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The Tropical Biomass & Carbon Project–An app for forest biomass and carbon estimates

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Abstract

This article introduces the project called Tropical Biomass & Carbon – TB&C, available on the permanent link www.tropicalbiomass.com. The App requires input attributes of the forest stand or diameter class easily obtained, being: smallest and largest diameters, number of trees ha^{-1}, and parameters of the diameter distribution. The output attributes are at the stand and tree levels. At stand level, the App delivers mean aboveground biomass (AGB) and carbon (AGC), in Mg ha^{-1}, as well as their confidence intervals (CIs) and uncertainties. The tree-level outputs are AGB and diameter for every tree in the stand. The project TB&C comprises four Brazilian forest (and non-forest) formations: Campinarana, Floresta estacional, Floresta ombrofila, and Savana. This article aims to disclose the algorithm written for the TB&C App. This phase counts on a standardized database of 1,428 trees with dry AGB destructively measured. Model uncertainties were incorporated into the modeling process. In addition to its reliability, we cite as great advantages of the TB&C App; (i) simplicity and a user-friendly layout, (ii) AGB and AGC estimates provided along with robust CIs, and (iii) estimates at the stand and tree levels with consistent totals. As a secondary product, the project TB&C delivers a dataset of 64,000 simulated plots, informing dry AGB, tree density, basal area, Lorey's height, and shape of the diameter distribution.

Keywords: Tropical Forest. Aboveground biomass. Uncertainty analysis. Stand- and tree-level estimates. Web application.

Introduction

Forests are known to play important roles in global biogeochemical cycles, especially in the carbon (C) cycle (Brown et al. 1993; Houghton 2003a). This importance is basically due to three reasons. First, forests and forest soils are large C pools, especially tropical forests (Morais et al. 2020; David et al. 2017). Second, large forest areas are deforested year by year, emitting increasingly more C into the atmosphere (Brown et al. 1993; Houghton 2003b). And third, forests cover 31% of the world's total land area, totaling about 4.06 billion hectares (FAO & UNEP 2020). This means that global warming forecasts and climate surveys rely on, among others, a consistent quantification of C emissions caused by deforestation, needing thus monitoring of the global forest C (Le Toan et al. 2011).

Once every type of forest formation features its own tree composition and structure, the C stored in the forests could be better estimated through a forest type-specific modeling (Henry et al. 2015; Jara et al. 2015). This necessity motivated the creation of the project here introduced, the Tropical

Biomass & Carbon (hereafter 'TB&C'). The product this project offers is an interactive, open-access web application – the TB&C App –, built with a robust and specific modeling technique. The main purpose of the project is to help researchers by providing estimates of aboveground biomass (AGB) and carbon (AGC) with more reliability than unspecific approaches. The App also outputs confidence intervals (CIs) for AGB and AGC based on a model uncertainty analysis. The importance of assessing uncertainties and delivering estimates along with CIs is due to variation in biomass existing among trees and forests (Qin et al. 2020; Fu et al. 2017).

In compliance with Henry et al. (2015) and Jara et al. (2015), the TB&C aligns to the belief that the global forest C stock could be better predicted if every country had its own specific equations. Our aim in this paper is to disclosing the algorithm of the TB&C App. Tips for use, limitations and other issues related to the application are also addressed.

Methodology/approach

Our database is a compilation of tree samples selected in forest and non-forest remnants located in the four national formations here studied. About 62% of our database comes from Brazilian researchers on forest biomass, and the remaining (38%) data source is a subset of the global database published by Chave et al. (2014). The remnants where tree samples were taken are located along nine Brazilian states, to know; Amazonas, Mato Grosso, Minas Gerais, Pará, Paraná, Rio Grande do Sul, Rondônia, Roraima, and Santa Catarina. Visit www.tropicalbiomass.com to locate the remnants in the map of Brazil.

