# ARTIFICIAL NEURAL NETWORKS TO ESTIMATE THE PHYSICAL-MECHANICAL PROPERTIES OF AMAZON SECOND CUTTING CYCLE WOOD

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*In memoriam of Dr. Thomas C. MANNES*

## ABSTRACT

Timber from the second cutting cycle may make up the majority of future crop volumetric. However, there are few studies of the physical and mechanical properties of this timber, which are important to support the consolidation of new species. This study aimed to use Artificial Neural Networks to estimate the physical and mechanical properties of wood from the Amazon, based on basic density. The properties were: shrinkage (tangential, radial and volumetric), static bending, parallel and perpendicular to the fiber compression, parallel and transverse to the fibers, Janka hardness, traction, splitting and shear. The estimate followed the tendency of the data observed for the tangential, radial and volumetric shrinkage. The network estimated the mechanical properties with significant accuracy. Distribution of errors, static bending, parallel compression and perpendicular to the fiber compression also showed significant accuracy. Artificial Neural Networks can be used to estimate the physical and mechanical properties of wood from Amazon species.

**Keywords**: Artificial intelligence, modeling, timber potential, tropical wood, wood technology.

## INTRODUCTION

The period between one selective logging harvest and another is called the cutting cycle. During this period, forests have time to regrow harvested stock. These recovery periods are determined by Brazilian legislation (Brasil 2006).

Many studies demonstrated the feasibility of the second cutting cycle in relation to carbon stock recovery. They also showed that the first harvest helps the recovery of the forest volume and basal area, boosting the growth of the remaining forest, as reported in studies by Reis *et al.* (2010), Reis *et al.* (2014) and Reis *et al.* (2015).

The Tapajós National Forest completed its second monitored cutting cycle in 2014. It is the first forest in the world to achieve this outcome, demonstrating that selective wood harvesting in native forests is sustainable. According to Reis *et al.* (2010), over 28 years the forest managed to recover its total volumetric stock. This showed that the second cutting cycle in this experimental location is possible, mainly due to the dominant stock of species that were not used in the first harvest. Second cycle wood comes from species that were favored by forest harvesting and increased their density in the area. Even with little commercial attractiveness, it may have a significant market, increasing manager production and subsequently, income.

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According to Adeodato *et al.* (2011), studies have indicated that the commercialization of second line wood (with only potential or no consolidated markets) may increase revenue per hectare by 40% to 50% in forestry management. There is a great effort from research organizations to analyze the physical characteristics of wood whose species are unknown in the market or which have low commercial value, to replace those with higher commercial value (Almeida *et al.* 2010).

In order to promote new species, we require a better understanding of the physical-mechanical properties of wood, to back its introduction into the market. The determination of physical and mechanical wood properties is important to decide on its correct use. This will increase the number of available species and reduce pressure on the most common commercial species. It also helps in forestry management, since the growth in the number of potential species makes it possible to increase production per area unit and to adopt more harvesting options.

To estimate these properties, Artificial Neural Networks (ANN) have been used. These are computational models inspired by the nervous system of living beings. They can be defined as a massive set of parallel processing units, characterized by artificial neurons linked by a great number of interconnections. ANN's have a natural ability to store experimental information making it available for subsequent use (Silva *et al.* 2010). Various studies have been conducted using ANN's in forest areas, providing successful estimates, in both even and uneven-aged populations (Ashraf *et al.* 2015, Diamantopoulou *et al.* 2015, Reis *et al.* 2016, Richards *et al.* 2008) as well as in wood technology areas (Avramidis *et al.* 2006, Avramidis and Iliadis 2005, Esteban *et al.* 2009, Tiryaki and Aydın 2014)

ANN's show advantages in terms of regression analyses, due to their inherent properties and capacities, such as: non-linearity, learning capacity, generalization abilities, adaptability, fault tolerance and data organization (Silva *et al.* 2010). Since they present data such as the physical and mechanical wood properties, which have many intra and interspecies variations, ANN's may improve the adjustments to estimate these properties.

