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ESTIMATING THE DIAMETER OF TREE USING THE NEURO-FUZZY INFERENCE SYSTEM AND ARTIFICIAL NEURAL NETWORKS FROM THE TOTAL HEIGHT VARIABLE

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Resumo

Estimativa do diâmetro de árvores utilizando sistema de inferência neuro-fuzzy e redes neurais artificiais a partir da variável altura total. Estudos que busquem identificar técnicas potenciais para obtenção dos valores de diâmetro à 1,30 m do solo a partir de dados de altura de árvores são necessários principalmente ao se considerar a utilização do Lidar aerotransportado na atividade de inventário florestal. Nesse sentido, este trabalho objetivou avaliar duas ferramentas de inteligência artificial para tal finalidade, sendo elas os sistemas de inferência neuro-fuzzy e as redes neurais artificiais. Foram testados quatro modelos para obtenção de estimativas para a variável diâmetro, os quais foram elaborados pela combinação das variáveis independentes área útil por planta, idade e altura. Após o processamento, foram calculadas as estatísticas de bias, raiz quadrada do erro quadrático médio em porcentagem, correlação e erro percentual médio, além da elaboração de gráficos de dispersão e histograma de resíduos. Observou-se que, para a estimativa do diâmetro em ambas as técnicas, o uso do modelo com todas as variáveis independentes obteve os melhores valores para as estatísticas de análise. Pode-se concluir que ambas as ferramentas podem ser utilizadas para estimativa do diâmetro, sendo o sistema de inferência neuro-fuzzy mais indicado por sua rapidez de processamento e pequena variabilidade entre os valores obtidos em diferentes treinamentos para uma mesma base de dados.
Palavras-chave: Inteligência Artificial; Dendrometria; Mensuração Florestal.

Abstract

Studies that seek to identify potential techniques for obtaining diameter values at 1.30 m from the ground from tree height data are necessary, especially when considering the use of airborne Lidar in forest inventory activity. In this sense, this work aimed to evaluate two artificial intelligence tools for this purpose, namely the neuro-fuzzy inference systems and the artificial neural networks. Four models were tested to obtain estimates for the diameter variable, which were prepared by combining the independent variables useful area per plant, age and height. After processing, the statistics of bias, square root of the mean squared error in percentage, correlation and mean percentage error were calculated, in addition to the preparation of scatter plots and histogram of residues. It was observed that, for the estimation of the diameter in both techniques, the use of the model with all independent variables obtained the best values for the analysis statistics. It can be concluded that both tools can be used to estimate the diameter, with the neuro-fuzzy inference system being more suitable for its processing speed and small variability between the values obtained in different training sessions for the same database.
Keywords: Artificial Intelligence; Dendrometry; Forest Mensuration.

INTRODUCTION

The Brazilian forest sector has developed considerably since the tax incentives that occurred in the 1970s. Since then, several aspects of forestry and forest management have been improved, either by introducing tools and technologies developed in other areas of knowledge, or by improving the techniques inherent to the forestry sciences. Such developments have contributed greatly to improve both the yield of forest stands and the quality of analyses about forest development.

One of the aspects that underwent significant changes is the way dendrometric variables are obtained, mainly in terms of measuring the diameter and height of trees. Initially, they were made manually, with the aid of a centimetric tape and a graduated ruler, going through the measurement with electronic sutas and digital clinometers (CAMPOS; LEITE, 2013), until reaching the current state of obtaining data from remote sensors, both terrestrial (CABOA *et al.*, 2018; KOREN et al, 2017) and airborne (COSENZA *et al.*, 2018).