Three primary conditions were assumed to acquire tree samples that composed our database. First, no tree sample could come from forest plantations or agroforestry systems. This constraint was assumed due to the difference in bole and crown shapes that trees may assume while growing in natural forest formations, in relation to human-altered vegetation (Ali et al. 2019; Pretzsch et al. 2015; Goodman et al. 2014). So, we presumed that this difference is an important source of variation of tree AGB, that consequently affects parameters of biomass models. The second condition is that the tree AGB has to be directly measured (using scale), not allowing AGB resulting of, for example, the conversion 'volume to biomass' using a mean wood density, or estimates based on stochastic equations. This condition eliminates the source of uncertainty associated with indirect estimates of tree AGB. Third, we limited our database to woody, self-standing species only. Shrub-like and herbaceous species, palms and ferns, are therefore out of list. Mass of other aboveground components of the forest, as litter, shrub, and any dead mass are not target of this study as well.

Under such constraints, all trees that comprise our database were felled and had their fresh AGB measured in field, including trunk, branches, and leaves. Fresh samples of these tree compartments were collected and taken to laboratory for kiln-drying, to then finally compute dry AGB of the trees. The number of trees sampled was 1428 at four forest non/forest formation is presented in "Table 1" of the original paper of the project TB&C.

Results

General information for users

The TB&C App is an interactive web application programmed in R using the R-package 'shiny' (Chang et al. 2020). The TB&C App allows users to set the input attributes shown in the upper half of Table 1, and informs the output attributes shown in the lower half of Table 1.

Table 1: Input and output attributes of the TB&C App.

Input Attributes	
• **Forest/non-forest formation**	
	- *Campinarana*
	- *Floresta ombrofila*
	- *Floresta estacional*
	- *Savana*
• **Level of information**	
	- Stand
	- Diameter class
• **Tree information**	
	- Smallest diameter (Level of information 'Stand')
	- Largest diameter (Level of information 'Stand')
	- 10-cm diameter class (Level of information 'Diameter class)
	- Number of trees/ha (Level of information 'Stand' and 'Diameter class')
Parameters of the beta distribution	
	- Parameter α
	- Parameter β
Output Attributes	
• **Panel 1: Stand level**	
	- Diameter distribution (graphical representation)
	- Basal area
	- Tree density
	- Mean AGB (Mg ha^{-1}) and CI* fixed by uncertainty analysis
	- Mean AGC (Mg ha^{-1}) and CI* fixed by uncertainty analysis
	- Absolute (Mg ha^{-1}) and relative (%) errors for mean AGB
• **Panel 2: Tree level**	
	- Diameter
	- Tree AGB

* Confidence interval at 95% probability level. AGB and AGC are, respectively, aboveground biomass and carbon. Terms in English for the formations are, respectively: *Campinarana*, Seasonal Forest, Ombrophilous Forest, and Savannah.

The App requires that users (a) select one of the four forest/non-forest formations, (b) select the level of information (stand or diameter class) desired for the output attributes, (c) insert information (from *census* or sample-based inventory) of the trees observed in the forest, as diameter range and tree density, and (d) select parameters α and β of the beta distribution. The beta distribution is here adopted as the probability density function (p.d.f.) that portrays the diameter distribution of the forest. We chose it due to its good flexibility and, more importantly, because we can set the lower and upper diameters of the distribution. This last benefit allows users to predict biomass and carbon for any diameter range.

The output attributes of the TB&C App are delivered at two levels: stand (Panel 1) and tree (Panel 2). Panel 1 TB&C App's presents an illustration of diameter distribution of the forest. The shape of the diameter distribution is sensible to the parameters α and β of the beta distribution, whereas the smallest and largest diameters rule its range. Panel 1 also shows a table stand-level biomass and carbon in Mg ha^{-1} and their uncertainties, as well as basal area and tree density. Panel 2 of the TB&C App (Table 1) tabulates diameter and AGB of all trees of the simulated stand. These trees are the same that compose the diameter distribution shown in Panel 1.

Panel 1: Stand level

The following subsections describes the step-by-step process for reproducing the algorithm implemented for Panel 1. An overview of it is presented in Fig. **1**.

