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Predicting teak tree (*Tectona grandis* Linn F.) height using generic models and artificial neural networks

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Abstract

The continuous monitoring of dendrometric variables provides estimates that assist in conducting fast-growing stands. In this study, we aimed to investigate the performance of generic models and artificial neural networks to estimate total height of *Tectona grandis* in a forest stand in the Eastern Amazon. Continuous forest inventory was performed in this population, where total height and diameter at breast height were measured. The variables such as age and the square root of the average diameter (dg) of the plots were used to compose the methods adopted to estimate the height of the trees. The accuracy of these methods was assessed using the residual standard error of the estimate, the coefficient of correlation, and the graphical analysis of residues. The aggregated difference and ANOVA were calculated to compare the methods. The independent variables mentioned were able to describe the height behavior of individuals. We concluded that the methods have good residual dispersion, normal distribution of errors and little tendency to overestimate height. It was found that the generic models and the ANNs do not differ significantly from each other and are efficient to estimate the height of individuals. We also concluded that the ANNs, especially those that included dg, presented superior statistical indicators.

Keywords: Amazonia; clonal planting; forest management; modeling, Teak.

Abbreviations: dbh_diameter at breast height; ht_the total height; dg_mean quadratic diameter; Syx_residual standard error of estimate absolute; Syx%_residual standard error of estimate percentage.

Introduction

The *Tectona grandis* Linn F., popularly known as teak, is a native species from Southeast Asia and Indian subcontinent (Deb et al., 2017; Pelissari et al., 2014). The species highlights for presenting alternative wood characteristics to supply forest industries, being used in civil construction, as well as in the production of luxury furniture and boats (Pelissari et al., 2014, 2017). Currently, there are about 6,887 million hectares of *T. grandis* planting, distributed among the Asian (6,071 million hectares), African (538 thousand hectares) and South American (278 thousand hectares) continents (Midgley et al. 2015). Nowadays, in Brazil there are approximately 94 thousand hectares destined for the planting of this species (IBÁ 2019). The measurement and prediction of *T. grandis* forest stock is essential to gather and provide information for advising deliberations in the forestry area, and thus to optimize production and meet demands of this specie (Campos et al., 2016; Lauro et al., 2018; Leite and Andrade 2003). It is important to measure the diameter, height, basal area, and volume of trees present at the stands for this purpose (Campos and Leite, 2017; Lauro et al., 2018). It is necessary to obtain the heights of the trees inserted in the forest stand, and to correlate these heights to other variables to classify the forest site, to estimate and to verify the volumetric increase and then to determine the stem taper. However, the measurement of this variable, especially in dense and extensive stands, makes forest management activities onerous and perhaps even unviable (Kohler et al., 2017; Mendonça et al., 2014; Moreira et al., 2015). Generic models have been used to solve this problem. These models estimate height through association with variables that are easier to measure and may also include the diversity of population characteristics (De Barros et al., 2002; Filho et al., 2016). Recently, artificial neural networks (ANN) have also been used for this purpose (De Barros et al., 2002; Binoti et al., 2013; Costa Filho et al., 2019; Martins et al., 2016; De Souza et al., 2008). This method consists of computational models, which resemble the nervous system of living beings (Díncer and Tosun 2018; Leite and Andrade 2003; Martins et al., 2016; Vendruscolo et al., 2017). The ANN's can acquire and manage knowledge through information provided (Binoti et al., 2013; Díncer and Tosun 2018; Oliveira et al., 2011; Vendruscolo et al., 2017). Furthermore, the network is characterized by representing a set of processing units, which are formed by artificial neurons. These neurons are associated by many interconnections, called artificial synapses (Rocha et al., 2013; Santos and Andrade, 2019).

Studies which assess the capacity of regression models and artificial neural networks to estimate the height of common species, such as the genus Pinus and Eucalyptus are easily found in the literature (Campos and Leite (2017); Costa Filho et al., (2019) and Martins et al., (2016). However, there is a shortage of studies on some other species, such as on *T. grandis* (Vendruscolo et al., 2017). Therefore, this study aimed at the Eastern Amazon stands out. According to Santos et al. (2020), there is still a lack of available information on this location to support forest management in a *T. grandis* stand. Research focused on clonal plantations of this species in this region is even scarcer.

