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REGULAR ARTICLE

Modeling the evaluation of methods for determining the basic density of wood in forest species based on data from a neuro-fuzzy inference system

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EZG: Conceptualization. Experimental data collection. Data storage. Data analysis. Supervision. Funding acquisition; RMB: Data storage. Data analysis. Manuscript writing. Manuscript revision; MASA: Literature review. Manuscript writing. Manuscript revision; CDZF: Literature review. Manuscript writing. Manuscript revision.

Abstract

The forestry sector is one of the agribusiness sectors that generates the most wealth for the national economy, as it brings benefits to society, from the wood itself for industries, biomass for energy production, and to the environment, reducing pressure on native forests and the reuse of land degraded by agriculture. In view of this, this study was carried out to predict the different basic densities in tree species under the influence of two factors, nine different tree species in relation to three different density methodologies using the Neuro-Fuzzy System. Tree basic density modeling was carried out using effective species parameters and different calculation methodologies adapted to the Neuro-Fuzzy Inference System (ANFIS). In the ANFIS model, 67% and 33% of the total data were considered as training and test data, respectively. The numbers of pertinence functions were selected 9 for species and 3 for methodologies for the input data. ANFIS training was carried out using the hybrid method. The average R2 determination coefficients were 87.32% and 97.42% for the field and ANFIS models, respectively. The model obtained using ANFIS showed a high accuracy of 4.36%. Compared to the field data, the ANFIS model was highly accurate and can be used to estimate the basic density of the trees in this study.

Keywords

ANFIS; Agriculture; Artificial neural network; Agroforestry; Modeling.

Introduction

Within the industrial wood production process, some items must be considered when producing wood in the field, such as uniformity in color characteristics, mechanical resistance, workability and even basic density (Alves, Oliveira and Carrasco, 2017). The density of wood reflects its anatomical structure, as it has a direct influence on wood anisotropy (Moutinho et al., 2017). Therefore, Benin, Watzlawick & Hillig (2017) report that the higher the density of the wood, the greater the volumetric shrinkage and swelling, with a practically linear relationship between these properties.

Density can be expressed mathematically as the ratio of the body's mass to its volume according to Alves, Oliveira and Carrasco (2017). There are two forms of density, the basic density of wood, which can be called specific mass, an important physical property, as it has relationships with other properties, such as mechanical strength and dimensional variation. (Moutinho et al., 2017). Another characteristic is qualitative, as it varies according to the environment and its genotype, as well as variation within the species and even within the tree itself. (Silva et al., 2017).

Basic density is of major importance in a qualitative assessment of wood (Benin, Watzlawick and Hillig 2017), because it reflects the combination of various anatomical factors, as well as others such as age, origin, spacing, growth rate, among others (Santos et al, 2021).

For this reason, it is essential to know the quality of the wood, especially the basic density, which can be determined using the stereometric method, the gravimetric method (hydrostatic balance method) and the maximum moisture content, which, unlike the other two, does not use volume in its determination (Vivian et al., 2022 and Silveira, Rezende and Vale, 2013)

Considering some limitations in analytical methods, in the relationships between tree species, in the use of different soil parameters, or even in the preparation of the best sample for data collection, researchers are including in their work the use of artificial intelligence to predict the best method for evaluating basic density in the species used.

Madhu, Sowmya Dhanalakshmi and Mathew (2020) stated systems based on artificial intelligence tend to work with functions of great difficulty in various areas of knowledge, looking for patterns, identifications, classifications, image processing, among others, and in this case fuzzy logic and its ANFIS system stand out.

The fuzzy logic ANFIS system works with neural networks that produce ambiguous models when given training data, while fuzzy logic requires an expert in the field to

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recognize the system developed (Huang et al., 2022). However, ANFIS combines fuzzy logic with neural networks, in other words, ANFIS is a fuzzy system that explains qualitative expression, like neural networks with variable structures (Vasaki et al., 2021).

The parameters of the pertinence functions of this system are developed through algorithms combining it with the least squares method (Shaban et al., 2021). As the models presented to describe the relationship between the different basic density methodologies and the various tree species, especially when evaluating the physical and physiological aspect of each tree species, may not be precise and, in many cases, have been presented for a single density method for any tree species, they may result in incomplete data and no real application of a relationship between basic density in relation to a particular species.

