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Article

Ecophysiology modeling by artificial neural networks for different spacings in eucalypt

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Abstract

Growth and production models are widely used to predict yields and support forestry decisions. Artificial Neural Networks (ANN) are computational models that simulate the brain and nervous system human functions, with a memory capable of establishing mathematical relationships between independent variables to estimate the dependent variables. This work aimed to evaluate the efficiency of eucalypt biomass modeling under different spacings using Multilayer Perceptron networks, trained through the backpropagation algorithm. The experiment was installed in randomized block, and the effect of five planting spacings was studied in three blocks: 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 e T5 – 3.0 x 3.0 m. A continuous forest inventory was carried out at the ages of 48, 61, 73, 85 and 101 months. The leaf area, leaf perimeter and specific leaf area were measured at 101 months in one sample tree per experimental unit. Two thousand ANN were trained, using all inventoried trees, to estimate the eco-physiological attributes and the prognosis of the wood biomass. The artificial neural networks modeling was adequate to estimate eucalypt wood biomass, according to age and under different spacings, using the diameter-at-breast-height and leaf perimeter as predictor variables.

Keywords: wood biomass, planting density, ecophysiology, artificial intelligence, prognosis

Introduction

Clean energy production from forest biomass is a sustainable alternative to fossil fuels (non-renewable). Technological advances that aim to increase productivity are necessary and provide subsidies in choice of the most adapted genetic material, better planting methods, conducting and harvesting a forest stand.

Dry matter accumulation is an integrated measure of plant physiological performance over time (Merchant et al., 2010). The correlation of this accumulation with photosynthesis indicates that it is able to express competition for space, nutrients, water, solar energy, temperature, carbon dioxide, utilization efficiency of these resources and interaction among them (Almeida et al., 2007; Montaldo et al., 2008; Costa et al., 2009).

Biomass quantity and quality can be affected by competition imposed by the planting spacing. Greater initial biomass production by area is expected in more densely planted and growth stagnation occurs at younger ages, due to intensification of resource utilization. Throughout the rotation, differences in growth between different densities tend to be minimized (Campos & Leite, 2013).

Growth and production models are widely used to predict yields and assist silvicultural decision making. Mechanistic models (or process

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models) are flexible to certain environmental characteristics, encompassing growth trends and biological assumptions (Miehle et al., 2009; Campos & Leite, 2013). These models provide estimates of forest productivity by weighing the influence of environmental factors (Almeida et al., 2007). The leaf area, specific leaf area and perimeter are eco-physiological parameters that influence photosynthetic capacity and leaves respiration (Alcorn et al., 2008; Montaldo et al., 2008; Ferreira et al., 2016), besides being useful to characterize plant adaptations to environmental conditions. Among these, specific leaf area is routinely used in prediction models, such as 3-PG (Physiological Processes Predicting Growth) and CABALA (Nouvellon et al., 2010).

As alternative to traditional regression modeling, Artificial Neural Networks (ANNs) are composed of a massive parallel system integrated of simple processing units (artificial neurons), which calculate certain mathematical functions and allow to generalize assimilated knowledge to unknown data (Gorgens et al., 2009; Binoti, 2010; Binoti et al., 2015; Zanuncio et al., 2016). For the training of multilayer perceptron networks (multilayer), traditionally, backpropagation algorithm is adopted to optimize predictive capacity. This algorithm extends network's ability to solve non-linearly separable problems (Braga et al., 2007).

This work aimed to evaluate the efficiency of eucalypt biomass production modeling under different spacings using artificial neural networks technique.

Material and Methods

This work was conducted in Itamarandiba municipality – MG, at 17° 50' south latitude and 42° 49' west longitude, Aperam Bioenergia area. The predominant climate in region is classified as Cwa by Köppen international system (Köppen, 1936), with mild and dry winters and hot, rainy summers. The dry season is well defined, from April to September, with a monthly water deficit of 30 to 50 mm (INMET, 2010). Annual averages of rainfall and temperature are 1,160 mm and 20°C, respectively (Pulrolnik et al., 2009).

The experiment was installed in December 2002 using a hybrid of *Eucalyptus grandis* W. Hill ex Maiden x *E. camaldulensis* Dehnh, on flat relief terrain, Red-Yellow Latosol and at 1,097 m altitude. The design was in three random blocks. The treatments consisted of the following planting spacings: 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, 3 m was the fixed distance between planting lines. Each experimental unit was defined as six lines with 28 trees, totaling 168 individuals, of which 48 were measured, due to adoption of double border.

