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# Artificial Neural Networks with Skip Layer Connections to Estimate the Volume of Forest Formations in the State of Minas Gerais

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**ABSTRACT**

The ANNs are networks of artificial neurons connected together to operate as simple processing elements in order to perform a specific task. There are different types of ANNs, including Multilayer Perceptron (MLP), and some MLP networks, may have special connections called Skip Layer, where some input signals have a direct connection to the output layer. In this sense, the aim of this study was to implement and evaluate artificial neural networks (ANN) adjusted by Skip Layer Connections algorithm, in the volumetric estimation of eleven forest formations occurring in the state of Minas Gerais. The computer system used to implement Skip Layer Connections algorithm was 3.3 NeuroForest, in which we tested networks with recurrence and without recurrence. For comparison purposes, volumetric equations were applied. Accuracy measures and residual graphs constructed from the ANNs, showed similar results to the adjusted networks with and without recurrence, both of which are suitable for production modeling of natural stands. In general, for all forest types analyzed, despite the slight tendency to overestimate the volume of smaller trees, ANNs showed equivalent or better results compared to volumetric equations and for Arboreal Caatinga, Campo Cerrado, Cerrado, Primary Forest, Secondary Forest and Liana Transitional Forest, networks were superior to the usual regression model. This study confirms the applicability of artificial neural networks with Skip Layer Connections, proving its potential for production modeling of native stands.

## INTRODUCTION

One way to reduce the deforestation process in forest formations is to promote its rational use from the preparation of management plans. Therefore, it is extremely important to know the structure and the commercial stock of these vegetation, since the latter can be supplied from the variables total and commercial volume or volume of the parts of the tree (Rufini *et al.*, 2010).

However, the estimation of the volume of native vegetation, may be hampered by high variability among species and among individuals of the same species, caused among other factors, by changes in the trunk and canopy shapes (Rezende *et al.*, 2006). This variability justifies the development of efficient methods to quantify the production, giving managers tools to assist in the decision-making process.

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The procedures widely used to estimate the variable volume in forest inventories are based on traditional statistical methods, which use regression models (Scolforo *et al.,* 1994; Rezende *et al.,* 2006; Imaña-Encinas *et al.,* 2009). However, techniques of artificial and computational intelligence as Artificial Neural Networks (ANNs), have also been used to estimate the volume of trees, with higher accuracy compared to the usual regression techniques (Diamantopoulou andMilios, 2010; Özçelik *et al.,* 2010; Gorgens *et al.,* 2014; Binoti *et al.,* 2015).

The ANNs are networks of artificial neurons connected together to operate as simple processing elements in order to perform a specific task. The knowledge acquired by the network from its environment is similar to the processing of neurons in the human brain, where information is obtained from a learning process and stored from connection strengths between neurons, also called synaptic weights (Braga *et al.,*2007; Haykin, 2001).

There are different types of ANNs, including Multilayer Perceptron (MLP), which has been widely used for solving regression problems (Diamantopoulou, 2012; Binoti *et al.,* 2014; Castro *et al.,* 2015). This network model has an input layer (source nodes), one or more hidden layers (compute nodes) and an output layer (compute nodes). Since the input layer has the function of receiving input signals and the output and hidden layers are responsible for processing and propagating the received signals (Braga *et al.,* 2007; Haykin, 2001).

Some MLP networks, may have special connections called Skip Layer, where some input signals have a direct connection to the output layer, ie implementing the hidden layer (Ripley, 1996). Though easy to implement, few studies have been developed by testing the application of network model, which requires research to explore their potential.

In this sense, the present study aimed to evaluate the accuracy of total volume estimates of eleven forest formations occurring in the state of Minas Gerais, using Artificial Neural Networks with Skip Layer connections, as well as to compare, based on statistical criteria, with the estimates obtained by volume equations.

## MATERIALSAND METHODS

### *Data base:*

Data were obtained from a forest inventory conducted by the Fundação Centro Técnológico de Minas Gerais (CETEC) - Technological Center Foundation of Minas Gerais (Cetec, 1995), of eleven forest formations occurring in this state. The number of cubed trees per forest formation was established according to the proportional distribution of trees per diameter classes, totaling 3680 cubages, as follows: 414 trees of Cerrado, 210 of Cerradão, 414 of Campo Cerrado, 266 of Primary Forest, 448 of Secondary Forest, 365 of Riparian Forest, 302 of Dry Forest, 301of Liana Transitional Forest, 351 of Jaíba Transitional Forest, 309 of Arboreal Caatinga and 300 trees of Shrubby Caatinga.

