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Conversion Factor Estimation of Stacked Eucalypt Timber Using Supervised Image Classification with Artificial Neural Networks

Vinicius Andrade de Barros[1], Carlos Pedro Boechat Soares[1], Gilson Fernandes da Silva[2], Gianmarco Goycochea Casas[1]* and Helio Garcia Leite[1]

[1]*Department of Forest Engineering, Federal University of Viçosa. Av. Purdue, s/n, University Campus, 36570-900 Viçosa, Minas Gerais, Brazil*

[2]*Department of Forest and Wood Sciences, Federal University of Espírito Santo, 29550 Jerônimo Monteiro, Espírito Santo, Brazil*

ABSTRACT

Stacked timber is quantified in-store units and then adjusted with a conversion factor for volume estimation in cubic meters, which is important for the wood trade in South America. However, measuring large quantities accurately can be challenging. Digital image processing and artificial intelligence advancements offer promising solutions, making research in this area increasingly attractive. This study aims to estimate conversion factors of stacked *Eucalyptus grandis* timber using supervised image classification with Artificial Neuronal Network (ANN). Measured data and photographs from an experiment involving thirty stacks of timber were used to achieve this. The conversion factor was determined using photographic methods that involved the applications of equidistant points and ANN and subsequently validated with values observed through the manual method. The ANN method produced more accurate conversion factor estimates than the equidistant points method. Approximately 97% of the ANN estimates were within the ±1% error class, even when using low-resolution digital photographs.

Keywords: *Eucalyptus grandis*, forest inventory, forest management, image processing, machine learning

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E-mail addresses:
vandradebx@gmail.com (Vinicius Andrade de Barros)
csoares.ufv@gmail.com (Carlos Pedro Boechat Soares)
gilson.silva@pq.cnpq.br (Gilson Fernandes da Silva)
gianmarco.casas@ufv.br (Gianmarco Goycochea Casas)
hgleite@ufv.br (Helio Garcia Leite)
* Corresponding author

INTRODUCTION

Quantifying the timber volume that arrives at processing yards and the quantity stored there is essential for planning forest activities in the field and for the company. It includes harvest planning, payment for

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forest transportation, and standardization of the wood quality that will be converted into the final product.

Foresters have used a variety of methods to quantify the volume of logs, including mathematical expressions and conversion factors (Soares et al., 2011), weighing the load on trucks (Carvalho & Camargo, 1996), xylometry (Husch et al., 1993; Santana et al., 2023), laser scanning of truckloads (Nylinder et al., 2009), and software for digital image assessment (Campos & Leite, 2017).

Stacked timber quantified in stere units represents the combined timber volume and the air space between the logs. It must be converted to cubic meters using the conversion factor to isolate the timber volume only. Conversion factor estimation is used in the timber industry to determine the amount of space timber occupies when stacked. It is important for calculating transportation and storage costs, as well as for determining the amount of timber that can be transported in a single load. The conversion factor can vary depending on several issues, including the species of the tree, the size of the logs, the method of stacking, moisture content, temperature, and dimensions of timber stacks (Campos & Leite, 2017; Meyen & O'Connell, 2012; Soares et al., 2011). The significant challenge in determining the conversion factor is accurately calculating the actual volume of logs, particularly when dealing with large quantities. This process can consume a considerable amount of time for the forestry operator and can result in measurement errors due to the inherent complexities of the task.

Software tools such as Digitora and NeuroDIC quantify stacked timber through image analysis. Digitora employs an equidistant points method (Bertola et al., 2003; Gouveia Filho et al., 2022; Husch et al., 1993; Soares et al., 2003), while NeuroDIC utilizes artificial neural network (ANN) models to classify images (Campos & Leite, 2017; Silveira, 2014). Both tools enable the quantification of empty spaces and logs within stacked timber, which helps determine conversion factors.

The Trestima Stack mobile application is a valuable tool for quantifying the volume of a timber pile. Computer vision accurately determines the volume based on images captured through a smartphone or tablet. Actual volume is counted based on the surface area of the pile, log length, and an automatically generated coefficient factor. This user-friendly application proves especially helpful when conducting inventory assessments of timber stacks at roadside landing sites, particularly in cases involving multiple measurement batches (Kärhä et al., 2019). Furthermore, alternative applications like IFOVEA and Timbeter enable the measurement of timber volumes and the creation of panoramic views using multiple photographs. However, it is important to note that a known reference value, such as the width of the stacked timber, must be obtained using a tape measure (Moskalik et al., 2022).

ANNs are a type of artificial intelligence inspired by how the human brain works. ANNs are made up of interconnected nodes, which are like the neurons in the brain. These nodes process and transmit information and can be trained to perform complex tasks such as classification and regression (Haykin, 2009; Montesinos López et al., 2022). ANNs are composed of input variables, the data the model is trained on, and output variables, which are the data the model tries to predict or classify. The model is structured in layers: the input layer, where data is initially received; hidden layers, which process information through weighted connections, with their quantity and neuron count determining model complexity; and the output layer, which produces predictions. The number of neurons in a layer influences its learning capacity, impacting the model's performance (Aggarwal, 2018; Campesato, 2020).

ANN models have been used in forestry to solve diverse problems such as height-diameter models (Bueno et al., 2020; Casas et al., 2022a; Da Rocha et al., 2021; Ercanlı, 2020), whole-stand models (Casas et al., 2022b; Cordeiro et al., 2022; De Andrade et al., 2022; De Freitas et al., 2020; De Oliveira Neto et al., 2022), stem taper (Da Cunha Neto et al., 2019; De Souza et al., 2023; Sandoval & Acuña, 2022; Seki, 2023; Tavares Júnior et al., 2021), survival and mortality (Bayat et al., 2019; Da Rocha et al., 2018; Reis et al., 2018) and timber price forecasting (Kożuch et al., 2023).

