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Modeling of tree recruitment by artificial neural networks after wood harvesting in a forest in eastern Amazon rain forest

Modelagem do recrutamento de árvores por redes neurais artificiais após a colheita de madeiras em floresta no leste da Amazônia

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Abstract

Recruitment models in tropical forests are important for studies on forest management sustainability because they provide adequate support to recovery of wood stocks. The objective of this work was to estimate recruitment after wood harvesting by using an artificial neural network (ANN) model. The study area is located at Tapajós National Forest (55° 00' W, 2° 45' S), Pará state. In 64 ha of the study area, in 1979, an intensive harvest of 72.5 m^3 ha^{-1} was carried out. In 1981, 36 permanent plots of 50 m x 50 m were randomly installed. These plots were measured in 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010 and 2012. For recruitment modeling, the variables of the target subplot and its vicinity were considered. The estimates obtained in ANN training and generalization were evaluated by statistics: correlation () and root mean square error (RMSE) were determined: RMSE 35.6% and 0.89. Recruitment tendency could be modeled over time in tropical forests after wood harvesting.

Keywords: Ingrowth; Artificial intelligence; Forest management

Resumo

A modelagem do recrutamento em florestais tropicais é importante para estudos de sustentabilidade do manejo florestal, por dar subsídio adequado à recuperação do estoque de madeira. O objetivo do trabalho foi estimar o recrutamento após a colheita de madeira, empregando um modelo de rede neural artificial (RNA). A área de estudo está localizada na Floresta Nacional do Tapajós (55°00' W, 2°45' S), Pará. Em 64 ha da área de estudo, em 1979, foi realizada colheita intensiva de 72,5 m^3 ha^{-1}. Em 1981 foram instaladas, aleatoriamente, 36 parcelas permanentes de 50 m x 50 m. Essas parcelas foram mensuradas em 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010 e 2012. Para modelar o recrutamento foram consideradas as variáveis da subparcela-alvo e a sua vizinhança. As estimativas obtidas no treino e na generalização da RNA foram avaliadas pelas estatísticas: correlação () e raiz quadrada do erro quadrático médio (RQRQM), sendo obtido RQRQM 35,6% e 0,89. Foi possível modelar a tendência do recrutamento ao longo do tempo em florestas tropicais, após a colheita de madeira.

Palavras-chave: Ingresso; Inteligência artificial; Manejo Florestal

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Introduction

In the forest management activity, post-harvest analysis of the species regeneration is important to devise techniques as support to the best practices. Analysis of species recruitment in the target community, especially species which are harvested, can be a good indicator of sustainability. This recruitment is the future of subsequent harvests; thus, the economic regeneration of forests after harvesting depends on the establishment of natural regeneration of commercial species (REIS *et al*., 2014).

Recruitment or entrance is the process by which, considering a minimum inclusion diameter, trees not measured on a particular occasion are included in measurements made in the subsequent years (ROSSI *et al*., 2007). Modeling and estimating recruitment for future harvests is important to determine the cutting intensity and the size of the cutting cycle; they should be performed by species or group of species, since such recruitment varies by species and over time. Disregarding recruitment may result in a biased estimate of the forest growth and the future yield (ZHANG *et al*., 2012).

Recruitment can be modeled by using dynamic or static models (VANCLAY, 1994). The static approach does not consider many details about the community conditions in its respective construction, and it predicts a constant amount of recruitment over time. Furthermore, it is less sensitive to the effects or impact of harvesting, and it is employed in stand table projection and in matrix methods (ROSSI *et al*., 2007). On the other hand, dynamic models are broader and use more stand-related variables such as density, floristic composition, and growth. Moreover, they may use variables linked to the harvest intensity.

