Modeling and Spatialization of Biomass and Carbon Stock Using Lidar Metrics in Tropical Dry Forest, Brazil: Preliminary Results

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Research

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Modeling and Spatialization of Biomass and Carbon Stock Using Lidar Metrics in Tropical Dry Forest, Brazil: Preliminary Results

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Abstract

Background: In recent years, with the growing environmental concern regarding climate change, there has been a search for efficient alternatives in indirect methods for studies on the quantification of biomass and forest carbon stock. In this article, we seek to obtain pioneering and preliminary results of estimates of biomass and carbon using data from conventional forest inventory and LiDAR technology in a dry tropical forest in Brazil. We used data from conventional forest inventory in two areas together with data from the LiDAR overflight, generating local biomass estimates from a developed local equation and the carbon levels obtained from local species. With data from LiDAR technology, we extracted the metrics from the point cloud and were used as an independent variable. For the construction of the biomass and carbon allometric models per hectare, we approach three types of models for data analysis: Multiple linear regression with Principal Components - PCA, Conventional multiple linear regression and Multiple linear regression with Stepwise, the generated equations were analyzed by comparisons of statistical criteria (R^2aj and RMSE). After selecting the best equation, we generate the carbon estimates by area by assessing the plot level.

Results: The best fit TAGB and TAGC model was the multiple linear regression with Stepwise, concluding, then, that LiDAR data can be used to estimate biomass and total carbon in dry tropical forest, proven by an adjustment considered in the models employed, with a significant correlation between the LiDAR metrics.

Conclusions: Our preliminary results provide important information about the spatial distribution of TAGB and TAGC in the study area, which can be used to manage the reserve for optimal carbon sequestration.

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

Introduction

The increase in the carbon dioxide concentration (CO_2) in the atmosphere in the last decades and its consequences on the environment have been attracting the attention of society and being addressed as a matter of global controversy (Crowther et al. 2015). The high CO_2 concentration in the atmosphere is worrying, as it generates an increase in the greenhouse effect, and consequently causes global warming (Achard and House 2015; Coomes et al. 2017; Brahma et al. 2018). In this scenario, dry tropical forest areas play an important role, and the Caatinga vegetation in northeastern Brazil significantly contributes to the global carbon cycle through the aboveground biomass and carbon stock (Sampaio and Silva 2005; Althoff et al. 2018).

There is currently a rich ongoing discussion among scientists around the world about the main tools and methods for generating measures to mitigate climate change. The first guiding question to be answered is “how do we measure the impacts of global climate change and how can we slow its progress?” The second key question is “what tools and methods should be used to ensure a reliable estimate?” n many cases, the variables best known for generating rapid responses for dry tropical forest ecosystems are aboveground biomass and carbon.

However, the destructive sampling of trees is a limiting factor for calibrating statistical models, mainly due to the high cost employed in field work (Duncanson et al. 2017). These methods are currently based on forest inventory data using carbon factors and equations which transform the biometric parameters of the forest such as diameter at breast height (DBH) and height (Ht) of individuals in estimating the carbon stock contained in aboveground forest biomass (Somogyi et al. 2007).

Remote sensing techniques combined with optical sensors have recently been presented as a viable alternative for estimating the biomass and carbon stock in planted and natural forests (Silva et al. 2016; Silva et al. 2017a). Among the current remote sensing techniques, laser tillering, also known as LiDAR (Light Detection and Raging), has prominently emerged in the forest scenario (Li et al. 2017), by which biomass and carbon stock estimates can be systematically and efficiently obtained in the field (Duncanson et al. 2017).

LiDAR is an active system, and its principle consists of emitting a laser pulse which interacts with an object on the earth's surface and subsequently returns to the sensor in a given time interval. The technology makes it possible to accurately reproduce Digital Terrain Models (DTM, models which enable describing the elevation of land free of objects), Digital Surface Models (DSM, models which enable describing the elevation of the terrain including the objects present), and Digital Height Models (DHM, models which describe the height of all objects, with the cloud points referring to the ground normalized to zero).

Although LiDAR technology is an efficient alternative and widely applied in forest inventory in countries like the United States, Finland and Sweden, there are still obstacles to its use in other countries such as Brazil. The limitations are not due to the functioning of the technology itself, but mainly because it is still an emerging technology in Brazil (Silva et al. 2017b). The elaboration of processing methodologies aimed at Brazilian needs is still recent, and in this respect the execution of this work is mainly justified by the search for a scientific technical advance which provides developing routines which can assist in LiDAR data acquisition and processing, and in turn seeking to efficiently attain above-ground biomass and carbon stock estimates in a Brazilian dry tropical forest.

In particular, LiDAR technology has the ability to directly measure the vegetation attributes (metrics) on a vertical scale with high precision, and therefore a system can be developed to sample the biomass and carbon stock of the trees in situ in environmental gradients, providing a potential solution to outstanding problems related to forest biomass and above-ground carbon stock (Saatchi et al. 2009; Avitabile et al. 2011). Biomass and carbon estimates at local and regional levels, as well as the spatialization of these variables using maps can provide an overview of biodiversity and forest structure (Martinuzzi et al. 2013; Nelson et al. 2017; Becknell et al. 2018). This information is extremely important for the caatinga vegetation domain in Pernambuco for possible payments for environmental services and other projects aimed at reducing emissions from deforestation and forest degradation (REDD +).

Due to the great importance of caatinga forest resources, quantifying and mapping biomass and carbon stock using LiDAR metrics is a key factor to meet the legal aspects concerning sustainable management, mainly reconciling sustainable wood production and stock maintenance of carbon in the area. This task is one of the main long-term planning tools, because in addition to dimensioning the forest's stock and productivity, it generates information which will direct ecosystem maintenance through conservation and/or preservation (Mohebalian and Aguilar 2018).

In this sense, this work was developed with the intention of generating information on biomass and carbon stock using LiDAR metrics in different dry tropical forest areas in the municipality of Floresta, Pernambuco. Specifically, it is intended to: a) Estimate the total biomass and carbon stock for the parcels inventoried in two areas using a local allometric model; b) Use the aerial LiDAR system to generate attributes in plots in the different dry forest areas inventoried in Pernambuco; c) Develop an allometric model for estimating biomass and carbon stock using LiDAR metrics for the

126 different dry forest areas inventoried in Pernambuco; d) Generate biomass and carbon
127 stock maps for the different dry forest areas inventoried in Pernambuco.

128 **Results**

129 ***Preliminary results***

130 The average minimum and maximum elevation values which correspond to the tree
131 heights obtained by the LiDAR metrics ranged from 1.49 to 4.77 meters with an
132 average of 3.06 m for the *Correntão* area. There is little difference in the minimum
133 elevations per plot (1.39 m) for the *Transposição* area, but this area had the lowest
134 average elevation (2.88 m) and the highest maximum elevation (5.05 m). The highest
135 biomass and total carbon concentration per hectare was observed in the *Correntão* area
136 with values ranging from 0.61 to 129 $Mg.ha^{-1}$, with an average of 24.93. TAGB
137 estimates for all plots in the *Transposição* area ranged from 1.22 to 29.37 $Mg.ha^{-1}$, with
138 an average value of 9.32 $Mg.ha^{-1}$.

139 The component loads (correlations between each variable and each principal
140 component), the eigenvalues and the variation percentage of the principal components
141 for the LiDAR metrics for the *Transposição* and *Correntão* areas are shown in Tables 4
142 and 5, respectively. The principal component analysis of the Transposição metrics
143 produced three principal components which synthesized 85.6% of the variability in the
144 data. The first principal component (PC1) of the metrics in this area had a high load of
145 all variables with maximum contribution from the average increase (0.996). The
146 principal component analysis for the metrics of the *Correntão* area also produced three
147 principal components which synthesized 82.8% of the variability in the data. The first
148 principal component (PC1) for the metrics in this area had maximum loads for
149 maximum elevation and average elevation. The principal components which only
150 represented a small amount of variance were not used in the regression analysis.

Table 4. Component loads, eigenvalues and percentage of variation of the main components (PC) for the LiDAR metrics in the Transposição area.

Principal component	Components (eigenvectors)											
	Elev. minimum	Elev. maximum	Elev. mean	Elev. mode	Elev. stddev	Elev. CV	Elev. skewness	Elev. kurtosis	Elev. MAD. median	Elev. P01	Auto valores	Var (%)
PC1	0.285	0.678	0.996	0.759	0.719	0.333	-0.231	-0.192	0.689	0.420	12.463	51.929
PC2	-0.395	0.621	0.070	-0.020	0.675	0.902	0.738	0.151	0.590	-0.508	5.841	76.266
PC3	0.622	0.281	-0.009	-0.070	-0.027	0.016	0.597	0.672	-0.203	0.602	2.255	85.663

Table 5. Component loads, eigenvalues and percentage of variation of the main components (PC) for the LiDAR metrics in the *Correntão* area.

Principal component	Components (eigenvectors)											
	Elev. minimum	Elev. maximum	Elev. mean	Elev. mode	Elev. stddev	Elev. CV	Elev. skewness	Elev. kurtosis	Elev. MAD.median	Elev. P01	Auto valores	Var(%)
PC1	0.019	0.825	0.999	0.709	0.708	0.158	-0.192	0.170	0.557	0.305	13.233	55.136
PC2	-0.130	0.423	0.018	-0.302	0.675	0.943	0.708	-0.179	0.633	-0.234	4.119	72.299
PC3	0.765	-0.283	0.016	-0.106	0.074	0.110	-0.103	-0.805	0.359	0.636	2.524	82.815

The results of the step-by-step regression analysis for each area are shown in Table 6. The variables which did not significantly contribute to the TAGB prediction for each area were simultaneously eliminated during the analysis. The determination coefficient (R^2aj) of the models for the *Transposição* area varied from 0.17 to 0.42 and the RMSE varied from 3.18 to 5.99 Mg.ha^{-1}. Models with higher R^2 values and lower RMSE indicate better TAGB prediction. Models developed using the principal component technique of the LiDAR metrics for each area generally had an unsatisfactory performance.

