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Prognoses of diameter and height of trees of eucalyptus using artificial intelligence

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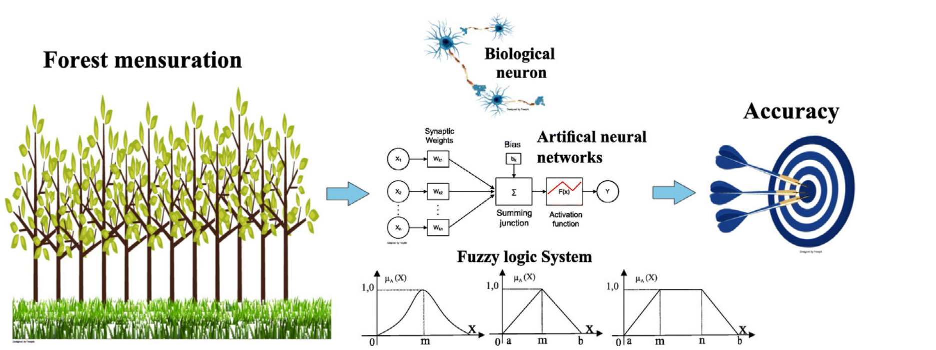
HIGHLIGHTS

- We use artificial neural networks to estimate the growth in DBH and height of eucalyptus trees.
- Using new techniques in forestry measurement.
- The techniques of artificial intelligence showed accuracy in growth estimation in DBH and total height.
- The techniques of artificial intelligence are appropriate in estimating the growth of eucalyptus trees.
- The techniques used can be adapted to other areas and forest crops.

GRAPHICAL ABSTRACT



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ABSTRACT

Models of individual trees are composed of sub-models that generally estimate competition, mortality, and growth in height and diameter of each tree. They are usually adopted when we want more detailed information to estimate forest multiproduct. In these models, estimates of growth in diameter at 1.30 m above the ground (*DBH*) and total height (*H*) are obtained by regression analysis. Recently, artificial intelligence techniques (AIT) have been used with satisfactory performance in forest measurement. Therefore, the objective of this study was to evaluate the performance of two AIT, artificial neural networks and adaptive neuro-fuzzy inference system, to estimate the growth in *DBH* and *H* of eucalyptus trees. We used data of continuous forest inventories of eucalyptus, with annual measurements of *DBH*, *H*, and the dominant height of trees of 398 plots, plus two qualitative variables: genetic material and site index. It was observed that the two AIT showed accuracy in growth estimation of *DBH* and *H*. Therefore, the two techniques discussed can be used for the prognosis of *DBH* and *H* in even-aged eucalyptus stands. The techniques used could also be adapted to other areas and forest species.

1. Introduction

Forest planning depends on a large quantity of information, emphasizing the prediction and the prognosis of growth and forest yield as the most important tools in the generation of this information (Andreassen and Tomter, 2003).

Often it is interesting to express the growth and yield of individual trees to get more details. When this happen, regression models are used to estimate the growth in diameter at breast height (*DBH*) and total height (*H*), which are components of these models (Andreassen and Tomter, 2003; Clutter et al., 1983; Davis and Johnson, 1987; Martins et al., 2014; Soares and Tomé, 2002). In addition to these

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variables, the estimation of mortality (Monserud and Sterba, 1999; Yang et al., 2003; Yao et al., 2001) and the use of competition indexes (Bella, 1971; Castro et al., 2013; Contreras et al., 2011; Martins et al., 2014; Pukkala and Kolström, 1987) are modeling elements of this kind of model. As examples of using regression models to express the growth and yield of individual trees, we can cite the works of Adame et al. (2008), Crecente-Campo et al. (2012), Lynch and Murphy (1995), Mabvurira and Miina (2002), Martins et al. (2014), Da Silva et al. (2002), Tennent (1982), Vospernik et al. (2010).

In search of more efficient methods of estimating growth prognosis and forest yield, the use of artificial intelligence techniques (AIT) has been highlighted. Among all AIT, artificial neural networks (ANN) are an alternative to traditional methods of modeling individual trees, i.e., the statistical regression models (Guan and Gertner, 1991). The ANNs have greater generalizability, less susceptibility to noise and outliers, and the ability to model nonlinear relations unknown to the modeler, among other features (Haykin, 2009) compared to the regression models. These characteristics are important in modeling the growth and yield of forest stands.

