



# Prognosis on the diameter of individual trees on the eastern region of the amazon using artificial neural networks



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## ARTICLE INFO

### Article history:

Received 24 June 2016

Received in revised form 6 October 2016

Accepted 9 October 2016

Available online 15 October 2016

## ABSTRACT

The prognosis of forest structure along the cutting cycle, using models of individual trees, is one of the alternatives to manage tropical forests aiming at sustainability. Currently, in forest management practiced in the Amazon Region, growth and production models are not used to predict the future stock of the forest. Thus, the sustainable economic and environmental aspects of this activity remain uncertain. The aim of this present work was to model the growth of individual trees in a forest managed in the Amazon Region, by using artificial neural networks (ANN) to serve as subsidy to the wielder in obtaining future stock after logging, thus reducing uncertainty on forest management sustainability. Selective harvest was carried out in 1979 with an intensity of  $72.5 \text{ m}^3 \text{ ha}^{-1}$  in a 64 ha area in the Tapajós National Forest - PA. In 1981, 36 permanent plots ( $50 \text{ m} \times 50 \text{ m}$ ) were installed at random and inventoried. There were nine successive measurements in 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010, and 2012. In the modeling of the future diameter, training and testing of ANN were carried out, including different semi-independent competition indexes (*DSICI*). All ANN, with and without *DSICI*, presented correlation above 99%, RMSE below 11%, and EF above 0.98. Based on the prognosis of tree growth, we were able to conclude that ANN can be effectively used to assist in the management of tropical forests and, thus, allow for the most suitable cutting intensity and cutting cycle per species, ensuring environmental and economic sustainability of forest management.

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## 1. Introduction

In 2011, 403 million hectares of tropical forest in the world were directed toward wood production (Putz et al., 2012). Publications revealed that the selective wood cutting, conducted according to the principles of the sustainable forest management, substantially maintains the biodiversity (85–100%), carbon stocks (76%) (Putz et al., 2012) and the wood volume (88%) considering the intensity that is currently applied on the Amazon (Reis et al., 2010), after the harvest, and that the yields increase if the reduced impact exploration and forestry treatments are used.

The management of tropical forests is a production activity that assures the legality and sustainability of the wood production

throughout time, both from the environmental (Reis et al., 2015, 2010) and economic (Santana et al., 2012) perspectives. Despite that, the growth and production modeling is neglected on the Brazilian forest management plans. Modeling, mainly of individual trees, is one of the tools that may guide the long-term planning, offering technical subsidies for the decision on the cut intensity and the most adequate cutting cycle for the sustainability of the forest (Huth and Ditzer, 2001; Phillips et al., 2004; Valle et al., 2007).

On individual tree models, the tree is the modeling unit used to simulate the growth, input and mortality, considering some level of competition (competition index). Therefore, they get closer to the complexity of the ecosystem of tropical native forest, as well as allow the simulation of different forest harvesting interventions. However, few models have been developed for tropical forests of the Amazon, highlighting CAFOGROM, a cohort model; and SYMFOR, an individual tree model (Alder and Silva, 2000; Azevedo et al., 2008; Phillips et al., 2004).

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In addition to the traditional adjustment method for the models on an individual tree level, based on linear and non-linear regression, alternatively, artificial intelligence may be used, through the Artificial Neural Networks (ANNs) (Diamantopoulou, 2005). ANNs are computer models inspired by the nervous system of living beings. One ANN creates a set of parallel processing units, characterized by artificial neurons that are interconnected through a large number of interconnections (Silva et al., 2010).

Some studies have shown the successful application of ANNs for the modeling of individual trees, such as, for example, to estimate the growth and mortality on uneven-aged forests (Ashraf et al., 2015; Castro et al., 2015; Richards et al., 2008) and on even-aged forests (Castro et al., 2013a,b). However, no study has used artificial neural networks (ANNs) for the modeling of individual trees on managed uneven-aged forests.