Information about species, diameter at 1.30 m height in cm (*dbh*), total height in m (*ht*), number of primary branches, heights of each section (m) and their respective diameters. Individual volumes were obtained by applying the *Smalian* formula (Husch *et al.,* 1982). The minimum commercial diameter with bark considered was 4 cm and the sections along the stem were measured at intervals of 1 m.

### *Artificial Neural Networks:*

To obtain the volume per tree by the ANN, we used quantitative input variables, the *dbh*, the *ht*, the weighted variable $1/(dap^2ht)$ and the number of branches. As categorical variable, we considered the diameter class (Table 1).

The database of each forest formation was randomly divided into two groups: 80% for training and 20% for generalization, and in this last group, networks generated in training were applied in order to assess the capability of the network to produce suitable outputs for unknown entries (Haykin, 2010).

The computer system used to implement the algorithm NEAT was NeuroForest 3.3 (Binoti, 2012). The system adjusts networks recurrence and no recurrence, or artificial neural networks which have (or not) feedback connections (feedback loops) between nodes in the same layer or different layers (Braga *et al.,* 2007; Haykin, 2001).

We trained five ANNs for each formation and testing (networks with recurrence and without recurrence), totaling 110 ANNs adjusted. The number of neurons in the input layer varied according to the forest formation, one neuron for each numeric variable and categorical variable class, and a fixed neuron representing the activation threshold or bias, as Haykin (2001). The networks were composed of only one hidden layer with eight neurons and the activation function used in the hidden layer and in the output one was Sigmoidal (also known as Logistics).

As stopping criterion, we set the number of times in 3000 or root mean square error equal to 0.0001, in other words, the training of each ANN was finished when one of the two criteria was reached.

### *Artificial Neural Networks with Skip Layer connections:*

Considering a multilayer network (MLP), can be represented mathematically (Equation 1), the signal received from the nodes of the input layer, by the hidden layer, wherein each input variable is multiplied by a respective weight and its sum is added to a bias (Haykin, 2001):

$$y_k = \phi_k\left(\sum_{j=1}^{m} w_{kj}.x_j + b_k\right) \tag{1}$$

where:$x_1 \ldots\ldots.. x_m$ are input signals; $w_{kj}$is the synaptic weight where the $k$ index represents the neuron and the *j* index at the input terminal which relates to the weight (here the hidden layer); $b_k$is the bias which has the effect of increasing the net inflow of activation function, in case it assumes positive value or decreases if negative; $\phi(.)$ refers to the activation function; $y_k$ is the output of *k* neuron.

Assuming that the signals processed by the hidden layer are the inputs of the output layer and that the signal processing is performed in the same way, the output can be represented as follows (Velten, 2009):

$$y_i = \phi_i\left(b_i + \sum_{l=1}^{n} w_{il}\,.\phi_k\left(\sum_{j=1}^{m} w_{kj}.x_j + b_k\right)\right) \tag{2}$$

where: $w_{il}$ is the synaptic weight where the index *i* represents the neuron and the index *l* the input terminal which refers to the weight (here the output layer); $b_i$is the bias added by the node of the hidden layer *l*.

Equations 1 and 2 represent, in mathematical terms, the output of a neuron of a MLP network in the hidden and outlet layer, respectively. With the inclusion of Skip Layer connections in equation 1, the output is as represented in equation 3 (Venables and Ripley, 2002; Velten, 2009)

$$y_i = \phi_i\left(b_i + \sum_{l=1}^{m} w_{kl}.x_l + \sum_{l=1}^{n} w_{il}\,.\phi_k\left(\sum_{j=1}^{m} w_{kj}.x_j + b_k\right)\right) \tag{3}$$

**Table 1:** Diameter classes of the eleven forest formations used as categorical variables for the adjustment of the ANNs.