The present study seeks to use Artificial Neural Networks to estimate the physical and mechanical properties of second cutting cycle timber from the Amazon starting from basic density.

## MATERIALS AND METHODS

The species studied are found in the Tapajós National Forest (Flona do Tapajós), which is located 67 km (55° 00' W, 2° 45' S) along the BR-163 Highway, Cuiabá-Santarém (Reis *et al.* 2010).

In 1975, a forest census was realized and in 1979, 64 wood species were harvested, removing 72.5 $m^3$ $ha^{-1}$. In 1981, 36 permanent plots (50x50m) were randomly positioned in the study area. In these plots, all dbh ≥ 5 cm trees were botanically identified *in loco* and samples were collected for subsequent identification at the IAN Herbarium of the Embrapa Eastern Amazon (Reis *et al.* 2010).

In December 2014, Flona do Tapajós completed its first cutting cycle (34 years) and in 2010, studies already determined the feasibility of the second cycle. Despite the high intensity harvest, a recovery of the future species stock (*dbh* ≥ 50 cm) even higher than that observed prior to the harvest was observed (Reis *et al.* 2010). This stock mainly consisted of established and potential timber species, such as: *Virola michellii* Heckel, *Carapa guianensis* Aubl., *Protium apiculatum* Swart, *Goupia glabra* Aubl, *Couratari stellata* A. C. Sm., *Tachigali chrysophylla* (Poepp.) Zarucchi & Herend., *Helicostylis pedunculata* Benoist, *Cordia bicolor* A. DC., *Ocotea neesiana* (Miq.) Kosterm., and *Eschweilera grandiflora* (Aubl.) Sandwith.

In 2014, the harvesting area was divided into two treatments: the first cycle area where harvesting had not taken place had 39 ha (T1), while the second cycle area where harvesting had occurred in 1979 had 31,5 ha (T2). The two areas totaled 70,5 ha. Thirty-five species were harvested from the two areas, with an average intensity of 3,76 trees $ha^{-1}$ and 15,3324 $m^3$ $ha^{-1}$.

The physical and mechanical property data of the timber was obtained from studies about species

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from the Amazon region. Sources were publications by the Forest Product Laboratory (FPL 2016).

In order to estimate wood properties, basic density (kg.m$^{-3}$) was considered an independent variable. For data regarding wood shrinkage, literature meeting the Pan-American Commission for Technical Standards (Copant) was considered. To obtain mechanical properties, all references consulted used test samples with a 12% moisture content, also in agreement with COPANT standards.

Artificial Neural Networks (ANN) were used to estimate the physical and mechanical variables of timber with no added commercial value, belonging to the species list from the survey conducted in 2014 in Flona do Tapajós.

Data was divided into two groups, one for ANN training (85%) and the other for the generalization-test (15%); this was to evaluate the generalization capacity of the networks. The training group was not part of the ANN test group.

The ANN input variable was basic wood density (*Bd* – kg.m$^{-3}$). ANN simple and simultaneous output variables (multiple outputs) were: Tangential shrinkage (*TS* - %); Radial shrinkage (*RS* - %); Volumetric shrinkage (*VS* - %); Static Flexion - Rupture Module (*FRM* - MPa); Static Flexion - Elasticity Module (*FEM* - 1000 MPa); Fiber Parallel Compression (*FParC* - MPa); Fiber Perpendicular Compression (*FPerC* - MPa); Janka hardness parallel to fibers (*PJH* - MPa); Janka hardness transversal to fibers (*TJH* - MPa); Traction (*Tr* - MPa); Splitting (*Sp* - MPa); Shearing (*Sh* - MPa).

Three thousand nine hundred ANN's were trained using basic density as an input. 3600 ANN's were trained with simple outputs and 300 more were trained with multiple outputs (Table 1).

