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Effect of growth and yield modelling on forest regulation and earnings

Larissa Bitti Vescovi[1], Helio Garcia Leite[1], Carlos Pedro Boechat Soares[1], Márcio Leles Romarco de Oliveira[2], Daniel H. B. Binoti[3], Leonardo Pereira Fardin[1], Gabriela Cristina Costa Silva[1], Lucas Sérgio de Sousa Lopes[1], Rodrigo Vieira Leite[1], Ricardo Rodrigues de Oliveira Neto[1] and Simone Silva[1]*

[1]Department of Forest Engineering, Universidade Federal de Viçosa, Av. Purdue, S/N, Campus Universitário, 36.570-900, Viçosa, Minas Gerais, Brazil.
[2]Department of Forest Engineering, Universidade Federal do Vale do Jequitinhonha e Mucuri, Diamantina, Campus JK - MGT 367 - Km 583, nº 5000 Alto da Jacuba, 39100-000, Diamantina, Minas Gerais, Brazil.
[3]Dap Florestal. Rua Papa João XXIII, n 9, Lourdes, 36.570-900, Viçosa, Minas Gerais, Brazil.

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The elaboration of a forest schedule involves constructing and solving a forest regulation model. The regulated structure is not easy to obtain, considering the fluctuations in the effective planting area during the planning horizon, technological advances, and changes in annual demand. Nevertheless, the establishment and implementation of a regulation model often results in an improvement of the forest, in terms of the distribution of age classes. The successful use of regulation models and consequent definition of a forest management plan depends on the quality of data from forest inventory plots and prediction accuracy of stand wood stock. This study evaluated the effect of different alternatives of growth and yield modelling on the regulation of a eucalyptus even-aged forest. Each alternative was used to create yield tables, which were used as inputs in a linear programming model. In this model, restrictions of area, demand, and regulation were included, with the goal of maximising the total net present value. The most consistent forest schedule was obtained with a total stand model.

Key words: Forest management, forestry planning, scheduling, growth, yield models.

INTRODUCTION

Forest management is the application of analytical techniques in the selection of management alternatives to meet the objectives of a company or forestry organisation (Bettinger et al., 2017; Araujo et al., 2018). The best choice among these alternatives depends on the accuracy of information on forest resources (both data and models used to estimate and predict population variables, like wood volume), (Carvalho et al., 2016) and the intensity of interventions during the planning horizon (Clutter et al., 1983; Duvemo and Lämas, 2006). Due to the substantial investments required for management of timber production, highly accurate models of tree

*Corresponding author. E-mail: simone.silva.ufv@gmail.com.

attributes and stand development are required (Burkhart and Tomé, 2012).

To develop a management plan for an even forest requires knowledge of the three essential elements of management: land classification, establishment of prescriptions, and prediction or projection of growth and harvest stock. According to Campos and Leite (2017), modelling growth and stand production is related to the first and third of these elements.

Data from inventory can be used to construct site index curves and map stand production capacity. This information together with the forest historic and physiographic maps of soils and roads, results in a detailed description of each forest compartment and growth and production models can be adjusted and employed to examine forestry and logging options, to determine sustainable production, to examine the impacts of management options and guide forest policy (Davis and Johnson, 1987).

Growth and yield models looking for describe precisely how a forest population grows, providing information for decision making (Peng, 2000; Fahlvik et al., 2014), help managers to exploit forest resources in a sustainable way (Vanclay, 1994) and can be used as input for models to regulate the forest production (Casas et al., 2018). Choosing the appropriate approach for growth and yield modelling depends on the management's purpose, the stratification of the forest, and on the size, quality, and representativeness of the data from the permanent plots or stem analysis (Campos and Leite, 2017). These models can be divided according to the level of detailed: total stand, diameter distribution and trees (Palahí et al., 2003; Castro et al., 2013).