Image classification is a supervised learning task that involves the identification of target classes within images and can be used with ANN methods. A predefined set of classes is established, and a model is trained using images. ANN treats each pixel as an independent feature, and the spatial structure of the image is not considered (Aggarwal, 2018; Mather & Tso, 2016).

The digital processing of images using specialised software reduces the need for human intervention, which can lead to fewer errors and more accurate estimates (da Silva et al., 2005). ANNs have made significant progress in recent years, and one potential application is to use image classification to determine the conversion factor of stacked timber. This study aims to estimate the conversion factors of stacked eucalypt timber using supervised image classification using the ANN method.

MATERIALS AND METHODS

Experimental Description

This study utilised data from 30 stacks of *Eucalyptus grandis* timber that were carefully arranged and measured. The experiment was conducted in the Silviculture sector of the Department of Forestry Engineering at the Federal University of Viçosa, located in Viçosa, Minas Gerais. The data was collected as part of a study developed by Bertola et al. (2003).

For each stack, the actual volume of the log (m^3) was determined using Smalian's formula (Equation 1) applied to each log:

$$V = \frac{A_1 + A_2}{2} L \tag{1}$$

Where V = Volume of the log (m^3); A_1 = Area of the small end of the log (m^2); A_2 = Area of the large end of the log (m^2); and L = Length of the log (m).

The stack volume (st) was calculated by multiplying the dimensions of the stacks (Equation 2):

$$V = xyz \tag{2}$$

Where V = Stack volume (st); x = Width of the stack (m); y = Length of the stack (m); and z = Height of the stack (m).

In addition, photographs of both sides of each stack were taken using a Kodak DC 210 camera. A total of 60 photographs were taken at a resolution of 1,152 × 864 dpi, zoomed to the maximum position, and with the observer positioned at 3 m. Consequently, the observed conversion factor was calculated as the ratio between the stack volume (st) and the actual log volume with bark (m^3).

Conversion Factor Estimation

The estimated conversion factors for each side of the stacks were calculated using the Digitora and NeuroDic software tools, and the final estimated conversion factors were obtained by averaging the factors from both sides.

Conversion Factor Using the Equidistant Point Method

The Digitora software creates a grid of equidistant points that cover either a part or the entirety of the photograph (Figure 1). The conversion factor for each side of the stacks was obtained by manually counting the points that overlap with the logs and the empty spaces. Subsequently, the software calculates the percentage of empty spaces on the side of the stack, which was used to determine the conversion factor.

Figure 1. Processing of stacked eucalypt timber with equidistant points technique using Digitora software tools
Note. Example of a low-resolution photograph processed in this studio

Conversion Factor Using Artificial Neural Network Method

Image Processing and Classification

The NeuroDIC software was used to calculate the conversion factors, following the method described by Silveira (2014). The software uses an artificial neural network to perform supervised image classification. After importing the photographs of the stack sides into the software, image filters were applied, and two classification classes were selected: wood and space, resulting in a black-and-white image representing each class (Figure 2).

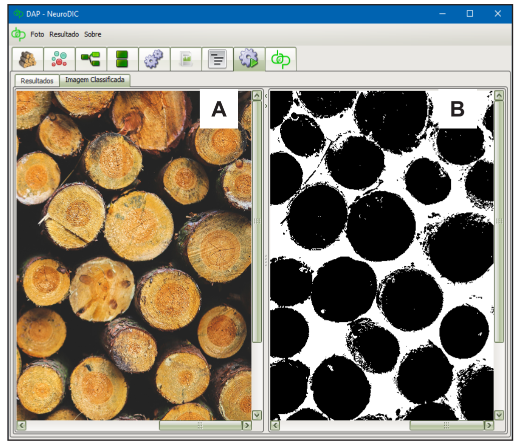


Figure 2. Processing of stacked eucalypt timber with the artificial neural network using NeuroDic software tools: Stacked timber before (A) and after (B) filter applications

Image Filter Selection

The version of the software utilised in this study consisted of eight distinct filters, including *Contrast*, which adjusts the brightness and contrast of the image; *Curves*, which modifies points within the tonal range of an image; *Gain*, similar to the Contrast filter but with a wider range; *Invert*, which reverses the colours of the image, transforming it into its negative; *Solarize*, similar to the Invert filter, but with a "*V*" shaped transformation function; *Threshold*, which converts the original image into black and white, allowing for the determination of empty spaces or wood based on varying settings; *Black and White*, transforming the original image into grayscale; *GrayLevels*, which converts the original image into a grayscale scale (Silveira, 2014).

The selection of the best filters for training the artificial neural networks was based on analysing pixel histograms for each filter, focusing on identifying distribution patterns for the wood and space classes.

Input and Output Variables Selection

The following input and output variables were defined to train the ANN model:

Input variables: The input variables are the pixel values from the images' red, green, and blue (RGB) bands. The ANN learns to identify the patterns in the RGB bands associated with each class. Once the ANN model is trained, it can predict the class of the same or new image by feeding its pixel values into the network and getting the output prediction.

Output variable: The output variable is a binary class value, with 1 representing wood and 0 representing space. This variable represents the class of each pixel in the image.

