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Dinâmica da Biomassa Acima do Solo na Amazônia Brasileira Usando Dados LiDAR
Dynamics of Above-Ground Biomass in the Brazilian Amazon Using LiDAR Data

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Resumo

A biomassa de florestas tropicais desempenha um papel importante no ciclo global do carbono. Portanto, é importante entender melhor as variações nos estoques, dinâmica e estrutura das florestas tropicais para uma melhor compreensão do ciclo global do carbono. Nesse sentido, o objetivo deste estudo foi avaliar a dinâmica da biomassa acima do solo (BAS) em uma floresta tropical, utilizando dados LiDAR (*Light Detection and Ranging*) em um período de dois anos (2011-2013). Técnicas automáticas de detecção de copas foram utilizadas de forma complementar para observar se mudanças estruturais podem influir na dinâmica da BAS. O estudo foi conduzido na Floresta Nacional do Jamari, em Rondônia. A metodologia foi composta de processamento LiDAR e classificação de objetos (Copas). Foram geradas estimativas de BAS via LiDAR para as parcelas do inventário florestal e para a amostra da área de estudo. Fortes correlações foram observadas entre as estimativas de AGB (r > 0,88). As mudanças estruturais identificadas das copas delineadas não influenciaram nos valores obtidos para a área amostral, que apresentou um padrão de redução (5,64%). Apesar das mudanças negativas ocorridas, não houve diferença significativa (p > 0,05; teste Tukey) da BAS entre o período avaliado. A tecnologia LiDAR apresenta grande potencial para detectar mudanças em ampla escala, sendo possível obter informações (BAS) precisas do ambiente. O enfoque utilizado pode contribuir para futuras análises que visem avaliar mudanças dos estoques de BAS.
Palavras-chave: Amazônia; inventário; laser

Abstract

Tropical forest biomass plays an important role in the global carbon cycle. Thus, a better understanding of variations in the stocks, dynamics and structure of tropical forests is important to understanding the global carbon cycle. In this sense, the objective of this study was to evaluate the dynamics of above-ground biomass (AGB) in a rainforest using LiDAR (Light Detection and Ranging) data over a period of two years (2011-2013). Automatic crown detection techniques were used in a complementary way to observe whether structural changes may influence the dynamics of AGB. The study was conducted in Jamari National Forest in Rondonia. The methodology was composed of LiDAR processing and classification of objects (Crowns). Estimates of AGB were generated via LiDAR for the forest inventory plots and for the sample of the study area. Strong correlations were observed between estimates of AGB (r> 0.88). The structural changes identified in the outlined crowns did not influence the values obtained for the sample area, which presented a reduction pattern (5.64%). Despite the negative changes that occurred in this study, no significant difference (p> 0.05; Tukey test) of AGB was found among the evaluated period. The LiDAR technology has great potential for detecting large-scale changes and it is possible to obtain accurate environmental information (AGB). The approach used in the study may contribute for further analyses aimed at evaluating changes in AGB stock.
Keywords: Amazon; inventory; laser

1 Introduction

In the last years, remote sensing of forest above-ground biomass (AGB) has been receiving increasing attention because of its relevance to global carbon cycle modeling and to the international programs aimed at reducing GHG (greenhouse gases) emissions in tropical areas, such as the United Nations Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation (REDD +) (Laurin *et al*., 2014)

Regarded as the largest rain forest in the world, the Amazon Forest occupies 5.4 million km² and plays a key role in water cycling, carbon storage and local and regional climate regulation (Clement & Higuchi, 2006; Nobre *et al*., 2006). Yet, because of the raise in mortality rates related to temperature rise and severe droughts (mainly caused by El Niño), forests may act as a source of carbon (Clark, 2004). Indeed, rainforests are sensitive to anthropogenic disturbances, such as deforestation or logging, causing large-scale forest degradation (Van Der Werf *et al*., 2009), which is another way of acting as a source of carbon, emitting GHG into the atmosphere at significant proportions (Fearnside, 1997; Houghton *et al*., 2000).

In this sense, the observation of dynamics of terrestrial biomass becomes a major challenge and one of the main sources of uncertainties in the global carbon cycle (Le Quer *et al*., 2016). Rainforest management requires effective tools to monitor landscapes over time. Field-based tools are valuable, but spatially limited (West & West, 2009). In this medium, among current mapping technologies, LiDAR is considered the most accurate remote sensing technology for biomass mapping (Zolkos *et al*., 2013) and presents a prominent position due to its superior ability to solve the 3D vegetation structure (Vierling *et al*., 2008).

