ISSN impresa 0717-3644
ISSN online 0718-221X

Maderas. Ciencia y tecnología 2023 (25): 30, 1-12

DOI: 10.4067/s0718-221x2023000100430

# ARTIFICIAL INTELLIGENCE TO GROWTH STRESSES PREDICTING IN *Eucalyptus* CLONES USING DENDROMETRIC VARIABLES AND WOOD DENSITY

***Thiago Campos Monteiro*[1,♠]**

http://orcid.org/0000-0002-3819-7035

***Carlos Alberto Araújo Júnior*[2]**

http://orcid.org/0000-0003-0909-8633

***Jean Henrique dos Santos*[1]**

https://orcid.org/0000-0001-5675-4803

***Thiago Cardoso Silva*[1]**

http://orcid.org/0000-0001-6553-4204

***Thiago Magalhães do Nascimento*[1]**

https://orcid.org/0000-0001-5576-492X

***José Luiz Ferraresso Conti Junior*[3]**

http://orcid.org/0000-0001-6812-6070

***Jorge Luis Monteiro de Matos*[1]**

http://orcid.org/0000-0003-3388-5258

***Ricardo Jorge Klitzke*[1]**

http://orcid.org/0000-0001-6839-9415

***Márcio Pereira da Rocha*[1]**

http://orcid.org/0000-0002-5420-8478

## ABSTRACT

*Eucalyptus* planted forests contribute to maximizing lumber production but problems such as longitudinal growth strain can negatively influence the quality of the products. Knowing dendrometric variables and wood properties can help in the prediction of longitudinal growth strain, mainly with the help of artificial intelligence. Thus, the aim of this research was to evaluate the use of artificial neural networks to predict longitudinal growth strain in *Eucalyptus* trees based on dendrometric variables, spacing between trees and wood density. The longitudinal growth strain was measured in trees of four *Eucalyptus* clones planted in three spacings. The diameter and height of each tree were measured. The basic wood density was determined. Artificial neural networks were used to estimate longitudinal growth strain as a function of dendrometric variables, tree spacing

[1]Universidade Federal do Paraná. Departamento de Engenharia e Tecnologia Florestal. Curitiba, PR, Brazil.
[2]Universidade Federal de Minas Gerais. Instituto de Ciências Agrárias. Montes Claros. MG, Brazil.
[3]ArborGen Tecnologia Florestal. Campinas, SP, Brazil.
♠Corresponding author: thiago.monteiro@ufpr.br
Received: 21.02.2021 Accepted: 11.04.2023

and wood density. The results showed that the artificial neural networks presented good results for training and validation, with most of them resulting in high correlation coefficient values. The trained artificial neural networks showed a correlation coefficient above 0,56. Artificial neural networks showed that the variables clone and basic wood density were the ones that most contributed to the prediction of longitudinal growth strain. On the other hand, the spacing between trees, the height of the tree and the diameter at breast height were not relevant to predict growth stresses.

**Keywords:** Artificial neural networks, basic density, *Eucalyptus* clones, growth stresses, longitudinal growth strain.

## INTRODUCTION

Growth stresses are important, as they help to reorient stems and branches in trees. These stresses are also important to achieve vertical growth and to avoid external influence on a plant, such as the wind (Archer 1986, Fournier *et al.* 1994, Braz *et al.* 2017, Gril *et al.* 2017). In fast-growing trees like those of the *Eucalyptus* genus, these tensions are higher and interfere with the quality of timber products (Trugilho *et al.* 2006, Gril *et al.* 2017). The effect of high growth stress levels on a tree may result in cracks and twists in the logs and lumber (Gril *et al.* 2017, Amer *et al.* 2019). This parameter can also be a predictor of sawlog quality (Valencia *et al.* 2011) in the alteration of the wood physical, mechanical (Diaz Bravo *et al.* 2012, Omonte and Valenzuela 2015), and anatomical properties (Kojima *et al.* 2011, Li *et al.* 2018).

Factors such as species and silvicultural treatments influence growth stresses (Fournier *et al.* 1994, França *et al.* 2017, Gril *et al.* 2017). In addition to these factors, the trees are exposed to various external disturbances that can cause a permanent change in the orientation of the trunk and change the angle or position of the branches, for example, due to soil properties, extreme snow load, and exposure to prevailing strong winds (Archer 1986, Braz *et al.* 2017). Also, little is known about the effect of dendrometric variables on growth stresses and, consequently, on wood quality. Some studies have shown a low or even no correlation between the diameter and the height of the trees and growth stresses (Braz *et al.* 2017, França *et al.* 2017).

These isolated factors or the interaction between them result in different wood quality trees. This quality depends on the species, environment, and interaction between these factors (Zobel and Van Buijtenen 1989). The prediction of growth stresses in different *Eucalyptus* genetic materials grown under different management conditions, such as spacing between trees, is important for optimizing the use of the tree in forest-based industries. The use of fast, low-cost, and accurate methods to estimate growth stresses can contribute to the valorization of *Eucalyptus* wood products.

The longitudinal growth strain (LGS) is a variable that can be obtained using a non-destructive technique, the CIRAD-Fôret method (Trugilho and Oliveira 2008, Valencia *et al.* 2011, Beltrame *et al.* 2012), and can be considered an indirect and reliable estimate of the longitudinal growth stresses (Trugilho and Oliveira 2008, Valencia *et al.* 2011). This method is relatively simple, quick, only locally destructive, and used on the standing tree (Archer 1986). The measurement of dendrometric variables such as the height and diameter of the trees are also easily determined. The basic density is another variable that is easy to measure and correlates with many of the wood's technological properties. Several studies on the relationship between wood properties or dendrometric variables and LGS in trees have been carried out with simple correlations and traditional statistical models (Cardoso Junior *et al.* 2005, Valencia *et al.* 2011, Diaz Bravo*et al.* 2012, Omonte and Valenzuela 2015, França *et al.* 2017, Xavier *et al.* 2018).

