Corrigendum to Biogeosciences, 13, 1553–1570, 2016
www.biogeosciences.net/13/1553/2016/
doi:10.5194/bg-13-1553-2016-corrigendum

Biogeosciences Open Access EGU

Corrigendum to "Predicting biomass of hyperdiverse and structurally complex central Amazonian forests – a virtual approach using extensive field data" published in Biogeosciences, 13, 1553–1570, 2016

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Published: 27 April 2016

1 Mistake in the published paper and its impact

In our paper "Predicting biomass of hyperdiverse and structurally complex central Amazonian forests – a virtual approach using extensive field data" (Biogeosciences, 13, 1553–1570, 2016), the biomass estimation models were fit using fresh and not dry tree mass data. Thus, the models reported in our paper are valid for the estimation of fresh aboveground biomass (AGB) of trees and not dry AGB as reported. A direct implication of this mistake is that our evaluation of the pantropical biomass estimation model from Chave et al. (2014) is incorrect in the published paper. The pantropical model was fit with dry mass data. For this reason, it underestimated the biomass of the heavier fresh trees used in our paper. In this corrigendum we have redone the analyses in the paper using dry mass data, which allowed us to reassess different models' performance across our proposed forest scenarios. The correction from wet to dry mass affected both the AGB values of trees and the models for predicting AGB. Thus, the main conclusions in our paper about which models best represent/capture the variations in AGB across our forest scenarios have not changed. However, the absolute values of the models' parameters are different (see Table 3, which should replace Table S3 in the Supplement). For completeness, we give the results of re-analysis here, i.e. the evaluation of our models and the pantropical model from Chave et al. (2014).

2 Obtaining dry mass data and estimating new model parameters

A detailed description of the harvesting method was provided in Sect. 2.2 of the paper. Water content was measured for 66 randomly selected trees, following the procedures also described in Sect. 2.2 of the paper and including samples representing different components (i.e., trunk, coarse branches, fine branches, leaves and flowers/fruits – when available). The weighted water content of the 66 trees was 47.4 % ± 0.01 % (mean ± 95 % CI). This value is similar to those reported for other *terra firme* forests in the eastern (Araújo et al., 1999), central (Higuchi et al., 2004) and western (Brown et al., 1995; Lima et al., 2012) Amazon. For this corrigendum, we calculated a weighted mean water-content

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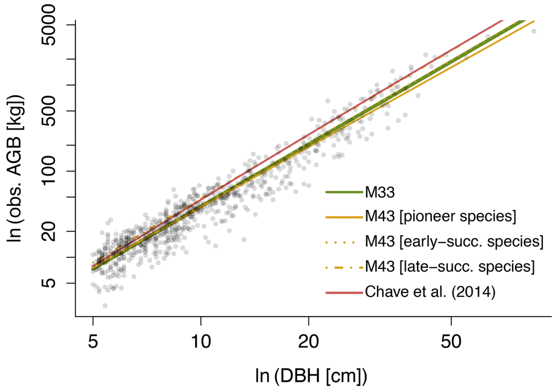

Figure 1. (Correction to Fig. S1 of the Supplement). Comparison of the two best tree aboveground estimation models (M33 and M43) – corrected now to predict dry AGB – with the prediction from the pantropical model from Chave et al. (2014). Note that the pantropical model overestimates the biomass of small and, especially, of large-sized trees (diameter at breast height ≥ 21 cm). This pattern was also observed at the landscape level (see Fig. 2).