Considering the competitiveness of the increasingly forest-based market, regulating a forest also means maintaining a sustainable production that meets fluctuating market specifications and demand and satisfies capital and operational constraints. It also ensures regular employment (Bachmatiuk et al., 2015; Troncoso et al., 2011) and presents minimum costs and maximum returns within a planning horizon (Heinonen, 2007; Mäkinen et al., 2012; Pereira et al., 2015; Martin et al., 2016).

The regulation of forest production consists of obtaining continually forest products of the same volume, size, and quality. To regulate a forest, managers must determine where, how, and when to sustainably produce goods and services from the forest, to better achieve the objectives of the owner (Pukkala, 2002; Heinonen, 2007; Bouchard et al., 2007). Forestry regulation can ensure continuous production of various products and use of forests regarding sustainability.

The two main models used for the forest production regulation are known as Models I and II (Johnson and Scheurman, 1977). In this classical approach, each management unit should be assigned to one prescription. The basis for this formulation is the initial subdivision of the forest into homogeneous age classes, prescribing a set of requirements for each class (Carvalho et al., 2015). The difference between these two models is that in Model I, the prescriptions assigned to a management unit remained in place until the end of the planning horizon (Buongiorno and Gilles, 2003).

The influence of the growth and yield model on the forest schedule is straightforward because this model generates future information on the expected harvest (Siipilehto and Rajala, 2019). Managers usually select the best model based on its statistical performance, without considering its effect on the management plan (Castro et al., 2016).

The objective of this study is demonstrating the effect of the growth and yield models on the regulation of a eucalyptus even-aged stand.

MATERIALS AND METHODS

Data

For the regulation models, we built yield tables using five growth and yield models. These models were adjusted using data from a continuous forest inventory of a eucalyptus stand located in northern Minas Gerais, Brazil in an area of about 17,000 ha. The area is used for producing wood for charcoal and contains 13 different clones of *Eucalyptus* spp in a 3.0 x 3.0 m spatial arrangement.

2700 permanent plots of 600 m^2 were installed in the stand and the trees had their height and diameter at the breast height (*dbh*) measured in four different years (2005 thru 2008). Tables 1 and 2 show the statistics information of all measurement.

The data was used to adjust the whole-stand and the diameter-distribution models. When possible, we adjusted the models after arranging the data according to genetical material (clone) *stratrum*. The plots were grouped in bigger groups, called management units (m.u.), by having the same genetic material, age class and productivity capacity.

Site index

To determine the productive capacity of the stands, we defined site indexes using the guide-curve method (Clutter et al., 1983) with an index age of 60 months. The guide-curve method was adjusted for each genetic material using the logistic model (Draper and Smith, 1998):

$$Hd = \beta_0 (1 + \beta_1 e^{-\beta_2 Age})^{-1} + \varepsilon \tag{1}$$

where *Hd* denotes the dominant height, in meters; *Age* denotes the age in months; β_0, β_1 e β_2 are the model parameters, and ε is the random error $\varepsilon \sim NID(0, \sigma^2)$.

Yield tables and costs

The yield tables used in this study were built using five growth and yield modelling alternatives: four whole-stand (Models 1 to 4) and one diameter-distribution model (Model 5) as shown in Table 3.

Table 1. Number of trees per hectare of each clone.

Clone	2005	2006	2007	2008
A	1312	1294	1145	1053
B		1147	1086	1080
C		1214	1103	
D		1190	1091	
E	1131	1161	1100	1048
F		1137	1127	1083
G	1125	1156	1118	1061
H		1156	1104	1076
I	1103	1134	1068	1022
J	1306	1313	1222	1234
K	1138	1138	1087	1098
L	1115	1119	1099	1099
M	1179	1190	1139	1135
N	1308	1313	1226	1189

Table 2. Statistics for Dbh and height for each year.