A continuous forest inventory was carried out at the ages of 48, 61, 73, 85 and 101 months. The Diameter-at-Breast-Height overbark (DBH - at height of 1.30 m from the ground, cm) and total Height (H, m) of all trees were measured. At 101 months, 50 trees were felled in each spacing for rigorous cubage up to commercial height (diameter 4 cm), distributed in classes with regular intervals of 5 cm DBH.

Wood biomass ($Mg.ha^{-1}$) was estimated for all trees measured in the inventories, using multiplicative relationship between underbark Volume (V, m^3) and Basic Density (BD, g cm^{-3}). Volume was estimated fitting linearized model of Schumacher & Hall (1933) (Table 1). At the age of 101 months, 6 cm thick discs were removed at 0% (base), 25%, 50%, 75% and 100% (top) of commercial height in one sample tree (the one with mean square diameter) per experimental unit, totaling 15 trees. From each disc, opposite wedges were obtained, which were used to determine BD according with water immersion method. The BD for wood biomass estimation ranged from 0.518 to 0.567 g cm^{-3} between spacings.

In the same sample trees, it was measured: Leaf Area (LA), Leaf Perimeter (LP), Specific Leaf Area (SLA), leaves number and leaves biomass. LA and LP were obtained with leaf area meter (CI-203, CID Inc., USA) of 10 leaves collected in each third of the canopy (upper, middle and lower), adding up to 30 units per canopy. Leaves were collected from the fifth insertion of branches, which were in the center of thirds. The leaves were dried at 65°C until constant weight in a oven with forced air circulation and, from the dry biomass, specific leaf area was calculated using the formula:

$SLA = LA.DM^{-1}$ (eq 1), where DM represents foliar dry mass. LA, LP and SLA data were submitted to Pearson correlation analysis. Leaves number per hectare was estimated as a function of number versus biomass ratio of leaves sampled. To obtain leaves biomass, this component was weighed in field and subsamples were collected to obtain dry mass.

Table 1. Equations used to estimate underbark volume and average values found for Basic Density (BD) of eucalypt in different planting spacings

Spacings	Equations	$\bar{R}^2$	BD (g cm^{-3})
3.0 x 0.5 m	$LnV = -9.966^{*} + 2.278^{*}LnDBH + 0.702^{*}LnH$	0.995	0.524 ± 0.006
3.0 x 1.0 m	$LnV = -10.103^{*} + 1.958^{*}LnDBH + 0.987^{*}LnH$	0.991	0.554 ± 0.001
3.0 x 1.5 m	$LnV = -10.336^{*} + 1.944^{*}LnDBH + 1.060^{*}LnH$	0.994	0.559 ± 0.003
3.0 x 2.0 m	$LnV = -10.569^{*} + 1.745^{*}LnDBH + 1.309^{*}LnH$	0.989	0.564 ± 0.003
3.0 x 3.0 m	$LnV = -10.787^{*} + 1.644^{*}LnDBH + 1.454^{*}LnH$	0.983	0.546 ± 0.023

*significant at 5% probability by t-test; DBH (cm); H (m); V = underbark volume (m^3); and $\bar{R}^2$ = adjusted determination coefficient. Residual standard errors of the equations were lower than 0.1m^3. BD values indicate mean ± standard deviation, calculated from 3 trees with mean diameter by spacing (totaling 15 units).

The ANN input variables for simultaneous estimation of eco-physiological attributes were numerical (DBH, H and spacing between plants (Spa, m) and categorical (ECF: LA (dm^2) – 1, LP (m) – 2 and SLA (cm^2 g^{-1}) – 3). From the generated network, LA, LP and SLA were estimated for all measured trees in the inventories, which average results per plot extrapolated to a hectare unit.

For the wood biomass future projection (B_2), ANN models were looked for from the functional relations between numerical variables.

$$B_2 = f(DBH_1, H_1, LA_1, LP_1, SLA_1, A_1, A_2, Spa) \qquad \text{(eq. 2)}$$

where: A_1 (age, months); DBH_1 (cm); H_1 (m); LA_1 (m^2), LP_1 (Km) and SLA_1 (cm^2 g^{-1}) refer to the current values of these variables; B_2 (Mg ha^{-1}) and A_2 (months) at their future values and Spa (m,) plant spacing. We defined 19 ANN models (Table 2).

