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Artificial Neural Networks to Estimate Nutrient Use Efficiency in Eucalypt

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ABSTRACT

Background: Nutrient use efficiency (NUE) is the basis for fertilizer recommendations in eucalypt plantations in Brazil needs to be calculate individually for each nutrient and spacing. The possibility of superior performance to conventional models of regression and interpolation can be obtained by Artificial Neural Networks (ANN) enabling its use for solve complex problems. The ANN are being used in environmental science, but still studies on forest nutrition are poor. **Objective:** To evaluate the efficiency of NUE estimation in the Eucalyptus stem, under different spacing using ANN. **Results:** The nonlinear activation functions in the hidden layer generating local receptive fields were observed in all networks. Specific leaf area contributed to capture the biological realism and increased the ability of generalization of MLP's networks. Its generalization capability and connectivity allowed use only one network to perform the estimation of the stem's NUE.**Conclusion:** The modeling by ANN using multilayer perceptron architecture is a suitable alternative, accurate and biologically realistic to estimate the NUE by macronutrient, used in different spacings.

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INTRODUCTION

Several characteristics influence the biomass production and their estimation on fast-growing plantations in tropical areas. These characteristics include growth rate, total forest stand nutrient demand, efficiency of nutrient absorption from the soil, and tree nutrient use efficiency. Because nutrient requirements of a stand are closely related to growth rate, high yields require intensively fertilization to maintain the site quality (Santana *et al*., 1999).

Nutrient use efficiency (NUE) defined as the amount of dry matter produced per gram of assimilated nutrient, also known as index of nutrient efficiency, is the basis for fertilizer recommendations and for nutritional classifications of forests sites implanted with Eucalyptus in Brazil (Barros *et al*., 1996). The nutrients exportation estimated by NUE must receive special attention from the foresters regarding the tree component that will be exported by harvest and to the indication of species and provenances that are best suited for each edaphoclimatic condition, with the purpose of minimize their exportation and maximize the forest production (Santana *et al*., 1999) especially, under conditions of limited water resources and deficit of nutrients in the soil.

The ANN, or connectionism, are computational models that seek to reproduce the functions of the biological networks, its basic system and its dynamics (Maeda *et al*., 2009). The analogy neurobiological refers to parallel computing units that communicate via synaptic connections, the feature detectors and modularization of these connections (Braga *et al*., 2007). The simple processing units are called artificial neurons and, when linked together, enable us to relate independent variables to estimate dependent variables by adjustable weights on its associative and distributive memory (Coelho *et al*., 2007).

The possibility of superior performance to conventional models of regression and interpolation can be obtained by ANN enabling its use for solve complex problems (Haykin, 2001, Scrinzi *et al*., 2007). This is due to its features such as fault tolerance and noise, neurobiological architecture, adaptability of the weights of the

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connections to the changes of the environment, input and output mapping, and generalization of assimilated knowledge by learning, for a set of unknown data.

The networks are being used in environmental science, but still studies on forest nutrition are poor. Recent applications include studies on estimating monthly total nitrogen concentration in streams (He *et al*., 2011) and prediction of the nutrient content in dairy manure (Chen *et al*., 2008).

Advanced statistical techniques like the ANN associated with nutritional studies may be feasible to estimate the dynamic of the forest stands development. In this context, the objective of this work was to evaluate the efficiency of NUE estimation in the *Eucalyptus* stem, under different spacing using ANN.

MATERIAL AND METHODS

The study was conducted at 17° 50'south latitude and 42° 49' west longitude in an area of Aperam Bioenergy, in the city of Itamarandiba-MG. The climate prevailing in the region is the Cwa type, according to the Köppen classification, annual averages of temperature and rainfall of 20 ° C and 1160 mm, respectively (Pulrolnik *et al*., 2009).

The experiment was conducted in December 2002 using a hybrid of *Eucalyptus grandis* W. Hill ex Maiden x *Eucalyptus camaldulensis*Dehnh on oxisol in a plan relief to 1907 m of altitude. We adopted a randomized block design, with three blocks, being studied the effect of five treatments consisting by the following planting spaces: T1 – 3.0 x 0.5 m; T2 – 3.0 x 1.0 m; T3 – 3.0 x 1.5 m; T4 – 3.0 x 2.0 m and T5 – 3.0 x 3.0 m, being 3 meters of fixed distance between the planting rows. In each treatment were established 6 planting rows with 28 trees, totaling 168 individuals, of which 48 were measured, because it has been adopted the double border between plots.