Year	Min Dbh	Average Dbh	Max Dbh	Dbh standard deviation	Dbh variance	Min height	Average height	Max height	Height standard deviation	Height variance
2005	3.47	8.96	16.27	2.57	2.89	3.77	10.87	19.00	1.70	6.58
2006	4.04	9.74	20.05	4.58	4.08	3.63	11.67	24.00	2.02	21.01
2007	0.16	10.67	24.19	5.17	7.67	1.68	15.39	31.00	2.77	26.67
2008	3.28	10.77	25.24	6.37	8.45	3.00	15.79	47.20	2.91	40.55

The models were adjusted for each genetic material stratum, except those that contained insufficient data to fit a specific model; in this case, the models were fitted using all the data without stratification. The yield tables for each management unit were constructed using the results from the last inventory as the input. Five yield tables were obtained for each of the 341 management units using the fitted models. Productive capacity was used as an input in alternatives 2 and 4. The simulated costs were based on Melido (2012) study and timber price was set as €25.00/m^3. Brazilian currency (R$) values were converted to euros (€) using the conversion factor of 2.436 (€1.00 = R$ 2.436), as on 1 August, 2008 (European Central Bank, 2019), the last year that the plots were measured.

Projection errors

We used the correlation coefficients to evaluate the models' goodness of fit, bias, relative bias (bias%), and error variance to assess the estimation precision of timber stocks (Islam et al., 2009):

$$r_{y\hat{y}} = \frac{n^{-1}\sum_{i=1}^{n}(\hat{Y}_i - \hat{Y}_m)(Y_i - \bar{Y})}{\sqrt{n^{-1}\sum_{i=1}^{n}(\hat{Y}_i - \hat{Y}_m)^2 \, n^{-1}\sum_{i=1}^{n}(Y_i - \bar{Y})^2}};$$

$$bias = \frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)}{n}; \quad Bias\% = 100\frac{\frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)}{n}}{\frac{\sum_{i=1}^{n}(Y_i)}{n}}$$

$$Variance(\hat{Y}_i - Y_i) = \frac{\left[bias - (\hat{Y}_i - Y_i)\right]^2}{n-1}; \quad RSME = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}{n}};$$

$$RSME\% = \frac{100\sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}{n}}}{\frac{\sum_{i=1}^{n}(Y_i)}{n}}$$

where $\hat{Y}_i$ and Y_i are the estimated and observed production values and n is the number of permanent plots.

The models were categorised into four groups according to the magnitude and variance of relative bias (Figure 1). The groups are named: LBLV (low bias % and low variance), LBHV (low bias % and high variance), HBLV (high bias % and low variance), and HBHV (high bias % and high variance) (Islam et al., 2009).

Table 3. Models adjusted as alternatives to analyse their effects on the regulation of the production of eucalyptus stands.

Alternative	Statistical model
1 - Exponential	$V = \theta_0 + e^{\theta_1/AS} + \varepsilon$
2 – Logistic (1961)	$V = \dfrac{\theta_0}{1+\theta_1 e^{-\theta_2 AS}} + \varepsilon$
3 - Clutter (1963)	$LnB_2 = LnB_1\left(\dfrac{A_1}{A_2}\right) + \theta_0\left(1-\dfrac{A_1}{A_2}\right) + \theta_1\left(1-\dfrac{A_1}{A_2}\right)S + \varepsilon$ $LnV_2 = \beta_0 + \dfrac{\beta_1}{A_2} + \beta_2 S + \beta_3 LnB_2 + \varepsilon$
4 - Buckman (1962)	$V = \beta_0 + \beta_1 BHd + \varepsilon$ $LnICAB = \beta_0 + \beta_1 S + \beta_2 \dfrac{1}{A} + \beta_3 B_1 + \varepsilon$
5 - Nogueira (2003)	$d\min_2 = d\min_1 e^{-\theta_1(A_2^{\theta_2} - A_1^{\theta_3})} + \varepsilon$ $Ln\gamma_2 = Ln\gamma_1 e^{-\theta_1(A_2^{\theta_2} - A_1^{\theta_3})} + \varepsilon$ $d\max_2 = d\max_1\left(\dfrac{A_1}{A_2}\right) + \theta_1\left(1-\dfrac{A_1}{A_2}\right)\theta_2 + \varepsilon$ $\beta_2 = \beta_1\left(\dfrac{A_1}{A_2}\right) + \theta_1\left(1-\dfrac{A_1}{A_2}\right)d\max_2 + \varepsilon$ $N_2 = N_1 e^{\theta_1(A_2^{\theta_2} - A_1^{\theta 2})} + \varepsilon$