Table 2. Identification and inputs used in Artificial Neural Networks (ANN) to estimate eucalypt biomass up to 101 months old

ANN	N	Architecture	Numerical inputs
1	60	MLP 8-5-1	A_1, A_2, Spa, DBH_1, H_1, LA_1, LP_1, SLA_1
2	60	MLP 7-12-1	A_1, A_2, Spa, DBH_1, LA_1, LP_1, SLA_1
3	60	MLP 7-4-1	A_1, A_2, Spa, H_1, LA_1, LP_1, SLA_1
4	60	MLP 6-4-1	A_1, A_2, Spa, LA_1, LP_1, SLA_1
5	60	MLP 6-10-1	A_1, A_2, Spa, DBH_1, LA_1, LP_1
6	60	MLP 6-8-1	A_1, A_2, Spa, DBH_1, LA_1, SLA_1
7	60	MLP 6-3-1	A_1, A_2, Spa, DBH_1, LP_1, SLA_1
8	60	MLP 5-11-1	A_1, A_2, Spa, LA_1, LP_1
9	60	MLP 5-6-1	A_1, A_2, Spa, LA_1, SLA_1
10	60	MLP 5-7-1	A_1, A_2, Spa, LP_1, SLA_1
11	60	MLP 5-9-1	A_1, A_2, Spa, DBH_1, H_1
12	60	MLP 5-4-1	A_1, A_2, Spa, DBH_1, LA_1
13	60	MLP 5-3-1	A_1, A_2, Spa, DBH_1, LP_1
14	60	MLP 5-3-1	A_1, A_2, Spa, DBH_1, SLA_1
15	60	MLP 4-7-1	A_1, A_2, Spa, DBH_1
16	60	MLP 4-5-1	A_1, A_2, Spa, H_1
17	60	MLP 4-10-1	A_1, A_2, Spa, LA_1
18	60	MLP 4-3-1	A_1, A_2, Spa, LP_1
19	60	MLP 4-3-1	A_1, A_2, Spa, SLA_1

n = observations number.

Feedforward networks trained through the backpropagation algorithm were employed. Data normalization and equalization were realized in all pre-processing. The data was randomly divided into training groups (80% of samples) and validation (20%), mutually exclusive (Holdout method).

Two thousand ANN of the Multilayer Perceptron (MLP) type were trained: 100 for estimation of eco-physiological attributes and

1900 for projection of wood biomass (100 for each functional relation). From these ANN, one was selected per functional relationship based on deviations between observed and estimated values. We chose MLP due to its ability to solve greater complex problems in input space, which increases the number of adjusted parameters (Braga et al., 2007). The layers amount and of neurons per layer was optimized by Intelligent Problem Solver (IPS) tool of Statistica 7.0 software (Statsoft, 2007).

Points that extrapolated the general trend, in each planting spacing, were not removed in order to verify networks' ability to deal with outliers. Accuracy assessment and comparison between phases of training and validation of networks were based on the correlation coefficient, relative error, Root Mean Square Error (RMSE,%), bias (%) and visual analysis of dispersion graphs and distribution of percentage frequency of residues. Estimated and observed values were compared among themselves by paired t-test at 5% significance, as suggested by Gorgens et al. (2009), Lafetá et al. (2014) and Cabacinha & Lafetá (2017).

All statistical analyzes were performed using with the help of Statistica 7.0 software (Statsoft, 2007).

Results and Discussion

The artificial neural network structure for eco-physiological attributes estimation was 6-8-1 (neurons number in input, intermediate and output layers, respectively) with exponential activation functions in intermediate and output layers. In view of eco-physiological interaction complexity and of plant growth, the accuracy was considered satisfactory. Training and validation phases presented around 6.58% RMSE and 0.48% Bias. Distribution behavior of percent residuals was homocedastic, concentrating deviations between -12.5 to + 7.5% (Figure 1). This interval was acceptable and it is in accordance with observed for projections of dendrometric attributes of ± 12.5% error for the projections of DBH, total height and eucalypt volume (Binoti, 2010) and up to ± 17.5% for height estimation in pine and eucalypt plantations (Campos et al., 2016), using ANN.

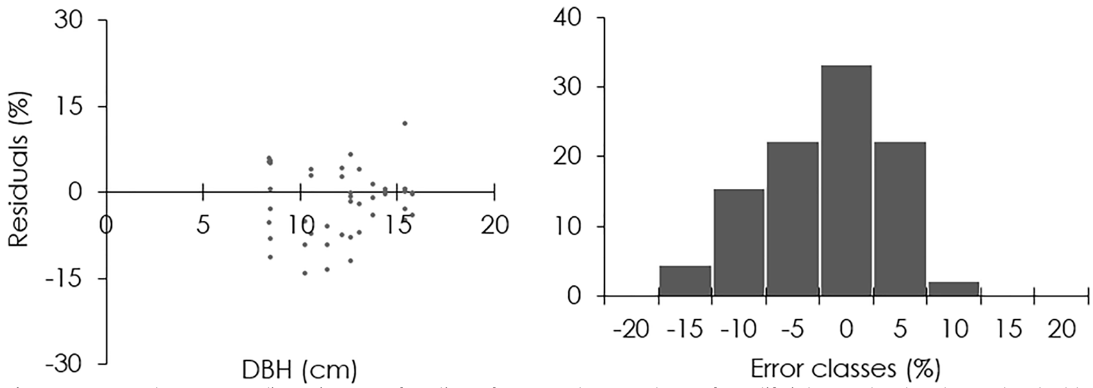

Figure 1. Percentage errors dispersion as a function of DBH and errors classes for artificial neural network constructed to eco-physiological attributes estimate (leaf area, leaf perimeter and specific leaf area) of eucalypt at 101 months old.