In view of this, this study was carried out to predict the different basic densities in tree species under the influence of two factors, nine different tree species in relation to three different density methodologies, using the Neuro-Fuzzy System.

Materials and methods

The field experiment was conducted on trees cut down under an electrification network during its periodic maintenance by the local electrification company. The collection area is located at 23°16' S e 48° 38' W, city of Itatinga, state of São Paulo, Brazil. In this study, to measure and determine the factors influencing basic density in each species and methodology applied, a statistical design was used with 27 treatments, arranged in a 3 x 9 factorial scheme, with 3 basic density methods and 9 species.

The species used in the experiment were scientifically identified at the Wood Anatomy and Quality Laboratory of the Institute of Science and Engineering of the São Paulo State University as: *Cecropia* sp. (Embaúba), *Myrcia* sp. (Cambuí), *Copaifera* sp. (Copaíba), Inga sp. (Ingá), *Nectandra megapotamica* (Canelinha), *Stryphnodendron adstringens* (Barbatimão), *Anadenanthera falcata* (Angico-do-cerrado), *Moquiniastrum polymorphum* (ex. *Gochnatia polymorpha*) (Cambará) and *Libidibia ferrea* (ex. *Caesalpinia ferrea*) (Pau-ferro). The methodologies used to determine basic density were the Hydrostatic Balance Method, the Stereometric Method and the Maximum Moisture Content Method.

In this section, Matlab® software was used under license from the AGROENERBIO research group at the Faculty of Animal Science and Food Engineering at the University of São Paulo, within the ANFIS toolbox to predict basic density, considering the nine tree species and the three methodologies for determining basic density as the influence of the following factors. For this analysis, 67% of the total data obtained in the field was used as training data and the remaining 33% was used for validation. By partitioning the grid of method, type and number of pertinence functions, the following were determined for the input and output parameters in the Neuro-Fuzzy System. Two inputs were considered for the development of the system: species and methodologies. For the membership functions (MFs), nine were considered for species and 3 for methodologies. In this model, the "gauss2mf" type was selected for the association of input and output parameters. To train the ANFIS structure, the hybrid optimization method was applied, which is a combination of the least squares method and backpropagation (reduction method) (Adedeji et al., 2020), according to Figure 1.

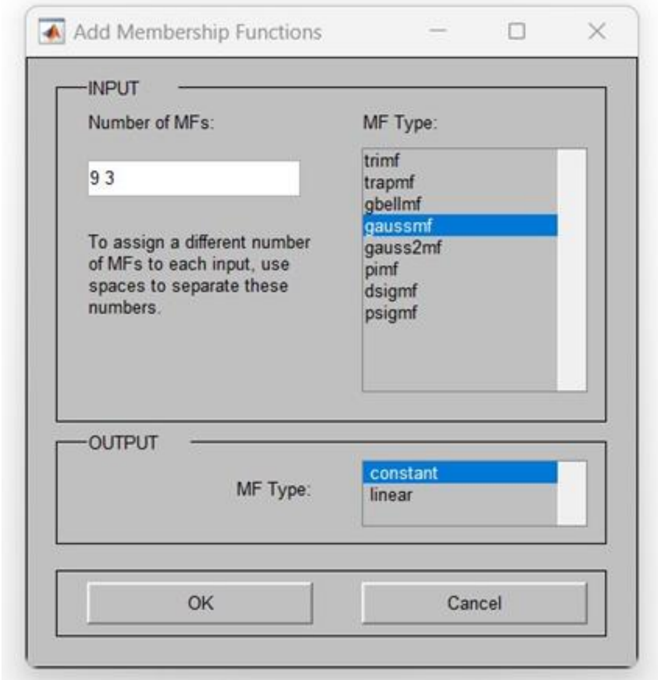

Figure 1. Combination of the least squares method and reduction.

Results and discussion

Figure 2 shows a relationship between the root mean square error and the optimization process for the training and verification steps, together with the error of the training data with the signal (*).