V: volume in m^3ha^{-1}; *A*: age, in years; *S*: site index (m) in the index age of 60 months, B: basal area, m^2ha^{-1}; *ΔB*: basal area increase, m^2ha^{-1} per year; *c*: constant of relative approximation on the sum of the maximum and minimum rates of basal area growth; *γ*: shape parameter of Weibull function, *β*: scale parameter of Weibull function; *dbh*: diameter at 1.3 m height (in cm); *dmax*: maximum diameter in cm; *dmin*: minimum diameter in cm, *N*: number of trees per hectare; *Δdbh*: diameter increment, cm per year; *BAL*: competition index measured by the sum of sectional area of trees with diameter greater than the evaluated tree, m², *H*: total height in m; *Hd*: dominant height in m; *Ddom*: the diameter of the dominant tree in cm, *D*: Square root of the diameter in cm, *Ln*: Napierian logarithm; *β0, β1, β2, β3e* θ_0: model parameters.

Forest production regulation

For the yield tables, cost worksheet, price of wood, and definition of regulatory rotation (6 years), planning horizon (18 years), and management prescriptions, we formulated the forest regulation model using linear programming (LP) model I (Leuschner, 1984; Dykstra, 1984), so named by Johnson and Scheurman (1977). The only difference between the five management plans was the yield table employed. We used the 12% annual interest rate. The management prescription was clear cut with 6 years followed by replanting. We consider that the genetic materials and yield of a plot does not change from one cutting cycle to another.

The objective function defined to maximise the total net present value (NPV) of the stand is as follows:

$$Maximize = \sum_{i=1}^{M}\sum_{j=1}^{N} C_{ij} X_{ij} \qquad (2)$$

where,
C_{ij} denotes the NPV of management unit *i* assigned to prescription *j*;
X_{ij} denotes the area (ha) of management unit *i* assigned to prescription *j*;
M denotes the number of management units, M = 341; and
N denotes the number of alternative prescriptions.

The net present value (NPV) is calculated as Equation 3:

$$C_{ij} = \sum_{k=0}^{n} R_k (1+w)^{-k} - \sum_{k=0}^{n} C_k (1+w)^{-k} \qquad (3)$$

where,
C_{ij} denotes the NPV management unit *i* assigned to prescription;
R_k denotes revenue at the end of period *k*, k = 0, 1, ..., 17;
C_k denotes final cost in period *k*, k = 0, 1, ..., 17;
w denotes interest rate = 0.12;
n denotes the max(k) = the horizon planning (18); and
k denotes period in years.

The area (4), production (5 and 6), and regulatory constraints (7)