However, the artificial neural networks (ANNs) technique can contribute to improve the accuracy of these relationships, as well as allow the use of few parameters to estimate LGS and consequently cause a reduction in the cost of the analysis. The use of ANNs has been highlighted in the forest and wood sciences' research area. Some examples are the studies about tree taper estimation (Nunes and Görgens 2016, Fang and Strimbu 2017), for reducing sample intensity used to predict the commercial volume of *Eucalyptus* clones (Tavares Junior *et al.* 2019), to predict relationships between individual tree height and diameter at breast height (Ercanlı 2020), to estimate basic density with a non-destructive method (Silva *et al.* 2018) and predicting energy potential in a savanna woodland area (Carrijo *et al.* 2020).

Soon, we expect to develop more plantation forests and utilize more wood as industrial resources. In this case, the ANNs used to predict growth stresses in trees can show higher accuracy compared to the traditional regression models. Even today, studies using dendrometric variables and wood properties data with artificial intelligence tools, such as ANN, to predict the LGS levels are quite unusual. Thus, the aim of this study was to evaluate the use of ANNs to estimate the LGS in *Eucalyptus* clones, based on the genetic materials, plant spacing, dendrometric variables and wood density.

## MATERIALS AND METHODS

### Description of the local and material

Four genetic materials were selected (C1, C2, C3 and C4 clones), three of them belong to the species *Eucalyptus urophylla* S.T. Blake x *E. grandis* W. Mill ex Maiden and one of them to the species *E. saligna* Sm. All trees were seven years old. The trees of the different clones were planted at 3 m x 3 m, 3 m x 6 m and 3 m x 8, 25 m spacing, with space for each tree of 9,18 m² and 25 m² per tree, respectively, without pruning or thinning. Three individuals were selected for each treatment, with a total of 36 trees evaluated. The data were collected from an experimental plantation located in the city of Chapadão do Sul, in the Mato Grosso do Sul state, Brazil (18° 47' 39'' S, 52° 37' 22'' W, average altitude 820 m).

### Longitudinal growth strain (LGS)

The method used to measure the growth deformation used was that recommended by the Centre de Coopération Internationale em Recherche Agronomique pour le Développement, Département dês Forêt (CIRAD-Fôret), which uses a digital dial gauge (strain gauge) to predict (mm) the longitudinal growth strain (LGS) released in the region the trunk, according to (Fournier *et al.* 1994, Trugilho and Oliveira 2008, França *et al.* 2017).

All trees were sampled to determine the LGS in the four cardinal directions (North, South, East, and West). The LGS measurements were estimated in the absence of wind in the area to avoid overestimated values since the less movement of the trees influences the internal sustaining forces sustaining, which can alter the result.

### Dendrometric variables

The evaluation of the size of the trees was performed by direct measurement. The trees were felled and measured from the base to the commercial height (~5 cm in diameter). We measured the diameter at breast height (DBH) with a tape measure at 1,30 m from the ground. The basic wood density (BWD) was determined on a disk removed at a height of 1,30 m from the soil in the tree and determined in the laboratory, according to ABNT NBR 11941 (2003).

### Statistical calculation

To establish a relationship between the longitudinal growth strain (LGS) and dendrometric variables, wood density and spacing per tree, 10000 artificial neural networks (ANNs) were trained and the best one was chosen to estimate the LGS of the sampled individuals. The ANNs input variables were those obtained in the field: species (x1), genetic material (x2), the useful area occupied by plant, in m² (x3), BWD, in kg/m³ (x4), DBH (x5), and total height (x6) (Figure 1). As the species and genetic material variables are defined as categorical, dummy variables were created for each category. The output variable was the LGS (y) obtained in the tree tests. The data were grouped randomly between data for training and data for validation in the proportion of three to one.

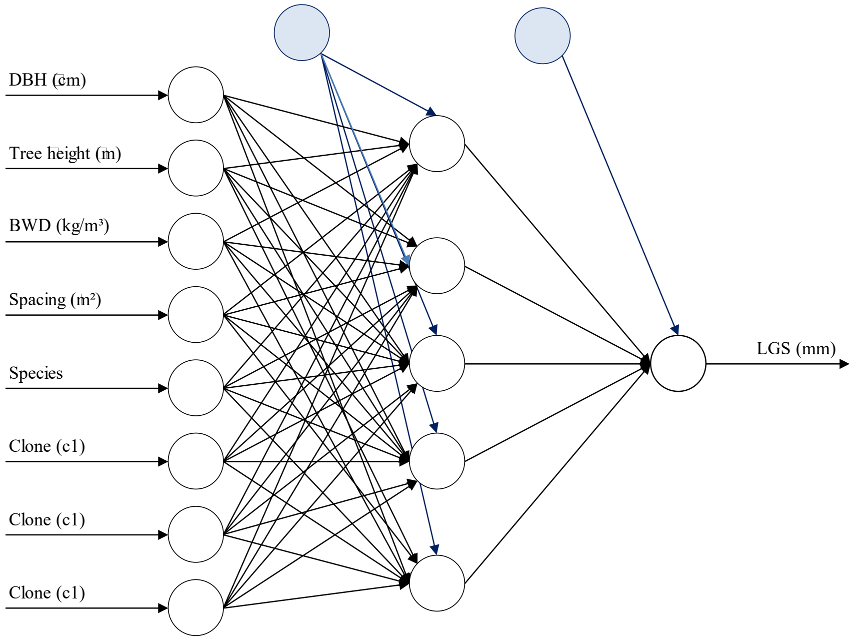


**Figure 1:** Artificial neural network structure model to estimate longitudinal growth strain with eight input neurons, five hidden neurons, and one output neuron.

The trained ANNs were of the Multilayer Perceptron (MLP) type, each with five neurons in the middle layer and only one hidden layer. The activation function was of the logistic type and the algorithm used was the Resilient Backpropagation. We defined this configuration due to its simplicity, which optimizes the time needed for training. The Neuralnet package (Fritsch *et al.* 2019) of the R software (R Core Team 2019) was used to obtain the weight values of the neural networks. The best neural network was the one with the highest correlation coefficient value between the observed values and the estimated values for the validation data.