Table 6. Multiple linear regression models adjusted for the biomass estimate, obtained by LiDAR data

Area		Biomass predictive models	R^2ajd	RMSE
Transposição	Multiple regression	TAGB = - 86.809 -33.295(Elev.minimum) + 5.446(Elev.maximum) + 195.226(Elev.mean) + 3.774 (Elev.mode) -92.658(Elev.stddev) + 206.851(Elev.CV) + 13.627(Elev.skewness) -1.734 (Elev.kurtosis) + 24.360(Elev.MAD.median) + 29.676(Elev.P01) - 25.707(Elev.P10) -64.704(Elev.P20) + 49.118(Elev.P25) -26.958(Elev.P30) -44.133(Elev.P50) -21.226(Elev.P60) -11.419(Elev.P75) 2.295(Elev.P80) - 27.855(Elev.P90) -15.740(Elev.P95) + 98.142(Canopy.relief.ratio) + 0.024(Percentage.all.returns.above.1.30)	0.1924	3.18
	Stepwise regression	**TAGB = -21.08 -35.756(Elev.minimum) + 119.784 (Elev.mean) + 4.582(Elev.mode) -63.752 (Elev.stddev) + 101.103(Elev.CV) + 27.823(Elev.P01) -17.626(Elev.P10) -29.152(Elev.P20) - 44.745(Elev.P50) -18.032(Elev.P90)**	**0.4239**	**3.51**
	PCA regression	TAGB = 9.145 + 0.607(Dim.1) + 1 (Dim.3)	0.1723	5.99
Correntão	Multiple regression	TAGB = 341.760 + 0.932(Elev.minimum) + 123.520(Elev.maximum) -298.028(Elev.mean) + 1.734(Elev.mode) -14.288(Elev.stddev) + 712.426(Elev.CV) -8.027(Elev.skewness)- 36.267(Elev.kurtosis) + 103.257(Elev.MAD.median) +114.736(Elev.P01) + 79.665(Elev.P10) + 54.843(Elev.P20) + 39.873(Elev.P25) + 90.032(Elev.P30) + 20.564(Elev.P50) + 5.063(Elev.P60) -129.573(Elev.P75) -33.779(Elev.P80) + 57.286(Elev.P90) 53.403(Elev.P95) + 519.378(Canopy.relief.ratio) - 0.103(Percentage.all.returns.above.1.30)	0.4239	13.61
	Stepwise regression	**TAGB = -269.86 + 145.44(Elev. maximum) - 402.19(Elev.mean) + 440.13(Elev.CV) - 53.26(Elev.kurtosis) + 88.49(Elev.P01) + 93.09(Elev.P10) + 165.73 (Elev.P30) -67.6(Elev.P75) + 673.35(Canopy.relief.ratio)**	**0.533**	**14.76**
	PCA regression	TAGB = 30.270-6.465 (Dim.3)	0.09621	28.45

The models which combined the step-by-step selection of the metrics showed better results in both areas compared to models which use the traditional multiple

regression modeling, although the prediction error of the multiple model was slightly lower. Based on the adjustment statistics, the Stepwise regression model was considered the most suitable for predicting TAGB for both areas and this can be illustrated in the figure 5.

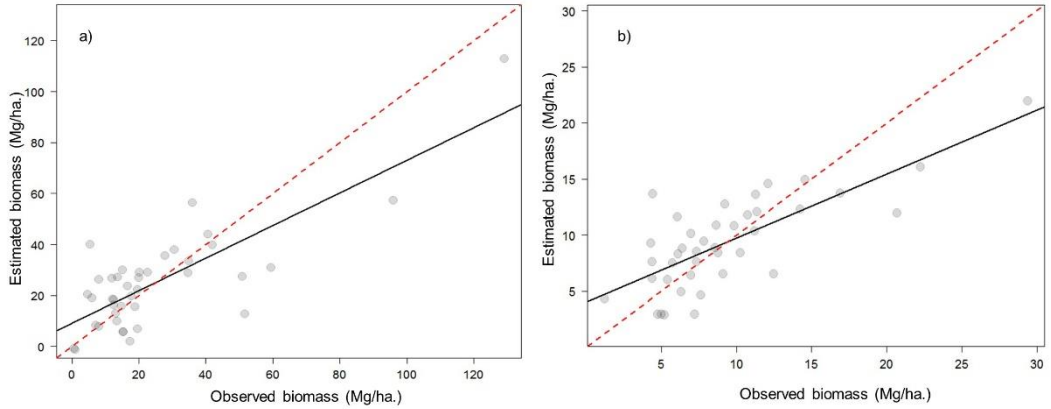


Fig. 5 Predictions of the best allometric equations for the *Correntão* area (a) and *Transposição* (b) using the LiDAR metrics selected step by step in relation to the observed values. The solid black line indicates the fit of the equation and the red dotted line indicates the ideal fit in a 1: 1 ratio.

The most significant predictor variables for the model for the *Transposição* area, and therefore the most suitable for predicting local TAGB, were Elev.minimum, Elev.maximum, Elev.mean and Elev.P01; the last two were found in all tested models. The final model for the *Correntão* area predicts that the total biomass stock may be more significant from the Elev metrics. Maximum, Elev.mean, Elev.CV, Elev.kurtosis, Elev.P01, Elev.P10, Elev.P30, Elev.P75 and Canopy.relief.ratio.

The Stepwise regression model was applied to map the density of TAGB in the study areas (Fig. 6). The TAGB map was converted to carbon stock/Mg.ha^{-1} (TAGC) maps to predict the total stock in the areas using the average carbon fraction (0.48), as estimated in this study. The estimated average density of TAGB and TAGC for the

Transposição area was 9.2 ± 6.1 Mg.ha^{-1} and 4.6 ± 14 Mg.ha^{-1}, respectively. Most plots in both areas had a low density of TAGB above 30 Mg.ha^{-1} (85.8%), storing approximately 44.1% of the TAGC stock. About 1.2% of the forest stand in the area in both locations had a TAGB density greater than 50 Mg.ha^{-1}. Areas with TAGB below 100 Mg.ha^{-1} cover about 99% of the forest stand. Low density areas of TAGB and TAGC, as shown in the maps, are potential areas for assisted regeneration and enrichment planting to increase the carbon sequestration capacity of the forest stand.

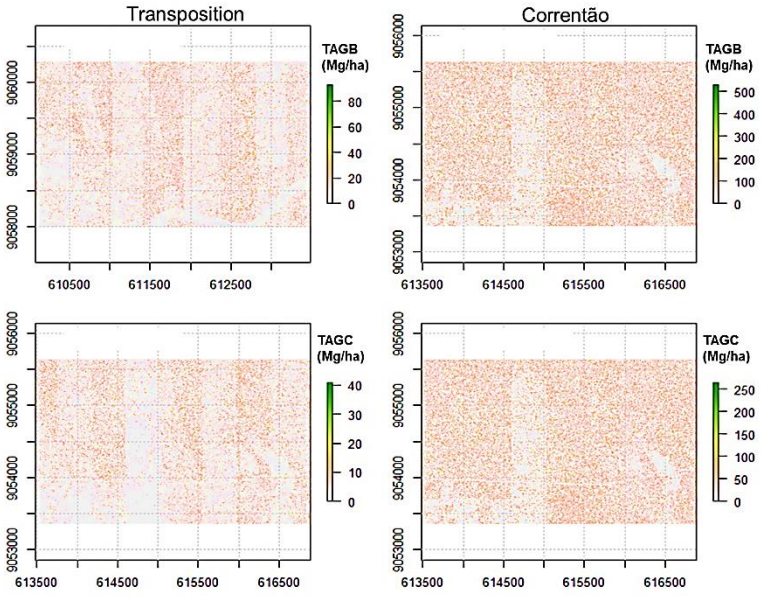


Fig. 6 Spatialization of biomass and carbon based on Stepwise regression models defined according to the LiDAR metrics for the *Transposição* and *Correntão* areas.

When comparing the areas, it is noted that the most preserved area (*Transposição*) presented a lower carbon stock than the most degraded area (*Correntão*) (Fig. 6). This can be explained in the inventories carried out in the degraded area, which showed individuals with greater dominance than in the preserved area, strongly influencing the predicted biomass and carbon values.

These results are not only absolute numbers of the inventoried variables, but also other variables obtained from the LiDAR technology and should be considered for

214 better interpretation of the results obtained in this work, namely: the density of pulses
215 emitted by LiDAR, the characteristics of the vegetation trunks/stems studied and the
216 effect of water stress on leaves.
217
218 **Discussion**
219 The preliminary results of this study indicate that the LiDAR metrics provided reliable
220 estimates of TAGB and TAGC for the two study areas. The results show a good
221 statistical relationship between field biomass data and height (elevation) metrics,
222 suggesting that it is an important predictor of local biomass, especially when selected
223 using the Stepwise method. However, the relationship was weaker in both areas when
224 all metrics were incorporated into the traditional modeling process or when using
225 regression with principal components. Only the individual categories of the height
226 metrics (minimum, average and maximum) explained more than 40% of the variance.
227 This suggests that the incorporation of height data may be necessary to improve the
228 prediction of TAGB and TAGC.
229 The R^2 and RMSE values of the best-fit models vary in similar studies which
230 used LiDAR data and metrics to estimate and map the aboveground biomass of trees in
231 dry forests. (Anderson et al. 2018) reported R^2 values ranging from 0.36 to 0.71 and
232 RMSE values from 99 to 175 $Mg.ha^{-1}$ in Idaho (USA) based on machine learning data.
233 In a dry tropical forest in Mexico, (Hernández-Stefanoni et al. 2015) reported R^2 from
234 0.77 and RMSE from 21.6 to 25.7 $Mg.ha^{-1}$ based on linear regression and LiDAR data.
235 Also in Idaho (USA), (Li et al. 2017) reported R^2 of 0.87 and RMSE of 3.59 kg based
236 on linear regression and data on percentage plant cover derived from ALS. (Chen et al.
237 2015) reported R^2 ranging from 0.38 to 0.64 in the Amazon based on mixed-effect

238 models and LiDAR data from agroforestry systems. The biomass estimates by the tested
239 methodologies showed satisfactory and promising results in all of these cases.