| Forest Formation | Diameter classes |
|---|---|
| Shrubby Caatinga | <= 5 |
| | > 5 <= 11 |
| Arboreal Caatinga | < 5 |
| | > = 5 < 10 |
| | > = 10 < 15 |
| | > = 15 < 20 |
| | >= 20 |
| Campo Cerrado | < 5 |
| | > = 5 < 10 |
| | > = 10 |
| Cerradão | > = 5 < 10 |
| | > = 10 < 15 |
| | > = 15 < 20 |
| | > = 20 |
| Cerrado | < 8 |
| | > = 8 < 15 |
| | > = 15 |
| Riparian Forest | < 5 |
| | > = 5 < 10 |
| | > = 10 < 15 |
| | >= 15 |
| Primary Forest | < 8 |
| | > = 8 < 15 |
| | > = 15 < 20 |
| | > = 20 < 25 |
| | >= 25 |
| Secondary Forest | < 8 |
| | > = 8 < 15 |
| | > = 15 < 25 |
| | >= 25 |
| Dry Forest | < 8 |
| | > = 8 < 15 |
| | > = 15 < 25 |
| | >= 25 |
| Liana Transitional Forest | < 8 |
| | > = 8 < 15 |
| | > = 15 < 20 |
| | >= 20 |
| Jaíba Transitional Forest | < 8 |
| | > = 8 < 15 |
| | > = 15 < 20 |
| | >= 20 |

The Skip Layer connection appears in the equation in terms $w_{kl}.x_l$, where the result of the input node k is processed by the output node l, ie the network topology Skip Layer has some direct connections of input nodes to the output ones, transposing the hidden layer as depicted in Figure 1.

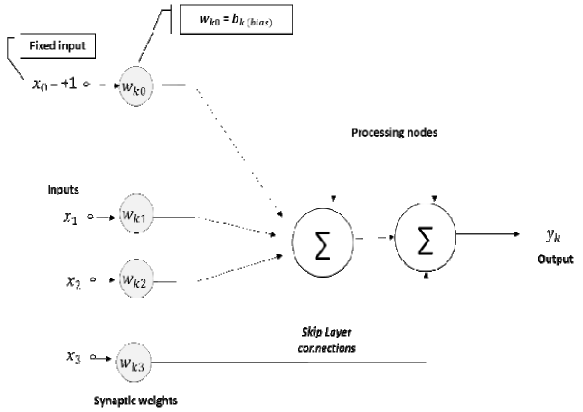


**Fig. 1:** Network model Skip Layer considering three input variables, the bias, a neuron in the hidden layer, na output variable and a Skip Layer connection (adapted by Haykin 2001).

### *Volumetric Model:*

By having represented the most accurate model for all forest types studied, we applied Schumacher and Hall (1993) equations in its nonlinear form, fitting by Cetec (1995):

$$V = \beta_0 dbh^{\beta_1} Ht^{\beta_2} \varepsilon$$

where: $V$ = volume (m³); $\beta_i$ = regression parameters, for i = 0.1 and 2; $dbh$ = diameter at breast height; $ht$ = total height (m) ; and$\varepsilon$ = random error, $\varepsilon \backsim N(0, \sigma^2)$.

### *Statistical Evaluation:*

The accuracy of the estimates was assessed using the coefficient of correlation between observed and estimated volumes, and also by the square root of the mean squared error percentage (RMSE %), as follows:

$$RQEQM(\%) = \frac{100}{\bar{V}} \sqrt{\frac{\sum_{i=1}^{n} (V_i - \hat{V}_i)^2}{n}} \tag{4}$$

Where: $\bar{V}$ It is the average of the observed total volumes; $V_i$ is the volume observed in the inventories at the ith observation; $\hat{V}_i$ is the volume estimated by the ANN at the ith observation and n the total number of observations.

In order to assess the presence of outliers and possible bias in the estimates, we generated scatter plots of percentage errors. The formula for calculating the relative percentage error is represented in Equation 5.

$$e\% = 100 \left( \frac{\hat{Y}_i - Y_i}{Y_i} \right) \tag{5}$$

Where: $\hat{Y}_i$is the volume estimated by the ANN at the ith observation; $Y_i$ is the volume observed in the inventories at the ith observation.

## RESULTS AND DISCUSSION

The description of the ANNs and the statistics obtained during the training and the generalization are presented in Table 2. The parameter estimates and statistics calculated by applying the equations are presented in Table 3.