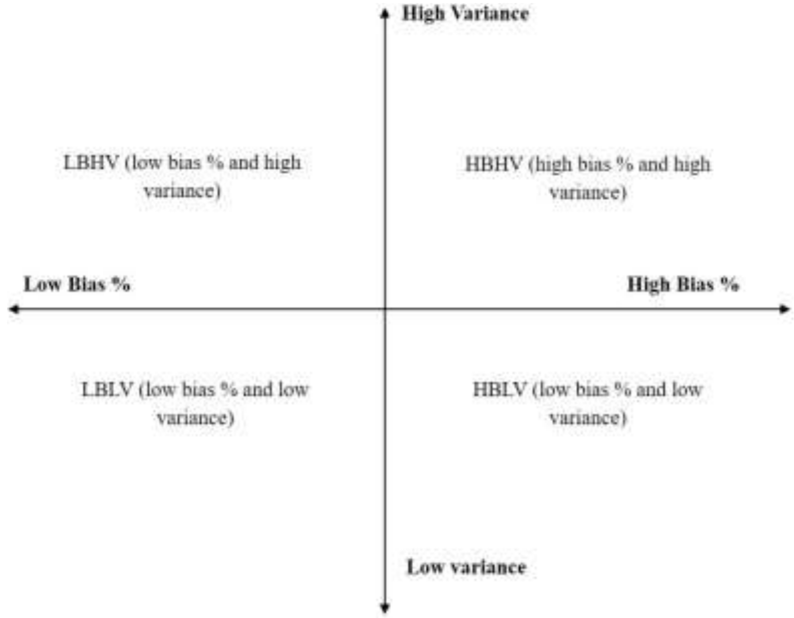

Figure 1. Categorization of measures of accuracy bias% and error variance of the volume estimations of the seven growth and yield modeling alternatives, with bias % and error variance crossing their medians.

are shown below:

$$\sum_{i=1}^{M} \sum_{j=1}^{N} X_{ij} \leq A_i \forall i = (1...m) \quad (4)$$

$$\sum_{i=1}^{M} \sum_{j=1}^{N} V_{ijk} X_{ij} \geq D\min \forall k = (0...h-1) \quad (5)$$

$$\sum_{i=1}^{M} \sum_{j=1}^{N} V_{ijk} X_{ij} \leq D\max \forall k = (0...h-1) \quad (6)$$

$$\sum_{i=1}^{M} \sum_{j=1}^{N} X_{ijt} \geq \frac{A_t}{r} \forall k = (1...r) \quad (7)$$

where,
A_i = Area of the *i*th management unit (i = 1, 2, ..., 341);
V_{ijk} = Volume (m^3) of management unit *i* assigned to prescription *j* at year k;
D_{min} *and* D_{max} = Minimum and maximum demand for timber in year *k;*
X_{ij} = area of the *i*th management unit in the *j*th prescription;
X_{ijt} = area of the *i*th management unit in the *j*th prescription, where trees have *t* years during the final period of the planning horizon; and
r = number of age class, equal to 6 years (regulatory rotation).

Five different management plans were generated using the yield tables resulted from the five growth and yield models tested. The results from the LP problems were compared in terms of their prognosis errors to detect their effect on the prescribed management plan. Additionally, the standard deviations of the costs and harvesting were considered to verify their uniformity during the planning horizon. The LP models were solved using Lindo Systems Inc. (http://www.lindo.com).

RESULTS

All models had satisfactory results, with correlation coefficients above 0.7. The whole-stand models better describe the volume yield, especially the Clutter et al. (1983) model, for the different clone *strata* with correlation coefficients from 0.87 to 0.98, indicating that the independent variables contributed effectively to explain the production variations. The results for each model are presented in Tables 4 and 5.

The categories defined for bias and variance values show that Model 3 is both most accurate and precise. From a comparison of the prognosis errors (bias), we verified that there is a direct relationship between the error categories and the total NPV from the optimization (Table 6). That is, the models with lower biases and variances yield a higher overall NPV. The obtained NPV has high amplitude, ranging from about € 50 (Model 5) to € 94 million (46.5% difference) (Model 3).

The complete formulation of the LP problem for yield regulation resulted in 16,401 decision variables (X_{ij}), with 341 area constraints. As only one restriction is required for each management unit, 18 demand constraints, one

Table 4. Estimates of the parameters of the growth and production models at the settlement level of alternatives 1, 2, 3, and 4 adjusted for each stratum and respective correlation coefficients genetic material.