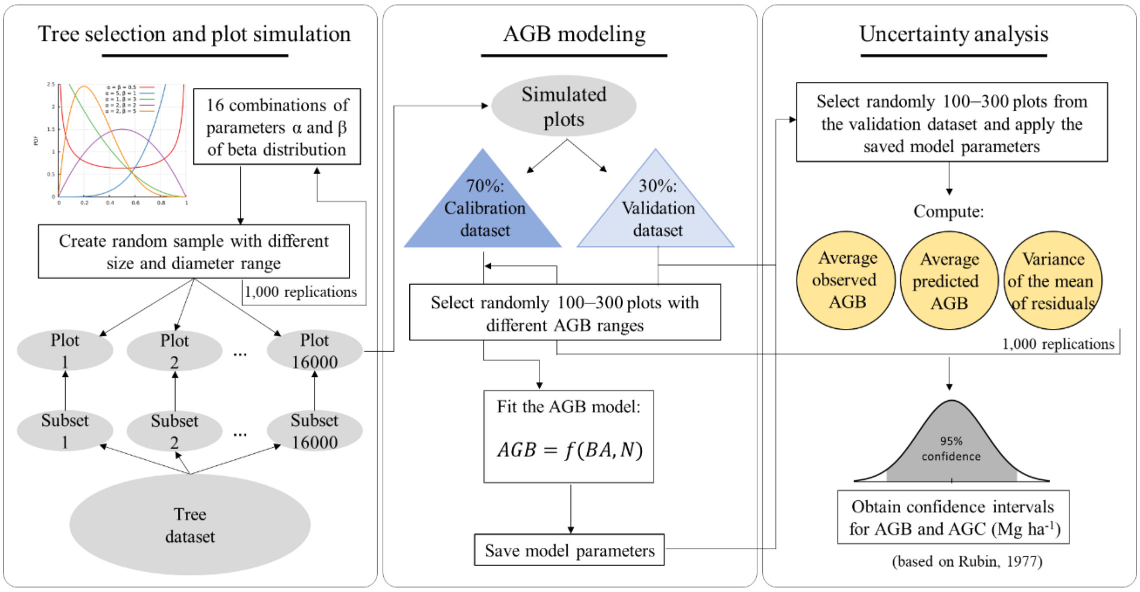

Fig. 1: Overview of the algorithm implemented for Panel 1 of the TB&C App.

To select trees from our database and then simulate 1-ha plots, we developed an approach that combines the Monte Carlo (MC) simulation and Bootstrap technique. The idea was, first, to simulate field plots (MC) with tree dbhs following the beta distribution (Gupta and Nadarajah, 2004), and second, to select trees (Bootstrap) from the database obeying the dbh distribution of the simulated plots.

The simulated 1-ha plots were created in accordance with the parameters of the beta distribution, number of trees ha^{-1}, and dbh class available in the TB&C App. The TB&C App embeds an algorithm for selecting trees from our database used to simulate the plots. Such algorithm counts on 16,000 replications per forest/non-forest formation (64,000 in total), which corresponds to the set of simulated plots. Note that these plots differ each other in tree density, diameter range, and shape of the diameter distribution curve. Next, for the *j*-th (simulated) plot, we computed: AGB (in Mg ha^{-1}, Eq. 1), basal area (in m^2 ha^{-1}, Eq. 2), Lorey's height (Saatchi et al. 2011) (Eq. 3), and number of trees (N_j).

$$AGB_j = \sum_{i=i}^{n_j} b_{tree,ij} \Big/ 1{,}000 \tag{1}$$

$$BA_j = \pi \sum_{i=i}^{n_j} dbh_{ij}^2 \Big/ 40{,}000 \tag{2}$$

$$H_{Lorey,j} = \sum_{i=i}^{n_j} \left(\frac{dbh_{ij}^2 \, ht_{ij}}{dbh_{ij}^2} \right) \tag{3}$$

where, $b_{tree,ij}$: dry AGB, in kg. dbh_{ij} is diameter at breast height, in cm. n_j is the number of trees. ht_{ij} is total height, in m, of the *i*-th tree, in the *j*-th plot. For *Campinarana*, dbh_{ij} is replaced by d_{0ij}.