In this context, the present study investigated techniques that assist the estimation of variables for the management of fast-growing stands of *T. grandis*, through the continuous monitoring of diameter, total height and age. Thus, the aim was to assess the performance of the generic models and the ANN to predict the height of individuals belonging to *T. grandis* stands in the Eastern Amazon. For this purpose, it was intended to incorporate predictive variables into generic models and ANN's. We also investigated the ability to fit, or train, compare, and select the most accurate method for estimating total height.

Results

Statistics and correlation

Pairs of diameter and height of 882 trees were measured in the inventory process.

The behavior of the studied variables is shown in Table 1.

The correlation between the independent variables and the variable of interest generated a positive degree of association, ranging from moderate to high (Table 2).

The variance inflation factors (VIF) were less than 10, showing that the independent variables can be used together in both models and networks, so that there is no overlap when explaining the dependent variable (Table 3).

Height modeling using regression

The models adjustment, as well as the respective adjustment and precision indicators, are shown in Table 4. All equations were significant regarding the F test ($p < 0.05$), highlighting the existence of regression.

In general, all models in the present study fitted to the database with fit and precision statistics close. The standard error of the estimate varied between 1.13 and 1.18 m (7.48 and 7.72%), highlighting equation 2, which presented the smallest error. By analyzing the correlation coefficient it was possible to attest to the superiority of equation 2, presenting value of R closest to one, i.e., this model had a higher degree of association between the observed values and estimation.

The biggest precision of the nonlinear model (2) once again became evident when analyzing the residual graphs of the generic models submitted to fitting, for height estimate of *T. grandis* stands. The distribution of the percentage residues of this model did not show bias, or showed low bias, in the estimate of the total height, with a residual amplitude of less than ± 30%, concentrated in the ± 10% error classes and presenting a high correlation (> 0.8) (Fig. 1).

Height modeling using ANN

We observed a slight variation in the adjustment and precision statistics of the ANN's, as well as in the regression modeling. It is noteworthy that the networks 6, 7, 8, 9 and 10 showed low values for the standard errors of the estimate, with values ranging from 0.88 to 1.00 m (5.84 and 6.64%). The other networks had higher errors, ranging from 1.01 to 1.09 m (6.65 to 7.20%) (Table 5). Based on the correlation coefficient, it is possible to highlight the slight superiorities of artificial neural networks 2, 6, 7, 8, 9, 10 in relation to the others. Therefore, these presented values of r closer to 1.

The highest precision of the MLP 7-10-1 network (9) stands out again in the evaluation of the ANNs residue graphs. In other words, this network showed a concentration of residual errors in 30%, with errors prevailing between 0 and 10% (Fig. 2; Fig. 3).

Comparison between regressions and ANNs

The superiorities of artificial neural networks stand out to estimate the height of the *T. grandis* trees when we analyzed standard error of the estimates obtained and compared to regression modeling. However, it was necessary to analyze these methods graphically to complete this comparison, because, through this evaluation, it is possible to verify the accuracy of the methods used, as well as to visualize their tendency to overestimate and/or underestimate the height.

We noted a slight tendency to overestimate the height of trees in the regression models and in the artificial neural networks, when we analyzed the distribution graphs of the percentage estimation errors. This characteristic becomes even more explicit when we analyzed the aggregated difference between the equation and the selected network. The aggregate difference showed negative values for the selected artificial neural network (-0.98), as well as for the selected model (-3.68).

It is evident that the ANN and the selected model have no significant difference among each other and between them and the observed values, even though the ANN's present statistical indicators superior to those presented by the regression models. This statement is based on the inferiority of the calculated F-value (0.13), at a significance level of 5%, regarding the tabulated F value (3.85), obtained through the analysis of variance (Table 6). Therefore, it is claimed that both methods used are capable of accurately estimating the height of *T. grandis* trees.

Discussion

Statistics and correlation

In general, we observed a moderate to high positive relationship between the independent variables and the response variable (Table 2). According to Hinkle et al. (2003) a low relationship is characterized when Pearson's correlation ranges from 0.30 to 0.49, moderate, when ranging from 0.50 to 0.69, and high when there are values greater than 0.7.

Table 1. Statistics of *T. grandis* clonal stands in the study area, in eastern Amazon, Brazil.

