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DYNAMICS OF BIOMASS STOCKS IN AREAS OF SECONDARY FOREST LOCATED IN WESTERN AMAZON BETWEEN 2016 AND 2020

SUMMARY

Secondary forests are portions of forest areas that were previously deforested. In general, secondary forests are characterized by fast-growing species, an alternative for reducing net carbon emissions and mitigating climate change; However, these forest environments are still poorly studied. In this context, this work aimed to adjust predictive models of biomass concerning the height and diameter of trees, analyzing temporally and quantitatively the biomass stocks in areas of secondary vegetation located in Rondônia, Western Amazon, aiming at quantification of aerial biomass in these ecosystems and discuss the implication of abundance of individuals in the estimates. To adjust the allometric equations it was necessary to measure all trees with a circumference at breast height above 15 cm in plots with 200m². After the measurements, a plot tree representing the average diametric variable was selected and slaughtered to calculate its biomass. The adjusted equations presented adjusted r² ranging from 0.49 to 0.57, root means square error (RMSE) from 247 to 296 kg, and residual standard error (Syx) from 49 to 53 kg. In 2016, the plots had an average of 41.47 $t.ha^{-1}$ of biomass, and 2020 recorded 81.66 $t.ha^{-1}$. In this sense, we observed a total increase of 96.92% between 2016 and 2020. Through biomass estimates it was possible to observe that secondary forests are a potentially significant biomass sink due to the rapid accumulation rates of this component. Therefore, biomass stocks were increased over the years of this study, demonstrating the capacity for biomass growth in forests undergoing restoration.

Keywords: Allometric equations; Forest recovery; Amazon biome; Temporal analysis; Tropical Rainforest.

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INTRODUCTION

Human expansion in the Amazon biome has converted large areas of climax-stage tropical forest into landscapes consisting primarily of pasture, agriculture, and secondary forest mosaics. This type of forest is defined as those formed because of the human impact on areas with forest cover. According to Poorter et al. (2016) and Wang et al. (2020b), secondary forests comprise approximately 21 % of the previously deforested areas in the Brazilian Amazon. In general, secondary forests are characterized by fast-growing species (pioneers) and are good alternatives to reduce net carbon emissions, mitigating climate change (Chazdon et al. 2016).

In recent years, new forms of forest and ecological restoration that offer ways of converting degraded tropical forests have been tested. These restoration techniques include improvements in secondary forests management, reforestation, and enrichment planting as more complex reforestation where forest cover has been lost (Matos et al. 2019; Barros et al. 2020). While forest loss continues in Brazil at variable rates, techniques are implemented to develop secondary forests where primary forests have been completely removed by human processes.

The extent and age of Amazonian secondary forests have already been quantified, and their spatiotemporal patterns are highly dynamic (Wang et al. 2020a; Nunes et al. 2020). In this context, these forests are a crucial component in the Brazilian Amazon, as their cover restores the structure and nutrient cycling in the soil. Despite the importance of these forests for conservation planning, environmental policy, and management of forest areas in the Brazilian Amazon, they have been less studied compared to primary tropical forests (Barlow et al. 2007; Carvalho et al. 2019; Teixeira-Santos et al. 2020).

Understanding biomass stocks in secondary forests is essential for forest management and restoration; therefore, biomass estimates are highly sensitive to choosing a particular allometric equation (Chave et al. 2005; Van Breugel et al. 2011). Although local allometric models generally perform well for a particular location or forest type, they are inaccurate in biomass estimates when applied to other sites and different forest types (Chave et al. 2005; Sanquetta et al. 2014b, a; Feng et al. 2017; Corte et al. 2020; Tejada et al. 2020).

Estimating biomass at different scales mainly depends on equations or remote sensing techniques for prediction and analysis at regional and national scale mapping (Mohd Zaki and Abd Latif 2017; Mitchell et al. 2017; Tripathi et al. 2018). These equations are statistical models used to predict biomass based on tree measurement characteristics measured during forest inventory processes. Biomass estimation is particularly challenging in tropical forests due to difficulties with collecting field data in these ecosystems, characterized by a high heterogeneity of individuals, tree measurement variables, vertical structure, and horizontal distribution.

Allometric equations are important for their application in forest biomass and carbon assessments both locally and nationally. Generalized pan-tropical models of biomass estimation equations have been developed by several researchers (Kenzo et al. 2020; Virgulino-Júnior et al. 2020; Romero et al. 2020; Zhou et al. 2021; Latifah et al. 2021; Saha et al. 2021). The adjustments to these equations were obtained by measuring multiple tree species and several distinct locations and are intended to be applied to a wide variety of tropical forests. However, a large error is observed when estimates are generated by adopting generic pan-tropical allometric equations for specific forest types (Ngomanda et al. 2014; Vinh et al. 2019).

With limited research on secondary forests and their biomass stocks, it is possible that these stocks are quantified through allometric equations arising from measurements and field observations and that this prediction can be used for the temporal analysis of these stocks in forest environments. In this sense, this work aimed to adjust predictive models of biomass concerning the height and diameter of trees, analyzing temporally and quantitatively the biomass stocks in areas of secondary vegetation located in Rondônia, Western Amazon, aiming at quantification of aerial biomass in these ecosystems and discuss the implication of abundance of individuals in the estimates.