Eco-physiological attributes estimates from ANN generalization were able to discriminate differences between spacing as a function of age (Figure 2). This fact has great practical importance, since it enables to make inferences related to established stands competition in different planting densities, as well as potential inputs for mechanistic models adjustment of growth and production. Leaf area, leaf perimeter and specific leaf area increased as planting density and DBH increased, although there was little variation as a function of age. This same trend for LA, LP and SLA was observed by Maire et al. (2011), which investigated MODIS reflectance time series to estimate leaf attributes in eighteen *Eucalyptus* spp. management units. Adaptive anatomical changes in leaves can occur when there is change intensity / light quantity in the canopy (Nascimento et al., 2015). These results are consistent with number and amount of leaves estimated as a function of biomass sampling (Figure 3).

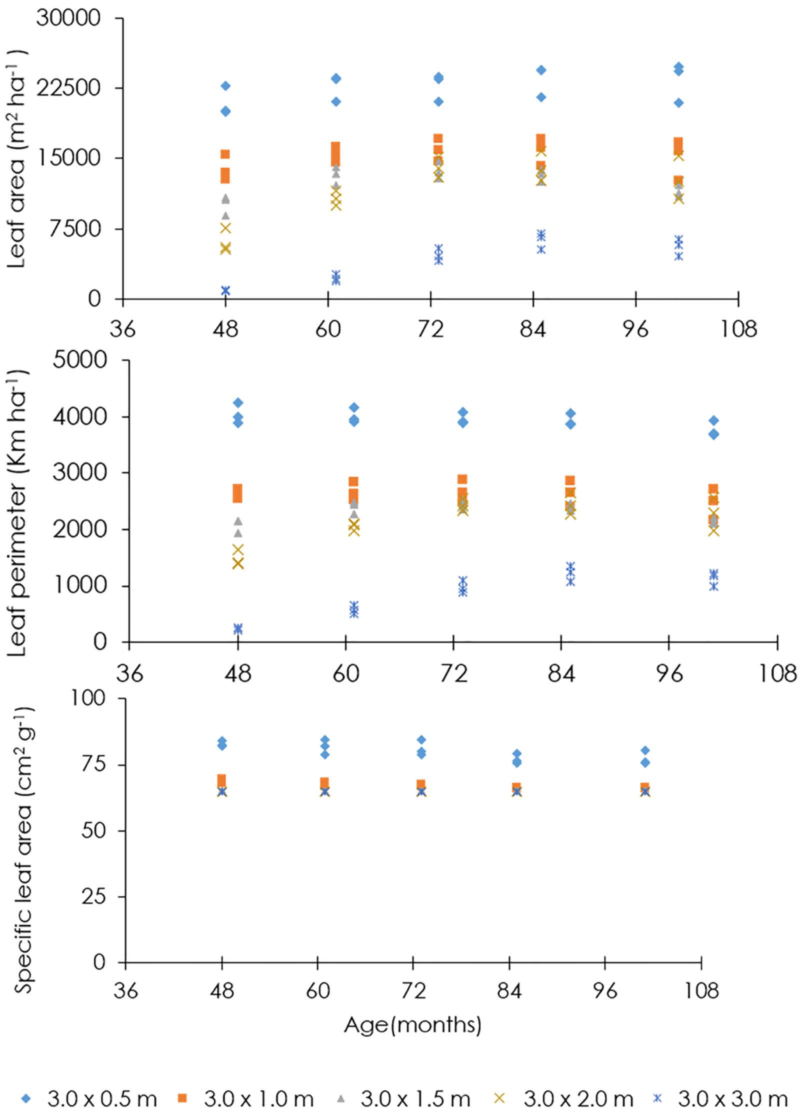

Figure 2. Eco-physiological attributes estimates of eucalypt plants, per hectare, through artificial neural networks throughout ages, grown at different spacings.