Considered a promising technology for quantifying and monitoring AGB in forest ecosystems, LiDAR provides essential information to understand their dynamics (Lim *et al*., 2003; Wulder *et al*., 2012). The use of airborne laser scanning (ALS) contributes to the enlargement of the sampled area (Asner *et al*., 2012; Asner & Mascaro, 2014), and has been widely used to estimate forest parameters in rainforests (ex. Drake *et al.,* 2002; Saatchi *et al*., 2007; D'Oliveira et al., 2012; Andersen et al., 2014). In addition, it allows to generate a crown eight (CHM) model that can be used for individual tree detection, crown delineation, and later in the estimation of biometric parameters such as volume and biomass (Falkowski *et al*., 2009; Vauhkonen *et al*., 2012; Hu *et al*., 2014; Duncanson *et al*., 2015; Kankare *et al*., 2015; Rex *et al*., 2019). However, most of these studies have mainly focused on improving biomass estimates. To the best of our knowledge, no study on AGB estimation using LiDAR data has been developed to identify structural changes and relate it to biomass stocks. Thus, our study it is the first work that uses LiDAR multitemporal data to understand whether or not automatically identified structural changes may influence biomass stocks.

According to Pereira (2014) tree design holds its elementary application in forest inventory and management, and it has been extensively exploited, with a series of different methods for the detection and measurement of individual trees (Pitkänen *et al*., 2004; Weinacker *et al*., 2004; Heinzel *et al*., 2008; Li *et al*., 2012). In addition, it is an important step of studies whose objective is the extractions of dendrometric information (Suárez *et al.*, 2005). The use of image segmentation techniques with an object-oriented approach are of great help in the classification and segmentation of laser images (Miqueles & Centeno, 2003) and are primordial in the face of advances in the scientific field to obtain more and more accurate information.

Hence, the objective of this study is to evaluate the dynamics of above-ground biomass (AGB) in a rainforest using LiDAR (Light Detection and Ranging) data over a two-year period. So, the main focus was split within the scope of: (i) identifying and individualizing the crowns of the tree individuals by means of automatic processes; (ii) to estimate AGB via LiDAR and to compare it with forest inventory estimates; (iii) to determine whether significant differences occurred between AGB estimates; (iv) and to evaluate whether the changes occurring in the period present significant differences in the stocks of forest AGB.

2 Material and Methods

2.1 Study Area

The study was conducted at Jamari National Forest (Flona), which is located in the north of the state of Rondônia, in the southwestern Brazilian Amazon, between 09º00'00''S and 09º30'00''S, and 62º44'05''W and 63º16'64''W (Figure 1). Jamari Flona was created in 1984 and it is located in the municipalities of Itapuã do Oeste, Cujubim and Candeias do Jamari, covering a total area of 220 thousand hectares. Moreover, the Jamari National Forest is the first to be under concession in Brazil, with an area of approximately 96,000 hectares currently under sustainable management by private companies, while the remaining area is destined to conservation and use by traditional populations (Amata, 2013).

According to the physio-ecological classification of IBGE (2012), it is predominantly covered by Dense Ombrophylous Forest, with some portions of Open Ombrophylous Forest, predominantly of palm trees. In 2008, the Brazilian Forest Service granted 96,000 hectares of Jamari Flona for forest exploitation, split into three Forest Management Units (FMU). Exploration of the first Annual Production Units (APU) started in September 2010.

2.2 Utilized Data

The data used in this study were acquired from the Brazilian Sustainable Landscapes Project, supported by the Brazilian Agricultural Research Corporation (EMBRAPA), the United States Forest Service (USFS), the United States Agency for International Development (USAID) US Department of State.

Forest inventory data were collected in December of 2011 and 2013, with six transects set for the collection of the year 2011 and 24 plots for 2013. In 2011, six 500-m long and 20-m wide transects were set for forest measurement based on a weighted sample of basal area with a 1:10 ratio for trees larger than 5 cm. The forest inventory for 2013 totaled 24 plots of 50x50m systematically arranged along 6 reference rows (transects). Each plot is 50 m x 50 m in size. Within the plots, 10 m x 50 m sub-plots were allocated.