MATERIAL AND METHODS

This study was carried out in a region of the Amazon rainforest located in the state of Rondônia, Brazil, between the meridians 62º44'05" and 63º16'54" and parallels 9º00'00" and 9º30'00" of south latitude, as shown in Figure 1. The areas refer to forest restoration plantations, containing 20 plots with 200 m² (20 x 10 m) monitored annually to assess the growth of trees, natural regeneration of new species, and biomass stock monitoring (Figure 1).

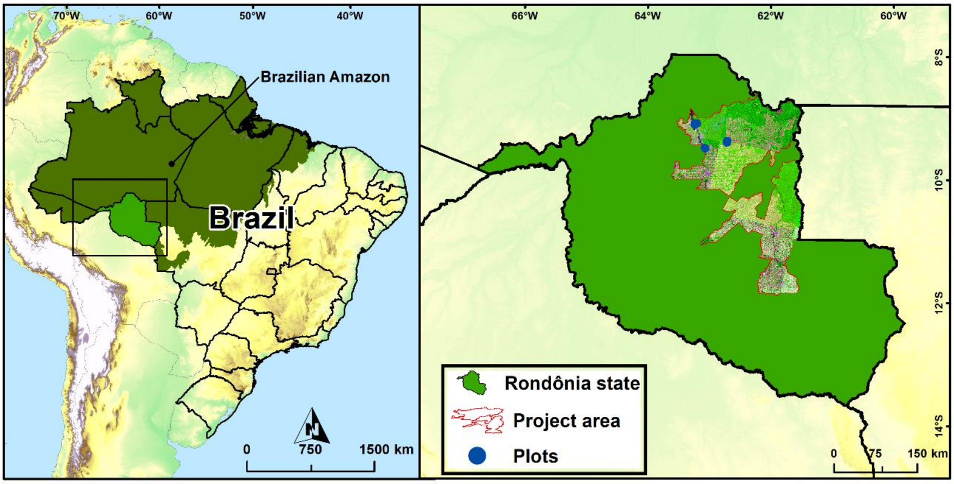

Figure 1. Location of the study area and experimental plots.

All trees in the plots with a circumference at breast height (CBH) above 15 cm were identified to measure their CBH and total height (ht), the circumferences were measured using tape measures and total heights were measured with telescopic rods. The species that could not be identified in the field had some branches collected and, when possible, also the reproductive structures. Exsiccates were made, identified, herborized, and registered at the Federal University of Rondônia (UNIR), with the support of the Museu Paraense Emilio Goeldi de Botânica.

Acquisition of forest biomass

After the forest inventory, the species with the greatest phytosociological importance were listed to determine the biomass by the destructive method. On the other hand, the diametric distribution was used to select individuals to be slaughtered and measured; that is, the average diameter at breast height (DBH) of the plot was represented by a single individual that had approximately that diameter.

To determine the biomass, 30 trees were felled and sectioned into bole, branches, foliage, and miscellaneous (fruits, flowers, shoots, among others). The root system was exposed until 50 cm depth; all exposed parts were collected and cleaned. The fractions collected from the trees were weighed separately using a digital scale with a precision of 100g, obtaining the fresh weight of each compartment. Approximately 500g biomass was taken from each fraction of fresh samples and placed in single packages to be taken to the laboratory. These samples were dried in a forced circulation oven at 65 ºC until reaching constant weight. Then, the conversion into dry biomass of each compartment was performed according to Equation 1.

$$bs_x = bf_x \frac{(100 - u_x)}{100} \qquad \textbf{eq. 1}$$

Where:
bs_x = tree dry biomass of fraction x (kg);
bf_x = tree fresh biomass of fraction x (kg); and
u_x = tree moisture content of fraction x (%).

To obtain the total biomass of each tree, the sum of each biomass fraction was performed according to Equation 2.

$$W = \sum ba + bf + br \qquad \textbf{eq. 2}$$

Where:
W = total biomass (kg);
ba = tree aboveground dry biomass (kg);
bf = tree bole dry biomass (kg);
br = tree root dry biomass (kg).

Adjusting the equations

The data obtained in the field - ht, Biomass (W), and CBH (later converted to DBH - diameter at breast height) - were used to adjust equations to estimate tree individual biomass. The R software version 4.04 (R team, 2021) was used to adjust the equations with the *olsrr* package from which by inserting the variables (dependent and independent), it is possible to obtain all combinations between the independent variables. In addition to linear equations, we also analyzed non-linear, exponential, logarithmic, and polynomial models, as shown in Table 1.