**Table 2:** Characteristics and statistics of accuracy of the best artificial neural networks adjusted by the algorithm Skip Layer connections to estimate total volume with bark in different formations of the state of Minas Gerais.

| Formation | ANN | Recurrence | Trainning | | Generalization | |
|---|---|---|---|---|---|---|
| | | | r | RQEQM% | r | RMSE% |
| ShrubbyCaatinga | 3 | WtR | 0.971 | 15.12 | 0.963 | 15.71 |
| Shrubby Caatinga | 8 | WR | 0.971 | 15.14 | 0.964 | 15.37 |
| ArborealCaatinga | 2 | WtR | 0.996 | 12.25 | 0.992 | 16.20 |
| Arboreal Caatinga | 9 | WR | 0.993 | 15.53 | 0.992 | 14.41 |
| Campo Cerrado | 1 | WtR | 0.989 | 20.82 | 0.983 | 20.81 |
| Campo Cerrado | 9 | WR | 0.989 | 20.78 | 0.984 | 18.68 |
| Cerradão | 4 | WtR | 0.993 | 15.54 | 0.975 | 25.74 |
| Cerradão | 8 | WR | 0.997 | 10.82 | 0.973 | 22.29 |
| Cerrado | 2 | WtR | 0.991 | 24.14 | 0.981 | 23.13 |
| Cerrado | 5 | WR | 0.992 | 23.65 | 0.985 | 20.99 |
| Riparian Forest | 1 | WtR | 0.991 | 32.63 | 0.995 | 23.19 |
| Riparian Forest | 10 | WR | 0.991 | 31.62 | 0.994 | 24.20 |
| Cerrado | 2 | WtR | 0.991 | 24.14 | 0.981 | 23.13 |
| Cerrado | 5 | WR | 0.992 | 23.65 | 0.985 | 20.99 |
| Riparian Forest | 1 | WtR | 0.991 | 32.63 | 0.995 | 23.19 |
| Riparian Forest | 10 | WR | 0.991 | 31.62 | 0.994 | 24.20 |
| Primary Forest | 1 | WtR | 0.995 | 16.65 | 0.986 | 22.73 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Primary Forest | 10 | WR | 0.995 | 15.94 | 0.984 | 23.41 |
| Secondary Forest | 5 | WtR | 0.993 | 19.55 | 0.997 | 16.11 |
| Secondary Forest | 10 | WR | 0.992 | 20.78 | 0.997 | 16.58 |
| Dry Forest | 3 | WtR | 0.993 | 18.61 | 0.995 | 24.50 |
| Dry Forest | 10 | WR | 0.991 | 20.17 | 0.989 | 27.85 |
| Liana Transitional Forest | 2 | WtR | 0.995 | 18.29 | 0.988 | 11.45 |
| Liana Transitional Forest | 10 | WR | 0.996 | 18.25 | 0.988 | 11.56 |
| Jaíba Transitional Forest | 5 | WtR | 0.992 | 15.12 | 0.988 | 15.26 |
| Jaíba Transitional Forest | 6 | WR | 0.992 | 15.61 | 0.988 | 14.85 |

r = Pearson's linear correlation coefficient. RMSE%: = square root of the mean squared error percentage. WtR: no recurrence. WR: with recurrence.

**Table 3:** Parameter estimates of Schumacher and Hall model and statistics of accuracy calculated for total volume with bark in different formations of the state of Minas Gerais.

| Formation | Coefficients | | | | |
|---|---|---|---|---|---|
| | $\beta_0$ | $\beta_1$ | $\beta_2$ | r | RMSQ% |
| Shrubby Caatinga | 0.000076 | 2.016673 | 0.761171 | 0.947 | 19.70 |
| ArborealCaatinga | 0.000041 | 2.235526 | 0.823993 | 0.980 | 25.19 |
| Campo Cerrado | 0.000055 | 2.607496 | 0.402432 | 0.951 | 42.03 |
| Cerradão | 0.000071 | 1.986487 | 0.904408 | 0.907 | 53.15 |
| Cerrado | 0.000066 | 2.475268 | 0.300031 | 0.981 | 33.88 |
| Riparian Forest | 0.000066 | 2.084681 | 0.752201 | 0.985 | 39.81 |
| Primary Forest | 0.000245 | 2.265779 | 0.150005 | 0.989 | 23.87 |
| Secondary Forest | 0.000074 | 1.707353 | 1.168725 | 0.973 | 40.68 |
| Dry Forest | 0.000075 | 1.818557 | 1.061158 | 0.984 | 27.94 |
| Liana Transitional Forest | 0.000007 | 1.644977 | 2.234670 | 0.991 | 24.13 |
| Jaíba Transitional Forest | 0.000058 | 1.911893 | 1.075100 | 0.983 | 24.07 |