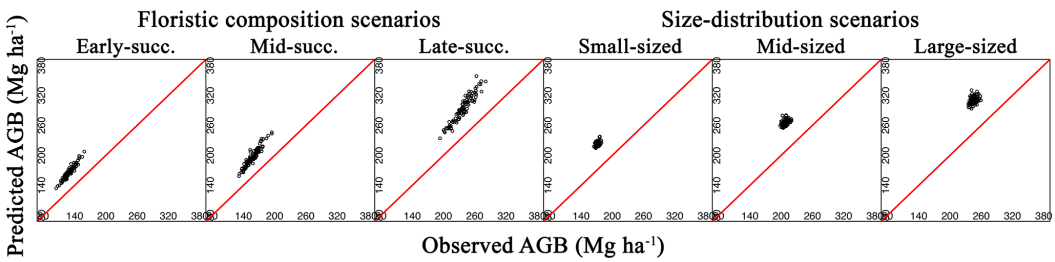

Figure 2. (Correction to Fig. S2 of the Supplement). Predicted vs. observed aboveground biomass (AGB) along six forest scenarios composed of 100 1 ha plots. The line of equality (1 : 1 line) is shown as a red/straight line. Forest scenarios were designed to reflect landscape-level variations in floristic composition and size distribution of trees, typical of central Amazon *terra firme* forests. Floristic composition and size-distribution scenarios followed the sampling scheme described in Sect. 2.4.2 (Fig. 2) of the paper. Here, the predictions were made by using the pantropical model of Chave et al. (2014), which has diameter at breast height (DBH), tree total height (H) (estimated from a DBH: H relationship), wood density (WD) and environmental stress as predictors.

value for each of our successional groups (i.e., pioneer, mid- and late-successional species). There were 49.2, 45.0 and 43.8 %, for pioneer, mid- and late-successional species, respectively (Table 1).

The mean water content of each successional group was used to convert fresh mass to dry mass for each tree and those (Table 2) were used in all subsequent re-analyses. Although water content is related to wood density (Suzuki, 1999) and thus can vary among species (Muller-Landau, 2004; Williamson and Wiemann, 2010), individuals and tree compartments (Higuchi et al., 1998; Plourde et al., 2015), our approximation reflects both the variability among sites and in community composition (i.e., from pioneer to late-successional species). Moreover, Chambers et al. (2001) reported little effect of the variation in water content (i.e., the use of mean and individual-specific water-content values) on prediction error for both individuals and groups of trees harvested in the same region as our study.

With respect to our models, since there was little variation in water content among tree species and successional groups, and because corrections affected both the predicted variable and the models, we expected our analysis of how well the various models performed to be the same as initially. However, those interested in using biomass estimation models to estimate dry biomass need to use the new coefficients provided in Table 3 of this corrigendum, rather than those reported in Table S3 of the Supplement.

3 Evaluation of the pantropical model

We evaluated the pantropical model from Chave et al. (2014) with our corrected dry mass data. In our paper, the model understandably underestimated biomass because we were comparing estimated dry weight with our wet weight data. When we compared the estimates with our data after correction, i.e., removing the weight of water, we found that the pantropical model overestimated the biomass of individual trees on average by 29.8 % resulting in a root-mean-square error (RMSE) of 210.2 kg (Fig. 1).