An alternative method of recruitment modeling is the use of artificial neural networks (ANN). Applications of this computational intelligence technique in forestry have become very relevant because they have been achieving successful results. Examples include diameter distribution modeling (DIAMANTOPOULOU *et al*., 2015; REIS *et al*., 2018b), optimization of competition indices (RICHARDS; MCDONALD; AITKENHEAD, 2008), volume estimation (BINOTI *et al*., 2014), prediction of forest fires in the Brazilian Amazon (MAEDA *et al*., 2009), classification of successional stages in the Brazilian Amazon (KUPLICH, 2006), tree height estimation (DIAMANTOPOULOU, 2012), modeling individual tree mortality and survival in uneven-aged forests (CASTRO *et al*., 2015; ROCHA *et al*., 2018), production prognosis of even-aged stands (BINOTI *et al*., 2015), modeling of diameter growth and individual tree survival and mortality in the Brazilian Amazon (REIS *et al*., 2016; 2018a), and estimation of physical and mechanical properties of wood species in the Amazon (REIS *et al*., 2018c).

Recruitment modeling is difficult to perform because of plot size, time interval between inventories, minimum size for inclusion, regeneration variability and vast diversity of species (ROSSI *et al*., 2007), it can be hypothesized that there will be considerable gains in the prognosis by using ANN through its inherent properties and capabilities, e.g., nonlinearity, learning ability (supervised or unsupervised), and skills such as generalization, adaptability and data organization (HAYKIN, 2001; SILVA; SPATTI; FLAUZINO, 2010).

Therefore, the objective of this study was to model tree species recruitment by using artificial neural networks after timber harvesting in the Tapajós National Forest.

Material and methods

Study area

The study area is located in 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 its 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. Mean relative humidity is 86%, with mean annual rainfall ranging from 1,900 to 2,200 mm. It has a flat to wavy surface, and presence of a Dystrophic Yellow Latosol (COSTA FILHO; COSTA; AGUIAR, 1980; ALVARES *et al*., 2013).

In Tapajós National Forest, especially in the study area, Costa Filho, Costa and Aguiar (1980) reported the use of selective harvesting, in the 1940s, 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, 64 wood species were intensively harvested in 64 ha of the study area, 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. Together, they accounted for 47.4% of the total extraction volume (REIS *et al*., 2010). Harvesting was based on two treatments: cutting all trees with dbh ≥ 45 cm, in 39 ha; and cutting trees with dbh ≥ 55 cm, in 25 ha (COSTA FILHO; COSTA; AGUIAR, 1980). However, the treatments were analyzed together, thus creating only one community, because of the high level of similarity found in the comparisons (REIS *et al*., 2010).

In 1981, 36 permanent plots (50 m x 50 m each) were randomly installed, where all trees with dbh ≥ 5 cm were botanically identified on-site. New measurements for these permanent plots were made in 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010, and 2012.

Variables and data used for training and testing neural networks

The permanent plots were divided into two groups: one group with 29 plots for training the ANN and one group with 7 plots for the generalization of the trained networks, respectively accounting for 80% of data for training and 20% for generalization.

For recruitment modeling purposes, the variables of the target subplot itself and its vicinity were taken into consideration, and the input variables used in these subplots were: basal area (BA-m^2 ha^{-1}), density (N-trees ha^{-1}), time period (years) between measurements (P), time period (years) for timber harvest (HP), forest class (FC), periodic annual increment in diameter (PAI_{dbh} - mm $year^{-1}$) and maximum diameter (dbh_{max} - mm) as a measure of competition.

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.