240 The best-fit TAGB model consisted of 10 LiDAR predictor variables for the
241 *Transposição* area and 9 LiDAR predictor variables for the *Correntão* area. These
242 variables indicate that the vertical profile of vegetation at different elevations
243 (minimum, medium and maximum heights) are potential predictors for TAGB. TAGB
244 estimation and mapping for the studied forest was based on the best-fit model.

245 The spatial distribution pattern of TAGB is related to the structure and
246 composition of the forest landscape, where low TAGB areas correspond to low forest
247 cover areas, while high biomass areas correspond to densely forested areas. The overall
248 average TAGB of 32 $Mg.ha^{-1}$ for two areas is comparable and is within the range of
249 values reported for mature dry tropical forests in previous studies, indicating that the
250 modeling approach used in this study provides reasonable predictions of TAGB
251 (Martinuzzi et al. 2013; Kachamba et al. 2017; Naveenkumar et al. 2017).

252 Uncertainties in the TAGB estimates in this study could result from errors
253 associated with field measurements, however plot TAGB estimates are based on a
254 location-specific allometric equation with the breadth of data covering a wide sample in
255 the model development, showing an accurate TAGB estimate. Any errors associated
256 with the TAGB estimate at the plot level using a pantropical equation would propagate
257 to the TAGB regression model, and therefore to the TAGB estimates (Chave et al.
258 2005; Chave et al. 2014). However, another possible source of error in biomass
259 predictions may be the density of points adopted, as 0.5 (pulses/m²) were adopted in the
260 data used, while carbon quantification works generally work with 4 to 25 points (Silva
261 et al. 2014; Figueiredo et al. 2016; Nelson et al. 2017; Coomes et al. 2017). Through
262 tests with point density, Silva et al. (2017) found that its reduction can result in a

263 decrease in R^2 and an increase in RMSE, in addition to increasing the variance of AGB
264 estimates. (Leitold et al. 2015) obtained bias in height estimates which translated into
265 errors of 80-125 $Mg.ha^{-1}$, when the operator worked with the pulse density below 4 m^2.
266 Pulse densities from moderate to high changes are invariant and only relatively
267 little affect results; however, once the pulse drops to $1/m^2$, it makes metrics related to
268 coverage (canopy coverage, tree density and shrub coverage) more sensitive to changes
269 in this density (Magnusson et al. 2007). Thus, the increase in RMSE can be explained
270 by the less accurate classification of soil returns (Silva et al. 2017a; Silva et al. 2017b).
271 However, it is worth noting that the low density of points can also be related to good
272 results, depending on the variable to be studied, such as canopy metrics (Thomas et al.
273 2006) or volume (Takahashi et al. 2010). In addition, the TAGC for the study area was
274 estimated based on the TAGB and the average carbon fraction of the trees; any errors in
275 the TAGB estimate would extend to the TAGC estimates. However, the results of this
276 study indicate that the TAGB model provided reliable TAGB estimates for the study
277 area.
278
279 **Conclusions**
280 According to the results found in this work, we concluded that LiDAR data can be used
281 for estimating biomass and total carbon in dry tropical forest, as confirmed by an
282 adjustment considered in the models used, with good correlation between the LiDAR
283 metrics and the biomass data observed in the field. More specifically, we have the
284 following conclusions and recommendations for future work:
285
286 i) Using Stepwise to reduce the metrics proved to be more effective for better
287 adjustment of the models;

ii) The LiDAR metrics which were most present in the models were: Elev.minimum, Elev.maximum, Elev.mean and Elev.P01, with the last two being found in all models;

iii) The most preserved area had a lower carbon stock than the most degraded area, this occurrence can be explained in the inventories carried out in the area that showed a higher DAB number in the degraded area than in the preserved area, strongly influencing the estimated carbon values in the areas;

iv) The pulse density, even though it is not a variable within the models, indirectly influenced the accuracy of the models, therefore, it is recommended that data be tested with a higher pulse density in future works.

v) The model is limited to the TAGB estimate in the study area and may not be suitable for application in other forests. This is due to differences in forest structure, species composition, vegetation vigor and impacts of atmospheric conditions and soil moisture and precipitation.

vi) New studies are recommended to assess the transferability of the model to other protected forests with forest structure and similar species composition. Other studies that will test the ability of non-parametric algorithms (such as random forest) to develop TAGB estimation models for the study area, in comparison with linear regression analysis, are also recommended.

vii) Our preliminary results provided important information on the spatial distribution of TAGB and TAGC in the study area, which can be used to manage the reserve for optimal carbon sequestration.

Materials and methods

Study area

The work was carried out in two semiarid areas of Itapemirim farm. Its extension is approximately 60 km^2 (Fig. 1 D), located in the Municipality of Floresta in the São Francisco mesoregion in Pernambuco, northeast Brazilian (8° 30′ 37" S and 37° 59′ 07" W).

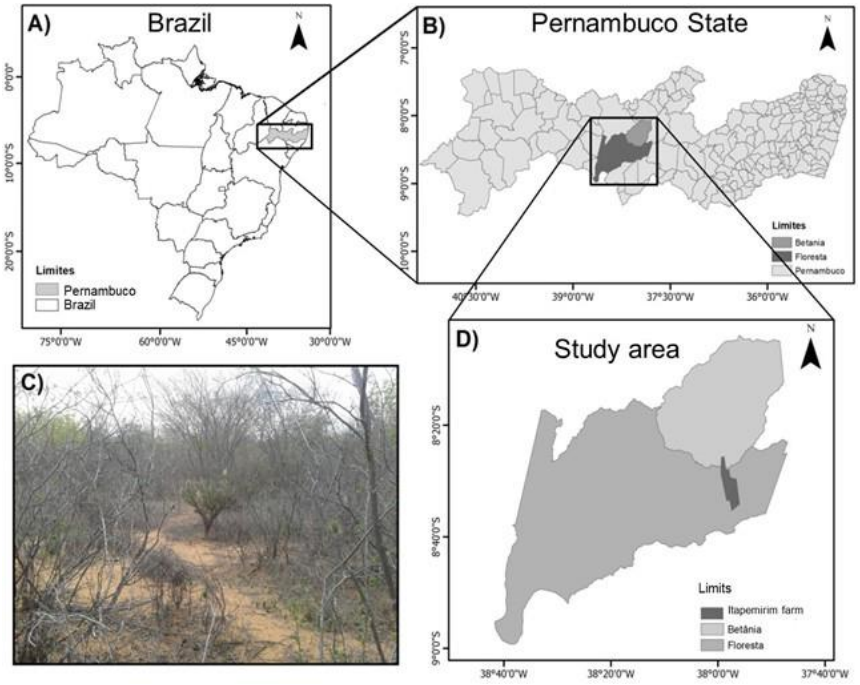


Fig. 1 Coverage of the study area: A, B and D, and profile photo in Floresta C, in the hinterland of Pernambuco, Brazil.

The two study areas differ from each other in terms of preservation conditions. The first to the north is called "*Transposição*" with 40 permanent plots of 400 m^2 (20 x

20 m), having an extension of approximately 50 ha and is considered preserved (55 years of lesser anthropic disorders). The second area further south, also with 40 permanent plots of 400 m^2 (20 x 20 m) called "*Correntão*", underwent logging using the *Correntão* technique in 1987 for planting eucalyptus, but was abandoned and has been undergoing regeneration for 29 years (Fig. 2).

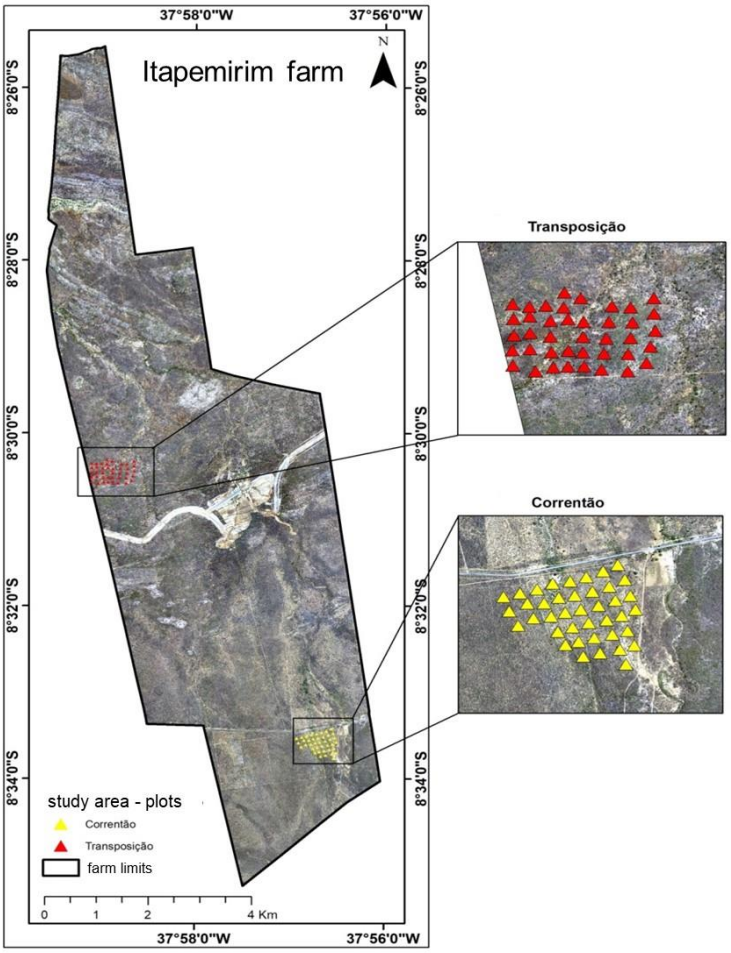
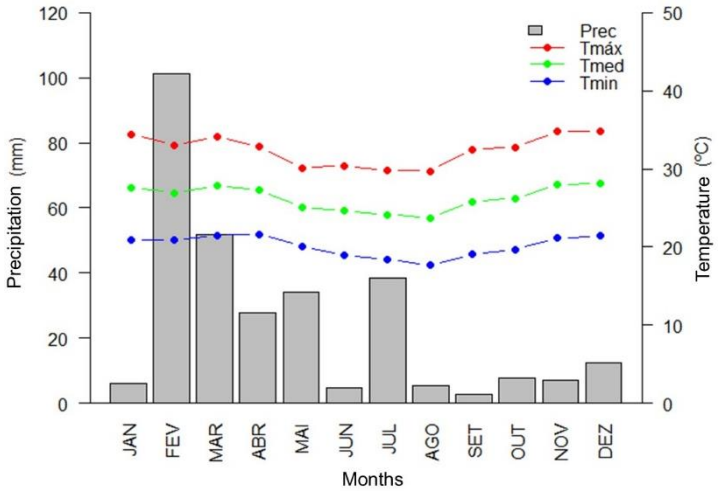