Variables	Age	4	5	6	7	9	Average
	Minimum	8.70	9.90	11.60	12.10	12.10	
	Average	11.77	14.16	16.59	15.86	16.82	
ht	Maximum	14.3	17.2	19.4	19.2	20.2	15.16
	Standard devitation	1.16	1.22	1.19	1.28	1.97	
	CV	9.86	8.63	7.21	8.06	11.73	
	Minimum	10.03	11.55	14.84	15.60	16.84	
	Average	15.19	18.27	22.44	23.14	26.41	
dbh	Maximum	20.31	22.98	27.66	29.16	34.57	21.16
	Standard devitation	1.98	1.96	2.38	2.32	4.18	
	CV	13.02	10.71	10.60	10.04	15.83	
	Minimum	14.39	15.25	19.21	16.96	20.83	
	Average	15.29	18.33	22.51	23.17	26.57	
dg	Maximum	17.63	20.28	25.90	25.99	31.81	21.09
	Standard devitation	0.99	1.24	1.62	1.81	3.38	
	CV	6.45	6.76	7.18	7.82	12.74	

ht = total height of the tree (m); dbh = diameter at 1.30 m from the ground (cm); dg = mean square diameter per plot; CV = coefficient of variation (%).

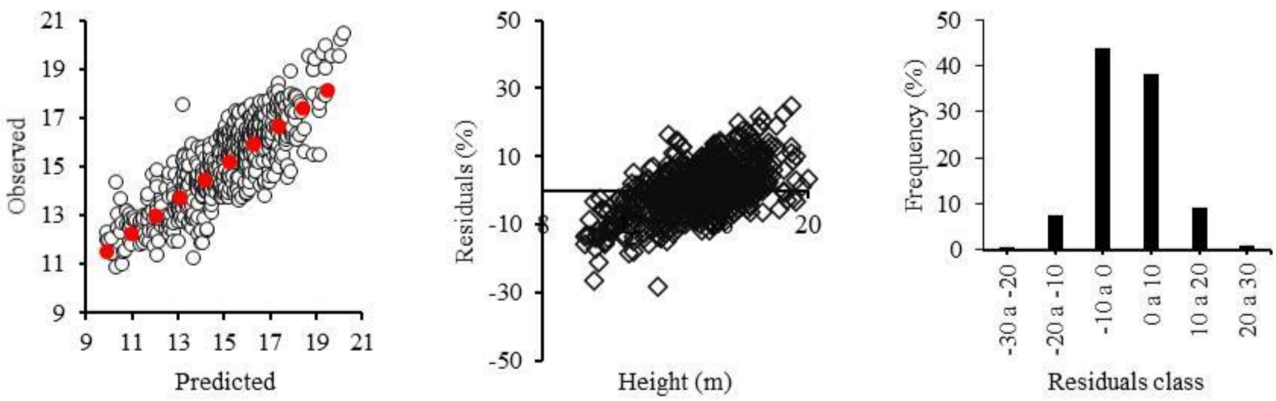

Fig 1. Graphical representation of the correlation between observed and predicted heights (A), distribution of estimation errors (B) and histogram of the frequency of relative error generated by the nonlinear equation 2 (C), adjusted to the data of the clonal stands *T. grandis* in the eastern Amazon, Brazil.

Table 2. Correlation matrix between the independent (dbh, q and age) and dependent (ht) variables obtained in clonal *T. grandis* stands in the eastern Amazon, Brazil.

	ht	dbh	q	a
ht	1.00			
dbh	0.81*	1.00		
dg	0.79*	0.91*	1.00	
a	0.63*	0.77*	0.84*	1.00

dbh = diameter at 1.3 m from the ground (cm); dg = mean square diameter; a = age (years), significant for α 0.05.