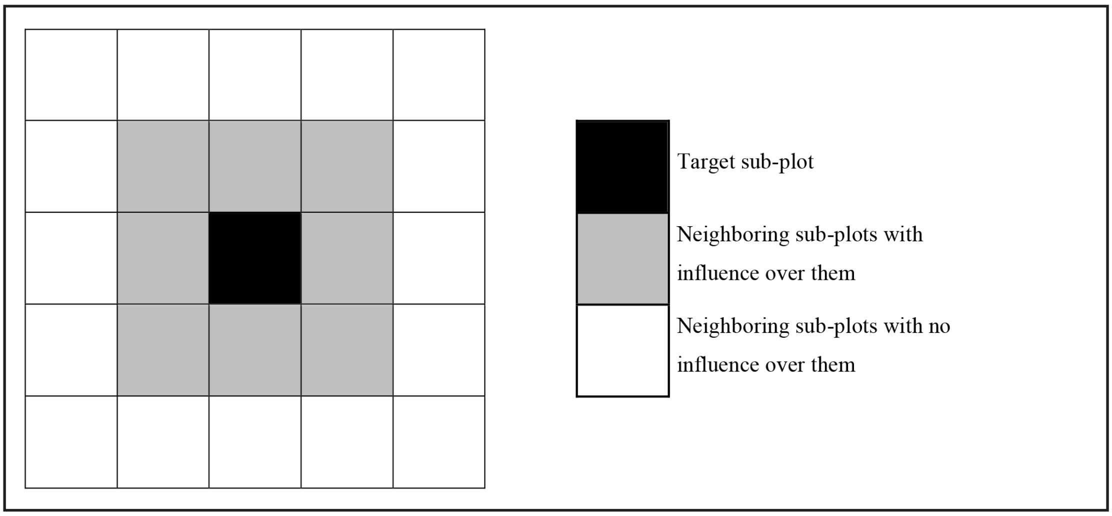
2. Forest under construction: the sub-plot has at least one tree with the diameter equal to or larger than 10 cm and smaller than 40 cm.

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 definition of vicinity is based on a two-dimensional grid formed from the target subplot of 10 x 10 m on a plot of 50 x 50 m (Figure 1); that plot is divided into 25 subplots. Many of the variables contained in the zone of influence of recruitment were considered in modeling, because recruitment is influenced not only by the characteristics of the target subplot but also by the surroundings of this subplot in a given zone of influence.

Figure 1– Representation of the zone of influence of the modeled subplot, a 50 x 50 m plot divided into 25 10 x 10m subplots. Adapted from Phillips *et al.* (2004).

Figura 1 – Representação da zona de influência da subparcela alvo da modelagem. Parcela de 50 x 50 m dividida em 25 subparcelas de 10 x 10 m. Adaptado de Phillips *et al.* (2004).



Source: Leonardo Pequeno Reis (2017)

ANN Training and evaluation

ANN training is the application of a set of ordered steps to adjust the weights and the limits of neurons. Thus, this adjustment process, also known as learning algorithm, is aimed at tuning the network so that its answers are similar to the desired values (SILVA; SPATTI; FLAUZINO, 2010).

To model the recruitment of the total community, 1,800 ANNs were trained, 300 for each composition of variables with the vicinity and 300 ANN without using the adjacent area. This was the simplest ANN in the modeling process (Table 1).

Table 1 – Variables used for training artificial neural networks (ANN) in a forest after harvesting.

Tabela 1 – Variáveis utilizadas no treinamento das redes neurais artificias (RNA) em uma floresta após colheita.

ANN	Input variables	Number of training sessions	Output
1	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}, BA_1, BA_2, BA_3, BA_4, BA_5, BA_6, BA_7, BA_8, N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8, PAI_{dbh1}, PAI_{dbh2}, PAI_{dbh3}, PAI_{dbh4}, PAI_{dbh5}, PAI_{dbh6}, PAI_{dbh7}, PAI_{dbh8}, dbh_{max1}, dbh_{max2}, dbh_{max3}, dbh_{max4}, dbh_{max5}, dbh_{max6}, dbh_{max7}, dbh_{max8}	300	NR
2	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}	300	NR
3	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}, BA_1, BA_2, BA_3, BA_4, BA_5, BA_6, BA_7, BA_8	300	NR

Continued...

Table 1 – Conclusion...
Tabela 1 – Conclusão...