ANN Model Architecture and Configuration

The data were split into training (70%) and validation (30%) to establish the ANN models. Multilayer Perceptron (MLP) type was used with five neurons in the hidden layer and the sigmoid activation function (Equation 3). The stopping criterion was based on a mean error of 0.0001, 3,000 epochs and 20 convergence process numbers.

$$f(\alpha) = \frac{1}{(1 + e^{-\alpha})} \tag{3}$$

Note here that f is the function that represents the non-linear activation used in the entire neural network, b is the bias for the neuron activation threshold, x_i and w_i denote the input values of the unit or neuron and their weights; α denotes the weighted combination (Equation 4):

$$\alpha = \sum_{j=1}^{n} w_i x_i + b \tag{4}$$

The Resilient Propagation (Rprop) algorithm (Equation 5) (Riedmiller & Braun, 1993) was used following the rule for each weight (ω_{ij}) an individual step-size (Δ_{ij}):

$$\Delta_{ij}^{(t)} = \begin{cases} \min(\eta^{+} * \Delta_{ij}^{(t-1)}, \Delta_{\max}),\ if\ \dfrac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \dfrac{\partial E^{(t)}}{\partial \omega_{ij}} > 0 \\ \max(\eta^{-} * \Delta_{ij}^{(t-1)}, \Delta_{\min}),\ if\ \dfrac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \dfrac{\partial E^{(t)}}{\partial \omega_{ij}} < 0 \\ \Delta_{ij}^{(t-1)} \qquad\qquad\qquad\quad , otherwise. \end{cases} \tag{5}$$

where $0 < \eta- < 1 < \eta+$ and each iteration, the new weights (Equation 6) are given by:

$$\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta\omega_{ij}^{(t)} \tag{6}$$

If the partial derivative $\partial E / \partial \omega_{ij}$ possesses the same sign for consecutive steps, the step size is increased, whereas if it changes the sign, the step size is decreased.

This study employed the positive, resilient propagation (Rprop+) algorithm (Equation 7) variation. The pseudocode below illustrates one iteration of the Rprop+ algorithm (Igel & Hüsken, 2003):

$Rprop+$

for each ω_{ij} do {

$$
\begin{aligned}
&\text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0 \text{ then } \{ \\
&\Delta_{ij}^{(t)} = \min(\Delta_{ij}^{(t-1)} * \eta^{+}, \Delta_{\max}) \\
&\Delta \omega_{ij}^{(t)} = -\operatorname{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)} \\
&\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)} \\
&\ \} \\
&\text{elseif } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0 \text{ then } \{ \\
&\Delta_{ij}^{(t)} = \max(\Delta_{ij}^{(t-1)} * \eta^{-}, \Delta_{\min}) \\
&\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t-1)} \\
&\frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0 \\
&\ \} \\
&\text{elseif } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} * \frac{\partial E^{(t)}}{\partial \omega_{ij}} = 0 \text{ then } \{ \\
&\Delta \omega_{ij}^{(t)} = -\operatorname{sign}(\frac{\partial E^{(t)}}{\partial \omega_{ij}}) * \Delta_{ij}^{(t)} \\
&\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta \omega_{ij}^{(t)} \\
&\ \} \\
&\}
\end{aligned} \tag{7}
$$

300 ANN models with the same architecture and configuration were trained, five models for each image to improve the model's accuracy. The best model for each image was then selected, resulting in 60 models, two for each analysed stack. The statistical performance of each selected model can be seen in Supplementary Table 1.

Comparative Analysis of Stacking Factors

The comparison between the conversion factors obtained from Digitora and NeuroDIC software tools was evaluated by considering the average of percentage deviations (APD%) (Equation 8), root mean square percentage error (RMSE%) (Equation 9), per cent relative error (RE%) (Equation 10), and the dependent samples t-test at a significance level of 5% (Soares et al., 2003).

$$APD\% = 100N^{-1}\sum_{i=1}^{n}\frac{\hat{Y}_i - Y_i}{Y_i} \quad (8)$$

$$RMSE\% = 100\bar{Y}_i^{-1}\sqrt{N^{-1}\sum_{i=1}^{n}(Y_i - \hat{Y}_I)^2} \quad (9)$$

$$RE\% = 100\left(\frac{\hat{Y}_i - Y_i}{Y_i}\right) \quad (10)$$

Where $\hat{Y}_i$ = Estimated conversion factor; Y_i = Observed conversion factor; $\overline{Y_i}$ = Average of observed conversion factor; and N = Number of observations.

RESULTS

The conversion factors estimated from the NeuroDIC and Digitora software tools did not show statistically significant (n.s.) variance compared to the observed factors (tcalc = -1.763 n.s. and -0.921 n.s., respectively). The conversion factors estimated from the NeuroDIC software were more accurate than those obtained from Digitora, as evidenced by the estimates of the APD (%) and RMSE (%) statistics (Table 1) and the distribution of percentage differences (Figure 3).

In Figure 3, stack number 13 showed the highest percentage difference for both evaluated software tools. Upon analysing the photograph of this stack (Figure 4), it is noticeable that a significant portion of it was shaded due to the weather conditions at the time, resulting in incorrect classification of the wood and space classes in the NeuroDIC software and visually misleading results in the Digitora software. Despite these conditions, the results were relatively desirable.

Table 1
Observed and estimated conversion factors obtained from the NeuroDIC and Digitora software tools, along with corresponding statistics

Number of Stack	Conversion Factors			RE (%)	
	Observed	NeuroDIC	Digitora	NeuroDIC	Digitora
1	1.3842	1.3758	1.3819	-0.6103	-0.1662
2	1.3666	1.3690	1.4147	0.1759	3.5197
3	1.3048	1.3063	1.2705	0.1157	-2.6288
4	1.3501	1.3320	1.2929	-1.3397	-4.2367
5	1.3318	1.3322	1.3505	0.0320	1.4041
6	1.3128	1.3117	1.2684	-0.0810	-3.3821
7	1.3034	1.3024	1.3019	-0.0737	-0.1151