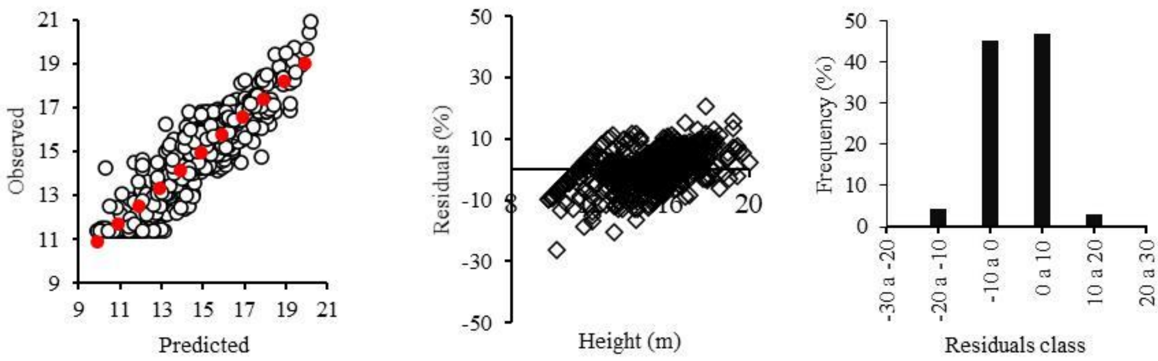

Fig 2. Graphical representation of the correlation between observed and predicted heights (A). distribution of estimation errors (B) and histogram of the relative error frequency generated by the MLP 7-10-1 artificial neural network (C) adjusted to the clonal stands data *T. grandis* in the eastern Amazon. Brazil.

Table 3. Multi-collinearity analysis between the independent variables obtained in clonal *T. grandis* stands in the eastern Amazon, Brazil.

	dbh	dg	a
VIF	5.6334	7.8545	3.3149

VIF = variance inflation factor; dbh = diameter 1.3 m from the ground; q = mean square diameter.

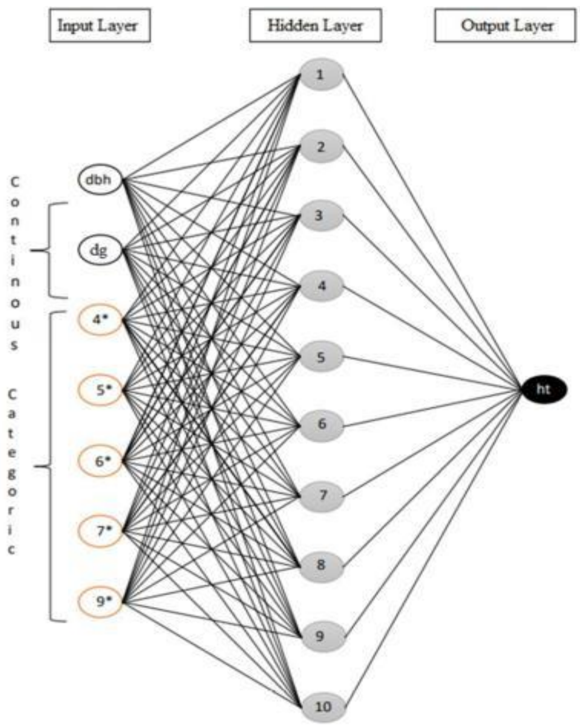

Fig 3. ANN architecture selected and trained to the data from the *T. grandis* clonal stands in the eastern Amazon, Brazil. Where: dbh: diameter at 1.30 m from the ground; q: square mean diameter; ht: total height of the tree. * Age in years.

Table 4. Precision measurements of hypsometric models adjusted to the data from *T. grandis* clonal stands in the eastern Amazon, Brazil.

#		Coefficient	Standard Error	F	r	Syx	Syx %
	β0	5.7098*	0.2750				
1	β1	0.2620*	0.0274	27477.73*	0.8289	1.14	7.54
	β2	0.2516*	0.0373				
	β3	-0.2216*	0.0701				
	β0	2.0964*	0.1440				
2	β1	0.3420*	0.0363	27948.90*	0.8321	1.13	7.48
	β2	0.3597*	0.0512				
	β3	-0.0860*	0.0290				
	β0	1.8452*	0.1153	35544.93*			
3	β1	0.1738*	0.0231		0.8228	1.16	7.66
	β2	0.6214*	0.1826				
	β0	2.4175*	0.1696	34079.10*			
4	β1	-0.0781*	0.3020		0.8144	1.18	7.82
	β2	0.5725*	0.0167				

β0, β1, β2 and β3 = obtained coefficients; Ep: standard error; F = calculated F (α = 0.05); * = significant for α = 0.05; r = correlation coefficient; Syx = standard error of the estimate in meters; Syx% = standard error of the percentage estimate.