ANN	Input variables	Number of training sessions	Output
4	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}, N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8	300	NR
5	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}, PAI_{dbh1}, PAI_{dbh2}, PAI_{dbh3}, PAI_{dbh4}, PAI_{dbh5}, PAI_{dbh6}, PAI_{dbh7}, PAI_{dbh8}	300	NR
6	BA, N, P, PC, FC, PAI_{dbh}, dbh_{max}, dbh_{max1}, dbh_{max2}, dbh_{max3}, dbh_{max4}, dbh_{max5}, dbh_{max6}, dbh_{max7} dbh_{max8}	300	NR
Total		1800	

Continuous input variables: *BA* = basal area (m^2 ha^{-1}); *N* = number of trees ha^{-1}; *P* = period in years between measurements; *PC* = period in years after the harvest; PAI_{dbh} = Annual Periodical Increase on dbh, in mm $year^{-1}$; dbh_{max}: Maximum diameter found in the subplot (mm); Categorical input variables: *FC* = forest class, composed of Mature Forest, Forest under Construction and Clearings; Continuous output: *NR* = number of recruited trees; 1, 2, 3, ..., 8: Variables of the adjacent subplots.

In the training sessions, the multilayer feedforward architecture was used, i.e., the *Multilayer Perceptron* (MLP). The Intelligent Problem Solver (IPS) tool of the software Statistica 13 (STASOFT INC, 2016) was used to choose the activation functions (Identity, Logistics, Hyperbolic tangent and Exponential Linear Unit) of the intermediate layer and of the output. In the training sessions, only one hidden layer was used, and the interval of the number of neurons in this layer was set through the Fletcher-Gloss method (SILVA; SPATTI; FLAUZINO, 2010). The interval of the number of neurons according to the number of input and output variables was given by the following equation:

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

where n is the number of network inputs, n_1 is the number of neurons in the hidden layer while n_2 is the number of neurons in the output layer.

The maximum defined by the method was to avoid storing the input data (overfitting) or to insufficiently extract information during training (underfitting).

For each training session, five networks were retained. One network was chosen for each training session based on the correlation among the estimated and observed values. For the selection and comparison of the ANNs to be used in the prognosis, evaluations were made

$$Error\ \% = \frac{(\hat{Y} - Y)}{Y}\ .100 \quad (2)$$

$$r_{Y\hat{Y}} = \frac{Cov\ (Y, \hat{Y})}{\sqrt{S^2(Y)S^2(\hat{Y})}} \quad (3)$$

$$RMSE = 100.\bar{Y}^{-1}\sqrt{n^{-1}\sum_{i=1}^{n}(Y_i - \hat{Y})^2} \quad (4)$$

where:Ŷ= values estimated by ANNs; Y = values observed on the permanent plots, S^2 = variance, Cov. = covariance, and n = number of observations.

of the statistical correlation between the estimated and actual values ($r_{Y\hat{Y}}$) and the root mean square error (RMSE) in training and generalization. A graphical analysis was also made on the dispersion of percentage errors (Error %) as compared to the observed values:

Results and discussion

The input variables that correlate the most with recruitment were period of time between measurements (*P*) and period of time after the timber harvest (*PC*), above 25% (Table 2). The only variable that showed no significant correlation was maximum *dbh* of the subplot. Number of trees ha^{-1} and basal area (*BA*) showed negative correlations while *PAI* in diameter showed a positive correlation. Even though they all had significant correlations, they were below 20%.

Table 2 – Linear correlation between the input and output variables used for training and testing the ANNs.

Tabela 2 – Correlação linear entre as variáveis de entrada e saída usadas no treinamento e teste das RNA.