The accuracy measures and the residual graphs, constructed from the estimates obtained by the ANNs in training and generalization, showed similar results adjusted for networks with and without recurrence, i.e., the feedback in this case, showed no significant differences, presenting estimates with a good degree of accuracy by both methods.

However, the formations Riparian Forest, Primary Forest, Secondary Forest, Dry Forest and Liana Transitional Forest showed greater coefficient of correlation and less error (RMSE%) from the adjusted network without recurrence, and the other formations adjusted from the networks with recurrence. In Figure 2 we represented the residual graphs of the best test for each formation.

For Shrubby Caatinga formation, the ANNs showed showed satisfactory statistical indices when compared to non-linear Schumacher and Hall equation. Lima (2014), testing the application of artificial neural networks with *Backpropagation* algorithm in estimating the volume of Shrubby Caatinga in Pernambuco, found in generalization stage RMSE (%), around 30, which shows the good fit obtained from Skip Layer connections algorithm. The residual graphs (Figure 2a) show that the network fitted with the equation, despite the good distribution of residuals, showed the greater deviations for lower volume trees.

For Arboreal Caatinga, the graph built with the estimated volumes by the network with recurrence showed better distribution of residuals than equation, showing no bias as shown in Figure 2b. The same happened to the estimates obtained by the equation for Campo Cerrado formation, with lower coefficient of correlation, greater residual amplitude and high tendency to underestimate lower volume trees (Figure 2c).

Cerrado showed for both fitting methodologies, high values of coefficients of correlation. However, the estimates obtained by the equation and networks, differ in terms of RMSE (%), presenting lower residual amplitude from the ANNs (Figure 2d). Rufini *et al.*(2010), researching volumetric equations for three regions of Cerrado in the strictest sense of the São Francisco Basin, percentage error ranging from 26.19 to 41.66%, showing the good results obtained by the network, which showed an average error of 23.9 and 22.06% in the training and generalization phases.

For Cerradão, residual graphs built with the estimates obtained by the network with recurrence (Figure 2d), show that in the generalization stage, ANNs showed bias to overestimate the trees of lesser volume. Same behavior was observed by the equation, which shows high residual dispersion, increasing the amplitude of RMSE (%) calculated.

High coefficient of correlation values (r > 0.99) were found for the Riparian Forest in the training and generalization phases. Imaña-Encinas and Klein (2001), estimating the volume in three gallery forests located in the Midwestern region of Brazil, they claim that it is possible to estimate the volume of this type of vegetation with a high degree of accuracy, since the sections of stems usually have geometric shapes next to the cylinder. However, even with good statistical indices, residual graphs (Figure 2f) showed bias, overestimating the volume of smaller trees. The equations also showed higher deviations in the lower classes, but with opposite trend presented by the ANNs (underestimating the smaller trees).

Statistics calculated for the estimates obtained by the networks and equation for Primary Forest formation were similar. However, analyzing the residual graphs (Figure 2g), we observed that the traditional method of fitting, showed a strong tendency to overestimate the volume of smaller trees, unobserved behavior by networks without recurrence in the training and generalization stages.