GM	Alternative 1			Alternative 2				Alternative 3							Alternative 4			
	Exponential (V=f(*I*,*S*))			Logistic (V=f(*I*))				Clutter (1963)							Buckman (1962)			
	β_0	β_1	$r_{\hat{y}y}$	β_0	β_1	β_2	$r_{\hat{y}y}$	α_0	$r_{\hat{y}y}$	β_0	β_1	β_2	β_3	$r_{\hat{y}y}$	β_0	β_1	β_2	$r_{\hat{y}y}$
A	514.711	-1629.962	0.91	211.366	42.202	0.096	0.90	3.418	0.93	2.259	-9.211	0.015	1.125	0.96	17.402	3.017	4.051	0.87
B	841.612	-2111.571	0.82	105.942	297.489	0.172	0.82	3.617	0.79	1.294	-4.042	-	1.385	0.93	17.548	3.122	4.479	0.45
C	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
D	743.944	-1746.733	0.78	209.246	65.843	0.111	0.69	-	-	-	-	-	-	-	18.386	2.876	4.348	0.83
E	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
F	-	-	-	-	-	-	-	-	-	-	-	-	-	-	18.988	2.722	5.431	0.88
G	670.872	-1918.402	0.85	171.197	236.906	0.167	0.85	3.824	0.50	0.427	-1.161	-	1.675	0.87	-	-	-	-
H	649.951	-1826.501	0.95	206.132	65.028	0.112	0.94	3.749	0.95	0.840	-4.008	0.001	1.529	0.98	20.164	2.527	4.723	0.86
I	521.662	-1666.443	0.84	209.246	65.843	0.111	0.82	3.681	0.94	0.864	-13.639	-	1.649	0.97	25.327	3.096	5.608	0.74
J	816.143	-1957.544	0.95	241.114	79.370	0.120	0.93	3.731	0.87	1.336	-13.132	0.004	1.385	0.98	15.623	3.269	4.661	0.80
K	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
L	211.104	-1079.423	0.95	100.214	67.464	0.106	0.94	-	-	-	-	-	-	-	15.875	4.378	5.000	0.80
M	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
N	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
General	635.010	-1740.821	0.91	209.246	65.843	0.111	0.89	3.707	0.95	0.965	-8.203	0.002	1.509	0.98	21.703	3.155	4.861	0.87

*($r_{\hat{y}y}$)= correlation coefficient; *GM*= genetic material.

Table 5. Estimates of the parameters of the stratified non-linear equations of alternative 5 and their respective correlation coefficients ($r_{\hat{y}y}$).

GM	Minimum diameter			Beta		Number of trees			Maximum diameter		Gama		
	β_0	β_1	$r_{\hat{y}y}$	β_0	$r_{\hat{y}y}$	β_0	β_1	$r_{\hat{y}y}$	β_0	$r_{\hat{y}y}$	β_0	β_1	$r_{\hat{y}y}$
A	1.2310	-1.0480	0.8000	-	-	-	-	-	-	-	-	-	-
B	1.0430	-1.0880	0.8610	-	-	-	-	-	-	-	-	-	-
C	-	-	-	0.8000	0.0630	-	-	-	-	-	-	-	-
D	-	-	-	0.8610	0.8280	0.0002	4.4240	0.5600	-	-	-	-	-
E	-	-	-	1.2200	0.9590	-	-	-	-	-	-	-	-
F	1.2980	-1.0630	0.4090	1.3180	0.2140	0.0100	3.0920	-0.0180	-	-	-	-	-
G	-	-	-	1.2930	0.9170	-	-	-	-	-	-	-	-
H	1.3930	-1.2450	0.8120	1.2490	0.8320	-	-	-	-	-	-	-	-
I	1.7060	-0.6420	0.8780	1.3110	0.9320	-	-	-	-	-	-	-	-

Table 5. Contd.