The algorithm proposed by Garson (1991) was used to identify the most important variables for estimating the LGS considering the trained ANNs. This was done using the Garson function of the NeuralNet Tools package (Beck 2018) of the R software (R Core Team 2019).

## RESULTS AND DISCUSSION

The minimum, average and maximum values of the variables of planting density, basic wood density (BWD), dendrometric variables (height and diameter at breast height), and the response variable measured (longitudinal growth strain) are shown in Table 1, with their respective standard deviation.

The spacing in m² per tree used in this study has potential for agroforestry systems (Table 1). In addition to the possibility of using agricultural and pastoral crops between the trees in the wider spacing, multiple uses of the trees were also possible, especially trees with a larger diameter. The wider spacing can reduce the forest biomass produced, but it can also reduce the potential water stress (Hakamada *et al.* 2017). On the other hand, annual increment reached a higher and earlier peak at narrow spacing, and in addition, the light use efficiency (stem volume growth per unit of light intercepted) can be about twice as great for trees at narrow spacing than at wider spacing (Stape and Binkley 2010).

**Table 1:** Descriptive statistic for the data used in the artificial neural networks' training.

| Specie | Clone | Statistic | Spacing ($m^2$) | Tree height (m) | DBH (cm) | BWD ($kg/m^3$) | LGS (mm) |
|---|---|---|---|---|---|---|---|
| *E. urophylla* x *E. grandis* | C1 | Minimum | 9,00 | 26,20 | 18,05 | 486,93 | 0,082 |
| | | Average | 17,35 | 29,26 | 24,08 | 523,36 | 0,102 |
| | | Maximum | 24,75 | 33,00 | 28,74 | 563,23 | 0,122 |
| | | SD | 6,86 | 1,91 | 3,76 | 25,47 | 0,013 |
| *E. saligna* | C2 | Minimum | 9,00 | 24,50 | 17,41 | 505,76 | 0,062 |
| | | Average | 17,35 | 26,56 | 23,74 | 535,70 | 0,072 |
| | | Maximum | 24,75 | 28,20 | 28,97 | 565,38 | 0,082 |
| | | SD | 6,86 | 1,14 | 4,37 | 22,41 | 0,006 |
| *E. urophylla* x *E. grandis* | C3 | Minimum | 9,00 | 29,90 | 17,67 | 503,06 | 0,065 |
| | | Average | 17,35 | 33,17 | 23,66 | 523,21 | 0,083 |
| | | Maximum | 24,75 | 34,30 | 28,65 | 567,14 | 0,100 |
| | | SD | 6,86 | 1,40 | 3,79 | 20,21 | 0,011 |
| *E. urophylla* x *E. grandis* | C4 | Minimum | 9,00 | 27,10 | 19,07 | 542,17 | 0,075 |
| | | Average | 17,35 | 29,32 | 24,57 | 581,68 | 0,102 |
| | | Maximum | 24,75 | 31,20 | 30,81 | 611,30 | 0,127 |
| | | SD | 6,86 | 1,36 | 4,20 | 21,71 | 0,017 |
| | | Minimum | 9,00 | 24,50 | 17,41 | 486,93 | 0,062 |
| | | Average | 17,35 | 29,57 | 24,01 | 540,99 | 0,090 |
| | | Maximum | 24,75 | 34,30 | 30,81 | 611,30 | 0,127 |
| | | SD | 6,56 | 2,78 | 3,88 | 32,53 | 0,018 |

Where: DBH = diameter at breast height; BWD = basic wood density; LGS = longitudinal growth strain; SD = Standard deviation.

The dendrometric variables evaluated showed height and diameter at the diameter at breast height (DBH) values consistent with those presented for *Eucalyptus* plantations in Brazil (Table 1). The slight variation between heights is due to the homogeneity of the region's environmental characteristics, such as the same soil and consequently the same site index (Calegario *et al.* 2005, Soares *et al.* 2016). The DBH showed a slightly higher variation (CV ~16%). On the other hand, this result with higher variation is expected due to the different spacing between the trees evaluated. The direct and positive relationship between diameter and spacing is widely reported in studies (Schönau and Coetzee 1989, Ferreira *et al.* 2014). Comparing the values with other studies, different genetic materials of *Eucalyptus*, cultivated in the Bahia and Espírito Santo state (Brazil), with different ages and spacing between trees presented average values for height and DBH of the trees equal to 25,74 m and 19,64 cm, respectively (Ferraz Filho *et al.* 2018).

The basic wood density (BWD) showed an average value of ~541 $kg/m^{-3}$ (Table 1), with little variation (CV ~6%). The knowledge of the wood density allows a better use for the wood of these plantations, being a parameter of easy determination and with high correlation with other technological properties of the wood and its use (Ramage *et al.* 2017). The average values found for BWD were consistent with those presented for the *Eucalyptus* genus with similar ages and the same spacing between trees (Table 1). *Eucalyptus benthamii*, *E. dunnii,* and *E. grandis* cultivated with spacing between trees varying between 1,5 $m^2$ and 4,5 $m^2$ per plant and age of ~6,2 year sold showed average, minimum and, maximum density equal to 497 $kg/m^3$, 402 $kg/m^3$ and 610$kg/m^3$, respectively (Resquin *et al.* 2020).