Table 1. Generic equations used in adjustments

Generic equations
$y = x_1 + \cdots + x_k$
$y = x_1 + \cdots + x_k + [\log(x_1 + \cdots + x_k)]$
$y = x_1^2 + \cdots + x_k^2$
$y = \log(x_1 + \cdots + x_k)$
$y = \dfrac{x_1 + \cdots + x_k}{x_2 + \cdots + x_k}$
$\log y = x_1 + \cdots + x_k$
$\log y = x_1^2 + \cdots + x_k^2$
$\log y = x_1^2 + \cdots + x_k^2 + [\log(x_1 + \cdots + x_k)]$
$y = x_1^{x_2} + \cdots + x_k^{x_j}$
$y = x_1^{\beta_1} + \cdots + x_k^{\beta_j}$
$y = \exp(x_1 + \cdots + x_k)$
$y = \exp(x_1^2 + \cdots + x_k^2)$

For all models tested in this study, biomass (kg) was used as dependent variable (y), and DBH and ht as independent variables. The Kolmogorov-Smirnov normality test was used to check the residuals normality of the dependent variable with the independent. The Bartlett variance homogeneity test was used to compare the variance of two or more samples to decide whether they are taken from populations with equal variance.

The selection of the model that best suited our data was performed using adjustment metrics: sum of squared estimate of errors (SSE), r^2 (determination coefficient), adjusted r^2 (adjusted determination coefficient), RMSE (root mean squared error), Bias, x^2 (chi-square), Syx% (standard error of the estimated percentage) and Syx (estimated standard error). The Meyer Correction Factor was used to correct the logarithmic discrepancy in models in which the dependent variable was submitted to logarithmic transformation

Model validation was performed using the K-fold technique with separation of 10 subsets (k = 10); this cross-validation method involves dividing the dataset into k-subsets. Each subset is maintained while the model is trained on all other subsets; the fitted model is then used to test the subset that was not used. The models that obtained the best statistical metrics were submitted to visual analysis of their fit lines (Observed data versus Adjusted data) and analysis of standardized residuals.

RESULTS

Table 2 shows the characteristics of the 30 trees cut in sections and measured. These individuals represented 22 species and 11 families (Table 2). Diameters ranged from 5.41 to 13.06 cm, with a mean of 9.47 cm and a standard deviation of 2.57 cm. Heights ranged from 5.23 to 11.80 m, with a mean of 8.18 m and a standard deviation of 1.75 m.

Table 2. Species collected and descriptive statistics of diameters and heights of felled trees for biomass calculation.

Family	Epithet	DBH (cm)	*ht* (m)
Anacardiaceae	*Anacardium* sp.	9.87	8.90
Bignoniaceae	*Handroanthus* sp.	12.10	8.00
	Handroanthus sp.	12.29	8.46
	Handroanthus serratifolius L.	10.83	7.02
Bixaceae	*Bixa orellana* L.	7.17	7.00
Boraginaceae	*Cordia alliodora* (Ruiz & Pav.) Cham.	12.19	10.97
Euphorbiaceae	*Hevea brasiliensis* L.	8.12	9.35
Fabaceae	*Stryphnodendron* sp.	10.50	8.80
	Hymenolobium pulcherrimum Ducke	6.05	6.15
	Inga cylindrica (Vell.) Mart.	10.98	8.60
	Enterolobium sp.	5.89	5.80
	Schizolobium amazonicum Huber ex Ducke.	12.73	10.80
	Parkia multijuga Benth.	11.94	7.70
	Hymenaea courbaril L.	13.05	9.80
	Enterolobium schomburgkii (Benth.) Benth.	5.73	6.30
	Schizolobium amazonicum Huber ex Ducke.	7.42	7.35
	Hymenaea courbaril L.	5.44	5.23
	Apuleia leiocarpa (Vogel) J. F. Macbr.	9.90	9.50
	Dipteryx odorata (Aubl.) Willd.	7.48	6.55
	Enterolobium schomburgkii (Benth.) Benth.	9.24	9.90
	Dipteryx odorata (Aubl.) Willd.	7.32	11.00
	Enterolobium schomburgkii (Benth.) Benth.	9.39	8.60
	Acacia mangium Wild.	13.06	9.20
	Parkia multijuga Benth.	7.64	6.95
Hypericaceae	*Vismia guianensis* (Aubl.) Choisy	5.41	7.00
Malvaceae	*Ceiba pentandra* (L.) Gaertn.	10.66	6.25
Melastomataceae	*Bellucia grossularioides* (L.) Triana	8.92	6.40
Meliaceae	*Cedrela odorata* L.	7.51	6.65
	Cedrela odorata L.	13.06	9.50
	Descriptive statistics	**DBH (cm)**	***ht* (m)**
	Average	9.47	8.18
	Standard error	0.47	0.32
	Median	9.63	8.23
	Standard deviation	2.57	1.75
	Sample variance	6.61	3.07
	Minimum	5.41	5.23
	Maximum	13.06	11.80

Figure 2 shows the diametric distributions for 2016 and 2020. In the first year of monitoring, there were more trees with smaller diameters than those measured in 2020, when fewer individuals with larger diameters were measured. In this sense, this image shows that the years of monitoring have seen a mortality of trees and a development of the remaining trees. The blue column shows the individuals measured in 2016 and the yellow column shows the individuals in 2020, it can be seen that there is a higher frequency of trees in 2016 compared to 2020.