Despite this evolution, not all the inconveniences of measuring diameter and height have been resolved. The use of digital clinometers is still dependent on the viewing conditions of the canopy, which is difficult when there is strong wind at the measurement site, very dense spacing and terrain with uneven ground. This makes measuring heights an imprecise and costly process (BINOTI *et al.*, 2013a), aggravated by the existence of errors in the use of equipment. As a result of this and the high correlation between height and diameter of trees, heights of only a few individuals existing in the sample plots are collected, and the others are estimated by regression (LEITE *et al.*, 2011) or artificial intelligence techniques (BINOTI *et al.*, 2013b).

More recently, with the evolution of remote sensing technologies, especially with the use of unmanned aerial vehicles, measuring tree heights has become less laborious. This is largely due to the use of high-precision systems such as LiDAR (Light Detection and Ranging), which allow three-dimensional data to be collected quickly from the overflight of a forest.

However, in contrast to the traditional field inventory method, directly obtaining tree diameters from data generated by LiDAR is still unfeasible, as most light pulses are intercepted by the crowns before reaching the trunk profile. In this case, it is necessary to use methods to estimate this variable and obtain it indirectly (BI *et al.*, 2012). As demonstrated by Cosenza *et al.* (2018), several models are available (linear or not) aimed at estimating the dap as a function of dendrometric characteristics, such as tree height and crown area. However, the accuracy of these models is lower than those normally verified for height estimates in homogeneous plantations, with adjusted coefficients of determination (R^2) being described as lower than 87% for the diametric models (OLIVEIRA *et al.* 2014) and reaching up to 97% for hypsometrics (RIBEIRO *et al.* 2010).

In this case, an alternative to improve the quality of diameter estimates is the application of artificial intelligence (AI) techniques, such as artificial neural networks (ANN) and neuro-fuzzy inference systems (ANFIS), which are already being used successfully in estimating height, diametric distribution, among others (BINOTI *et al.*, 2013b; BINOTI *et al.*, 2013c; VENDRUSCOLO *et al.*, 2015; MARTINS *et al.*, 2016; VENDRUSCOLO *et al.*, 2017). Although these procedures do not obey the parameterization of regression models, they have the advantage of relating large amounts of variables, linearly or not, in order to establish correspondence among them.

With this potential, it is questioned whether such techniques can contribute to improve diameter estimates, to the detriment of traditional regression procedures. If this hypothesis is confirmed, ELA technicians and researchers will be able to rely on this new data processing methodology to make the forest inventory even more accurate. Therefore, this work aimed to evaluate the performance of both ANN and ANFIS to estimate tree diameter from height data.

MATERIAL AND METHODS

Data

The data used in this study come from continuous forest inventories carried out in forest plantations of hybrid eucalyptus clones (*E. grandis* X *E. urophylla*) in the northern region of the state of Minas Gerais, Brazil. A total of 932 sample plots were considered, totaling 32,424 data pairs of diameter at 1.30 meter from the ground (dbh) and height (h) of trees, measured under different conditions of location, spacing, genetic material and management regime.

The database was randomly divided into two sets, with 70% of the data destined for ANN and ANFIS training and the remaining 30% considered for model validation, as suggested by Vendruscolo *et al.* (2015).

Artificial Neural Networks

To estimate the weights of the artificial neural networks, the NeuroForest software version 4.0.2 was used considering the Resilient Backpropagation algorithm (HAYKIN, 2009), 8 neurons in the intermediate layer, activation functions of the sigmoidal type for neurons in the intermediate and output layers and interruption of training after 500 cycles. Such parameterization was defined from tests carried out previously. 30 neural networks were trained, and the one that presented the best values for the evaluation statistics was chosen.

Neuro-Fuzzy Inference System

Neuro-fuzzy inference systems (ANFIS) have been used in a series of studies that seek to map the behavior of existing patterns between input and output variables of the system (NAGHD *et al.*, 2016). They were proposed by Jang (1993) and have as their main characteristic the fact that they use the advantages of the non-linearity of ANNs, as well as their learning capacity, and the benefits of establishing fuzzy rules from the concepts of Fuzzy Logic (ARAÚJO JÚNIOR *et al.*, 2016).

