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Artificial Neural Networks Effectiveness to Estimate Mortality in a Semi-Deciduous Seasonal Forest

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ABSTRACT

This study aims to evaluate the effectives of artificial neural networks to estimate the regular mortality of single-trees in a Semi-deciduous Forest fragment. Data from 10 permanent plots was used; these plots were observed for 14 years, in five occasions and are located in Viçosa, Minas Gerais, Brazil. The data set was randomly divided in two groups: training group, consisting of six plots with a total of 3,556 cases during five measurements, which 231 mortality cases were noticed and the generalization group, consisting of four plots that were used in the mortality simulation, a total of 2,062 cases was observed, 181 being mortality cases. The networks for tree mortality estimates were evaluated qualitatively and quantitatively. The first one refers to label the trees as living or dead between two measuring periods (classification network). The second refers to the mortality probability estimate that each tree has between two measuring periods (function approximation network), applied along with the mortality rule proposed by Pretzsch *et al*., (2002), based in the estimated probability compared to a random number. Furthermore, different structures and network models were evaluated (Multilayer Perceptron - MLP and Radial Basis Function - RBF). The activation functions employed by MLP network were: identity, tangential and exponential logistics. Input numerical variables (*dap*, total height, measuring year and distance independent, dependent and semi-independent competition indexes) and categorical variables (liana infestation level, crown illumination, crown quality, ecologic group and botanic family) were established. Using neural networks for function approximation was effective to predict mortality. The MLP: 60-14-1 network, with exponential activation function, using the distance dependent index, was more effective to mortality estimation.

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INTRODUCTION

The growth models and forest production are important to predict growth and allow simulating the natural dynamic, under exploration hypothesis or liable to physical and biotic agents (Tomé, 1991; Vanclay, 1994). They can be divided according to the information level, composed by only one equation or by an equation set (Vanclay, 1994).

Among the model components, mortality is the hardest to model (Hamilton Jr., 1986; Hamilton Jr., 1990; Flewelling e Monserud, 2002; Yang *et al*., 2003; Martins, 2011).

The trees die due competition, injuries, diseases or because they reached silvicultural rotation. When death occurs due anthropogenic actions, it is defined as irregular. This mortality type also occurs due pest damage, wind damage or fires (Staebler, 1953; Campos e Leite, 2009), making its estimation impossible.

The regular mortality occurs due competition among trees or even due the tree's age (Dixon, 2011, apud Groom *et al*., 2012). For being predictable factors, its estimation is possible (Monserud, 1976; Zhao *et al*., 2006; Martins, 2011; Castro, 2011; Groom *et al*., 2012).

The most used method for single-tree mortality studies consists in estimate the mortality probability of each specimen in a set period of growth related to a group of population characteristics and to the tree

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itself (Hasenauer *et al*., 2001). In this case, deciding if a tree lives or dies during a simulation is up to the estimated probability compared to a random number (between 0 and 1). If the random number is smaller than the calculated probability, the tree is eliminated from the list (dead) (Pretzsch *et al*., 2002).

The mortality probability can be interpreted as proportions and the number of living trees can be taken from the list based on the predicted proportion (Rossi, *et al*., 2007; Martins, 2011).

In the tree mortality model, is usual to predict the mortality probability with asymptotic sigmoid functions (Logistics, Gompertz, Weibull, Chapman-Richards, etc.), because in these functions, the predicted values are limited between 0 and 1 (Hamilton Jr. e Edwards; 1976). This method is recognized for predict tree mortality in homogeneous forests around the world (Hamilton Jr., 1986; Yao *et al*., 2001; Hurst *et al*., 2012).

In uneven-aged forests with great diversity, there are few mortality studies in a single-tree level, probably, due the absence of proper data for modeling and the different mortality behaviors among the species (Vanclay, 1994; Hamilton Jr., 1986). Obtaining a mortality equation for each species is impossible, due the great amount of species and reduced data number (low abundance) for many of them, which prevents the development of reliable relations (Rossi *et al*., 2007).

The artificial neural network (ANN) arise, then, as an efficient alternative to tree mortality study (Hasenauer e Merkl, 1997), mostly in this type of forest, due the possibility of inclusion of independent qualitative variables, such as: tree health, ecologic groups, botanic families and others elements that influence the mortality directly.

Neural networks can be applied in function approximation problems, classification patterns, temporal series and patterns recognition (Jain *et al*., 1996; Haykin, 2001; Barreto, 2002, Binoti, 2010). The neural networks' learning method can be supervised, when the user indicates the input and output variables, or non-supervised, when there isn't an external agent indicating the desired answer for the input patterns (Haykin, 2001).

The supervised learning has been the most used in Forestry Science (Diamantopoulou, 2005; Görgens *et al*., 2009; Binoti, 2010; Leite *et al*., 2010; Castro, 2011), and the most known algorithm is the error back-propagation.

The ANN structure is based on the way the neurons are organized and its connections, on other words, the number of network tiers, the number of neurons in each tier and the type of connection between the neurons (Braga *et al*., 2000).

The most used network types in the forestry study field are *Multilayer Perceptron* (MLP) and *Radial Basis Function* (RBF). The MLP networks are multi-tiers that possess one or more neurons tiers between the input and output tiers, called hidden tier, which can extract non-linear patterns from the data (Lippann, 1987, Braga *et al*., 2000).

In this model all the neurons are connected to the sub-sequent tier neurons, there isn't a connection with the lateral neurons (from the same tier) and also there isn't feedback. The RBF networks are used for the same purpose of the MLP, and they are very similar (Haynkin, 2001). The RBF main characteristics are the existence of only one intermediate (hidden) tier; the output tier neurons are always linear; the intermediate neurons tier has radial basis function (Gaussian) as activation function, instead of sigmoid functions, applied in the MLP network (Braga *et al*., 2000).

The use of ANNs techniques to predict the tree mortality is recent in the forestry area. Guan and Gertner (1991) built a model using RBF networks getting precise tree mortality estimates for *Pinus* trees. Hasenauer and Merkl (1997) estimated the *Picea abies* mortality in Austria and Castro (2011) used MPL networks to estimate the *Eucalyptus* mortality in Brazil. The limitation for studies using ANN is deciding if a tree dead or alive by comparing the predicted probability with a given random number.

Another possibility is using the neural networks for classification purposes, in other words, in mortality studies; the network itself can predict the tree status, after an interval, as alive or dead.

Working with the possibility of using neural networks to predict tree mortality in forests, this study's goal is to verify the effectiveness of the RBF and MPL networks different structures to estimate single-trees mortality in a Montane Semi-deciduous Seasonal Forest.