The next procedure is to test stand-level models to predict AGB in Mg ha^{-1}. We previously examined the contribution of the set of variables (*BA*, H_{Lorey}, *N*) available to predict AGB per unit area. Was noted that the Lorey's height plays an important role in the modeling (Sullivan et al. 2018; Mitchard et al. 2013; Feldpausch et al. 2011; Saatchi et al. 2011). With this, we noticed that the AGB in Mg ha^{-1} should be modeled through specific-to-formation models.

After testing a large number of models and set of variables in the AGB modeling, we observed two important issues. First, the Lorey's height had no longer significant contribution in the modeling when BA and N were input variables. This occurred because the formation-type grouping sufficiently homogenized the data in terms of Lorey's height. Second, we verified that the AGB model performed much better while using the ln-ln scale (Chave et al. 2014). The model that best performed for all forest/non-forest formations is presented in Eq. (4). From this model, specific-to-formation AGB equations were obtained.

$$ln\left(A\hat{G}B_j\right) = \hat{\beta}_0 + \hat{\beta}_1\, ln\left(BA_j\right) + \hat{\beta}_2\, ln\left(N_j\right) + \hat{\varepsilon} \qquad (4)$$

where, $\hat{\beta}_i$: model parameters. $\hat{\varepsilon}$: model residual.

To fit Eq (5), we implemented an algorithm for executing modeling with uncertainty analysis, this last based on the *m* out of *n* Bootstrap (Bickel et al. 1994; Bickel and Ren 1995). Those plots simulated in the previous subsection corresponded to our Bootstrapped samples. The *m* out of *n* Bootstrap (in our case, $n = n_{total}$ and $m = n_{selected}$) was chosen rather than the original Bootstrap technique, mainly as a means of mitigating the computation burden caused by the size of n_{total}. The aim with this is to compute CIs for AGB and AGC with model uncertainty quantification. The method we applied to compute CI is based on Rubin (1977, p. 75-81), proper for surveys with replications.
In this cited procedure, we capture *m* times a certain class of $\hat{Q}$ (average quantity of AGB). It is ensured that all possible classes of $\hat{Q}$ be captured 250 times each. With this, the algorithm forces the selection since low to high AGB stocks for model calibration, providing 250 pairs of $\bar{Q}_m/T_m$ per forest/non-forest formation. The maximum Tm observed in each class of $\hat{Q}$ was selected, and then we fit Eq. (5) using the pairs $\bar{Q}_m$/maximum T_m.

$$ln\left(max\hat{T}_m\right) + 10 = \hat{\beta}_0 + \hat{\beta}_1\, ln\left(\bar{Q}_m\right)^{\hat{\beta}_2} + \hat{\varepsilon} \qquad (5)$$

where, $max\hat{T}_m$: maximum total variance of $(Q - \bar{Q}_m)$. In Eq. (5), $\bar{Q}_m$ is the estimate of AGB in the original scale, i.e., $A\hat{G}B_j$. Eq. (5) is applied to provide estimates of CIs for any quantity of AGB and AGC, computed respectively as in Eq. (6) and Eq. (7). The conversion factor 2:1 was applied to convert AGB into AGC, which is a generic factor recommended by IPCC (2006).

$$A\hat{G}B_j \pm t_v(\alpha/2)\sqrt{max\hat{T}_m} \qquad (6)$$

$$1/2\left[A\hat{G}B_j \pm t_v(\alpha/2)\sqrt{max\hat{T}_m}\right] \qquad (7)$$

In Eqs. (14)–(15), $v = (m-1)\left(1 + 1/r\right)^2$, $r = \left(1 + 1/\mathrm{m}\right) B_m/\bar{U}_m$, and $1-\alpha$ is the confidence level (=.95). For this study and for users of the TB&C App, t_v can be safely approximated to 1.96. The last estimators we computed were the absolute and relative errors for AGB in Mg ha^{-1}, respectively expressed by Eq. (16) and Eq. (17).

$$e_a = \pm\, t_v(\alpha/2)\sqrt{max\hat{T}_m} \qquad (8)$$

$$e_r = \pm 100\, \frac{t_v(\alpha/2)\sqrt{max\hat{T}_m}}{A\hat{G}B_j} \qquad (9)$$

In brief, the mean AGB tabulated in Panel 1 of the TB&C App is obtained through Eq. (2); AGC is half of AGB; CIs for the mean AGB and AGC are obtained through Eqs.(6)–(7); and the errors are given by Eqs.(8)–(9).

