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RESEARCH ARTICLE

HEIGHT PREDICTION OF TECTONA GRANDIS TREES BY MIXED EFFECTS MODELLING AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This study evaluated the performance of artificial neural networks (ANNs), and a mixed linear regression model to predict the height of trees of *Tectona grandis*, teak, due to categorical and numerical variables. The data were originated from forest inventories carried out at 11 and 16 years of age. The prediction of the time by networks was simulated with different combinations of variables input and neurons numbers in the middle layer. We also evaluated different scenarios, by reducing the number of trees in training / adjustment. The two techniques were compared by statistical indicators and graphical analysis. Neural networks provide results similar to those of regression, with high predictive capacity, and the statistics variation was lower than 1% between the two techniques. The use of ANNs was superior in predicting the height of larger diameters trees when compared to the mixed regression.

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INTRODUCTION

Obtaining tree height is extremely important for several operations and decision-making in forest management. During the activities of forest inventories for quantitative purposes, the main information collected from the forest refers to the diameter measured at 1.3 m in height and the total height of the tree. These are the variables traditionally used in predictive models of individual tree volume. However, it is not always possible to measure the height of all trees in the forest inventory plots, either because of the cost or time available. Thus, almost entirely of the height of unmeasured trees is predicted as a function of diameter, age, site index, and other variables (Mendonça *et al.,* 2011; Thiersch *et al.,* 2013). However, if the estimation is done by regression the relationship between height and diameter is known as hypsometric relation (Curtis, 1967). The hypsometric relation is influenced by environmental factors and stand characteristics, such as: productive capacity, age and genetic material (Curtis, 1967; Fang and Bailey, 1998).

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The inclusion of other settlement characteristics in these relations results in greater accuracy, however, the inclusion of other variables may hinder the modelling, due to the non-linear nature and presence of many qualitative and categorical variables (Binoti *et al.,* 2013b). An alternative to estimate the trees height, including the effect of tree, stand and environmental variables, is the use of generic mixed effects models or artificial neural networks. Nowadays, with the advancement of computer science and software, these techniques have become more accessible and more frequently used in the most diverse areas of science. Among the works that contemplated the use of mixed models in the hypsometric relation, we highlight: Jayaraman and Lappi (2001) with *Tectona grandis* in India; Sharma and Parton (2007) in species of the Boreal forest in Canada; Adame *et al.* (2008) for *Quercus pyrenaica* in Spain; and Mendonça *et al.* (2015) with *Eucalyptus* spp in Brazil. The use of neural networks in the prediction of tree height was approached, among others, by Diamantopoulou (2012) for natural forests in Greece; Özçelik *et al.* (2013) for *Juniperus excelsa* in southern and southwestern of Turkey; Binoti *et al.* (2013ab) and Vendruscolo *et al.* (2015) for *Eucalyptus* spp in Brazil. Artificial Neural Networks (ANN) are defined as parallel computing systems made up of simple processing units, also called artificial neurons or nodes, connected in a specific way to perform a certain task. These artificial neurons are simplified biological neurons and process the information received and weighted by synaptic weights, providing a unique response (Braga *et al.,* 2000; Silva *et al.,* 2010). The first research in the forest area was more restricted to evaluate the efficiency of ANN for estimation of height, volume and other variables. More recently, different theoretical aspects of ANN have been studied using forest data, such as the estimation of mortality (Castro *et al.,* 2015) and basic wood density (Leite *et al.,* 2016). However, for some species there is still a need to evaluate the modelling efficiency by neural networks, like in the species object of this study, *Tectona grandis*. Therefore, the objective of this study was to evaluate the predictive quality of the height by the mixed effect linear modelling and artificial neural networks for *Tectona grandis* trees in function of numerical and categorical variables.

