtained in the different repetitions.  
330 All computations and analyzes were performed using the R<sup>®</sup> statistical software (R  
331 Development Core Team, 2019).

332 Local equations, with height and without, were selected to verify the influence of  
333 this variable on the biomass predictions at the tree level. All the generated equations were  
334 analyzed by comparing the following statistical criteria:

$$335 \text{ AIC} = -2\text{LL} + 2k \quad \text{Eq.(1)}$$

$$336 R_{aj}^2 = R^2 - \left[ \frac{k-1}{n-k} \right] \times (1-R^2) \quad \text{Eq.(2)}$$

$$337 \quad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\text{AGB}_i - \overline{\text{AGB}}_i)^2}{n}} \quad \text{Eq.(3)}$$

$$338 \quad \text{Bias} = \frac{\sum_{i=1}^n (\text{AGB}_i - \overline{\text{AGB}}_i)^2}{n} / \overline{\text{AGB}} \quad \text{Eq.(4)}$$

339 where  $\text{AGB}_i$  is aboveground biomass (i);  $\overline{\text{AGB}}_i$  is the estimate of aboveground biomass  
 340 and  $n$  is the total number of observations.  $\overline{\text{AGB}}_i$  is mean aboveground biomass.

341

### 342 Allometric predictions

343 The local equations developed in this study were compared with generic local/pan-  
 344 tropical equations developed for dry forest areas using only diameter, or and in  
 345 combination with height (Ht) and wood density (wd) as predictor variables (Table 3).

**Table 3** Generic allometric equations of local and pantropical scope used to estimate the above ground biomass (kg) in dry tropical forest based on diameter (Db, cm), height (Ht, m) and basic wood density (WD, gcm<sup>3</sup>).

Autor/Abragência	Equações - AGB (kg)
Brown et al. (1989): Pan-tropical	$\text{AGB} = 34.4703 + 8.0671 \times (\text{Db}) + 0.6589 \times (\text{Db}^2)$
Brown et al. (1997): Pan-tropical	$\text{AGB} = \exp(-1.996 + 2.32 \times \log(\text{Db}))$
Návar (2015): Pan-tropical	$\text{AGB} = 0.0841 \times \text{Db}^{2.41}$
Chave et al. (2005) - Type II.1: Pan-tropical	$\text{AGB} = \exp(-1.023 + 1.821 \times \log(\text{Db}) + 0.198 \times \log(\text{Db}^2) - 0.0272 \times \log(\text{Db}^3) + 0.388 \times \log(\text{wd}))$
Chave et al. (2005) - Type II.3: Pan-tropical	$\text{AGB} = \exp(-0.73 + 1.784 \times \log(\text{Db}) + 0.207 \times \log(\text{Db}^2) - 0.0281 \times \log(\text{Db}^3) + \log(\text{wd}))$
Chave et al. (2005) - Type I.1: Pan-tropical	$\text{AGB} = \exp(-2.68 + 1.805 \times \log(\text{Db}) + 1.038 \times \log(\text{Ht}) + 0.377 \times \log(\text{wd}))$
Chave et al. (2005) - Type I.5: Pan-tropical	$\text{AGB} = \exp(-2.843 + \log(\text{Db}^2 \times \text{Ht} \times \text{wd}))$
Sampaio and Silva (2005): Local	$\text{AGB} = 0.0292 \times (\text{Db} \times \text{Ht})^{1.6731}$
Dalla-Lana et al. (2018): Local	$\text{AGB} = \exp(-1.288 + 1.610 \times \log(\text{Db}) + 0.434 \times \log(\text{Ht}))$
Barreto et al. (2018): Local	$\text{AGB} = 0.38 \times \text{Db}^{1.73} \times \text{Ht}^{0.11}$

346

347 These pan-tropical allometric equations developed for dry tropical forests were  
 348 applied to the sample trees in this study and are widely applied to predict stock  
 349 assessments of AGB and C in dry tropical regions (ABICH et al., 2018). We compared  
 350 the observed average AGB and the predicted AGB.