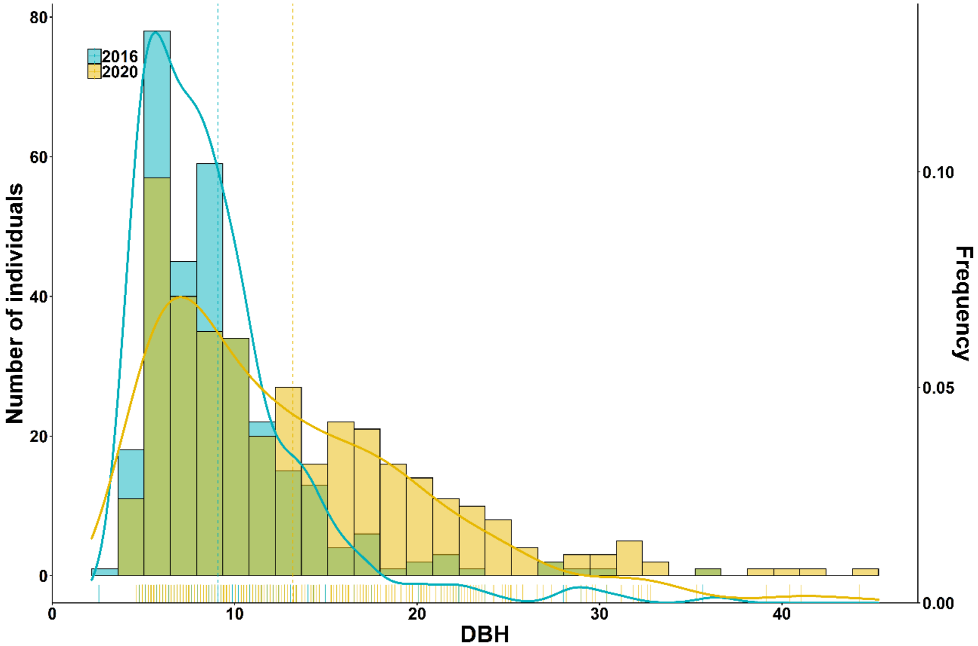

Figure 2. Diametric distributions of trees in 2016 and 2020.

Adjusted equations

The Kolmogorov-Smirnov test showed that the residuals are normal (ρ = 0.2514). Thus, it was possible to adjust the models without transforming the variables. We also obtained the homogeneity of the variance through the Bartlett test (ρ = 0.4304).

Figure 3 demonstrates the comparison of observed and adjusted data from the five best models. It presented similar behaviors to the adjustment, with an overestimation when the biomass exceeds 35 kg. The residuals demonstrate that this overestimate can reach up to 25 kg more than the observed biomass and, with values less than 35 kg, there is an underestimate varying up to 25 kg less.

