J. For. Res. (2020) 31(5):1663–1672
https://doi.org/10.1007/s11676-019-00920-1

ORIGINAL PAPER

The growth and production modeling of individual trees of *Eucalyptus urophylla* plantations

João Victor Nobre Carrijo[1] · Ana Beatriz de Freitas Ferreira[1] · Marcela Costa Ferreira[1] · Mário César de Aguiar[1] · Eder Pereira Miguel[1] · Eraldo Aparecido Trondoli Matricardi[1] · Alba Valéria Rezende[1]

Received: 11 September 2018 / Accepted: 4 December 2018 / Published online: 29 March 2019

Abstract Individual tree models (ITMs) are classified as growth and production models for projecting current and future forest stands. ITMs are more complex than other growth and production models, show a higher level of detail and, consequently, produce a better modeling resolution. However, the accuracy and efficiency of ITMs have not been properly assessed to date. In this study, we estimated the growth in height, diameter, and individual tree volume of a *Eucalyptus urophylla* plantation by applying an ITM. We used a continuing forest inventory dataset in which 1554 individual trees within 29 permanent plots were measured in the field over a 6-year period (24 to 72 months). Each individual tree volume was estimated for future tree age. To achieve this, we adjusted the model to predict the height and diameter growth, and the probability of mortality as a function of the competition index. The ITM accuracy was assessed based on the analysis of variance results and, subsequently, the multiple mean comparison test at the 5% significance level. The tree volumes predicted by the ITM for the forest stand aged 72 months, beginning at ages 24, 36, 48, and 60 months, were compared to the field measured tree volume acquired from the 72-month forest inventory that was used as the reference age. Estimated and observed tree volumes were similar when the estimation was based on the 48-month forest plots. These results might help to reduce financial costs of forest inventory because the ITM produces accurate future predictions of forest stand stocks. Our estimated ITM for *Eucalyptus* plantations using measurement intervals up to 2 years is recommended because it significantly reduced the projected volume discrepancy compared to the field measurements.

Keywords Competition index · Forest production · Forest site · Simulation models · Tree mortality

Project funding: The work was supported by the Coordination for the Improvement of Higher Education Personnel (CAPES) and the Brazilian National Council of Science and Technology (CNPQ).

The online version is available at http://www.springerlink.com

Corresponding editor: Tao Xu.

✉ João Victor Nobre Carrijo
joao.ncarrijo@gmail.com

1 Department of Forestry, Faculty of Technology, University of Brasília, Brasília 70910-900, Brazil

Introduction

There are several categories of growth and forest production models. The most commonly used models are the stand-level models, diametric distribution models, and individual tree models (ITMs; Davis et al. 2005).

Individual trees are the basic modeling unit of an ITM that are used to simulate tree growth (diameter and height) and mortality (Campos and Leite 2017). Although these models vary in structures and utilities (Weiskittel et al. 2011), they are more complex than the models of total forest stand and diametric distribution because they use individual trees in each stand as the model input (Chassot et al. 2011) and depend on the adjustment of several submodels (Campos and Leite 2017). The most current and important studies related to this research topic were conducted by Castro et al. (2013a, b), Martins et al. (2014), Hevia et al. (2015), Vospernik et al. (2015), Orellana et al. (2016), Weiskittel et al. (2016), Miranda et al. (2017), and Moreno et al. (2017).

Forest plantations increased in area by approximately 0.5% between 2016 and 2017 in Brazil. Most of the planted forests are *Eucalyptus* spp, which currently encompass approximately 5.7 million hectares in Brazil (IBÁ 2017). *Eucalyptus urophylla* is the most planted species in forest stands in several South American countries because of its high rates of productivity and adaptation (Mendes et al. 2011; Rangel et al. 2017). This forest species shows high productive and economical potential for energy generation, panel production, and in pulp and paper industries (Reis et al. 2012; Guimarães Júnior et al. 2015; Jardim et al. 2017; Rangel et al. 2017).

However, advanced knowledge is required to improve forest management due to the silviculture complexity and product variety in this species. Growth and production models can help simulate tree growth (height and diameter) to predict forest productivity at different levels (total stand level, diameter classes, or ITM) of detail.

In the last few decades, improvements in planting techniques and silvicultural treatments have helped to improve forest production (Reiner et al. 2011; Tian et al. 2017). Currently, forest production have been improved based on scientific studies, especially those that have modeled short-cycle planted forests. Such advances have globally increased profits from plantation forestry, especially in Brazil (Pereira et al. 2016).

The objectives of the present study were to apply, adjust, and assess model accuracies to estimate the volume of *E. urophylla* trees. We also aimed to assess individual tree growth in permanent plots by applying an ITM.

Materials and methods

Study area

Our study site was in a forest clonal stand encompassing 320 ha of *E. urophylla* S.T. Blake, planted in 2010, spatially located in the Rio Verde municipality, state of Goiás, Brazil (central coordinates: 18°00′45″S and 50°53′15″W). According to the Köppen climatic classification system, the study site was an Aw climate region, and it was characterized by average annual precipitation of 1713 mm and average annual temperature of 24.6 °C with a wet and rainy summer and a dry winter (Alvares et al. 2014). The study region is mostly covered by dystrophic, deep, and well-drained red-yellow latosols (Embrapa 2013).

Dataset

We recorded field data from continuous forest inventory of trees measured at 24, 36, 48, 60, and 72 months of age. We measured trees in 29 permanent plots of 25 m length × 20 m width (500 m^2) that were randomly distributed and demarcated over the study area. Trees were planted on a grid of 3 × 2 m in this forest stand, corresponding to a planting density of 1666.66 trees per hectare.

The diameter at breast height (*DBH*) and total height (*Ht*) of trees were measured using a diametric tape and vertex hypsometer, respectively, for every tree of DBH > 5 cm. Additionally, the dominant tree height (*Hdom*) for each plot was estimated using the Assmann (1970) definition. A total of 586 trees were strictly cubed during the study period and the measured volume of each cubed tree was determined using the Smalian equation (Spurr 1952).