The following were recorded and collected for each tree: common name, family and species, wood density, basal area, breast height diameter, aboveground biomass, total and commercial height, Cartesian rays, UTM coordinates and date of collection.

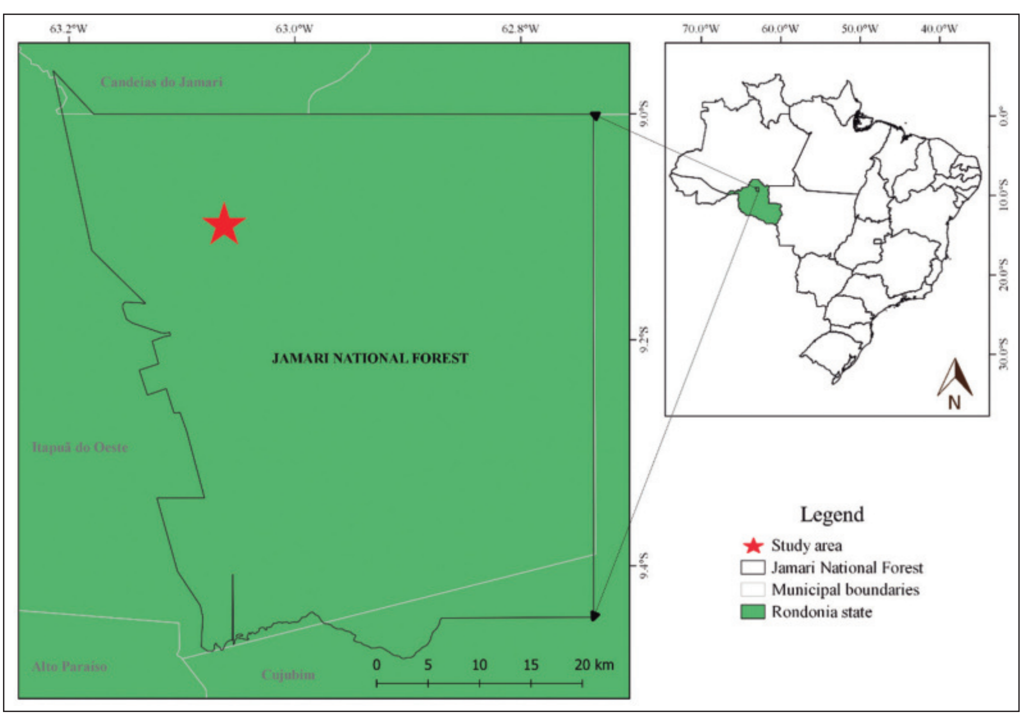

Figure 1 Study site location: the Jamari National Forest, Rondônia state, Brazil.

The LiDAR data are the overflights performed in the same years of field data collection (2011-2013). The area covered in each flyover was 500 ha. Table 1 presents the overflight parameters of the two years.

Specification	2011	2013
Acquisition date	11/17/2011	09/20/2013
Datum	Sirgas 2000	Sirgas 2000
UTM coordinate system:	20S	20S
Total area	500ha	500ha
Pulse density average /m²	15.43 ppm²	15.48 ppm²
Flight average height	850 m	853 m
Field of vision	11,1 °	11.1 °
Scanning frequency	59.8 Hz	67.5 Hz
Overlapping percentage	65%	65%

Table 1 Specification of the overflights for LiDAR cloud collection in 2011 and 2013.

2.3 LiDAR Data Processing

LiDAR data processing was done using FUSION software version 3.60 (McGaughey, 2016), which was developed by the North American Forest Service. This software allows the analyses and visualization of LiDAR data besides being an efficient processing tool (McGaughey, 2014).

First, the "laz" format LiDAR data was selected, and the Windows system M-DOS environment was prepared for processing. Then, the catalog command was used to produce the descriptive report of the LiDAR dataset. Subsequently, the groundfilter command was used to classify the ground points, which is grounded on the filtering algorithm, based on Kraus & Pfeifer (1998). After that, the Digital Terrain Models (DTM) were generated using the product of the previous step, that is, the classified soil points. In this procedure the gridsurfacecreate command was used. This method identifies the point or points within each output raster cell and assigns an elevation value to the cell based on the averaging z value of those points. If there are no points within the output cell, this is filled using the neighboring cell heights (Montealegre *et al*., 2015).