With 101 months old, it was measured the diameter at 1.30 m height (DBH) and total height (H) of all trees. One sample tree, tree with quadratic mean diameter, was harvested to perform the quantification of leaf area and dry matter of the stem (bark + wood).

In the middle portion of each third of the canopy of the samples-trees was collected 10 completely formed leaves and it was measured the leaf area with equipment CI-203 CID Inc. Then the specific leaf area was calculated (SLA cm²/g) by the following formula: $SLA=LA.DM^{-1}$, where in LA = leaf area (cm²) and DM = dry mass (g).

The plant material was weighed in the field, and sub-sampled for dry weight determination (oven-dried at 65 °C) and nutrient analysis. Plant tissue was wet digested with hot nitric acid and perchloric acid (3:1) and analyzed for phosphorus (P - by colorimetry), potassium (K- by photometry of flame emission), sulfur (S - by turbidimetry), calcium and magnesium (Ca and Mg - by atomic absorption spectrophotometry). Nitrogen (N) was analyzed by the micro-Kjeldahl procedure after sulfuric digestion. The ratio between mean stem biomass and men nutrient content in the stem was used as an index of Nutrient Use Efficiency (NUE - kg dry matter per kg of nutrients) (Barros *et al*., 1996).

The artificial neural network training, also called learning, consists in adjusting network parameters (weights and bias) through a learning algorithm. For NUE estimation of the stem by macronutrient using samples trees, it were generated 3 models of ANN from the functional relationships between the categorical variable ID (N – 1, P – 2, K – 3, Ca – 4, Mg – 5 e S – 6) and the numerical DBH (cm), H (m), SLA (cm^2/g) and SPA (plant spacing, m). Thus, the ANN templates were based on:$NUE_{stem}=f(ID_x, DHB, H, SLA \text{ and } SPA)$where x = macronutrient (N, P, K, Ca, Mg e S).

It were used feedforward networks trained by the error retropropagation algorithm (back propagation), in other words, during the training were performed calculations from the network input layer to the output and the error propagated to previous layers. In all pre-processings it was performed the normalization and equalization of the data with enhanced sensitivity to their variation, to better capture their behavior. The data were divided into calibration groups (80% of the data) and validation (20%) using the random sampling method.

Were trained 600 ANN to estimate simultaneously the NUE of the stem per macronutrient, being 300 architecture with multilayer perceptron (MLP, 100 for each functional relationship) and 300 Radial Basis Function (RBF, 100 for each functional relationship).We adopted a heuristic model backward elimination. From these ANN was selected one of each type, based on the deviation of the estimated and observed values. The definition of the network architecture, in other words, the number of layers and number of neurons per layer was optimized by tool *intelligent problem solver* of the software Statistica (Statsoft, 2007).

The evaluation of the accuracy and precision and comparison of artificial neural networks training was performed according to Table 1. The points that extrapolated the general trend of each spacing were not eliminated, in order to verify the ability of artificial neural networks to deal with outliers or noises.

Table 1: Following deployed in selection of Artificial Neural Networks (ANN) built to estimate the Nutrient Use Efficiency (NUE) of the stem by macronutrient in *Eucalyptus* at 101 months old.

Step(1)	----------------------------- Sequence -----------------------------	Literature
1.	Comparison between the observed and predicted values for each network by a 5% probability test	Gorgens *et al.*, 2009
2.	Comparison of RMSE%(2) and BIAS% between networks and between processing stages: $RMSE_{\%} = 100\left(\sqrt{\sum(y_i - \hat{y}_i)^2/(n-1)}\right)/(\sum \hat{y}_i/n)$; $Bias_{\%} = 100\left(\sum(y_i - \hat{y}_i)\right)/(\sum \hat{y}_i/n)$;	Mabvurira&Miina (2002)
3.	Comparison of the relatives errors% between networks; $erro_{\%} = ((\hat{y} - y)/y)100$	
4.	Comparison between networks from the graphs of dispersion and distribution of the percentile frequency of percentile residues	
(1)Step can be performed simultaneously. (2)Root of the mean square of error. y_i = observed values. $\hat{y}_i$ = predicted values.		

To verify that the estimated data met the assumptions for performing the analysis of variance, the normality was tested according to Lilliefors test and homogeneity of variances by graphical analysis and Cochran test. All statistical analyzes were performed using the software Statistica (Statsoft, 2007).

