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Artificial neural networks: Modeling tree survival and mortality in the Atlantic Forest biome in Brazil

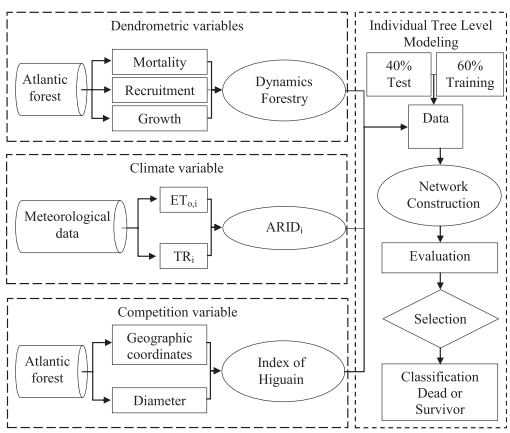
Samuel José Silva Soares da Rocha [a,*], Carlos Moreira Miquelino Eleto Torres [a], Laércio Antônio Gonçalves Jacovine [a], Helio Garcia Leite [a], Eduardo Monteiro Gelcer [b], Karina Milagres Neves [a], Bruno Leão Said Schettini [a], Paulo Henrique Villanova [a], Liniker Fernandes da Silva [c], Leonardo Pequeno Reis [d], José Cola Zanuncio [e]

[a] Departamento de Engenharia Florestal, Universidade Federal de Viçosa, 36.570-900 Viçosa, Minas Gerais, Brazil
[b] Ensoag LLC, Gainesville, 32607, Florida, United States of America
[c] Departamento de Engenharia Florestal, Universidade Federal do Recôncavo da Bahia, 44380-000, Cruz das Almas, Bahia, Brazil
[d] Instituto de Desenvolvimento Sustentável Mamirauá, 69.553-225 Tefé, Amazonas, Brazil
[e] Departamento de Entomologia/BIOAGRO, Universidade Federal de Viçosa, 36570-900 Viçosa, Minas Gerais, Brazil

HIGHLIGHTS

- The tree survival and mortality in rainforest were estimated with artificial intelligence;
- The accuracy rate of the surviving trees classification was above 99%;
- Artificial Neural Networks with inclusion of meteorological variables improve modeling of mortality in the Atlantic Forest.

GRAPHICAL ABSTRACT



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ABSTRACT

Models to predict tree survival and mortality can help to understand vegetation dynamics and to predict effects of climate change on native forests. The objective of the present study was to use Artificial Neural Networks, based on the competition index and climatic and categorical variables, to predict tree survival and mortality in Semideciduous Seasonal Forests in the Atlantic Forest biome. Numerical and categorical trees variables, in permanent plots, were used. The Agricultural Reference Index for Drought (ARID) and the distance-dependent competition index were the variables used. The overall efficiency of classification by ANNs was higher than 92% and 93% in the training and test, respectively. The accuracy for classification and number of surviving trees was above 99%

* Corresponding author.
E-mail addresses: samuel.rocha@ufv.br (S.J.S.S. Rocha), carlos.eleto@ufv.br (C.M.M.E. Torres), jacovine@ufv.br (L.A.G. Jacovine), hgleite@ufv.br (H.G. Leite), eduardo@ensoag.com (E.M. Gelcer), karina.neves@ufv.br (K.M. Neves), bruno.schettini@ufv.br (B.L.S. Schettini), paulo.villanova@ufv.br (P.H. Villanova), liniker@ufrb.edu.br (L.F. Silva), leonardo.reis@mamiraua.org.br (L.P. Reis), zanuncio@ufv.br (J.C. Zanuncio).

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in the test and in training for all ANNs. The classification accuracy of the number of dead trees was low. The mortality accuracy rate (10.96% for training and 13.76% for the test) was higher with the ANN 4, which considers the climatic variable and the competition index. The individual tree-level model integrates dendrometric and meteorological variables, representing a new step for modeling tree survival in the Atlantic Forest biome.