For the normalization of the heights of the study area, ClipData command was used, and the CHM was generated with the canopymodel command. Yet, PolyClipdata command was used to perform the cut of the measured plots in the field, as well as the tree individuals delineated by the segmentation process, which is explained next. From the CloudMetrics command, the LiDAR metrics derived from the plots were extracted, while the GridMetrics command was used to produce the same LiDAR metrics, as calculated with CloudMetrics, but now within grid cells of 50X50m spatial resolution across the landscape according to the methodology presented in Longo *et al.,* (2016) and Silva *et al.,* (2017).

At LiDAR data processing, it was noted that it would not be possible to use the entire data set as some plots of the forest inventory were partially outside the LiDAR overfly, so for 2011, five plots were taken and for 2013, 18 plots were extracted, justifying the fact that not all the plots were used.

2.4 Crown Individualization Via LiDAR

For the individualization of the trees, CHM was used as an input model for segmentation of the crowns in the study area. For this procedure, it was used the algorithm of segmentation per growth of regions implemented in the Cognition software whose main characteristic is an object-oriented approach, which is a great help for the classification and segmentation of laser images (Miqueles & Centeno, 2003).

Because it is a rainforest with great heterogeneity of species and heights as well, a series of values for the segmentation of the CHM was tested. The tree crown segmentation consisted of combinations of Scale Parameters and Shape and Compactness values. The values tested were, as follows: Scale Parameter – SP, ranging from 10 to 50 with an interval of 5, whereas for Shape and Compactness, the values that were tested ranged from 0.1 to 0.9 with a 0.1-interval between parameters.

Following segmentation procedure, the results were exported to the software Arcgis 10.4 and homologous crowns among the evaluated years were selected upon CHM. Afterwards, the corresponding values of total height of individuals were extracted via LiDAR cloud, as well as the crown area (CA) in square meters (m²).

2.5 AGB Estimation Via Field Data

As the forest inventory data set holds breast height diameter data and species identification, the equation developed for biomass estimation proposed by Chave *et al.,* (2005) was applied as a function of diameter and density. Chave *et al*. (2005) used data from 28 sites in tropical forests across a wide latitudinal range (12° S to 25° N) to develop a pantropical allometric models for tree mass based on DBH, total height, and wood density.

$$AGB = \rho * exp\left(-1{,}499 + 2{,}148\, ln(BHD) + 0{,}207\, (ln(BHD))^2 - 0{,}0281\, (ln(BHD))^3\right) \quad (1)$$

Where: AGB is the above ground live woody biomass (kg), ρ is the wood density (g.cm³) and BHD is the breast height diameter (1.30 m).

2.6 AGB Estimation Via LiDAR Metrics

The AGB estimation were predicted using the equation that have been taken from D'oliveira *et al*., (2012). A multiple linear regression model using the 25th percentile height above ground of all lidar returns (P25); and the variance of all lidar return heights above ground (VAR) as predictor variables provided a robust, parsimonious regression model for AGB estimation via LiDAR metrics. D'oliveira *et al*., (2012) calibrated the model based on 50x50-m field plots. So, to avoid inconsistencies at the application of the equation in the present dataset, a 50-m resolution grid was generated for the year 2011, and later, the estimation and extraction of AGB of the transects (500x20m). Despite the data set referring to the year of 2013, the metrics for AGB estimation were generated directly in the plots (50x50m). In a second moment, the estimates were obtained for the entire LiDAR study area, considering the 50-m resolution grid.

$$AGB = (3{,}119 + 0{,}564\, P25 + 0{,}062\, Var)^2 + 1{,}74 \quad (2)$$

Where: AGB = above ground biomass (Mg.ha-1 tree DBH ≥ 10 cm); P25 = equals to the returns in the first quartile or 25% percentile; Var = elevation variation.

2.7 Dynamics of AGB and Structural Changes in the Crowns

The dynamics of the AGB in the study area was evaluated based on the 50-m resolution grids, generated for both years. However, the crown design served as a complementary evaluation to observe whether structural changes in crowns and heights of tree individuals could influence the dynamics of AGB.

2.8 Statistical Evaluation

The relationships between the generated estimates of the plots biomass were evaluated by the coefficient of determination (R²) and by the Pearson correlation coefficient (r). However, the AGB changes estimated by LiDAR in 2011-2013 period were analyzed in terms of estimated values, which were submitted to analysis of variance (ANOVA) and to the test of Tukey at 5% of probability.