351 The model error (RSE) and the tree level variation coefficient (CV) were defined for each  
352 equation as follows:

$$353 \quad RSE = \frac{1}{N} \sum_{i=1}^N [AGB_{ALTi} - AGB_{REFi}] / AGB_{REFi} \quad (\text{Eq.5})$$

$$354 \quad \overline{AGB}_{(i)} = \frac{1}{N_{(j)}} \sum_{i \in (j)} AGB_{REF}(i) \quad (\text{Eq.6})$$

$$355 \quad CV(i)\% = \frac{RSE(i)}{\overline{AGB}(i)} \times 100 \quad (\text{Eq.7})$$

356 In which:  $AGB_{ALTi}$  and  $AGB_{REFi}$  are the biomass estimate of tree  $i$  obtained from  
357 alternative equations with and without height (pan-tropical) and reference (local models  
358 with and without height), respectively. A large CV value (i) would be acceptable as long  
359 as the bias is low, because the model is generally applied to many trees within a site and  
360 therefore random errors tend to cancel each other out (Chave et al. 2014).

361 We also calculated new measures of mean prediction errors (bias) and in addition, the  
362 models were evaluated based on Pseudo- $R^2$  as follows:

$$363 \quad \text{Pseudo - } R_{aj}^2 = 1 - \frac{SSR}{\sum_{i=1}^N (AGB_i - \overline{AGB}_i)} \quad \text{Eq.(8)}$$

364

### 365 **List of abbreviations**

366 IBGE – Instituto Brasileiro de Geografia e Estatística

### 367 **Availability of data and materials**

368 The data are available upon a reasonable request to the Authors.

### 369 **Ethics approval and consent to participate**

370 Not applicable.

### 371 **Consent for publication**

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377

378 **Authors' contributions**

379 Cinthia Oliveira and Rinaldo Ferreira planned the study and wrote the manuscript,  
380 Robson Lima and José Aleixo da Silva participated in the processing, calculation and  
381 modeling of the data and wrote the manuscript. Francisco Alves Júnior Emanuel Silva  
382 collected and processed the data. They also commented on the manuscript. The authors  
383 read and approved the final manuscript.

384

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392

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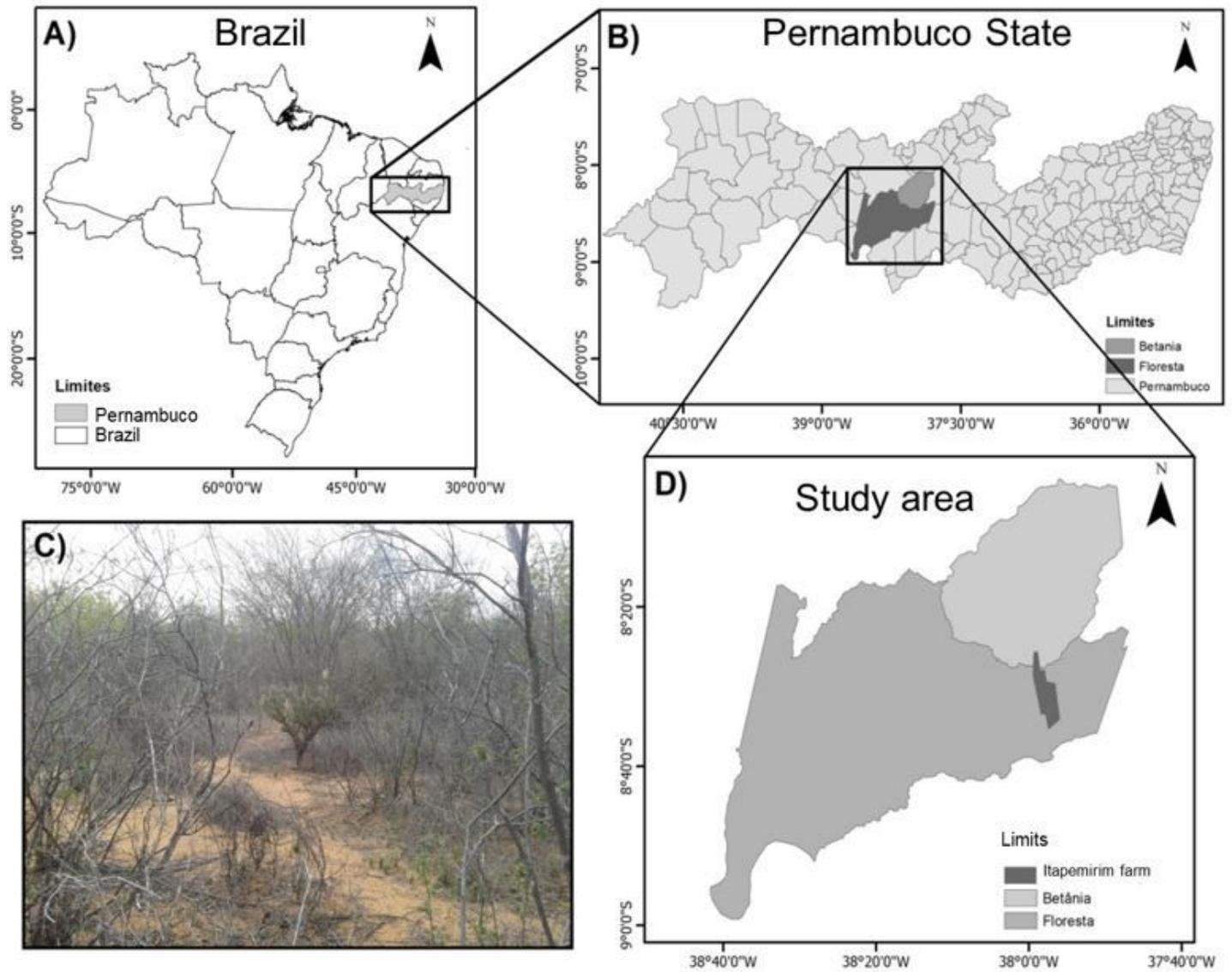
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# Figures