The mean longitudinal growth strain (LGS) also showed values close to those presented for the genus *Eucalyptus* (Table 1). However, this parameter showed greater variation (CV ~22%) than the other trees' dendrometric variables and BWD. Variations in the wood properties of the trees and, consequently, in the growth stresses to which they are subjected, may vary according to the genetic material, according to the environment, in this case, the spacing between the trees, and also according to the interaction between these factors (Zobel and Van Buijtenen 1989). Comparing with other LGS studies, a *Eucalyptus* clone evaluated at five ages (3, 5, 7, 8 and 9 year sold) and three tree spacings (9,24 $m^2 \cdot tree^{-1}$ and 40 $m^2 \cdot tree^{-1}$) showed an average LGS of 0,065 mm (Cardoso Junior *et al.* 2005). Another study with 15-year-old *Eucalyptus nitens* trees and tree spacing ranging from 14 $m^2$ to 33 $m^2$ per plant showed an average LGS equal to 0,141 mm (Diaz Bravo *et al.* 2012). In a more recent study, 20 *Eucalyptus grandis* x *E. urophylla* clones that were 13 year sold showed an LGS mean equal to 0,082 mm (França *et al.* 2017). The variations in LGS between studies and also the results in Table 1 can be due to the evaluation of different genetic materials, environmental development conditions (e.g.: soil, precipitation, and winds), ages, and other factors.

**Network training**

Artificial neural networks (ANNs) trained to predict growth stresses based on longitudinal growth strain (LGS) based on tree spacing, dendrometric variables, and wood density showed correlation coefficients (R) between the observed and estimated values ranging from 0,76 to 0,99 for training data and between -0,47 and 0,90 for validation data (Figure 2). The mean and median values for training data were 0,86 and 0,84, and those values for validation data were equal to 0,56 and 0,58.

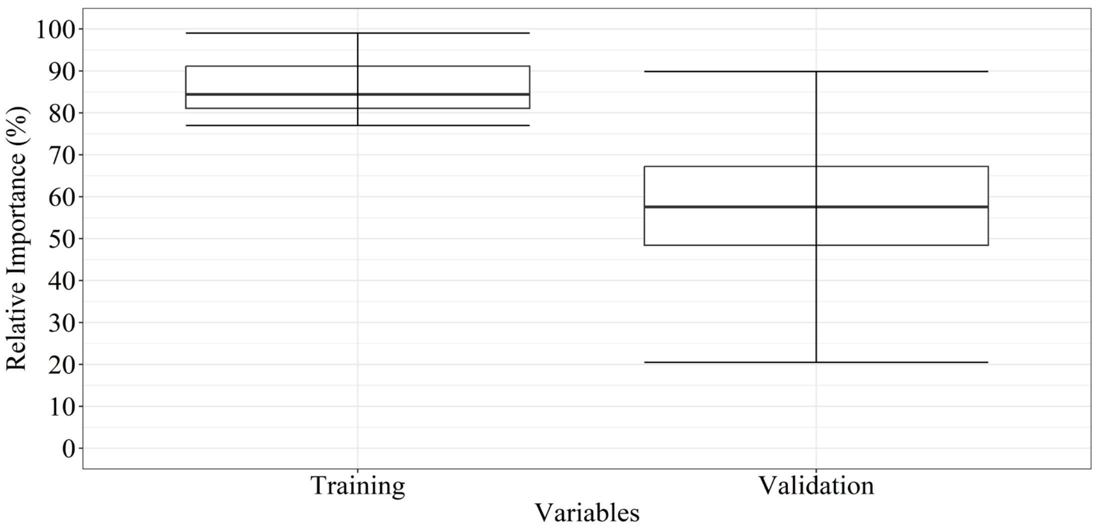


**Figure 2:** Boxplot for correlation between observed and estimated values considering training and validation data.

Artificial neural networks (ANNs) showed satisfactory results for training, with most of them resulting in high correlation values between observed and estimated values (Figure 2). As for validation, performance is lower than training, as expected, but most trained neural networks correlated above 0,56. That can be considered good, given the little variability in training data. These results demonstrate the potential of ANNs to predict growth stress in *Eucalyptus* trees based on tree spacing, dendrometric variables, and wood density.

**Adjusted networks**

The most important variable for the estimation of the LGS values was the *Eucalyptus* clone, represented in Figure 3 by the dummy variables “c1”, “c2”, and “c3”. The basic wood density was the second most important variable. The diameter at breast height (DBH) and the species contributed the least or had the least relative importance. The spacing for the development of each tree in m² and the height of the trees presented medium importance when compared to the other variables.

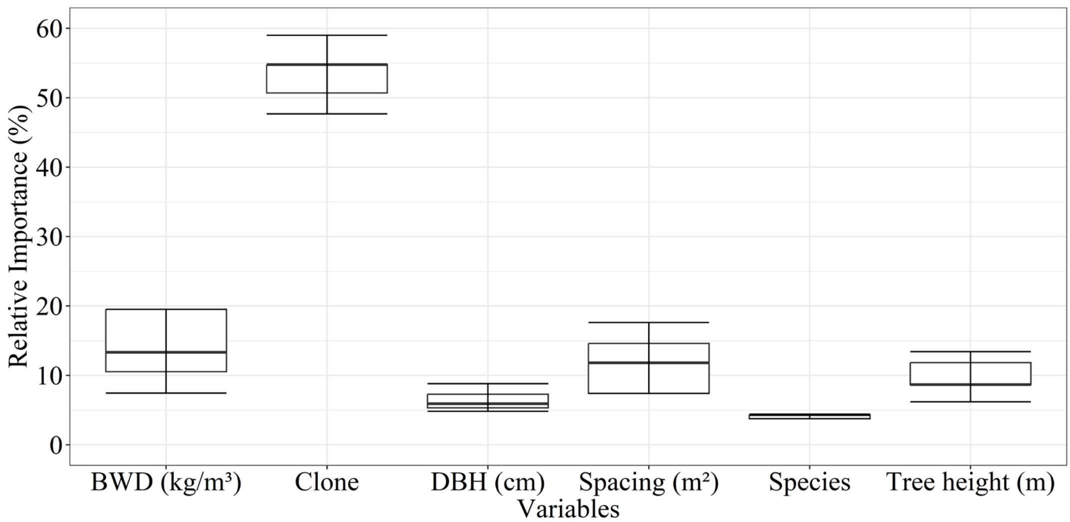


**Figure 3:** Boxplot for relative importance of artificial neural network input variables.
Where: DBH = diameter at breast height; BWD = basic wood density; and LGS = longitudinal growth strain.