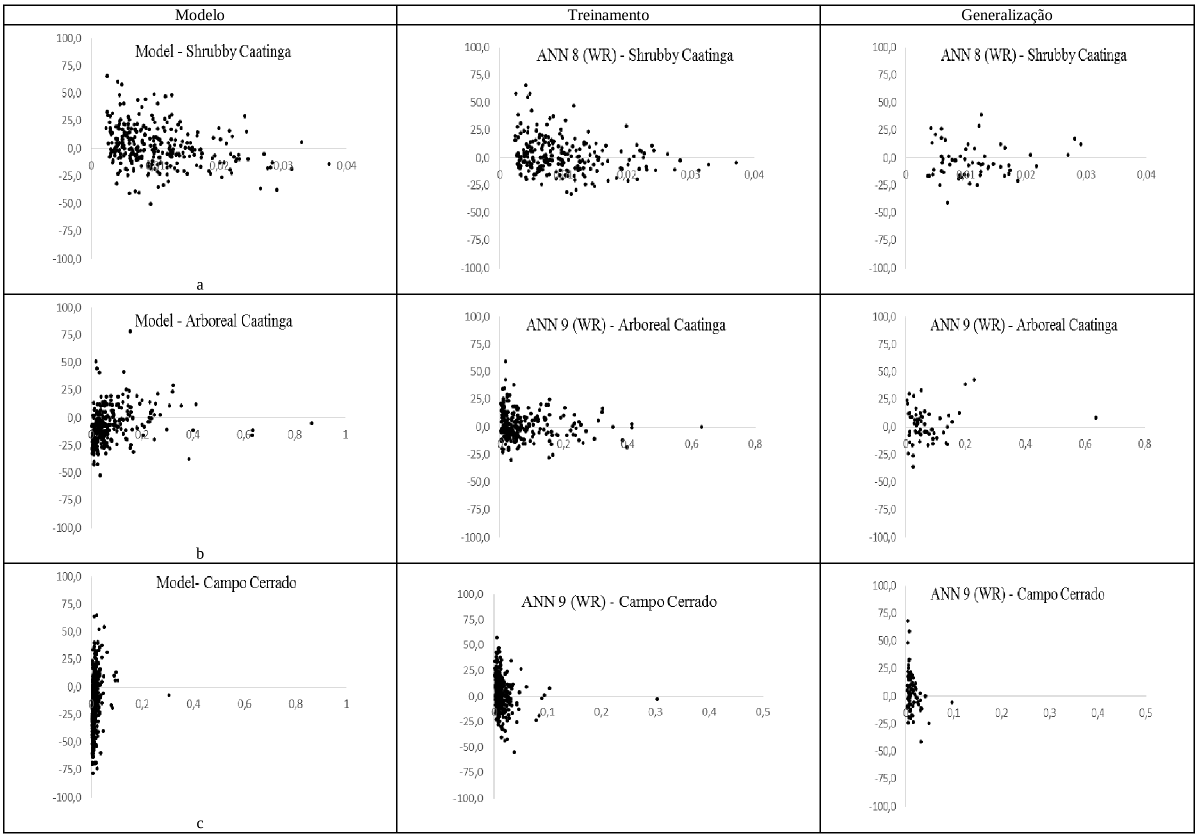
The estimates obtained with the application of networks for Secondary Forest, presented RMSE (%) lower and coefficient of correlation greater than the equation. The residual graphs also show a more uniform distribution and less deviation for trees of greater volume, as shown in Figure 2h.