Adjustment of volumetric models

Volumetric model adjustment was based on field measurements of 90% of the cubed trees using linear and nonlinear models (Table 1). Linear models were adjusted using Microsoft Excel® 2013 by applying the ordinary least squares method. The nonlinear models were adjusted by applying the Levenberg–Marquardt method (Levenberg 1944; Marquardt 1963) available in the Statistica® 7 software program (Statsoft 2007). The remaining trees (10%) were used for model validation.

Site classification

The widely used guide curve method was used to classify the productive capacity of each sample plot (Petrou et al. 2015). Five sigmoidal site index (*S*) models (Table 2) were tested and adjusted during this analysis by applying the Levenberg–Marquardt method (Levenberg 1944; Marquardt 1963) available in the Statistica® 7 software program (Statsoft 2007). This type of index is efficient for describing the growth of living organisms and accurately estimates forest stand variables, thus enabling classification of the different productive units in forest plantations (Machado et al. 2010; Zlatanov et al. 2012; Retslaff et al. 2015).

A total of 75% of the sample plots were randomly selected and used for the site index model adjustments. The remaining plots (25%) were used to validate and select the best adjusted model.

Competition indices and probability of mortality

Competition indices (CIs) are commonly used to estimate and simulate forest growth and production to improve forest management (McTague and Weiskittel 2016; Pothier 2017). In the present study, 10 distance-independent *CI*s were estimated (Table 3). Conceptually, indices that consider the tree spatial arrangement and further spatial

Table 1 Candidate models for estimation of observed volume and structural components of individual tree modeling—ITM

Volumetric models	
Spurr	$V = \beta_0 + \beta_1 DBH^2 Ht + \varepsilon_i$
Schumacher-Hall	$V = \beta_0 DBH^{\beta_1} Ht^{\beta_2} + \varepsilon_i$
Naslund	$V = \beta_0 + \beta_1 DBH^2 + \beta_2 DBH^2 Ht + \beta_3 DBHHt^2 + \beta_1 Ht^2 + \varepsilon_i$
Takata	$V = {}^{(DBH^2 Ht)}\!/\!_{(\beta_0 + \beta_1 DBH)} + \varepsilon_i$
Meyer	$V = \beta_0 + \beta_1 DBH + \beta_2 DBH^2 + \beta_3 DBHHt + \beta_4 DBH^2 Ht + \beta_5 Ht + \varepsilon_i$
Probability of mortality models	
Logistic	$Pm = {}^{a}\!/\!_{1 + be^{-cCI}} + \varepsilon_i$
Negative exponential	$Pm = \beta_0 + e^{(\beta_1 + \beta_2 CI)} + \varepsilon_i$
Allometric	$Pm = \beta_0 CI^{\beta_1} + \varepsilon_i$
Logistic of Hamilton	$Pm = \left(1 + e^{(\beta_0 + \beta_1 CI)}\right)^{-1} + \varepsilon_i$
DBH and total height at future age models	
Linear adapted by Martins et al. (2014)	$Y_2 = Y_1 + \left(\beta_0 + \beta_1\left(\frac{1}{I_2} - \frac{1}{I_1}\right) + \beta_2 BAI + \beta_3 S\right) + \varepsilon_i$
Schumacher	$Y_2 = Y_1 + e^{(\beta_0 + \beta_1 I_2)} - e^{(\beta_0 + \beta_1 I_1)} + \varepsilon_i$
Lundqvist-Korf—A	$Y_2 = Y_1 e^{k\left[\left(\frac{1}{I_1^m}\right) - \left(\frac{1}{I_2^m}\right)\right]} + \varepsilon_i$
Richards—A	$Y_2 = Y_1 \left[\frac{1 - e^{(-kI_2)}}{1 - e^{(-kI_1)}}\right]^{\left(\frac{1}{1-m}\right)} + \varepsilon_i$
Hossfeld	$Y_2 = {}^{A}\!\Big/\!_{1 - \left[1 - \left(\frac{A}{Y_1}\right)\right]\left(\frac{I_1}{I_2}\right)^k} + \varepsilon_i$

V volume (m^3), *DBH* diameter at breast height (cm), *Ht* total height (m), *Pm* probability of mortality, *CI* competition index, Y_2 DBH (cm) or Ht (m) at future age, Y_1 DBH (cm) or Ht (m) at current age, I_2 future age, I_1 current age, *BAI* basal area index (BAI di_2/q_2; d_i- DBH of tree "i" (cm), *q* mean square diameter (cm)), *e* exponential; β_0, β_1, β_2, β_3, *a*, *b*, *c*, *k*, *m*, *A* parameters to be estimated, ε random error

Table 2 Models tested for *Hdom* estimation and classification of forest sites

Hdom models	
Logistic	$Hdom = {}^{a}\!/\!_{1 + be^{-cI}} + \varepsilon_i$
Gompertz	$Hdom = ae^{-e^{b-cI}} + \varepsilon_i$
Richards	$Hdom = {}^{a}\!\Big/\!_{\left(1 + e^{b-cI}\right)^{\frac{1}{d}}} + \varepsilon_i$
Weibull	$Hdom = a - be^{-cI^d} + \varepsilon_i$
MMF	$Hdom = {}^{\left(ab + cI^d\right)}\!/\!_{\left(b + I^d\right)} + \varepsilon_i$

Hdom dominant height, *I* age of forest stand, *a*, *b*, *c*, *d* parameters of the equation, εi random error

information are expected to achieve better modeling results. However, studies comparing these two types of indices do not indicate large differences between them (Burkhart and Tomé 2012; Maleki et al. 2015). Thus, we assumed that there was no difference in the spatial arrangement and therefore in the area of the competitive influence of individual trees, following Campos and Leite (2017).

The optimum index was selected by analysis of correlation between the index and the annual variation of the number of individuals. The correlation test was applied between the *CI*s and the density of individuals per area unit (N/ha) that estimates the relationship between the *CI*s and stand mortality (Daniels et al. 1986; Tomé and Burkhart 1989). Based on this, the index showing the highest correlation with N/ha was defined as the optimum CI for the predictive probability of mortality (Pm) in the ITM. Subsequently, four models based on the CI results were adjusted to estimate *Pm* (Table 1).

For the adjustment of the Pm models, 75% of the sample plots were randomly selected and the remaining plots (25%) were used to validate and select the best adjusted model by applying the Levenberg–Marquardt method (Levenberg 1944; Marquardt 1963) available in the Statistica® 7 software program (Statsoft 2007).