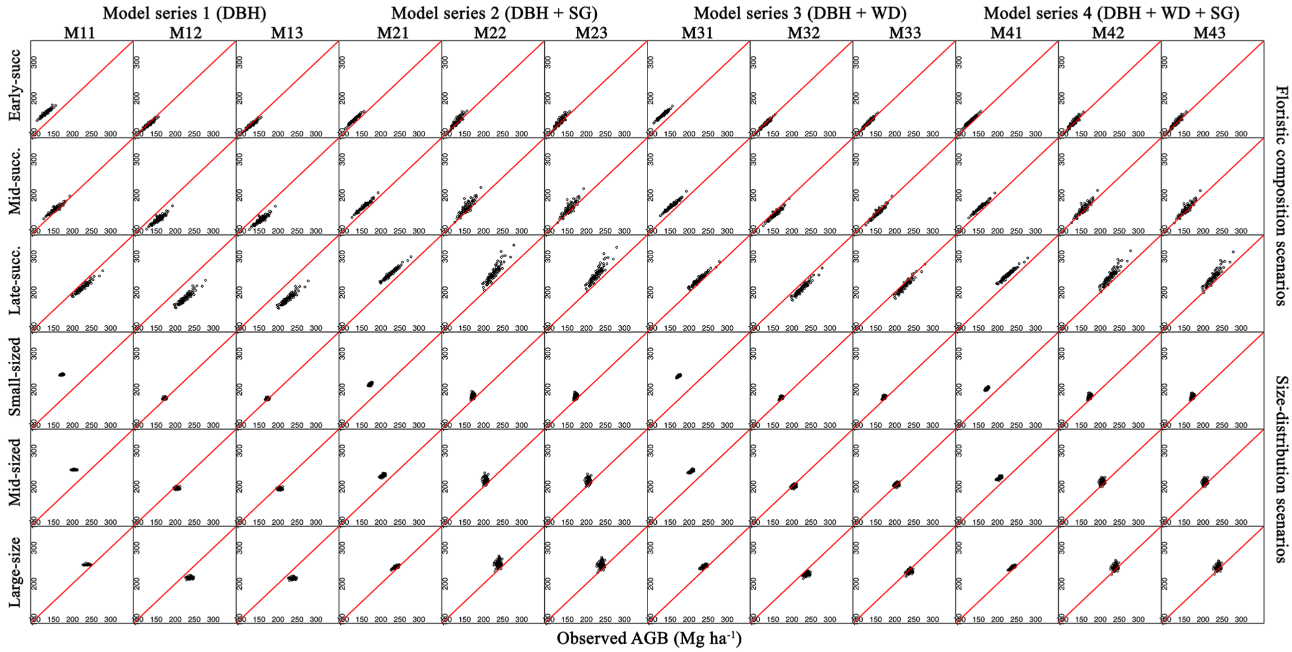

Figure 3. Predicted vs. observed aboveground biomass (AGB) along six forest scenarios composed of 100 1 ha plots. The line of equality (1 : 1 line) is shown as a red/straight line. Forest scenarios were designed to reflect landscape-level variations in floristic composition and size distribution of trees, typical of central Amazon *terra firme* forests. Floristic composition and size-distribution scenarios followed the sampling scheme described in Sect. 2.4.2 of the paper. Models' predictors: diameter at breast height (DBH) (cm), species' successional group (SG) (pioneers, mid- and late successional) and wood density (WD) (g cm^{-3}). See Table 2 for the variance modeling approach of different equations. Note that models containing total tree height (H) as predictor were excluded here.

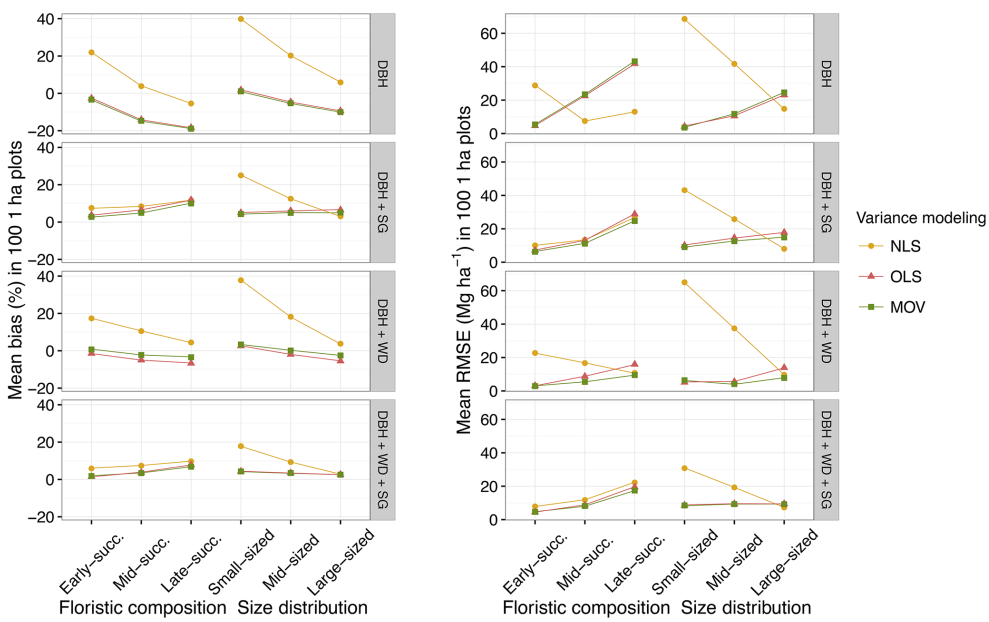

Figure 4. Profiles relating the bias and the root-mean-square error (RMSE) of 12-tree aboveground biomass estimation models tested across six forest scenarios composed of 100 1 ha plots. Forest scenarios (for details see Sect. 2.4.2 of the paper) were designed to reflect landscape-level variations in floristic composition and size distribution of trees, typical of central Amazon *terra firme* forests. Models' predictors: diameter at breast height (DBH) (cm), species' successional group (SG) (pioneers, mid- and late-successional species) and wood density (WD) (g cm^{-3}). Variance modeling approaches: non-linear least square (NLS), ordinary least square with log-linear regression (OLS) and non-linear with modeled variance (MOV). Note that models containing total tree height (H) as predictor were excluded here.