MATERIALS AND METHODS

Data:

The data used in this study were obtained in Viçosa, Minas Gerais, Brazil, in a forest fragment the belongs to the Viçosa's University (Universidade Federal de Viçosa) that measures 17ha (the longitude is 42°52'W and 42° 50'W and the latitude is 20° 44'S and 20° 47'S), it is part of the Montane Semi-deciduous Seasonal Forest phyto-ecological region, in an average succession stage.

For the study's development one hectare was sampled, it was divided in ten rectangular plots, non-continuous, measuring 1,000 m² each (20m x 50m), randomly spread through the fragment (Meira Neto and Martins, 2000).

In each plot, the trees were identified and were measured the diameters with 1.3m height (*dap*) and total height (*Ht*) of all the trees with $dap \geq 5$ cm; also the specimens that died between the measuring were identified; the measuring occurred in 1994, 1997, 2000, 2004 and 2008. For each tree were determined coordinates *x* and *y* related to the origin of its plot, to create a map with the specimens' location and to calculate competition indexes.

All the measured specimens were classified considering the liana infestation level, crown illumination and crown quality (Silva e Lopes, 1984), in ecologic groups (Gandolfi *et al*., 1995), according to the grading indicated in Table 1. The main quantitative characteristics of the population study are in Table 2.

Table 1: Grading criterion for specimen classification related to the liana infestation, crown illumination, crown quality and ecologic group.

Grading Criteria	Class
Liana Infestation	
No liana presence	1
Liana presence only on the bole	2
Liana presence only on the crown	3
Liana presence on the bole and on the crown	4
Crown Illumination	
Crown receiving solar radiation directly on its upper and lateral part	1
Crown receiving solar radiation directly on its upper part	2
Absence of solar radiation directly in the crown	3
Crown Quality	
High: normal crown, no damage presence	1
Average: crown with a low scale damage	2
Low: crown with serious damage, with few branches and leaves	3
Ecologic Group	
Species dependent of light and that do not exist on the lower story, growing in glades or on forest edges	Pioneers (PI)
Develop in average shading conditions, such as small glades and lower story not densely shaded	Early Secondary (SI)
Develop in the lower story in light or dense shading conditions, it can grows until the over-story	Late Secondary (ST)
Species that due lack of information were not included in none of the categories	No Grading (NG)

Table 2: Inventory data summary from the Montane Semi-deciduous Forest fragment, in average succession phase, located in Viçosa - Minas Gerais.

Variable	Measuring Year				
	1994	1997	2000	2004	2008
Minimum *dap* (cm)	5.1	5.1	5.1	5.1	5.0
Average *dap* (cm)	11.6	11.8	12.0	12.0	12.2
Maximum *dap* (cm)	80.2	82.1	84.0	85.6	91.0
q (cm)	14.2	14.6	14.9	15.0	15.3
Minimum *Ht* (m)	2.5	2.5	2.5	2.4	2.4
Average *Ht* (m)	10.4	11.1	11.4	12.4	12.5
Maximum *Ht* (m)	32.1	32.4	33.0	39.2	39.4
Basal area (m^2 ha^{-1})	24.1	25.9	26.2	26.2	27.5
Volume (m^3 ha^{-1})	235.5	275.2	291.4	323.9	342.1
Botanic Families	43	43	43	42	42
Botanical Generas	100	98	99	99	103
Species Identified	136	135	137	135	148
Species Non-identified	4	3	4	3	5
Number of boles (ha)	1521	1540	1497	1474	1492
Density (trees per ha^{-1})	1379	1383	1331	1307	1326
Shannon-Weaver Index (H')	4.07	4.02	4.00	3.96	4.02
Joined specimens number (ha)*	-	114	79	57	134
Dead specimens number (ha)*	-	95	122	80	115

* Number of specimens that joined / died since the previous measuring.

The data set was randomly divided in two groups, with restrictions of variability representativeness of each group data. The first one refers to artificial neural network training data, consisting of six plots, a total of 3,556 cases with five measuring, which 231 mortality cases were observed. The second refers to generalization data, consisting of four plots that were used in the mortality simulation, a total of 2,062 cases, which were observed 181 mortality cases.

Competition Indexes:

To each bole (basic study unit), in each measuring were estimated three competition indexes, a distance independent index (DII), a distance dependent index (DDI) and a distance semi-independent one (DSI), selected in previous studies to estimate the mortality variable, being:

$$\text{DII} = \frac{Ht_i}{\overline{Ht}} \quad (1)$$

$$\text{DDI} = \sum_{j=1}^{nj} \frac{DAP_i}{DAP_j \cdot L_{ij}} \quad (2)$$

$$\text{DSI} = \frac{DAP_i^{\,2}}{\overline{D}_n^{\,2}} \quad (3)$$

Which: Ht_i = subject-tree's bole total height (m); $\overline{Ht}$ = sampled unit bole's average height (m); dap_i = bole diameter including the bark of the subject-tree measuring 1.30 m (cm); L_{ij}= distance between the subject-tree and the competitor tree (cm); n_j = competitors bole number limited to a competition radius measuring 6m; $\overline{D}_n$ = arithmetic mean of the trees near the subject-tree (cm), limited to a competition radius measuring 6m.

In each measuring were accounted the dead specimens. The mortality probability (*Pm*) was obtained by calculating the dead boles proportion by diameter class, for each plot between the measuring intervals (Martins, 2011; Castro, 2011, adapted).

$$Pm = 100.\frac{\left(n_{j1} - n_{j2}\right) - I_{j1j2}}{\sum_{i=1}^{j} n_{j1}} \quad (4)$$

Which n_{j1} is the number of living boles in the j-th diameter class, in the beginning of the period, n_{j2} is the number of living boles in the j-th diameter class in the end of the period, minus the specimens the joined between the measuring sequent periods (I_{j1j2}).

Artificial neural networks Training:

During the neural network training and development, the Statistica 10.0 (Statsoft, Inc, 2012), software was used, different structures were tested for the MLP (*Multilayer Perceptron*) and RBF (*Radial Basis Function*) networks.

For MLP networks, four different activation functions matchups were evaluated in the intermediate and output tiers (identity, logistics , tangential and exponential). For RBF networks, output tiers neurons have always been linear (identity function) and the intermediate tiers neurons have radial basis function (Gaussian) as activation function.

The networks were enabled for pattern grading and function approximation. In the first case, the goal was to qualify the trees as dead or alive, between two measuring periods, being represented by the letter M. On the second case, the goal was to estimate each tree mortality probability, between two measuring periods (*Pm*).

The training was feed-forward; the supervised method and input variables were selected based on the possible relation with the analyzed output variable. 1,800 networks were trained for the categorical variable M and 1,800 networks for the quantitative variable *Pm* (Table 3).