Considering this gap, this study was developed with the purpose of modeling the projection of the future diameter of individual trees on a managed forest on the Amazon, using artificial neural networks to subsidize technical decisions on forest management.

## 2. Material and methods

### 2.1. Studied area

The studied area is located on the Tapajós National Forest, near Km 67 (55°00'W, 2°45'S) of the BR-163 Highway, Cuiabá-Santarém. It is part of the Amazon biome and the typology is Dense Ombrophilous Forest with solid ground. The climate of the region is humid and tropical with mean annual temperature of 26 °C, and it is classified as Ami according to Köppen's system. The mean relative humidity corresponds to 86%, with mean annual rainfall from 1900 to 2200 mm. It has a flat to wavy topography, with the occurrence of a Dystrophic Yellow Latosol (Alvares et al., 2013; Costa Filho et al., 1980).

On the Tapajós National Forest, especially on the studied area, Costa Filho et al. (1980) reported the use of selective harvest, conducted during the 1940's, for four species with high commercial value: Brazilian rosewood (*Aniba rosaeodora* Ducke), Brazilian redwood (*Manilkara huberi* (Ducke) A. Chev.), Brazilian walnut (*Cordia goeldiana* Huber) and cedar (*Cedrela odorata* L.).

In 1979, on 64 ha of the studied area, an intensive harvest of 64 wood species was conducted, with mean extraction volume of 72.5 m<sup>3</sup> ha<sup>-1</sup> (Reis et al., 2010).

The species that stood out in terms of harvest volume, at the time, were: *Hymenaea courbaril* L., *Carapa guianensis* Aubl., *Manilkara huberi*, *Lecythis lurida* (Miers) S. A. Mori., *Bertholletia excelsa* Humb. & Bonpl., *Astronium lecontei* Ducke, *Goupia glabra* Aubl., *Virola michelii* Heckel, *Erisma uncinatum* Warm. and *Terminalia amazonia* (J. F. Gmel) Exell, which, together, represented 47.4% of the total extracted volume (Reis et al., 2010). The harvest was conducted according to two treatments: cutting all trees with *dbh* ≥ 45 cm, on 39 ha; and cutting the trees with *dbh* ≥ 55 cm, on 25 ha (Costa Filho et al., 1980). However, the treatments were considered together, creating only one community, considering the high similarity observed on the comparisons conducted (Reis et al., 2010).

In 1981, 36 permanent plots of 50 m × 50 m each were randomly installed, where all trees with *dbh* ≥ 5 cm were botanically identified *in loco*. New measurements for these permanent plots occurred in 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010, and 2012.

### 2.2. Variables and data used for the training and testing of neural networks

The permanent plots were divided into two groups: one group constituted by 29 plots for the training of ANNs, and the other

group with 7 plots, for the generalization of trained ANNs, at a total of 80% of data for training and 20% for generalization (validation). The plots used in generalizing (validation) were not part of the training. This was to evaluate the model with independent data to the training of ANNs.

In order to model the projection of the future diameter of the individual trees, the input variables were: *dbh*, measured diameter at a height of 1.30 m (mm) in relation to the soil, forest class (FC), trunk identification class (TIC), competition index (CI), growth groups (GG), liana infestation intensity (LI0: non-observed variable; LI1: no liana on the tree; LI2: presence of liana, however, not causing damages; and LI3: presence of liana, restricting growth); and crown lighting (CL0: non-observed variable; CL1: emerging crown or completely exposed to the light; CL2: partially lighted crown, that is, partially covered by neighboring tree crowns; and CL3: crown completely covered by neighboring tree crowns). The output variable was the Annual Periodical Increment on *dbh* ( $API_{dbh}$  – mm year<sup>-1</sup>) which was then used to calculate the future diameter (*dbh*<sub>2</sub>).