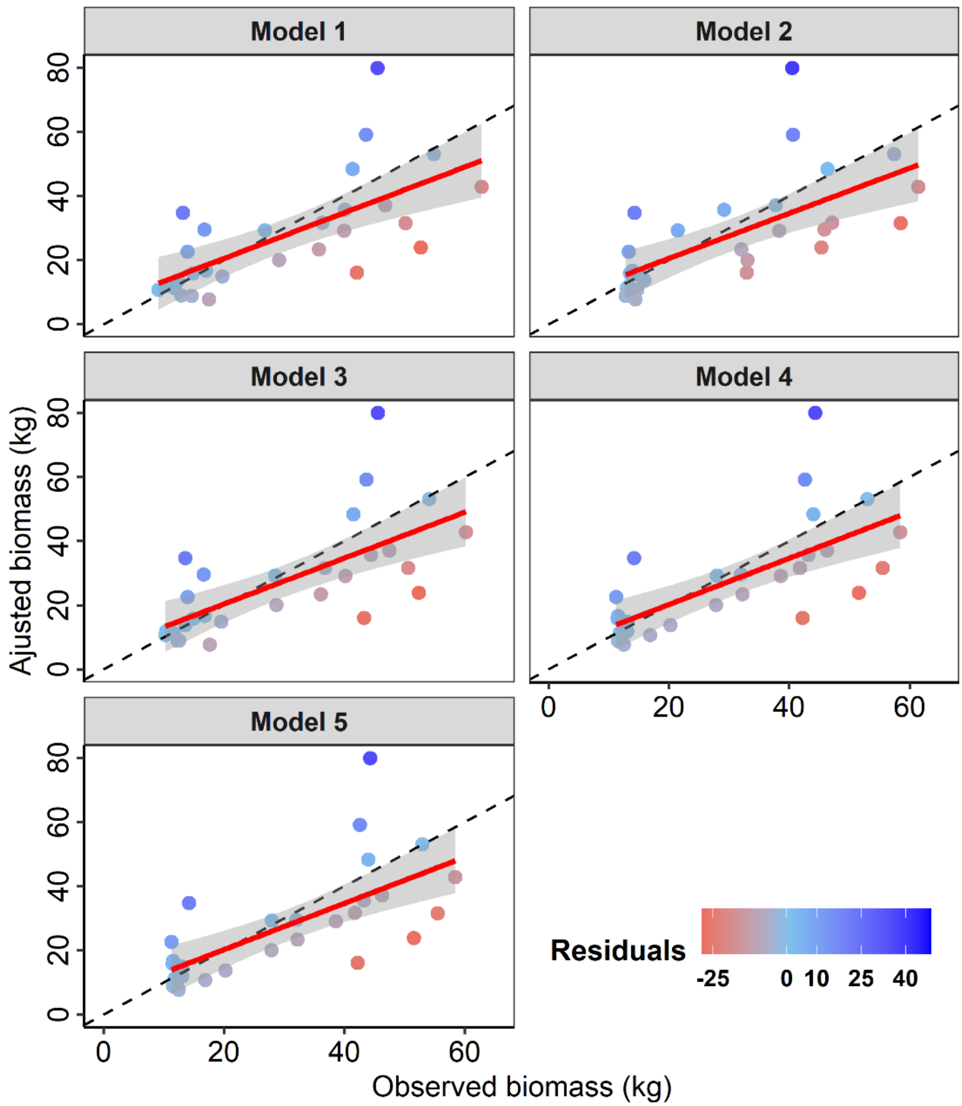

Figure 3. *Comparison* of the five best models against observed and adjusted data.

Table 3 shows the five best fits for predicting biomass using the DBH and total height variables. Model 1 presented the best values concerning comparative statistics. Later, this model was used to calculate the biomass for all trees measured in the plots for each year.

The residuals shown in Figure 4 demonstrate that the error variances are constant (homoscedastic) and that the independent variables (DBH and ht) have a linear relationship with the dependent variable (w). We observed that the standardized residuals were randomly dispersed around zero, with constant variance, concentrated between -1 and 1.

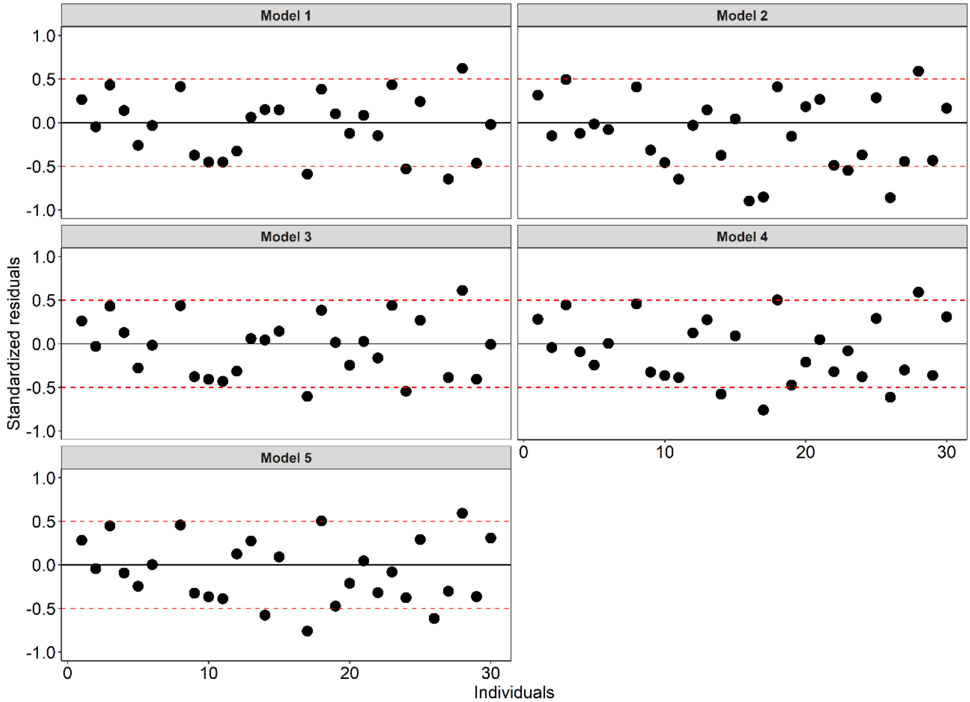

Figure 4. Graphical distribution of total biomass standardized residuals for the five best-fitted models, the y axis indicates the standardized residuals, while the x indicates the total observations.

Table 3. Five best equations obtained through adjustments, according to statistical criteria.

	Models	SSE	r^2	r^2_{ajus}	Bias	RMSE	Syx (kg)	Syx %	x^2
1	$w = 142.54 - 35.25DBH - 18.08ht + 5.77DBH.ht$	7416.86	0.55	0.57	$-9.28x10^{-15}$	247.22	15.72	49.30	201.16
2	$w = 525.23 - 161.41DBH - 100.41ht - 20.30 \log DBH.ht$	7745.75	0.54	0.55	$5.58x10^{-16}$	258.19	16.06	50.38	204.84
3	$w = -34.46 + \frac{1.65DBH}{0.02DBH.ht}$	8836.56	0.47	0.49	$5.57x10^{-16}$	294.55	17.16	53.81	218.31
4	$w = -6.04 + 1.72ht^2 - 1.52DBH$	8868.51	0.47	0.49	$-2.04x10^{-15}$	295.61	17.19	53.91	218.61
5	$w = -6.04 + \frac{-1.52ht}{1.72DBH}$	8889.78	0.47	0.49	$-1.85x10^{-15}$	296.32	17.21	53.97	214.07

Where: SQE = Error sum of squares, r^2 = Determination coefficient, r^2_{ajus} = Adjusted determination coefficient, RMSE = Root mean squared error, x^2 = chi-square, Syx = Estimated standard error, and Syx% = Standard error of the estimated percentage.