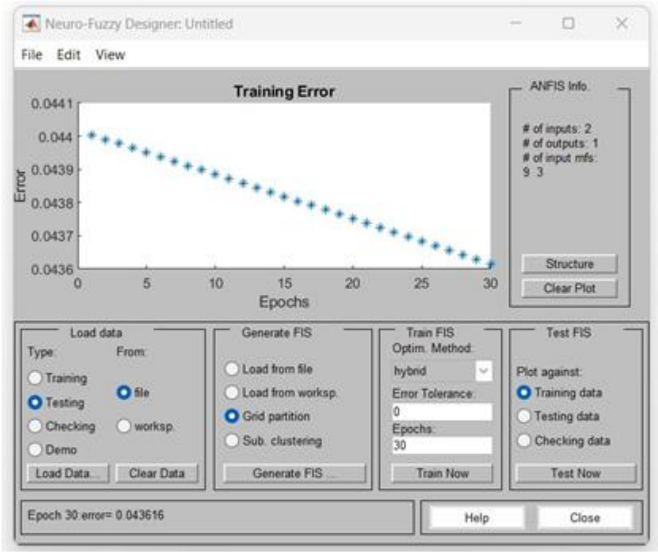

Figure 2. Training errors.

After training and validating the ANFIS model for different input parameters, the root mean square error (RMSE) for the training data was 0.06585 and for the validation data it was 0.043616. The output obtained from ANFIS was compared with the training and verification data, and the results are shown in Figure 2. In Figure 3, the training data is marked with (O) and the modeling data is marked with (*).

Figure 4 shows the structure of the Neuro-Fuzzy System developed. In this model, 27 rules were built based on the pertinence values of each input (species and methodology). All the rules are activated, correlating one by one.

Figure 5 shows the type and range of dedicated membership functions for species parameters and methodologies. These pertinence functions help to convert linguistic variables into numerical variables. The variables were developed from the artificial intelligence of ANFIS.

The model used to develop the ANFIS system is the incorporated hydride, as it presents a greater degree of hybridization, where it is not possible to separate the systems, as shown in Figure 6.

The response surface and contour map of the results are shown in Figures 7 and 8, respectively, according to the species and methodologies.

Figure 7 is presented in 3D format, which improves the visualization of the plotted points. This tool is considered efficient and effective for specialists working with optimization processes in various production processes.

The Neuro-Fuzzy (ANFIS) model developed in this study shows the complete advantage of the ANFIS system in predicting basic density as supported by the statistical parameters applied in the system. The results also showed that the Neuro-Fuzzy System (ANFIS) has a great advantage over the factorial statistical model and can be used reliably as a tool for modeling basic density in these species evaluated, thus combining the advantages of the Neural Network and Fuzzy Logic that offer good results.

The results presented indicate that experimental data is reliable for AI computational analysis. Traditionally, data used for AI modeling can be divided into training (calibration), testing (verification) and validation for a large data set, while for a limited data set when applied to the field it is smaller, but can be employed for AI development in a Neuro-Fuzzy use, as reported in several studies (Nassef et al., 2020, Nardez et al., 2018, Anh et al., 2018, Rousseau-Figueroa et al., 2016 and Landin, 2017). Using the Neuro-Fuzzy model and field data, it was possible to validate the basic density values, obtaining coefficients of variation of $R^2 = 0{,}8732$ for the field results and $R^2 = 0{,}9742$ for the Neuro-Fuzzy modeling results.