**Table 1.** Input and output variables used for the training of the ANN's and numbers of trainings performed.

| ANN | Input | Output | Number of trainings |
|---|---|---|---|
| 1 | *Bd*[a] | Simple output – *TS*[b], *RS*[c], *VS*[d], *FRM*[e], *FEM*[f], *FParC*[g], *FPerC*[h], *PJH*[i], *TJH*[j], *Tr*[k], *Sp*[l], *Sh*[m] | 3600 |
| 2 | *Bd* | Multiple output - *TS, RS, VS, FRM, FEM, FParC, FPerC, PJH, TJH, Tr, Sp, Sh* | 300 |
| Total | - | - | 3900 |

*Bd*[a]: Basic density (kg.m$^{-3}$); *TS*[b]: Tangential shrinkage (%); *RS*[c]: Radial shrinkage (%); *VS*[d]: Volumetric shrinkage (%); *FRM*[e]: Static Flexion - Rupture Module (MPa); *FEM*[f]: Static Flexion - Elasticity Module (1000 MPa); *FParC*[g]: Fiber parallel compression (MPa); *FPerC*[h]: Fiber perpendicular compression (MPa); PJH[i]: Janka hardness parallel to fibers (MPa); *TJH*[j]: Janka hardness transversal to fibers (MPa); *Tr*[k]: Traction (MPa); *Sp*[l]: Splitting (MPa); *Sh*[m]: Shearing (MPa).

ANN training consists of the application of an ordained step set that aims to adjust the weights and thresholds of its neurons. Such adjustment processes, also known as learning algorithms, seek to fine tune the network so that its responses are closer to the desired values (Silva *et al.* 2010).
Training was based on the generalized delta rule, also known as the backpropagation algorithm, applied in multi-layer feed forward networks - Multilayer Perceptron (MLP).

The backpropagation algorithm is performed through successive applications of two specific phases. According to Silva *et al.* (2010) and Reis *et al.* (2018) the first phase to be applied is called "forward propagation", in which signals $\{x_1, x_2,..., x_n\}$ of a sample of the training set are inserted into the network inputs and are propagated layer by layer until the respective outputs are produced. The application of this phase only aims to obtain the network responses, taking into account only current values of synaptic weights and thresholds of its neurons, which will remain unchanged during each execution. Subsequently, the responses produced by the outputs of the network are compared with the respective desired responses that are available. The respective deviations (errors) between the desired responses and those produced by the output neurons are then calculated. This will then be used to adjust the weights and thresholds of all their neurons. Because of these error values, the second phase of the

backpropagation method, called "reverse propagation" (backward), is then applied. The changes (adjustments) of the synaptic weights and thresholds of all the neurons of the network are executed during this phase (Silva *et al*. 2010).

In summary, the successive applications of the forward and backward phases make the synaptic weights and thresholds of the neurons automatically adjust at each iteration, implying a gradual decrease in the sum of the errors produced by the responses of the network compared with the desired ones (Silva *et al*. 2010, Reis *et al.* 2018).

For training, the Intelligent Problem Solver (IPS) tool of the Statistica 13 software (StaSoft Inc 2016) was used to analyze the activation functions of the intermediate and output layers (Identity, Logistics, Hyperbolic Tangent and Exponential). The initial weights of the networks were randomly generated, and the stopping criterion of the algorithm occurred when the mean square error or the cross-entropy error began to increase. When this happened, training was interrupted. Network training continued up to 10000 cycles as long as the error was decreasing (Reis *et al.* 2018).

During training, only one hidden layer was used, and the interval of the neuron number in this layer was defined by the Fletcher-Gloss method, where the interval of the neuron number is defined according to the number of input and output variables. This was defined by the Equation (1):

$$2\sqrt{n} + n_2 \leq n_1 \leq 2n + 1 \qquad (1)$$

where $n$ is the network input number, $n_1$ is the neuron quantity in the hidden layer and $n_2$ is the neuron quantity in the output layer.

The maximum neuron number was defined by the Fletcher-Gloss method and the minimum was a single neuron. This was done to analyze the generalization capacity of a simpler topology. The maximum defined by the method was to avoid excessive input data memorization (overfitting) or insufficient information extraction during training (underfitting).