Variables	*NR*	*PC*	*P*	**N**	**BA**	**PAI$_{dbh}$**	**dbh$_{max}$**
NR	1.0000						
PC	0.2682*	1.0000					
P	0.3468*	0.8050*	1.0000				
N	-0.1743*	-0.0150^{ns}	-0.0339*	1.0000			
BA	-0.0469*	0.1448*	0.1138*	0.2632*	1.0000		
PAI$_{dbh}$	0.2008*	-0.3636*	-0.3483*	-0.1455*	-0.1257*	1.0000	
dbh$_{max}$	-0.0181^{ns}	0.1201*	0.0968*	0.0701*	0.8957*	-0.1056*	1.0000

* = Significant at 5%; non-significant. *NR* = number of recruited trees; *BA* = basal area (m^2 ha^{-1}); *N* = number of trees ha^{-1}; *P* = period in years between measurements; *PC* = period in years after harvesting; PAI_{dbh} = annual periodic increase in diameter (mm year^{-1}) and dbh_{max} = Maximum diameter found in the subplot (mm).

All of the tested ANNs, with different inputs and architectures, presented simple correlations above 80% and a square root of the mean squared error below 45% (Table 3). The ANN that had the best performance to estimate recruitment (ANN 1, Figures 2 and 3) was ANN 1 with the highest correlation and the lowest RMSE in the test. This network used all of the structural and dynamic variables of the subplots. The ANN that had the worst result was ANN 6, with the lowest correlation and the highest RMSE. This network used the maximum diameter of the subplot as an input variable for infer about the competition in the subplot.

Despite some outliers in the recruitment, the estimated recruitment of the ANN was set with the observed recruitment (Figure 2), represented by the most distant points of the trendline. ANN 1 showed the best fit and the estimated and observed data follow the same trend, both in training and in the test.

Table 3 – Training precision measurements and artificial neural network (ANN) testing for the estimation of tree recruitment

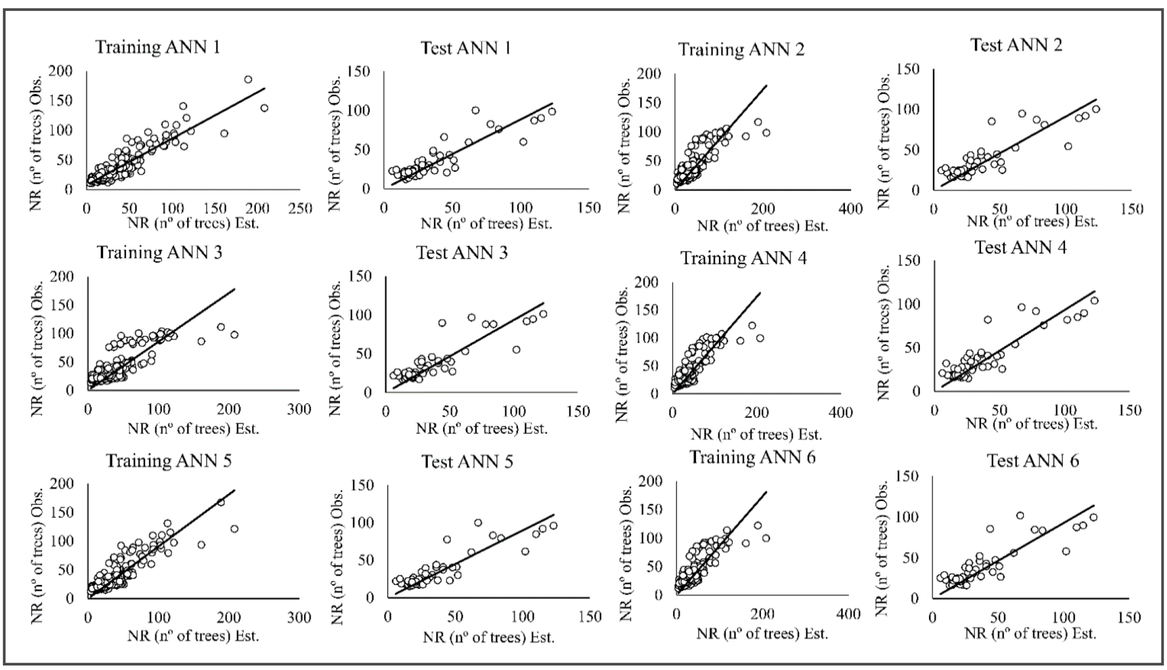
Tabela 3 – Medidas de precisão do treinamento e teste das redes neurais artificiais (RNA) na estimativa de recrutamento de árvores