Estimated biomass

Figure 5 demonstrates the application of the adjusted model to all trees measured in the plots concerning diameter and height. There is a higher concentration of trees in the classes up to 20 cm in diameter with biomass up to 200 kg; However, from the class with 20 cm, there is a smaller number of individuals with biomass above 200 kg per tree (Figure 5A). Regarding heights, there is a concentration of trees above 5 m and smaller than 15 m.

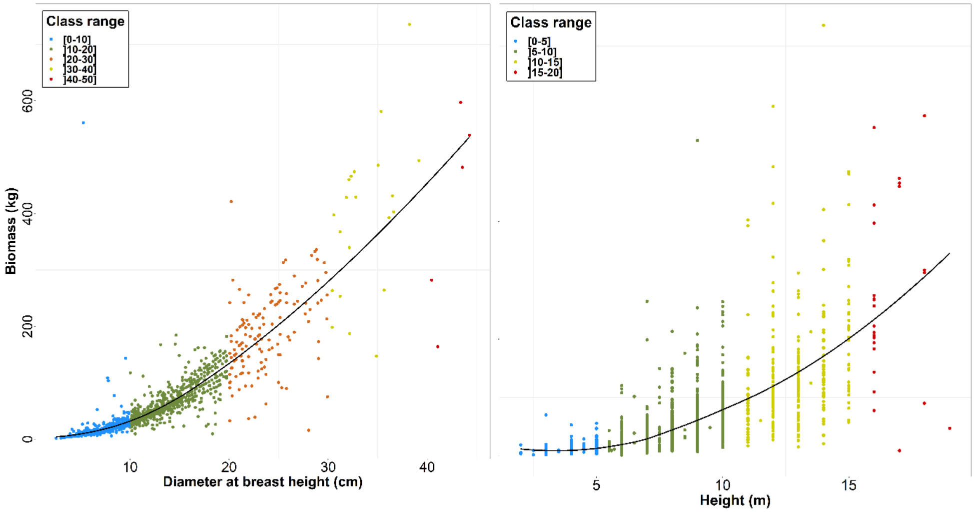

Figure 5. Biomass distribution concerning diameter and height class range.

Biomass stock in the plots

The prediction of biomass showed that, except for Plots 6, 7, 18, and 19, it was affected by an increasing trend in biomass stock between the years 2016 to 2020; However, in four plots (1, 2, 17, and 18) it was not possible to obtain data for all years of the inventory. The following growth percentages were observed between the years under study: Plot 3 (93.42 %), Plot 4 (30.39 %), Plot 5 (89.69 %), Plot 6 (25.96 %), Plot 7 (115.23 %), Plot 8 (73.39 %), Plot 9 (66.09 %), Plot 10 (94.32 %), Plot 11 (175.54 %), Plot 12 (123.87 %), Plot 13 (65.59 %), Plot 14 (141.46 %), Plot 15 (137.28 %), Plot 16 (113.84 %), Plot 18 (117.55 %), and Plot 19 (90.74 %) (Figure 6).

In 2016, the largest stock of biomass among the inventoried plots was in Plot 18 (55.42 t.ha^{-1}) and the smallest in Plot 14 (15.86 t.ha^{-1}), while in 2020, Plot 11 presented the largest stock (135.23 t.ha^{-1}), and the lowest value was 30.91 t.ha^{-1} (Plot 6). It is observed that Plots 6, 15, 18, and 19 showed a reduction in their stock between 2019 and 2020 (-4.99, -2.25, -6.25, and -18.31 t.ha^{-1}, respectively).

Regarding the abundance of individuals per hectare, it was possible to observe that Plots 3, 12, 13, 16, and 19 were not affected by a reduction in individuals in 2019, while in the other Plots there was a decrease in the number of trees. The average number of trees in the plots was: 2016 (1,198 trees.ha^{-1}), 2018

(1,466 trees.ha^{-1}), 2019 (1,118 trees/ha), 2020 (1,468 trees.ha^{-1}). It is observed that Plot 8 has the greatest abundance (2,200 trees.ha^{-1}), while Plot 16 had only 738 trees.ha^{-1}.