Table 1 *(continue)*

Number of Stack	Conversion Factors			RE (%)	
	Observed	NeuroDIC	Digitora	NeuroDIC	Digitora
8	1.2998	1.3023	1.2954	0.1892	-0.3385
9	1.2968	1.2976	1.2785	0.0598	-1.4112
10	1.3081	1.3082	1.2647	0.0085	-3.3178
11	1.2967	1.3033	1.2346	0.5126	-4.7891
12	1.3037	1.3040	1.2934	0.0217	-0.7901
13	1.2465	1.2091	1.2959	-2.9983	3.9631
14	1.2887	1.2908	1.2425	0.1659	-3.5850
15	1.2799	1.2798	1.2830	-0.0069	0.2422
16	1.3249	1.3210	1.3092	-0.2937	-1.1850
17	1.2887	1.2927	1.2912	0.3108	0.1940
18	1.2676	1.2588	1.2394	-0.6968	-2.2247
19	1.2644	1.2568	1.2276	-0.5975	-2.9105
20	1.2534	1.2610	1.2290	0.6051	-1.9467
21	1.2761	1.2654	1.2912	-0.8400	1.1833
22	1.2520	1.2576	1.2481	0.4448	-0.3115
23	1.3344	1.3364	1.3102	0.1500	-1.8135
24	1.2632	1.2623	1.2970	-0.0676	2.6757
25	1.2534	1.2583	1.2588	0.3895	0.4308
26	1.2712	1.2669	1.2825	-0.3402	0.8889
27	1.2625	1.2631	1.2327	0.0453	-2.3604
28	1.2522	1.2471	1.2989	-0.4043	3.7294
29	1.2519	1.2370	1.2908	-1.1931	3.1073
30	1.2554	1.2492	1.2991	-0.4944	3.4810
APD (%)		-0.2270	-0.4231		
RMSE (%)		0.0151	0.6277		
Calculated t-value		-1.7337^{ns}	-0.9214^{ns}		

Note. t_{tab} (5%; 29df) = 2.040; ns = not significant

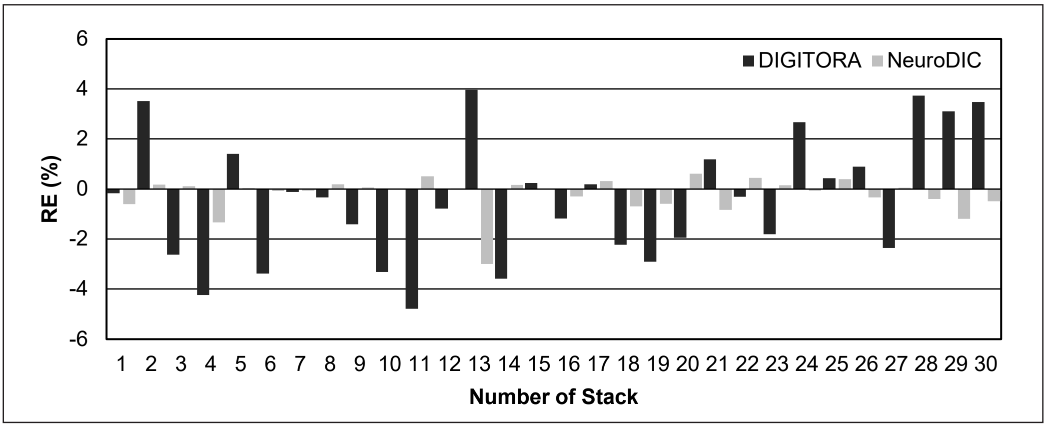


Figure 3. Percent relative error of conversion factor estimated from the NeuroDIC and Digitora software tools

The distribution of the relative percentage errors obtained with the NeuroDIC and Digitora software tools was compared (Figure 5). NeuroDIC had a narrower distribution of errors, with approximately 96.7% of the percentage differences between the observed and estimated factors concentrated in the ±1% error class interval. It means that 50% of the NeuroDIC estimates were within 1% of the observed values, 40% were exactly equal, and 6.7% were within 1% below the observed values (Figure 5A). In contrast, Digitora had a wider distribution of errors, with only 43.3% of the percentage differences within the ±1% error class interval (Figure 5B). The higher concentration of the percentage differences in the intervals of smaller error classes for NeuroDIC indicates that it is generally more accurate than Digitora. NeuroDIC is more likely to produce estimates close to the true values.

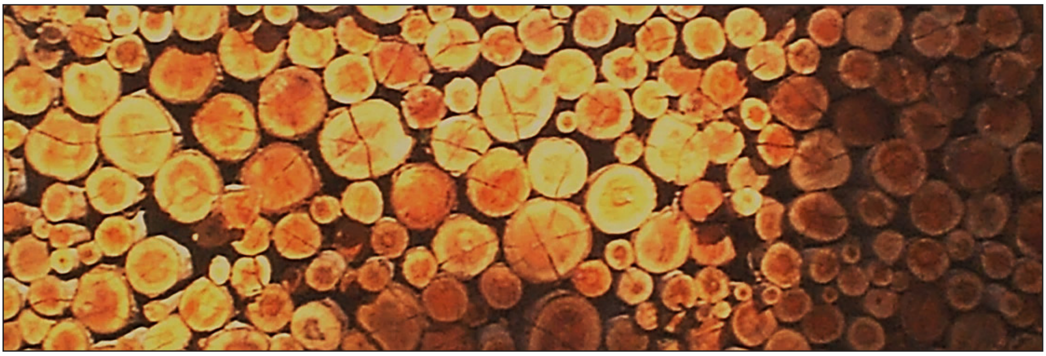
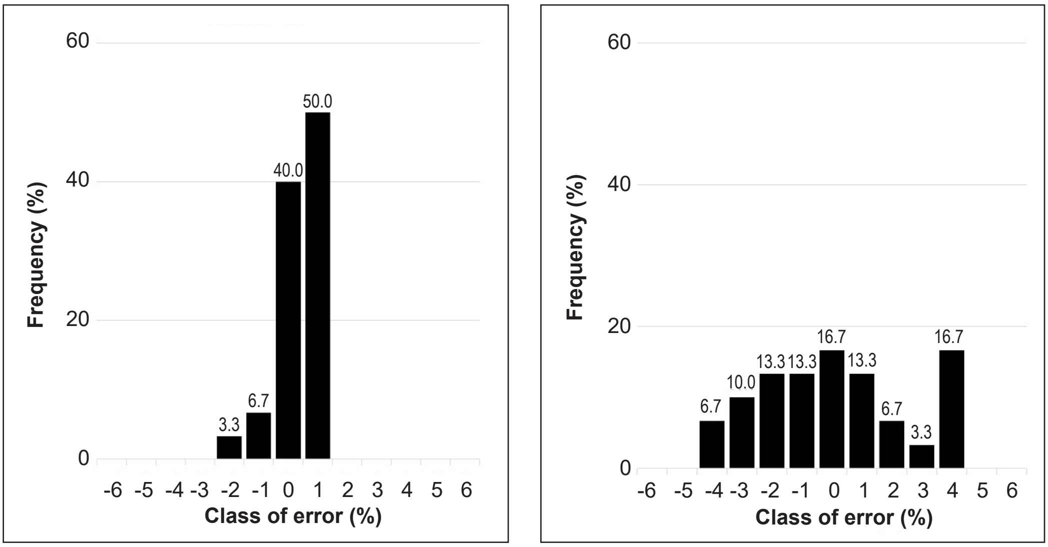