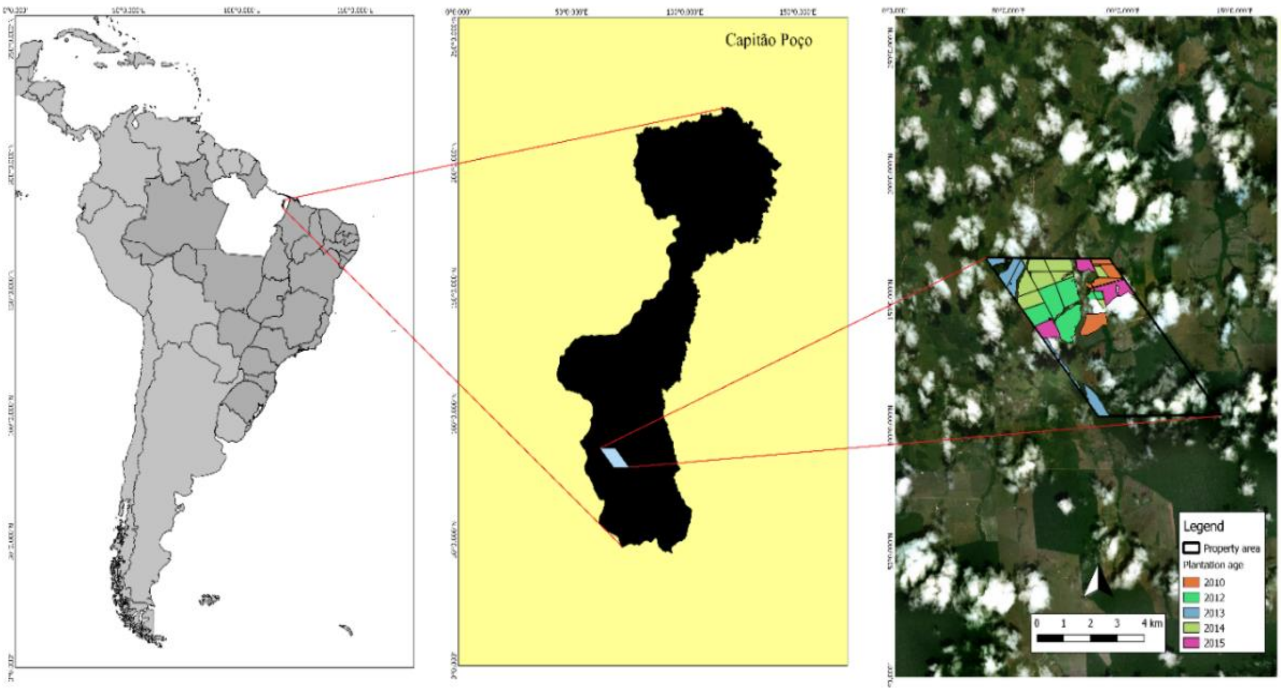

Fig 4. Location of the study area in the eastern Amazon, Brazil.

Table 5. Precision measurements of artificial neural networks trained for data from *T. grandis* clonal stands in eastern Amazonia. Brazil.

#	Type/Architecture	Input Layer	Activation function Hidden Layer	Output Layer	Nº of cycles	r	Syx	Syx%
1	MLP 6-9-1		Identity	Exponential	20	0.84	1.09	7.20
2	MLP 6-7-1		Tanh	Identity	651	0.87	1.01	6.65
3	MLP 6-3-1	dbh e a	Tanh	Logistics	462	0.86	1.03	6.85
4	MLP 6-8-1		Exponential	Tanh	10000	0.86	1.02	6.77
5	MLP 6-7-1		Exponential	Logistics	10000	0.86	1.02	6.74
6	MLP 7-4-1		Identity	Identity	22	0.87	1.00	6.64
7	MLP 7-4-1		Logistics	Tanh	9954	0.89	0.93	6.17
8	MLP 7-4-1	dbh. dg e a	Logistics	Exponential	352	0.89	0.94	6.24
9	MLP 7-10-1		Tahn	Exponential	10000	0.90	0.88	5.84
10	MLP 7-8-1		Logistics	Logistics	10000	0.90	0.88	5.85

dbh = diameter at 1.30 m from the ground (cm); q = mean square diameter; i = age; r = correlation coefficient; Tanh = hyperbolic tangent; Syx = standard error of the estimate in meters; Syx% = standard error of the percentage estimate.

Table 6. Analysis of variance (ANAVA) applied to real and estimated heights by the selected regression model and artificial neural network.