1. Introduction

The Brazilian Atlantic Forest has one of the richest biodiversities in the world (Delgado et al., 2018; Joly et al., 2014; Myers et al., 2000), even though only 12.5% of its original coverage remains in forest fragments with most having <100 ha (Ribeiro et al., 2009; SOS Mata Atlântica, 2015). The negative effects of climate change, such as drought, have affected the growth dynamics of forest remnants, leading to high tree mortality (Bretfeld et al., 2018; Hartmann et al., 2015; Hendrik and Maxime, 2017; Manso et al., 2015).

The development of individual tree-level models to predict the drought effect on tree mortality is fundamental for conservation and preservation strategies for this biome (Meir et al., 2015; Vieira et al., 2018). These studies provide information of forest dynamics and are required for correct prognosis of tree numbers, basal area, diameter distribution and production (Reis et al., 2016).

The model parameters can be estimated using regression and artificial intelligence, mainly Artificial Neural Networks– ANN (Hasenauer et al., 2001; Reis et al., 2016; Vahedi, 2016). ANNs may be more accurate than regression due to complex relationships between biologically dependent or non-biological factors (Vahedi, 2016, 2017).

ANN models are efficient to estimate tree growth (Ashraf et al., 2015; Reis et al., 2016), biomass and carbon (Corona-Núñez et al., 2017; Nandy et al., 2017; Santi et al., 2017), species richness and composition mapping (Foody and Cutler, 2006), prognosis of tree diameter and height (Diamantopoulou and Özçelik, 2012; Diamantopoulou et al., 2015; Vieira et al., 2018) and mapping tropical forest structure (Ingram et al., 2005).

ANN use to predict and classify tree mortality and survival is still incipient, with low gain compared to traditional statistical techniques (Guan and Gertner, 1991; Hasenauer et al., 2001; King et al., 2000). The precision of ANNs to estimate tree mortality in a managed tropical forest in the Brazilian Amazon was low (Reis et al., 2018). This was mainly due to the complexity of random factors, such as droughts and storms, which may influence tree mortality (Hasenauer et al., 2001).

The inclusion of distance-dependent competition index and drought index in ANNs to predict and classify tree mortality and survival may increase prognosis accuracy, since water and nutrient availability in the forest affects the growth dynamics of native forests (Allen et al., 2015; Caminero et al., 2018; Das et al., 2011; McDowell et al., 2018). These variables have not yet been tested as inputs for ANNs. Therefore, the present study proposes a novel experimental approach to model