Growth modeling of height and diameter

Two essential components for modeling individual trees are *Ht* and DBH future projections. The two variables were estimated using five statistical models (Table 1) by applying the Levenberg–Marquardt method (Levenberg

Table 3 Distance independent competition indices (CI) tested

Distance independent competition indices (CI)	
Glover and Hool (1979) (1)	$IC = d_i^2/\bar{D}^2$
Glover and Hool (1979) (2)	$IC = d_i^2 h_i/\bar{D}^2\bar{H}$
Stage (1973)	$IC = BAL_i$
Lorimer (1983)	$IC = \sum_{j=1}^{n} d_j/d_i$
Daniels et al. (1986)	$IC = \frac{d_i^2}{\left(\sum_{j=1}^{n} d_j^2\right)}/n_j$
Tomé and Burkart (1989) (1)	$IC = d_i/q$
Tomé and Burkart (1989) (2)	$IC = d_i/d_{\max}$
Tomé and Burkart (1989) (3)	$IC = d_i/d_{\mathrm{dom}}$
Tomé and Burkart (1989) (4)	$IC = d_i^2/d_{\max}^2$
Tomé and Burkart (1989) (5)	$IC = d_i^2/d_{\mathrm{dom}}^2$

d_i Diameter of the object tree (cm), d_j diameter of competing tree (cm) $\bar{D}$ mean diameter of the sample unit trees (cm); h_i height of the object tree (m), $\bar{H}$ mean height of the sample unit trees (m), BAL_i total basal area of larger trees than the object tree, n_j number of competing trees, q quadratic diameter (cm), d_{max} maximum diameter of the trees in the sample unit (cm), d_{dom} diameter of the dominant trees, defined as the quadratic diameter of the dominant trees

1944; Marquardt 1963) available in the Statistica® 7 software program (Statsoft 2007). The model adjustment was performed based on 75% randomly selected sampled plots while the remaining plots (25%) were used to validate each tested model.

Model selection and testing criteria

The selection of the best model to estimate volumetric, *S*, *Pm*, *Ht*, and DBH growth was based on the following statistics of fit and precision: residuals dispersion graph, standard error of estimate (Syx%), and coefficient of determination (R^2) (Draper and Smith 1998). We then used the "observed-estimated" graph, the error classes graph, and the Akaike index (AIC) to select our overall optimum model. The coefficient of determination was replaced by the correlation coefficient (R) for the Hdom models because they are nonlinear models.

Individual tree modeling

The future survival (36, 48, 60, and 72 months) applied to the ITM growth and forest production was initially determined based on the field data acquired at 24 months of age. The estimated *Pm* of each sampled tree was compared to a random value simulated by the Monte Carlo method as described by Castro et al. (2013a). The tree was considered dead when the estimated Pm was greater than the random value (Pretzsch et al. 2002).

Ht and DBH of all surviving trees were estimated, which enabled estimation of their volumes. The total volume for each plot was estimated based on the sum of the individual tree volumes at the reference age (72 months) and extrapolated to volume per hectare.

Modeling using the ITM started from four different initial ages (24, 36, 48, and 60 months), each projecting the volume for forest stands at 72 months of age (the reference age). The projected volumes of 24, 36, 48, and 60 months of age and the observed forest stand volume at 72 months of age (control) were defined as the five treatments. For the forest stands aged 72 months, five different volume values were estimated for each sampled plot/hectare with four values projected, and an observed value determined. The ITM was performed using the Microsoft Excel® 2013 program and eight previously defined validation plots.

Statistical analysis

Projected volume data (treatments) and traditional inventory data (control) were tested using the Shapiro and Wilk (1965) normality test followed by the Bartlett (1947) homogeneity of variance test. By assuming data normality and a completely randomized block design ($\alpha = 0.05$), analysis of variance (ANOVA) was performed. Different sites were considered as blocks, whereas the different time intervals of the volume projection up to the forest stands aged 72 months (reference age) were considered as treatments, where (T1) was the volume projection of forest stands aged 24 months, (T2) was for stands of 36 months, (T3) was for stands of 48 months, (T4) was for stands aged 60 months, and (T5) was the control, the observed volume based on field measurements (forest inventory) at the reference age (72 months).

Finally, a multiple mean comparison test was used to identify potential treatment differences using Tukey's (1953) test at the 5% level of significance.

Results

Based on the Syx% results, most of the tested models of each analyzed variable showed satisfactory adjustment. The Schumacher and Hall model was selected for the volume estimation (Table 4). The adapted Hossfeld model and the adapted Lundqvist-Korf model (Table 5) were selected for the estimation of DBH and Ht at future age.

The allometric model (Table 6) was selected for the estimation of *Pm*. The residual distribution patterns of the selected models for volume, DBH2, and Height2

Table 4 Parameter estimators and precision statistics of volumetric models

Models	Model parameter estimators						Precision statistics	
	β_0	β_1	β_2	β_3	β_4	β_5	S_{yx} (%)	R^2adj
Spurr	0.005214	0.000038					5.81	0.98
Schumacher-Hall	0.000012	1.597028	1.687941				4.92	0.99
Naslund	0.040457	0.000122	0.0000093	0.000030	− 0.000227		4.97	0.99
Takata	22893.89	153.09					5.64	0.98
Meyer	0.192431	− 0.019255	− 0.0000043	0.001472	0.00000040	− 0.01122	4.98	0.99

β_0, β_1, β_2, β_3, β_4, β_5 parameters of the models, S_{yx}% standard error of estimate (%), R^2_{adj} adjusted coefficient of determination

Table 5 Parameter estimators and precision statistics of DBH and total height at future age models

Models	β_0	β_1	β_2	β_3	A	K	M	Precision statistics		
								S_{yx} (%)	*R*	AIC
DBH model parameter estimators										
Linear adapted by Martins et al. (2014)	− 0.2772	− 49.1574	− 0.0160	0.0389				5.06	0.99	− 3185.72
Schumacher	8.3483	0.000019						5.45	0.98	− 2552.25
Lundqvist-Korf-A						3.5015	0.1354	4.05	0.99	− 5097.56
Richards-A						0.0045	− 2.1484	4.06	0.99	− 5085.81
Hossfeld					− 11.5585	0.1278		3.89	0.99	− 5455.96
Total height model parameter estimators										
Linear adapted by Martins et al. (2014)	− 0.826	− 123.058	− 0.048	0.098				3.91	0.87	− 1814.54
Schumacher	9.6833	0.000011						5.16	0.98	579.46
Lundqvist-Korf-A						5.0586	0.4512	2.85	0.99	− 4536.02
Richards-A						0.0188	0.3404	2.86	0.99	− 4524.15
Hossfeld					112.1988	0.5292		3.22	0.99	− 3495.71