For the case of the neuro-fuzzy inference system, the MATLAB software (https://www.mathworks.com/) was used, considering 3 Gaussian membership functions for each input variable and 5 epochs of training. Data partitioning was made using the grid partition method due to the small amount of input variables and membership functions (MESIAROVÁ-ZEMÁNKOVÁ; AHMAD, 2010). The Takagi-Sugeno model (JANG; SUN, 1995) was used, which does not require a defuzzyfication process at the end of the process, and the system output is given by a polynomial resulting from the combination of the outputs of each rule (IBRAHIM, 2003). The training was carried out using the hybrid method, according to Araújo Júnior *et al.* (2016).

Modeling

For each of the AI techniques, four models were evaluated to obtain estimates for the dap variable, which were prepared by combining the independent variables useful area per plant (ap), age of stand (I) and total height (h) (Table 1). 30 ANNs were trained for each case, and the best ones were selected for analysis and comparison with the values obtained by the neuro-fuzzy inference system.

Table 1. Dependent and independent variables used in different modelling to obtain diameter variable.
Tabela 1. Variáveis dependente e independente utilizados nas diferentes modelagens para obtenção da variável diâmetro.

Modeling	Dependent Variable	Independent variables
1	dbh	h
2	dbh	h; ap
3	dbh	h; I
4	dbh	h; ap; I

Modelos de Regressão

Previous researches have already shown the need to establish mathematical relationships between diameter and height to estimate the first variable (Oliveira *et al.*, 2014). To assess whether the results found by artificial intelligence techniques are compatible with regression models, the following models were tested, obtained from the works of Oliveira *et al.* (2014) and Cosenza *et al.* (2018):

$$\text{dbh} = \beta_0 + \beta_1 \text{h} + \varepsilon \quad \text{(Reg 1)}$$

$$\text{dbh} = \beta_0 + \beta_1 \text{h} + \beta_1 \text{h}^2 + \varepsilon \quad \text{(Reg 2)}$$

$$\text{Ln(dbh)} = \beta_0 + \beta_1 \text{Ln(h)} + \varepsilon \quad \text{(Reg 3)}$$

$$\text{dbh} = \beta_0 + \beta_1 \left(\frac{1}{\text{Ln(h)}}\right) + \varepsilon \quad \text{(Reg 4)}$$

$$\text{Ln(dbh)} = \beta_0 + \beta_1 \text{h} + \varepsilon \quad \text{(Reg 5)}$$

For all cases, the same training and validation data used to adjust the parameters of the artificial neural network models and the neuro-fuzzy inference system were considered. The adjustments of the regression models were performed by stratum, which was defined as the combination of attributes region, farm, management regime (tall bole or coppice), genetic material and spacing, totaling 55 adjustments for each equation.

Evaluation of Results

Scatter plots were constructed, considering the estimated and observed values, and histograms of residuals of the estimates for evaluating the results. Error values for each observation (e_i) were obtained using Eq. 1. Bias statistics (Eq. 2), root mean square error (RMSE) in percentage over the mean (Eq. 3), correlation between estimated and observed values (Eq. 4) and mean percentage error (Eq. 5).

$$e_i = \hat{y}_i - y_i \quad \text{(Eq. 1)}$$

$$\text{bias} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right) \quad \text{(Eq. 2)}$$

$$\text{RMSE\%} = \frac{100}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad \text{(Eq. 3)}$$

$$r_{y\hat{y}} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad \text{(Eq. 4)}$$

$$\text{MPE} = \frac{1}{n}\sum_{i=1}^{n}\left[100.\frac{(y_i - \hat{y}_i)}{y_i}\right] \quad \text{(Eq. 5)}$$

where $\hat{y}_i$ is the estimated value and and y_i is the observed value for the ith data, n is the total number of observations, $\bar{y}$ is the average of the observed values, and $\bar{\hat{y}}$ is the average of the estimated values.