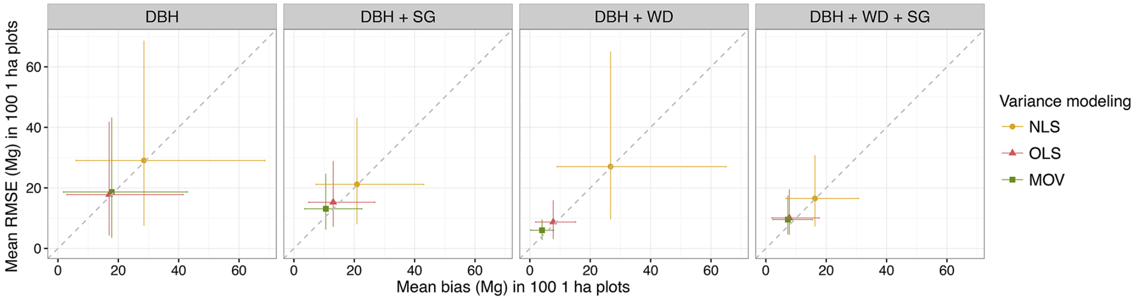

Figure 5. (Correction to Fig. 6 of the paper). Overall performance of 12-tree aboveground estimation models across six forest scenarios composed of 100 1 ha plots. Forest scenarios were designed to reflect landscape-level variations in floristic composition and size distribution of trees, typical of central Amazon *terra firme* forests. Models are rated by the absolute mean bias and root-mean-square error (RMSE), both in Mg. Solid points and bars represent mean and range values, respectively. Models' predictors: diameter at breast height (DBH) (cm), species' successional group (SG) (pioneers, mid- and late-successional species) and wood density (WD) ($g\,cm^{-3}$). Variance modeling approaches: non-linear least square (NLS), ordinary least square with log-linear regression (OLS) and non-linear with modeled variance (MOV). Note that models containing total tree height (H) as predictor were excluded here.

Table 1. Contribution of tree compartments to the total aboveground biomass (AGB) (mean), water content of different tree compartments and weighted tree water content of the successional groups included in the paper and this corrigendum (mean ± 1 standard deviation, both).

Compartments	Contribution to the total AGB (%)	H_2O content (%)	Weighted H_2O content (%)
Pioneer species ($N = 39$)			
Trunk/bole	65.6	48.1 ± 6.1	49.2 ± 0.9
Thick/coarse branches	11.7	43.7 ± 4.1	
Thin/fine branches	17.8	52.5 + 7.1	
Leaves	4.7	64.8 + 7.4	
Flowers/fruits	0.2	61.2 ± 4.8	
Mid-successional species ($N = 22$)			
Trunk/bole	77.4	43.0 ± 4.5	45.0 ± 1.0
Thick/coarse branches	0.0	0.0	
Thin/fine branches	17.0	48.6 ± 3.9	
Leaves	5.6	61.7 ± 9.6	
Flowers/fruits	0.0	0.0	
Late-successional species ($N = 5$)			
Trunk/bole	60.9	41.6 ± 3.3	43.8 ± 1.1
Thick/coarse branches	0.0	0.0	
Thin/fine branches	26.2	42.9 ± 7.7	
Leaves	12.9	56.3 ± 11.8	
Flowers/fruits	0.0	0.0	

The pantropical model also systematically overestimated the AGB of our scenarios (Fig. 2). We observed biases ranging from +29.2 % (mid-succession) to +30.8 % (early succession) (mean of +29.8 %) and RMSE raging from 40.5 $Mg\,ha^{-1}$ up to 71.0 $Mg\,ha^{-1}$ (mean of 56.4 $Mg\,ha^{-1}$) (Table 4). Overestimation was also reported in previous studies that tested pantropical models in *terra firme* Amazon forests (Alvarez et al., 2012; Lima et al., 2012; Ngomanda et al., 2014).

In our study area, trees larger than 60 cm diameter at breast height (DBH) occur in densities < 1 ha^{-1} (Vieira et al., 2004). Moreover, trees ≤ 40 cm DBH account for more than 90 % of the total tree density (Higuchi et al., 2012). We attribute the overestimation of the pantropical model to the great importance that this model gives to large trees (Sect. 4.1 and 4.2, and Fig. S3 of the paper; Figs. 1 and 2 of this corrigendum). As we have shown, the pantropical model does not represent the size distribution of trees from our study region. The results from this corrigendum highlight that site differ-

Table 2. (Correction to Table 1 of the paper). Trees were harvested in the Estação Experimental de Silvicultura Tropical, a contiguous *terra firme* forest reserve near Manaus, Amazonas, Brazil. The corrected AGB values have been calculated using the correction from wet to dry weight.