In order to choose and compare ANN's, the correlation statistics between estimated values and bibliographic values  and the root-mean-square error (RMSE) were used. The graphic analysis of percentage error dispersion (*Error* %) in relation to the observed values was also used (Equation 2):

$$Error\ \% = \frac{\left(\hat{Y} - Y\right)}{Y} x100 \qquad (2)$$

where :  estimated values by ANN; Y: bibliographic values.

The correlation indicates the intensity of the relationship between estimated and observed values. The closer to 1, the higher the correlation between the variables. The correlation was calculated using the Equation (3):

$$r_{Y\hat{Y}} = \frac{Cov\left(Y, \hat{Y}\right)}{\sqrt{S^2\left(Y\right)S^2\left(\hat{Y}\right)}} \qquad (3)$$

where : estimated values by ANN; *Y*: observed values; $S^2$: variance and *Cov*: covariance.

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As for the root-mean-square error (RMSE), the lower the estimates, the more reliable the training or generalization. In order to calculate RMSE for the comparison between ANN's, the Equation (4) was used:

$$RMSE = 100.\overline{Y}^{-1}\sqrt{n^{-1}\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right)^2} \qquad (4)$$

where : values estimated by ANN; *Y*: observed values; n: number of observations.

## RESULTS AND DISCUSSION

After observing ANN test results (generalization), the wood properties: tangential shrinkage (*TS*), radial shrinkage (*RS*), volumetric shrinkage (*VS*) and fiber perpendicular compression (*FPerC*) presented more correlation in the simple output network, whereas the properties: static flexion (rupture module - *FRM*), static flexion (elasticity module - *FEM*), fiber parallel compression (*FParC*), parallel Janka hardness (*PJH*), transversal Janka hardness (*TJH*), traction (*Tr*), splitting (*Sp*) and shearing (*Sh*) obtained higher correlation in the multiple output network (Table 2).

**Table 2.** Characteristics, input and output variables of trained and validated ANNs. R: correlation coefficient; *RMSE*%: root mean square error. RMS: Multiple output network.

| ANN | Input | Design | Activation function | Output | Training R | Training RMSE% | Test R | Test RMSE% |
|---|---|---|---|---|---|---|---|---|
| 4 | Bd[a] | MLP 1-2-1 | Tangential/identity | *TS*[b] | 0,3021 | 17,35 | 0,569 | 15,64 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *TS − RMS* | 0,3334 | 15,52 | 0,383 | 15,20 |
| 5 | Bd | MLP 1-3-1 | Tangential/exponential | *RS*[c] | 0,4628 | 21,58 | 0,475 | 23,63 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *RS − RMS* | 0,2712 | 19,73 | 0,263 | 17,92 |
| 4 | Bd | MLP 1-3-1 | Exponential/identity | *VS*[d] | 0,3786 | 16,20 | 0,641 | 17,13 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *VS − RMS* | 0,4616 | 15,16 | 0,554 | 17,53 |
| 4 | Bd | MLP 1-3-1 | Exponential/Exponential | *FRM*[e] | 0,9499 | 9,57 | 0,978 | 7,91 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *FRM − RMS* | 0,9400 | 9,39 | 0,981 | 7,88 |
| 1 | Bd | MLP 1-3-1 | Logistic/identity | *FEM*[f] | 0,8993 | 9,53 | 0,945 | 9,50 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *FEM − RMS* | 0,9238 | 7,74 | 0,976 | 6,34 |
| 3 | Bd | MLP 1-3-1 | Logistic/logistic | [g]*FParC* | 0,9384 | 10,79 | 0,984 | 7,56 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *FParC − RMS* | 0,9208 | 11,31 | 0,994 | 4,31 |
| 2 | Bd | MLP 1-1-1 | Identity/exponential | [h]*FPerC* | 0,9072 | 21,29 | 0,976 | 12,38 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *FPerC − RMS* | 0,8911 | 19,29 | 0,952 | 23,31 |
| 1 | Bd | MLP 1-3-1 | Exponential/Logistic | [i]*PJH* | 0,8590 | 25,26 | 0,933 | 19,45 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *PJH − RMS* | 0,8686 | 21,55 | 0,968 | 14,61 |
| 1 | Bd | MLP 1-3-1 | Logistic/identity | [j]*TJH* | 0,9255 | 22,27 | 0,963 | 17,98 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *TJH − RMS* | 0,9150 | 20,45 | 0,979 | 14,02 |
| 2 | Bd | MLP 1-3-1 | Exponential/Exponential | [k]*Tr* | 0,6621 | 21,23 | 0,777 | 15,71 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *Tr − RMS* | 0,6933 | 20,25 | 0,802 | 20,71 |
| 5 | Bd | MLP 1-1-1 | Exponential/Exponential | [l]*Sp* | 0,8084 | 18,68 | 0,666 | 19,73 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *Sp − RMS* | 0,7876 | 15,39 | 0,720 | 21,26 |
| 3 | Bd | MLP 1-3-1 | Logistic/tangential | [m]*Sh* | 0,8899 | 16,11 | 0,910 | 16,35 |
| 5 | Bd | MLP 1-3-12 | Logistic/exponential | *Sh − RMS* | 0,8756 | 15,07 | 0,942 | 13,59 |
| | Bd | | Average | Simple Output | 0,7486 | 17,49 | 0,8180 | 15,25 |
| | Bd | | | Multiple Output | 0,7402 | 15,90 | 0,7928 | 14,72 |

