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Estimation of mortality and survival of individual trees after harvesting wood using artificial neural networks in the amazon rain forest

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ABSTRACT

Modeling individual trees in tropical rain forests in the Amazon allows for the safe use of scarce resources in a sustainable way. Unfortunately, in the Brazilian Amazon, rain forest growth and production models are not yet used to estimate future forest stock. Thus, forest management plans do not present technical-scientific support that guarantees sustainable production of wood throughout the cutting cycle. Therefore, this work aims to estimate the survival and mortality of individual trees in a selectively harvested forest using Artificial Neural Networks (ANN) to support silvicultural decisions in forest management in the Amazon rain forest. In 1979, a selective harvest was carried out, with 72.5 m3 ha-1 in an area of 64 ha in Floresta Nacional do Tapajós, in the state of Pará, Brazil. In 1981, 36 permanent plots were installed at random and inventoried. Nine successive measurements were carried from 1982 to 2012. In the modeling, classification, survival, and mortality, training and ANN testing were performed, using input variables such as: different semi-distance-independent competition indices (*DSICI*), diameter measured (*dbh*), forest class (*FC*), trunk identification class (*TIC*), competition index (*CI*), growth groups (*GG*), liana infestation intensity (*liana*); and crown lighting (*CL)*; Damage to tree (*D*) and tree rotting (R). The categorical output variables (Classification) were Dead or Surviving tree. Overall efficiency of the classification was above 89% in training and above 90% in the test for all ANNs. Survival classification hit rate was above 99% in the test and training for all ANNs but the mortality score was low, with hit rates below 6%. The overall Kappa coefficient was below 8% for all ANNs (ranked “poor”) but all ANNs were above 55% in the survival classification (ranked “good”). ANN estimates the individual survival of trees more accurately but this does not occur with mortality, which is a rarer event than survival.

1. Introduction

Studies on the dynamics of rain forests are important to understand the evolution of the forest ecosystem after anthropic disturbances, for example, during forest management for wood production. These studies provide information to model growth and production, and for prognosis on the forest structure throughout the cutting cycle. One of the main contributions is the use of models for individual trees, which is one of the alternatives to manage rain forests with a view to sustainability (Reis et al., 2016).

The individual tree models estimate the survival and mortality, these components of forest dynamics are required for correct prognosis on number of trees, basal area, distribution of diameters and production.

One of the problems in modeling mortality is that several random factors may cause the death of trees. For example, regular mortality is

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caused by aging, suppression and competition, as well as events that occur less frequently, for example, normal incidence of plagues and diseases, and meteorological phenomena (droughts, storms, etc.); by comparison, irregular mortality may be caused by large-proportion fires, plague and disease outbreaks, as well as more severe adverse meteorological conditions (Vanclay, 1994). Mortality also occurs as a result of injuries induced by wood harvesting, which may damage roots and barks, creating points of entry of plagues and diseases; as well as disturbances on the canopy, which may lead to disadvantages to some tree species (Vanclay, 1994).

Tree mortality ratio may be reached using regression (Phillips et al., 2004, 2003; Valle et al., 2007). These authors used a system of equations to estimate the likelihood of natural mortality of trees by considering only a diameter-dependent stochastic process, or artificial intelligence methods, mainly Artificial Neural Networks (ANNs) (Diamantopoulou, 2005; Reis et al., 2016). 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).

Different studies that modelled mortality and survival of individual trees using ANN found a more adequate fit than traditional statistical techniques (Guan and Gertner, 1991a, 1991b; King et al., 2000). They have shown that it is possible to have a prognosis on the individual survival and mortality of trees using ANN. These authors used two models to estimate tree mortality: one model with two independent variables, DBH and increase in DBH, and one model with three variables, with an extra categorical variable which represented the condition of the tree. The output was categorical (classification), that is, the dead tree was coded with 0 and the survivor with 1. The ANN results were compared with logistic regression, and better responses were found to predict mortality.