MATERIALS AND METHODS

Study area characterization

The research was carried out at the Federal Institute of Education Science and Technology of MatoGrosso, OlegárioBaldo campus. According to Ugulino *et al.* (2014), the regional climate is characterized as a dry season with monthly precipitation average of 37.8 millimetres from April to September. The total annual precipitation varies from 1,300 to 1,600 mm and the average temperature from 24 to 26 ° C (Alvares *et al.,* 2013). The terrain relief is flat and the soil classified as Dystrophic Red-Yellow Latosol (Passos *et al.,* 2006). The *Tectona grandis* was planted in December 1998 by stump-type seedlings in 40 x 40 cm pits, fertilized with 190 g of single superphosphate and 10 g of Frited Trace Elements BR-15. In the first year, three weeds removing and two cover fertilizations were performed manually, one at 60 days and the other at the ninth month, each with 95 g / pit of NPK 20-05-20, plus 5 g / pit of FTE BR-15. About the experimental design, the experiment was conducted in randomized blocks (DBC), with three replications and eight treatments (spacings), four in single rows: 3 x 2 m (1,666); 4 x 2m (1,250); 5 x 2 m (1,000) and 6 x 2 m (833) and four in double rows 3 x 2 x 2 m (2,000); 4 x 2 x 2 m (1,667); 5 x 2 x 2 m (1,429); And 6 x 2 x 2 m (1,250). The numbers in brackets comprise the theoretical total of trees per hectare. The area of the field plots is variable according to the spacing. In both arrangements, the plots are formed by lines in the direction of planting in the east-west direction with 30 pits each. In the single and double spacing plots the number of planting lines is 5 and 6 respectively. Trees around the plots were not considered in the present study, thus avoiding a possible edge effect. The artificial pruning of the trees was made at 9, 14 and 22 months of age. Three weeds removing were made: at 30 and 90 days and at 14 months, and two mechanized brushings at 17 and 22 months (Passos *et al.,* 2006). Thinning were not made in the study area.

Data base

The data from the study came from forest inventories carried out on two occasions, one at 11 years and the other at 16. The numerical variables considered in the construction of the height prediction models were: age in years; diameter at 1.3 m soil height in centimeters, and the dominant height in meters. As categorical variables, were considered eight spacings (E).A brief description of some of the main settlement variables is presented in Table 1.

Network training

Tree height predictions were obtained by different combinations of input variables and numbers of neurons in the middle layer. The data were divided into two sets, one for training the networks and the other to validate the networks. According to this procedure, three scenarios (a, b and c) were tested. In scenario "a" the data set was divided into 80% for training and 20% for validation, totalling 1916 and 479 trees respectively. In scenario "b", the data were divided in 50% for the training and 50% for the validation, totalling for both, 1198 trees. Finally, in scenario "c", the training of the networks was performed with 20% of the data and validated with 80%, totalling 479 and 1916 trees respectively. The validation procedure was applied to verify the ability of a neural network to produce adequate outputs for inputs that were not present during training as suggested by Binoti *et al.* (2015). The height estimation was performed by training five networks, for each architecture and scenario, totalling 90 networks. ANNs were multi-layered perceptron type, commonly known as MLP (Multilayer Perceptron), which according to Hornik *et al.* (1989) has universal capability of approaching functions. These networks present an entrance layer that receives the input variables age; diameter; total height; dominant height; and spacing, which consequently transfers them weighted by synaptic weights to the intermediate or hidden layer, where it transfers them to the output layer throughthe responses that are the predicted heights. Further details on the foundations of the Artificial Neural Networks method can be found in Bragra *et al.* (2000); Haykin (2001) and Silva *et al.* (2010). The numerical variables were normalized in intervals of 0 to 1 (Eq. 1), and the categorical variables were codified, that is, each variable receives a binary code that makes possible the calculation of the artificial neuron.

$$x_{norm} = \frac{(x - x_{min})(b - a)}{(x_{max} - x_{min})} + a \quad \text{..............................} (1)$$