[a]*Bd*: Basic density (kg.m⁻³); [b]*TS*: Tangential shrinkage (%); [c]*RS*: Radial shrinkage (%); [d]*VS*: Volumetric shrinkage (%); [e]*FRM*: Static Flexion - Rupture Module (MPa); [f]*FEM*: Static Flexion - Elasticity Module (1000 MPa); [g]*FParC*: Fiber parallel compression (MPa); [h]*FPerC*: Fiber perpendicular compression (MPa); [i]*PJH*: Janka hardness parallel to fibers (MPa); [j]*TJH*: Janka hardness transversal to fibers (MPa); [k]*Tr*: Traction (MPa); [l]*Sp*: Splitting (MPa); [m]*Sh*: Shearing (MPa).

When analyzing *RMSE*%, the volumetric shrinkage (*VS*), fiber perpendicular compression (*FPerC*), traction (*Tr*) and splitting (*Sp*) had a better performance in the simple output network. Tangential shrinkage (*TS*), radial shrinkage (*RS*), static flexion (rupture module - *FRM*), static flexion (elasticity module - *FEM*), fiber parallel compression (*FParC*), parallel Janka hardness (*PJH*), transversal Janka hardness (*TJH*), and shearing (*Sh*) presented a better performance, that is, a lower error in the multiple output network (Table 2).

The network estimate for tangential and volumetric shrinkage was not as precise as the tested mechanical properties. Observing the correlation matrix (Table 3), the correlation between basic density and radial shrinkage was not significant.

**Table 3.** Pearson correlation coefficient of basic density and physical and mechanical properties.

| Variables | $Bd^a$ |
|---|---|
| $Bd^a$ | 1,000 |
| $TS^b$ | 0,362* |
| $RS^c$ | 0,232[ns] |
| $VS^d$ | 0,489* |
| $FRM^e$ | 0,952* |
| $FEM^f$ | 0,930* |
| $FParC^g$ | 0,936* |
| $FPerC^h$ | 0,912* |
| $PJH^i$ | 0,881* |
| $TJH^j$ | 0,924* |
| $Tr^k$ | 0,679* |
| $Sp^l$ | 0,773* |
| $Sh^m$ | 0,890* |

[a]$Bd$: Basic density (kg.m$^{-3}$); [b]$TS$: Tangential shrinkage (%); [c]$RS$: Radial shrinkage (%); [d]$VS$: Volumetric shrinkage (%); [e]$FRM$: Static Flexion - Rupture Module (MPa); [f]$FEM$: Static Flexion – Elasticity Module (1000 MPa); [g]$FParC$: Fiber parallel compression (MPa); [h]$FPerC$: Fiber perpendicular compression (MPa); [i]$PJH$: Janka hardness parallel to fibers (MPa); [j]$TJH$: Janka hardness transversal to fibers (MPa); [k]$Tr$: Traction (MPa); [l]$Sp$: Splitting (MPa); [m]$Sh$: Shearing (MPa). *: Significant at 5% probability; [ns]: Non-significant at 95% probability.