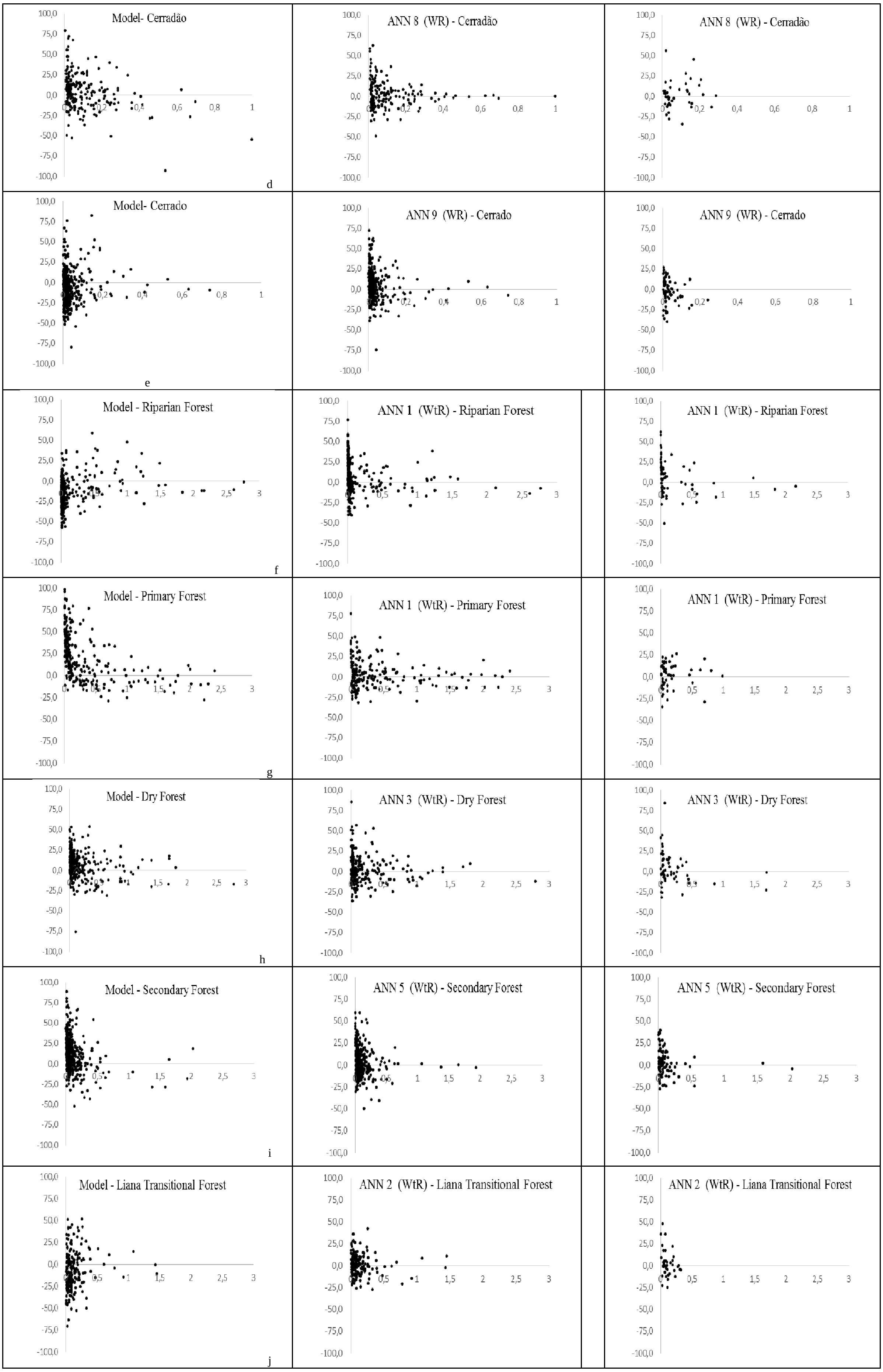
For Liana Transitional Forest and Jaíba Transitional Forest, both fitting methods differentiate primarily in terms of RMSE (%), with smaller error from the estimates obtained with the application of networks. Residual graphs built for Liana Transitional Forest, corroborate this result, showing a distribution even more uniform than the equation (Figure 2j).

For Jaíba Transitional Forest, we observe that despite good statistical indices obtained from the application of networks, residual graphs showed a slight tendency to overestimate the volume of smaller trees (Figure 2k).

In general, all types analyzed had higher deviations in lower volume classes, and, for ANNs we observed an overestimation tendency for this group of trees. According to Machado *et al.* (2008), individual trees with smaller in diameter have different relationship between the variables volume, dbh and height. This behavior is expected because smaller trees despite having the same total height, can have different proportions of crown and diameter, what influences the variable volume, increasing its variability. Other work related to volumetric modeling showed similar behavior, Campos *et al.*(2001), estimating the volume of mixed stands in Minas Gerais found the same overestimation for volume in dbh classes up to 20 cm, similar trend was found by Rezende *et al.* (2006) and Scolforo *et al.* (1994).

Good results obtained by the application of artificial neural networks in different areas of scientific means, are due to other factors, the use of continuous and categorical variables that have biological relationships and / or mathematics with the variable to be estimated, and also the ability that they have to deal with complex non-linear relationships and presence of noise (Haykin, 2001). Diamantopoulou and Milios (2010), estimating total volume with and without pine bark, discuss some characteristics that provide advantages to networks in comparison to conventional methods, the ability to deal with data that have nonlinear relationships, multicollinearity, or presence of noise.