J	1.3760	-1.8450	0.7250	1.2290	0.8600	0.0050	3.0810	0.7320	-	-	-	-	-
K	-	-	-	-	-	0.0001	4.6250	0.6010	-	-	-	-	-
L	-	-	-	1.2410	0.2060	0.0020	3.2310	0.3810	-	-	-	-	-
M	-	-	-	1.1200	0.7940	-	-	-	-	-	-	-	-
N	-	-	-	1.0750	0.2540	-	-	-	-	-	-	-	-
General	1.3210	-1.1520	0.6570	0.8700	0.9590	0.9590	1.9770	0.7300	2.1550	0.9120	0.0020	2.1570	0.8860

*GM= genetic material.

Table 6. Categorisation of error measures of growth modelling and production alternatives.

Alternative	Model	|Bias%|	Variance	Category	RSME	RSME%	e%	Total NPV (€)
1	Exponential	1.92	3,421.94	LBLV	21.01	4.08	-2.24	87,075,185.81
2	Logistic (1961)	9.39	3,237.26	HBLV	28.46	7.04	-9.8	58,824,087.38
3	Clutter (1963)	2.72	3,021.99	LBLV	20.00	3.53	3.72	94,682,749.56
4	Buckman Mod (1962)	9.32	4,492.54	HBHV	30.67	4.12	-9.32	61,239,149.18
5	Nogueira (2003)	4.27	5,536.63	HBHV	39.43	5.31	2.95	50,643,657.87
Medium		4.27	3,421.94		28.46	4.12	-2.24	61,239,149.18

for each year of the planning horizon, and six regulatory restrictions were defined by the regulating age. For all five management plans, restrictions were met, but with differences in overall NPV, annual costs, and annual cutting area during the planning horizon (Table 7 and Figure 2).

In this study, the best model was a whole-stand model (Model 3) for both the overall NPV and evenness of harvested areas within the planning horizon. This model had the lowest standard deviation for annual harvested areas. Although Model 5 had the lowest standard deviation for annual costs, followed by Models 1, 4, and 3 (Table 7), it performed poorly on forest regulation and had the lowest NPV.

The differences in costs between Model 3 and Models 4, 5, 2, and 1 were -41.3, -7, 5, -6.2, and -5.0%, respectively. Conversely, the corresponding percentage differences in the total NPV were -35.3, 46.5, 37.9 and -8.0%, respectively. Therefore, even with fluctuating costs over the years, the profitability was at least 8% greater in Model 3.

By adopting the second-best modelling alternative (Model 1), based on the measures of precision, accuracy, the forest manager would have a reduction in the updated cost for the zero year of 5%. However, there would be an 8% reduction in return on investment (NPV). This and the results in Table 7 show the consequences of using inefficient modelling alternatives.

The use of a poor modelling alternative, such as alternative 4, would result in great chances of not reaching the objectives established when formulating the regulation model. Alternative 4 had resulted in a strong bias, with underestimation of production. Thus, the use of this alternative would result in a great chance of not meeting the management objectives over the planning horizon.

DISCUSSION

The Clutter et al. (1983) model was the most representative for the volume data used in this study. Whole-stand models are explicit, less complex, require less information and, therefore, have fewer errors (Soares et al., 2004; Oliveira et al., 2009; Scolforo et al., 2019). In relation to the

Table 7. Solution of the Linear Programming model using yield data for the 5 growth and yield model alternatives, where NPV is the maximization of the objective function, Area (ha) is the annual harvested area, and Cost (€ 103) is the cost during each period of the planning horizon.