Figure 4. Photograph of stacked eucalypt timber number 13 exhibiting a higher relative error due to the image quality



(a) (b)

Figure 5. Error class plot between frequency in stacked eucalypt timber estimated: (a) NeuroDIC; and (b) Digitora software tools

DISCUSSION

Stacked timber is quantified in in-store units, which are then adjusted using a conversion factor to more precisely estimate timber volume in cubic meters. This adjustment is necessary due to the prevalent use of cubic meters for wood commercialization, particularly in South America. The conversion factor measures the stacking efficiency and the space occupied by the stacking volume compared to the actual log volume. However, measurement inaccuracies can occur due to the challenges in accurately determining the volume of logs in large quantities. Digital image processing and significant advancements in artificial intelligence have shown remarkable efficacy in contributing to these cases, making research in this field more appealing and captivating.

Earlier studies have proven the accuracy of conversion factor estimation using low-resolution digital photographs (Bertola et al., 2003). The results of this study, which also used low-resolution digital photographs, further support the efficacy of Digitora (equidistant points method) and NeuroDic (ANN method) software tools in determining conversion factors. Despite the challenges posed by low natural lighting conditions, including cloud cover and variations in the time of day during image capture, the estimates were highly accurate.

When applied under controlled experimental conditions with manually stacked timber, Digitora accurately estimated conversion factors, with a mean difference (APD%) from observed factors of -0.4231% (Table 1). However, when evaluating mechanically stacked timber in a field condition at a forestry company, the mean difference increased to 3.2259% (Soares et al., 2003). It suggests that the accuracy of Digitora software tools may vary depending on the stacking method employed.

NeuroDic showed a mean difference (APD%) from observed factors of -0.2270% (Table 1), showing its superior accuracy compared to Digitora in this study. This finding was consistent with the research conducted by Silveira (2014), who found a 2.0% difference in the average estimation of conversion factors obtained by NeuroDic, once again proving its greater accuracy.

Additionally, da Silva et al. (2005) have used Matlab software to evaluate an image segmentation method for stacked eucalypt timber, which involves dividing the image into segments with uniform attributes based on pixel adjacency and similarity conditions (Andrade et al., 1994). They reported an average difference of 0.6370% between observed and estimated factors, higher than in the two software tools evaluated in this study. It highlights the effectiveness of the alternative method of determining conversion, such as the one in this study.

The traditional method of manual log scaling, which is relatively costly and time-consuming, can be replaced using NeuroDic. The adoption of NeuroDic enables increased sampling intensity with a cost reduction of up to 90%, as demonstrated by Silveira (2014).

In other words, digital image processing and artificial intelligence can improve the accuracy of timber volume measurement, which is important for commercialization purposes.

A study by Bertola et al. (2003) concluded that forest operator training influences the accuracy of the conversion factor. Therefore, the most knowledgeable forest operator in this study obtained the observed conversion factor. The influence of genetic factors on conversion factors further underlines the importance of accurate estimation methods. The study found significant differences in conversion factors between the two clones, while no significant differences were seen within the same clone (de Andrade Sandim et al., 2019). The conversion factors can vary depending on the mid-diameter and the crook, which show strong correlations between the factors (Heinzmann & Barbu, 2017)—according to De Miguel-Díez et al. (2023), who evaluated a detailed literature review, thirty parameters influence conversion factors. The conversion factor may vary according to the image quality due to field weather conditions. These conditions contribute to the variability of the conversion factors and highlight the importance of reliable estimation techniques offered by computer tools using photographic methods,

CONCLUSION

The analysis of conversion factors using the NeuroDic (ANN) and Digitora (equidistant points method) software tools revealed no statistically significant variance compared to the observed factors. The ANN method provided more accurate conversion factor estimates than the equidistant points method. Both methods prove that an inferior quality photograph, affected by weather conditions, introduces errors in the estimations, albeit within acceptable limits.

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REFERENCES

Aggarwal, C. C. (2018). *Neural networks and deep learning*. Springer International Publishing. https://doi.org/10.1007/978-3-319-94463-0

Andrade, M., Peixoto, F. C., & Araújo, A. (1994). Segmentação de imagens através de rede neuronal por satisfação de restrições em ambiente paralelo [Image segmentation using a neural network that fulfils constraints in a parallel environment]. *Anais do VII SIBGRAPI*, 47-52.