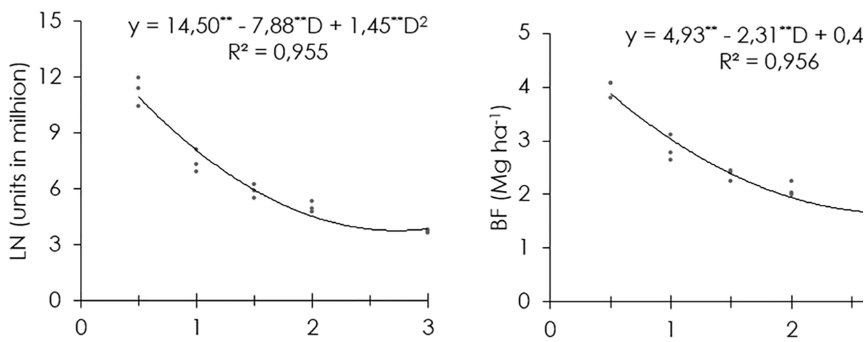

Figure 3. Number (LN) and biomass (LB) of eucalypt plants leaves, per hectare, as a function of distance between plants (D) at 101 months old. *significant at 5% probability by t-test.

The greater specific leaf area in smaller spacings may be a plant morphological response to compensate greater shading between leaves imposed by competition, which begins with canopies contact. Similarly, Ferreira et al. (2016) studying *Bertholletia excelsa* Bonpl. plantations to identify spatial and temporal factors effects on leaf attributes, observed a greater specific leaf area in leaves subjected to shading. It is important to note that both perimeter and leaf area can be regulated by environmental variables such as temperature, precipitation and light intensity (Vieira et al., 2014; Ferreira et al., 2016). As it reduces spacing, trees tend to get smaller due to increased competition. In general, trees height and diameter growth, per hectare, correlated negatively with the eco-physiological attributes (Table 3). Correlations were significant ($p < 0.05$), the highest value (in modulus) was observed between DBH and leaf perimeter ($|-0{,}851^*|$)

Table 3. Pearson correlation coefficients between dendrometric variables, conventionally measured in forest inventories, and eucalyptus eco-physiological variables

Variables	LA	LP	SLA
DBH	-0.819*	-0.851*	-0.789*
H	-0.637*	-0.686*	-0.788*

*significant at 5% probability by t-test; LA = leaf area; LP = leaf perimeter and SLA = specific leaf area.

ANN for wood biomass estimation showed a predominance of non-linear activation functions in intermediate layers (Table 4). According to Braga et al. (2007), this behavior allows successive layers composition to have greater predictive capacity, facilitating generation of global receptive fields by MLP. Considering dendrometric and eco-physiological inputs (ANNs 15 to 19), greater complexity expressed by neurons number in the intermediate layer was observed for leaf area. ANNs 7, 13, 14, 18 and 19 were the simplest, as it can be observed by smaller neurons number in their architecture.

Table 4. Artificial Neural Networks (ANN) characteristics built to eucalypt wood biomass projection up to 101 months old

ANN	Architecture	Correlation coefficients		Cycles	Activation Functions	
		Training	Validation		Intermediate	Output
1	MLP 8-5-1	0.9846*	0.9382*	878	Logistic	Exponential
2	MLP 7-12-1	0.9730*	0.9403*	121	Identity	Identity
3	MLP 7-4-1	0.9660*	0.9063*	235	Tangential	Logistic
4	MLP 6-4-1	0.9529*	0.8542*	709	Tangential	Identity
5	MLP 6-10-1	0.9494*	0.9399*	83	Identity	Exponential
6	MLP 6-8-1	0.9702*	0.9474*	451	Logistic	Logistic
7	MLP 6-3-1	0.9722*	0.9614*	10000	Exponential	Exponential
8	MLP 5-11-1	0.9112*	0.7869*	2321	Logistic	Exponential
9	MLP 5-6-1	0.9220*	0.7851*	771	Tangential	Tangential
10	MLP 5-7-1	0.9145*	0.5769*	517	Logistic	Tangential
11	MLP 5-9-1	0.9657*	0.9486*	319	Logistic	Logistic
12	MLP 5-4-1	0.9757*	0.9493*	215	Logistic	Tangential
13	MLP 5-3-1	0.9715*	0.9262*	264	Logistic	Identity
14	MLP 5-3-1	0.9747*	0.9485*	395	Logistic	Identity
15	MLP 4-7-1	0.9769*	0.9635*	10000	Exponential	Exponential
16	MLP 4-5-1	0.9608*	0.8383*	10000	Exponential	Exponential
17	MLP 4-10-1	0.9033*	0.7802*	473	Logistic	Logistic
18	MLP 4-3-1	0.8873*	0.7241*	215	Logistic	Tangential
19	MLP 4-3-1	0.8698*	0.8207*	1177	Exponential	Logistic

*significant at 5% probability by t-test.