Shrinkage results were not as precise as the tested mechanical properties, because shrinkage is strongly influenced by the anatomical structure of the wood. According to studies by Zhang and Zhong (1992) analyzing the relation between anatomical structures and physical-mechanical properties of wood, fiber diameter is the anatomical characteristic that most influences tangential and radial shrinkage, followed by vessel and fiber proportion, which influence the radial and tangential shrinkage, respectively. To improve the accuracy of the model in relation to the shrinkage of the wood, laboratory tests and inclusion of wood structure variables, such as vessel and fiber length, should be carried out.

Wood shrinkage is also affected by other factors, such as the microfibril angle of the cell wall central secondary layer (Chauhan and Walker 2006, Poubel *et al.* 2011) and the structural characteristics of wood that are resistant to shrinkage, such as ray quantity in the radial direction (Poubel *et al.* 2011). Despite this, the estimate could follow the tendency of the observed data for tangential, radial and volumetric shrinkage.

Regarding error distribution, we noticed that the tangential, radial and volumetric shrinkage tended to estimate lower errors for the highest values (Figure 1).
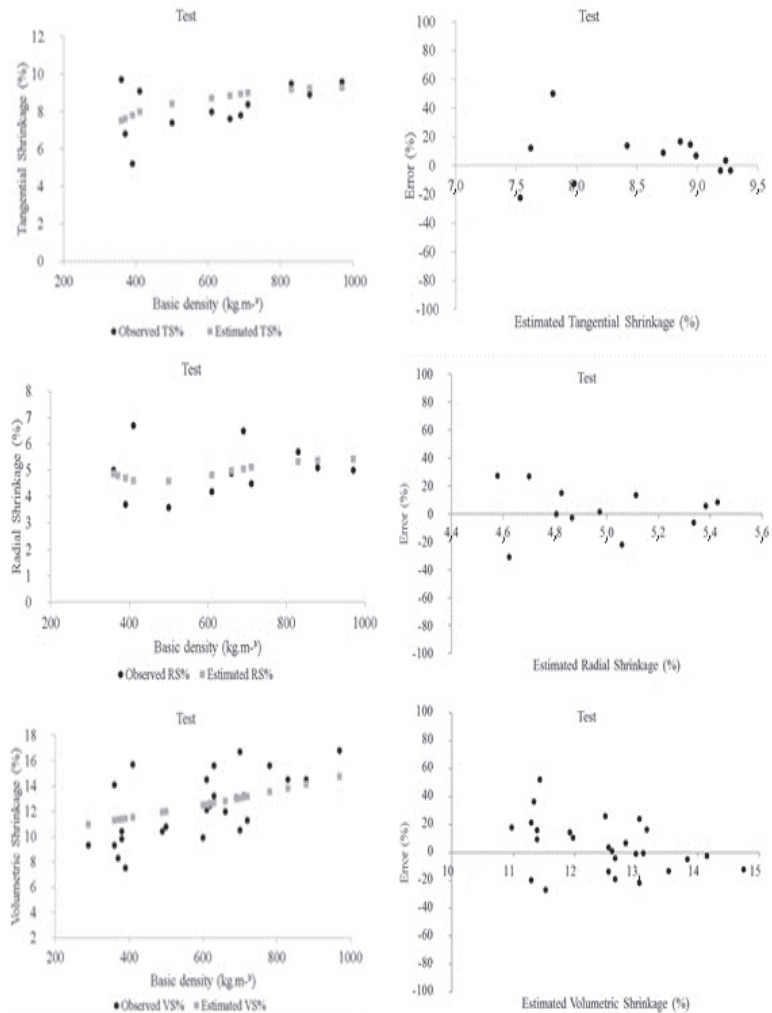
**Figure 1.** Basic wood density in relation to the estimated tangential, radial and volumetric shrinkage, and error% in relation to the estimated variables.