β_0, β_1, β_2, β_3, *A*, *K*, *m* parameters of the models, S_{yx}% standard error of estimate (%), *R* correlation coefficient, *AIC* Akaike index

Table 6 Parameter estimators and precision statistics of probability of the mortality models

Models	Pm model parameter estimators						Precision statistics		
	β_0	β_1	β_2	A	*b*	*c*	S_{yx} (%)	*R*	AIC
Logistic				0.00031	− 0.99521	0.11026	66.58	0.034	− 580.19
Negative exponential	− 0.91190	− 0.02294	− 1.99436				66.58	0.005	− 580.18
Allometric	0.09179	0.04565					66.20	0.017	− 580.21
Logistic of Hamilton	2.66094	28.85211					66.21	0.005	− 580.19

β_0, β_1, β_2, *a*, *b*, *c* parameters of the models, S_{yx}% standard error of estimate (%), *R* correlation coefficient, *AIC* Akaike index

estimations were acceptable (Fig. 1a1, a3, and a4), and the estimates of the dependent variable were accurate (Fig. 1b1, b3, and b4). Based on the frequency histogram (Fig. 1c1, c3, and c4), we observed a higher concentration of residuals in the central classes; therefore, the selected models proved unlikely to overestimate or underestimate the values of each of the analyzed variables.

However, the residuals of the probability model showed a greater degree of dispersion (Fig. 1a2), indicating weaker correlation between observed and predicted values (Fig. 1b2) and a stronger trend toward overestimation or underestimation (Fig. 1c2).

Based on the site classification, S (21), S (25), S (29), and S (33), four productivity curves were plotted. The

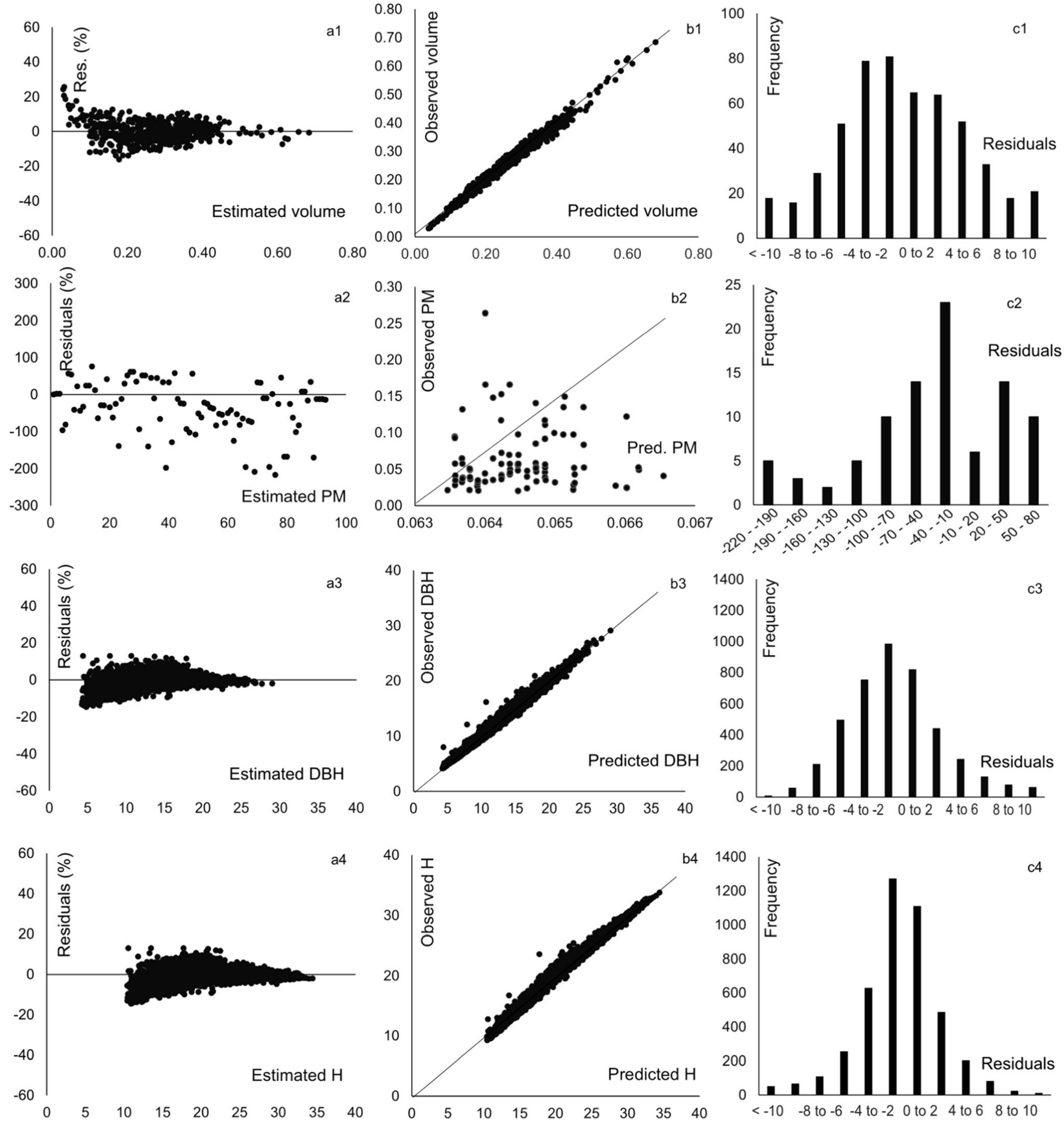

Fig. 1 Percentage of the residual distribution (**a**), observed values used to predict tree volume (**b**), and slope distribution (**c**) of volume estimates (1), probability of tree mortality (2), breast height diameter (3) and height (4)

generated curves accurately described the behavior of Hdom compared to age (Fig. 2b1). All models showed similar accuracy and degree of fit (Table 7), however, the logistic model was chosen because it yielded lower Syx%. The residual distribution was homogeneous without great bias and was stable in site classification (Fig. 2a1). We observed overestimation and underestimation of Hdom in the model estimation (Fig. 2c1).