Panel 2: Treelevel

Here, individual-tree level equations were tested. Data calibration is the same as the used in Panel 1. More detail can be consulted in the original paper of the project TB&C.

Discussion

Advantages of the TB&C App. The inputs (smallest and largest diameters, and number of trees) of the TB&C App are routinely assessed in forest inventories, not increasing field collection efforts. The App provides AGB and AGC estimates along with CIs fixed by uncertainty analysis. These CIs are robustly stemmed from the Bootstrap technique, involving iterative programming processes, which is not so friendly for many. All the estimation process is rapidly computed and with low computational burden, being this a third advantage. Fourth, estimates are given at the stand and tree levels with consistent totals. This is an important benefit for biomass and carbon assessments in which the individual-tree or diameter-class levels are needed, in addition to stand level estimates.

Tips for use. The first tip relates to stand level estimates. The user should make sure that BA and N observed in the forest (or diameter class) are exactly those inputted in the App. For a better use, the BA outputted by the App should be exactly (or approximately) equal to the BA observed in the forest/plots. The importance of inputting exact values of BA and N is because the mean AGB is modeled as a function of these two variables (see Eqs. 19–22). Because of it, the other inputs than BA and N turn into unimportant in the stand-level model predictions. Secondly, at the tree level, users should ensure that the diameter distribution of the observed forest is faithfully depicted in the TB&C App. For this, all input attributes are important, especially parameters of the beta distribution. And the third tip concerns how to obtain these parameters. Users may either estimate alfa and beta by parameterization of the beta p.d.f. – see applications in Lima et al. (2015), Burkhart and Tomé (2012, p. 261–298), and Zheng and Zhou (2010) –, or approximate them by comparing the diameter distribution depicted in the App, with that one observed in their forest/plots. This last option is simpler and easier, in addition to deliver results generally good enough.

Limitations. Due to the lack of data, the TB&C App does not provide information per subclass of the studied formations. Also, not all subclasses of *Campinarana* and *Savana* are covered. The implication of missing subclasses is that the AGB models inherent to *Campinarana* and *Savana*, when applied to these missing subclasses, may offer a misleading estimate of AGB and AGC, although it is unlikely due to the similarity of trees among such subclasses.

Reliability of the TB&C App. For all studied formations, more than 95% (n = 16,000) of observed AGB′s correctly fit into the predicted CI outputted by the TB&C App. Here, it is said ‘observed AGB′s’ because the real AGB in these n simulated plots is known. I.e., these findings are reliable and reveals a great quality and robustness of the TB&C App. As the TB&C App is supported by the largest tree-biomass database compiled so far in Brazil, besides being developed based on Bootstrap and Monte Carlo approaches, and formation-type-specific modeling, it is expected more reliable AGB estimates from this novel application.

Conclusions/ wider implications of findings

The project TB&C brings novelties in the line of the necessity of counties to compose big databases to produce specific biomass equations. The project TB&C have unified smaller datasets collected in the four most important forest/non-forest formation of Brazil. This unification obeyed standards in data collection and measurement criteria, e.g., the condition of the AGB to be destructively measured. These standardizations are recommended by studies as Chave et al. (2014) as a mean of ensuring uniformity of the calibration database. With this, one of our greater contributions is to deliver more reliable, specific equations to researchers that need to know about the AGB and AGC stored in Brazil's forests. The use of the TB&C App is then recommended as alternative to generic and global equations. As a secondary product, the project TB&C delivers a database of plots, informing their dry AGB (Mg ha^{-1}), density (trees ha^{-1}), basal area (m² ha^{-1}), Lorey's height (m), and parameters of shape of the diameter distribution. An amount of 16,000 simulated plots per forest/non-forest formation can be observed.

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