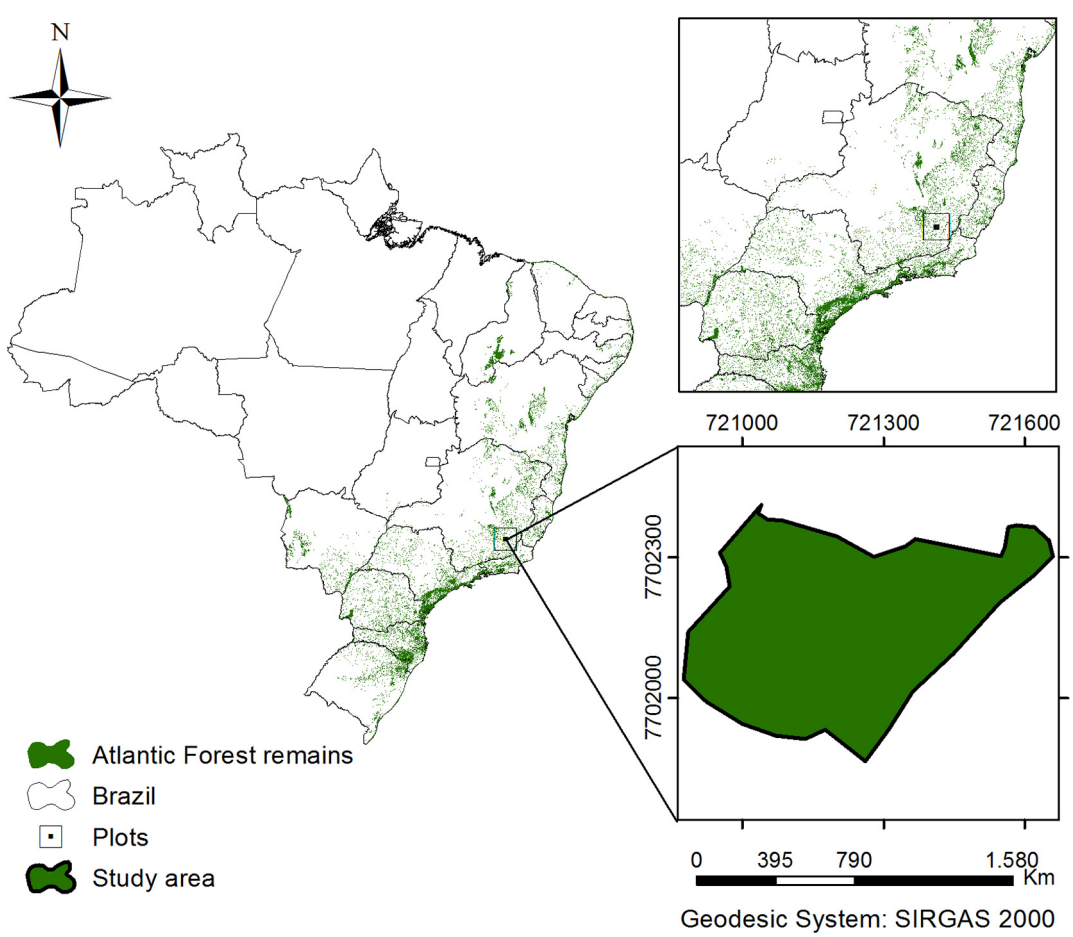

Fig. 1. Plots Location in the Atlantic Forest fragment.

tree mortality and survival at the individual level in tropical forests around the world.

The accuracy of ANNs using dendrometric variables as inputs and also with the inclusion of climatic variables and competition index to classify tree mortality and survival at the individual level in a secondary forest fragment of the Atlantic Forest was evaluated.

2. Material and methods

2.1. Study area characterization

The study was carried out in a regenerated fragment of Semideciduous Seasonal Forest in the Atlantic Forest biome, with 17 ha in Viçosa, Minas Gerais, Brazil (Fig. 1). The area suffered from wood extraction, agricultural activities and other anthropogenic actions. In 1936, the Universidade Federal Viçosa interrupted these activities and since then it has protected this area for research (Meira Neto and Martins, 2003), guaranteeing ecological succession for >80 years.

The local climate, according to the Köppen-Geiger classification, is Cwa type, with temperature, humidity and average annual precipitation of 21.9 °C, 79% and 1.274 mm between 1968 and 2015, respectively (UFV, 2016). The local topography is rugged with strong undulating mountainous relief and narrow, humid valleys. The fragment is in an area at an altitude between 670 and 730 m. Red-yellow alsicose latosol predominates at the top of the hills and slopes and the cambic yellow-red podzolic in the terraces (Ferreira Júnior et al., 2012).

2.2. Data collection and analysis

2.2.1. Dendrometric characteristics

Ten permanent plots, with 0.1 ha (20 × 50 m) each, were randomly marked in the area. The CBH (Circumference at Breast Height, 1.3 m), height of the stem (beginning of the crown), and total height (Ht) of trees with DBH (Diameter at Breast Height, 1.3 m) greater than or equal to 5.0 cm, were measured. In addition, these plants were inventoried and identified in monitoring during 1994, 1997, 2000, 2004, 2008, 2010, 2013 and 2016.

The vegetation is classified as Semideciduous Seasonal Forest Montana (IBGE, 2012) in the mid regeneration stage with woody species with a diameter at breast height (DBH) of 10 to 20 cm and height of 5 to 12 m (Table 1).