RESULT AND DISCUSSION

The nonlinear activation functions in the hidden layer generating local receptive fields were observed in all networks (Table 2). The Gaussian transformation is usually seen in the hidden layer in architectures RBF's, and the sigmoidal (soft nonlinear), which is continuously differentiable in MLP's, according to Braga *et al*. (2007) and Haykin (2001). The inherent ability, in both architectures, of performing nonlinear approximations in the hidden layer allows the composition of functions in successive layers, be capable of solving the problems of higher order in the input space, even though the classes are not linearly separable (Haykin, 2001). The number of neurons in the hidden layer has increased with the amount of numerical entries in RBF's and resulted in a greater complexity to their networks. This was already expected, since the number of radial basis functions increases exponentially with the dimension of the input (Braga *et al*., 2007). The optimal values for the number of hidden layers or of neurons happen as a function of expected intelligence and not of a generalized method. It's important to highlight that the input layer is unique and doesn't process information, it only receives the input variables and direct them to the next layer.

Table 2: Characteristics of Artificial Neural Networks (ANN) built to estimate the Nutrient Use Efficiency (NUE) of the stem by macronutrient in *Eucalyptus* at 101 months old.

ANN	n(1)	Architecture	-------- Inputs --------		-- ActivationFunction--	
			Numerical	Categorical	Intermediate	Output
1	90	MLP 10-10-1	DBH(2), H(3), SLA(4). SPA(5)	ID(6)	Tangential	Exponential
2	90	RBF 10-18-1	DBH, H, SLA, SPA	ID	Gaussian	Identity
3	90	MLP 9-9-1	DBH, H, SPA	ID	Tangential	Logistics
4	90	RBF 9-16-1	DBH, H, SPA	ID	Gaussian	Identity
5	90	MLP 8-10-1	SLA, SPA	ID	Logistics	Logistics
6	90	RBF 8-15-1	SLA, SPA	ID	Gaussian	Identity
(1)Observations number. (2)Diameter at 1,30 m above the soil (cm). (3)H = total height (m). (4)cm²/g. (5)Plants spacing(m). (6)When: 1 – N, 2 – P, 3 – K, 4 – Ca, 5 – Mg e 6 – S.						

Table 3: Precision statistics of Artificial Neural Networks (ANN) built to estimate the Nutrient Use Efficiency (NUE) of the stem by macronutrient in *Eucalyptus* at 101 months old.

ANN	Phases	RMSE%	Bias%	Relative errors (%)			T test
				Maximum	Average	Minimum	$p^{(1)}$
1	Training	1.3	-0.2	35.3	1.3	-18.4	0.5891
	Validation	23.5	-4.0	43.9	9.7	-33.7	0.4736
2	Training	14.3	0.0	69.8	4.0	-51.8	1.0000
	Validation	31.6	-6.7	192.9	22.9	-40.7	0.3716
3	Training	5.7	0.6	42.1	1.4	-20.2	0.6830
	Validation	28.6	-1.2	56.1	6.5	-34.0	0.8641
4	Training	13.2	0.0	121.4	8.4	-48.3	0.9984
	Validation	34.1	-5.2	147.0	19.8	-57.3	0.5187
5	Training	8.1	0.3	45.7	2.8	-26.0	0.8577
	Validation	26.9	-3.6	48.2	10.0	-38.1	0.5709
6	Training	15.1	0.0	89.6	5.4	-54.9	1.0000
	Validation	27.2	-10.0	113.9	24.4	-37.7	0.1118
(1) Probability by the t test paired.							

The better performance of the ANN in training phase and the worst in the validation (Table 3), not necessarily was generated by an excessive memorization of the training data, its characteristics and noises. The overfitting leads the estimated function contemplate to most of the training points, fact which is not observed in these networks (Braga *et al*., 2007). Furthermore, was applied a data normalization as heuristic, and the hidden layer was not formed by many neurons. Normalize data is important and common on statistical processing of ANN, what allows an approximation of ideal solution (Soares *et al*., 2011). The networks constructed to estimate NUE of the stem by macronutrient, showed lack of statistical significance by *t*-test paired at 5.0% of probability. Although the networks RBF's have submitted a higher probability value in the training phase, it did not imply strong evidence that the estimates are similar to the NUE observations, considering the high deviations and amplitude of the relative error in processing steps (on average from 145.3% in training, and 196.5% in validation).

In general, MLP's networks presented a simpler architecture (Table 2), fewer deviations, expressed by smaller Bias, RMSE% and amplitude of error (Table 3), showing better learning ability. Although the MLP network training is more difficult because their bases are not orthogonal, efficient on high-dimensional spaces, its better statistics may be due to the ability of global learning (it responds to any input space). While the RBF's of local learning, respond in a special way, to a particular limited area of the input space, except when it incorporates multi-quadratic functions in the hidden layer (Braga *et al*., 2007). The RBF network's training was easier, but need in this case, to optimize more the centers (better define the set of centers, and the position of this centers in the input space) and the widths of the Gaussian activation functions. This can also be found in evolutionary algorithms, as noted in price forecast of *Eucalyptus* stem (Coelho *et al*., 2007). There are several techniques to improve the generalization capability of the network, like optimize the regularization parameter or stop training earlier (fewer cycles and interactions), but the objective of this study was not to evaluate them (Braga *et al*., 2007). Therefore, networks MLP's were the most appropriate for estimating NUE of stem than the RBF.