Table 3: Variables used during ANN's training to estimate trees mortality in a Montane Semi-deciduous Seasonal Forest fragment in Viçosa, MG.

Network Number	Type	Output	Numeric Entry	Categorical Entry	Total of trained networks
1 a 300	MLP	M	A_1, A_2, dap_1, Ht_1, DII	F, GE, C, IC,QC	900
301 a 600	MLP	M	A_1, A_2, dap_1, Ht_1, DDI	F, GE, C, IC,QC	
601 a 900	MLP	M	A_1, A_2, dap_1, Ht_1, DSI	F, GE, C, IC,QC	
901 a 1,200	RBF	M	A_1, A_2, dap_1, Ht_1, DII	F, GE, C, IC,QC	900
1,201 a 1,500	RBF	M	A_1, A_2, dap_1, Ht_1, DDI	F, GE, C, IC,QC	
1,501 a 1,800	RBF	M	A_1, A_2, dap_1, Ht_1, DSI	F, GE, C, IC,QC	
1,801 a 2,100	MLP	*Pm*	A_1, A_2, dap_1, Ht_1, DII	F, GE, C, IC,QC	900
2,101 a 2,400	MLP	*Pm*	A_1, A_2, dap_1, Ht_1, DDI	F, GE, C, IC,QC	
2,401 a 2,700	MLP	*Pm*	A_1, A_2, dap_1, Ht_1, DSI	F, GE, C, IC,QC	
2,701 a 3,000	RBF	*Pm*	A_1, A_2, dap_1, Ht_1, DII	F, GE, C, IC,QC	900
3,001 a 3,300	RBF	*Pm*	A_1, A_2, dap_1, Ht_1, DDI	F, GE, C, IC,QC	
3,301 a 3,600	RBF	*Pm*	A_1, A_2, dap_1, Ht_1, DSI	F, GE, C, IC,QC	

Witch MLP are *Multilayer Perceptron* networks and RBF are *Radial Basis Function* networks; M is the categorical output that qualifies the specimens as dead or alive between two measuring periods, *Pm* is the mortality probability between two measuring periods; A_1 and A_2 are the measuring years, current and future, respectively; dap_1 is the current diameter measuring 1,3 m (cm); Ht_1 is the current total height; DII, DDI, DSI are the distance independent, dependent and semi-independent competition indexes, respectively; F is the specimen's botanic family; GE is the ecologic group; C is the liana infestation level; IC is the crown illumination level and QC is the crown quality level.

Artificial neural networks training evaluation:

After the trainings, the best network of each kind (MLP and RBF) was selected and all competition indexes were used to the M and P*m* variables.

To select the mortality (M) grading networks, the estimated dead tree number that was closer to the real value was evaluated, also the estimated rate of correct classification in each network, in other words, verify if the trees graded as dead were the ones actually dead.

The best networks to estimate mortality probability (*Pm*) were selected according to the correlation coefficient between the observed and estimated probabilities, associated to the average trees number correctly qualified.

After obtaining each specimen mortality probability (*Pm*), a random number (Pa), between 0 and 1, was generated and compared to estimated probability. The rule that defined if a tree was dead was: if *Pm* > Pa the specimen is dead, otherwise, it remains alive (Pretzsch *et al*., 2002). The proceeding was repeated 30 times, in order to obtain an average mortality tendency to each tree.

It is necessary to emphasize that before starting this method, the rule (Pretzsch *et al*., 2002) to evaluate the effectiveness of the observed P*m* (training data) studied data was applied.

Artificial neural network generalization:

After selecting the training best networks, the generalization using independent data proceed. The predictions were made for the immediately consecutive measuring, from 1994 to 1997; from 1997 to 2000; from 2000 to 2004 and from 2004 to 2008. The trained networks application to generalization data was done with the Statistica 10.0 software.

To evaluate the M and P*m* network generalization power; the number of dead trees related to its real value and correct grading rate on each network were evaluated. To each P*m* network, 30 repetitions occurred, using the rule proposed by Pretzsch *et al*., (2002). The repetition that approached the average value the most during the 30 repetitions was selected to later analysis.

The best networks with generalist power were selected, and based on them bar graphs were elaborated to compare the predicted data with real data, according to the following variables:

a) Frequency of dead specimens between each measuring period;

b) Frequency of dead specimens related to qualitative variables (liana infestation level, crown illumination level, crown quality level and ecologic group), used as categorical input variables;

c) Frequency of dead and alive specimens by diameter class and height, related to observed distribution in the last measuring year (2008);

d) Frequency of mortality to each botanic family existent in the studied area.

To verify the adherence of mortality estimates on the selected networks with real values, the Kolmogorov-Smirnov's (K-S) non-parametric test was used (Sokal and Rohlf, 1969), whose statistic is given by:

$$dn = Max\ \left|F_o(x) - F_e(x)\right| \quad (5)$$

Which: *dn* is the K-S statistic value calculated; $F_o(x)$ is the accumulated frequency observed; $F_e(x)$ is the estimated accumulated frequency.

The null hypothesis (H_0: estimates do not differ from real values) was rejected for the *dn* calculated value greater than the tabled value, significance level of α equals to 5%.

RESULTS

The effectiveness of the method proposed by Pretzsch *et al*., (2002), to qualify the trees as dead, after calculated all probabilities, was proven for training data. After 30 repetitions, the average number of trees qualified as dead was 229 ± 12, and the real value was equal to 231 (Figure 1).

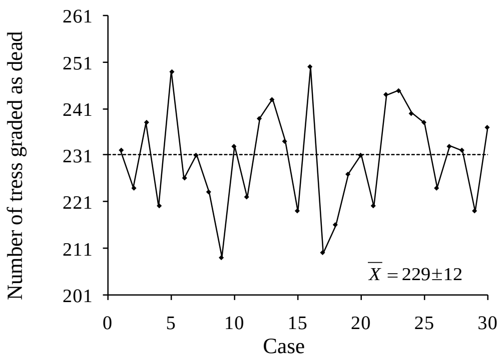

Fig. 1: Dead trees estimate number by applying the methodology proposed by Pretzsch *et al*. (2002) for the observed data during the artificial neural networks training.

The most appropriated neural networks to estimate mortality (M) and mortality probability (*Pm*) are submitted on tables 4 and 5, respectively.

The "scientific name" (specie) variable wasn't used as input variable on the neural networks training, so the networks could acquire a more generalist pattern, in other words, they wouldn't be efficient to estimate the mortality of species existent only on the training.

Among the categorical output network M (Table 4), the network 3 (MLP) was the only one that presented a good performance during the grading networks training, with the estimated number of dead trees (228) closer to the observed value (231). However, the number of dead trees was underestimated during the generalization.