Fig. 2 Sampling procedure used in the two inventoried areas in the Municipality of Floresta, Pernambuco

The vegetation in these areas is predominantly Caatinga (dry tropical forest), meaning savanna-steppe characterized by shrub-tree vegetation along with the presence of cacti and herbaceous strata (IBGE, 2012). The climate is BSh according to the

342 Köppen classification, a hot semi-arid region with an average annual precipitation of
343 approximately 400 to 500 mm, with a rainy period from January to April, and an
344 average annual temperature of 26.1°C. Its distribution in temperature and precipitation
345 throughout the year studied (2014) in the municipalities belonging to the study area are
346 shown in Figure 3. The municipality has an area of 3,643.97 Km^2 and an average
347 altitude of 323 m (EMBRAPA, 2007).
348



349

350 **Fig. 3** Distribution of air temperature and precipitation over the year 2014 in the study
351 area by the nearest weather station. Source: Agritempo adjusted. Source: Agritempo,
352 2018 (adjusted).
353

354 ***Estimation of the biomass/carbon stock in the field***

355 Plots, which had already been inventoried, were used to facilitate logistics and data
356 collection in each area (Fig. 2). A total of 40 plots in each area have been monitored
357 since 2008. They are systematically distributed and each has 20 x 20 m (400 m^2). They
358 are 80 m apart, 50 m from the edge. All arboreous individuals with circumference
359 measured at 1.30 m above the ground (CAP) ≥ 6.0 cm were identified, labeled and
360 measured, and the total heights (Ht) were measured by a clinometer.

Local biomass estimates in each plot in the different areas were generated from a previously developed local equation (Equation 1), with subsequent conversion to carbon stock ($Mg.ha^{-1}$). Thus, we were able to perform local estimates of the biomass logarithm using DAP and Ht logarithms as independent variables, as shown in the equation below:

$$TAGB = \exp(-3.5336 + 1.9126 \times \ln(DAP) + 1.2438 \times \ln(Ht)) \quad (1)$$

Where: DBH is the diameter of the tree at breast height (1.30 m) in cm; Ht is the height of the tree (m). This equation was developed for the site and reported an Akaike Information Criterion (AIC) value of 573.77; an adjusted determination coefficient (R^2Adj) of 0.90; absolute square errors (RMSE) of 18.28 $kg.trees^{-1}$ and bias of 0.20 $kg.trees^{-1}$, respectively.

Next, the estimated biomass was converted using the average carbon fraction ($CF \approx 48\%$) of the caatinga woody species (Dalla-Lana et al. 2019) for carbon stock estimates ($Mg.ha^{-1}$). In addition, it has traditionally been assumed that the carbon content of a tree's dry biomass is 50% for estimating carbon stocks for sites (Brown and Lugo, 1982; Roy et al. 2001; Malhi et al. 2004), but it should be emphasized that the carbon fraction of the wood may exhibit some small variations between species (Elias and Potvin, 2003). Thus, the carbon stock is assumed as follows:

$$TAGC = TAGB \times CF \quad (2)$$

Where: TAGC is the estimated total aboveground carbon stock ($Mg.ha^{-1}$); TAGB is the total estimated aboveground biomass ($Mg.ha^{-1}$); CF is the carbon fraction (48%).

In summary, the forest inventory data analyzed for this study as well as the biomass and carbon predictions were for 2014 and are summarized in Table 1. The choice of this measurement period was defined according to the same LiDAR flyover year in the areas.

Table1. Descriptive values (mean and standard deviation) and number of individuals and total shafts sampled in the permanent plots of the study areas (2014).

Areas	DBH (cm)		Ht (m)		AGB (Mg.ha^{-1})		AGC (Mg.ha^{-1})		N° Plots	Nº Ind.	Nº stem
	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ			
Transposição	3,85	2,37	3,97	0,95	9,327	5,442	4,66	27	40	1728	4576
Correntão	11,44	5,4	3,64	0,92	24,94	24,95	12,47	12,47	40	996	2903

Estimation of the biomass/carbon stock by LiDAR data

The LiDAR data used in this study were made available by the Pernambuco Three-Dimensional Program (PE3D) inserted in the Pernambuco Water Sustainability Program (PSHPE) with the objective of mapping the entire territory of the State of Pernambuco using its services covering aerophotogrammetric and laser profiling. They were collected in August 2014 using a Leica ALS50 system coupled to a BEM-810 C - Seneca II - Prefix PT-RQA aircraft, with it being possible to view their characteristics below (Table 2).

Table 2. Details of acquisition of LiDAR data.

Atributo	**Valores**
Lidar System	ALS-50 LEICA
Flight altitude (m)	3.068
Data de aquisição	10/08/2014
opening angle (°)	34,5
Scanner frequency (Kz; Hz)	36,8 Hz
Pulse density (pulses·m^2)	0,5
Datum	Sirgas 2000

After acquiring the point clouds of the areas to be analyzed on the Pernambuco Tridimensional Program website (http://www.pe3d.pe.gov.br/mapa.php), it was necessary to change the format from ".xyzi" to ".las "using the LAS Utility software. Thus, a descriptive report with several important characteristics of the LiDAR data set was produced with the Fusion3.8 software program using the "Catalog" tool.

Therefore, the returns which were on the soil surface (points on the soil surface) were filtered from the LiDAR point cloud using the "Ground Filter" tool. The next step for both areas was to obtain the Digital Terrain Model (DTM) using the "Grid Surface Create" tool and the Digital Surface Model (DSM) using the "canopy model" tool.

It was first necessary to normalize the data in order to carry out the subsequent analyzes with the metrics of only the trees. This task was performed by subtracting the DSM data from the DTM data using the "clipdata" tool. The next step was to obtain the Canopy Height Digital Model (CHM) with the aid of the "canopymodel" tool to obtain the metric value for each plot of the two areas, in which it was necessary to perform the clipping by plot using the shape file of the plots with the point cloud using the "Polyclip DATA" tool.

The LiDAR metrics calculate a series of estimates of descriptive statistical parameters of the LiDAR point cloud and in this study were generated from the "cloud metrics" tool. Thus, a total of 26 metrics were generated at the end of the data processing by the point clouds in each sample unit in the different areas. These metrics are the most used in biomass and carbon estimation studies, categorized according to their origin and calculated symbology (Table 3).

Table 3. List of LiDAR metrics evaluated in the study, obtained from the cloudmetrics tool of the Fusion v. 3.8

Category	LiDAR metrics	Symbology
Height	Maximum height	Elev.maximum
	Minimum height	Elev.minimum
	Mean height	Elev.mean
	Modal height	Elev.mode
	Standard deviation of heights	Elev.stddev
	Height variation coefficient	Elev.CV
	Height asymmetry	Elev.skewness
	Kurtosis of height	Elev.kurtosis
	Median of absolute deviations from the general mean	Elev.MAD.median
	01th Percentile of height	Elev.P01
	05th percentile of height	Elev.P05
	10th percentile of height	Elev.P10
	20th percentile of height	Elev.P20
	25th percentile of height	Elev.P25
	30th percentile of height	Elev.P30
	40th percentile of height	Elev.P40
	50th percentile of height	Elev.P50
	60th percentile of height	Elev.P60
	70th percentile of height	Elev.P70
	75th percentile of height	Elev.P75
	80th percentile of height	Elev.P80
	90th percentile of height	Elev.P90
	95th percentile of height	Elev.P95
	99th percentile of Height	Elev.P99
Canopy density	Canopy Relief Ratio[1]	Canopy.relief.ratio
	Percentage of all returns above 1.30	Percentage.all.returns.above.1.30

[1]Canopyreliefratio ((HMEAN 2 HMIN)/(HMAX 2 HMIN));

Some of the main metrics used in predicting biomass and carbon are described below:

Elev.maximum = Maximum height: this is the highest value found in the measurement range in meters within each sample unit, considering variations at each meter along the walking axis.

Elev.mean = Mean height: this is the mean value of the highest points, considering variations every meter in the measurement range in meters within each sample unit (Equation 3).

439 $$Elev.mean = \frac{1}{n} \times \sum_{i=1}^{n} h_i$$

440 (3)

441 Elev.stddev = Standard deviation of height in the LiDAR point cloud:

442 $$Elev.stddev = \sqrt{\frac{1}{n-1} \times \sum_{i=1}^{n} (h_i - h_{med})^2}$$

443 (4)

444 Where: hmean = mean height of the point cloud.

445 Elev.CV = Height variation coefficient in the LiDAR point cloud:

446 $$h_{cv} = \frac{h_{desv}}{h_{med}}$$

447 (5)

448 Height percentiles in the LiDAR point cloud (hpi): The i-th percentile of n points
449 traditionally represented in the LiDAR point cloud, ordered in height values
450 corresponds to the value which occupies the K position of the data set, as in the
451 following equation:

452 $$K = \frac{h_{pi}(n+1)}{100}$$

453 (6)

454 Where: K = value that occupies the i-th percentile in height in the point cloud; h pi = i-th
455 percentile in height in the point cloud.