Bayat, M., Ghorbanpour, M., Zare, R., Jaafari, A., & Pham, B. T. (2019). Application of artificial neural networks for predicting tree survival and mortality in the Hyrcanian forest of Iran. *Computers and Electronics in Agriculture*, *164*, Article 104929. https://doi.org/10.1016/j.compag.2019.104929

Bertola, A., Soares, C. P. B., Ribeiro, J. C., Leite, H. G., & Souza, A. L. D. (2003). Determination of piling factors through Digitora software. *Revista Árvore*, *27*(6), 837-844. https://doi.org/10.1590/S0100-67622003000600010

Bueno, G. F., Costa, E. A., Cristina, A. N., Soares, A. A. V., de Miranda, R. O. V., & Schons, C. T. (2020). Effect of number of hidden layer neurons for height-diameter relationship of eucalyptus using artificial neural networks. *BIOFIX Scientific Journal*, *5*(2), 222-230. http://dx.doi.org/10.5380/biofix.v5i2.71374

Campesato, O. (2020). *Artificial Intelligence, Machine Learning, and Deep Learning*. Mercury Learning and Information.

Campos, J. C. C., & Leite, H. G. (2017). *Mensuração florestal: Perguntas e respostas* (5. ed. atual. e ampl.) [Forest measurement: Questions and answers (5th ed.)]. Universidade Federal de Viçosa.

Carvalho, A. M., & Camargo, F. R. A. (1996). Avaliacao do metodo de recebimento de madeira por estere [Evaluation of the method of receiving wood by stere]. *Revista O Papel*, *57*, 65-68.

Casas, G. G., Fardin, L. P., Silva, S., de Oliveira Neto, R. R., Binoti, D. H. B., Leite, R. V., Domiciano, C. A. R., de Sousa Lopes, L. S., da Cruz, J. P., dos Reis, T. L., & Leite, H. G. (2022a). Improving yield projections from early ages in eucalypt plantations with the Clutter model and artificial neural networks. *Pertanika Journal of Science & Technology*, *30*(2). https://doi.org/10.47836/pjst.30.2.22

Casas, G. G., Gonzáles, D. G. E., Villanueva, J. R. B., Fardin, L. P., & Leite, H. G. (2022b). Configuration of the deep neural network hyperparameters for the hypsometric modeling of the Guazuma crinita Mart. in the Peruvian Amazon. *Forests*, *13*(5), Article 697. https://doi.org/10.3390/f13050697

Cordeiro, M. A., Arce, J. E., Guimarães, F. A. R., Bonete, I. P., Silva, A. V. D. S., Abreu, J. C. D., & Binoti, D. H. B. (2022). Volumetric estimates in eucalyptus stands using support vector machines and artificial neural networks. *Madera y bosques*, *28*(1), Article e2812252. https://doi.org/10.21829/myb.2022.2812252

Da Cunha Neto, E. M., Bezerra, J. C. F., Veras, H. F. P., Gouveia, D. M., Araujo, E. C. G., & Silva, T. C. (2019). Eucalyptus stem taper estimate through artificial intelligence techniques. *BIOFIX Scientific Journal*, *4*(2), 166-171. http://dx.doi.org/10.5380/biofix.v4i2.65831

Da Rocha, J. E. C., Junior, M. R. N., Júnior, I. D. S. T., de Souza, J. R. M., Lopes, L., & da Silva, M. L. (2021). Configuration of artificial neural networks for height-diameter relationship of Eucalyptus spp. *Scientia Forestalis*, *49*(132), Article e3706.

Da Rocha, S. J. S. S., Torres, C. M. M. E., Jacovine, L. A. G., Leite, H. G., Gelcer, E. M., Neves, K. M., Schettini, B. L. S., Villanova, P. H., Silva, L. F. D., Reis, L. P., & Zanuncio, J. C. (2018). Artificial neural networks: Modeling tree survival and mortality in the Atlantic Forest biome in Brazil. *Science of the Total Environment*, *645*, 655-661. https://doi.org/10.1016/j.scitotenv.2018.07.123

Da Silva, M. C., Soares, V. P., Pinto, F. D. A. C., Soares, C. P. B., & Ribeiro, C. A. Á. S. (2005). Determination of the volume wooden stacked through processing of digital images. *Scientia Forestalis*, *69*, 104-114.

De Andrade Sandim, A. S., Mota, A. C., dos Santos, M. L., dos Santos Barros, W., Costa, B. C., & de Andrade, V. M. S. (2019). Stacked volume conversion factor for geometric volume of Eucalyptus sp. *Revista Agro@mbiente On-line*, *13*, 46-54. https://doi.org/10.18227/1982-8470ragro.v13i0.5312

De Andrade, V. C. L., Cardoso, A. M., & Binotti, D. H. B. (2022). Growth and yield prognosis of Corymbia citriodora using artificial neural networks. *Advances in Forestry Science*, *9*(2), 1735-1744. https://doi.org/10.34062/afs.v9i2.12829

De Freitas, E. C. S., de Paiva, H. N., Neves, J. C. L., Marcatti, G. E., & Leite, H. G. (2020). Modeling of eucalyptus productivity with artificial neural networks. *Industrial Crops and Products*, *146*, Article 112149. https://doi.org/10.1016/j.indcrop.2020.112149

De Miguel-Díez F., Purfürst T., Acuna M., Tolosana-Esteban E., Cremer T. (2023). Estimation of conversion factors for wood stacks in landings and their influencing parameters: a comprehensive literature review for America and Europe. *Silva Fennica*, *57*(1), Article 22018. https://doi.org/10.14214/sf.22018

De Oliveira Neto, R. R., Leite, H. G., Gleriani, J. M., & Strimbu, B. M. (2022). Estimation of Eucalyptus productivity using efficient artificial neural network. *European Journal of Forest Research*, *141*, 129-151. https://doi.org/10.1007/s10342-021-01431-7

De Souza, J. R. M., de Oliveira Castro, R. V., Júnior, I. D. S. T., Marcelino, R. A. G., da Silva, R. M., & Moretti, S. D. A. (2023). Stem tapering of eucalyptus spp. using different configurations of artificial neural networks. *Floresta*, *53*(2), 136-144. http://dx.doi.org/10.5380/rf.v53i2.78754