The network precisely estimated wood mechanical properties. Estimated data followed the tendency of the observed data. It was also possible to observe the high correlation between basic density and mechanical properties, which presented significant values (Table 3).

For all mechanical properties analyzed, increased density values were mirrored by increased property values (Figure 2). This is caused by the high correlation (Table 3) between density and other mechanical properties. Armstrong *et al.* (1984) demonstrated that density as an independent variable explains mechanical properties (*FEM*, *FRM* and *FParC*) with a correlation coefficient above 0,70 for a 95% reliability level, in green and dry wood conditions. Araújo (2007) also obtained significant results between wood density and mechanical properties. Other studies such as those by Abruzzi *et al.* (2012) and Protásio *et al.* (2012) also observed a relationship between density and mechanical properties.
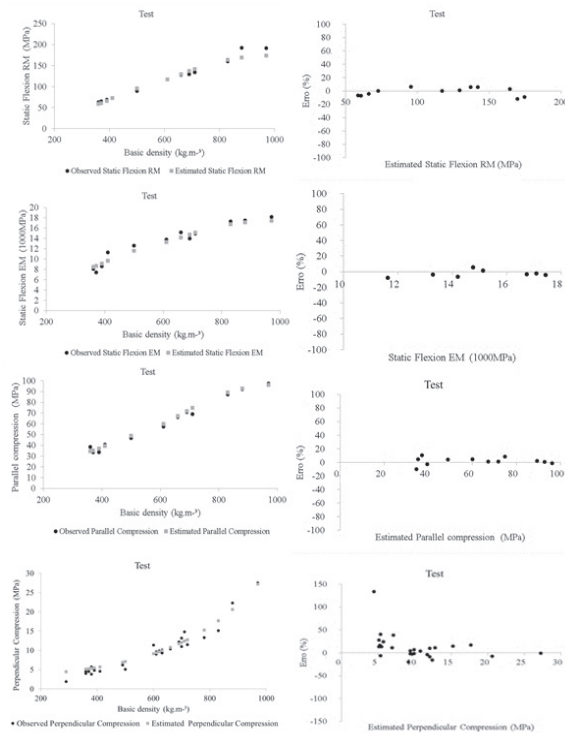
**Figure 2.** Modulus of rupture (*MR*) and modulus of elasticity (*ME*), estimated parallel and perpendicular to the fiber compression in relation to the basic wood density and error% in relation to the estimated variables.

Density is one of the most important properties for recommended wood usage (Leite *et al.* 2016) and (Peres *et al.* 2012). It is one of the properties that provides the most information regarding wood characteristics and is related to its resistance.

With the results obtained, it is possible to observe that all mechanical properties studied have a correlation with basic wood density. Mechanical wood properties depend on basic density (Lobão *et al.* 2004).

The variability of most mechanical wood properties may be estimated based on density variations. The properties of resistance to static flexion and its elasticity module are correlated with density, which in turn is correlated to cell dimension. The relationship between density and mechanical properties may be changed by the presence of extractives that are added to wood mass, mainly increasing wood resistance to axial shrinkage (Lobão *et al.* 2004, Panshin and Zeeuw 1980).

Regarding error distribution, the properties: static flexion, fiber parallel compression and fiber perpendicular compression had lower errors and, consequently, higher precision (Figure 2).

Studies conducted by Beltrame *et al.* (2010) showed that mechanical properties define wood behavior when submitted to mechanical stress, allowing comparison to other woods with known properties.

Regarding static flexion, fiber parallel compression, fiber perpendicular compression and fiber parallel shearing, the correlation result was high and the error result low (Table 2), indicating that the mentioned properties may be estimated with artificial neural networks using basic density. According to Lisboa *et al.* (1993), these properties are extremely important to obtain information about possible final uses.

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# CONCLUSIONS

Artificial Neural Networks may be used to estimate shrinkage (tangential and volumetric), static flexion, fiber parallel and perpendicular compression, Janka hardness, traction, splitting and shearing, starting from basic density. ANN's are a nondestructive test option for wood.

# ACKNOWLEDGMENTS

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