For all trained neural networks, the variable clone had the greatest relative importance, with little importance for the variables diameter (DBH) and species (Figure 3). Although three of the four clones studied are of the same species, their properties, mainly of wood quality, may present peculiarities. Furthermore, within the same clone, the wood properties differ between trees and within the tree. In *Eucalyptus* clone trees, the variation of the physical and mechanical properties of the wood can be greater in the radial direction when compared to the longitudinal one, interfering in the potential use of the sawn wood processed depending on its location from the layers closest to the bark towards the pith (Cruz *et al.* 2003). The wood properties of each clone can reflect its growth stresses and, consequently, its LGS.

Most studies evaluating the effects of wood properties or tree growth variables in LGS did not include the effect of genetic material in modeling. In these cases, the clones were only objects of study, or the difference between the LGS of the clones was evaluated. For example, in the LGS evaluation of 20 *Eucalyptus grandis* x *E. urophylla* hybrid clones, of 13 year sold, the LGS results varied between 0,037 mm and 0,116mm, with two statistically distinct groups and 11 clones in the group with the highest LGS (França *et al.* 2017). In another study, the LGS found in ten hybrids of *E. urophylla* × *E. grandis* clones of approximately three years old, varied significantly between 0,060 mm and 0,116mm (Braz *et al.* 2017). Unlike these studies, using the ANNs, it was possible to include the variable clone to predict LGS and this parameter was the most relevant (Figure 3). In addition, the clone as a variable in modeling with ANNs may reflect a series of peculiarities of tree growth as well as the quality of its wood. This quality depends on factors related to genetic characteristics, the environment where the tree grows, and the interaction between these two factors (Zobel and Van Buijtenen 1989).

It is important to report that the alteration of the development environment of the clones, in this study evaluated with the different spacing between the trees, presented median relative importance in the ANN. That is, the development environment of the clones was not significant in predicting the growth stresses of the *Eucalyptus* clones. This result is important, especially in agrosilvopastoral systems, with wider spacing between trees and the possibility of cultivating other agricultural or livestock crops between the planting lines and the potential for multiple uses of wood (Luz *et al.* 2019), especially for products with higher added value, such as lumber, for example. On the other hand, even in dense homogeneous plantations, with the suitable clone selection, it is possible to produce small-diameter trees with fewer wood defects such as cracks and twists caused by growth stresses. These small-diameter logs demonstrated the potential to be used in minimally processed round segments as structural elements in buildings, bridges, towers, and other infrastructures (Bukauskas *et al.* 2019). The low effect of environmental conditions on the LGS of *Eucalyptus* trees has also been found in other studies. The thinning effect of *E. nitens* trees at seven and nine years old did not affect the LGS at 15 year sold (Diaz Bravo *et al.* 2012). On the other hand, the evaluation of a *Eucalyptus* clone in different spacings showed a negative correlation, with an $R^2$ equal to 95,4% (Cardoso Junior *et al.* 2005).

The growth conditions of *Eucalyptus* trees reflected in the dendrometric variables height and DBH were also of low importance in ANNs for predicting LGS (Figure 3). In fact, the correlation between LGS and the variables height and diameter is null, with values of 0,04 and 0,02. Still, the small variability in the height and diameter data were also not enough for the trained neural networks to present greater weights in the connections involving such variables. On the other hand, these variables ended up helping to fine-tune the ANNs to obtain the LGS values. The relationship between height and DBH with LGS would be expected, as the phenomenon of photosynthesis that occurs in the leaves of the tree reflects in the development of the apical (primary growth) and cambial meristem (secondary growth). The primary and secondary growth of trees is desired for producers, mainly for lumber production. In addition, measurements of DBH and height of trees are easy when compared to the determination of other parameters, mainly of wood quality.

It was expected that the higher growth rates of meristematic cells could raise growth stresses (Archer 1986). However, following the same behavior of the results shown in Figure 3, other studies also report the absence of correlation between LGS and dendrometric variables in *Eucalyptus* plantations. Several studies for *Eucalyptus* of different species/clones, ages, and regions observed low correlations and even non-significance between DBH and tree height with the LGS (Diaz Bravo *et al.* 2012, França *et al.* 2017). Another study with *Eucalyptus* found a significant and negative correlation with DBH and no significant relationship with height (Beltrame *et al.* 2012). In another research, the species *Peltophorum dubium* in a 14-year-old restoration plantation presented a significant and positive correlation between the LGS and DBH (Xavier *et al.* 2018). These results show how diversified the interactions of the LGS are with the growth characteristics between clones or species.

Finally, the second most relevant parameter in the prediction of LGS was the basic wood density (BWD) (Figure 3). This result is important because it demonstrates the potential of ANNs to predict growth stresses with a wood quality parameter relatively easy to be determined. In addition to easy determination, BWD has a good correlation with the anatomical, chemical and, mechanical properties of wood. The significant and positive relationship between LGS and BWD in *Eucalyptus* trees is reported in other studies (Trugilho *et al.* 2006, Diaz Bravo *et al.* 2012). However, the significant relationship in *E. dunnii* was found only at the age of 15, and at the ages of 8, 13, and 19 it was not significant (Trugilho and Oliveira 2008). The relationships between LGS and BWD not significant in *Eucalyptus* were also presented in other studies (Beltrame *et al.* 2012, Braz *et al.* 2017). These results demonstrate the importance of BWD as a predictor parameter for LGS, but it shows attention according to the species and age evaluated.

**Accuracy of artificial neural networks**

The best ANN presented a correlation equal to 0,97 for training data and 0,90 for data validation. The most important variables were genetic material and BWD. The least important variables were DBH and species (Figure 4a). The residues obtained from the estimates generated by the best ANN are distributed around the 45 º degree line, indicating good estimates and with no visible trends (Figure 4b).