Crown information, liana infestation, crown lighting, and stem quality of the trees measured were also collected (Table 2).

The forest species were divided into the pioneer ecological groups (dependent on high light and common in open areas and clearings), initial secondary (intermediate light conditions) and late secondary (shady environments, that is, understory) (Gandolfi et al., 1995; Leitão Filho, 1993).

Table 2
Criteria for the tree classification of trees in the Atlantic Forest fragment.

Class	Criteria		
	Liana infestation	Crown lighting	Stem quality
1	Absent	Total	No damage
2	Present in the stem	Partial	Small damages
3	Present in the crown	Shadow	Severe damage
4	Present in both	–	–

2.2.2. Climate variable

Drought was analyzed with the Agricultural Reference Index for Drought (ARID) (Woli et al., 2012) ARID values range from 0 to 1, where 1 indicates total water deficit and 0 indicates absence of water deficiency. ARID was calculated with the equation:

$$ARID_i = 1 - \frac{TR_i}{ET_{o,i}} \quad (1)$$

where: $ARID_i$- ARID during the day i; TR_i- transpiration during the day i (mm d^{-1}); $ET_{o,i}$- reference evapotranspiration during the day o,i (mm d^{-1}).

The permanent wilt point values (PWP) and field capacity (FC) for the forest were determined based on those of Seasonal Semideciduous Forests in Visconde do Rio Branco, Minas Gerais, Brazil (Portugal et al., 2007). The transpiration (mm d^{-1}) was estimated by:

$$T_i = \min\left(\alpha\zeta\theta^{ad}_{a,i-1}, ET_{o,i}\right) \quad (2)$$

where: ζ - root system depth (mm); $\theta^{ad}_{a,i-1}$—water content available for the plant after drainage at the end of the previous day (mm mm^{-1}).

The ETo was estimated daily using the FAO-56 Penman-Monteith equation (Eq. 3) to estimate the daily ARID value. The R_n was calculated with the Angström-Prescott equation (Eq. 4).

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (3)$$

where: R_n- daily radiation balance (MJ m^{-2} d^{-1}); G- daily total heat flow in the soil (MJ m^{-2} d^{-1}); T- average daily air temperature at 2 m in height (°C); u_2- wind speed of 2 m high (m s^{-1}); e_s- steam saturation pressure (kPA); e_a- current steam pressure (kPA); e_s- e_a - is the difference in vapor pressure (kPA); Δ- slope of the vapor pressure curve with respect to the temperature (kPA °C^{-1}); ϒ- psychrometric constant (0.0677 kPA °C^{-1}).

$$R_s = \left(a_s + b_s\frac{n}{N}\right)R_a \quad (4)$$

where: R_s- global solar radiation (MJ m^{-2} d^{-1}); n- number of hours of sunshine (h d^{-1}); N- number of hours of sunshine (h d^{-1});

Table 1
Dendrometric measurements (mean ± standard deviation) in the Atlantic Forest fragment.

Year	Dendrometric measurements				
	Ns	DBH (cm)	H (m)	Hs (m)	BA (m^2)
1994	1532 ± 254.54	11.690 ± 8.25	10.448 ± 4.40	6.948 ± 3.39	24.634 ± 5.09
1997	1553 ± 267.45	11.870 ± 8.69	11.101 ± 4.85	7.279 ± 3.69	26.420 ± 5.80
2000	1513 ± 264.32	12.027 ± 8.96	11.385 ± 5.22	7.447 ± 3.88	26.716 ± 6.05
2004	1492 ± 259.30	12.085 ± 9.06	12.379 ± 5.88	7.391 ± 4.04	26.730 ± 6.42
2008	1518 ± 270.21	12.228 ± 9.40	12.360 ± 5.94	7.863 ± 4.10	28.356 ± 7.15
2010	1466 ± 264.45	12.363 ± 9.58	12.183 ± 5.99	7.836 ± 4.30	28.164 ± 7.88
2013	1388 ± 245.43	12.834 ± 10.05	12.749 ± 6.09	8.246 ± 4.41	28.972 ± 8.94
2016	1394 ± 292.58	12.532 ± 10.22	12.710 ± 6.21	8.723 ± 4.00	28.632 ± 9.95
Mean	1482 ± 61.79	12.193 ± 0.34	11.891 ± 0.66	7.717 ± 0.53	27.323 ± 1.46