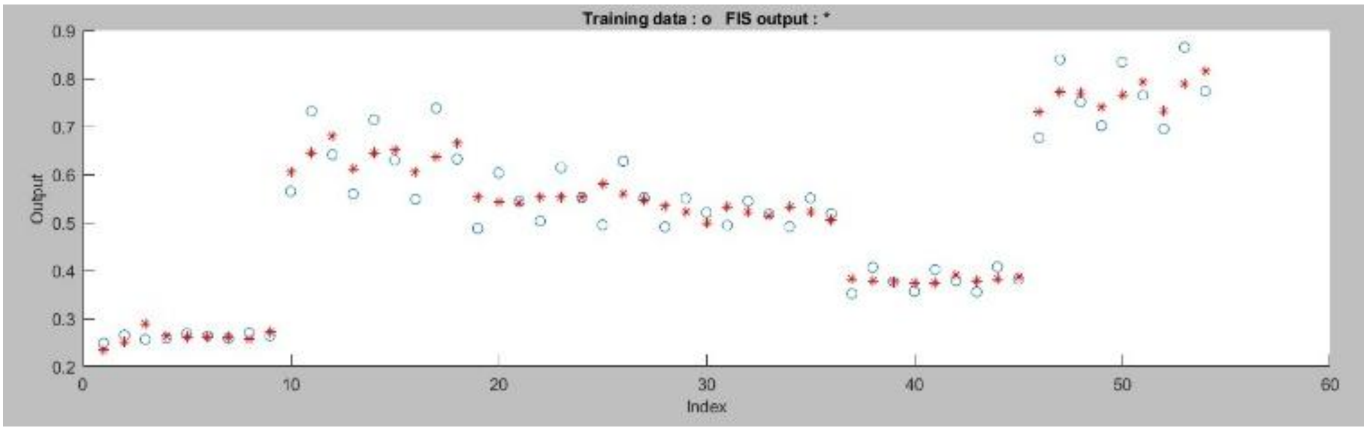

Figure 3. Changes in the error of training and validation data. The star and filled circle symbols mark the training and validation data, respectively.

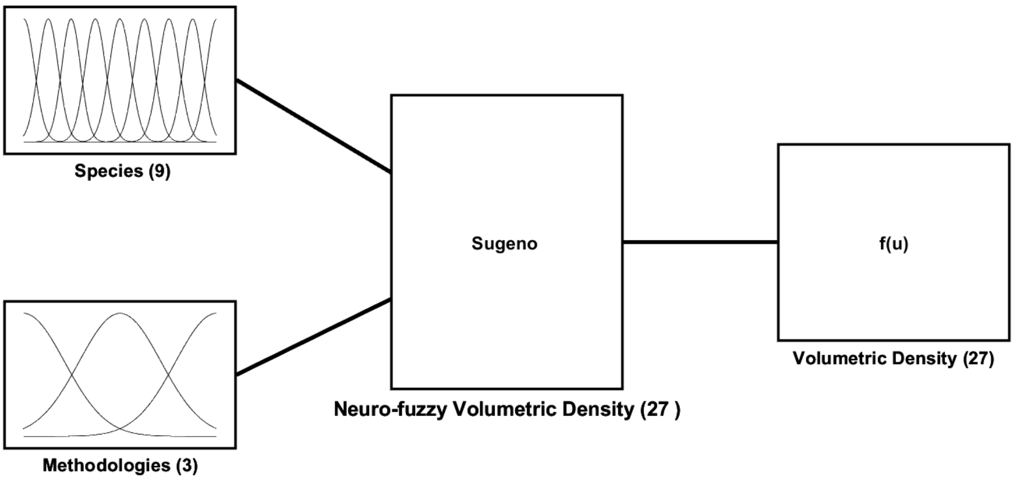

Figure 4. Structure of the Neuro-Fuzzy System for volumetric density.