The grading networks M were not efficient for this study. A possible explanation for this is the low mortality frequency in a huge number of data about living trees.

The networks 7 and 9 resulted on more precise mortality probability estimates on training and generalization phases (Table 5).

Among the *Pm* variables networks, none presented an appropriated precision regarding to mortality rates during training and generalization, were observed rates below 13%, which indicates that the specimens graded as dead were not the ones actually dead.

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Table 4: Selected artificial neural network's abstract to qualify single-trees mortality in a Montane Semi-deciduous Natural Forest, Viçosa, MG

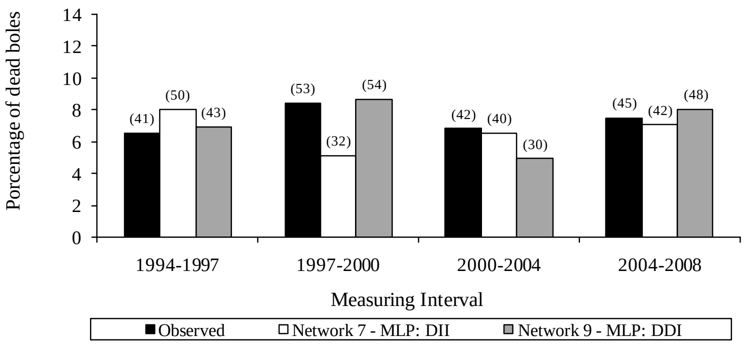
Selected Networks	Competition Indexes	Type	Structure*	Output (categorical)	Activation function		Training		Generalization	
					Intermediate Tier	Output Tier	Number of deaths (231)	Mortality Accuracy Rates	Number of deaths (181)	Mortality Accuracy Rates
1	DII	MLP	60-42-1	M	Logistic	Logistic	78	23.8%	37	8.3%
2	DII	RBF	60-182-1	M	Gaussian	Identity	102	10.4%	55	5.5%
3	DDI	MLP	60-31-1	M	Tangential	Tangential	228	47.6%	38	8.8%
4	DDI	RBF	60-200-1	M	Gaussian	Identity	98	12.2%	27	4.4%
5	DSI	MLP	60-56-1	M	Logistic	Exponential	75	14.4%	39	3.3%
6	DSI	RBF	60-107-1	M	Gaussian	Identity	18	10.5%	33	3.9%

Which MLP are *Multilayer Perceptron* networks and RBF are *Radial Basis Function* networks; (*) indicates the number of neurons in each input, intermediate and output tiers, respectively; M is the categorical output variable that indicates the tree's status as dead or alive between two measuring years.

Table 5: Selected artificial neural networks' abstract to estimate single trees mortality probability in a Montane Semi-deciduous Natural Forest, Viçosa, MG.

Selected Networks	Competition Indexes	Type	Structure*	Output (numerical)	Activation Function		Training			Generalization		
					Intermediate Tier	Output Tier	Number of deaths (231)	Mortality Accurance Rate	$r_{\hat{y}y}$	Number of deaths (181)	Mortality Accurance Rate	$r_{\hat{y}y}$
7	DII	MLP	60-12-1	*Pm*	Exponential	Exponential	237 ± 14	8.7%	0.49	164 ± 12	5.5%	0.35
8	DII	RBF	60-21-1	*Pm*	Gaussian	Identity	238 ± 17	7.0%	0.26	166 ± 13	5.1%	0.17
9	DDI	MLP	60-14-1	*Pm*	Exponential	Exponential	233 ± 15	12.1%	0.58	175 ± 10	5.8%	0.41
10	DDI	RBF	60-21-1	*Pm*	Gaussian	Identity	240 ± 17	7.1%	0.25	168 ± 13	5.2%	0.08
11	DSI	MLP	60-11-1	*Pm*	Exponential	Logistic	239 ± 15	8.9%	0.49	165 ± 12	5.8%	0.25
12	DSI	RBF	60-21-1	*Pm*	Gaussian	Identity	237 ± 16	7.0%	0.14	166 ± 13	5.1%	0.05

Which MLP are *Multilayer Perceptron* networks and RBF are *Radial Basis Function* networks; (*) indicates the number of neurons in each input, intermediate and output tiers; *Pm* is the numerical output variable that estimates tree's mortality probability between the measuring years.



K-S test with 5% significance - *Network 7: 0.078$^{n.s.}$; Network 9: 0.042$^{n.s.}$*

Fig. 2: Percentage of dead specimens observed and estimated by networks 7 and 9 for the generalization data, between the measuring periods.
The values above the bars, brackets, represent the number of specimens qualified as dead.
"n.s" indicates not significant differences regarding to 5% significance.

However, this precision is not essential for modeling in a single-tree scale. The important during the simulation, is that the dead trees must have similar characteristics to the ones that actually died, such as size and health, also, they have to occur on the right period of time; resulting in precise estimates on terms of population dynamic.

The mortality frequency observed between the intervals ranged from 6.5 to 8.4 %, in 1994 to 1997 and 2000 to 2004, respectively (Figure 2). The estimates of 7 and 9 networks were statically equal to the observed values.

On figure 3 the mortality predictions are presented related to the liana infestation level (a), crown illumination (b) and crown quality (c).

The mortality observed during the study period related to the liana infestation level ranged from 2.6% for trees with liana presence on the crown and bole, to 8.3% for trees without liana presence, as for the crown illumination, the mortality ranged from 3.9 to 16.5% for partial and total crown illumination class, respectively. For both variables, the 7 and 9 network estimates were statistically equals to the observed values, which did not occurred with the crown illumination variable level, whose the

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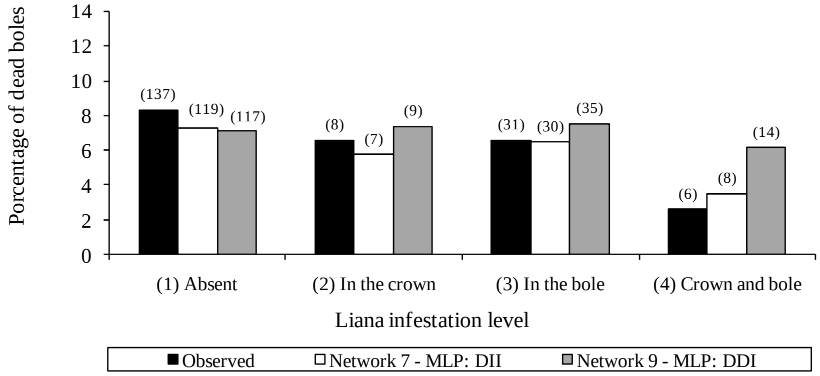
Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 435-444

mortality rate ranged between 4.4 and 11.1%, values that match with average and low quality classes, respectively.