Ns = Number of stems; DBH_1 = diameter measured at a height of 1.30 m (cm); H = Height (m); Hs = Stem height (m); BA = Basal area (m^2).

R_a- extraterrestrial radiation (MJ m^{-2} d^{-1});a_s- coefficient that expresses the fraction of the extraterrestrial radiation reaching the earth on cloudy days ($n = 0$);$a_s + b_s$- fraction of the extraterrestrial radiation that hits the earth on sunny days (n = N).

The data for insolation, maximum and minimum daily temperature, precipitation, relative humidity and wind, between 1991 and 2016 were obtained at the meteorological station of the National Institute of Meteorology (INMET) of Viçosa, Minas Gerais, Brazil (INMET, 2017).

2.2.3. Competition variable

The distance-dependent competition index (IDD) was used (Hegyi, 1974) (Eq. 5). Competitive subjects were those with DBH > 5 cm within a radius of six meters from the tree-object.

$$IDD = \sum_{j=1}^{nj} \frac{DBH_i}{DBH_j . D_{ij}} \quad (5)$$

where:DBH_i- Diameter at breast height, 1.3 m;DBH_j- Diameter at breast height of the competing tree measured at 1.30 m height (cm);N_j- number of competitor stems in the competition radius of 6 m;D_{ij}- distance between the tree evaluated and the competitor (cm).

The competition radius was defined (Béland et al., 2003) and varied the competition radius between 3 and 9 m for the proposed model (Hegyi, 1974) indicating the competitive radius of 6 m after the regression model simulation. To automate the index calculation, we developed an application for each index category in the Visual Basic for Applications.

2.2.4. Training and testing of neural networks

The networks were constructed with the permanent plots randomly divided into a group of six for ANN training and another of four for the generalization of trained ANNs (validation) with 60% of the data for training and 40% for generalization.

Tree mortality and survival were individually modeled with input variables and training and exit numbers (Table 3). The effect of the insertion of climatic variables and of competition to train the networks was evaluated. In the modeling process, 1200 ANNs were formed, 300 for each variable set.

The networks were constructed and trained with Statistica 13 software (StatSoft Inc, 2016) with MLP (Multilayer Perceptron) architecture, consisting of two artificial neuron layers that process the data (intermediate and output layers) and one of artificial neurons that receives the data (input layer) and directs it to the intermediate layer. The identity, logistic, hyperbolic tangent and softmax and exponential activation functions were tested in the intermediate and output layers.

The classification accuracy rates and the projected and observed diameter distribution of the surviving individuals were evaluated. The statistical significance of the distributions was tested with the chi-squared ($\times^2$) adherence test at a 5% probability level.

BIAS was used to evaluate accuracy and shows the average difference between predicted and observed data (Eq. 6).

$$BIAS = \frac{\sum_{j=1}^{n} (O_j - P_j)}{n} \quad (6)$$

where:O_j- denotes observed values of tree i;P_j-is the associated predicted value;n- the number of data.

3. Results

The accuracy for the classification of the number of surviving trees was above 99%. The total efficiency was higher than 92% in the training and 93% in the test for all ANNs (Table 4). This characterizes an efficient ANN generalization for independent data.

The classification accuracy of the number of dead trees was low, <15% for the test in all ANNs (Table 4). This low hit rate represents the trees that were mistakenly included in a certain class when they should have been assigned to another.