To evaluate whether the models statistically differ from each other, the method identity test was applied, as suggested by Leite; Oliveira (2002). In this test, the estimated values are submitted to three tests: (a) the Graybill F test (σ =5%) between the observed and estimated values; (b) the t test (σ =5%) to verify whether the mean of the residuals differs from zero; and, finally, (c) the comparison between the average percentage error (in absolute values - $\bar{e}$) and the statistic $r_{y\hat{y}}$ already described, being rejected in the test if $r \geq (1- |\bar{e}|)$.

In order to analyze the diametric distribution obtained from the values estimated by each modeling, the Kolmogorov-Smirnov (KS) test was applied, according to Araújo Júnior *et al.* (2013), in order to identify whether the estimated distributions are statistically similar to the distributions observed for the validation data.

RESULTS

The results for the ANN models that consider the variable h as output showed statistical values close to those found in the modeling with ANFIS, with a slight superiority of this in relation to the statistics of Bias and RMSE% both for the training stage and for the validation stage. Modeling 4, which considers height, age and useful area per plant as input variables, was the one that presented the best results for both techniques.

Both techniques showed good results (Table 2), with high correlation between estimated and observed values (r ≥ 0.89), as well as low bias values (|bias| ≤ 0.04), root mean square error (RMSE ≤ 11.08) and mean percentage error (MPE ≤1.68).

Table 2. Calculated statistics for each modeling adopted in ANN and ANFIS for total height and diameter estimates.
Tabela 2. Estatísticas calculadas para cada modelagem adotada nas RNA e ANFIS referentes às estimativas de diâmetro.

Output	Stage	Modeling	ANN				ANFIS			
			Bias	RMSE%	$r_{y\hat{y}}$	MEP	Bias	RMSE%	$r_{y\hat{y}}$	MEP
Diameter	Training	1	-0,02	13,96	0,89	2,22	0,00	13,87	0,89	2,52
		2	-0,02	13,23	0,90	1,98	0,00	13,06	0,90	2,23
		3	-0,03	11,40	0,93	1,28	0,00	11,23	0,93	1,55
		4	-0,04	11,28	0,93	1,36	0,00	10,96	0,93	1,45
	Validation	1	-0,09	13,80	0,88	1,83	-0,07	13,73	0,89	2,09
		2	-0,10	13,01	0,90	1,53	-0,07	12,85	0,90	1,79
		3	-0,09	11,17	0,93	0,94	-0,06	11,04	0,93	1,24
		4	-0,10	11,05	0,93	0,99	-0,06	10,80	0,93	1,16

Table 3. Calculated statistics for each modeling adopted in ANN and ANFIS for total height and diameter estimates.
Tabela 3. Estatísticas calculadas para cada modelagem de regressão referentes às estimativas de diâmetro.

Output	Stage	Regression	Bias	RMSE%	$r_{y\hat{y}}$	MEP
Diameter	Training	1	0,00	10,18	0,91	1,34
		2	0,00	9,98	0,91	1,20
		3	-0,08	10,22	0,91	0,65
		4	0,00	10,56	0,90	1,24
		5	-0,08	10,54	0,90	0,72
	Validation	1	0,01	10,29	0,91	1,52
		2	0,01	10,09	0,91	1,40
		3	-0,07	10,33	0,91	0,82
		4	0,01	10,84	0,90	1,29
		5	-0,08	10,65	0,90	0,90

Such results are evidenced by the scatterplots and residual histograms for the diameter estimates (Figure 1). The graphs show that modeling 4 presented better estimates, with errors ranging between -25% and 35%.