In which: X_{norm}: normalized value; X_{min} and X_{max}: minimum and maximum variable values, respectively; a: lower limit of normalization (0); and b: upper limit of normalization (1). The Neuroforest® software (http://neuroforest.ucoz.com), widely used in works with ANNs (Binoti *et al.,* 2014; Leal *et al.,* 2015;Vendruscolo *et al.,* 2015; Medeiros, 2016) was used to configuration, training and validation of neural networks. The type of training used was Resilient Propagation ($RPROP^+$), with sigmoid activation function, which is more usual for ANN construction (Haykin, 2001). We chose the Resilient Propagation training algorithm (Riedmiller and Braun, 1993), since it represents a variant of the backpropagation algorithm and has the advantage of being able to calculate and acquire learning about a given problem, because its adjustment of weights depends more of the error gradients signal. The determining process of the neurons number in the hidden layer is defined by the user in the NeuroForest, so it was considered that an excessive number of neurons could lead to the memorization of training data, a process known as overfitting. On the other hand, a small number of neurons in the hidden layer may not be sufficient to perform the desired task, a phenomenon known as underfitting (Braga *et al.,* 2000; Silva *et al.,* 2010). Thus, it is best to choose simple configurations (Binoti *et al.,* 2014; Leal *et al.,* 2015). Therefore, as a stopping criterion for the network training, the total number of cycles equal to 3,000 or the mean square error of less than 1% was used in order to avoid the excessive or reduced number of cycles (Chen *et al.,* 2014).

Mixed effect regression model

In order to generate the estimates and predictions of the heights by regression, a linear generic model (Eq. 2) was adjusted for the same scenarios (a, b and c) evaluated in the modelling by Artificial Neural Networks.

$$ln(H_i) = \beta_0 + \beta_1\left(\frac{1}{DBH_i}\right) + \beta_2\left(\frac{1}{DBH_i.I_i}\right) + \varepsilon \quad \text{……………. (2)}$$

Where *ln*: logarithm neperian; H_i: height of the i-th tree in m; β_i: coefficients to be estimated in the regression; DBH_i: diameter in cm of the i-th tree measured at 1.3 m soil height; I_i: age of the i-th tree in years and ε: random error. Once the influence of planting spacing on the hypsometric relation was verified (Curtis *et al.,* 1967), the effect of spacing as a random component of the fixed model (Eq. 2) was introduced in the adjustment procedures, resulting in Equation 3.

$$Y_i = X_i\beta + Z_ib_i + \varepsilon_i \quad \text{……………………………………. (3)}$$

Where: Y = dependent variable total height in m; β = vector of fixed effects that correspond to the trees diameters; b = vector of random effects corresponding to the different spacings; X and Z are the matrices of theregressors variables of fixed and random effects, respectively; and Ɛ = random error between groups. As described by Pinheiro and Bates (2000), "i" ranges from 1 to M (value associated with each variable in each group), $b_i \sim N(0,\sum)$ e $\mathcal{E}_i \sim N(0,\sigma^2 I)$.

Evaluation of estimates

The precision of the regression estimates and the neural networks was evaluated by the following statistics: multiple correlation coefficient between observed and estimated values (Eq.4); Square root of the mean square error (Eq. 5) and graphical analysis of the residues. The correlation between the observed and estimated values (Eq. 4) indicates the correlation between the observed height (H) and the estimated height ($\widehat{H}$). Although it does not allow directly to infer on the unity equality between observed and estimated values (Campos and Leite, 2013), the correlation indicates the level of association between observed and estimated values that, together with the residue analysis, allows to infer about the predictive quality model.

$$r_{H\widehat{H}} = \frac{cov(H,\widehat{H})}{\sqrt{S^2(H)S^2(\widehat{H})}} \quad \text{…………..……………………… (4)}$$

The root mean square error, RMSE, (Eq. 5) evaluates the mean quadratic difference between the observed values and the estimated values. The lower the value, the better the accuracy of the estimate (Mehtätalo *et al.,* 2006), where $\overline{H}$ is the observed mean height and *n* is the total number of data.