Variables	Old-growth forest	Secondary forest (23-year old)	Secondary forest (14-year old)
NT	131	346	250
SR	81	63	50
DBH	5.0–85.0	5.0–37.2	5.0–33.1
H	5.9–34.5	3.9–27.0	4.2–27.0
WD	0.348–0.940	0.389–1.000	0.395–1.000
AGB	4.5–4216.5	2.7–861.6	3.9–859.3

Variables: number of trees (NT); species richness (SR); diameter at breast height (DBH) (cm); total tree height (H) (m); wood density (WD) ($g\,cm^{-3}$); and aboveground biomass (AGB) (dry mass in kg).

ences in size distribution of trees need to be considered both when parameterizing and applying biomass estimation models.

4 Fitting models with the dry mass data

We fit models for estimating dry biomass using the same equations and predictors as in the paper. Before fitting the models, we again tested our predictors for collinearity. Overall, the variance inflation factor (VIF) of the models did not change.

As observed in our models fit with fresh mass data, the non-linear least-square (NLS) approach yielded models with higher coefficient of determination (R^2) and adjusted coefficient of determination (R^2adj) than the models fit with the ordinary least square with the log-linear regression (OLS) and our non-linear with modeled variance (MOV) approach (Table 5). Consequently, the models fit with the NLS approach invariably had lower $S_{yx\%}$ values than those fit with the OLS and MOV approaches. Nonetheless, when considering Deviance Information Criterion (DIC) values as the most important criterion for model selection, our results are consistent with those we reported in the paper. Models fit with the OLS and our MOV approach still yielded the best-fitting models (lower DIC values). The models M33, M43 and M42 had the first, second and third lowest biases for individual tree predictions (underestimation of 0.8 % and overestimation of 3.0 and 3.1 % of dry AGB, respectively).

5 Biomass predictions across the scenarios

The corrected mean AGB (dry) in our 1 ha plots ranged from 107.2 to 170.9 $Mg\,ha^{-1}$ (floristic composition scenarios) and from 54.1 to 230.2 $Mg\,ha^{-1}$ (size-distribution scenarios) (Fig. 3). This variation was proportional to that observed for the fresh mass data reported in the paper and values are coherent with those reported for other Amazon regions including secondary (Lima et al., 2007; Saldarriaga et al., 1998) and old-growth forests (Higuchi et al., 2004; Lima et al., 2012; Vieira et al., 2004).

The goodness of fit of the models for predicting individual tree biomass (Table 5) was also reflected for the reliability of models when predicting AGB across our forest scenarios (Fig. 3). Overall, the patterns reported in the paper did not change. While some models predicted AGB accurately across all different scenarios, others systematically under- or overestimated the "true" AGB values (Fig. 4). As previously reported, despite having the highest R^2 and R^2adj values, the models fit with the NLS approach produced the least reliable landscape-level predictions with biases ranging from −5.4 % (underestimation) to +39.8 % (overestimation) (both values from the model M11) leading to RMSE of up to 68.6 $Mg\,ha^{-1}$. The models fit with the NLS approach performed better (lower RMSE and bias) at the late-successional and large-sized scenarios. The models fit with the OLS and MOV approaches performed satisfactorily and similarly across most of the scenarios. For model series 2 and 3, the models fit with our MOV approach performed slightly better than those fit with the OLS approach. The models fit with the OLS approach had biases raging from −18.4 to +11.9 %, with maximum RMSE of 41.8 $Mg\,ha^{-1}$; models fit with our MOV approach had biases ranging from −19 to 9.9 %, and maximum RMSE of 43.2 $Mg\,ha^{-1}$.

As observed from the DIC values of individual tree predictions (Table 5), our MOV and the OLS approaches produced the more reliable (smaller biases and RMSE) predictions when challenged across all scenarios (Fig. 5). As for the models fit with fresh data, independent of applied predictors, the NLS approach invariable had the highest mean and range of values for bias and RMSE. As previously reported, the best-performing model structures for predicting tree AGB at the landscape-level included species-specific predictors and either the OLS or MOV fitting approaches (Table 5 and Figs. 3–5). The best-performing models across all scenarios were M33 (bias of 2.1 % or 4.0 $Mg\,ha^{-1}$), M43 (3.7 % or 7.3 $Mg\,ha^{-1}$) and M32 (3.9 % or 7.7 $Mg\,ha^{-1}$).