Model- Cerradão
ANN 8 (WR) - Cerradão
ANN 8 (WR) - Cerradão
d
Model- Cerrado
ANN 9 (WR) - Cerrado
ANN 9 (WR) - Cerrado
e
Model - Riparian Forest
ANN 1 (WtR) - Riparian Forest
ANN 1 (WtR) - Riparian Forest
f
Model - Primary Forest
ANN 1 (WtR) - Primary Forest
ANN 1 (WtR) - Primary Forest
g
Model - Dry Forest
ANN 3 (WtR) - Dry Forest
ANN 3 (WtR) - Dry Forest
h
Model - Secondary Forest
ANN 5 (WtR) - Secondary Forest
ANN 5 (WtR) - Secondary Forest
i
Model - Liana Transitional Forest
ANN 2 (WtR) - Liana Transitional Forest
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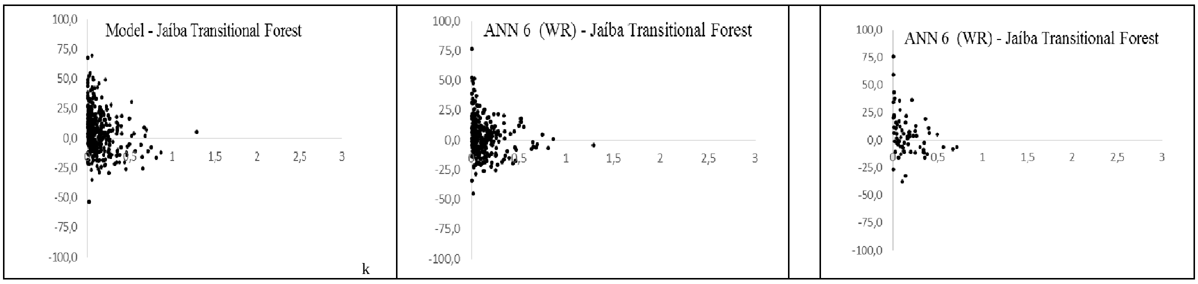

**Fig. 2:** Dispersion of percentage error (y-axis) in relation to observed values of volume (m³) for Schumacher e Hall nonlinear equations and by the best networks in the training and generalization for different forest formations occurring in Minas Gerais. WtR: no recurrence. WR: with recurrence.

Other research has been directed to the evaluation of artificial neural networks applied to the management of forest resources. In studies carried out by Blackard and Dean (1999) and Corne *et al.*(2004), they tested the potential of ANNs in the prediction of forest formations attributes considering topographic and cartographic variables. Comparing the results with traditional methods of classification and regression, Blackard and Dean (1999) found a 70.58% hit percentage for ANN against 58.38% by the statistical method. Corne *et al.* (2004) also found superior results with the application of ANNs, presenting classifications with hit percentage ranging from 80% to 90%.

Özçelik *et al.* (2010), estimating stem volume of four native species of Turkey, by ANNs and statistical models, found error values (RMSQ%) for the best statistical method analysed, ranging from 1.57 to 7.35% and for the best ANN model from 4.38 to 14.41%. However, despite the best results in terms of mean error and RMSE (%), authors found best results from residual graphs, a tendency of the model to overestimate the volume of trees. Özçelik *et al.* (2010) also discuss the most difficulty required by the statistical method field, which requires the measurement of different diameters and heights along the stem, variables not required by ANNs, which required only three measurements to get good accuracy in estimates.

Satisfactory results were also found by Diamantopoulou *et al.* (2015), when they evaluated the potential of ANNs in the prediction of diameter distribution of a pure stand in Turkey. The authors estimated Weibull function parameters and compare the results with those obtained by the method of maximum likelihood and moments, finding higher coefficient of correlation, less error and better distribution of residuals from the ANNs.

## ***Conclusions:***

Accuracy measures, the residual graphs and histograms built from ANNs, in the training and generalization phases, were similar for networks fitted with and without recurrence, i.e. for forest formations studied, networks with and without recurrence estimate volume with a good degree of accuracy.

For forest formations, despite the slight tendency to overestimate the volume of smaller trees, the ANNs, when compared to nonlinear equations of Schumacher and Hall, presented good results, and for Arboreal Caatinga, Campo Cerrado, Cerrado, Primary Forest, Secondary Forest and Liana Transitional Forest, networks were superior to the usual regression model.

Results of this study confirms the applicability of artificial neural networks with Skip Layer Connections, proving its potential for production modeling of native stands.

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