Networks complexity was not necessarily caused by a greater number of times in which training set was presented to architecture, since network 7 had few neurons in intermediate layer (3 units) and more cycles (10000) when compared to ANNs 5 and 17. Cycles and number neurons in the intermediate layer had a correlation coefficient of -0.15^{ns}. Most correlation coefficients were above 0.80. The difference between training and validation coefficients were, on average, 0.08, being higher in ANN 10 (difference of 0.34). It is likely that this difference found in ANN 10 related to higher variation amplitudes of relative error during the validation phase; in this network, the ratio between relative error amplitudes of validation and training phases was 1.43. In addition, performance of training and validation phases can be influenced by neurons and cycles number (Braga et al., 2007; Maeda et al., 2009).

All networks for wood biomass projection presented no statistical significance by t-test (p> 0.05) and no bias in the training phase, with low Bias, RMSE and error amplitude (Table 5). Obtained estimates with network 5 were not statistically significant. This may be related to an underfitting generated by a small number of cycles (Table 4), preventing network from achieving its best performance (Cabacinha & Lafetá, 2017). Underfitting phenomenon is common and related to network subtraining, which does not converge adequately during adjustment of its synaptic weights (Braga et al., 2007).

Table 5. Artificial Neural Networks (ANN) accuracy built to eucalypt wood biomass projection up to 101 months old

ANN	Phases	RMSE (%)	Bias (%)	Relative errors (%)			t-test
				Maximum	Average	Minimum	P
1	Training	2.41	-0.11	9.69	0.23	-4.52	0.7574
	Validation	3.97	1.00	4.32	-0.93	-11.09	0.3835
2	Training	3.23	0.15	9.31	0.04	-8.64	0.7438
	Validation	3.98	1.34	2.40	-1.24	-10.40	0.2395
3	Training	3.57	0.13	10.31	0.05	-11.11	0.7942
	Validation	4.66	0.86	8.84	-0.63	-9.40	0.5299
4	Training	4.16	0.00	12.74	0.20	-8.41	1.0000
	Validation	7.12	0.35	9.42	-0.40	-13.88	0.8680
5	Training	4.30	0.00	10.61	0.21	-11.16	0.9976
	Validation	4.72	2.60	1.59	-2.50	-11.79	0.0401
6	Training	3.38	0.18	9.89	0.02	-8.92	0.7197
	Validation	3.97	1.66	2.89	-1.61	-9.99	0.1338
7	Training	3.21	-0.03	10.19	0.17	-9.35	0.9430
	Validation	3.31	0.66	3.83	-0.70	-7.85	0.4920
8	Training	5.65	-0.10	13.50	0.45	-8.64	0.8988
	Validation	7.93	3.54	6.98	-3.14	-12.99	0.1082
9	Training	5.31	0.01	13.64	0.26	-8.98	0.9922
	Validation	8.28	3.61	7.44	-3.28	-16.63	0.1178
10	Training	5.55	0.05	12.84	0.26	-9.56	0.9532
	Validation	10.60	2.65	16.26	-2.16	-16.42	0.3884
11	Training	3.65	0.24	11.04	-0.02	-8.90	0.6467
	Validation	4.07	1.97	2.41	-1.89	-9.93	0.0773
12	Training	3.04	0.20	10.73	-0.06	-9.22	0.6554
	Validation	3.67	0.93	4.21	-0.91	-9.04	0.3823
13	Training	3.25	0.00	9.21	0.12	-7.78	1.0000
	Validation	4.40	1.40	3.84	-1.29	-10.68	0.2655
14	Training	3.06	0.00	10.83	0.11	-9.02	1.0000
	Validation	3.67	0.89	5.43	-0.86	-8.41	0.4028
15	Training	2.93	-0.04	10.77	0.16	-9.48	0.9292
	Validation	3.49	1.25	3.66	-1.30	-9.39	0.2084
16	Training	3.80	0.00	13.58	0.16	-7.62	0.9982
	Validation	6.74	2.78	10.60	-2.44	-15.50	0.1408
17	Training	5.89	-0.07	12.68	0.44	-9.73	0.9359
	Validation	7.77	3.09	7.28	-2.70	-11.93	0.1576
18	Training	6.33	0.01	13.04	0.39	-12.33	0.9946
	Validation	8.86	3.67	7.89	-3.20	-14.77	0.1393
19	Training	6.76	-0.02	12.22	0.48	-12.25	0.9857
	Validation	7.18	3.19	8.71	-2.79	-11.83	0.1097

Although the ANNs presented a good training and a worse validation, RMSE and Bias varied little between processing phases and relative amplitudes errors were, on average, 20.65% training and 17.89% validation (Table 5). Due to smaller neurons number in the intermediate layer, higher correlation coefficient in validation phase and precision statistics values, ANNs 7, 13, 14 and 15 were chosen for subsequent graphical analyzes (Figure 4).