Table 3. Parameters (low [2.5 %] and high [97.5 %] confidence interval) of the 24-tree aboveground biomass estimation models fit in this corrigendum. See the Table 2 of the paper for checking the equations and variance modeling approaches, and the Table 5 of this corrigendum for checking models' statistics. Models were fit with dry mass data summarized in the Table 2 of this corrigendum.

Series	Model	SG	b1	b2	b3	b4	c1	c2
1	M11		0.504 (0.426,0.594)	2.078 (2.035,2.120)			108.8 (103.4,114.6)	
	M12		−1.762 (−1.883,−1.642)	2.329 (2.280,2.380)			0.368 (0.350,0.387)	
	M13		0.183 (0.162,0.207)	2.328 (2.274,2.380)			0.051 (0.041,0.064)	2.424 (2.334,2.517)
2	M21	pio	0.249 (0.130,0.416)	2.195 (2.025,2.379)			75.17 (71.41,79.16)	
		mid	0.153 (0.102,0.216)	2.436 (2.344,2.532)				
		lat	2.607 (2.226,3.010)	1.683 (1.646,1.723)				
	M22	pio	−1.547 (−1.723,−1.376)	2.203 (2.133,2.274)			0.345 (0.327,0.363)	
		mid	−1.940 (−2.175,−1.705)	2.418 (2.313,2.524)				
		lat	−1.893 (−2.090,−1.694)	2.476 (2.395,2.556)				
	M23	pio	0.227 (0.191,0.268)	2.201 (2.131,2.270)			0.076 (0.054,0.105)	2.201 (2.067,2.334)
		mid	0.156 (0.126,0.193)	2.408 (2.315,2.494)			0.106 (0.062,0.167)	2.105 (1.889,2.333)
		lat	0.159 (0.134,0.187)	2.472 (2.403,2.538)			0.050 (0.032,0.073)	2.449 (2.289,2.619)
3	M31		0.885 (0.776,1.008)	2.061 (2.029,2.094)	1.113 (1.022,1.205)		80.35 (76.34,84.55)	
	M32		−1.438 (−1.557,−1.323)	2.370 (2.324,2.416)	0.863 (0.740,0.989)		0.330 (0.313,0.347)	
	M33		0.230 (0.207,0.257)	2.406 (2.366,2.446)	0.880 (0.752,1.012)		0.076 (0.061,0.094)	2.213 (2.125,2.304)
4	M41	pio	0.165 (0.086,0.280)	2.587 (2.395,2.788)	1.236 (0.977,1.500)		67.81 (64.38,71.51)	
		mid	0.138 (0.075,0.226)	2.457 (2.346,2.576)	−0.098 (−0.460,0.266)			
		lat	2.152 (1.841,2.486)	1.786 (1.744,1.831)	0.555 (0.435,0.679)			
	M42	pio	−1.229 (−1.401,−1.053)	2.279 (2.211,2.345)	0.872 (0.688,1.049)		0.323 (0.307,0.340)	
		mid	−1.857 (−2.130,−1.581)	2.419 (2.319,2.518)	0.196 (−0.216,0.604)			
		lat	−1.684 (−1.907,−1.461)	2.461 (2.384,2.538)	0.548 (0.234,0.867)			
	M43	pio	0.275 (0.231,0.325)	2.324 (2.251,2.396)	0.878 (0.680,1.078)		0.109 (0.075,0.153)	2.009 (1.869,2.155)
		mid	0.182 (0.139,0.238)	2.409 (2.318,2.494)	0.353 (0.028,0.793)		0.102 (0.060,0.162)	2.121 (1.900,2.348)
		lat	0.193 (0.159,0.233)	2.460 (2.392,2.527)	0.539 (0.254,0.835)		0.048 (0.031,0.071)	2.442 (2.277,2.619)
5	M51		0.033 (0.021,0.049)	1.561 (1.491,1.632)	1.423 (1.241,1.607)		93.60 (88.91,98.52)	
	M52		−2.687 (−2.886,−2.490)	1.930 (1.844,2.015)	0.715 (0.590,0.845)		0.341 (0.324,0.359)	