	DF	SS	MS	Fcal
Treatment	2	13.30	6.65	0.13
Residue	2643	135461.51	51.25	Ftab
Total	2645	135474.82		3.85

DF: degree of freedom; SS = sum of square; MS = mean square; F cal = F calculated; F tab = tabulated.

Table 7. Hypsometric models adjusted to estimate the total height variable, in the eastern Amazon, Brazil.

Nº	Model	Category
1	$ht = \beta_0 + \beta_1$ dbh+ β_2 dbh+ β_3 a	Linear
2	$ht = \beta_0$ dbh β_1 dg β_2 a β_3	Non-linear
3	ht = β_0 (dbh / a) β_1 dg β_2	Non-linear
4	ht = β_0 (a / dg) β_1 dbh β_2	Non-linear

ht = total height of the tree (m); dbh = diameter at 1.30 m from the ground (cm); a = age (years); q = mean square diameter (cm²); β0, β1, β2 and β3 = coefficients to be fitted.

The correlation analysis showed a low degree of association among the independent variables, highlighting the reliability of their usage together a in a height model. The joint usage of these variables will not lead to errors in the regression estimate since there is an absence of multicollinearity.

Height modeling using regression

In general, all fitted models have presented small standard errors, with values representing less than 10%. When evaluating this statistical criterion, hypsometric models with errors of less than 10% are qualified as accurate (Scolforo 2006). However, eventually, it is not possible to reach these numbers (Miguel et al. 2018).

The superiority of model (2) is evident, considering the statistical criteria and the residual graphs, highlighting the efficiency of generic models for height estimate of *T. grandis* stands. Many authors have been obtained satisfactory results with generic models for height estimation.

Mendonça et al. (2018) recommended the use of generic models to estimate the height of trees, as they proved the accuracy, based on statistical criteria, of these models to estimate the height of Zeyheria tuberculosa (Vell.) Bur. Mendonça et al. (2014), studied the strategies and methodologies to estimate the height of *Pinus caribaea.* Based on statistical analysis, they concluded the applicability of generic models. Santos and Andrade (2019) also observed the precision of generic models to estimate the height of trees in this forest when analyzing hypsometric relationship for fragments of Cerrado sensu stricto.

Height modeling using ANN

All networks trained in this research proved to be accurate to estimate the height of *T. grandis*. However, the inclusion of the mean square diameter to the artificial neural networks results in networks which are equally or more efficient than the others according to the mentioned criteria. According to these results, it is also possible to characterize RNA 9 as the most accurate RNA. The structure of this RNA is described in Figure 3.

Artificial neural networks are considered efficient to estimate the height of trees. In research developed by Campos et al. (2016), they observed that it is possible to use only one ANN to estimate the height of trees of different species under different growing conditions. Rocha et al. (2013) concluded that ANN is precision to estimate the total height of *Eucalyptus* spp, based on statistical criteria. Another study present in the literature concluded that the use of precise networks is superior to the other method, when predicting the height of *T. grandis* using mixed effects modeling and ANN (Vendruscolo et al. 2016).

Comparison between regressions and ANNs

A slight superiority of the network is evident over the regression model when analyzing the training values of the network. Some studies showed a slight or non-existent tendency of these methods to overestimate height. Santos and Andrade (2019) observed an overestimation of the height of Cerrado trees by generic models. Soares et al. (2021) concluded that there is no apparent tendency to overestimate the height of *Eucalyptus globulus* and *Acacia mearnsii* estimated by ANN. Binoti and Leite (2013) found low or no tendency for ANN's to overestimate the heights of *Eucalyptus* sp. Based on graph of distribution of the errors of the estimate, it is noteworthy that the good residual dispersion of all adjusted models and trained ANN's were mostly in the range of 30%. It was possible to point out again that a small superiority of the neural networks based on the frequency histogram of relative error, especially ANN which included the mean square diameter, compared to the regression modeling. The regression models, as well as the ANN's, demonstrated satisfactory results, with the highest frequency of errors in classes of 0 and 10%. This occurred because the ANN's had a lower amount of error in the other classes, especially networks 6, 7, 8, 9 and 10. It is mentioned that both methods showed a normal distribution trend. Similar results have been found in other studies, such as in Campos et al. (2016) and in Vendruscolo et al. (2016). Artificial neural networks and generic models proved to be accurate to estimate the height of trees and showed a small discrepancy between statistical criteria. Similar results were also found by Mendonça et al. (2018). These authors observed superiority of the model Amateis compared to the ANN for estimating the total height of terry *Zeyheria tuberculosa*, although both appeared to be accurate. Ferreira and Oliveira (2019) verified the accuracy of generic models and ANNs to estimate the height of *Eucalyptus* sp., even though the network training has presented higher statistical values.