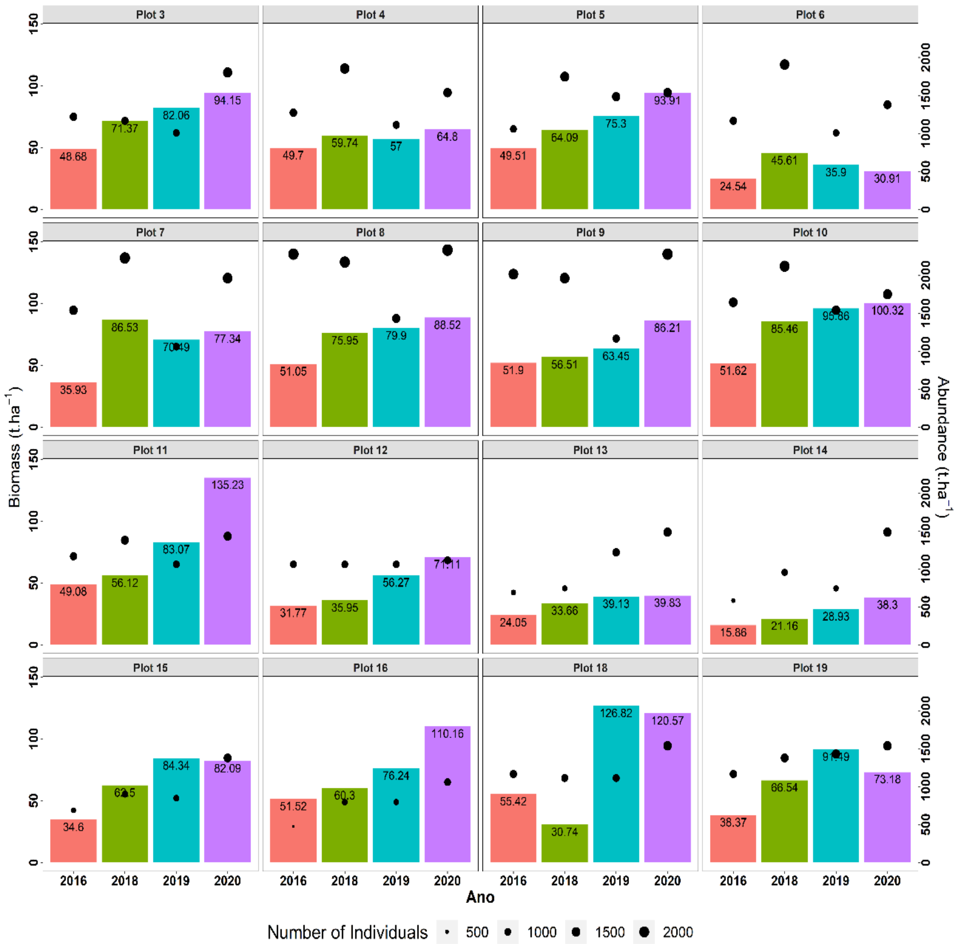

Figure 6. Biomass stock from plots inventoried in the years 2016 to 2020.

Figure 7 demonstrates the distribution of biomass stock in the plots concerning the years that the inventories took place. In 2016, the plots had an average of 41.47 t.ha^{-1} and a deviation of 12.29 t.ha^{-1}. 2018 presented a total of 57.02 t.ha^{-1} and 19.20 t.ha^{-1} deviation. 2019 presented an average 71.64 t.ha^{-1} and 24.77 t.ha^{-1} deviation. However, 2020 recorded an average of 81.66 t.ha^{-1} and 28.99 t.ha^{-1} deviation. In this sense, a total increase of 37.50% between 2016 and 2018 was observed, 25.64% from 2018 to 2019 and 13.99% from 2019 to 2020, therefore a total increase from 2016 to 2020 of 96.92% was observed.

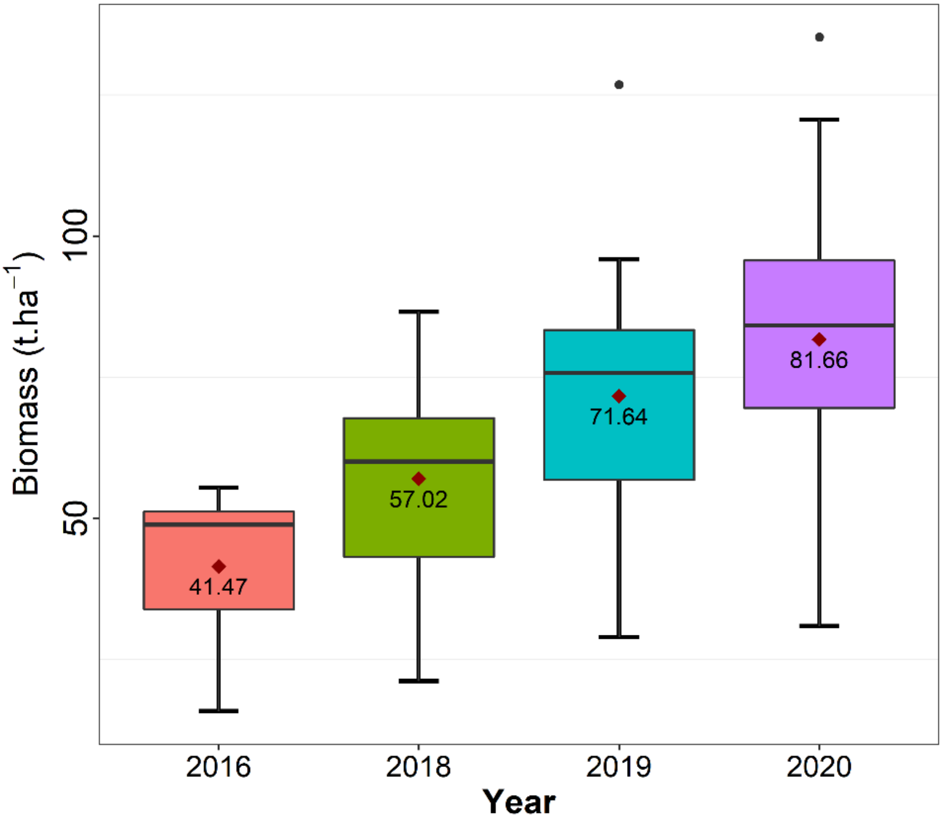

Figure 7. Total biomass stock of plots inventoried in the years 2016 to 2020.