3 Results

3.1 LiDAR Estimates Versus Forest Inventory

The relationship between AGB estimates via LiDAR versus Forest Inventory exhibit strong relationships with values of R^2 coefficient of determination of 0.9198 and 0.7918, for 2011 and 2013, respectively (Figure 2).

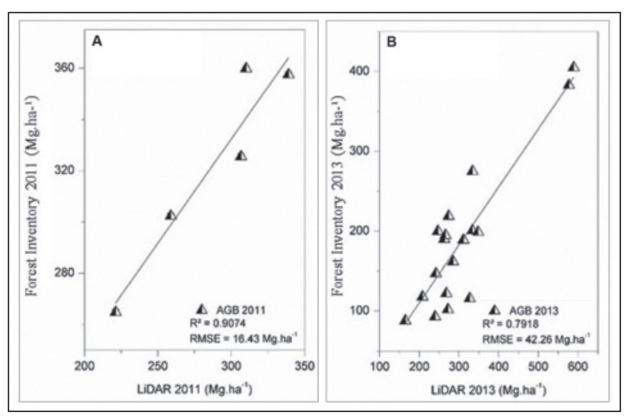

Figure 2 Relationships found for AGB estimates. AGB 2011) relationships of the estimates for 2011 transects; AGB 2013) Relationships of the estimates for plots in 2013.

The values found for the Pearson correlation coefficient were 0.9590 for 2011 and 0.8891 for 2013. The reduction found for the coefficient of determination R^2 in the 2013 estimates is related to the shape of the plot the sampling used for 2011was carried out in 1-ha transects and for 2013, sampling was performed in 0.25-ha square plots.

The AGB estimates via LiDAR data are close to estimates of the forest inventory data. The AGB estimated via LiDAR data for 2011 presented an average of 287.14 ± 46.77 $Mg.ha^{-1}$, whereas the average of AGB via forest inventory data was 321.98 ± 39.86 $Mg.ha^{-1}$.

The AGB estimated for 2013 presented greater variations. On average, the estimate via LiDAR was 308.47 $Mg.ha^{-1}$, while the estimate via field inventory was 189.19 $Mg.ha^{-1}$. For these estimates, higher values of standard deviation were also observed, such as 110.13 Mg.ha-1 and 89.97 Mg.ha-1 for the estimates via LiDAR and Field Inventory, respectively.

3.2 Crown Segmentation

The segmentation values that provided the best results for crown extraction for 2011 were: Scale Parameter (15 and 35), in which 0.60 and 0.30 are the values of shape and compactness that were the best fit, respectively, whereas for 2013, the following values were achieved: three Scale Parameter results (45; 35 and 25), and their respective values of shape and compactness of 0.30 - 0.60; 0.60 - 0.10 and 0.2-0.8. These values made up 40 crowns for each year.

The process of crown delimitation allowed to observe notorious changes in the forest canopy between the two-year period (Figure 3). The alternative for a segmentation with more than one result, allowed the extraction of varied forms of tree crowns since, because of the heterogeneity of the analyzed forest, the achievement of good results becomes very complex when only one parameter is defined for this procedure.

3.3 Structural Changes

The structural changes observed in CA and heights in the 2011-2013 period presented high values of coefficient of determination (Figure 4). The value R^2 = 0.9572 was found for the CH parameter, and for the heights, R^2 = 0.9856. Overall, in terms of values, these parameters were somewhat regular, showing some increments in the values over two years, since the angular coefficient of linear regression was significantly higher than 1.

The pattern of distribution observed for the extracted CAs presents a large majority of individuals with smaller crowns (36.9 - 180.3 m²)