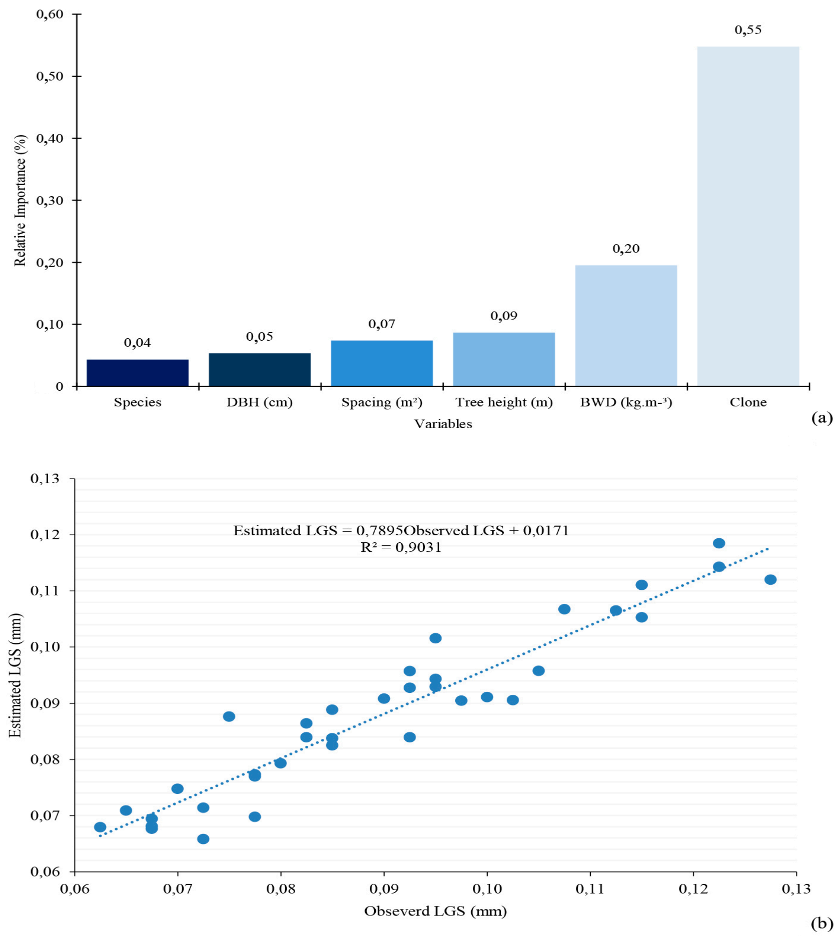


**Figure 4:** (a) Graph for Garson method analysis and (b) residual graph for the LGS estimates considering the best artificial neural network obtained. Where: DBH = diameter at breast height; BWD = basic wood density; and LGS = longitudinal growth strain.

The best artificial neural network (ANN) obtained to predict LGS confirmed the general trend of the importance of the variables clone and BWD (Figure 4a). As already discussed, the clone presents several peculiarities of both the tree and its wood. Thus, the clone had its own genetic material and consequently its own phenotypic characteristics, such as trunk and crown properties. In this same context, the BWD is a property that correlates with the anatomical, chemical, physical, and mechanical properties of wood. The prediction of growth stress in trees with these variables has the advantage of using parameters that are relatively easy and quick to be determined.

The estimates for both training and validation showed low dispersion around the 45degrees line in the residual graph (Figure 4b). These results using ANNs demonstrate an advantageous alternative when compared to the regression techniques for predicting growth stresses in *Eucalyptus* trees. These results reinforce the use of ANNs to predict wood properties, such as: estimating the basic wood density from Cerrado *sensu stricto* species with a non-destructive method (Silva *et al*. 2018), the estimate of mechanical properties of wood (Miguel *et al.* 2018), the prediction of quality parameters of wood panels (Melo and Miguel 2016) and the energy density of wood in the Cerrado area based on satellite images (Carrijo *et al.* 2020).

## CONCLUSIONS

The analysis allows us to conclude that it is possible to estimate the growth stresses in Eucalyptus clones from tree variables using an artificial neural network (ANN).

The ANNs showed that the variables clone and basic wood density were the ones that most contributed to the estimation of longitudinal growth strain (LGS). On the other hand, the spacing for the development of each tree and the dendrometric variables such as height and diameter at breast height were not relevant for predicting LGS.

Therefore, ANNs are a practical and efficient tool in wood quality testing. The results indicate that this tool can be used in a practical way by industries of the forestry sector to predict the growth stresses effectively and non-destructively in *Eucalyptus* trees.

## AUTHORSHIP CONTRIBUTIONS

T. C. M.: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing; C. A. A. J.: Data curation, Resources, Software, Validation, Formal Analysis, Writing – review & editing; T. C. S.: Methodology, Data curation, Writing – original draft, Writing – review & editing; T. M.D. N.: Methodology, Writing – original draft; J. L. F. C. J.: Funding acquisition, Supervision, Visualization; J. L. M.D. M.: Resources, Methodology, Supervision, Writing – original draft; R. J. K.: Project administration, Methodology, Supervision, Visualization; M. P.D. R.: Project administration, Methodology, Supervision, Visualization, Writing – original draft.

## REFERENCES

**Amer, M.; Kabouchi, B.; Rahouti, M.; Famiri, A.; Fidah, A.; Ziani, M.; El Alami, S. 2019.** Kinetic of cracks propagation related to the growth stress of clonal *Eucalyptus* wood. *Journal of the Indian Academy of Wood Science* 16: 155-161. https://doi.org/10.1007/s13196-019-00242-z

**Archer, R.R. 1986.** *Growth Stresses and Strains in Trees.* Springer: Berlin, Germany. Volume 3. ISBN : 978-3-662-02513-0

**Associação Brasileira de Normas Técnicas. ABNT. 2003.** Madeira - Determinação da densidade básica. NBR 11941. ABNT. Rio de Janeiro, Brazil.