456

457 ***Modeling the biomass/carbon stock using LiDAR data***

458 The "R Project for Statistical Computing" Lidar Data_Analysis Tools (R Development
459 Core Team, 2017) and ArcGIS 10® software programs were used to construct, validate
460 and apply predictive models and generate representative biomass and forest carbon
461 maps in the different areas.

462 The LidarData_Analysis Tools software program was developed by the USDA
463 Forest Service - Remote Sensing Applications Center, written in Python language, and
464 works as an interface of R. The Lidar Data_Analysis Tools was designed to streamline
465 the statistical regression analysis process involving LiDAR metrics generated by the
466 North American Forest Service, and in fact works as a graphical interface to access the
467 statistical modeling packages available in R which simplify processing large volumes of
468 data (Silva et al., 2017a).

469 Next, three data analysis approaches were used to construct the biomass
470 allometric models per hectare according to the LiDAR metrics for the two areas:
471 Multiple linear regression, Multiple linear regression with Stepwise and Multiple linear
472 regression with Principal Components – PCA.

473 First, traditional modeling was used employing multiple linear regression. Thus,
474 it is assumed that there is a linear relationship between a Y variable (biomass; carbon)
475 and k independent variables, xj (j =, ..., k = LiDAR point cloud metrics). The
476 mathematical model which expresses the equation of multiple linear regression has the
477 following form:

478 $$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$$

479 (7)

480 Where: Y = TAGB ($Mg.ha^{-1}$); β0 = intercept on the Y axis; βi = slope of the i-th
481 explanatory variable; k = number of explanatory variables; e = random error.

482

483 Regression analysis was used with an emphasis on solving most of the forest
484 problems, especially when it is intended to obtain estimates of forest parameters through
485 biometric relationships. A careful analysis was performed in selecting the best metrics
486 from the LiDAR point cloud candidates for modeling among the metrics generated by

487 the LiDAR data processing for construction the models. According to (Silva et al.
488 2017a), Pearson's linear correlation test (r^2) should first be applied for this selection to
489 obtain the correlation between the predictive variables and to evaluate the possible
490 existence of collinearity between them. Variables with $R^2 > 0.9$ will be excluded from
491 the analysis to avoid the presence of collinearity.

492 Second, the Stepwise technique was applied using the regsubsets function of the
493 "leaps" package in R to obtain subsets of independent variables which are candidates
494 for composing the definitive biomass and carbon models in the different areas. This
495 method performs an exhaustive search to select the best combinations of independent
496 variables by minimizing Akaike's information criterion (AIC), and rearranging them
497 into subsets which may later give rise to the selected models. Regsubsets require the use
498 of a maximum number (represented by the nvmax argument) of independent variables
499 for the growing construction of these subsets.

500 Third, the principal component technique (PCA) was applied to the selected
501 LiDAR metrics, and the metrics most likely to contribute to developing the model were
502 identified by inspecting the eigenvectors on each principal component. Then, the
503 metrics with the highest load on the PCs were used as input variables in multivariate
504 linear regression models that predicted biomass per hectare.

505 An example of using PCA including the equations used to obtain the
506 eigenvalues, eigenvectors and principal components (PC) can be found in Jensen
507 (2005). PCA was applied in the present study to the selected LiDAR metrics using the
508 prcomp function of the statistics package in R (R Core Team, 2017). A correlation
509 matrix derived from the LiDAR metrics provided the basis for calculating eigenvalues
510 and eigenvectors and for the subsequent determination of PC scores. Each score
511 represented a transformed metric from the linear combination of LiDAR metrics.

Differences in the contribution of each LiDAR metric to the variability in the data set, as well as the similarity in the calculated metrics (Silva et al., 2017a) can be established by analyzing the eigenvectors and the PC score.

Evaluation of models

The model parameters were estimated using the Ordinary Least Squares (OLS – Ordinary Least Squares) method in all the modeling methods described. The parameters were generally calculated using all plots sampled in each area and will be assumed to be the true parameters that represent the biomass and carbon stock at each location.

For each of the criteria established for the biomass estimation, the obtained equations were analyzed using comparisons of statistical criteria obtained according to the following equations:

$$R^2_{aj}=R^2-\left[\frac{k-1}{n-k}\right]\times\left(1-R^2\right) \quad (8)$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2}{n}} \quad (9)$$

In which: Yi is the replied variable (biomass and/or carbon) observed in the field (i); $\widehat{Yi}$ is the estimate (biomass and/or carbon), k is the number of parameters and n is the total number of observations.

Generation of stock maps using LiDAR data

After selecting the best model, the AsciiGrid Input function, available in the yaInpute in R package (Crookston and Finley, 2007), was used to view the estimates generated by the model on a map. The map expresses a grid where each cell represents a 5x5 m grid

colored according to the biomass and the estimated carbon content for that cell. The adopted methodology can be seen in the organization chart below (Fig. 4).

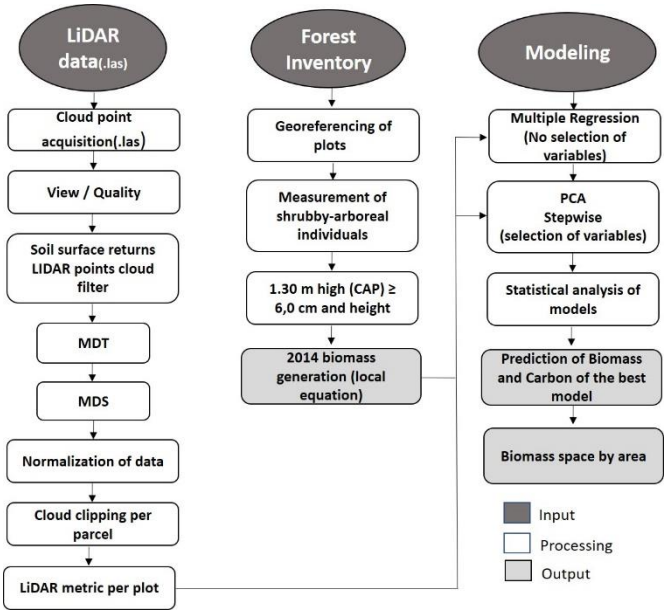


Fig. 4 Flowchart of the methodology adopted and the resulting products.

List of abbreviations

IBGE – Instituto Brasileiro de Geografia e Estatística

EMBRAPA – Empresa Brasileira de Pesquisa Agropecuária

TAGB – Total aboveground biomass

TAGC – Total aboveground carbon

Availability of data and materials

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

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no conflict of interest

Funding

Not applicable.

Authors' contributions

Cinthia Oliveira and Rinaldo Ferreira planned the study and wrote the manuscript, Cinthia Oliveira, Robson Lima and José Aleixo da Silva participated in the processing data LiDAR, calculation and modeling of the data and wrote the manuscript. Emanuel Silva, Josias Divino Lucena, Anderson da Silva, Nattan Adler dos Santos, Cybelle Souto Maior, Mayara Pessoa, Iran Jorge collected and processed the data inventory. They also commented on the manuscript. The authors read and approved the final manuscript.

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References

Achard F, House JI. 2015. Reporting carbon losses from tropical deforestation with Pan-tropical biomass maps. Environ Res Lett. 10(10):101002.

Althoff TD, Menezes RSC, Pinto A de S, Pareyn FGC, Carvalho AL de, Martins JCR, de Carvalho EX, Silva ASA da, Dutra ED, Sampaio EV de SB. 2018. Adaptation of the century model to simulate C and N dynamics of Caatinga dry forest before and after deforestation. Agric Ecosyst Environ. 254:26–34.

Anderson KE, Glenn NF, Spaete LP, Shinneman DJ, Pilliod DS, Arkle RS, McIlroy SK, Derryberry DR. 2018. Estimating vegetation biomass and cover across large plots in shrub and grass dominated drylands using terrestrial lidar and machine learning. Ecol Indic. 84:793–802.

Avitabile V, Herold M, Henry M, Schmullius C. 2011. Mapping biomass with remote sensing: a comparison of methods for the case study of Uganda. Carbon Balance Manag [Internet]. [accessed 2018 Sep 27] 6(1). https://cbmjournal.biomedcentral.com/articles/10.1186/1750-0680-6-7

Becknell JM, Keller M, Piotto D, Longo M, Nara dos-Santos M, Scaranello MA, Bruno de Oliveira Cavalcante R, Porder S. 2018. Landscape-scale lidar analysis of aboveground biomass distribution in secondary Brazilian Atlantic Forest. Biotropica. 50(3):520–530.

Brahma B, Nath AJ, Sileshi GW, Das AK. 2018. Estimating biomass stocks and potential loss of biomass carbon through clear-felling of rubber plantations. Biomass Bioenergy. 115:88–96.

Brown S, Lugo AE. 1982. The storage and production of organicmatter in tropical forests and their role in the global carboncycle. Biotropica. 14:161–187

Chave J, Andalo C, Brown S, Cairns MA, Chambers JQ, Eamus D, Fölster H, Fromard F, Higuchi N, Kira T, et al. 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia. 145(1):87–99.

Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WBC, Duque A, Eid T, Fearnside PM, Goodman RC, et al. 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob Change Biol. 20(10):3177–3190.

Chen Q, Lu D, Keller M, dos-Santos M, Bolfe E, Feng Y, Wang C. 2015. Modeling and Mapping Agroforestry Aboveground Biomass in the Brazilian Amazon Using Airborne Lidar Data. Remote Sens. 8(1):21.

Coomes DA, Dalponte M, Jucker T, Asner GP, Banin LF, Burslem DFRP, Lewis SL, Nilus R, Phillips OL, Phua M-H, Qie L. 2017. Area-based vs tree-centric approaches to mapping forest carbon in Southeast Asian forests from airborne laser scanning data.

Remote Sens Environ [Internet]. [accessed 2018 Nov 12] 194:77–88. https://linkinghub.elsevier.com/retrieve/pii/S0034425717301098

Crookston NL, Finley A. 2008. Yaimpute: An R package for k-NN imputation. Journal of Statistical Software**.** 23(10): 1–16. https://doi.org/10.18637/jss.v023.i10.