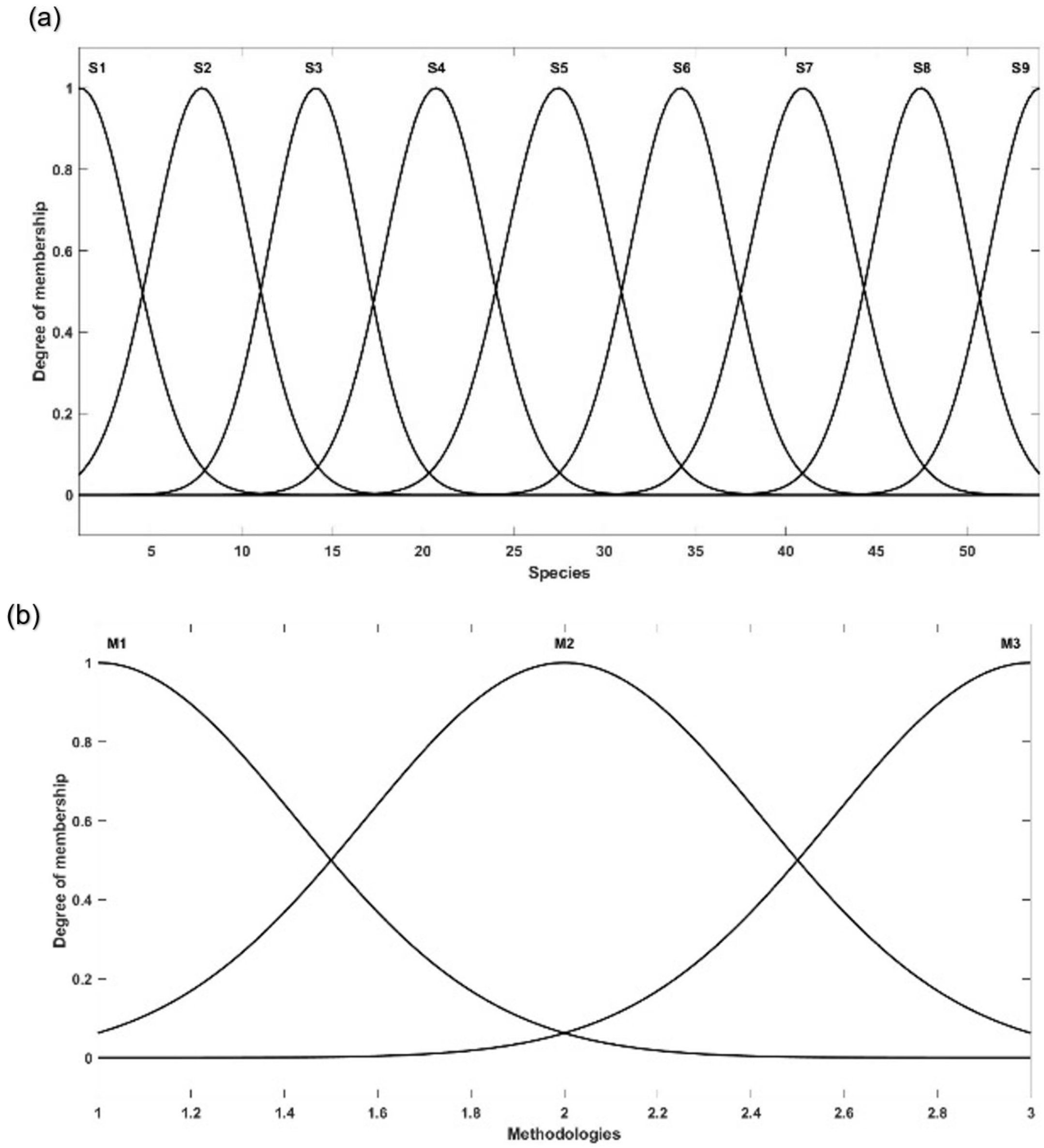

Figure 5. (a) Pertinence functions of the input variable – Species; **(b)** Variable pertinence functions – Methodologies.

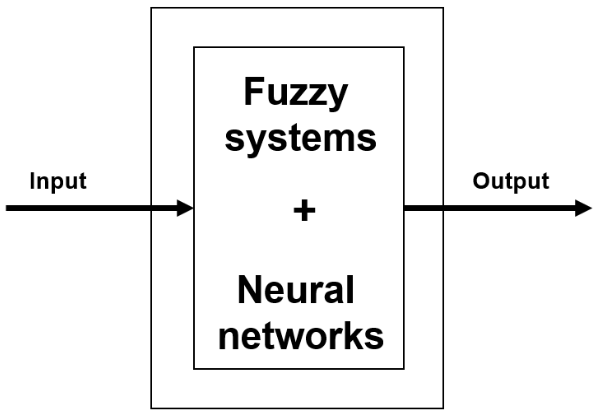

Figure 6. Built-in hydro system.