The generic models and/or artificial neural networks can estimate the height of the trees that were not measured in the sampling process, helping to reduction of costs of the forest inventory, as well as, increased precision, easier data processing and shorter sampling time (Andrade et al., 2015; Machado et al., 2019; Oliveira et al., 2011).

Therefore, the heights estimated by the studied methods can be used to compose volumetric models and tapering functions of the stem to classify forest site and verifying the increase in height and volume of the individual, and consequently, of the whole stand (Campos and Leite, 2017; Resende and Leite 2003; De Souza et al., 2008). Consequently, they can support decision-making in the forest sector.

Material and methods

Study area and characterization of stands

The study was developed in clonal stands of *T. grandis* at Fazenda São Luiz, owned by the company Tietê Agrícola Ltda, located in the municipality of Capitão Poço, Pará (Fig. 4).

The area is located in the region of Floresta Ombrófila Densa and/or Floresta Ombrófila Tropical, a constituent of the sub-region of the high plateaus Pará-Maranhão (IBGE 2012). As the Brazilian System of Soil Classification, the soils present in the region can be classified as concretory Petric Plinthsol (FFc), petroplinthic dystrophic Yellow Latosol (LAd) and typical dystrophic Yellow Oxisol (LAdt) (Embrapa 2013, 2017). The relief is predominantly characterized as smoothly wavy. Finally, according to the Koppen classification, the region has a humid or subsumed tropical climate (Am), transitory between the Af and Aw climatic types. This climate has average monthly temperatures above 18ºC in the cold months and reduced dry season which is attenuated by high levels of precipitation (Alvares et al. 2013).

The total planted area is 883 ha, distributed in 26 plots with stands of different ages (4, 5, 6, 7 and 9 years) and spacing (3, 5 x 3, 5 m, 3, 75 x 3, 75 m, 4 x 4 m). Systematic and/or selective thinning was carried out in the stands, with an intensity of 50% of the basal area removal, at five and nine years after planting.

Data collect

The continuous forest inventory was carried out in 80 fixed circular plots with a radius of 12.61 meters (500 m²). The sampling process was systematic, with 320 x 320 m grids being applied throughout the planting. The total height (ht) and the diameter at breast height (dbh) were measured, with the aid of a Vertex hypsometer and a diametric tape, respectively. The age of the sampled trees was also noted. The mean quadratic diameter (dg) was calculated with the dbh data. It is evident that, at the time of data sampling, about 60% of the analyzed forest stands had been thinned (Santos and Andrade 2019).

Data processing and statistical analysis

Sequentially, the degree of correlation between height and the DAP, dg and age variables was verified through Pearson's correlation for these variables to constitute the generic models and the ANNs. The variance inflation factor (VIF) was calculated using the Action Stat software to analyze the dependence between the regressors.

Four generic models were adjusted by the method of ordinary least squares (Table 7) using the statistic 13.5 software. This software was also used to train artificial neural networks, where the back-propagation training algorithm was used. The Quasi-Newton algorithm was also adopted, and through Intelligence Prover Solver (IPS), the total number of cycles or mean square error was optimized. The ANN are composed of total height (ht) in its output layer, dbh in its input layer, and between three to ten neurons in its hidden layer.

The residual standard error of estimate, both absolute and percentage (Syx and Syx%), the correlation coefficient between observed and estimated values (r), the aggregated difference, the graphical analysis of residuals, of the observed and predicted values and the distribution of errors were used to choose the best fitted equation and/or the best trained ANN to estimate the height variable.

The aggregated difference was calculated for validation of the studied methods. The analysis of variance (ANOVA) was carried out using a completely randomized design (DIC) to verify a significant difference between the values estimated by the model and the selected ANN, with height measured in the field (control).

Conclusions

The independent variables dbh, dg and age can describe the height behavior of individuals in the *T. grandis* stand. The generic models and artificial neural networks did not differ statistically and are efficient to estimate the height of *T. grandis* trees. However, artificial neural networks with multiple layers, which use the back-propagation training algorithm and included dg, showed superior statistical indicators.

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