**Beck, M.W. 2018.** Neural Net Tools: Visualization and analysis tools for neural networks. *Journal of Statistical Software* 1(11): 1-20. https://doi.org/10.18637/jss.v085.i11

**Beltrame, R.; Lazarotto, M.; Haselein, C.R.; Santini, E.J.; Schneider, P.R.; Aguiar, A.M. 2012.** Determinação das deformações residuais longitudinais decorrentes das tensões de crescimento em *Eucalyptus spp*. *Ciência Florestal* 22: 343-351. https://doi.org/10.5902/198050985741

**Braz, R.L.; Oliveira, J.T.S.; Rosado, A.M.; Vidaurre, G.B.; Oliveira, J.G.L. 2017.** Deformação residual longitudinal de clones de *Eucalyptus* em local sujeito a ventos. *Floresta e Ambiente* 24: e00028013. https://doi.org/10.1590/2179-8087.028013

**Bukauskas, A.; Mayencourt, P.; Shepherd, P.; Sharma, B.; Mueller, C.; Walker, P.; Bregulla, J. 2019.** Whole timber construction: a state of the art review. *Construction and Building Materials* 213: 748-769. https://doi.org/https://doi.org/10.1016/j.conbuildmat.2019.03.043

**Calegario, N.; Daniels, R.F.; Maestri, R.; Neiva, R. 2005.** Modeling dominant height growth based on nonlinear mixed-effects model: a clonal *Eucalyptus* plantation case study. *Forest Ecology and Management* 204: 11-21. https://doi.org/https://doi.org/10.1016/j.foreco.2004.07.051

**Cardoso Junior, A.A.; Trugilho, P.F.; Lima, J.T.; Rosado, S.C.S.; Mendes, L.M. 2005.** Longitudinal residual strain in different spacing and ages in hybrid clone of *Eucalyptus*. *Cerne* 11: 218-224. http://www.cerne.ufla.br/site/index.php/CERNE/article/view/439

**Carrijo, J.V.N.; Miguel, E.P.; Vale, A.T.; Matricardi, E.A.T.; Monteiro, T.C.; Rezende, A.V.; Inkotte, J. 2020.** Artificial intelligence associated with satellite data in predicting energy potential in the Brazilian savanna woodland area. *iForest - Biogeosciences and Forestry* 13: 48-55. https://doi.org/10.3832/ifor3209-012

**Cruz, C.R.; Lima, J.T.; Muniz, G.I.B. 2003.** Variações dentro das árvores e entre clones das propriedades físicas e mecânicas da madeira de híbridos de *Eucalyptus*. *Scientia Forestalis* 64: 33-47. https://www.ipef.br/publicacoes/scientia/nr64/cap03.pdf

**Diaz Bravo, S.D.; Espinosa, M.; Valenzuela, L.; Cancino, J.; Lasserre, J.P. 2012.** Efecto del raleo en el crecimiento y algunas propiedades de la madera de *Eucalyptus nitens* en una plantación de 15 años. *Maderas. Ciencia y Tecnología* 14(3): 373-388. https://doi.org/10.4067/s0718-221x2012005000009

**Ercanlı, İ. 2020.** Innovative deep learning artificial intelligence applications for predicting relationships between individual tree height and diameter at breast height. *Forest Ecosystems* 7:e12. https://doi.org/10.1186/s40663-020-00226-3

**Fang, R.; Strimbu, B.M. 2017.** Stem measurements and taper modeling using photogrammetric point clouds. *Remote Sensing* 9(7): e716. https://doi.org/10.3390/rs9070716

**Ferraz Filho, A.C.; Mola-Yudego, B.; Ribeiro, A.; Scolforo, J.R.S.; Loos, R.A.; Scolforo, H.F. 2018.** Height-diameter models for *Eucalyptus sp.*plantations in Brazil. *Cerne* 24: 9-17. https://doi.org/10.1590/01047760201824012466

**Ferreira, D.H.A.A.; Leles, P.S.D.S.; Machado, E.C.; Abreu, A.H.M.; Abilio, F.M. 2014.** Crescimento de clone de *Eucalyptus urophylla x Eucalyptus grandis* em diferentes espaçamentos. *Floresta* 44: 431-440. https://doi.org/http://dx.doi.org/10.5380/rf.v44i3.32188

**Fournier, M.; Chanson, B.; Thibaut, B.; Guitard, D. 1994.** Mesures des déformations résiduelles de croissance à la surface des arbres, en relation avec leur morphologie. Observations sur différentes espèces. *Annals of Forest Science* 51: 249-266. https://doi.org/10.1051/forest:19940305

**França, F.J.N.; Vidaurre, G.B.; Nutto, L.; Abad, J.I.M.; Batista, D.C.; Moulin, J.C. 2017.** Relation between dendrometric variables and growth stress in *Eucalyptus*. *Floresta e Ambiente* 24: e00128215. https://doi.org/10.1590/2179-8087.128215

**Fritsch, S.; Guenther, F.; Wright, M.N. 2019.** Neuralnet: training of neural networks. R package version 1.44.2.

**Garson, G.D. 1991.** Interpreting neural-network connection weights. *AI Expert* 6(4): 46-51. https://dl.acm.org/doi/abs/10.5555/129449.129452

**Gril, J.; Jullien, D.; Bardet, S.; Yamamoto, H. 2017.** Tree growth stress and related problems. *Journal of Wood Science* 63: 411-432. https://jwoodscience.springeropen.com/articles/10.1007/s10086-017-1639-y

**Hakamada, R.; Hubbard, R.M.; Ferraz, S.; Stape, J.L.; Lemos, C. 2017.** Biomass production and potential water stress increase with planting density in four highly productive clonal *Eucalyptus* genotypes. *Southern Forests: a Journal of Forest Science* 79: 251-257. https://doi.org/10.2989/20702620.2016.1256041

**Kojima, M.; Yamamoto, H.; Saegusa, K.; Yamaji, F.M.; Yoshida, M.; Yamashita, S.; Nakai, T. 2011.** Anatomical and chemical factors affecting tensile growth stress in *Eucalyptus grandis* plantations at different latitudes in Brazil. *Canadian Journal of Forest Research* 42: 134-140. https://doi.org/10.1139/x11-161