CI was significantly correlated with the number of trees per hectare at different ages. Thus, the distance independent index proposed by Daniels et al. (1986) yielded better correlation results. The correlations

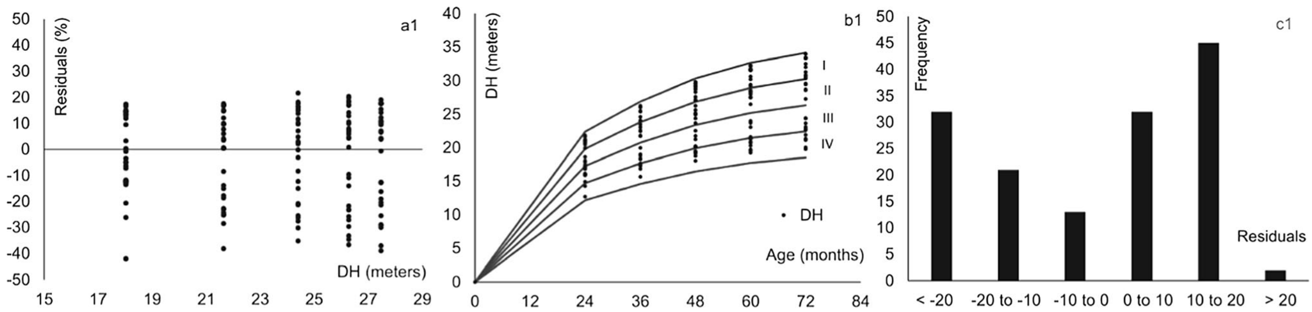

Fig. 2 Percentage of the residual distribution (**a1**), forest site curves (**b1**) and slope distribution (**c1**)

Table 7 Parameter estimators and precision statistics of site index classification models

Models	Site index model parameter estimators				Precision statistics	
	A	b	C	D	S_{yx} (%)	R
Logistic	29.1569	1.9597	0.0481	–	16.8300	0.6543
Gompertz	29.7665	0.2346	0.0385	–	16.8333	0.6541
Richards	28.1388	3.5332	0.0788	4.1065	16.8896	0.6545
Weibull	30.3809	24.1720	0.0234	1.0547	16.8963	0.6540
MMF	− 5.9608	12.5731	40.1395	0.8215	16.9049	0.6535

a, *b*, *c*, *d* parameters of the models, S_{yx}% standard error of estimate (%), *R* correlation coefficient

Table 8 Randomized block analysis of variance (ANOVA) results

VS	DF	SS	MS	F_{table}	F_{calc}
Block (forest sites)	3	13,156.00	4385.00	269.87	< 2e–16**
Treatment	4	420.00	105.00	6.47	0.000572**
Residuals	32	520.00	16.25		

*Significant at α = 0.05 **significant at α = 0.01

VS variation source, *DF* degrees of freedom, *SS* sum of squares, *MS* mean square, *Ftable* tabulated value of F, *Fcalc* calculated value of F

between CI and stand density varied between − 0.9974 and 0.9615.

After the preliminary simulations and adjustment of the ITM calculation, parameter estimates varied by initial age ($F(3, 4) = 6.55$, $p < 0.05$) (Table 8), and mostly, the variation was explained by the treatments. Using the classification of productive units as an environmental gradient was important to achieve these results.

The mean test comparison results showed significant differences between volumes predicted by the ITM and the volume measured by traditional inventory (control) at the reference age (72 months). Differences were attributable to higher variation among estimates based on initial measurements of stands aged 24 and 36 months. Estimates based on longer duration treatments were indistinguishable from the control (Table 9). Measurements of stands aged 48 months were adequate to accurately estimate the volume of stands at 72 months. Therefore, the ITM accurately predicted individual tree volume for a future interval of up to 2 years.

Table 9 Mean volumes ($m^3 ha^{-1}$) estimated at 72 months, estimated based on the projection of field data collected at different ages of the stand (24, 36, 48 and 60 months) and mean observed volume measured at 72 months (control)

Treatments	Mean volumes ($m^3 ha^{-1}$)
Projection from 24 to 72 months (T1)	212.21b
Projection from 36 to 72 months (T2)	216.38b
Projection from 48 to 72 months (T3)	233.88a
Projection from 60 to 72 months (T4)	238.95a
Control—72 months (T5)	242.45a

Means followed by the same letter are similar at α = 0.05. Least Significant Difference (LSD) equal to 11.55 m^3

Discussion

Adjustment of the various submodels proved suitable for the ITM. The models were selected from the best submodels adjusted to the dataset. The volumetric model of Schumacher and Hall that was selected to estimate tree volume is a classic model in the forest sector and is widely applied because of its statistical properties, which result in non-biased estimates (Campos and Leite 2017). This model has been used to estimate variables of planted forests (Leal et al. 2015; Sales et al. 2015; Carrijo et al. 2017) and natural forests (Colpini et al. 2009; Vibrans et al. 2015; Miguel et al. 2017).

Although the estimation of Hdom for site classification showed a standard error estimate greater than 15%, other studies using the guide curve method have estimated similar values of Syx% (Zlatanov et al. 2012; Miranda et al. 2014; Castro et al. 2015; Ribeiro et al. 2016). This result can be explained by the absence of the polymorphic curve construction in this method, which might not represent the different growth trends using the model (Binoti et al. 2012; Cosenza et al. 2017). However, such errors were considered satisfactory and did not compromise the accuracy of the modeling system when considered for different site classes.

The logistic model yielded the best results for forest site classification. This model is robust, is traditionally applied for classifying forest sites (Oliveira et al. 2008; Salles et al. 2012), is accurate, and is independent of tree species (Martínez-Zurimendi et al. 2015; Murillo-Brito et al. 2017). In addition, the logistic model was chosen based on the criterion of stability of the heights of dominant trees around the curves that express the forest site classes, which has been successfully applied in other studies (Scolforo 2006; Silva et al. 2018).