As examples of studies using ANNs in forest measurement, we can mention the studies of: Aertsen et al. (2010) used ANNs for prediction of site index in Mediterranean mountain forests; Diamantopoulou et al. (2015) used ANNs for estimation of Weibull function parameters for modeling tree diameter distribution; Diamantopoulou (2005) used ANNs as an alternative tool in pine bark volume estimation; Diamantopoulou and Özçelik (2012) used the generalized regression neural network technique has been applied for tree height prediction; Hasenauer et al. (2001) used ANNs of estimating tree mortality of Norway spruce stands; Ioannou et al. (2009) used ANNs to predict the prices of forest energy resources; Ioannou et al. (2011) used ANNs for predicting the possibility of ring shake appearance on standing chestnut trees (*Castanea sativa* mill.); Leite et al. (2011) used ANNs of estimation of inside-bark diameter and heartwood diameter of *Tectona grandis* Linn; Moisen and Frescino (2002) used ANNs for predicting forest characteristics; Özçelik et al. (2010); used ANNs of estimation breast height diameter and volume from stump diameter for three economically important species in Turkey; Özçelik et al. (2013) used nonlinear regression and artificial neural network models estimating crimean juniper tree height; Santi et al. (2017) used multifrequency SAR images and inversion algorithm based on ANNs for estimating forest biomass in Mediterranean áreas; Soares et al. (2011) used ANNs of estimation Recursive diameter prediction and volume calculation of eucalyptus trees; Vahedi (2016) used ANNs in comparison with modeling allometric equations for predicting above-ground biomass in the Hyrcanian mixed-beech forests of Iran; Vahedi (2017) used ANNs and traditional models for monitoring soil carbon pool in the Hyrcanian coastal plain forest of Iran.

Porras (2007) evaluated the growth in diameter and height of *Pinus cooperi* in Mexico; Castro et al. (2013), Leite et al. (2011), Da Silva et al. (2009) analyzed the growth in diameter and height for *Eucalyptus* spp. in Brazil.

The application of AIT in modeling of forest growth and yield is mostly restricted to the use of ANN. The use of other techniques such as fuzzy logic and adaptive neuro-fuzzy inference system (ANFIS) is still incipient. These techniques have the potential to improve estimation of growth and yield forest, as presented by satisfactory results in other areas of knowledge (Aish et al., 2015; Dongale et al., 2015; Maier and Dandy, 2000; Mashaly et al., 2015; Sarigul et al., 2003; Zarifneshat et al., 2012).

Fuzzy logic is a generalization of classical logic, which enables intermediate values between false and true, being suitable to solve problems that do not have well-defined borders, that is, when the transition from one class to another is smooth and not abrupt (Silvert, 2000; Tanaka, 1997; Zadeh, 1965). In the agricultural arena, fuzzy logic is used for multi-criteria analysis of image, image classification, vegetation mapping, assessment of soil suitability, and planning forest harvesting (Ahamed et al., 2000; Boyland et al., 2006; Fisher, 2010; Jiang and Eastiman, 2000; Joss et al., 2008; Malczewski, 2002; Oldeland et al., 2010; Phillips et al., 2011; Triepke et al., 2008).

The ANFIS consists of a fuzzy inference system (FIS) with a distributed parallel structure, such that the learning algorithms of neural networks are used to adjust the parameters of the FIS. Besides the advantages of fuzzy systems, the ANFIS has the advantage of using the learning ANN (Jang, 1993).

In growth and yield diameter at 1.30 m (*DBH*) and total height (*H*) models in level of individual trees, generally, the assumption of error independence is not met because the same tree is measured at different ages. The AIT does not guarantee some of the assumptions of regression models, such as normality and independence of errors. Another advantage of using AIT is the possibility to work with qualitative variables, such as yield class and genetic material. Considering the potential of AIT to be used in forest mensuration, this paper proposes the application of ANNs and ANFIS to predict growth in *DBH* and *H* of eucalyptus trees.

2. Methodology

The methodological steps (Fig. 1) required to perform the prognosis of growth in *DBH* and *H* for eucalyptus plantations using artificial intelligence techniques were:

1. Database generation;
2. Input variables of the proposed methods;
3. Site classification;
4. Methods for prognosis;
5. Evaluation of methods.

2.1. Step 1.1: description of the area and of the database

The data used in this study were obtained from eucalyptus plantations (*Eucalyptus grandis* x *Eucalytus urophylla*) in the county of Virginópolis, Minas Gerais state, Brazil. The geographical coordinates of the study area are 18°49′50″ S latitude and 42°41′46″ W longitude. The climate classification of the region is Cwa, according to Köppen (Alvares et al., 2013).

Were used data of continuous forest inventory from 28 eucalyptus clones. In those inventory were annually measured the variables *DBH*, *H*, and the dominant height according to the concept of Assmann (1970), for 398 plots ranging from 200 m^2 to 350 m^2, totaling 18,432 trees.

2.2. Step 1.2: partitioning of the database

The database was divided as follows: 85% of the plots were allocated for the fit of the regression models, training of ANN and ANFIS and 15% of the plots were used to test the accuracy of the three techniques. The data used in the training in the techniques of AI were classified into two sets: one with 70% used for training and one with 15% for validation. Database partitioning in this proportion performs well for large datasets like ours, with small deviations, being common in the literature as in the works of Alshahrani et al. (2017), Gramatikov (2017), Ondieki et al. (2017) and Ridolfi et al. (2014). The validation consists in the division of the database in a group for training and one for validation. The training is interrupts after each iteration to perform the validation, while the validation group error is less than the previous iteration error, the algorithm continues, and when the error increase, the training is complete.

2.3. Step 2. Input variables of the regression models and artificial intelligence techniques

The variables used in this study were *DBH*, *H*, dominant height, genetic material, basal area, number of trees per hectare, and the competition index independent of the distance. The average values of stand