The forest classes (FC) were defined according to the methodology suggested by Silva et al. (2005):

1. Mature forest: the sub-plot shows at least one tree with a diameter equal to or larger than 40 cm.
2. Forest under construction: the sub-plot has at least one tree with the diameter equal to or larger than 10 cm and smaller than 40 cm.
3. Clearing: there is an opening on the canopy of at least 50% of the area of the sub-plot and few or no trees with a diameter larger than 10 cm on the sub-plot. When existing, the crowns project outside the limits of the sub-plot.

The trunk identification classes (TIC) were defined using the methodology suggested by Silva et al. (2005):

1. Living standing tree, complete.
2. Living standing tree, no crown, trunk >4.0 m.
3. Living standing tree, no crown, trunk <4.0 m.
4. Living fallen tree.
5. Supported tree due to natural causa.
6. Bent tree due to natural cause.
7. Arched tree due to natural cause.

The competition indexes tested on this study were the distance semi-independent competition indexes (*DSICI*), among which are:

$DSICI_1 = \frac{\bar{d}^2}{D_t^2}$	Adapted (Glover and Hool, 1979)	(1)
$DSICI_2 = Bal_i$	Stage (1973)	(2)
$DSICI_3 = Z_1 \sum_{i=1}^{n_1} \frac{D_i}{D_t} + Z_2 \sum_{j=1}^{n_2} \frac{D_j}{D_t}$	Adapted from Phillips et al. (2004)	(3)

where  $D_t$  is the diameter of the studied tree;  $\bar{d}^2$  is the arithmetic mean of the diameters on the sub-plot of the studied tree;  $Bal_i$  is the sum of the sectional areas of the neighboring trees larger than the sectional area of the studied tree, on the sub-plot;  $Z_1$  and  $Z_2$  are the relative importance coefficient for competition of zones 1 and 2, respectively,  $D_i$  and  $D_j$  are the “over-topping” trees on both zones.  $n_1$  and  $n_2$  are the total number of “over-topping” trees on the three zones. The “over-topping” trees are the ones with the diameter larger than the studied tree on the sub-plots on both zones.

Zona 1 is a square with 10 × 10 m containing *t* trees (Fig. 1). Zone 2 is defined as relative to zone 1. Random weights are

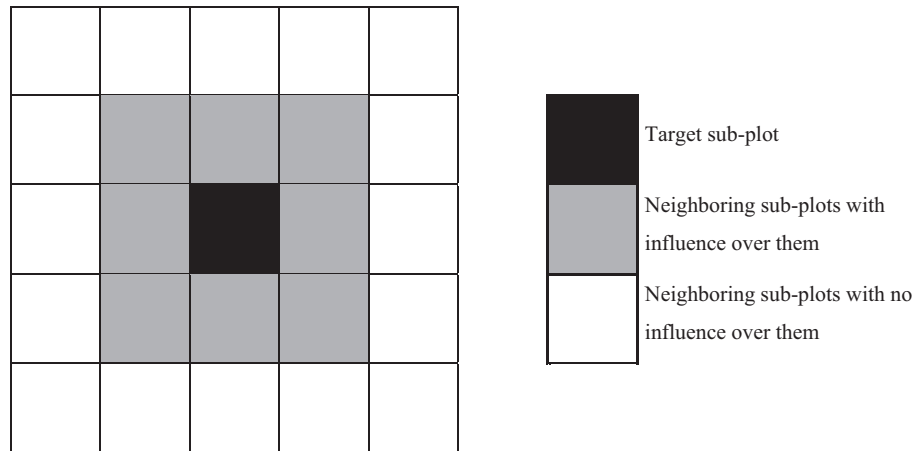


Fig. 1. Competition zones considering a tree on the sub-plot. Adapted from Phillips et al. (2004).

attributed, reflecting the competition on each zone, considering  $Z_1 = 9$  and  $Z_2 = 4$  (Phillips et al., 2004).