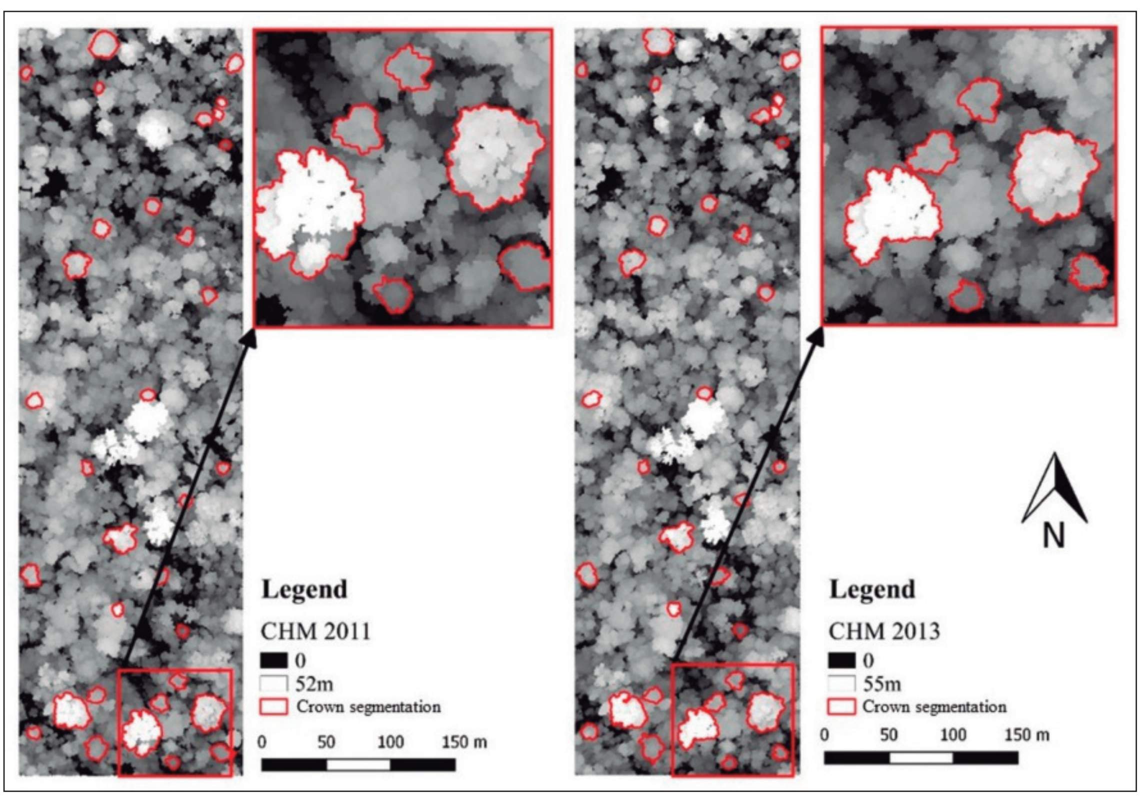

Figure 3 Crown segmentation results of Crown Height Models generated by LiDAR data processing.

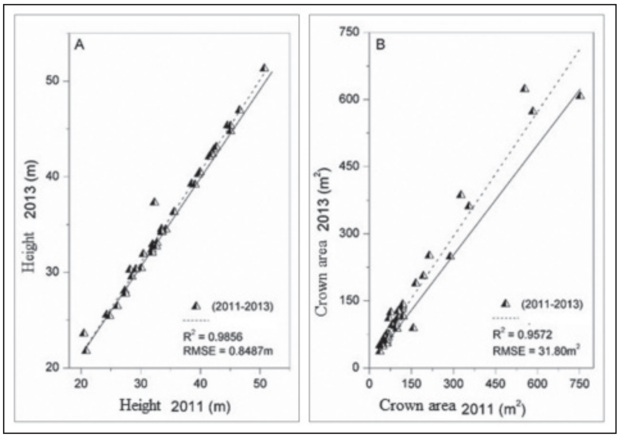

Figure 4 Relationships found for the parameters obtained with crown detection. A) Tree height extracted from CHM for 2011 and 2013. B) CA of trees extracted from CHM for 2011 and 2013.

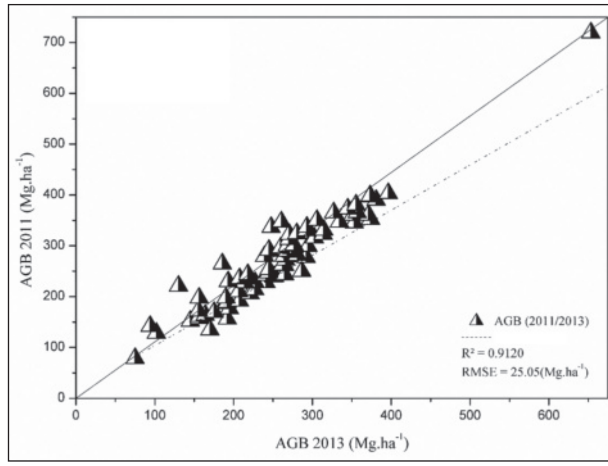

Figure 5 Distribution of the values found for estimates of above ground biomass of forest samples for 2011 and 2013.