Noise absence observed in Figure 4 demonstrated ANN ability to deal with outliers during the process of adjusting its weights through the learning algorithm. After network selection,

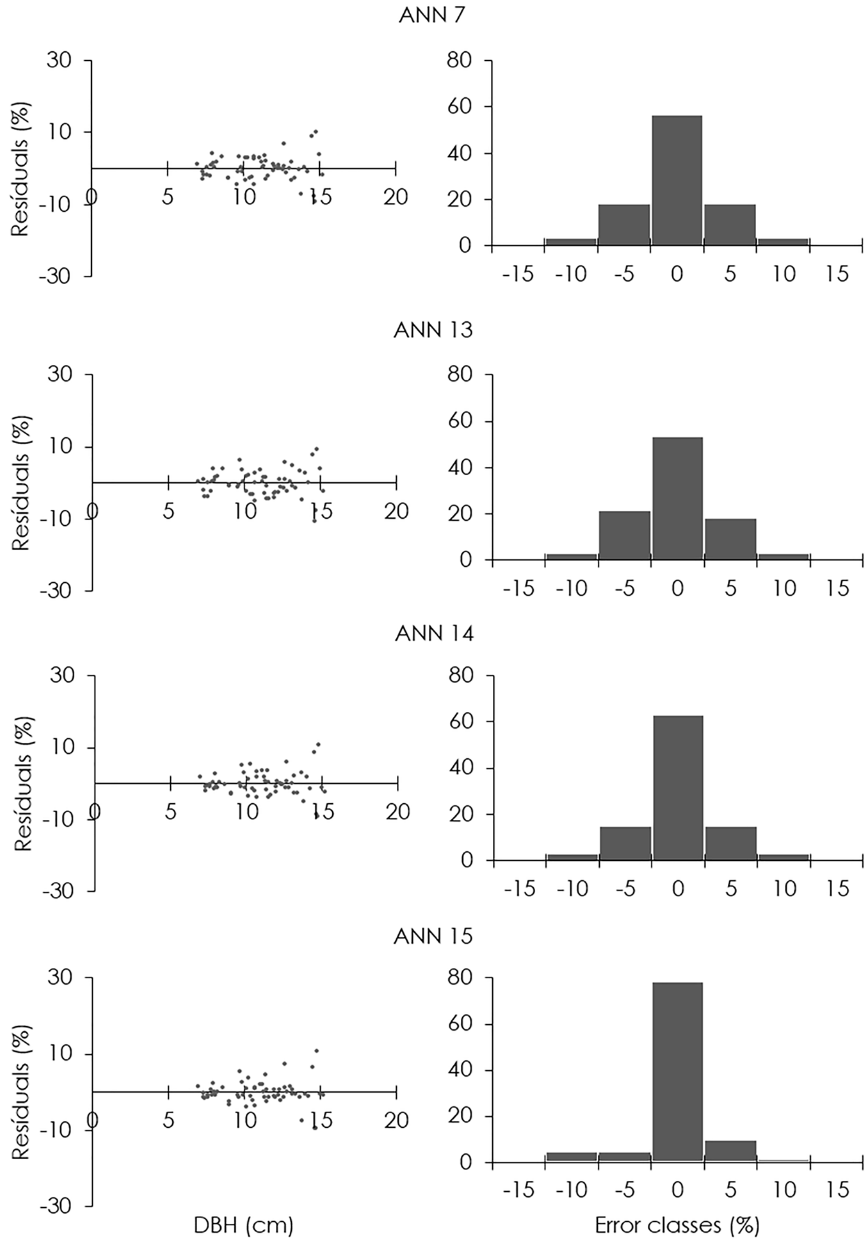

Figure 4. Percentage errors dispersion as a function of DBH and errors classes for Artificial Neural Networks (ANN) built to eucalypt wood biomass projection up to 101 months old.

future projection of wood biomass production was carried out considering current age of 48 months and graphical analysis of dispersion between observed and estimated values (Figure 5). Wood biomass prognosis with ANNs 7, 13, 14 and 15 did not generate similar projections. ANNs 7 and 15 did not generate biologically realistic estimates, disagreeing with observed values. This was probably consequence of excessive memorization of training data (10,000 cycles) or overfitting.