ANN	Index	Architecture MLP	RMSE		RMSE		Activation functions	
							Intermediate layer	Output layer
1	2	41-61-1	34.8791	0.9027	35.6462	0.8932	Hyperbolic tangent	Exponential
2	1	9-18-1	43.1114	0.8489	38.4479	0.8723	Logistic	Exponential
3	5	17-33-1	46.6002	0.8177	38.5054	0.8732	Logistic	Logistic
4	5	17-32-1	41.4371	0.8621	35.9185	0.8908	Logistic	Exponential
5	3	17-28-1	38.1384	0.8825	36.0299	0.8900	Hyperbolic tangent	Logistic
6	3	17-35-1	43.0030	0.8493	39.0262	0.8692	Logistic	Exponential

$r_{Y\hat{Y}}$ = correlation coefficient; RMSE = root mean square error (%)

Figure 2 – Distribution of the number of estimations of recruited trees (NR) in comparison to the values observed during training and testing of artificial neural networks (ANN).

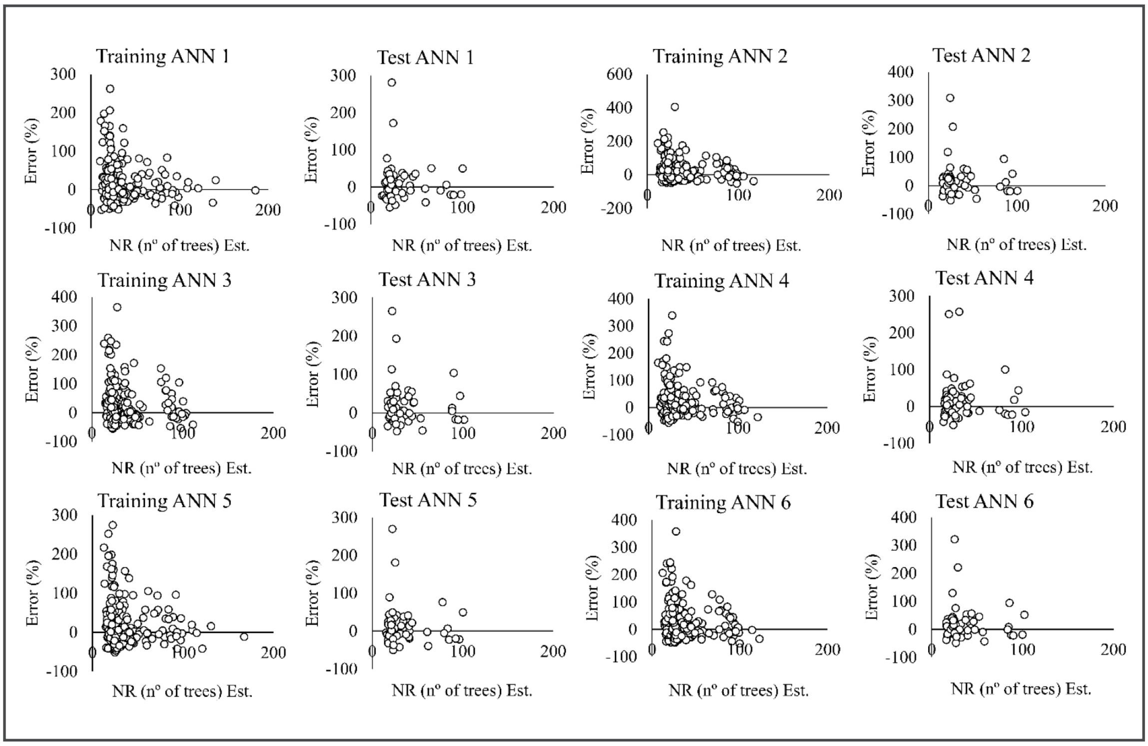
Figura 2 – Distribuição do número de árvores recrutadas (NR) estimadas em relação aos valores observados no processo de treinamento e teste de redes neurais artificiais (RNA).