DISCUSSION

The allocation and determination of biomass will play an important role based on previously degraded forests that have undergone restoration/recovery processes. In this context, the adjusted models predicting biomass from DBH and ht demonstrate that there is a low correlation between the dependent and independent variables. The adjusted correlation coefficients ranged from 0.49 to 0.57, which can be explained by the diversity of species sampled, increasing the variability of measured biomass, diameters, and heights among the sampled trees.

By analyzing Model 1, chosen among the five best ones, it was possible to observe that biomass prediction with this model was satisfactory because it presented values consistent with the area and with the values obtained in the field. However, Romero *et al.* (2020) observed superior statistical metrics when estimating the biomass of trees harvested in southWestern Amazonia and reported that the quality of the adjustments was characterized by the expressive quantity of samples collected (223 individuals). Karyati *et al.* (2019), observing secondary forests, showed similar results to this study and concluded that the heterogeneity of secondary forests significantly reduces the relationships between diameters, heights, and biomass.

In this sense, several factors influence the development of tree species in secondary forests; thus, characteristics such as canopy architecture, local productive capacity, and competition for light may be related to the low statistical values observed for the estimates made in this study. In addition to these factors, in native forests, forests undergoing restoration, and in mixed plantations, greater heterogeneity in tree development is to be expected, caused by the existence of interspecific competition, which contributes to obtaining standard error values for the highest estimate (Sanquetta et al. 2017; Lima et al. 2021).

The reduction observed in biomass stock in plots 6, 7, 18, and 19 is explained by the mortality of trees and illegal logging, which were responsible for the reduction of biomass in those plots, reducing trees density and consequently the total stock values. In particular, plots 18 and 19, which are on the transition with soybean crops, were affected by partial removal of forest vegetation for soybean implantation.

The results obtained in this study were consistent with those observed in Yang *et al.* (2020), where the authors estimated the aboveground biomass using remote sensing techniques for areas undergoing restoration with ages ranging from 1 to 8 years and biomass ranging from 20 to 70 $Mg.ha^{-1}$. Cassol *et al.* (2019) observed that areas in the Amazon undergoing a 10-year restoration process have less than 100 Mg/ha, with data obtained through Alos/Palsar-2. The difficulty in obtaining biomass in the field is a determining factor for this variable acquisition through remote sensors.

Studies show that the greater density of individuals in an area, the greater production of biomass per unit area; that is, the spacings between the denser individuals provide higher amounts of biomass than the smaller ones (Pereira 2013; Eloy et al. 2016; Favero et al. 2020; Castanho et al. 2020; Shen et al. 2020; Næsset et al. 2020). It was possible to observe in this study that Plots with lower abundances per hectare may also have biomass stocks equivalent to Plots with greater abundance as the size (height and DBH) of individuals directly influenced the mean value of biomass. In 2020, Plots 6 and 16 had an equal number of trees per hectare (1,300 $trees.ha^{-1}$) but biomass was respectively 30.91 and 82.09 $t.ha^{-1}$. It links to the average diameters and heights of trees in the plots, which was higher for Plot 15 with an average DBH of 15.6 cm and an average height of 9.4 m, while in Plot 6 averages were 12.8 cm and 7.4 m.

The information presented regarding secondary forests is essential for the monitoring and management of these areas because it subsidizes policies and proposals for environmental management in the Amazon. These forests are a possible solution for carbon absorption and climate change control, besides conserving biodiversity. Therefore, the reduction of deforestation, agriculture, and cattle raising allied to the maintenance of forest areas are vital to mitigate the impacts caused by climate change.

CONCLUSIONS

The adjusted models using diameter at breast height (DBH) and total height (ht) as independent variables present satisfactory statistics and can be used to estimate tree biomass with precision.

The results demonstrate that few trees with large dimensions are responsible for biomass stock in areas under restoration, while the abundance of individuals per hectare influences biomass stock. However, the main factor in these stocks were heights and diameters; in this sense, the larger the trees, the greater biomass stocks.

Through the biomass estimates, it was possible to observe that secondary forests are a potentially significant biomass sink due to the rapid accumulation rates of this component. Therefore, biomass stocks were increased over the years of study, demonstrating the capacity for biomass growth in forests undergoing restoration. However, frequent disturbances interrupt the recovery process and consequently the establishment of mature forests.

The value of secondary forests as a biomass stock needs to be determined within a context of dynamic land use, assessing stocks in primary forests concerning secondary forests and areas with other land uses.

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