A clustering analysis was conducted according to the Euclidean distance method in order to classify the species into growth groups using the annual periodical increment to the diameter ( $API_{dbh}$ ), in  $\text{mm year}^{-1}$ , of the botanical families over the different periods (1981–1982, 1982–1983, 1983–1985, 1985–1987, 1987–1992, 1992–1997, 1997–2007 and 2007–2012), where four growth groups were created (Table 1).

### 2.3. Training and evaluation of ANNs

The training of ANNs consisted on applying a set of organized steps with the purpose of adjusting the weights and thresholds of the neurons. Therefore, the purpose of such adjustment process, also known as learning algorithm, was to tune the network in order for the responses to be close to the output values (Silva et al., 2010).

On the modeling process, 1200 ANNs were trained, 300 for each competition index evaluated ( $DSIC_1$ ,  $DSIC_2$ , and  $DSIC_3$ ) and 300 ANNs without the competition index variable in order to simplify the ANNs on the modeling process (Table 2).

Continuous input variables:  $DSIC$ : Distance semi-independent competition index;  $dbh_1$ : Current diameter measured at 1.30 m

Table 1

Growth groups created from the Annual Periodical Increment on  $dbh$  ( $API_{dbh}$ ) of the botanical families after the forestry harvesting.

Groups	Families	$API_{dbh}$ ( $\text{mm year}^{-1}$ )
1	To be identified, Chrysobalanaceae, Connaraceae, Lamiaceae, Lecythidaceae, Myrtaceae, Ochnaceae, Opiliaceae, Quinaceae, Rubiaceae, Rutaceae, Sapindaceae, Siparunaceae and Violaceae	1.355
2	Achariaceae, Annonaceae, Apocynaceae, Aquifoliaceae, Boraginaceae, Burseraceae, Caryocaraceae, Celastraceae, Clusiaceae, Dichapetalaceae, Ebenaceae, Elaeocarpaceae, Euphorbiaceae, Hippocrateaceae, Lacistemaceae, Lauraceae, Leguminosae-papilionoideae, Malvaceae, Melastomataceae, Moraceae, Myristicaceae, Nyctaginaceae, Olacaceae, Polygonaceae, Salicaceae, Sapotaceae, Solanaceae and Ulmaceae	2.731
3	Anacardiaceae, Combretaceae, Goupiaceae, Humiriaceae, Leguminosae-caesalpinioideae, Malpighiaceae, Meliaceae and Simaroubaceae	3.856
4	Araliaceae, Bignoniaceae, Bixaceae, Caricaceae, Leguminosae-mimosoideae, Rosaceae, Urticaceae and Vochysiaceae	7.771

Table 2

Variables used to train the artificial neural networks (ANN) on a forest after forestry harvesting on the Eastern region of the Amazon.

Competition index	Input variables	Number of trainings	Output
$DSIC_1$	$dbh_1$ , FC, GG, TIC, Liana, CL, $DSIC_1$	300	$API_{dbh}$
$DSIC_2$	$dbh_1$ , FC, GG, TIC, Liana, CL, $DSIC_2$	300	$API_{dbh}$
$DSIC_3$	$dbh_1$ , FC, GG, TIC, Liana, CL, $DSIC_3$	300	$API_{dbh}$
No $DSIC$	$dbh_1$ , FC, GG, TIC, Liana, CL	300	$API_{dbh}$
General total		1200	

from the soil (mm); Categorical input variables: FC: forest class; GG: growth group; TIC: Trunk Identification Class; Liana: Infestation intensity by Liana and CL: Crown Lighting. Continuous output:  $API_{dbh}$  Annual Periodical Increment on  $dbh$ , in  $\text{mm year}^{-1}$ .

For the training of the network, the feedforward architecture was used for multiple layers, as well as the multi-layer Perceptron (MLP) and the Intelligent Problem Solver tool (IPS) from the Statistica 13 software (StaSoft Inc, 2016), in order to choose the activation functions (Identity, Logistics, Hyperbolic and Exponential Tangent) of the intermediate and the output layers. For the training, only one hidden layer was used, and the neuron number interval on this layer was defined using the Fletcher-Gloss method (Silva et al., 2010). The neuron number interval was established according to the number of input and output variables, considering the following expression:

$$(2 \cdot \sqrt{n} + n_2) \leq n_1 \leq (2 \cdot n + 1) \quad (4)$$

where  $n$  is the number of network inputs,  $n_1$  is the amount of neurons on the hidden layer, and  $n_2$  is the amount of neurons on the output layer.