The mortality rate (10.96% for training and 13.76% for the test) was higher with ANN4, with climatic variables and competition index, and lower with ANN1, without the drought index and competition data (1.75% for training and 3.36% for the test). This shows that the inclusion of such variables improves ANN classification.

The diametric distributions of surviving individual stems in all periods present an exponential with "J-inverted" negative distribution shape, characteristic of unequal forests (Fig. 2-a).

In terms of BIAS, the ANNs show good performance, especially for the larger trees (Fig. 2-b). Estimates of the surviving ridge numbers were close to those observed in most diametric classes.

The estimated tree diameter distribution for 1997–2000 and 2013–2016 with ANNs 3 and 4 ($p < 0.05$) differed from observed values (Table 5) due to the overestimation of survival in the smaller diameter class center (7.5 cm) (Fig. 2-b).

4. Discussion

The classification of individual survival shows the potential of Artificial Neural Networks for prognosis of this parameter for trees in forests of the Atlantic Forest biome. These models can contribute to forest management, through the creation of scenarios and simulations in extreme climatic situations (Anderegg et al., 2012) and to predict individual longevity (Holzwarth et al., 2013).

The accuracy rate for classification of surviving tree numbers above 99% and overall efficiency index higher than 92% in training and 93% in the test for all ANNs, agrees with results reported for the Amazon forest (Reis et al., 2018) and can be explained by the high flexibility and non-linearity of the discriminant function of ANNs, offering better classification compared to other techniques.

Table 3
Number (NR) and type (Type) of the network, input variables, training number (number) and output variables (Output) in the training of artificial neural networks (ANN) to estimate tree mortality and survival in the Atlantic Forest fragment.

ANN	Type	Input variables		Num.	Output
		Numerical	Categorical		
1	MLP	DBH_1, H_1, Hc_1, Y_1, Y_2,	F, EG,L, IC, QS	300	D/S
2	MLP	DBH_1, H_1, Hc_1, Y_1, Y_2, IDD	F, EG, L, IC, QS	300	D/S
3	MLP	DBH_1, H_1, Hc_1, Y_1, Y_2, ARID	F, EG, L, IC, QS	300	D/S
4	MLP	DBH_1, H_1, Hc_1, Y_1, Y_2, IDD, ARID	F, EG, L, IC, QS	300	D/S

MLP = Multilayer Perceptron; DBH_1 = diameter measured at a height of 1.30 m (cm) in year 1; H_1 = Height (m) in year 1; Hc_1 = Stem height (m) in year 1; Y_1 and Y_2 = Current and future years, respectively; F = Individual botanic family; EG = Ecological group; L = liana infestation intensity; CL = Crown lighting level; IDD = Distance dependent competition index; ARID = Agricultural Reference Index for Drought; QS = Stem quality. Categorical output: Dead Tree (D) or Surviving Tree (S).

Table 4
Training precision measures and Artificial Neural Network (ANN) test in the classification of survival (S) and mortality (M) of individual trees in the Atlantic Forest fragment.

ANN	MLP	AF		Training			Test		
		IL	OL	HR/S	HR/D	OE(%)	HR/S	HR/D	OE(%)
1	83-10-2	Log.	Exp	99.965	1.750	92.640	100.000	3.366	93.228
2	84-18-2	Exp.	Sof.	99.471	8.771	92.720	99.595	10.403	93.346
3	90-15-2	Exp.	Exp.	99.859	4.814	92.771	99.924	4.362	93.228
4	91-15-2	Log.	Sof.	99.259	10.96	92.687	99.368	13.758	93.369

AF = activation function, Log = Logistic function; Exp = Exponential function; Sof = softmax function; IL: Intermediate layer; OL: Output layer; MLP: multi-layer Perceptron; HR: Hit rate (%); OE: overall efficiency index (%); D = Dead Tree; S = Surviving Tree.