ANNs 13 and 14 showed less estimates dispersion and better projections along age. These networks were the only ones that exhibited logistic and identity activation functions in the intermediate and output layers, respectively. The combination of both activation functions may have favored network predictive capability with MLP architecture. However, a disadvantage observed in network 14 was loss in accuracy and underestimation of wood biomass estimated from 73 months, not capturing actual reduction of growth rate. ANN 13, which used DBH and leaf perimeter in its functional relationship, was able to learn and generalize assimilated knowledge to biomass projection, demonstrating that it

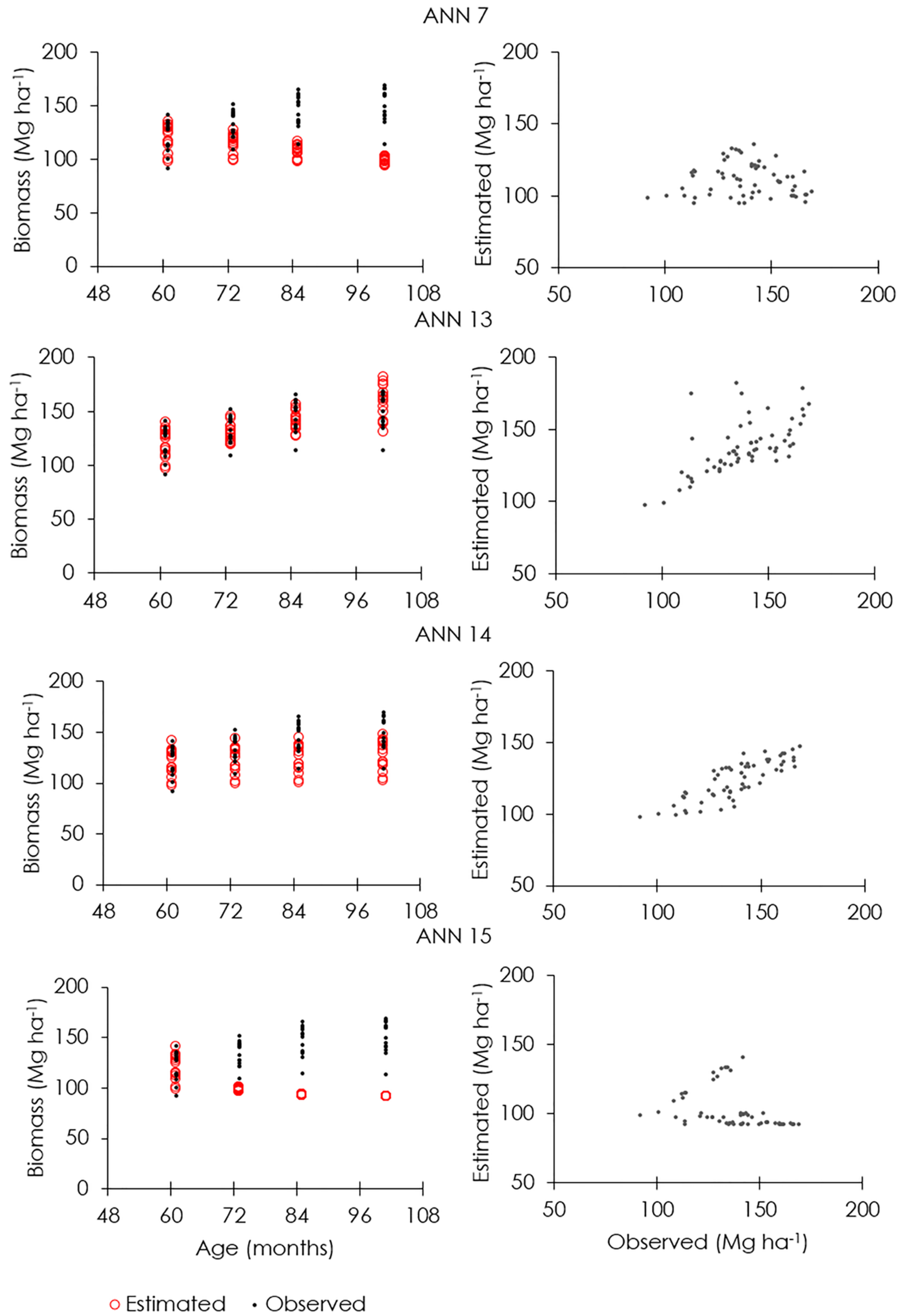

Figure 5. Future projection of eucalypt wood biomass production considering current age of 48 months and dispersion between observed and estimated values.

can capture biological realism of a cumulative production curve, characterized by a sigmoidal behavior.

Conclusions

Artificial neural network modeling, with Multilayer Perceptron architecture and trained by backpropagation algorithm, can be used with good precision to estimate eucalypt wood biomass at different planting spacings.

Artificial neural networks technique can be recommended for prediction of eucalypt wood biomass, using diameter-at-breast-height and leaf perimeter in set of predictor variables.

Dendrometric and eco-physiological predictors variables combination can be a viable alternative to improve quality of eucalypt wood biomass estimates.

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