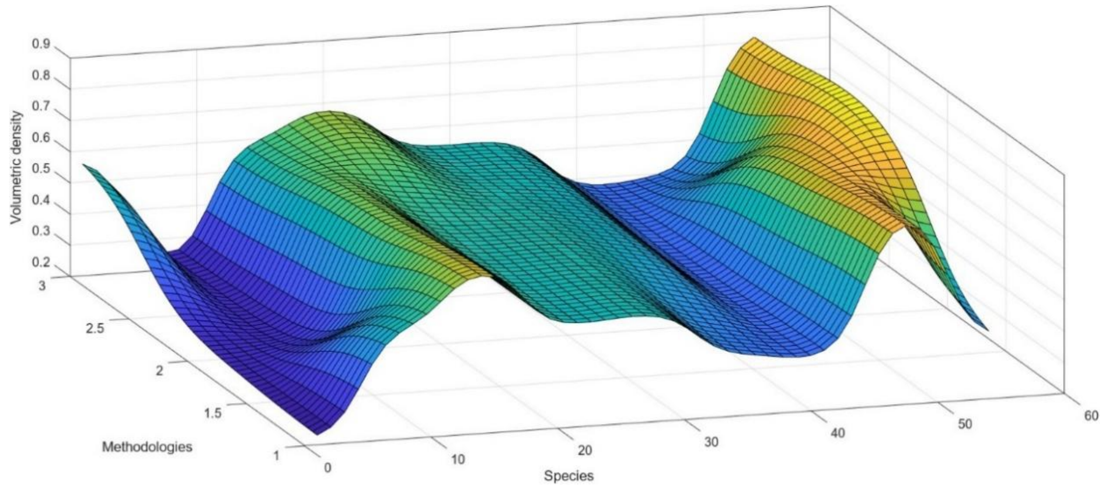

Figure 7. Optimized 3D basic density fuzzy set response.

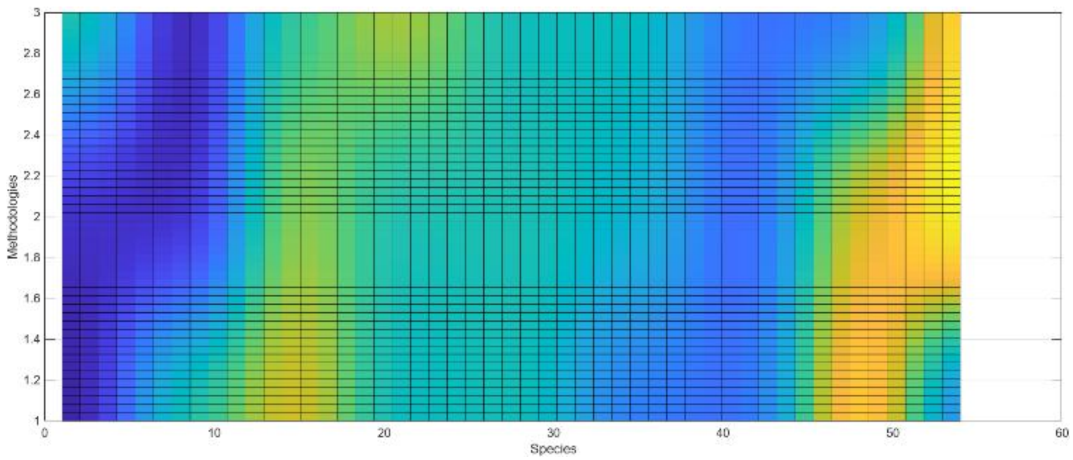

Figure 8. Contour map of the fuzzy surface, applied to the Neuro-Fuzzy model for basic density.

Conclusions

This study considered the prediction of basic density values using species parameters and methodologies in a field experiment and Neuro-Fuzzy. The results predicted by the Neuro-Fuzzy model showed values that were close to or even better than the field values. The model error and coefficient of determination obtained by the ANFIS model were 4.36% and 0.9742, respectively. The use of the Neuro-Fuzzy System (ANFIS) can be successfully applied as a powerful tool and the data resulting from the model has very high compatibility with experimental data. The model presented in this study can be used as a fast, accurate and low-cost method by researchers.

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