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

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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 $m^3\ ha^{-1}$ in a 64 ha area in the Tapajós National Forest - PA. In 1981, 36 permanent plots (50 m × 50 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 subsides 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 subside 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 $m^3\,ha^{-1}$ (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 lecointei* 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 $dbh \geqslant 45$ cm, on 39 ha; and cutting the trees with $dbh \geqslant 55$ 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 $dbh \geqslant 5$ 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 (*CF*), 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 $year^{-1}$) which was then used to calculate the future diameter (dbh_2).

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)
$DSICI_3 = Z_1 \sum_{i=1}^{n1} \frac{D_i}{D_t} + Z_2 \sum_{j=1}^{n2} \frac{D_j}{D_t}$	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

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