The maximum defined by this method avoids the memorization of input data (overfitting) or the insufficient collection of information during the training (underfitting).

For each training, five networks were retained. From them, one per training was chosen, considering the correlation between the estimated and the observed values. When choosing and comparing the ANNs to be used for the prognosis of the future diameters, during the training and generalization, the correlation statistics ( $r_{YY}$ ) between the estimated and the actual values, the root mean square error (RMSE) and calculating model efficiency (EF); the EF values can vary from  $-1$  (no fit) to  $+1$  (perfect fit) (Hung et al., 2016; Loague and Green, 1991) were evaluated, given by:

$$r_{YY} = \frac{Cov(Y, \hat{Y})}{\sqrt{S^2(Y)S^2(\hat{Y})}} \quad (5)$$

$$RMSE = 100 \cdot \bar{Y}^{-1} \sqrt{n^{-1} \sum_{i=1}^n (Y_i - \hat{Y})^2} \quad (6)$$

$$EF = \frac{\sum_{i=1}^n (Y - \bar{Y})^2 - \sum_{i=1}^n (\hat{Y} - Y)^2}{\sum_{i=1}^n (Y - \bar{Y})^2} \quad (7)$$

where  $\hat{Y}$ : values estimated by ANNs;  $Y$ : values observed on the permanent plots,  $S^2$ : variance,  $Cov.$ : covariance, and  $n$ , number of observations.

The graphic analysis of the dispersion of percentage relative errors (% Error) in relation to the observed values was also conducted, obtained by:

$$Erro \% = \frac{(\hat{Y} - Y)}{Y} \cdot 100 \quad (8)$$

**Table 3**

Linear correlation between the input and output variables, used for the training and test of ANNs.  $API_{dbh}$ : Annual Periodical Increment on dbh, in  $\text{mm year}^{-1}$ ;  $DSICI$ : distance semi-independent competition index;  $dbh_1$ : diameter at the beginning of time period  $t$  of the studied tree (mm).