$$RMSE_{\%} = \frac{100}{\overline{H}}\sqrt{\frac{\sum_{i=1}^{n}(H_i-\widehat{H}_i)^2}{n}} \quad \text{……..…………..………….. (5)}$$

The graphical analysis consisted in statistical verification of the dispersion of percentage errors (E) in relation to the observed and estimated values (Eq. 6).

$$E_{\%} = \frac{H-\widehat{H}}{H}100 \quad \text{………………………………………….. (6)}$$

RESULTS AND DISCUSSION

After the training procedure, the best network for each architecture and scenarios (a, b and c) was evaluated. The networks with the best statistical performance to estimate the total height of the teak for the three scenarios were ANN 1, 2 and 3, with twelve neurons in the entrance layer, six, eight and ten neurons in the hidden layer respectively, and one neuron in the output layer. These were the architectures capable of extracting the relation between the variables considered and the height with better effectiveness. According to Haykin (2001), the number of hidden neurons is directly related to the ability of ANN to detect implicit nonlinear relationsbetween the data and to extract satisfactory statistics. It was also found that the networks had similar statistics with each other, even with the exclusion of the dominant height variable in ANN 4. Already when the networks were trained with the absence of the numerical variable age (I) (ANN 5) and the categorical variable spacing (E) (ANN 6) a reduction in precision of up to 3.3% in training and 2.45% in validation when RMSE% was evaluated (Table 2). However, as in Braga *et al.* (2000), there is no linear correlation between the input variables and the output variables in Networks, thus suggesting that it cannot be judged which of the input variables were most important in the learning process of the network.

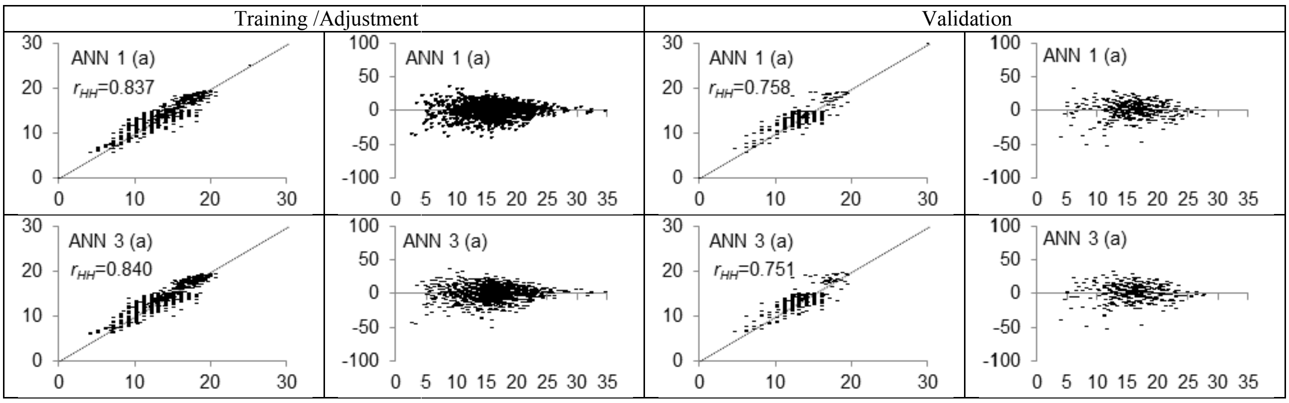
Regression modelling also performed well as in the networks. However, in the set used in the adjustment, a correlation reduction of 2.6%, 4.5% and 2.4% was verified, when compared to the best networks, for scenarios "a", "b" and "c" respectively. Regarding RMSE, the difference was less than 1.1%. In the validation, the two techniques presented highly similar statistics, with variation of $r_{H\widehat{H}}$ and RMSE less than 1% in the three scenarios. The use of mixed models generated highly satisfactory results, as observed in volumetric modelling (Gouveia *et al.,* 2015); hypsometric (Jayaraman and Lappi, 2001; Mendonça *et al.,* 2015) and taper (Garber and Maguire, 2003; Gómez-Garcia *et al.,* 2013), because it includes random effects and spatio-temporal processes, which can be considered a higher level of resolution when compared to the traditional fixed-effect models that is often used in the estimation process (Calegario *et al.,* 2005). From the three best networks (1, 2, and 3), which presented the best training, with the highest values of $r_{H\widehat{H}}$and lower RMSE%, for scenarios "a" and "c", was ANN3, but for validation, the best performance was ANN 1. For scenario "b", the best performance was obtained by ANN 3, both in training and in validation. When the potential of the networks in the three scenarios was evaluated, with the reduction of the data set used in training from 80% (scenario a) to 50% (scenario b) and to 20% (scenario c), it was verified that the ANNs presented satisfactory results, without loss of precision in the set used in the training when applied for validation. Similar results were obtained by Binoti *et al.* (2013b), in which the authors report on the possibility of conducting forest inventories with a reduction in sample intensity for the height variable due to the effectiveness and modelling capacity of ANNs.