**Figure 1**

Coverage of the study area: A, B and D, and profile photo in Floresta C, in the hinterland of Pernambuco, Brazil.

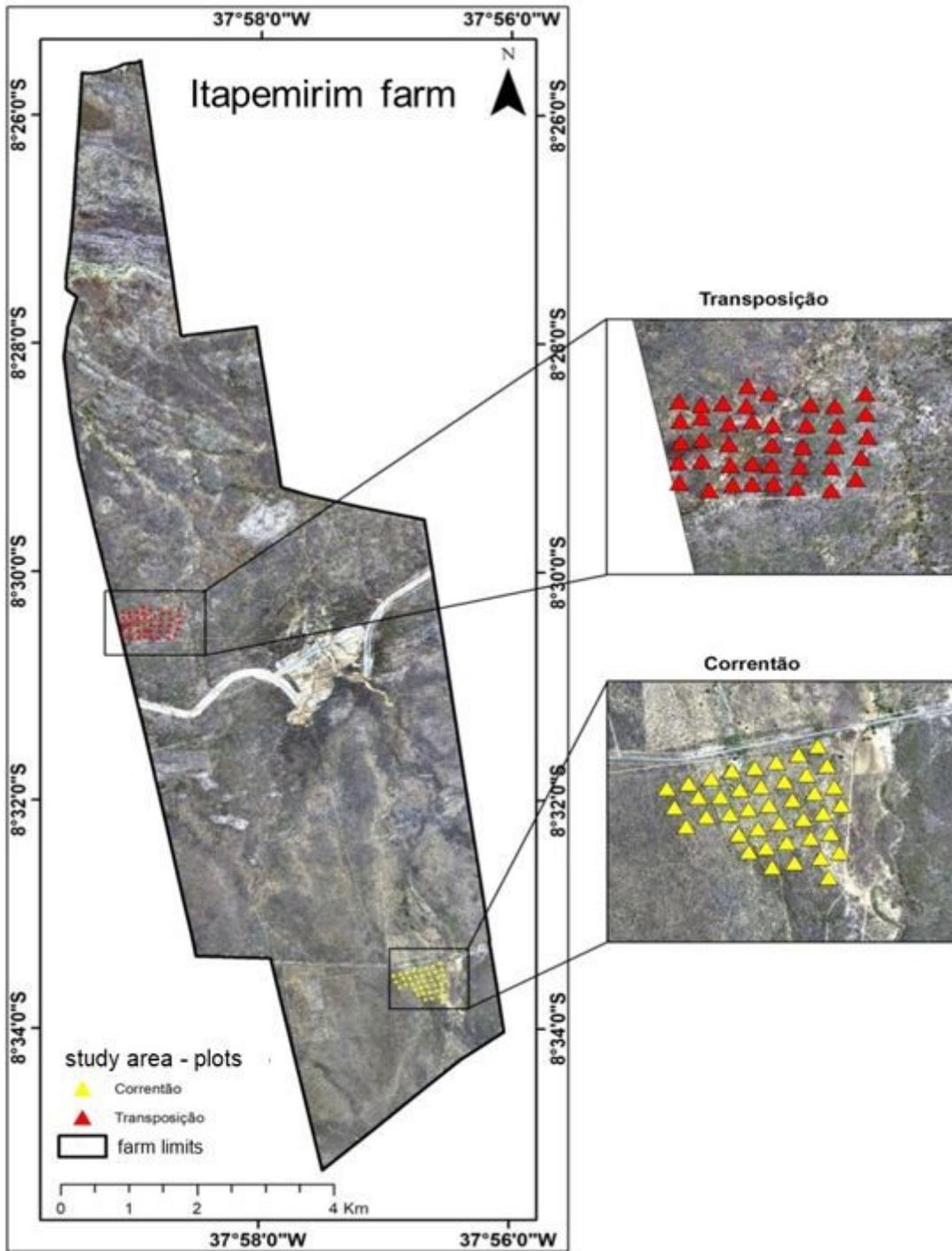
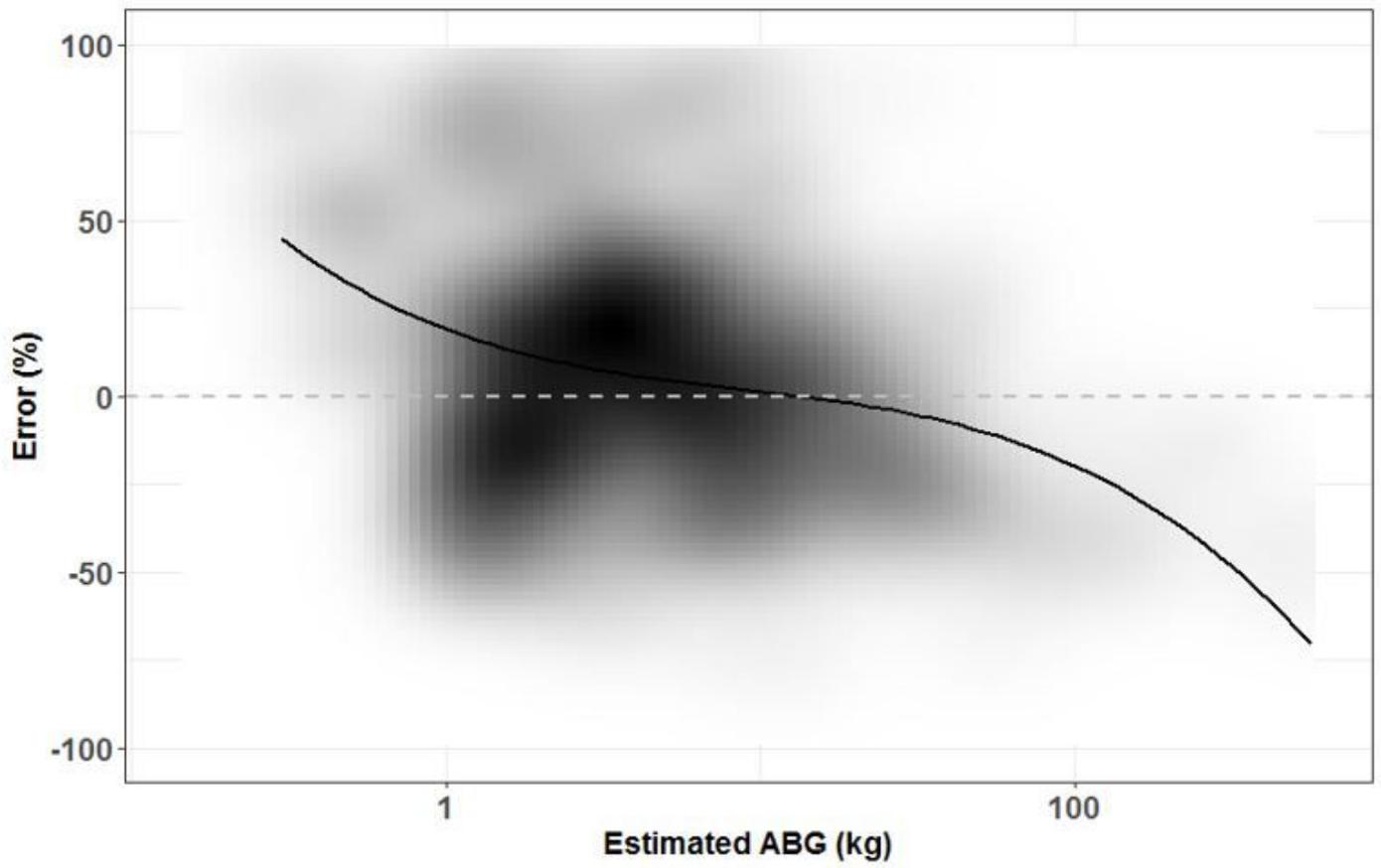