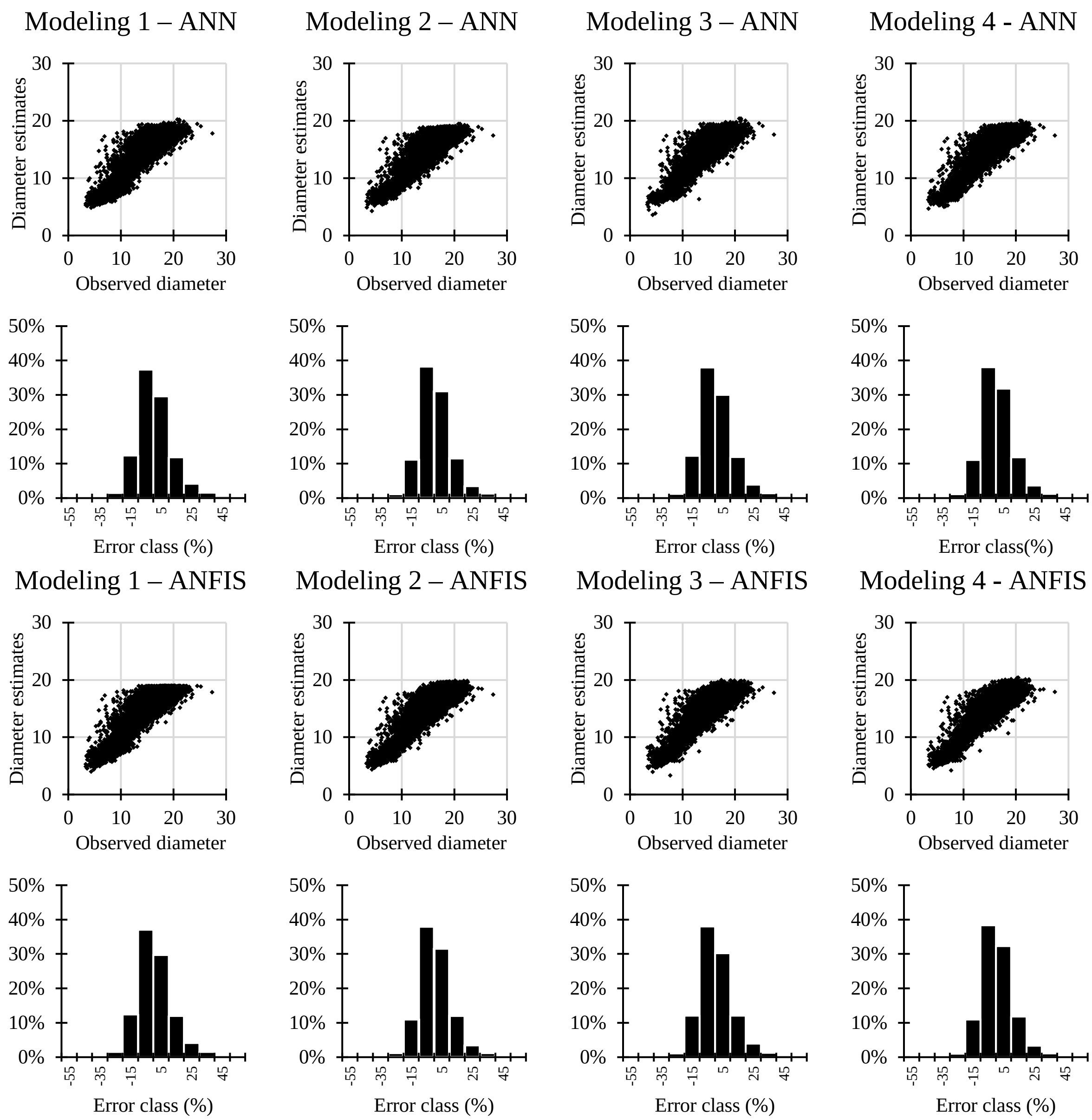

Figure 1. Residual graphs of diameter estimates using ANN and ANFIS.
Figura 1. Gráficos de resíduos das estimativas de diâmetro utilizando RNA e ANFIS.