It was chosen ANN 1, 3 and 5 for subsequent graphical analysis (Figure 1). The MLP network's waste followed a homoscedastic distribution as Cochran test and Figure 1. These networks had few noises when assuming as outliers the data lines that, after the processing, showed the NUE of stem by macronutrient upper than 2.5 units of standard deviation compared with the corresponding observed data. The addition of noise to the training patterns can improve the generalization capability of networks (Braga *et al*., 2007). This is consistent with Figure 2, proving the ANN ability of dealing with outliers during the process of adjusting its weights through a learning algorithm. ANN estimates by macronutrients tended to normality by Lilliefors test, allowing the use of most statistical techniques that are based on the central limit theorem. It was proceeded with selection of networks based on the symmetry of the distribution of error classes and dispersion.

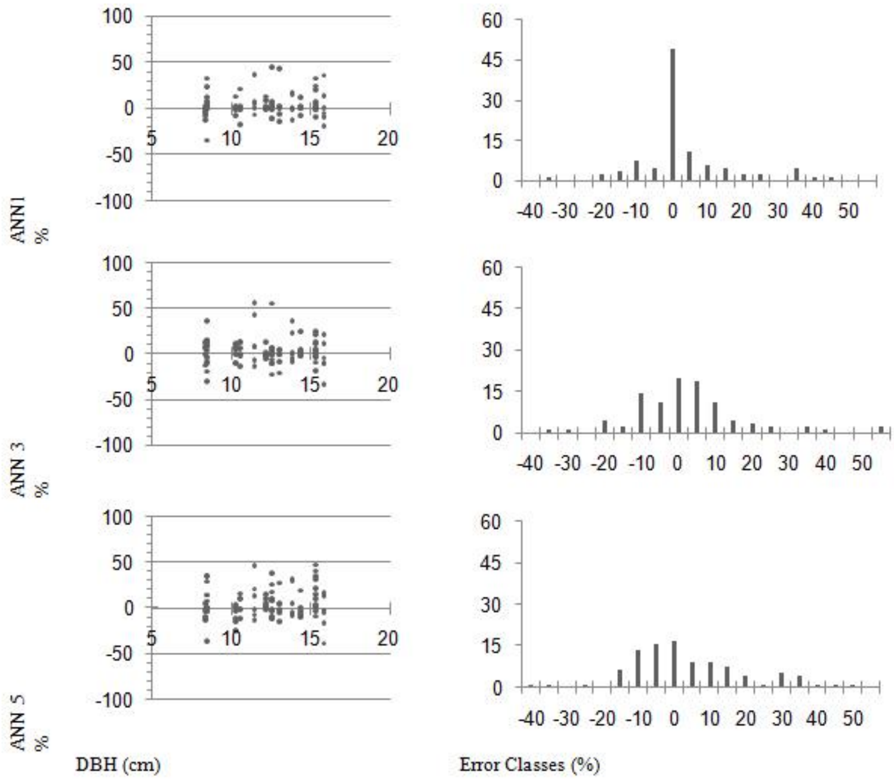

Fig. 1: Dispersion of percentage residuals as a function of DBH and error classes for the Artificial Neural Networks (ANN) with multilayer perception architecture built to estimate the Nutrient Use Efficiency (NUE) of the stem by macronutrient in *Eucalyptus* at 101 months old.

The predictions of the networks 1 and 3 did not generate similar estimates (Figure 2), while the ANN 1 showed better correlations between observed and estimated values. This way, demonstrated that it can capture the biological realism and that the incorporation of an ecophysiological variable, like the specific leaf area, can increase the ability of generalization of MLP's networks. Its generalization capability and connectivity allowed use only one network to perform the estimation of the stem's NUE by macronutrients for *Eucalyptus* in five planting spaces, in a more directly way and with only a statistical tool. Otherwise, the use of traditional methods would imply an analysis of variance, followed by averages test and regression, individually for each nutrient. In many cases the regression analysis are not successful in the estimation of NUE's, these estimates are obtained by the network.