Ercanlı, İ. (2020). Innovative deep learning artificial intelligence applications for predicting relationships between individual tree height and diameter at breast height. *Forest Ecosystems*, *7*, Article 12. https://doi.org/10.1186/s40663-020-00226-3

Gouveia Filho, K. V., Soares, T. S., Cruz, E. S., & Mathias, R. A. M. (2022). Determinação de fatores de empilhamento e volume de madeira empilhada por meio do processamento de imagens digitais [Determination of stacking factors and wood volume stacked through digital image processing]. *Advances in Forestry Science*, *9*(3), 1851-1858. https://doi.org/10.34062/afs.v9i3.13470

Haykin, S. (2009). *Neural networks and learning machines* (3rd ed.). Pearson Education India.

Heinzmann, B., & Barbu, M. C. (2017). Effect of mid-diameter and log-parameters on the conversion factor of cubic measure to solid measure concerning industrial timber. *Pro Ligno*, *13*(1), 39-44.

Husch, B., Miller, C. I., & Beers, T. W. (1993). *Forest mensuration* (3rd ed.). Krieger Publishing Company.

Igel, C., & Hüsken, M. (2003). Empirical evaluation of the improved Rprop learning algorithms. *Neurocomputing*, *50*, 105-123. https://doi.org/10.1016/S0925-2312(01)00700-7

Kärhä, K., Nurmela, S., Karvonen, H., Kivinen, V. P., Melkas, T., & Nieminen, M. (2019). Estimating the accuracy and time consumption of a mobile machine vision application in measuring timber stacks. *Computers and Electronics in Agriculture*, *158*, 167-182. https://doi.org/10.1016/j.compag.2019.01.040

Kożuch, A., Cywicka, D., & Adamowicz, K. (2023). A comparison of artificial neural network and time series models for timber price forecasting. *Forests*, *14*(2), Article 177. https://doi.org/10.3390/f14020177

Mather, P., & Tso, B. (2016). *Classification methods for remotely sensed data*. CRC Press.

Meyen, S., & O'Connell, K. (2012). *Stacked timber measurement*. The 2012 ITGA Forestry & Timber Yearbook. Teagasc Forestry Development Department. https://www.forestry.ie/images/MiscDocs/2012YearbookArticles/StackedTimberMeasurement2012.pdf

Montesinos López, O. A., Montesinos López, A., & Crossa, J. (2022). Fundamentals of artificial neural networks and deep learning. In *Multivariate Statistical Machine Learning Methods for Genomic Prediction* (pp. 379-425). Springer. https://doi.org/10.1007/978-3-030-89010-0_10

Moskalik, T., Tymendorf, Ł., van der Saar, J., & Trzciński, G. (2022). Methods of wood volume determining and its implications for forest transport. *Sensors*, *22*(16), Article 6028. https://doi.org/10.3390/s22166028

Nylinder, M., Kubénka, T., & Hultnäs, M. (2008). *Roundwood measurement of truck loads by laser scanning*. A field study at Arauco pulp mill Nueva Aldea.

Reis, L. P., de Souza, A. L., dos Reis, P. C. M., Mazzei, L., Soares, C. P. B., Torres, C. M. M. E., Da Silva, L. F., Ruschel, A. R., Rêgo, L. J. S., & Leite, H. G. (2018). Estimation of mortality and survival of individual trees after harvesting wood using artificial neural networks in the amazon rain forest. *Ecological Engineering*, *112*, 140-147. https://doi.org/10.1016/j.ecoleng.2017.12.014

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: The RPROP algorithm. *IEEE International Conference on Neural Networks*, *1*, 586-591. https://doi.org/10.1109/ICNN.1993.298623

Sandoval, S., & Acuña, E. (2022). Stem taper estimation using artificial neural networks for Nothofagus trees in natural forest. *Forests*, *13*(12), Article 2143. https://doi.org/10.3390/f13122143

Santana, A., Encinas, I., & Muñoz, R. (2023). Stacking factor in transporting firewood produced from a mixture of Caatinga biome species in Brazil. *International Journal of Forest Engineering*, *34*(1), 54-63. https://doi.org/10.1080/14942119.2022.2084674

Seki, M. (2023). Predicting stem taper using artificial neural network and regression models for Scots pine (*Pinus sylvestris* L.) in northwestern Türkiye. *Scandinavian Journal of Forest Research*, *38*(1-2), 97-104. https://doi.org/10.1080/02827581.2023.2189297

Silveira, D. D. P. (2014*). Estimation of the volume wooden stacked using digital images and neural networks* [Master dissertation]. Universidade Federal de Viçosa, Brazil. http://locus.ufv.br/handle/123456789/3169

Soares, C. P. B., Ribeiro, J. C., Nascimento Filho, M. B. D., & Ribeiro, J. C. L. (2003). Determination of piling factors through digital photography. *Revista Árvore*, *27*(4), 473-479. https://doi.org/10.1590/S0100-67622003000400007

Soares, C.B.S., Paula Neto. F., & Souza, A.L. (2011). *Dendrometria e inventário florestal* (2nd ed.) [Dendrometry and forest inventory (2nd ed.)]. Universidade Federal de Viçosa.