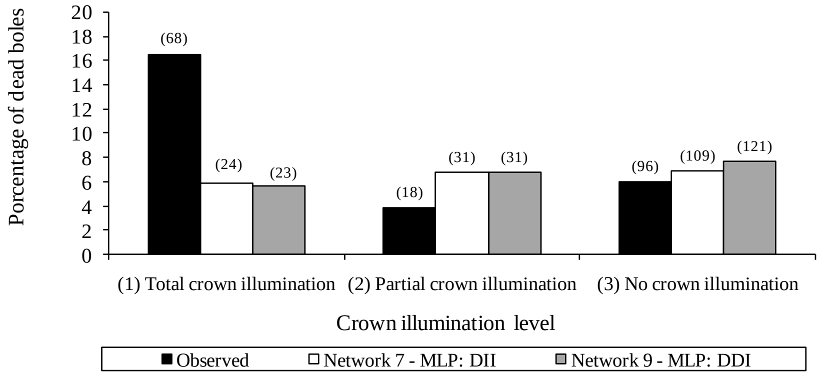
The mortality predictions related to the ecologic group (Figure 4) indicate that the mortality rates ranged from 5.2 to 17.7%, for specimens from the late secondary and pioneers groups, respectively. The networks 7 and 9 estimates were statically equal to the observed values.

(a)



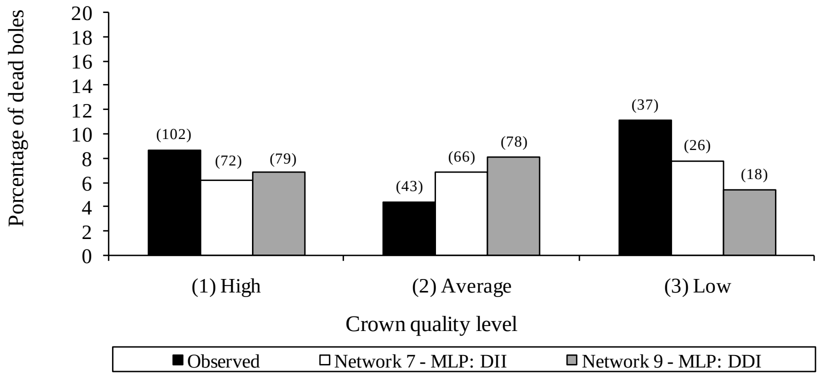
K-S test with 5% significance - *Network 7: 0.038$^{n.s;}$ Network 9: 0.084$^{n.s.}$*

(b)



K-S test with 5% significance - *Network 7: 0.227*; Network 9: 0.242**

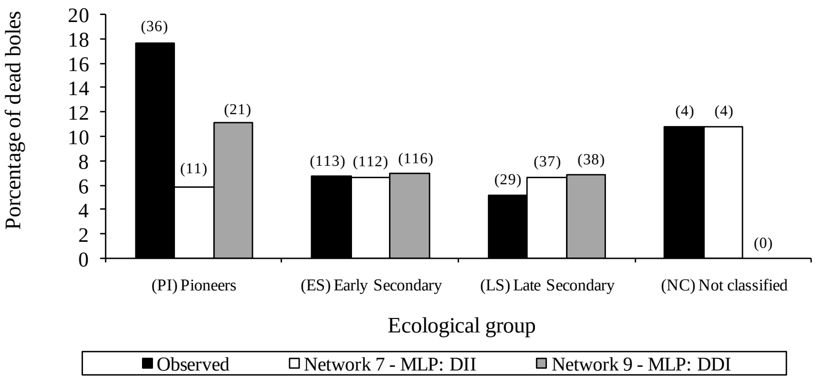
(c)



K-S test with 5% de significance - *Network 7: 0.121$^{n.s.}$; Network 9: 0.109$^{n.s.}$*

Fig. 3: Dead specimens observed and estimated by networks 7 and 9 for generalization data, regarding to liana infestation level (a), crown illumination (b) and crown quality (c), in a 14 years period.
The values above the bars, brackets, represent the number of specimen qualified as dead.
"n.s" indicates not significant differences and "" significant differences regarding to 5% of significance.*

Australian Journal of Basic and Applied Sciences, 9(5) March 2015, Pages: 435-444

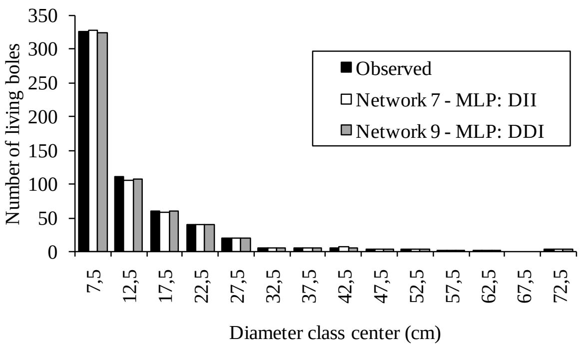


K-S test with 5% significance - *Network 7: 0.136$^{n.s.}$; Network 9: 0.078$^{n.s.}$*

Fig. 4: Dead specimens observed by networks 7 and 9 for generalization data, regarding to ecologic group, in a 14 years period.
The values above the bars, brackets, represent the number of specimen qualified as dead.
"n.s" indicates not significant differences regarding to 5% significance.

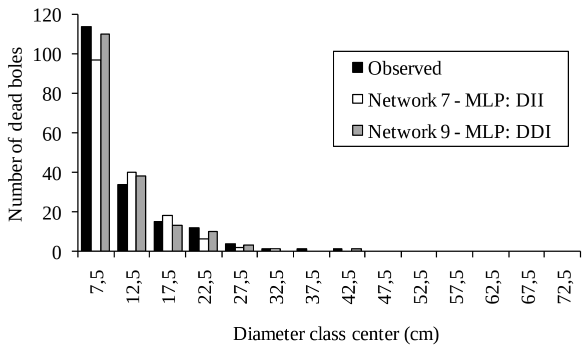
The diametric distribution of living trees and dead trees are represented in Figure 5. The mortality estimates obtained by networks 7 and 9 did not affect the tress diameter and height distribution of the remaining trees (alive) (Figure 5a and 5c). The tree mortality estimates were precise regarding to diameter and height class (Figure 5b and 5d).