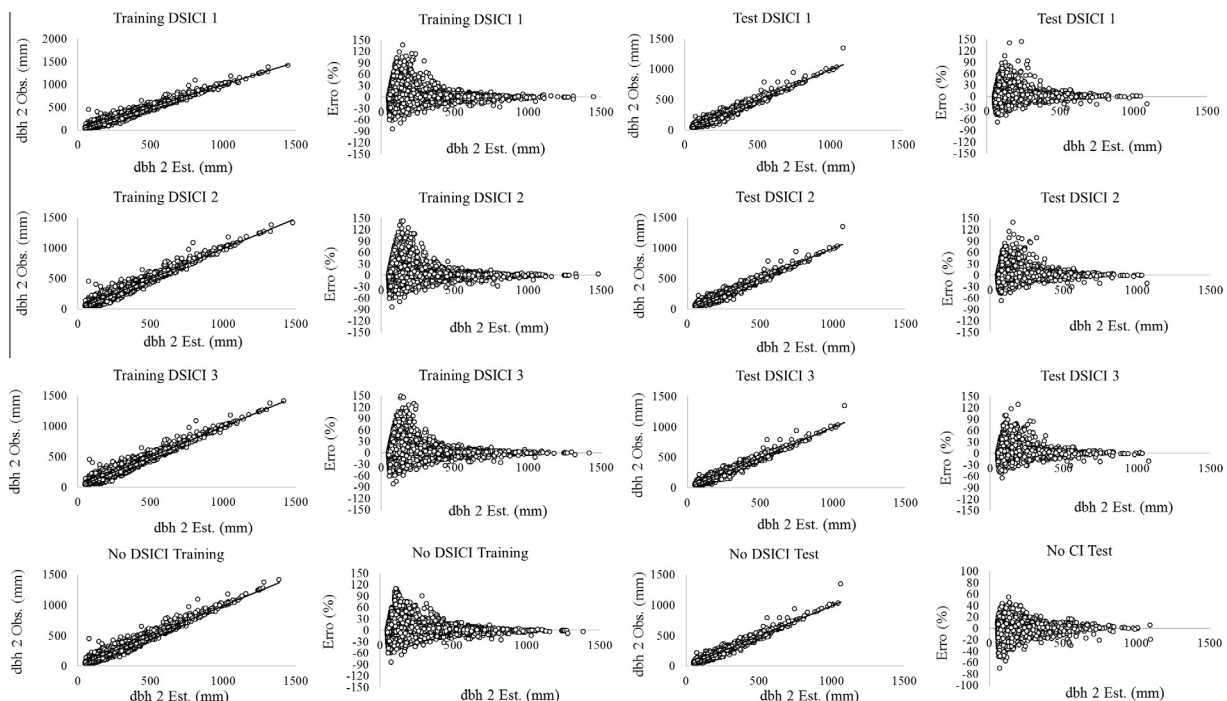
Variables	$API_{dbh}$	$dbh_1$	$DSICI_1$	$DSICI_2$	$DSICI_3$
$API_{dbh}$	1.0000	–	–	–	–
$dbh_1$	0.1497*	1.0000	–	–	–
$DSICI_1$	–0.1473*	–0.4871*	1.0000	–	–
$DSICI_2$	–0.1449*	–0.2459*	0.5580*	1.0000	–
$DSICI_3$	–0.2093*	–0.6816*	0.7681*	0.3967*	1.0000

\* Significant at 5%.

**Table 4**

Training and test accuracy measurements of artificial neural networks (ANNs) on the final diameter estimation ( $dbh_2$ ) of individual trees.  $DSICI$ : distance semi-independent competition index;  $r_{\hat{Y}Y}$ : correlation coefficient; RMSE: root mean square error (%); EF: model efficiency; MLP: multi-layer Perceptron.

ANN	Index	Architecture MLP	Training			Test			Activation functions	
			RMSE	$r_{\hat{Y}Y}$	EF	RMSE	$r_{\hat{Y}Y}$	EF	Intermediate layer	Output layer
$DSICI_1$	5	24–38–1	100,021	0.9922	0.9897	100,506	0.9916	0.9831	Exponential	Exponential
$DSICI_2$	1	24–39–1	100,587	0.9921	0.9841	101,181	0.9915	0.9828	Exponential	Logistic
$DSICI_3$	3	24–12–1	99,754	0.9923	0.9898	100,672	0.9916	0.9830	Hyperbolic tangent	Exponential
No $DSICI$	5	23–22–1	101,439	0.9920	0.9894	100,014	0.9917	0.9832	Exponential	Logistic



**Fig. 2.** Distribution of the final diameter estimations ( $dbh_2$ ) in relation to the observed values and the residues on the training and test process of artificial neural networks (ANNs).

However, it is noteworthy that the difference among these networks was lower than 1% on the test.

On all ANNs, the efficiency of the model (EF) was over 0.98 (Table 4), both on the test and on the training, considering that the ideal value in terms of efficiency would be as close as possible to 1. On the training, the ANN that showed the highest efficiency was the one that used  $DSICI_3$  and, on the test, it was the one that used  $DSICI_2$ . However, the difference among the ANNs was also lower than 1% on the training and on the test.

The trained networks showed similar distribution patterns for the errors, with the greatest errors on the smallest diameters (Fig. 2). Despite the presence of some discrepant data, represented by the furthestmost points of the trend line, all ANNs followed the trend of the observed data.