and later, a significant reduction of individuals with increased crown area (≥180.3m²). In terms of values, the average CA of the outlined trees were 145.81 m² and 151.53 m², for 2011 and 2013, respectively, and the total CA for 2011 was 5832.39 m² and 6061.52 m² for 2013. These values represent an increase by approximately 4% of the CA between the evaluated periods.

3.4 AGB Dynamics in the Study Area

The AGB values estimated for the forest (Figure 5) show regularity as well as the values of CA; however, the pattern for the forest LiDAR sample shows a reduction in the AGB between the evaluated years (angular coefficient less than 1). It is noticed the occurrence of an approximation in the line angle of the linear adjustment at 45 degrees, which characterizes the coincidence region of the estimate. In terms of values, a loss by 1220.28 Mg.ha-1 of AGB occurred between 2011 and 2013, representing a reduction of 5.64% in approximately two years.

The total AGB stock for the approximately 15ha of forest evaluated in 2011 presented the value of 21636.15 Mg.ha^{-1}, while for 2013, the stock value was found in 20415.87 Mg.ha-1. On average, the forest had values of 270.45 ± 90.26 Mg.ha^{-1} for 2011 and for 2013, the values were 255.19 ± 83.92 Mg.ha^{-1}.

The analysis of variance revealed no significant changes in the evaluated period (2011-2013) at a 5% probability level. The same pattern is also indicated by the means comparison test (p> 0.05; Tukey test).

4 Discussions

The values of crown height models represent the largest forest heights, and the use of crown height models of a large forest becomes a viable alternative in relation to the time and money invested (Castro & Centeno, 2005) since the high CHM data resolution offers the possibility of detecting the measurements of individual trees (Persson *et al*., 2002).

According to the classification proposed by Mukaka (2012), the correlations of the LiDAR estimates versus Forest Inventory indicate a very high positive correlation for 2011 and a high correlation for 2013. Regarding the sizes and shapes of the plots, Melo (2017) observed that an underestimation occurred for 0.25 ha because it did not effectively represent the diametric distribution of the forest.

In general, small plots (0.25 ha) are not adequate to calibrate biomass estimated via LiDAR data (Mascaro *et al*., 2011; Longo *et al*., 2016). The accuracy of biomass estimates based on LiDAR data increases as the size of field calibration plots is incremented (Asner & Mascaro, 2014; Mauya *et al*., 2015). The size and shape of the plots alter the sampling probability of large diameter trees (Higuchi *et al*., 1982; Brown *et al*., 1989), as well as the intensity of the edge effect, which results in an increase in the variance with 50-mx 50-m plots (0.25 ha) (Melo, 2017).

A number of surveys show good relationships between estimates generated via LiDAR data and field inventory data. Authors such as (Sato *et al*., 2015, Figueiredo *et al.,* 2016, Santos *et al*., 2017; Rex *et al*., 2018), obtained relevant results in their work using LiDAR data in rainforest. The average AGB via LiDAR of the plots analyzed in this study (287.14 ± 46.77 Mg.ha-1) was close to the average biomass of the Amazonian forests (Saatchi *et al.,* 2011; Baccini, 2012).

The heterogeneity in the native environment displays several shapes of crowns as well as great variation in the heights of the tree individuals. Consequently, it was observed in the segmentation process that some crowns were better segmented with lower values for the scale parameter, while other crowns were better adjusted with higher values. Similar result was observed by Ribas & Elmiro (2013) in which, the authors found more than one value in the segmentation of digital models generated by LiDAR in native environment.

The pattern found for CH is similar to the inverted-J, typical of natural forests where a large number of trees that populate the smallest diameter classes is found, following an exponential decrease in the number of large diameter trees (Odum, 2001). This pattern was also found by Sato *et al.,* (2016) when quantifying fire impacts on forest height and biomass in southwestern Brazilian Amazonia using LiDAR technology. Regarding the positive structural changes in crown areas, they may be related to the increase in the availability of resources, which increases the NPP (Net Primary Productivity), and, increases the growth rates of individuals, as a consequence.