This estimate with ANN for the purpose of classification, indicating whether the tree is dead or alive, shows that ANN has a far more complex function than traditional classification techniques. The final discriminant function is highly flexible and non-linear, and it offers better separation (King et al., 2000).

However, only one study was found on modelling of tree mortality in rain forests (Castro et al., 2015), but it did not involve an extended period of time nor was it conducted in a harvested forest, whose dynamics is quite different from unharvested areas (Reis et al., 2015).

Growth prognosis on the individual diameter of trees, after harvesting in a tropical rain forest in the Amazon, was precisely estimated using ANN (Reis et al., 2016), and the same occurred in other types of uneven-aged forests (Ashraf et al., 2015; Richards et al., 2008).

Given the problem in offering a prognosis on the survival and mortality of individual trees in tropical rain forests, the aim of this study was to offer a prognosis for the individual survival and mortality of trees using post-harvest artificial neural networks in the Amazon, in order to offer input for forestry decisions in forest management.

2. Material and methods

2.1. 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 the typology is solid-ground, Dense Ombrophilous Forest. 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 corresponds to 86%, with mean annual rainfall from 1900 to 2200 mm. It has flat to wavy topography, with the occurrence of a Dystrophic Yellow Latosol (Alvares et al., 2013; Costa Filho et al., 1980).

In the Tapajós National Forest, especially in the study area, Costa Filho et al. (1980) reported the use of selective harvest, conducted during 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, an intensive harvest of 64 wood species was conducted on 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, 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 $dbh \geq 45$ cm, on 39 ha; and cutting the trees with $dbh \geq 55$ cm, on 25 ha (Costa Filho et al., 1980). However, the treatments were considered together, by creating only one community, while taking into account the high similarity found in the comparisons which had been made (Reis et al., 2010).

In 1981, 36 permanent plots of 50 m x 50 m each were randomly installed, where all trees with $dbh \geq 5$ cm were botanically identified *in loco*. New measurements for these permanent plots occurred in 1982, 1983, 1985, 1987, 1992, 1997, 2007, 2010, and 2012 (Reis et al., 2016).

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

The permanent plots were divided into two groups: one group consisted of 29 plots for training of ANNs, and one group had 7 plots, for the generalization of trained ANNs, with a total of 80% of data for training and 20% for generalization (test). The plots used in the generalization (test) were not part of the training set. This was to evaluate the model with independent data to the training of ANNs (Reis et al., 2016). A total of 78,067 individuals were monitored over time; there were 8332 cases of mortality and 69,735 cases of survival. For mortality, the training used 6819 trees while the test used 1513. For survival, the training used 56,421 trees while the test used 13,314.

To model the mortality and survival of individual trees, the entry variables were: diameter measured at a height of 1.30 m (*dbh*), forest class (*FC*), trunk identification class (*TIC*), competition index (*CI*), growth groups (*GG*), liana infestation intensity (*liana*): variable not observed; *liana*1: no presence of liana on the tree; *liana*2: presence of lianas, however, with no injuries; and *liana*3: presence of lianas, restricting growth); and crown lighting (C*LI0*: variable not observed; CLI1: emerging top or completely exposed to light; CLI2: partially lighted top, that is, partially covered by neighboring tree tops; CLI3: top completely covered by neighboring tree tops) (Reis et al., 2016); injuries to the tree (D0: variable not observed; D1: tree with no injuries; D2: mild injuries caused by natural causes; D3: mild injuries caused by harvesting; D4: injuries caused by cutting the lianas; D5: severe injuries due to natural causes; D6: severe injuries caused by harvesting; D10: recovered injuries) and tree rotting (R0: variable not observed; R1: no rotting and R2: presence of rotting). The categorical output variables (Classification) were Dead or Surviving tree.

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 whose diameter is equal to or larger than 40 cm
2 Forest under construction: the sub-plot has at least one tree whose diameter is 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 themselves outside the limits of the sub-plot.

Trunk identification classes (*TIC*) were defined using the