Using all ANNs, it was observed that the estimated basal area, calculated with the future diameters estimated through  $API_{dbh}$ , followed the trend of the basal area observed on the total area, throughout time, after the forest harvesting (Table 3).

#### 4. Discussion

$DSICIs$  showed a negative correlation in relation to  $API_{dbh}$  (Table 3), this occurs because of the higher the number of competitors with larger diameters and sectional areas than the object-tree, limiting the development of the trees. This result was already

expected, since, with the growth of the competition index, the growth rate would be smaller (Richards et al., 2008).

The  $DSICI_3$  variable with a highly significant correlation to  $API_{dbh}$  (Table 3) and the lowest RMSE on the training, considering the training, was the most important continuous variable to estimate the growth rate.

The ANN that used  $DSICI_3$  represents the competition in a more realistic manner, since it considers the competition both within the plot of the object-tree and within the neighboring plots, considering that the growth of the diameter is mostly explained by the neighboring plots (von Oheimb et al., 2011); it uses the competing trees that are larger than the object-tree, due to the existing relationship between  $dbh$  and the competition mainly for light (Laurans et al., 2014); and it shows weights that consider the reduction on the competition as the object-tree is further away, representing the reduction on the competition as the distance between the trees increases (Valle et al., 2007). Competition indexes that show at least one distance relationship are better to describe the growth than the ones that do not depend at all on the distance (Wang et al., 2015).

Despite that, all models showed statistical estimations (Table 4) close to a RMSE and EF correlation, considering that, on the test, the ANN that did not use  $DSICI$  obtained the lowest RMSE. All ANNs followed the trend of the observed data (Figs. 2 and 3); this showed the high capacity of ANNs to model the complex dynamics of the

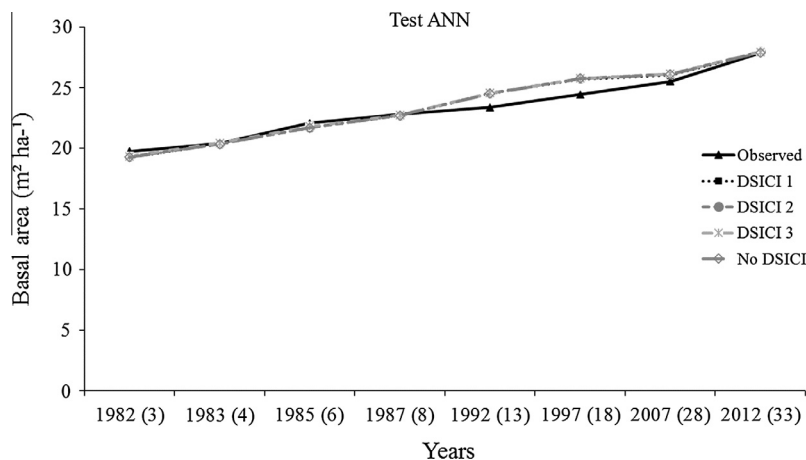


Fig. 3. Observed and estimated basal areas throughout time after the harvesting of wood. Values within parentheses represent the years after the forestry harvest.