Source: Leonardo Pequeno Reis (2017)

Figure 3 – Distribution of the number of estimations of recruited trees (NR) in comparison to the residues during training and testing of artificial neural networks (ANNs).

Figura 3 – Distribuição do número de árvores recrutadas (NR) estimadas em relação aos resíduos no processo de treinamento e teste de redes neurais artificiais (RNA).

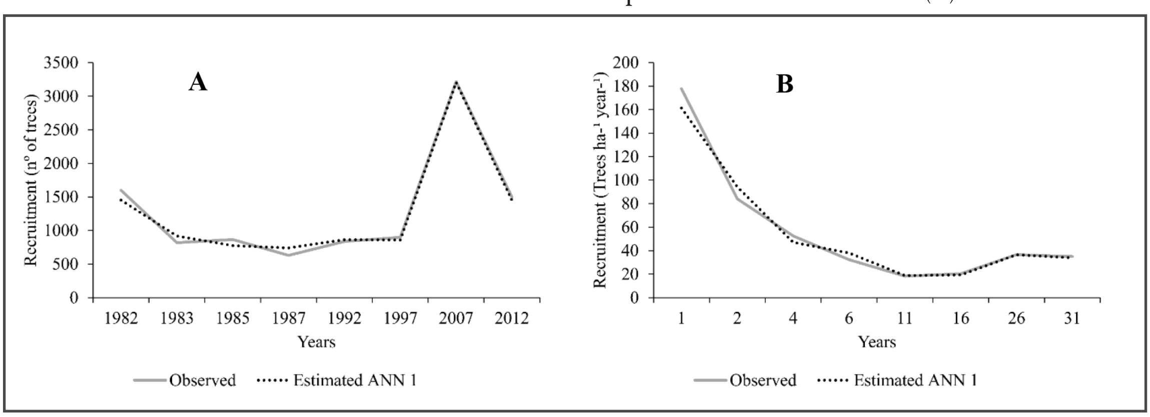


Source: Leonardo Pequeno Reis (2017)

For ANN 1, which had the best estimates of recruitment over time after harvesting, the estimated data followed the observed recruitment trend (Figure 4), with a small deviation in the first periods (1981-1987).

Figure 4 – Observed and estimated recruitment after forest harvesting (A) and observed and estimated recruitment rate after forest harvesting (B).

Figura 4 – Recrutamento observado e estimado após a colheita florestal (A) e taxa de recrutamento observado e estimado após a colheita florestal (B).



Source: Leonardo Pequeno Reis (2017)

After using all of the structural and dynamic variables, ANN 1 showed the best estimates of recruitment, even though the difference in correlation and RMSE is less than 3% when comparing ANN 1 to the other networks. This showed the great learning ability of the ANN to extract information with a small number of variables (HAYKIN, 2001; SILVA; SPATTI; FLAUZINO, 2010).

ANN 2, a simpler network that only used the variables of its own subplot without using the adjacent subplots, also produced very similar results to those of ANN 1, which used all of the variables of the adjacent subplots (Table 3), with a difference in correlation of 0.02% and of 3% in RMSE, with a higher bias towards overestimating the recruitment on the test data (Figure 3). This may be due to the lack of influence of the variables of the vicinity.

The most influential adjacent variable was tree density, estimated by ANN 3, which showed the lowest difference, with less than 1% in RMSE compared with ANN 1 (Table 3). This may be due to the negative and significant correlation of trees ha-1 in comparison to recruitment (Table 2). The higher the number of trees settled in the subplot, the greater the competition for space, nutrients, water and light in terms of recruitment.