	M53		0.084 (0.066,0.104)	1.970 (1.872,2.062)	0.621 (0.488,0.765)		0.045 (0.036,0.056)	2.457 (2.363,2.551)
6	M61	pio	0.014 (0.004,0.035)	1.915 (1.715,2.111)	1.276 (0.906,1.664)		67.65 (64.27,71.25)	
		mid	0.068 (0.027,0.133)	2.269 (2.131,2.420)	0.448 (0.109,0.798)			
		lat	0.524 (0.356,0.739)	1.408 (1.349,1.470)	0.803 (0.647,0.955)			
	M62	pio	−2.626 (−2.921,−2.337)	1.817 (1.713,1.927)	0.756 (0.581,0.925)		0.314 (0.298,0.331)	
		mid	−2.743 (−3.046,−2.438)	1.942 (1.784,2.099)	0.742 (0.539,0.942)			
		lat	−2.791 (−3.215,−2.353)	2.088 (1.904,2.270)	0.697 (0.393,0.994)			
	M63	pio	0.086 (0.059,0.118)	1.864 (1.745,1.979)	0.670 (0.482,0.879)		0.072 (0.051,0.100)	2.198 (2.059,2.335)
		mid	0.078 (0.054,0.108)	2.004 (1.830,2.173)	0.634 (0.411,0.861)		0.081 (0.046,0.132)	2.193 (1.963,2.432)
		lat	0.068 (0.044,0.099)	2.118 (1.953,2.273)	0.648 (0.386,0.936)		0.048 (0.031,0.071)	2.426 (2.263,2.599)
7	M71		0.063 (0.046,0.083)	1.581 (1.530,1.632)	1.342 (1.217,1.478)	1.024 (0.949,1.100)	64.91 (61.66,68.39)	
	M72		−2.253 (−2.441,−2.059)	2.027 (1.952,2.104)	0.605 (0.490,0.717)	0.773 (0.655,0.895)	0.308 (0.293,0.324)	
	M73		0.109 (0.088,0.134)	2.121 (2.047,2.194)	0.839 (0.711,0.966)	0.535 (0.416,0.657)	0.073 (0.057,0.092)	2.206 (2.110,2.305)
8	M81	pio	0.029 (0.010,0.061)	2.306 (2.118,2.513)	0.830 (0.523,1.167)	0.999 (0.764,1.231)	57.16 (54.30,60.21)	
		mid	0.058 (0.028,0.111)	2.072 (1.867,2.308)	0.761 (0.295,1.145)	0.420 (0.007,0.823)		
		lat	0.195 (0.134,0.281)	1.456 (1.401,1.514)	1.124 (0.967,1.276)	0.732 (0.636,0.831)		
	M82	pio	−2.086 (−2.396,−1.784)	1.978 (1.865,2.089)	0.560 (0.392,0.735)	0.710 (0.538,0.885)	0.300 (0.285,0.316)	
		mid	−2.671 (−3.016,−2.327)	1.946 (1.787,2.104)	0.737 (0.540,0.934)	0.162 (−0.221,0.548)		
		lat	−2.545 (−3.010,−2.070)	2.120 (1.938,2.301)	0.621 (0.316,0.915)	0.388 (0.084,0.691)		
	M83	pio	0.131 (0.091,0.182)	2.087 (1.976,2.202)	0.761 (0.571,0.957)	0.471 (0.290,0.650)	0.106 (0.074,0.150)	2.005 (1.861,2.147)
		mid	0.089 (0.059,0.127)	2.006 (1.835,2.170)	0.350 (0.037,0.733)	0.639 (0.427,0.872)	0.080 (0.045,0.132)	2.195 (1.962,2.432)
		lat	0.087 (0.055,0.129)	2.154 (1.995,2.309)	0.435 (0.153,0.725)	0.575 (0.310,0.852)	0.050 (0.032,0.074)	2.401 (2.234,2.578)

Model series predictors: 1 (diameter at breast height [DBH]); 2 (DBH and species' successional group [SG]); 3 (DBH and wood density [WD]); 4 (DBH, WD and SG); 5 (DBH and total tree height [H]); 6 (DBH, H and SG); 7 (DBH, H and WD); and 8 (DBH, H, SG and WD). Species' successional groups: pioneer (pio), mid-species (mid) and late-successional species (lat).