**Li, J.; Liu, S.; Zhou, L.; Liu, Y.M. 2018.**Growth strain in straight and inclined *Populus × euramericana cv. '74/76'* trees, and its relationship with selected wood properties. *European Journal of Wood and Wood Products* 76: 1715-1723. https://doi.org/10.1007/s00107-018-1333-9

**Luz, O.S.L.; Terra, T.G.R.; Lima, S.O.; Siebeneichlet, S.C.; Moraes, C.B.; Leal, T.C.A.B. 2019.** Luminous interception of eucalyptus clones at different structural arrangements for integrated production systems. *Floresta* 49: 227-236. http://dx.doi.org/10.5380/rf.v49i2.56962

**Melo, R.R.; Miguel, E.P. 2016.** Use of artificial neural networks in predicting particleboard quality parameters. *Revista Árvore* 40: 949-958. https://www.scielo.br/j/rarv/a/xMP3xctb4csp3g8FR963PRM/?format=html&lang=en

**Miguel, E.P.; Melo, R.R.; Serenini Junior, L.; Del Menezzi, C.H.S. 2018.** Using artificial neural networks in estimating wood resistance. *Maderas. Ciencia y Tecnología* 20(4): 531-542. https://doi.org/10.4067/S0718-221X2018005004101

**Nunes, M.H.; Görgens, E.B. 2016.** Artificial intelligence procedures for tree taper estimation within a complex vegetation mosaic in Brazil. *PLoS One* 11: e0154738. https://doi.org/10.1371/journal.pone.0154738

**Omonte, M.; Valenzuela, L. 2015**. Longitudinal growth stresses in *Eucalyptus nitens* trees with sawable dimensions. *Maderas. Ciencia y Tecnología* 17(3): 673-684. https://doi.org/10.4067/S0718-221X2015005000059

**R Core Team. 2019.** R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. http://www.r-project.org/.

**Ramage, M.H.; Burridge, H.; Busse-Wicher, M.; Fereday, G.; Reynolds, T.; Shah, D.U.; Wu, G.; Yu, L.; Fleming, P.; Densley-Tingley, D.; Allwood, J.; Dupree, P.; Linden, P.F.; Scherman, O. 2017**. The wood from the trees: The use of timber in construction. *Renewable and Sustainable Energy Reviews* 68: 333-359. https://doi.org/https://doi.org/10.1016/j.rser.2016.09.107

**Resquin, F.; Navarro-Cerrillo, R.M.; Carrasco-Letelier, L.; Rachid-Casnati, C. 2020.** Influence of *Eucalyptus benthamii*, *Eucalyptus dunnii* and *Eucalyptus grandis* planted in Uruguay. *New Forests* 51: 631-655. https://doi.org/10.1007/s11056-019-09749-2

**Schönau, A.P.G.; Coetzee, J. 1989.** Initial spacing, stand density and thinning in eucalypt plantations. *Forest Ecology and Management* 29: 245-266. https://doi.org/https://doi.org/10.1016/0378-1127(89)90097-2

**Silva, J.P.M.; Cabacinha, C.D.; Assis, A.L.; Monteiro, T.C.; Araújo Júnior, C.A.; Maia, R.D. 2018.** Redes neurais artificiais para estimar a densidade básica de madeiras do cerrado. *Pesquisa Florestal Brasileira* 38. https://doi.org/10.4336/2018.pfb.38e201801656

**Soares, A.A.V.; Leite, H.G.; Souza, A.L.; Silva, S.R.; Lourenço, H.M.; Forrester, D.I. 2016.** Increasing stand structural heterogeneity reduces productivity in brazilian *Eucalyptus* monoclonal stands. *Forest Ecology and Management* 373: 26-32. https://doi.org/https://doi.org/10.1016/j.foreco.2016.04.035

**Stape, J.L.; Binkley, D. 2010.** Insights from full-rotation nelder spacing trials with *Eucalyptus* in São Paulo, Brazil. *Southern Forests: a Journal of Forest Science* 72: 91-98. https://doi.org/10.2989/20702620.2010.507031

**Tavares Júnior, I. S.; Rocha, J.E.C.; Ebling, Â.A.; Chaves, A.S.; Zanuncio, J.C.; Farias, A.A.; Leite, H.G. 2019.**Artificial neural networks and linear regression reduce sample intensity to predict the commercial volume of *Eucalyptus* clones. *Forests* 10(3): 268. https://doi.org/10.3390/f10030268

**Trugilho, P.F.; Lima, J.T.; Pádua, F.A.; Soragi, L.C.; Andrade, C.R. 2006.** Deformação residual longitudinal (drl) e tangencial (drt) em seis clones de *Eucalyptus spp*. *Cerne* 12: 279-286. https://www.redalyc.org/pdf/744/74412308.pdf

**Trugilho, P.F.; Oliveira, J.T.S. 2008.** Relationships and estimates of longitudinal growth stress in *Eucalyptus dunnii* at different ages. *Revista Árvore* 32: 723-729. https://doi.org/10.1590/S0100-67622008000400014

**Valencia, J.; Harwood, C.; Washusen, R.; Morrow, A.; Wood, M.; Volker, P. 2011.** Longitudinal growth strain as a log and wood quality predictor for plantation-grown *Eucalyptus nitens* sawlogs. *Wood Science and Technology* 45: 15-34. https://doi.org/10.1007/s00226-010-0302-1

**Xavier, C.N.; Silva, C.E.S.; Santos, P.V.; Carvalho, A.M.; Nascimento, A.M.; Brancalion, P.H.S. 2018.** Growth stress in *Peltophorum dubium* and its correlation with the growth variables. *Floresta e Ambiente* 25(1): e20160252. https://doi.org/10.1590/2179-8087.025216

**Zobel, B.J.; Van Buijtenen, J.P. 1989.** *Wood variation: Its causes and control.* Springer-Verlag Berlin Heidelberg: Berlin, Germany.