Table 1. Descriptive statistics of the main dendrometric variables

SP (m)		11 years				16 years			
		Min	Mean	Max	S.D	Min	Mean	Max	S.D
3x2	DBH	3.2	14.8	22.9	3.2	10.0	18.2	26.1	3.9
	H	4.0	12.6	17.0	1.7	10.3	16.2	19.1	1.9
	DH	15.0	15.8	17.0	0.8	17.8	18.2	19.1	0.5
4x2	DBH	4.6	15.9	27.4	4.1	11.5	19.7	26.7	3.6
	H	6.0	12.5	16.0	1.8	12.2	16.6	20.5	2.2
	DH	15.0	15.3	16.0	0.4	18.9	19.7	20.5	0.6
5x2	DBH	3.4	16.2	27.7	3.4	8.6	21.3	34.5	5.4
	H	6.8	13.2	17.0	1.9	10.3	16.2	19.1	1.8
	DH	16	16.4	17.0	0.5	18.0	18.5	19.1	0.5
6x2	DBH	4.9	17.7	28.0	3.7	15.2	22.5	32.2	4.4
	H	6.0	13.1	16.5	1.5	14	17.0	19.5	1.3
	DH	15.5	16.0	16.5	0.4	18.6	19.1	19.5	0.4
3x2x2	DBH	2.5	14.1	21.1	3.3	7.7	13.6	22.0	3.5
	H	4.0	12.6	18.0	2.3	8.4	15.5	19.5	2.8
	DH	18.0	18.0	18.0	0.5	18.5	19.1	19.5	0.4
4x2x2	DBH	4.5	15.5	26.1	2.9	8.2	15.6	21.5	3.3
	H	5.0	13.5	17.0	1.6	11.9	16.8	20.6	1.9
	DH	16.0	16.2	17.0	0.4	18.7	19.3	20.6	0.8
5x2x2	DBH	4.1	15.3	22.3	3.4	5.9	15.8	25.4	4.2
	H	5.0	12.8	17.0	2.1	5.0	16.1	19.9	2.3
	DH	16.0	16.4	17.0	0.5	16.0	19.2	19.9	0.4
6x2x2	DBH	4.8	14.8	21.3	3.2	8.9	15.9	27.7	3.1
	H	5.0	11.8	14.1	1.5	11.2	16.2	19.1	2.2
	DH	14	14.1	14.1	0.5	18.5	18.8	19.1	0.3

Table 2. Characteristics of artificial neural networks (ANN) trained to estimate the total height of the trees in the scenario a, b and c