The L&O test applied showed that the modeling results differed statistically from each other (Table 4). The difference observed between the models was due to the non-compliance of only one of the criteria of the L&O test (the Graybill F test) in 50% of the cases analyzed for the estimate of dbh.

Table 4. Results of the L&O test considering the height and diameter estimates obtained by modeling 1, 2, 3 and 4 with ANN and ANFIS.
Tabela 4. Resultados do teste de L&O considerando as estimativas de altura e diâmetro obtidas pelas modelagens 1, 2, 3 e 4 com RNA e ANFIS.

	Modeling							
	ANN				ANFIS			
Modeling	1	2	3	4	1	2	3	4
1		*a, c*	*a, c*	*a, b, c*		*a, b, c*	*c*	*c*
2			*a, c*	*a, b, c*			*a, c*	*c*
3				*a, b, c*				*b, c*
4								

Where: The symbols represent the tests for which the null hypothesis was rejected (a: F-test; b: t-test; c: correlation test) and ns when the overall test result is not significant.

The KS test showed non-significant results for all cases considered (Figure 3). The values calculated for the test considering the models using the neuro-fuzzy system showed lower values than those obtained by the ANN.

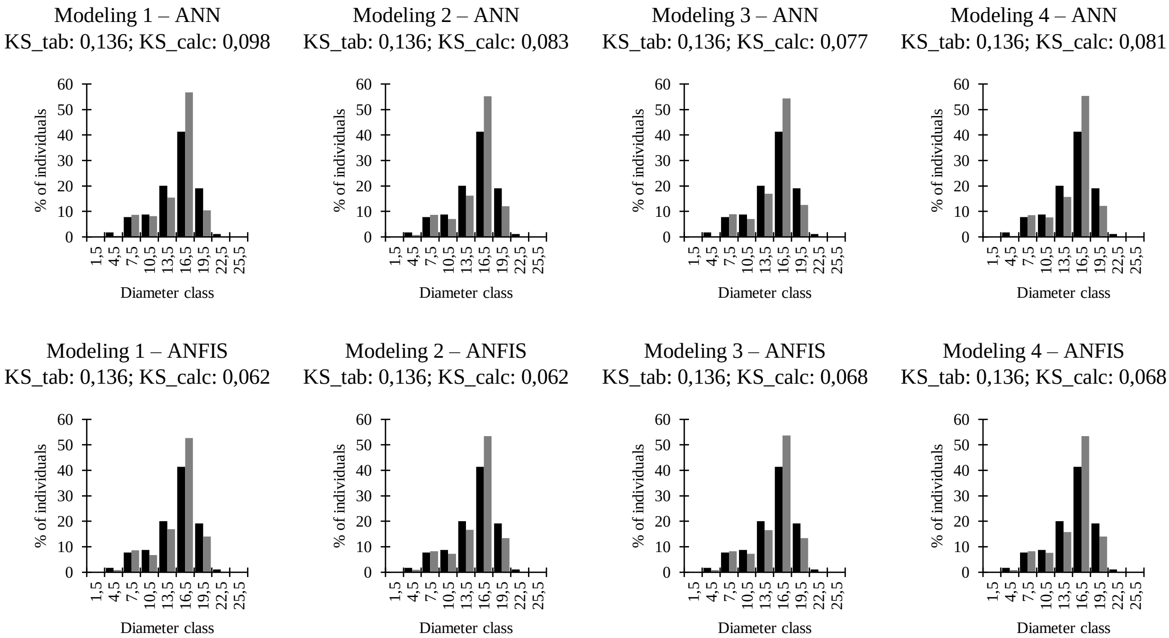

Figure 3. Graphs of observed diameter distributions (black bars) and estimated by ANN and ANFIS (gray bars).
Figura 3. Gráficos de distribuições diamétricas observadas (barras em preto) e estimadas por RNA e ANFIS (barras em cinza).