Crowther TW, Glick HB, Covey KR, Bettigole C, Maynard DS, Thomas SM, Smith JR, Hintler G, Duguid MC, Amatulli G, et al. 2015. Mapping tree density at a global scale. Nature. 525(7568):201–205.

Dalla Lana M. et al. 2018. Biomass equations for caatinga species. Nativa 6:517–525. http://dx.doi.org/10.31413/nativa.v6i5.5361

Duncanson L, Huang W, Johnson K, Swatantran A, McRoberts RE, Dubayah R. 2017. Implications of allometric model selection for county-level biomass mapping. Carbon Balance Manag [Internet]. [accessed 2018 Aug 16] 12(1). https://cbmjournal.biomedcentral.com/articles/10.1186/s13021-017-0086-9

Elias M, Potvin C. 2003. Assessing inter- and intra-specific variation in trunk carbon concentration for 32 neotropical tree species. **Canadian Journal of Forest Research.** 33(6): 1039–1045. https://doi.org/10.1139/x03-018.

Empresa Brasileira de Pesquisa Agropecuária- EMBRAPA. Zoneamento Agroecológico do Estado de Pernambuco – ZAPE. 2007. Disponível em: http://www.uep.cnps.embrapa.br/zape. Acesso em: 15 abr. 2017.

Figueiredo EO, d'Oliveira MVN, Braz EM, de Almeida Papa D, Fearnside PM. 2016. LIDAR-based estimation of bole biomass for precision management of an Amazonian forest: Comparisons of ground-based and remotely sensed estimates. Remote Sens Environ [Internet]. [accessed 2018 Nov 12] 187:281–293. https://linkinghub.elsevier.com/retrieve/pii/S0034425716303984

Hernández-Stefanoni JL, Johnson KD, Cook BD, Dupuy JM, Birdsey R, Peduzzi A, Tun-Dzul F. 2015. Estimating species richness and biomass of tropical dry forests using LIDAR during leaf-on and leaf-off canopy conditions.Goslee S, editor. Appl Veg Sci. 18(4):724–732.

Instituto Brasileiro de Geografia e Estatística, Coordenação de Recursos Naturais e Estudos Ambientais. 2012. Manual técnico da vegetação brasileira.

Jensen JR. 2005. Introductory digital image processing: a remote sensing perspective. Upper Saddle River, N.J: Prentice Hall.

Kachamba D, Ørka H, Næsset E, Eid T, Gobakken T. 2017. Influence of Plot Size on Efficiency of Biomass Estimates in Inventories of Dry Tropical Forests Assisted by Photogrammetric Data from an Unmanned Aircraft System. Remote Sens. 9(6):610.

Leitold V, Keller M, Morton DC, Cook BD, Shimabukuro YE. 2015. Airborne lidar-based estimates of tropical forest structure in complex terrain: opportunities and trade-offs for REDD+. Carbon Balance Manag [Internet]. [accessed 2018 Nov 12] 10(1). https://cbmjournal.biomedcentral.com/articles/10.1186/s13021-015-0013-x

Li A, Dhakal S, Glenn N, Spaete L, Shinneman D, Pilliod D, Arkle R, McIlroy S. 2017. Lidar Aboveground Vegetation Biomass Estimates in Shrublands: Prediction, Uncertainties and Application to Coarser Scales. Remote Sens. 9(9):903

Magnusson M. et al. 2007. Effects on Estimation Accuracy of Forest Variables Using Different Pulse Density of Laser Data. Forest Science. 53(6): 619-626. Disponível em: https://pub.epsilon.slu.se/3651/. Acesso em: 22 jun. 2018.

Malhi, Y. et al. 2004. The above-ground coarse wood productivity of 104 Neotropical forest plots. Global Change Biology**.** 10(5): 563–591. https://doi.org/10.1111/j.1529-8817.2003.00778.x.

Martinuzzi S, Gould WA, Vierling LA, Hudak AT, Nelson RF, Evans JS. 2013. Quantifying Tropical Dry Forest Type and Succession: Substantial Improvement with LiDAR. Biotropica. 45(2):135–146.

Mohebalian PM, Aguilar FX. 2018. Beneath the Canopy: Tropical Forests Enrolled in Conservation Payments Reveal Evidence of Less Degradation. Ecol Econ. 143:64–73.

Naveenkumar J, Arunkumar KS, Sundarapandian Sm. 2017. Biomass and carbon stocks of a tropical dry forest of the Javadi Hills, Eastern Ghats, India. Carbon Manag. 8(5–6):351–361.

Nelson R, Margolis H, Montesano P, Sun G, Cook B, Corp L, Andersen H-E, deJong B, Pellat FP, Fickel T, et al. 2017. Lidar-based estimates of aboveground biomass in the continental US and Mexico using ground, airborne, and satellite observations. Remote Sens Environ [Internet]. [accessed 2018 Nov 12] 188:127–140. https://linkinghub.elsevier.com/retrieve/pii/S0034425716304175

R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Roy J. 2001.Terrestrial global productivity. San Diego: Academic.

Saatchi S, Malhi Y, Zutta B, Buermann W, Anderson LO, Araujo AM, Phillips OL, Peacock J, ter Steege H, Lopez Gonzalez G, et al. 2009. Mapping landscape scale variations of forest structure, biomass, and productivity in Amazonia. Biogeosciences Discuss. 6(3):5461–5505.

Sampaio EV, Silva GC. 2005. Biomass equations for Brazilian semiarid caatinga plants. Acta Bot Bras. 19(4):935–943.

Silva C, Hudak A, Vierling L, Klauberg C, Garcia M, Ferraz A, Keller M, Eitel J, Saatchi S. 2017a. Impacts of Airborne Lidar Pulse Density on Estimating Biomass Stocks and Changes in a Selectively Logged Tropical Forest. Remote Sens. 9(10):1068.

Silva C, Hudak A, Vierling L, Klauberg C, Garcia M, Ferraz A, Keller M, Eitel J, Saatchi S. 2017b. Impacts of Airborne Lidar Pulse Density on Estimating Biomass Stocks and Changes in a Selectively Logged Tropical Forest. Remote Sens [Internet]. [accessed 2018 Nov 12] 9(10):1068. http://www.mdpi.com/2072-4292/9/10/1068

Silva CA, Klauberg C, Hudak AT. 2014. Mapeamento de estoques de carbono acima do solo utilizando dados LiDAR em plantações de Eucalyptus spp no estado de São Paulo, Brasil. Sci For. 42(104):14.

Silva CA, Klauberg C, Hudak AT, Vierling LA, Liesenberg V, Carvalho SPC e, Rodriguez LCE. 2016. A principal component approach for predicting the stem volume in Eucalyptus plantations in Brazil using airborne LiDAR data. Forestry. 89(4):422–433.

Somogyi Z, Cienciala E, Mäkipää R, Muukkonen P, Lehtonen A, Weiss P. 2007. Indirect methods of large-scale forest biomass estimation. Eur J For Res. 126(2):197–207.

Takahashi T, Awaya Y, Hirata Y, Furuya N, Sakai T, Sakai A. 2010. Stand volume estimation by combining low laser-sampling density LiDAR data with QuickBird panchromatic imagery in closed-canopy Japanese cedar (*Cryptomeria japonica*) plantations. Int J Remote Sens [Internet]. [accessed 2018 Nov 12] 31(5):1281–1301. https://www.tandfonline.com/doi/full/10.1080/01431160903380623

Thomas V, Treitz P, McCaughey JH, Morrison I. 2006. Mapping stand-level forest biophysical variables for a mixedwood boreal forest using lidar: an examination of scanning density. Can J For Res [Internet]. [accessed 2018 Nov 12] 36(1):34–47. http://www.nrcresearchpress.com/doi/10.1139/x05-230