ANN	Arc.	Num. input	Cat. input	Output	Training/Adjustment		Validation	
					$r_{H\hat{H}}$	RMSE%	$r_{H\hat{H}}$	RMSE%
Scenario a								
1	12-6-1	I, D, DH	SP	H	0.837	9.14	0.758	11.09
2	12-8-1	I, D, DH	SP	H	0.839	9.09	0.736	11.67
3	12-10-1	I, D, DH	SP	H	0.840	9.06	0.751	11.35
4	11-6-1	I, D	SP	H	0.838	9.11	0.734	11.64
5	9-5-1	D	SP	H	0.719	11.61	0.629	13.25
6	3-2-1	I, D		H	0.804	9.93	0.753	11.17
Mixed effect model					0.814	9.76	0.752	11.35
Scenario b								
1	12-6-1	I, D, DH	SP	H	0.832	9.35	0.780	10.49
2	12-8-1	I, D, DH	SP	H	0.834	9.29	0.785	10.38
3	12-10-1	I, D, DH	SP	H	0.836	9.27	0.791	10.23
4	11-6-1	I, D	SP	H	0.834	9.39	0.779	10.52
5	9-5-1	D	SP	H	0.723	11.64	0.665	12.68
6	3-2-1	I, D		H	0.792	10.29	0.756	10.88
Mixede ffect model					0.791	10.34	0.782	10.54
Scenario c								
1	12-6-1	I, D, DH	SP	H	0.858	8.86	0.758	11.20
2	12-8-1	I, D, DH	SP	H	0.864	8.67	0.749	11.38
3	12-10-1	I, D, DH	SP	H	0.866	8.62	0.738	11.81
4	11-6-1	I, D	SP	H	0.860	8.81	0.738	11.90
5	9-5-1	D	SP	H	0.723	11.93	0.639	13.06
6	3-2-1	I, D		H	0.780	10.79	0.755	11.95
Mixed effect model					0.842	9.340	0.758	11.62