(a)



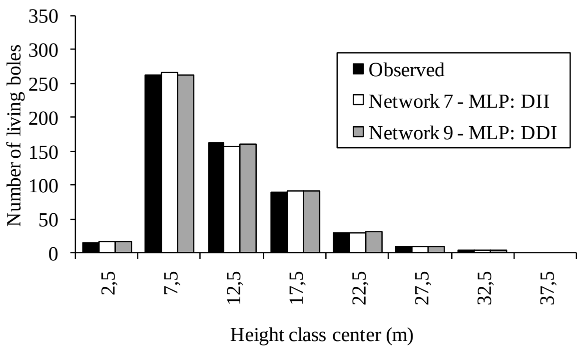
K-S Test - *Network 7: 0.008$^{n.s.}$; Network 9: 0.006$^{n.s.}$*

(b)



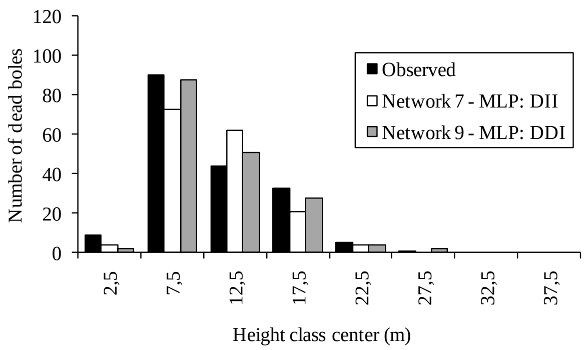
K-S Test - *Network 7: 0.040$^{n.s.}$; Network 9: 0.039$^{n.s.}$*

(c)



K-S Test - *Network 7: 0.009$^{n.s}$; Network 9: 0.003$^{n.s.}$*

(d)



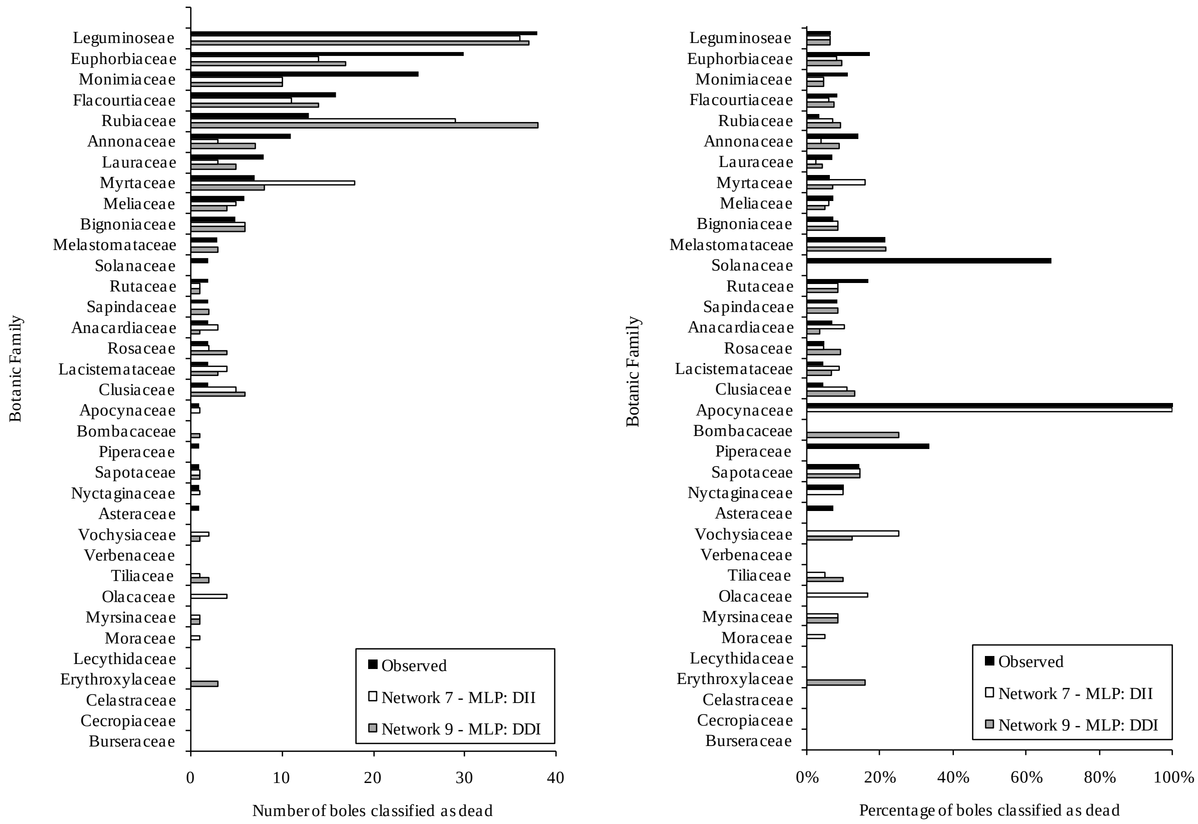
K-S Test - *Network 7: 0.118$^{n.s.}$; Network 9: 0.092$^{n.s.}$*

Fig. 5: Living and dead specimens' number observed and estimated by networks 7 and 9 for generalization data in 2008.
"n.s" indicates not significant differences regarding to 5% significance.

While analyzing a Montane Semi-deciduous Forest fragment in Minas Gerais, Pulz (1998) verified that mortality was greater among lower trees and light demanding species. In Australian forests, Monserud and Sterba (1999) also, found higher mortality rates among small trees, while the mortality rates reduction were related with trees' size.

The frequency of specimens classified as dead by the networks 7 and 9 during the last measuring year (2008) was statistically equal to the observed distribution regarding to the generalization groups' botanic families (Figure 6a). A greater frequency of dead specimens was observed in Leguminosae (38), Euphorbiaceae (30) and Monimiaceae (25) families. Greater mortality percentages among the families Apocynaceae (100%), represented by only one specimen; Solanaceae (67%) and (33%), both with only two specimens each (Figure 6b).

(a) (b)



K-S Test - *Network 7: 0.110*$^{n.s.}$*; Network 9: 0.099* $^{n.s.}$ K-S Test - *Network 7: 0.121*$^{n.s.}$*; Network 9: 0.102*$^{n.s.}$

Fig. 6: Mortality frequency (a) and mortality percentage (b) observed and estimated by networks 7 and 9 for generalization data regarding to botanic families in 2008.

"n.s" indicates not significant differences regarding to 5% significance.

DISCUSSION

Several studies reported how difficult is to estimate trees mortality, because is considered a rare occurrence, extremely variable, random and they don't have a defined occurrence periodicity (Lee, 1971; Crescente-Campo *et al*., 2009, Martins, 2011). However, during this study, solid estimates using P*m* networks were observed. It indicates that ANNs are propitious study fields for measuring scientific investigation and forestry modeling, especially for uneven-aged natural forests.