Figures

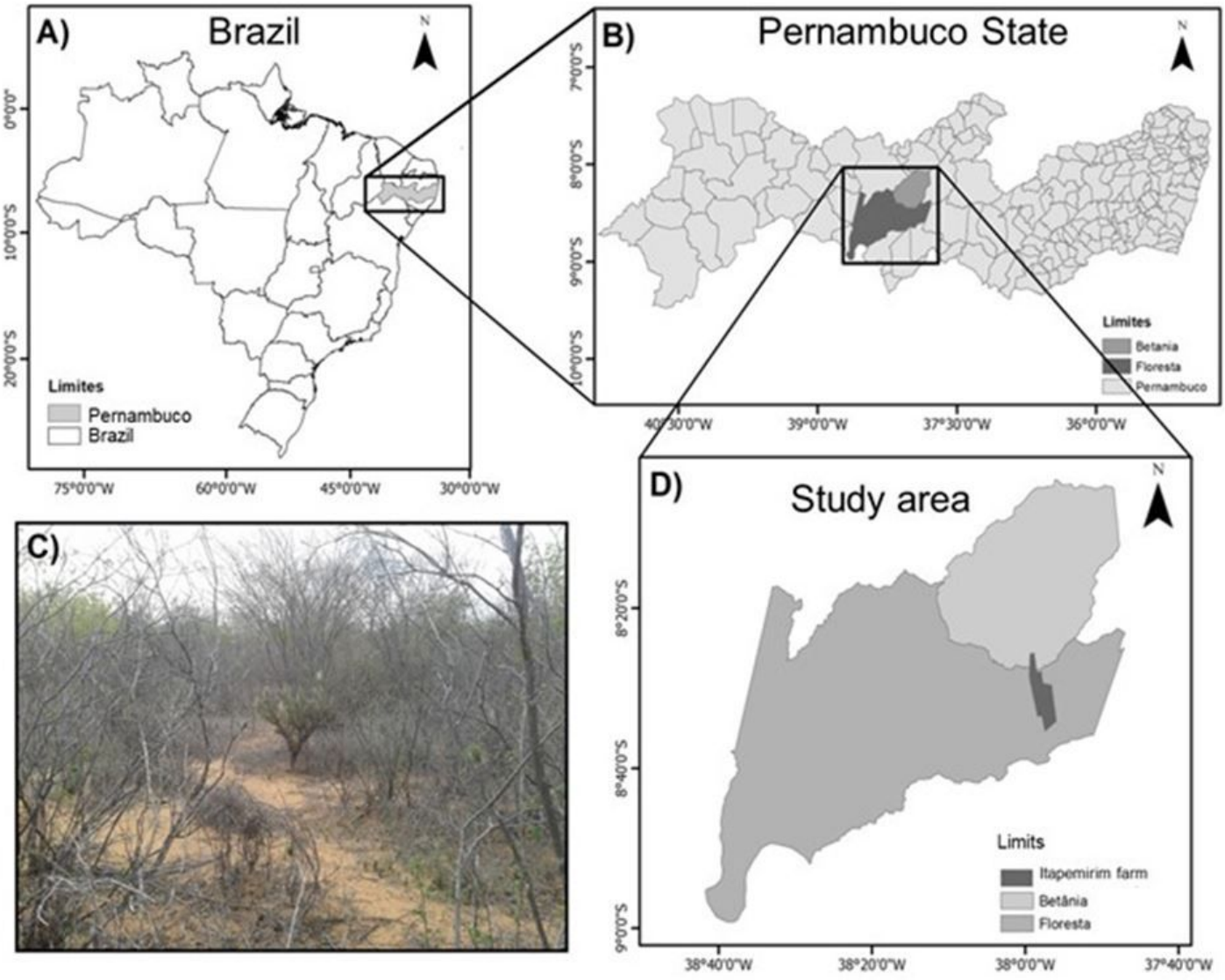

Figure 1

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

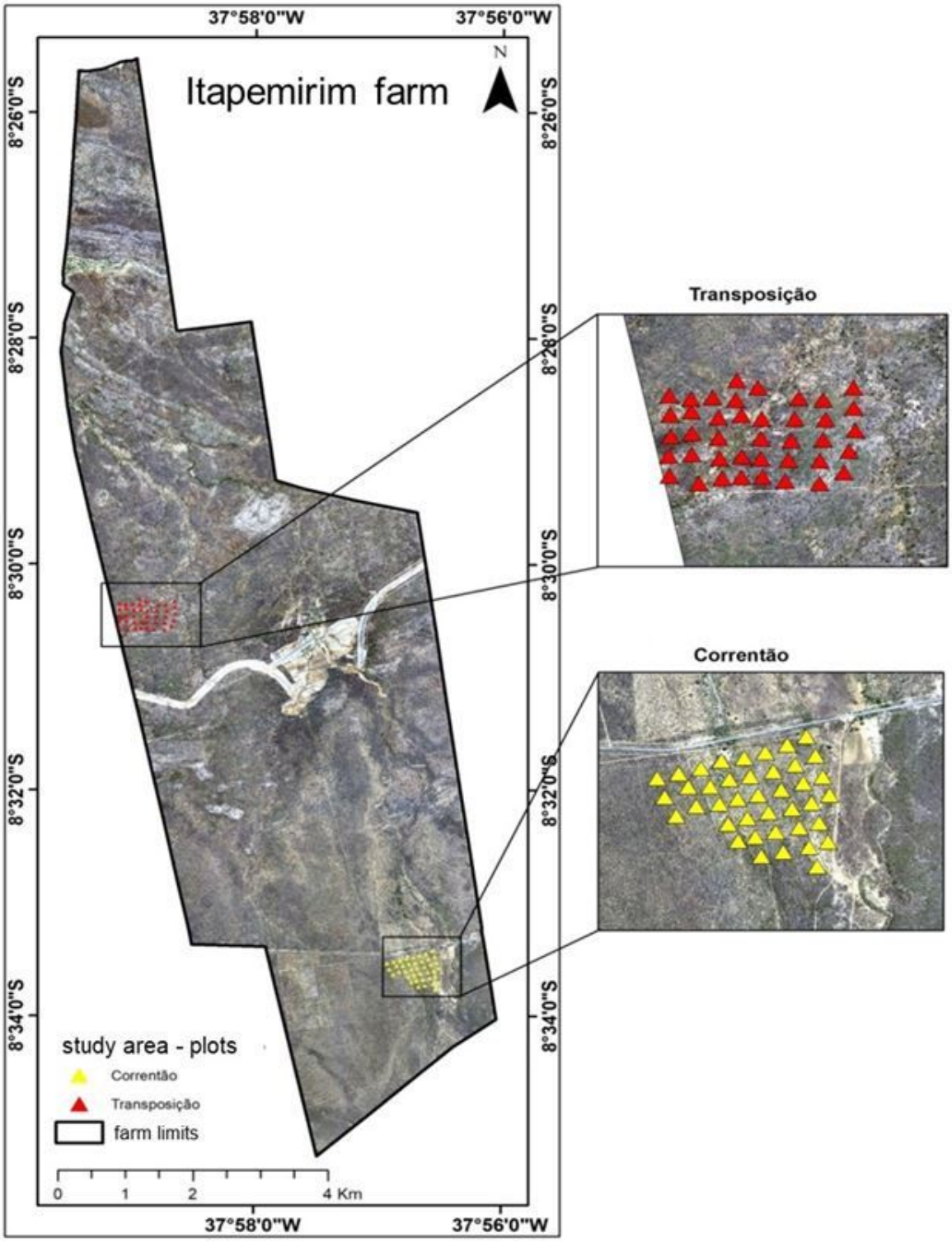

Figure 2

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

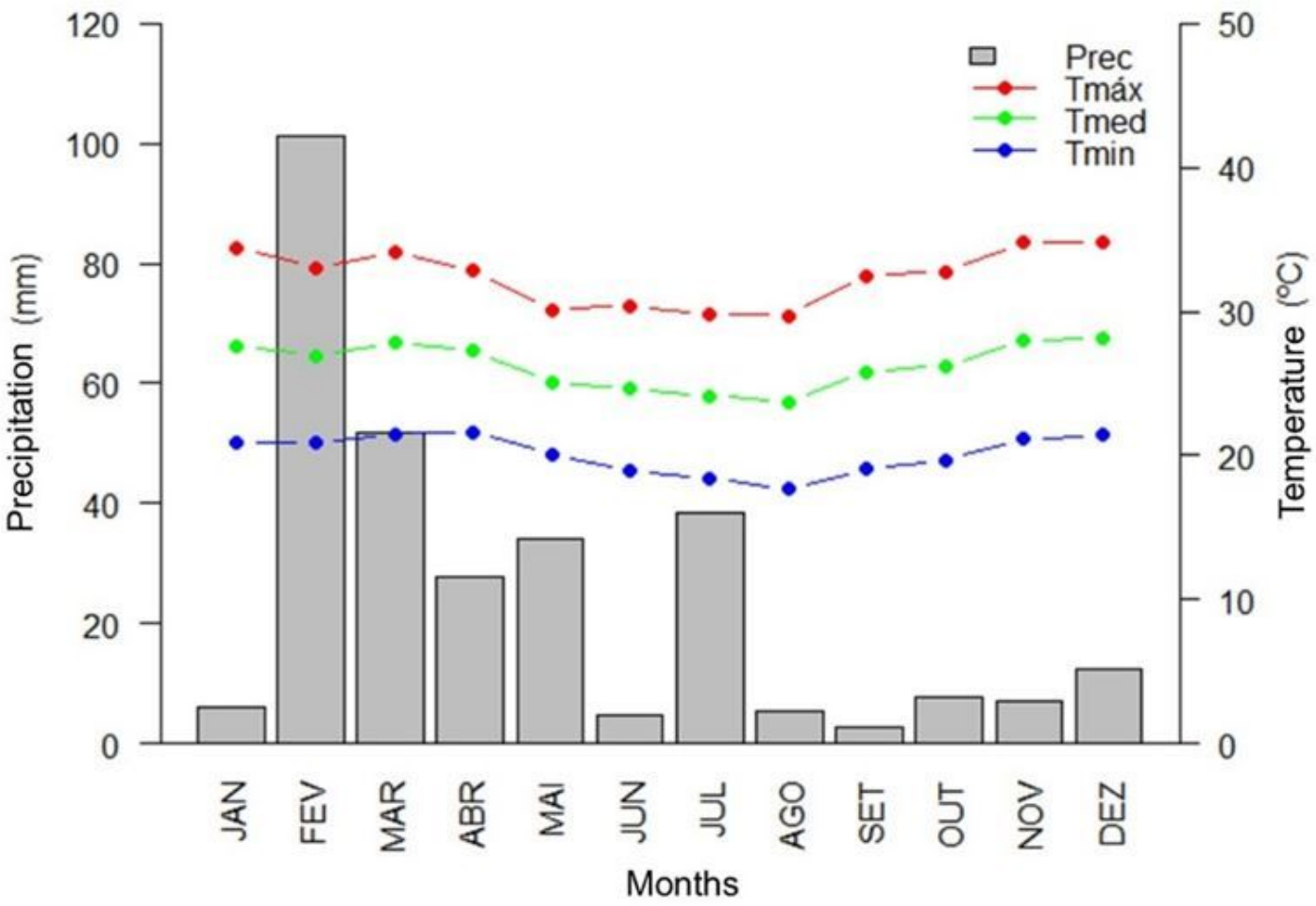

Figure 3

Distribution of air temperature and precipitation over the year 2014 in the study area by the nearest weather station. Source: Agritempo adjusted. Source: Agritempo, 2018 (adjusted).