Tavares Júnior, I. D. S., de Souza, J. R. M., Lopes, L. S. D. S., Fardin, L. P., Casas, G. G., Oliveira Neto, R. R. D., Leite, R. V., & Leite, H. G. (2021). Machine learning and regression models to predict multiple tree stem volumes for teak. *Southern Forests: a Journal of Forest Science*, *83*(4), 294-302. https://doi.org/10.2989/20702620.2021.1994345

APPENDIX

Supplementary Table 1
Statistical performance of the best-selected models trained using artificial neural networks for each side of the staked timber

Data splitting			Training			Validation		
Number of Stack	Stack side	ANN Model	bias	RMSE	r	bias	RMSE	r
1	A	2	0.0113	0.1840	0.9325	0.0149	0.1867	0.9307
1	B	5	0.0011	0.1972	0.9204	0.0074	0.1985	0.9191
2	A	1	0.0242	0.2081	0.9128	0.0176	0.2100	0.9099
2	B	5	0.0130	0.1769	0.9356	0.0114	0.1757	0.9372
3	A	3	0.0066	0.0908	0.9835	0.0045	0.1309	0.9656
3	B	1	-0.0026	0.1674	0.9436	0.0075	0.1991	0.9201
4	A	4	0.0059	0.1110	0.9753	0.0082	0.1198	0.9714
4	B	2	-0.0062	0.1368	0.9611	-0.0011	0.1081	0.9750
5	A	1	0.0013	0.0898	0.9838	-0.0041	0.0951	0.9819
5	B	1	0.0082	0.1454	0.9528	0.0134	0.1606	0.9428
6	A	4	0.0116	0.1525	0.9533	0.0107	0.1566	0.9504
6	B	1	0.0016	0.1246	0.9687	0.0053	0.1259	0.9676
7	A	4	0.0124	0.1777	0.9364	0.0174	0.1703	0.9402
7	B	2	0.0040	0.1263	0.9657	0.0063	0.1311	0.9625
8	A	3	0.0092	0.1679	0.9435	0.0147	0.1896	0.9284
8	B	3	-0.0065	0.1204	0.9711	-0.0057	0.1240	0.9692
9	A	4	0.0215	0.1783	0.9354	0.0234	0.1988	0.9192
9	B	1	-0.0075	0.1287	0.9661	-0.0015	0.1269	0.9673
10	A	1	0.0041	0.0830	0.9859	-0.0008	0.0751	0.9882
10	B	1	-0.0020	0.2072	0.9070	0.0032	0.2246	0.8913
11	A	3	0.0255	0.2955	0.8260	0.0437	0.3112	0.8089
11	B	2	0.0117	0.2339	0.8829	-0.0012	0.2137	0.9046
12	A	1	0.0194	0.2264	0.8957	0.0198	0.2413	0.8835
12	B	1	0.0021	0.2044	0.9159	0.0067	0.2074	0.9133
13	A	4	0.0045	0.2198	0.9027	0.0062	0.2281	0.8959
13	B	4	0.0069	0.3264	0.7752	0.0000	0.3618	0.7256
14	A	2	0.0203	0.2192	0.8929	0.0132	0.2263	0.8862
14	B	3	-0.0025	0.1613	0.9443	-0.0014	0.1600	0.9458
15	A	2	0.0338	0.2629	0.8544	0.0170	0.2461	0.8721
15	B	3	0.0038	0.1445	0.9561	0.0140	0.1795	0.9312
16	A	2	0.0366	0.2339	0.8865	0.0297	0.2437	0.8752
16	B	5	0.0181	0.2201	0.8971	0.0119	0.2144	0.9016

Data splitting			Training			Validation		
Number of Stack	Stack side	ANN Model	bias	RMSE	r	bias	RMSE	r
17	A	1	0.0257	0.2316	0.8932	0.0421	0.2673	0.8600
17	B	3	0.0108	0.1966	0.9220	0.0198	0.1971	0.9216
18	A	4	0.0226	0.2866	0.8366	0.0138	0.2866	0.8360
18	B	2	0.0149	0.1533	0.9514	0.0079	0.1151	0.9722
19	A	1	0.0126	0.1857	0.9268	0.0122	0.1784	0.9333
19	B	4	0.0160	0.3029	0.8166	0.0308	0.3038	0.8168
20	A	1	0.0298	0.2906	0.8303	0.0209	0.2973	0.8213
20	B	4	0.0077	0.2288	0.8935	0.0021	0.2320	0.8900
21	A	3	0.0162	0.2848	0.8379	0.0193	0.3134	0.8036
21	B	5	0.0079	0.2053	0.9095	0.0063	0.2273	0.8897
22	A	4	0.0184	0.2946	0.8247	0.0216	0.3217	0.7900
22	B	1	0.0024	0.0638	0.9913	0.0009	0.0534	0.9940
23	A	2	0.0309	0.2064	0.9166	0.0215	0.1938	0.9257
23	B	4	0.0024	0.1455	0.9577	0.0085	0.1594	0.9493
24	A	1	0.0367	0.2964	0.8230	0.0414	0.3099	0.8032
24	B	2	0.0056	0.1639	0.9456	0.0040	0.1620	0.9458
25	A	2	0.0348	0.2408	0.8848	0.0466	0.2505	0.8771
25	B	2	0.0228	0.1843	0.9330	0.0241	0.1946	0.9253
26	A	4	0.0099	0.1962	0.9225	0.0023	0.1894	0.9280
26	B	4	0.0035	0.1843	0.9296	-0.0040	0.1802	0.9328
27	A	3	0.0134	0.2721	0.8442	0.0110	0.2611	0.8557
27	B	1	0.0105	0.1912	0.9263	0.0061	0.1706	0.9411
28	A	2	0.0137	0.2528	0.8708	0.0070	0.2812	0.8399
28	B	4	0.0056	0.0799	0.9845	0.0038	0.1152	0.9673
29	A	1	0.0265	0.2445	0.8809	0.0453	0.2662	0.8588
29	B	3	0.0171	0.1711	0.9407	0.0175	0.1755	0.9377
30	A	1	0.0352	0.2959	0.8225	0.0273	0.2860	0.8338
30	B	3	0.0227	0.1425	0.9591	0.0130	0.1379	0.9621

Note. RMSE = Root Mean Square error and *r* = Coefcient Correlation