The average annual mortality value observed in the stand was 2%, corroborating with average mortality rates in other tropical forests. Köhler *et al*. (2001) observed mortality rates between 1 and 2% per year, on tropical forests in Malaysia. On a logged forest in Costa Rica, Finegan and Camacho (1999) observed mortality rates between 1.6 and 2.3 % per year. The values present in this study were slightly lower when compared with the ones presented by Pulz (1998) that observed mortality rates between 2.0 and 3.6% per year, and Coraiola (2003) that verified an annual rate of 2.78%.

The natural forests regular mortality in average succession phase is a natural event, that does not indicate stand decrepitude, contrary to the even-age stands, which the mortality can reduce the production per area unit. The natural forest goes through a continuous dynamic, and its balance is reached when the dead trees are replaced by new specimens (Rossi *et al*., 2007).

The observed mortality behavior regarding to liana infestation and crown illumination variables were not expected, since the specimens with higher liana infestation levels (greater competition) and less illuminated should present higher mortality rates (Phillips *et al*., 2005; Rego and Possamai, 2006).

The precise mortality estimation related to qualitative variables is important, since said variables can significantly interfere on the remaining trees' growth rates. Several researches attested theses variables affect on trees' development, they observed its influence on the growth rates related to the liana infestation level (Whigham, 1984; Grauel e Putz, 2004; Schnitzer *et al*., 2005; Campanello *et al*., 2007), and its reaction with distinct light quality and quantity, as well (Denslow *et al*., 1990; King, 1991; Popma and Bongers, 1991; Rego and Possamai, 2006).

Regarding to crown quality, a coherent mortality tendency was observed, trees with a low quality crown presented higher mortality rates (11.1%). A malformed crown can affect growth due relocation of the energy designed to new branches production and leaf replacement. If this stress occurs sorely trees' death probability increases (Freitas and Berti Filho, 1994).

The observed behavior is according with the expected tendency. Higher mortality rates are associated to species with greater light need (pioneers) (Alder e Silva, 2000; Köhler *et al*., 2001). Although the late secondary species, more adjusted to environmental variations, tend to present lower mortality rates.

The obstacle to estimate mortality in uneven-aged forests is due the existence of a-biotic and biotic factors least understood, as well the data base limitation (ROSSI *et al*., 2007). However, in this study precise mortality estimates were obtained, presenting great detail for a forest with huge species diversity and trees' forms.

According to presented results, the artificial neural networks were adequate to estimate single-trees mortality probability. The exponential activation function, used on network 9's (MLP: 60-14-1) intermediate and output neurons tiers, using distance dependent competition indexes, was the best alternative to estimate mortality probability.

CONCLUSION

With this study it can be conclude that:

1) Artificial neural networks can be efficient to estimate single-trees mortality in uneven-aged forests.

2) Use function approximation networks (mortality probability estimate) along with applying the mortality rule proposed by Pretzsch *et al*. (2002) is appropriate to predict mortality in Semi-deciduous Seasonal Forest during the average succession phase.

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REFERENCES

Alder, D., J.N.M. Silva, 2000. An empirical cohort model for management of Terra Firme forests in the Brazilian Amazon. Forest Ecology and Management, 130(1-3): 141-157.

Barreto, J.M., 2002. Introdução às redes neurais artificiais. Florianópolis: UFSC, 57 p.

Binoti, M.L.M.S., 2010. Redes neurais artificiais para prognose da produção de povoamentos não desbastados de eucalipto. 2010. 54 f. Dissertação (Mestrado em Ciência Florestal) - Universidade Federal de Viçosa, Viçosa.

Braga, A.P., A.P.L.F. Carvalho, T.B. Ludemir, 2000. Redes Neurais Artificiais: Teoria e Aplicações. Rio de Janeiro, RJ. Editora LTC, 262 p.

Campanello, P.I., J.F. Garibaldi, M.G. Gatti, G. Goldstein, 2007. Lianas in a subtropical Atlantic Forest: Host preference and tree growth. Forest Ecology and Management, 242: 250-259.

Campos, J.C.C., H.G. Leite, 2009. Mensuração florestal: perguntas e respostas. 3.ed. Viçosa-MG: UFV, 548 p.

Castro, R.V.O., 2011. Modelagem do crescimento em nível de árvores individuais utilizando redes neurais e autômatos celulares. 2011. 80 f. Dissertação (Mestrado em Ciência Florestal) - Universidade Federal de Viçosa, Viçosa.

Coraiola, M., 2003. Dinâmica de uma Floresta Estacional Semidecidual - MG: abordagem com processos de amostragem em múltiplas ocasiões. 168 f. 2003. Tese (Doutorado em Ciências Florestais) - Universidade Federal do Paraná, Curitiba.

Crescente-Campo, F., P. Marshall, R.R. Soalleiro, 2009. Modeling noncatastrophic individual tree mortality for *Pinus radiate* plantations in northwestern Spain. Forest Ecology and Management, 257(4): 1542-1550.

Denslow, J.S., J.C. Schultz, P.M. Vitousek, B.R. Strain, 1990. Growth responses of tropical shrubs to treefall gap environments. Ecology, 71: 165-179.

Diamantopoulou, M.J., 2005. Artificial neural networks as an alternative tool in pine bark volume estimation. Computers and Electronics in Agriculture, 48(3): 235-244.

Finegan, B., M. Camacho, 1999. Stand dynamics in a logged and silviculturally treated Costa Rican rain forest, 1988-1996. Forest Ecology and Management, 121(3): 177-189.

Flewelling, J.W., R.A. Monserud, 2002. Comparing methods for modelling tree mortality. In: USDA Forest Service Proceedings RMRS-P-25: 168-177.

Freitas, S., Berti E. Filho, 1994. Efeito do desfolhamento no crescimento de *Eucalyptus grandis* Hill ex Maiden (Myrtaceae). IPEF, 47: 36-43.

Gandolfi, S., H.F. Leitão Filho, C.L. Bezerra, 1995. Levantamento florístico e caráter sucessional de espécies arbustivo-arbóreas de uma floresta

Mesófila Semidecídua no município de Guarulhos, SP. Revista Brasileira de Biologia, 55(4): 753-767.

Görgens, E.B., H.G. Leite, H.N. Santos, J.M. Gleriani, 2009.Estimação do volume de árvores utilizando redes neurais artificiais. Revista Árvore, 33(6): 1141-1147.

Grauel, W.T., F.E. Putz, 2004. Effects of lianas on growth and regeneration of *Prioria copaifera* in Darien, Panama. Forest Ecology and Management, 190: 99-108.