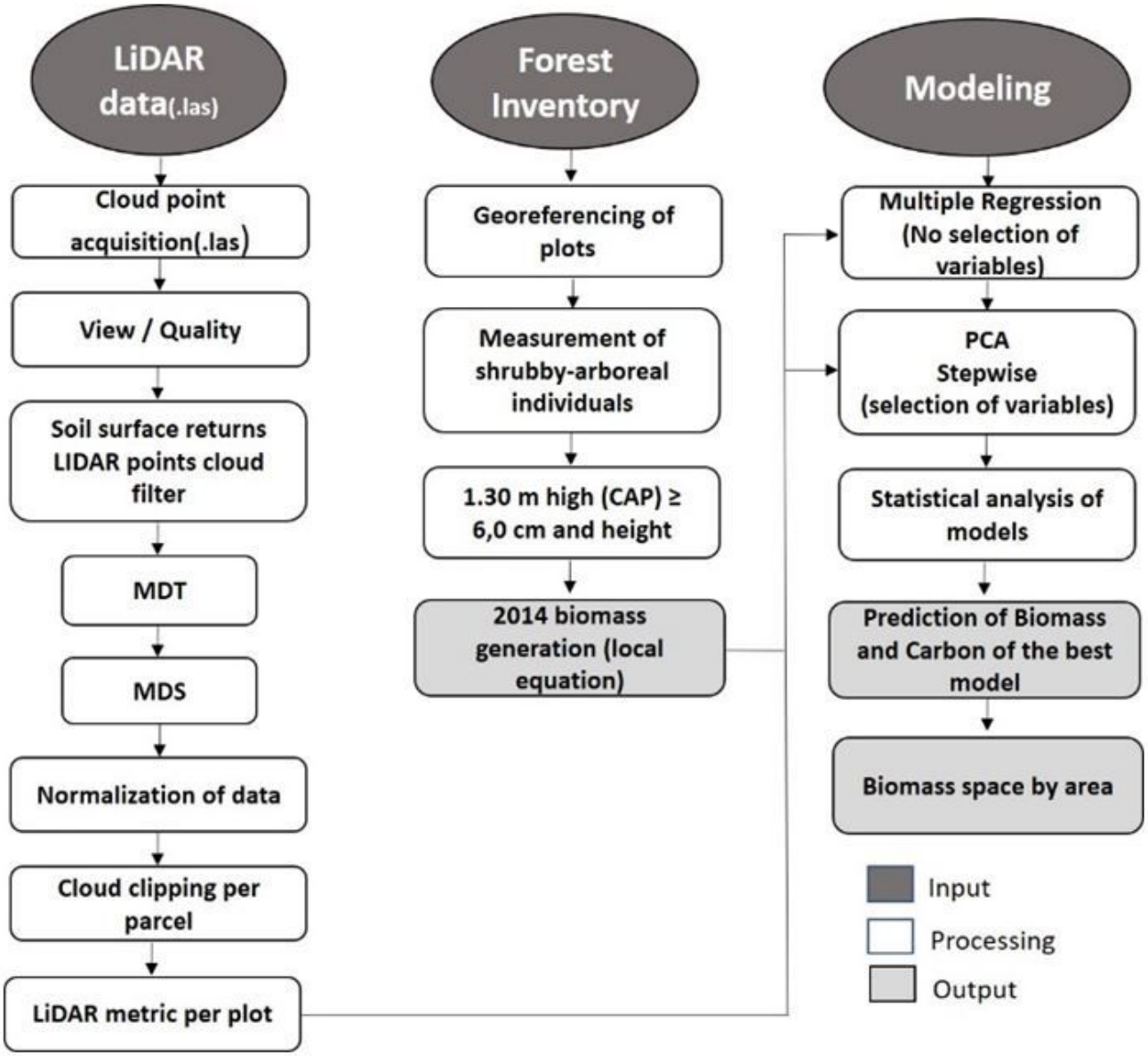

Figure 4

Flowchart of the methodology adopted and the resulting products.

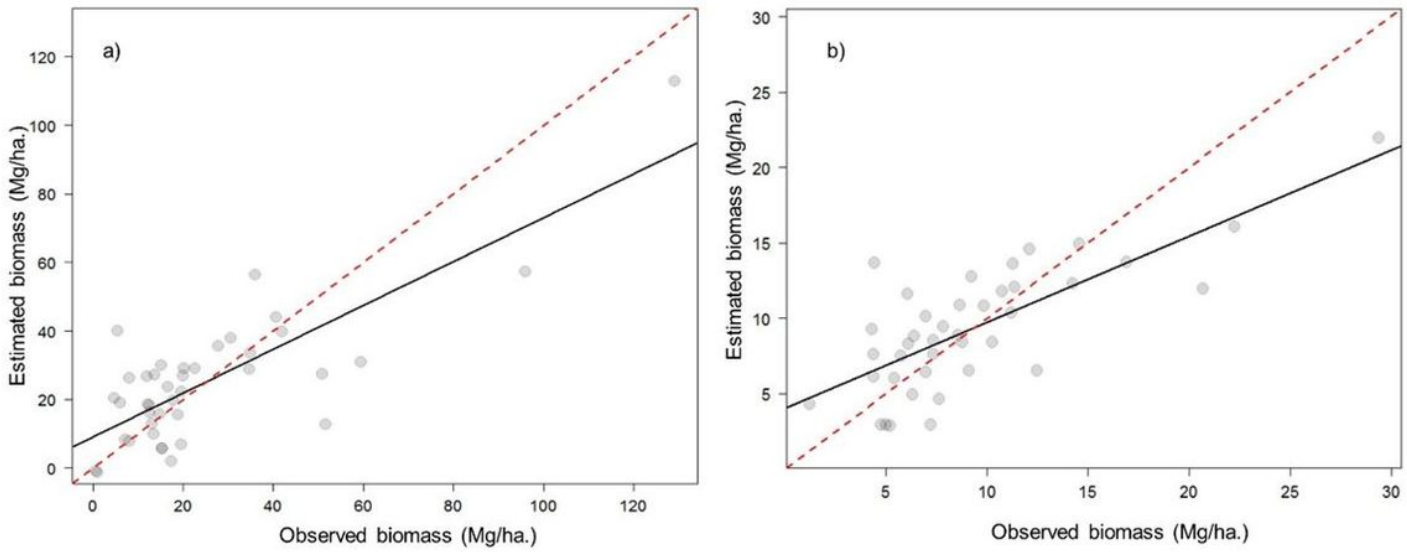

Figure 5

Predictions of the best allometric equations for the Correntão area (a) and Transposição (b) using the LiDAR metrics selected step by step in relation to the observed values. The solid black line indicates the fit of the equation and the red dotted line indicates the ideal fit in a 1: 1 ratio.

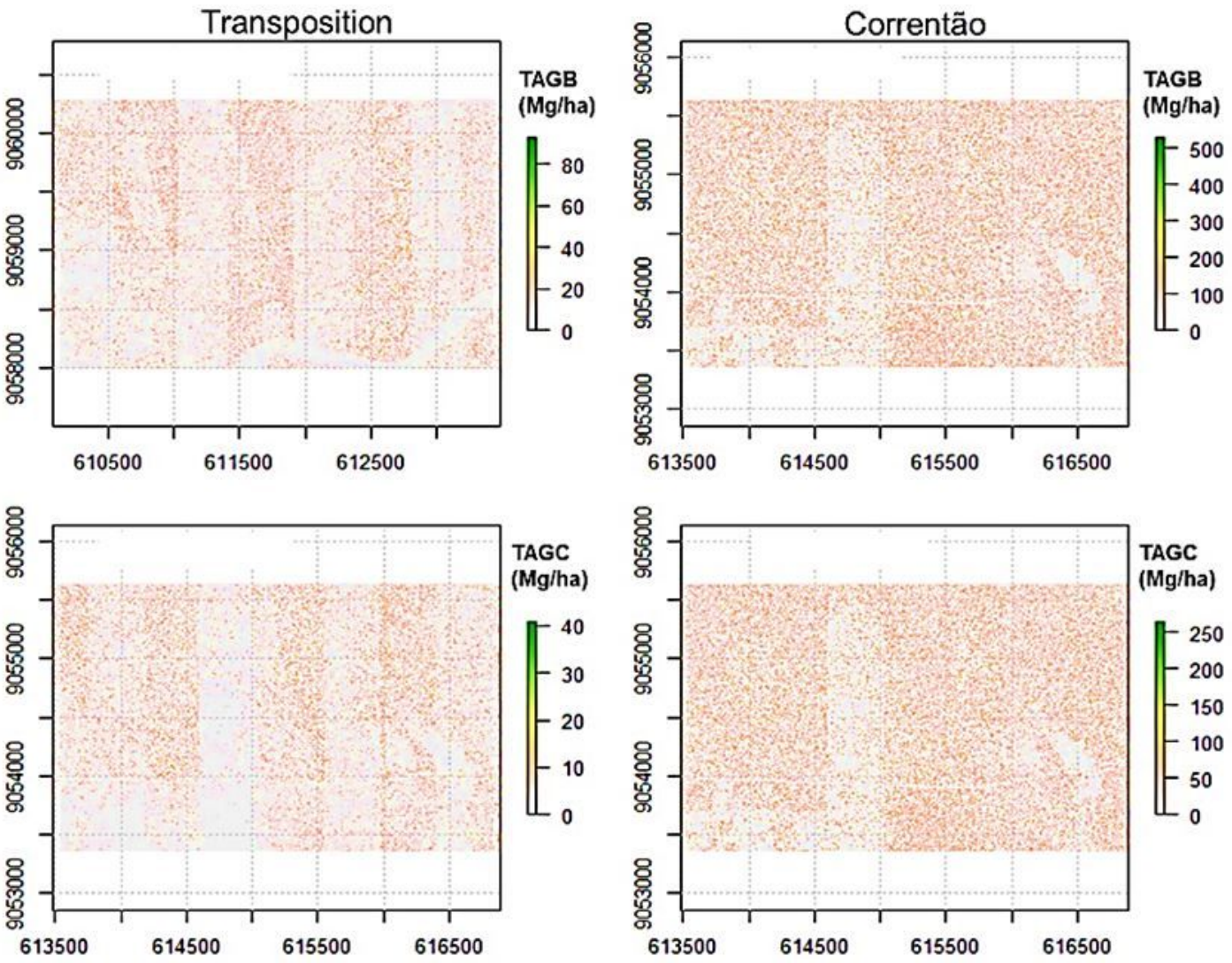

Figure 6

Spatialization of biomass and carbon based on Stepwise regression models defined according to the LiDAR metrics for the Transposição and Correntão areas.