The selection of the height projection model followed Martins et al. (2014), who reported precision in the estimates obtained via the Lundqvist-Korf model for both height and DBH. This can be explained by the suitability of this model family to simulate the DBH-height relationship (Krisnawati et al. 2010; Lumbres et al. 2015). However, the result for the DBH projection differed from the results reported by Krisnawati et al. (2010) and Lumbres et al. (2015) that were based on adaptation of the linear model to estimate DBH.

Several studies have reported significant correlation between *CI* and population variables. Martins et al. (2011) and Castro et al. (2014) reported strong correlation between the Pm of plots and *CI*. Hui et al. (2018) reported that dead trees in native forests had experienced greater competition, which indicated that there was a strong relationship between *Pm* and *CI*.

CI is often correlated with growth indicator variables of trees (Chassot et al. 2011; Contreras et al. 2011; Pedersen et al. 2012; Castro et al. 2014; Maleki et al. 2015; Pothier 2017). Our results show that use of a variable that expresses competition among individual trees will significantly improve the prediction of the dimensions and dynamics of tree growth, as reported by many studies (Contreras et al. 2011; Oheimb et al. 2011; Castro et al. 2014; Maleki et al. 2015; McTague and Weiskittel 2016). The competition index is the most important variable of individual tree growth models (Maleki et al. 2015) and, therefore, a high correlation between CI and stand variables is crucial to ensure accurate results when modeling individual trees.

The model used to estimate Pm in the present study was tested by Castro (2011), who reported a good model fit for his study population. Our results showed better precision statistics of the Pm model than those reported by Miranda et al. (2017), who used exponential and Buchman models and estimated errors (Syx%) greater than 100%. This probably resulted from the difficulty of estimating mortality, which reflects the uncertainties of future forest stand conditions (Yang et al. 2003; González et al. 2006; Castro et al. 2014). Despite these difficulties and the number of known and unknown variables that may affect tree mortality (Strimbu et al. 2017), the adjusted models used to estimate this probability have yielded satisfactory results (Hevia et al. 2015; Ma and Lei 2015; Maleki and Kiviste 2016; Strimbu et al. 2017).

Thus, we conclude that the ITM was efficient considering the time interval adopted. Castro et al. (2013b) reported accurate estimates from ITM when using a dataset based on field measurements recorded 3 years before harvest. Similarly, Lhotka (2017) demonstrated the effectiveness of ITM in predicting tree growth expressed by DBH up to 5 years before harvest.

Models that predict future production by considering the density of the stands help to improve our understanding of tree growth in forest plantations (Lhotka 2017). ITMs are considered a precise method to estimate tree growth and mortality, and to predict forest production.

In the present study, all submodels showed statistically productive adjustments, which indicates a great potential for predicting timber volume at different ages in *E. urophylla* plantations. Our ITM proved effective for use in *E. urophylla* stands for up to 2 years between the actual age and the reference age (in this case, 48 and 72 months), and allowed us to accurately predict future volumes. This can help decision makers estimate forest production, contributing to reduce the cost of forest inventories. However, it is recommended for intervals up to 2 years because greater intervals may cause overestimation of the predicted forest volume when compared to the observed volume (Weiskittel et al. 2016).

References

Alvares CA, Stape JL, Sentelhas PC, Gonçalves JLM, Sparovek G (2014) Köppen's climate classification map for Brazil. Meteorol Z 22(6):711–728

Assmann E (1970) The principles of forest yield study. Pergamon Press, Oxford, p 520

Bartlett MS (1947) Multivariate analysis. J R Stat Soc B 9(2):176–197

Binoti DHB, Binoti MLMS, Leite HG (2012) Aplicação da função hiperbólica na construção de curvas de índice de local. Rev Arvore 36(4):741–746

Burkhart HE, Tomé M (2012) Modeling forest trees and stands. Springer, Dordrecht, p 458

Campos JCC, Leite HG (2017) Mensuração florestal: perguntas e respostas. Editora UFV, Viçosa, p 636

Carrijo JVN, Miguel EP, Rezende AV, Gaspar RO, Martins IS, Meira Junior MS, Angelo H, Jesus CM (2017) Morphometric indexes and dendrometric measures for classification of forest sites of *Eucalyptus urophylla* stands. Aust J Crop Sci 11(9):1146–1153

Castro RVO (2011) Modelagem do crescimento em nível de árvores individuais utilizando redes neurais e autômatos celulares. Master's thesis, Departamento de Engenharia Florestal, Universidade Federal de Viçosa, Viçosa, p 80

Castro RVO, Soares CPB, Leite HG, Souza AL, Nogueira GS, Martins FB (2013a) Individual growth model for *Eucalyptus* stands in Brazil using artificial neural network. ISRN For 2013:1–12

Castro RVO, Soares CPB, Martins FB, Leite HG (2013b) Crescimento e produção de plantios comerciais de eucalipto estimados por duas categorias de modelos. Pesqui Agropecu Bras 48(3):287–295

Castro RVO, Soares C, Leite H, Souza A, Martins F, Nogueira G, Oliveira M, Silva F (2014) Competição em nível de árvore individual em uma floresta estacional semidecidual. Silva Lusit 22(1):43–66

Castro RVO, Cunha AB, Silva LV, Leite HG, Silva AAL (2015) Modelagem do crescimento e produção para um povoamento de *Eucalyptus* utilizando dois métodos para quantificação do índice de local. Sci For 43(105):83–90

Chassot T, Fleig FD, Finger CAG, Longhi SJ (2011) Modelos de crescimento em diâmetro de árvores individuais de *Araucaria angustifolia* (Bertol) Kuntze em floresta ombrófila mista. Cienc Florest 21(2):303–313

Colpini C, Travagin DP, Soares TS, Silva VSM (2009) Determinação do volume do fator de forma e da porcentagem de casca de árvores individuais em uma Floresta Ombrófila Aberta na região noroeste de Mato Grosso. Acta Amazon 39(1):97–104

Contreras MA, Affleck D, Chung W (2011) Evaluating tree competition indices as predictors of basal area increment in western Montana forests. Forest Ecol Manag 262(11):1939–1949