Groom, J.D., D.W. Hann, H. Temesgen, 2012. Evaluation of mixed-effects models for predicting Douglas-fir mortality. Forest Ecology and Management, 276: 139-145.

Guan, B.T., G.Z. Gertner, 1991. Modeling red pine tree survival with an artificial neural network. Forest Science, 37: 1429-1440.

Hamilton, Jr., D.A., 1986. A logistic model of mortality in thinned and unthinned mixed conifer stands of northern Idaho. Forest Science, 32: 989-1000.

Hamilton Jr., D.A., 1990. Extending the range of applicability of an individual tree mortality model. Canadian Journal of Forest Research, 20(8): 1212-1218.

Hamilton Jr., D.A., B.M. Edwards, 1976. Modeling the probability of individual tree mortality. Ogden: Forest Service / Intermountain Forest and Range Experiment Station, 22 p. (Research Paper, 185).

Hasenauer, H., D. Merkl, 1997. Forest tree mortality simulation in uneven-aged stands using connectionist networks. In: Neural Networks in Engineering Proc. Int. Conf. on Engineering Applications of Neural Networks, Stockholm, Sweden.

Hasenauer, H., D. Merkl, M. Weingartner, 2001. Estimating tree mortality of Norway spruce stands with neural networks. Advances in Environmental Research, 5: 405-414.

Haykin, S., 2001. Redes neurais: princípios e prática. 2. ed. Porto Alegre: Bookman, 900 p.

Hurst, J.M., G.H. Stewart, G.L.W. Perry, S.K. Wiser, D.A. Norton, 2012. Determinants of tree mortality in mixed old-growth *Nothofagus* forest. Forest Ecology and Management, 270: 189-199.

Jain, A.K., J. Mao, K.M. Mohiuddin, 1996. Artificial Neural Networks: A Tutorial. Computer, 29(3): 31-44.

King, D.A., 1991. Correlations between biomass allocation, relative growth rate and light environment in tropical forest saplings. Functional Ecology, 5: 485-492.

Köhler, P., T. Ditzer, R.C. Ong, A. Huth, 2001. Comparison of measured and modelled growth on permanent plots in Sabahs rain forests. Forest Ecology and Management, 144(1-3): 101-111.

Lee, Y.J., 1971. Predicting mortality for even-aged stands of Iodgepole pine. The Forestry Chronicle, 47(1): 29-32.

Leite, H.G., M.L.M. Silva, D.H.B. Binoti, L. Fardin, F.H. Takizawa, 2010. Estimation of inside-bark diameter and heartwood diameter for *Tectona grandis* Linn. trees using artificial neural networks. European Journal of Forest Research, 130: 263-269.

Lippnann, R., 1987. An introduction to computing with neural nets. ASSP Magazine, 4(2): 4-22.

Martins, F.B., 2011. Modelagem de crescimento em nível de árvore individual para plantios comerciais de eucalipto. 2011. 143 f. Tese (Doutorado em Ciência Florestal) – Universidade Federal de Viçosa, Viçosa.

Meira Neto, J.A.A., F.R. Martins, 2000. Estrutura da Mata da Silvicultura, uma Floresta Estacional Semidecidual Montana no município de Viçosa, MG. Revista Árvore, 24(2): 151-160.

Monserud, R.A., 1976. Simulation of forest tree mortality. Forest Science, 22(4): 438-444.

Monserud, R.A., H. Sterba, 1999. Modeling individual tree mortality for Australian forest species. Forest ecology and Management, 113(2): 109-123.

Phillips, O.L., Vásquez R. Martínez, Monteagudo A. Mendoza, T.R. Baker, Núñez P. Vargas, 2005. Large lianas as hyperdynamic elements of the tropical forest canopy. Ecology, 86: 1250-1258.

Popma, J., F. Bongers, 1991. Acclimation of seedlings of three Mexican tropical rain forest tree species to a change in light availability. Journal of Tropical Ecology, 7: 85-97.

Pretzsch, H., P. Biber, J. Durský, 2002. The single tree-based stand simulator Silva: construction, application and evaluation. Forest Ecology and Management, 162(1): 3-21.

Pulz, F.A., 1998. Estudo da dinâmica e a modelagem da estrutura diamétrica de uma floresta semidecídua montana na região de Lavras - MG. 155 f. Dissertação (Mestrado em Engenharia Florestal) - Universidade Federal de Lavras, Lavras.

Rego, G.M., E. Possamai, 2006. Efeito do sombreamento sobre o teor de clorofila e crescimento inicial do jequitibá rosa. Boletim de Pesquisa Florestal de Colombo, 53: l79-l94.

Rossi, L.M.B., H.S. Koehler, C.R. Sanquetta, J.E. Arce, 2007. Modelagem de mortalidade em florestas naturais. Revista Floresta, 37(2): 275-291.

Schnitzer, S.A., M.E. Kuzee, F. Bongers, 2005. Disentangling above- and below-ground competition between lianas and trees in a tropical forest. Journal of Ecololgy, 93: 1115-1125.

Silva, J.N.M., J.C.A. Lopes, 1984. Inventário florestal contínuo em florestas tropicais: a metodologia utilizada pela Embrapa-Cpatu na Amazônia brasileira. Belém- PA: Embrapa-CPATU, 36 p. (Documentos 36).

Sokal, R.R., F.J. Rohlf, 1969. Biometry: The principles and practice of statistics in biological research. San Francisco: Freeman and Company, 776 p.

Staebler, G.R., 1953. Mortality estimation in fully stocked stands of young-growth Douglas-fir. U.S. Forest Service, Research Paper 4, 8 p.

Statsoft, INC. Statistica (data analysis software system), version 10.0. 2012.

Tomé, M., 1991. Os modelos de produção florestal na gestão de povoamentos florestais. Revista Agros, 8(2): 32-36.

Vanclay, J.K., 1994. Modeling forest growth and yield: aplications to mixed tropical Forest. Wallingford: CAB International, 312 p.

Whigham, D.F., 1984. The influence of vines on the growth of *Liquidambar styraciflua* L. (Sweetgum). Canadian Journal of Forest Research, 14: 37-39.

Yang, Y., S.J. Titus, S. Huang, 2003. Modeling individual tree mortality for white spruce in Alberta. Ecological Modelling, 163(3): 209-222.

Yao, X., S.J. Titus, S.E. Macdonald, 2001. A generalized logistic model of individual tree mortality for aspen, white spruce, and lodgepole pine in Alberta mixed wood forests. Canadian Journal of Forest Research, 31: 283-291.

Zhao, D., B. Borders, M. Wilson, S.L. Rathbun, 2006. Modeling neighborhood effects on the growth and survival of individual trees in a natural temperate species rich forest. Ecological Modelling, 196(1): 90-102.