The NUE is the basis for fertilizer recommendations, and the statistical method proposed by this paper provides precise estimates. What makes the field sampling much faster, less expensive and economical, besides being less laborious by the possibility of using simple equipment and easy to handle like the trimmer to collect leaves and portable meter of leaf area. It is needed a constant measurement of the NUE of stem, due to variations that can occur in a same genetic material depending on environmental conditions (Santana *et al*., 1999). So, the MLP network reduces the operational activities to obtain NUE of stem.

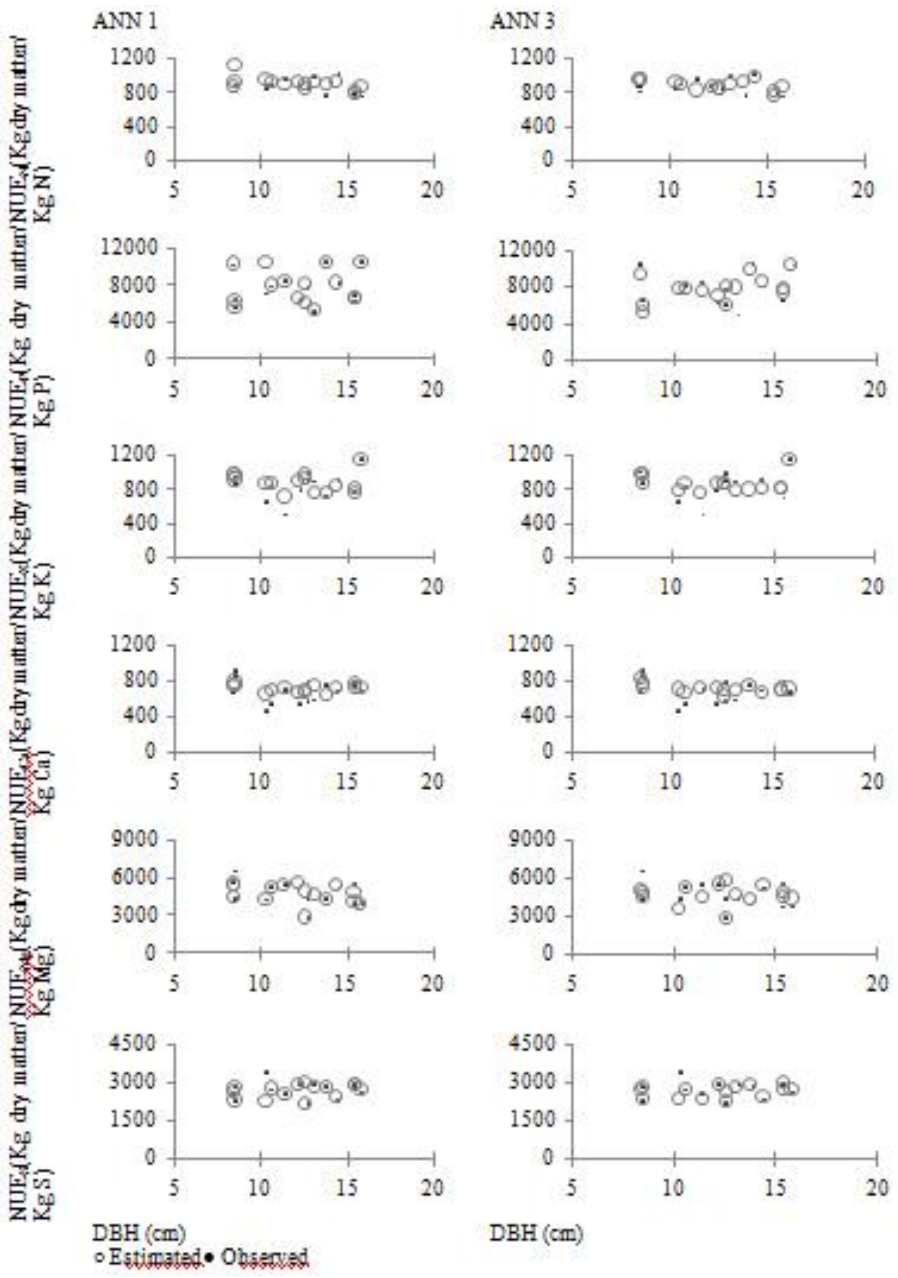

Fig. 2: Estimation of Nutrient Use Efficiency (NUE) of the stem by macronutrient in *Eucalyptus* by Artificial Neural Networks (ANN) with multilayer perception architecture built 101 months old.

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Conclusion:

The modeling by artificial neural networks using multilayer perceptron architecture is a suitable alternative, accurate and biologically realistic to estimate the nutrient use efficiency (NUE) by macronutrient, used in different spacings.

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