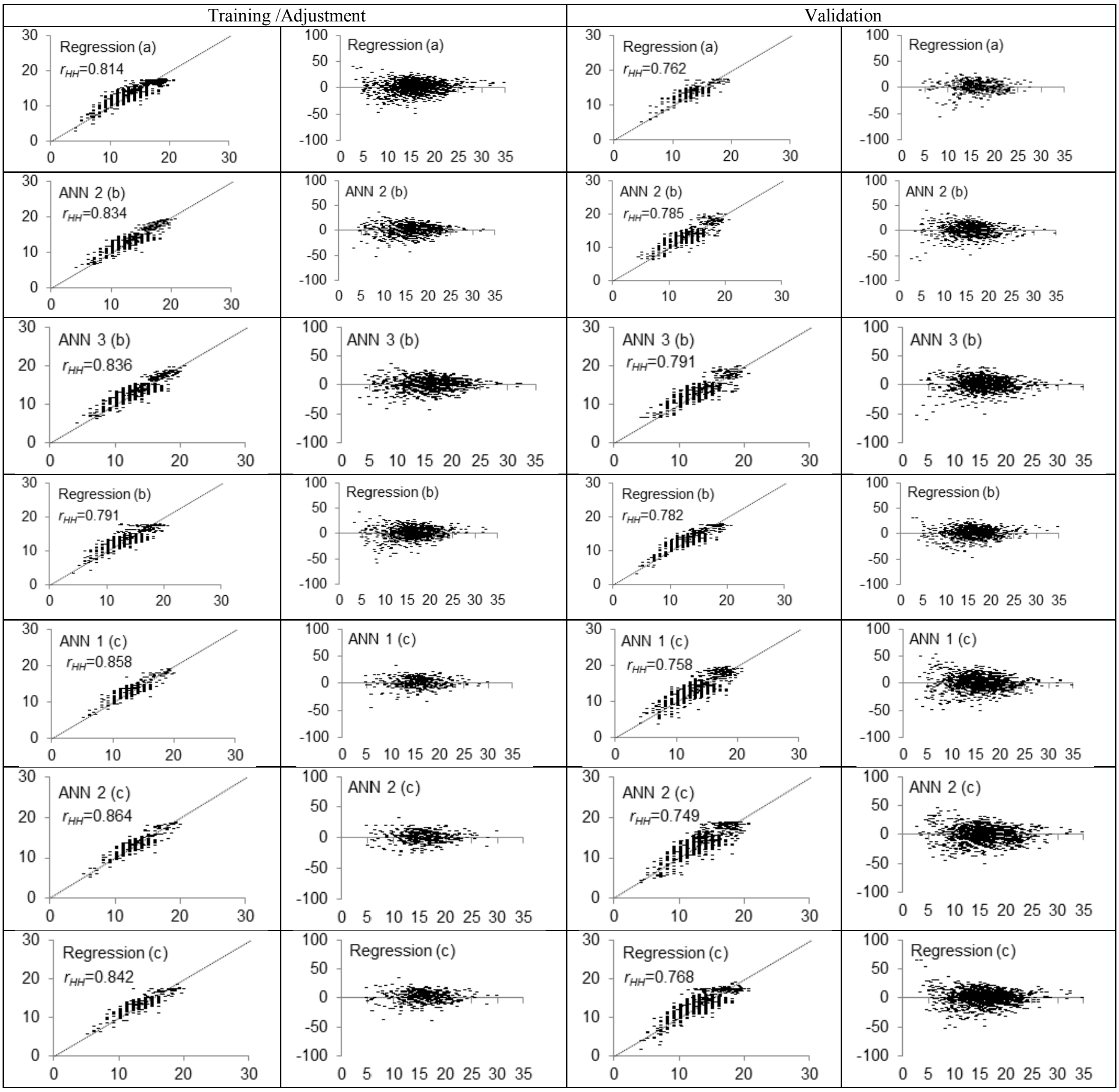


Figure 1. Observed height (x-axis) and the estimated (y axis), percentage error (y-axis) as a function of DBH (x-axis) for both networks and best regression in scenarios a, b and c

For the networks that presented the best statistical indicators and prediction potential 1 and 3 (scenario a), 2 and 3 (scenario b) and 1 and 2 (scenario c), a more detailed analysis was carried out in order to evaluate the behaviour of the estimated data. Therefore, were generated graphs of dispersion of the observed versus estimated heights and the graphs of errors distribution for the set of training and validation of the networks, and of the estimates generated by regression (Figure 1). The graphs of observed versus estimated heights, of networks residuals and of modelling by mixed effect regression, appear to have an adequate behaviour, but with a small bias of underestimation for height in the largest diameters when submitted to regression analysis. In this way, it is verified that adequate architectures of neural networks provide similar results to those of regression, and for larger trees the ANNs are superior to mixed effects modelling, which does not rule out their use and application. The results presented serve, therefore, as a starting point for future research, whereas Silva *et al.* (2009), affirm about the robustness of the Networks method to be associated to its architecture.

One of the major advantages with the use of ANNs is the ability to model with the presence of a large number of "categorical" variables, that is, the networks have a unique set of parameters to predict the dependent variable in several situations that are modelled by a single network. This capability in mixed effects modelling may be limited, since according to Calegario *et al.* (2005) is a complex technique. In Binoti *et al.* (2014), it can be verified that a network can explain the volumetric variation in relation to more than 50 volumetric models adjusted for different strata. Özçelik *et al.* (2013), evaluating the performance of neural networks for estimates of individual trees height, concluded that ANN modelling produces precise results, with a reduction of up to 20% of the mean square error compared to the nonlinear regression models used. Despite its recent application in Brazilian forestry science, some studies have already demonstrated satisfactory and promising results, being often superior to traditional regression methods such as in Gorgens *et al.* (2009) and Binoti *et al.* (2013a).

Conclusion

Artificial neural network and mixed effects regression modelling techniques were statistically efficient in predicting the individual height of *Tectona grandis*, with deviations below 12%, even with a reduction of 80% in the data used in training and adjustment. The use of ANN was superior in predicting the height of larger trees in diameter when compared to mixed regression. The results presented allow us to conclude on the importance of the study of ANN applications in the hypsometric relation modelling in *Tectona grandis* trees, inserting, for example, other categorical variables not addressed in this study, such as those related to climate and soil.

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