Cosenza DN, Soares AAV, Alcântara AEM, Silva AAL, Rode R, Soares VP, Leite HG (2017) Site classification for eucalypt stands using artificial neural network based on environmental and management features. Cerne 23(3):310–320

Daniels RF, Burkhart HE, Clason TR (1986) A comparison of competition measures for predicting growth of loblolly pine trees. Can J Forest Res 16(6):1230–1237

Davis LS, Johnson KN, Bettinger P, Howard TE (2005) Forest management: to sustain ecological, economic, and social values. Waveland Press, Long Grove, p 816

Draper NR, Smith H (1998) Applied regression analysis. Willey, New York, p 736

Embrapa (2013) Sistema brasileiro de classificação de solo. Embrapa Solos, Brasília, p 353

Glover GR, Hool JN (1979) A basal area ratio predictor of loblolly pine plantation mortality. For Sci 25(2):275–282

González MS, Río Md, Cañellas I, Montero G (2006) Distance independent tree diameter growth model for cork oak stands. For Ecol Manag 225(1–3):262–270

Guimarães Júnior JB, Protásio TP, Mendes RF, Mendes LM, Guimarães BMR, Siqueira HF (2015) Qualidade de painéis LVL produzidos com madeira de clones de *Eucalyptus urophylla*. Pesqui Florest Bras 35(83):307–313

Hevia A, Cao QV, Álvarez-González JG, Ruiz-González AD, Kv Gadow (2015) Compatibility of whole-stand and individual-tree models using composite estimators and disaggregation. For Ecol Manag 348:46–56

Hui GY, Wang Y, Zhang GQ, Zhao ZH, Bai C, Liu WZ (2018) A novel approach for assessing the neighborhood competition in two different aged forests. For Ecol Manag 422:49–58

IBÁ (2017) Relatório IBÁ 2017 ano base 2016. http://iba.org/images/shared/Biblioteca/IBA_RelatorioAnual2017.pdf [accessed 21.02.18]

Jardim JM, Gomes FJB, Colodette JL, Brahim BP (2017) Avaliação da qualidade e desempenho de clones de eucalipto na produção de celulose. O Papel 78(11):122–129

Krisnawati H, Wang Y, Ades PK (2010) Generalized height-diameter models for *Acacia mangium* Willd. plantations in south Sumatra. J For Res 7(1):1–19

Leal FA, Cabacinha CD, Castro RVO, Matricardi EAT (2015) Amostragem de árvores de *Eucalyptus* na cubagem rigorosa para estimativa de modelos volumétricos. Rev Bras de Biom 33(1):91–103

Levenberg K (1944) A method for the solution of certain nonlinear problems in least squares. Q Appl Math 2:164–168

Lhotka JM (2017) Examining growth relationships in *Quercus stands*: an application of individual-tree models developed from long-term thinning experiments. For Ecol Manag 385:65–77

Lorimer CG (1983) Test of age-independent competition indices for individual trees in natural hardwood stands. For Ecol Manag 6(4):343–360

Lumbres RIC, Lee YJ, Yun CW, Koo CD, Kim SB, Son YM, Lee KH, Won HK, Jung SC, Seo YO (2015) DBH-height modeling and validation for *Acacia mangium* and *Eucalyptus pellita* in Korintiga Hutani Plantation, Kalimantan Indonesia. For Sci Technol 11(3):119–125

Ma W, Lei XD (2015) Nonlinear simultaneous equations for individual-tree diameter growth and mortality model of natural Mongolian oak forests in northeast China. Forests 6:2261–2280

Machado AS, Figura MA, Silva LCR, Nascimento RGM, Quirino SMS, Teo SJ (2010) Dinâmica de crescimento de plantios jovens de *Araucaria angustifolia* e *Pinus taeda*. Pesqui Florest Bras 30(62):165–170

Maleki K, Kiviste A (2016) Individual tree mortality of silver birch (*Betula pendula* Roth) in Estonia. iForest 9:643–651

Maleki K, Kiviste A, Korjus H (2015) Analysis of individual tree competition effects on diameter growth of silver birch in Estonia. For Syst 24(2):e023

Marquardt DW (1963) An algorithm for least squares estimation of nonlinear parameters. SIAM J Appl Math 11:431–441

Martínez-Zurimendi P, Domínguez-Domínguez M, Juárez-García A, López-López LM, de-la Cruz-Arias V, Álvarez-Martínez J (2015) Índice de sitio y producción maderable en plantaciones forestales de *Gmelina arborea* en Tabasco México. Rev Fitotec Mex 38(4):415–425

Martins FB, Soares CPB, Leite HG, Souza AL, Castro RVO (2011) Índices de competição em árvores individuais de eucalipto. Pesqui Agropecu Bras 46(9):1089–1098

Martins FB, Soares CPB, Silva GF (2014) Individual tree growth models for *Eucalyptus* in northern Brazil. Sci Agric 71(3):212–225

McTague JP, Weiskittel AR (2016) Individual-tree competition indices and improved compatibility with stand-level estimates of stem density and long-term production. Forests 7(10):238–253

Mendes LM, Loschi FAP, Paula LER, Mendes RF, Guimarães Júnior JB, Mori FA (2011) Potencial de utilização da madeira de clones