DISCUSSION

It can be noted that there was a better quality of the estimates generated by the neuro-fuzzy systems in relation to the ANN for both processing steps (training and validation). Also noteworthy is the gain in terms of processing time due to the number of training cycles needed to achieve such results. The neuro-fuzzy models were trained with only 5 epochs in contrast to the ANNs that were trained with 500 cycles.

The modeling that considers the useful area per plant showed better statistics, which means that the techniques used are able to reproduce the biological behavior of the relationship between the variables, which advocates that the diameter is fundamentally affected by the spacing among the trees (LEITE *et al.* , 2011).

The analysis of the scatterplots and histograms of residuals for the estimates of dp allows the observation that there was a small dispersion of the errors. This is an important result, as it provides sufficient support for estimating tree diameters based on height without generating additional concern for the forest manager.

The results of the L&O test indicate the need to identify the best strategy to obtain estimates for the case of the dap. Despite this, it can be noted, in general, that the modeling considering the neuro-fuzzy inference system presented a smaller amount of criteria with statistically significant results. This demonstrates the potential of neuro-fuzzy systems, since they reveal greater homogeneity in terms of the estimates obtained even considering different models.

The results for the KS test demonstrate that the diameter estimates obtained, either by ANN or by ANFIS, resulted in a similar behavior to the diametric distribution of the analyzed stand. The lowest values for the test considering the models using the neuro-fuzzy system, compared with those found for the ANN, prove that the estimates generated by the first tool were closer to the real values than the second. Thus, it can be inferred that all the models considered did not show bias in the estimates, mainly in terms of the existing variability in relation to the number of individuals per diametric class.

The results presented for all the studied situations demonstrate how the techniques have potential for the intended use, which becomes more evident when comparing these results with those found in the literature. For example, Bi *et al.* (2012) found determination coefficients ranging between 0.55 and 0.78 for estimating the dbh of 3581 individuals of Pinus radiata (for 12 different equations considering only height as a predictor variable), in contrast to the variation between 0.79 and 0.83 found in this work. Cosenza *et al.* (2018) found RQEM values ranging between 7% and 16% for nonlinear equations for estimating dbh from height data.

One of the advantages of using artificial intelligence techniques is their high convergence rate for estimating parameters with minimal error, even in cases where the non-linearity among variables is marked, which is observed for the relationship between dap and h (Bi *et al.* al., 2012). Neuro-fuzzy systems have already been considered better than artificial neural networks and non-linear regression in other works, such as those by Çatal and Saplioglu (2015), for estimating bark volume in pine, Araújo Júnior *et al.* (2016) to estimate charcoal prices, and Vieira *et al.* (2018) for prognosis of the diameter and height of individual trees.

Such results are extremely important, as they contribute to the identification of possible techniques to be used to establish the relationship between the data measured using airborne laser scanning, especially the total height of trees, with other dendrometric variables, such as diameter. This is necessary so that volumetric models can then be applied, in order to obtain an estimate of the stand's wood production, given the low accuracy observed for models that estimate volume considering only height as a predictor variable (BI *et al.*, 2012).

Despite the good results presented by the neuro-fuzzy inference system, it is important to point out that the option for using only quantitative variables was due to the fact that the system generates a base of fuzzy logic rules to relate the input data with the results expected. Such rules depend on the amount of fuzzy sets that are considered for the input variables, which can make the model complex when many sets are used. When using qualitative variables, each category is considered as a fuzzy set, which can generate a large number of rules and make data processing unfeasible, which was proven in tests carried out previously.

CONCLUSÕES

The analyses carried out allow us to conclude that:

- The artificial neural networks (ANN) and the neuro-fuzzy systems used in the analyzes were efficient to estimate the diameter values.
- There was a slight superiority of the estimates generated by the neuro-fuzzy inference systems in relation to the estimates generated by the ANN.
- Neuro-fuzzy systems showed advantages mainly in relation to the number of interactions required for system training.

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