Our new results support that predicting biomass correctly at the landscape level in hyperdiverse and structurally complex tropical forests, such as the Amazon, still depends on the collection of plot-based allometric data and forest inventories including information on species composition, tree height and wood density. In forests subjected to more intense disturbance regimes (i.e., strong gradients of floristic composition and size distribution), reliable landscape-level biomass estimates may require models that include predictors approximating species-specific architecture and anatomy, and possible variations in the size distribution of trees.

We would like to emphasize the importance of the aspects related to model parameterization, selection and applicability, as discussed in Sect. 4 of our paper. Furthermore, we confirm the efficacy of our best-performance models for estimating dry aboveground biomass of central Amazon *terra firme* forests, and the adequacy of the methods that we employed. When data on species composition and wood density are available or can be accurately compiled from the literature, we suggest the use of models M33, M43 or M42, respectively. In case wood density data are not available or are available but in insufficient resolution, we suggest the use of model M23.

Table 4. (Correction to Table S4 of the Supplement). Root-mean-square error (RMSE) and bias (absolute and relative values) from tree aboveground biomass predictions across our forest scenarios by using the Chave et al. (2014)'s pantropical estimation model. Chave et al. (2014)'s pantropical estimation model has diameter at breast height (DBH), tree total height (H) (estimated from a DBH: H relationship), wood density (WD) and environmental stress as predictors.

Scenarios	RMSE (Mg ha^{-1})	Bias (Mg ha^{-1})	Bias (%)
Early-succession	40.5	40.1	30.8
Mid-succession	46.1	45.5	29.2
Late-succession	67.1	66.4	29.3
Small-sized	51.9	51.7	30.1
Mid-sized	61.8	61.6	30.0
Large-sized	71.0	70.8	29.6
Mean	56.4	56.0	29.8

Table 5. Statistics of aboveground biomass estimation models fit in this corrigendum. See Table 2 of the paper for the definition of models, predictors and variance modeling approaches.

Series	Model	Dev	pD	DIC	R^2	R^2adj	S_{yx}%	CF
1	M11	8880.2	2.926	8883.1	0.889	0.888	3.315	
	M12	5924.7	2.963	5927.6	0.867	0.867	3.615	1.070
	M13	5948.1	3.847	5952.0	0.867	0.867	3.619	
2	M21	8342.3	3.647	8345.9	0.947	0.946	2.296	
	M22	5827.3	7.001	5834.3	0.552	0.548	6.593	1.061
	M23	5827.5	10.534	5838.0	0.595	0.592	6.285	
3	M31	8439.3	3.972	8443.2	0.939	0.939	2.449	
	M32	5762.9	4.014	5766.9	0.901	0.901	3.119	1.056
	M33	5792.5	4.805	5797.3	0.882	0.881	3.412	
4	M41	8193.2	1.271	8194.5	0.957	0.956	2.077	
	M42	5732.8	10.007	5742.8	0.719	0.715	5.223	1.053
	M43	5737.6	13.126	5750.7	0.738	0.735	5.056	
5	M51	8661.5	−0.071	8661.4	0.918	0.917	2.853	
	M52	5810.7	4.052	5814.8	0.887	0.886	3.340	1.060
	M53	5858.2	4.652	5862.9	0.882	0.881	3.415	
6	M61	8189.8	−55.307	8134.5	0.957	0.956	2.071	
	M62	5690.5	10.118	5700.7	0.753	0.750	4.895	1.050
	M63	5720.5	11.602	5732.1	0.755	0.752	4.891	
7	M71	8129.0	2.234	8131.2	0.960	0.960	1.980	
	M72	5663.5	5.025	5668.5	0.935	0.934	2.539	1.048
	M73	5715.7	5.512	5721.2	0.927	0.927	2.681	
8	M81	7944.2	−38.934	7905.3	0.969	0.969	1.753	
	M82	5624.8	13.226	5638.0	0.818	0.815	4.205	1.046
	M83	5655.9	13.489	5669.4	0.821	0.818	4.187	

Legend: models' deviance (Dev), effective number of parameters (pD), Deviance Information Criterion (DIC), coefficient of determination (R^2), adjusted coefficient of determination (R^2adj), relative standard error ($S_{yx\%}$) and correction factor (CF) for models fit from ordinary least square with log-linear regressions.

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