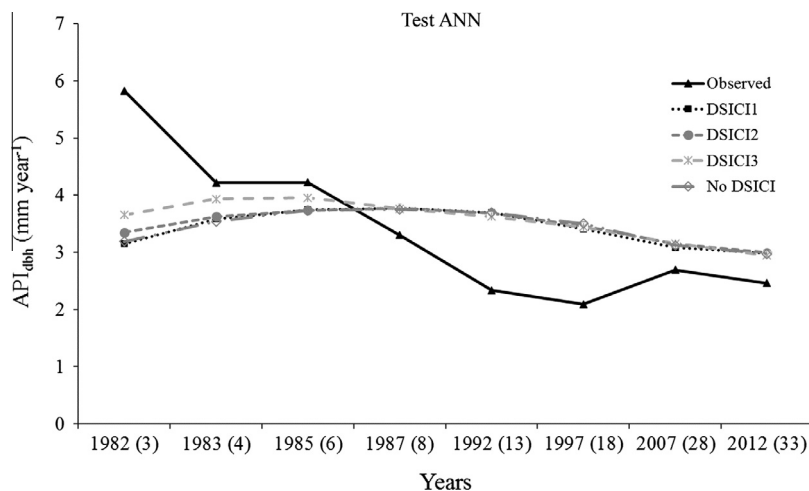


Fig. 4. Observed and estimated Annual Periodical Increment ( $API_{dbh}$  mm year<sup>-1</sup>) throughout time after the harvesting of wood. Values within parentheses represent the years after the forestry harvest.



forest after harvesting, even without including the competition variable.

The accuracy of the estimations was also due to the inclusion of the categorical variables, which, on several studies, showed a significant influence in relation to the growth, such as, for example, lighting of the treetop (Gustafsson et al., 2016), Liana infestation (Campanello et al., 2007; Reis et al., 2015); the forest class, represented by the different glade sizes (Stan and Daniels, 2014) and the growth groups (Azevedo et al., 2008; Valle et al., 2007), corroborating with the use of these variables to model uneven-aged forests.

The highest errors associated to the smallest diameters on all ANNs (Fig. 2) are a result of the major heterogeneity of the growth rates of the smaller trees, since they are the ones that suffer the most with the effects of competition.

Individuals with the same diameter but with very different growth rates are frequently observed (Rozendaal et al., 2015), not only due to the competition, but also due to the forest succession, represented by the different regeneration mosaics, which affect the establishment and development of the smaller trees (Farrior et al., 2016; Reis et al., 2014).

Calculating the estimation throughout time after the forest harvesting, all ANNs showed, in 1997, 18 years after harvesting, an overestimation of the basal area, observed in up to 5.4%. This is due to the strong deceleration of the growth rate from 1987 on, with the lowest rate occurring on 1997 (Fig. 4) and a rise of the growth after that year. The growth reduction in 1997 may have occurred due to the high drought caused by the El Niño phenomenon and later growth caused by the canopy opening due to tree mortality (Gloor et al., 2009; Phillips et al., 2010; Slik, 2004; Williamson et al., 2000).

The strong growth after harvesting and the initial deceleration was caused by the forest canopy opening, which increased the growth of the trees and, then, with the continuous canopy closing, promoted a reduction of the growth rate (Reis et al., 2015).

The ANNs on the prognosis of the annual periodical diameter increment showed a relatively constant growth, with later growth deceleration from 1992 on, 13 years after harvesting. Thus, an underestimation occurred right after harvesting, with an overestimation at the end of the analyzed period (Fig. 4). Despite that, the prognosis followed the trend of the observed data, and it was able to estimate the higher growth at the beginning and a continuous deceleration until the end of the period.

## 5. Conclusion

All tested ANN may be used in the prognosis of individual tree growth in tropical forests after harvest, for presenting RMSE below 11%, correlation above 99%, and model efficiency above 0.97. The ANN that did not use competition index as input variable was the simplest ANN with the lowest RMSE during the test.

The prognosis using ANN follows the data trend observed in relation to basal area over time (33 years), but there was underestimation of the growth rate soon after harvest, and a superstition at the end of this period, caused by random factors that have not been added as independent variables to the model.

Sustainable forest management currently practiced in the Amazon Region does not use growth and production models to predict future stock, causing environmental and economic uncertainty with regard to this activity. With an estimated growth of individual trees through ANN, one can calculate volume, basal area, and future diameter distribution of species. Moreover, it allows for determining the most suitable cutting cycle and intensity, avoiding species exploitation, and ensuring economic and environmental sustainability of forest management.

## Acknowledgements

To Capes and CNPq for granting the scholarships to the authors, and to Embrapa Amazônia Oriental for providing monitoring data from permanent plots.

## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.foreco.2016.10.022>. These data include Google maps of the most important areas described in this article.

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