de *Eucalyptus urophylla* na produção de painéis cimento-madeira. Cerne 17(1):69–75
Miguel EP, Rezende AV, Pereira RS, Azevedo GB, Mota FCM, Souza AN, Joaquim MS (2017) Modeling and prediction of volume and aereal biomass of the tree vegetation in a Cerradão area of central Brazil. Interciencia 42(1):21–27
Miranda ROV, David HC, Ebling AA, Môra R, Fiorentin LD, Soares ID (2014) Estratificação hipsométrica em classes de sítio e de altura total em plantios clonais de eucaliptos. Adv For Sci 1(4):113–119
Miranda ROV, Figueiredo Filho A, Machado AS, Castro RVO, Fiorentin LD, Bernett LG (2017) Modelagem da mortalidade em povoamentos de *Pinus taeda* L. Sci For 45(115):435–444
Moreno PC, Palmas S, Escobedo FJ, Cropper WP, Gezan AS (2017) Individual-tree diameter growth models for mixed *Nothofagus* second growth forests in southern Chile. Forests 8(12):506–521
Murillo-Brito Y, Domínguez-Domínguez M, Martínez-Zurimendi P, Lagunes-Espinoza LC, Aldrete A (2017) Índice de sitio en plantaciones de *Cedrela odorata* en el trópico húmedo de México. FCA Uncuyo 49(1):15–31
Oheimb GV, Lang AC, Bruelheide H, Forrester DI, Wäsche I, Yu MJ, Härdtle W (2011) Individual-tree radial growth in a subtropical broad-leaved forest: the role of local neighbourhood competition. For Ecol Manag 261(3):499–507
Oliveira MLR, Leite HG, Nogueira GS, Garcia SLR, Souza AL (2008) Classificação da capacidade produtiva de povoamentos não desbastados de clones de eucalipto. Pesqui Agropecu Bras 43(11):1559–1567
Orellana E, Figueiredo Filho A, Péllico Netto S, Vanclay JK (2016) A distance-independent individual-tree growth model to simulate management regimes in native Araucaria forests. J For Res-JPN 22(1):30–35
Pedersen RØ, Bollandsås OM, Gobakken T, Næsset E (2012) Deriving individual tree competition indices from airborne laser scanning. For Ecol Manag 280:150–165
Pereira JC, Dias PAS, Mergulhão RC, Thiersch CR, Faria LC (2016) Modelo de crescimento e produção de Clutter adicionado de uma variável latente para predição do volume em um plantio de *Eucalyptus urograndis* com variáveis correlacionadas espacialmente. Sci For 44(110):393–403
Petrou P, Kitikidou K, Milios E, Koletta J, Mavroyiakoumos A (2015) Site index curves for the golden oak species (*Quercus alnifolia*). Bosque 36(3):497–503
Pothier D (2017) Relationships between patterns of stand growth dominance and tree competition mode for species of various shade tolerances. For Ecol Manag 406:155–162
Pretzsch H, Biber P, Dursky J (2002) The single tree-based stand simulator SILVA: construction, application and evaluation. For Ecol Manag 162(1):3–21
Rangel L, Moreno P, Trejo S, Valero S (2017) Propriedades de tableros aglomerados de partículas fabricados com madera de *Eucalyptus urophylla*. Maderas Cienc Tecnol 19(3):373–386
Reiner DA, Silveira ER, Szabo MS (2011) O uso do eucalipto em diferentes espaçamentos como alternativa de renda e suprimento da pequena propriedade na região sudoeste do Paraná. Synerg Scyentifica 6(1):v10–v18
Reis AA, Melo ICNA, Protásio TP, Trugilho PF, Carneiro ACO (2012) Efeito de local e espaçamento na qualidade do carvão vegetal de um clone de *Eucalyptus urophylla* S. T. Blake. Floresta e Ambiente 19(4):497–505
Retslaff FAZ, Filho AF, Dias NA, Bernett LG, Figura MA (2015) Curvas de sítio e relações hipsométricas para *Eucalyptus grandis* na região os Campos Gerais Paraná. Cerne 21(2):219–225
Ribeiro A, Ferraz Filho AC, Tomé M, Scolforo JRS (2016) Site quality curves for African mahogany plantations in Brazil. Cerne 22(4):439–448
Sales FCV, Silva JAA, Ferreira RLC, Gadelha FHL (2015) Ajustes de modelos volumétricos para o clone *Eucalyptus grandis* × *Eucalyptus urophylla* cultivados no agreste de Pernambuco. Floresta 45(4):663–670
Salles TT, Leite HG, Neto SNO, Soares CPB, Paiva HN, Santos FL (2012) Modelo de Clutter na modelagem de crescimento e produção de eucalipto em sistemas de integração lavoura-pecuária-floresta. Pesqui Agropecu Bras 47(2):253–260
Scolforo JRS (2006) Biometria florestal: modelos de crescimento e produção florestal. FAEPE-UFLA, Lavras, p 393
Shapiro SS, Wilk MB (1965) An analysis of variance test for normality (complete sample). Biometrika 52(3/4):591–611
Silva GCC, Calegario N, Silva AAL, Cruz JP, Leite HG (2018) Site index curves in thinned and non-thinned eucalyptus stands. For Ecol Manag 408:36–44
Spurr SH (1952) Forestry inventory. Ronald Press, New York, p 476
Stage AR (1973) Prognosis model for stand development. USDA Forest Service, Washington, p 32p
Statsoft (2007) Statistica: data analysis software system, version 7. http://www.statsoft.com
Strimbu VC, Bokalo M, Comeau PG (2017) Deterministic models of growth and mortality for jack pine in boreal forests of western Canada. Forests 8(11):410–426
Tian N, Fang SZ, Yang WX, Shang XL, Fu XX (2017) Influence of Container Type and Growth Medium on Seedling Growth and Root Morphology of *Cyclocarya paliurus* during Nursery Culture. Forests 8(10):2–16
Tomé M, Burkhart HE (1989) Distance-dependent competition measures for predicting growth of individual trees. For Sci 35(3):816–831
Tukey JW (1953) The problem of multiple comparisons. Princeton University, Princeton, p 300
Vibrans AC, Moser P, Oliveira LZ, Maçaneiro JP (2015) Generic and specific stem volume models for three subtropical forest types in southern Brazil. Ann For Sci 72(6):865–874
Vospernik S, Monserud RA, Sterba H (2015) Comparing individual-tree growth modes using principles of stand growth for Norway spruce, Scots pine, and European beech. Can J For Res 45(8):1006–1018
Weiskittel AR, Hann DW, Kershaw JA Jr, Vanclay JK (2011) Forest growth and yield modeling. Wiley, Chichester, p 430
Weiskittel AR, Kuehne C, McTague JP, Oppenheimer M (2016) Development and evaluation of an individual tree growth and yield model for the mixed species forest of the Adirondacks region of New York USA. For Ecosyst 3:26
Yang YQ, Titus SJ, Huang SM (2003) Modeling individual tree mortality for white spruce in Alberta. Ecol Model 163(3):209–222
Zlatanov T, Velichkov I, Hinkov G, Georgieva M, Eggertsson O, Hreidarsson S, Zlatanova M, Georgiev G (2012) Site index curves for European chestnut (*Castanea sativa* Mill.) in Belasitsa Mountain. Šumar list 136(3–4):153–159

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.