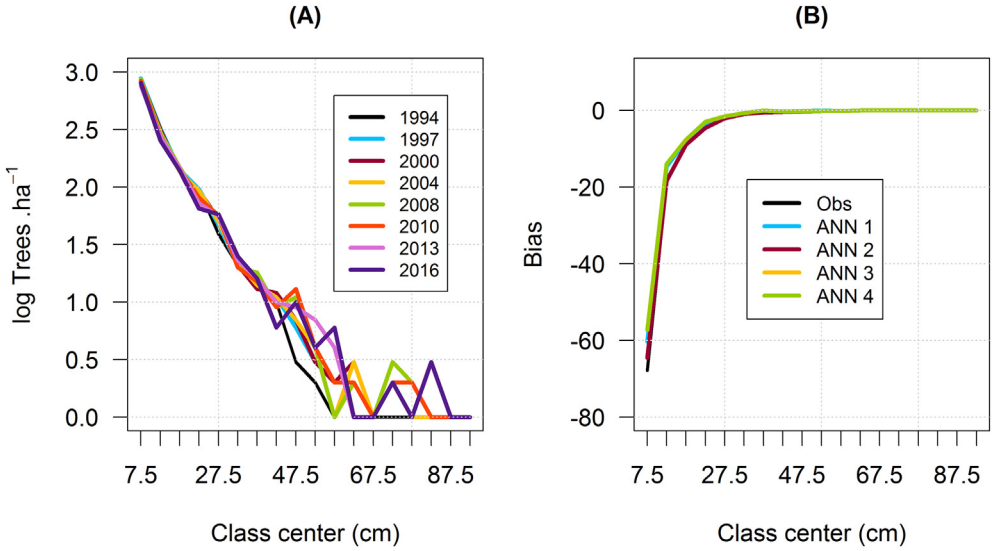

Fig. 2. Diametric distribution per year of surviving trees (A) and accuracy of ANNs to classify surviving trees (B) in a Semideciduous Seasonal Forest in Mata Atlantica biome.

The diameter distribution of the estimated and observed data of J-inverted surviving trees (Fig. 2-a) agrees with results observed for the Amazon forest in Brazil (Reis et al., 2018), and it is due to a higher individual density in the lower diameter classes, characterizing this negative exponential form (Rubin et al., 2006). This indicates that lower tree density supports a population of larger trees.

The overall performance of the model developed was, in general better in terms of BIAS to predict survival with the higher BIAS values in the first diameter classes due to the difficulty in predicting lower tree mortality. Tree mortality is induced by competition for resources (Looney et al., 2016; Sánchez-Salguero et al., 2015) with the availability of water modulated by drought intensity and competition (Gustafson et al., 2017; Primicia et al., 2015). Smaller diameter trees are less competitive in contexts of more limited resources and are more sensitive to additional stress (Grote et al., 2016) and probably the first to die. This makes the process of modeling smaller trees stochastic and difficult, explaining the non-adherence of some networks to observed data.

Differences in Chi-squared test for estimated tree diameter distribution for 1997–2000 and 2013–2016 ($p < 0.05$) is due to strong intensity (Bretfeld et al., 2018; Cashin et al., 2017) ENSO events (El Niño Southern Oscillation). This causes a positive temperature anomaly pattern for the sea surface (SST) (anomalous heating) over the eastern Pacific and generates extreme droughts in tropical regions (Córdoba-Machado et al., 2015). This may have affected the prognosis of individual survival during these periods. Trees in early-successional forests displayed stronger signs of regulatory responses to the drought (Bretfeld et al., 2018).

The low classification of the dead tree numbers agrees with modeling for mortality in other forests where ANNs also performed poorly (Hasenauer et al., 2001; Reis et al., 2018). This fact can be due to the reduced number of individuals, insufficient for a good classification by the networks, since the long tree life cycle makes mortality infrequent (King et al., 2000; Reis et al., 2018). In addition, the environmental, entomological, physiological, pathological and other factor effects (Hallinger et al., 2016; Hülsmann et al., 2016) make predicting, modeling and prognosis of tree mortality in tropical forests difficult (Manso et al., 2015; Reis et al., 2018). Tree mortality usually results from interactions between diverse factors, often in a gradual process (Kim et al., 2017), which may make mortality modeling even more complex.