The achievement of heights via LiDAR resulted in accurate values since regularity was observed in the measurements obtained in the evaluated period. According to Giongo (2010), obtaining tree heights via LiDAR presents great potential as this information is obtained in a direct way, different from other structural characteristics of the forest, such as AGB, basal area and diameter, which are obtained by modeling techniques and/or estimated from direct measurements (Dubayah *et al*., 2000). The ability to directly measure height and to derive other measurements from it is a great advantage over other forms of remote sensing (Ribas & Elmiro, 2013), and particularly in relation to the traditional methods of collecting this variable in rainforests because in forest inventories, tree height is visually attributed, which is extremely biased, since the notion of space may vary between a trained and an untrained observer (Kitahara *et al*., 2010; Fernandes da Silva *et al*., 2012).

The relationship between tree height versus crown area showed a moderate correlation (Mukaka, 2012). The values were 0.5898 and 0.5851 for 2011 and 2013, respectively. The increase in the height of Brazil nut tree (Bertholletia excelsa HBK), which is typical of the Amazon rainforest, is not followed at the same proportion by the increase in crown diameter (Tonini & Arco-Verde, 2005; Dionísio *et al*., 2017). This is corroborated by Hess *et al*. (2014) who reported that native species have tortuous stems, eventually generating a greater discrepancy in the h/d ratio, that is, high diameters and small heights, or elevated heights of smaller diameter, thus generating a low correlation between these two variables.

In average values of AGB of the analyzed area, it was found values similar to those of Silva *et al*. 2017, who used the same approach to predict AGB stocks in a forest in the state of Pará, although in the authors' study, no negative changes were found over a period of two years. Studies similar to the scope of this work report on impacts in forests that caused a reduction in AGB values. Silva (2014) analyzed impacts following exploration of the Jamari FLONA and pointed out a reduction of 23.5% in AGB. Yet, Mazzei *et al*. (2010) found a reduction of 10 to 40% post-exploration, represented by felled and damaged trees, while Gerwing (2002) observed a reduction in the aerial biomass of 20% in places that underwent moderate extraction (35 m^3.ha-1) and of 48% under intense exploration (69 m^3.ha-1). The reduction of 5.64% in AGB found in this study may be considered low in comparison to the reduction by 23.5% in reduction in AGB found by Silva (2014), and by Asner *et al*. (2005), who estimated post-handling carbon loss around 15%.

In this sense, it is possible to realize the potential of LiDAR technology as a tool to generate accurate information about the environment. Due to the large Amazonian biome, differences in the literature were expected to be found. According to Andersen *et al*. (2014), multitemporal LiDAR data may be used to detect and quantify AGB changes, even at a low level of AGB change (10-20 Mg.ha-1), which corroborates with the results found in this work for the evaluated period.

Even as results that did not differ significantly, we cannot disregard the fact that negative changes are occurring in forest AGB stocks, requiring a longer period of time for an assessment of changes in a forest with no evidence of large events, such as observed by Sato *et al*. (2016) who detected changes in forest biomass and height for a period equivalent to 10 years, at least, after the occurrence of a sub--forest fire event. These authors also point out that this type of disturbance may cause a persistent loss in AGB and subsequent reduction in forest carbon stocks, and that LiDAR is a powerful technology to exploit these impacts.

Using AGB estimates for the total study site, it was possible to identify the changes that occurred over the evaluated period. In addition, the structural changes observed in the crowns and in the heights of the tree individuals were not sufficient to influence the evaluated landscape. However, it is important to observe that variations in forest structure may have causes related to vegetation phenology and local weather conditions, and should be considered as repetitions of observations for studies on dynamics (Castillo *et al*., 2012).

5 Conclusions

The estimates generated via LiDAR data presented strong correlations with those obtained via forest inventory. The best relationship between the data was obtained for 2011, when the sampling used in the field was performed in 1-ha strips.

The use of LiDAR data is a great potential for estimates of AGB stocks in rain forests as well as detection of large-scale changes, which field-based measurements would require a good deal of work time and costly costs.

The methodology of tree crown individualization allowed to identify positive changes in the landscape, which were not reflected in the AGB estimates of the evaluated forest sample. Hence, this approach generates detailed information of the environment. Moreover, it accelerates the evaluation of temporal changes in the stocks of biomass and carbon, as well.

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