The second and third variables with the highest influence were Periodic Annual Increment in *dbh* (PAI_{dbh}) and basal area (*BA*), respectively, estimated by ANN 5 and ANN 4. Basal area and *PAI* are the most used variables for estimating recruitment in several studies on forest modeling (PHILLIPS *et al*., 2004; KLOPCIC; POLJANEC; BONCINA, 2012)data from a Slovenian forest inventory (67,563 plots, 200m2 each. The first one is a measure of density; it represents occupation in terms of biomass and has a significant negative correlation with recruitment (KLOPCIC; POLJANEC; BONCINA, 2012). The larger the basal area, the greater the competition and the canopy closure, thus reducing recruitment over time after harvesting (Figure 4B).

PAIdbh represents increased productivity of the subplots, and it is positively correlated (Table 2) with recruitment (PHILLIPS *et al*., 2004). The subplots with higher PAIdbh are formed by clearings and forests under construction, the same ones that have higher recruitment levels as a result of lower competition and higher solar radiation input by the activation of the seedling and seed bank (REIS *et al*., 2014).

ANN 6 had the worst performance in recruitment estimation, with lower correlation and higher RMSE than ANN 2, the simplest network. This was due to the low representativeness and influence of maximum diameter, as competition measurement, with a non-significant correlation with influence of recruitment (Table 2). Also, it is a redundant variable since the categorical variable (Forest Class), which is influenced by the maximum diameter of the subplots, was part of the whole training.

The bias shown in the estimate of recruitment was due to its highly stochastic process in the subplots, represented by an excess of zero count, without recruitment, which complicates modeling (ZHANG *et al*., 2012). Moreover, the high biodiversity of the area provides great variability of recruitment strategies, e.g., existence of species that regenerate through seed or seedling banks, which can impair modeling (RIVETT; BICKNELL; DAVIES, 2016). Different periods between measurements also interfere with modeling (VANCLAY, 1994); the shortest period was one year and the longest, 10 years (Figure 4A).

Recruitment may be observed in short periods in the less dynamic subplots or it may have few recruited individuals. This may be the cause of overestimation in the period from 1982 to 1983, when the forest showed an increase in growth and recruitment because of canopy opening resulting from forest harvesting. Nevertheless, after reduced-impact logging, recruitment is not significantly affected over time (RIVETT; BICKNELL; DAVIES, 2016). This can be observed in the best estimates in other periods as of 1987, despite high recruitment from 1997 to 2007, in which one of the factors was a long interval between measurements.

Although the effect of the interval between measurements interfered with recruitment rates, when there was a decline in rates with increased interval (ROSSI *et al*., 2007), ANN 1 followed the trend of decelerating the recruitment rate after forest harvesting (Figure 4B). This may be due to the inclusion of time variables (period between measurements and period after logging), which explains this variation in recruitment. These variables are the ones most closely correlated with recruitment (Table 2).

Recruitment is highly stochastic over time because it has different regeneration mosaics (Mature Forest, Forest under construction and clearings), which may affect estimates. This mosaic is represented as a categorical input variable in an attempt to capture this dynamic after harvesting, and plot measurements have different periods; however, ANN 1 followed the trend of recruitment over time (Figure 4 A and B). Thus, as a tool for prediction of recruitment, it is highly suitable to tropical forests. The smallest difference in the comparison of observed and estimated recruited trees was 0.01%, in the 1997-2007 period while the highest was 17.6% in the 1985-1987 period (Figure 4 A and B).

As the estimate of recruitment through the ANNs did not use groups of species separately, recruitment allocation can be determined in groups of species by the average probability of recruitment (VANCLAY, 1994; NASCIMENTO *et al*., 2013), and it serves as a basis for forest management.

Conclusion

The trained artificial neural networks followed the trend of tree recruitment over 31 years, using variables of horizontal structure, forest dynamics and site situation. They can be used in forest management areas in the Amazon. This allows estimating the most accurate regeneration of the forest growth stock over the planned cutting cycle.

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