The higher mortality rate with ANN4, with climatic variable and competition index, and lower with ANN1, without the drought and competition indices, confirms this parameter improvement with the variable insertion in the ANN4, since tree mortality is associated with the climate effect (Cortini et al., 2017) and competition between individuals (Kim et al., 2017). Similar models to predict mortality in the Amazon without these variables showed lower results in mortality prediction (Reis et al., 2018). This shows that it is essential to include variables describing competition and the climate effect to model tree mortality and survival in unequal forests.

Estimates of the surviving ridge numbers close to those observed in most diameter classes during all periods means that the ANNs have a high capacity to classify surviving individuals and confirms the high flexibility and non-linearity of their discriminant function. Besides the inclusion of the competition and climatic variables contributing to the classification, the categorical variables were also responsible for this high power to discriminate individuals, since, implicitly, they consider a range of mortality causes for individual trees (pathogens, mortal damage to small trees by falling logs, thunderstorms, etc.) (Bircher et al., 2015).

This is the first model to integrate ANN and drought and competition indexes to predict tree survival and mortality in the Atlantic Forest. ANN construction and training with the introduction of climatic and competition variables represents a promising alternative to predict tree survival in forests. The inclusion of other ecological and environmental factors, such as relief and degree of disturbance, as categorical variables in the models, can improve and increase the accuracy of tree mortality with the ANN technique (Vahedi, 2016). This is possible because the ANN technique allows the inclusion of new variables (Vahedi, 2017), based on biological theory and dynamic processes according to the ecological reality and not on accidental or random correlations.

Table 5
Chi-squared test ($\chi 2$) of adherence between the diameter distribution observed and estimated of the surviving trees in the Atlantic Forest fragment.

Period	ANN 1	ANN 2	ANN 3	ANN 4
1994–1997	0.232^{ns}	4.086^{ns}	1.856^{ns}	0.478^{ns}
1997–2000	6.535^{ns}	9.851^{ns}	9.851^{*}	4.262^{*}
2000–2004	3.862^{ns}	4.467^{ns}	4.682^{ns}	3.324^{ns}
2004–2008	7.260^{ns}	7.141^{ns}	7.141^{ns}	6.811^{ns}
2008–2010	6.108^{ns}	5.775^{ns}	5.775^{ns}	5.652^{ns}
2010–2013	7.128^{ns}	7.128^{ns}	7.128^{ns}	6.794^{ns}
2013–2016	25.067^{*}	25.263^{*}	25.263^{*}	25.263^{*}

p-value = 0.05; df = 17.

5. Conclusion

The dynamic and deterministic model at the individual tree level with artificial neural networks is adequate to model tree survival by integrating dendrometric and meteorological variables. The new input variables included in the models may help to predict the complex phenomenon of mortality.

The survival and mortality modeling with artificial intelligence and environmental variables (competition index and climatic variables) inclusion represents an important step to understanding forest dynamics and can support the decision-making conservation practices in this biome, especially in times of continuous climate change.

The methodology can be adjusted to understand forest dynamics in other regions of the world.

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Author contributions

S.J.S.S.R.; C.M.M.E.T. and L.A.G.J. conceived the study, S.J.S.S.R.; C.M.M.E.T.; K.M.N.; B.L.S.S. and P.H.V. conducted the experiment, S.J.S.S.R.; C.M.M.E.T.; H.G.L.; E.M.G.; L.F.S. and L.P.R. performed analyses, S.J.S.S.R. wrote the frst draf of the manuscript, and C.M.M.E.T.; H.G.L.; E.M.G.; L.F.S.; L.P.R. and J.C.Z. contributed substantially to write this manuscript. All authors reviewed the manuscript.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at doi: https://doi.org/10.1016/j.scitotenv.2018.07.123. These data include the Google map of the most important areas described in this article.

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