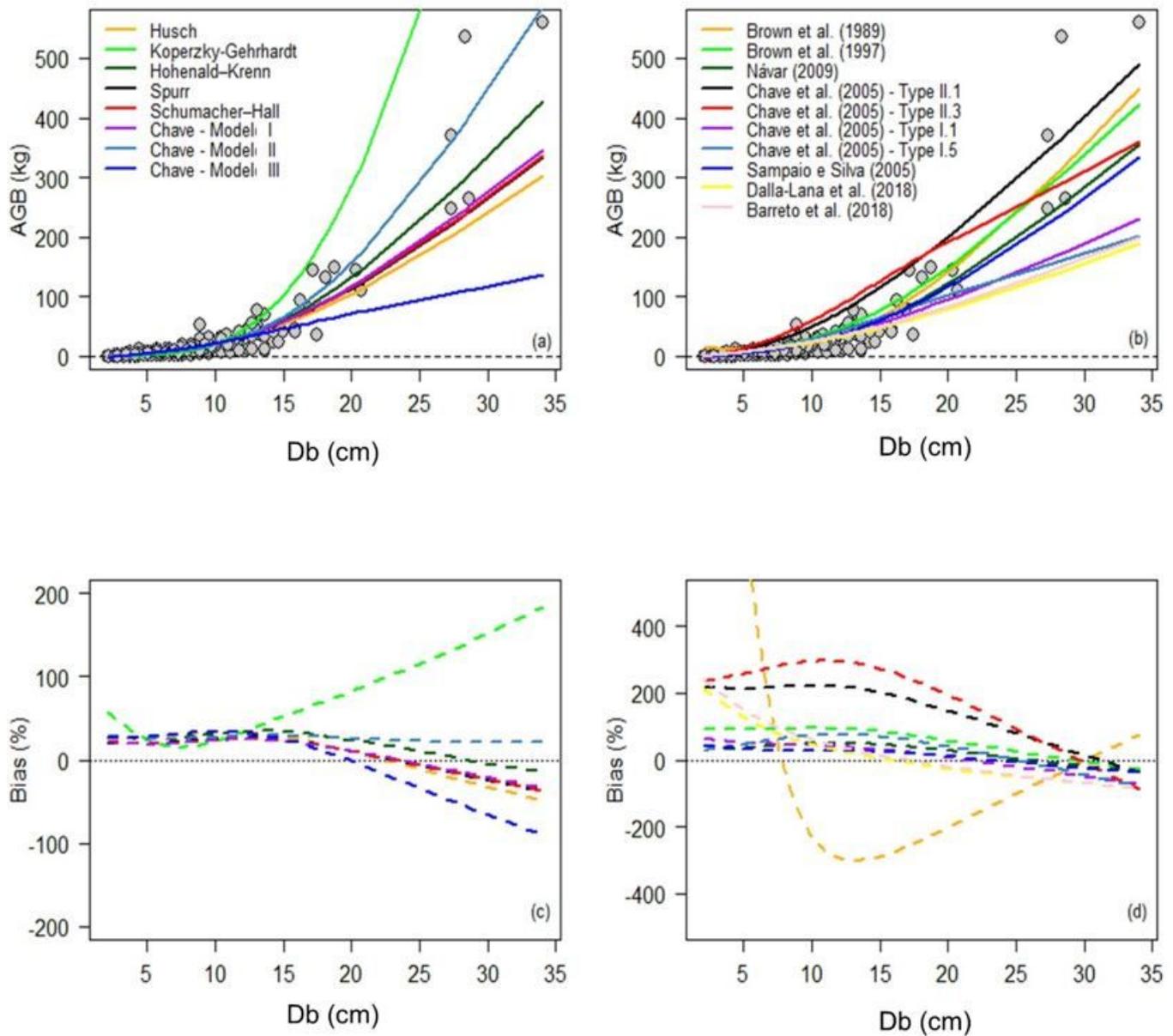
Figure 2

Sampling procedure used in the two inventoried areas in the Municipality of Floresta, Pernambuco



**Figure 3**

Dispersion of percentage residues for the Schumacher-Hall equation developed to predict biomass in dry tropical forest, northeastern Brazil.



**Figure 4**

Biomass prediction from the equations developed for the site (a) and from other local and pan-tropical equations (b); and percentage difference (bias) of biomass predictions at tree level by diameter class for local equations (c) and other local and pan-tropical equations (d).