PH	Model 1		Model 2		Model 3		Model 4		Model 5	
	Exponential		Logistic		Clutter (1963)		Buckman (1962)		Nogueira (2003)	
	NPV: 87,075,185.81		NPV: 58,824,087.38		NPV: 94,682,749.56		NPV: 61,239,149.18		NPV: 50,643,657.87	
	Area	Cost	Area	Cost	Area	Cost	Area	Cost	Area	Cost
0	2,062.50	210,404.02	2,054.10	99,519.32	2,679.90	145,286.49	2,315.50	459,600.87	1,506.80	302,172.34
1	2,451.60	160,036.46	2,791.10	135,230.36	3,041.90	235,369.28	1,500.00	615.94	2,981.00	384,036.30
2	3,147.40	447,142.61	2,785.40	242,421.71	2,941.70	370,347.35	2,628.80	381,679.11	2,279.10	335,843.72
3	1,751.40	343,860.76	3,177.10	588,114.85	2,530.70	434,858.33	2,457.20	119,052.68	2,934.50	142,176.90
4	2,548.30	329,184.33	2,784.90	516,292.20	3,083.00	482,830.94	2,507.50	121,489.18	2,298.60	171,960.91
5	3,111.60	177,116.17	2,474.10	119,867.61	3,292.00	159,498.75	3,500.00	1,437.19	2,575.90	140,293.11
6	2,829.60	144,263.46	2,722.90	136,929.74	2,578.30	124,918.41	2.31,3	263,161.79	2,392.40	309,606.78
7	2,732.40	173,640.13	2,799.10	136,774.57	2,494.80	155,927.77	2.89,6	137,770.66	2,923.60	296,318.73
8	2,474.90	362,285.47	2,794.00	244,094.69	2,503.30	254,728.49	1,800.00	739.13	1,181.20	224,999.96
9	2,822.00	434,486.39	3,011.20	588,235.00	2,618.20	509,998.03	2,102.50	409,545.11	1,579.10	310,245.14
10	2,120.80	425,290.81	2,507.50	502,853.45	2,832.90	568,113.54	1,445.20	289,810.91	1,427.70	286,309.20
11	2,800.00	135,659.67	2,800.00	135,659.67	2,934.50	142,176.90	2,934.50	142,176.94	2,934.50	142,176.90
12	2,800.00	135,659.67	2,800.00	135,659.67	2,934.50	142,176.90	2,934.50	142,176.90	2,934.50	142,176.90
13	2,800.00	135,659.67	2,800.00	135,659.67	2,934.50	142,176.90	2,934.50	142,176.94	2,934.50	142,176.90
14	2,800.00	237,528.03	2,800.00	237,528.03	2,934.50	248,939.15	2,934.50	248,939.10	2,934.50	248,939.10
15	2,800.00	545,409.60	2,807.70	546,917.26	2,934.50	571,611.67	2,934.50	571,611.66	2,934.50	571,611.67
16	2,800.00	561,506.18	2,800.00	561,506.26	2,934.50	588,481.58	2,934.50	588,481.54	2,934.50	588,481.54
17	3,531.80	171,117.73	2,800.00	135,659.67	2,934.50	142,176.90	2,595.20	125,735.15	2,342.90	113,511.23
SD	415.1	147,754.6	229.8	195,918.2	223.4	177,079.8	574	168,856.49	620	140,098.1

*SD= Standard Deviation.

other whole-stand models, the Clutter et al. (1983) model uses more explanatory variables other than age and site-index, making it more precise. Usually, models that consider only age as an independent variable do not explain yield variations properly (Silva et al., 2003; Nascimento et al., 2015; Novaes et al., 2017) and need maximum data classification. In this study, we have stratified data by genetic material, making these models specific and efficient for volume estimation. However, we would not recommend using this model for areas with no stratification.

The differences in NPV are associated with the predicted volume in each model. In some cases, the future volume of a stand is underestimated resulting in significant losses. In this study, the best model is a whole-stand model (Model 3) based on the yielded NPV. The same result may not be the same in different types of forests, especially if they do not have homogeneity in even-aged eucalyptus forests (Härkönen et al., 2010; McCullagh et al., 2017).

The lowest standard deviations for harvest and cost were obtained in Models 3 and 5, respectively. This is important because one of the benefits of regulation is maintaining regular employment, and lower standard deviations indicate a greater possibility of achieving this goal. For managers, less variation in annual harvest and annual costs facilitates the planting, harvesting, and replanting activities and workforce and equipment scheduling to perform those activities during the planning horizon (Rode et al.,

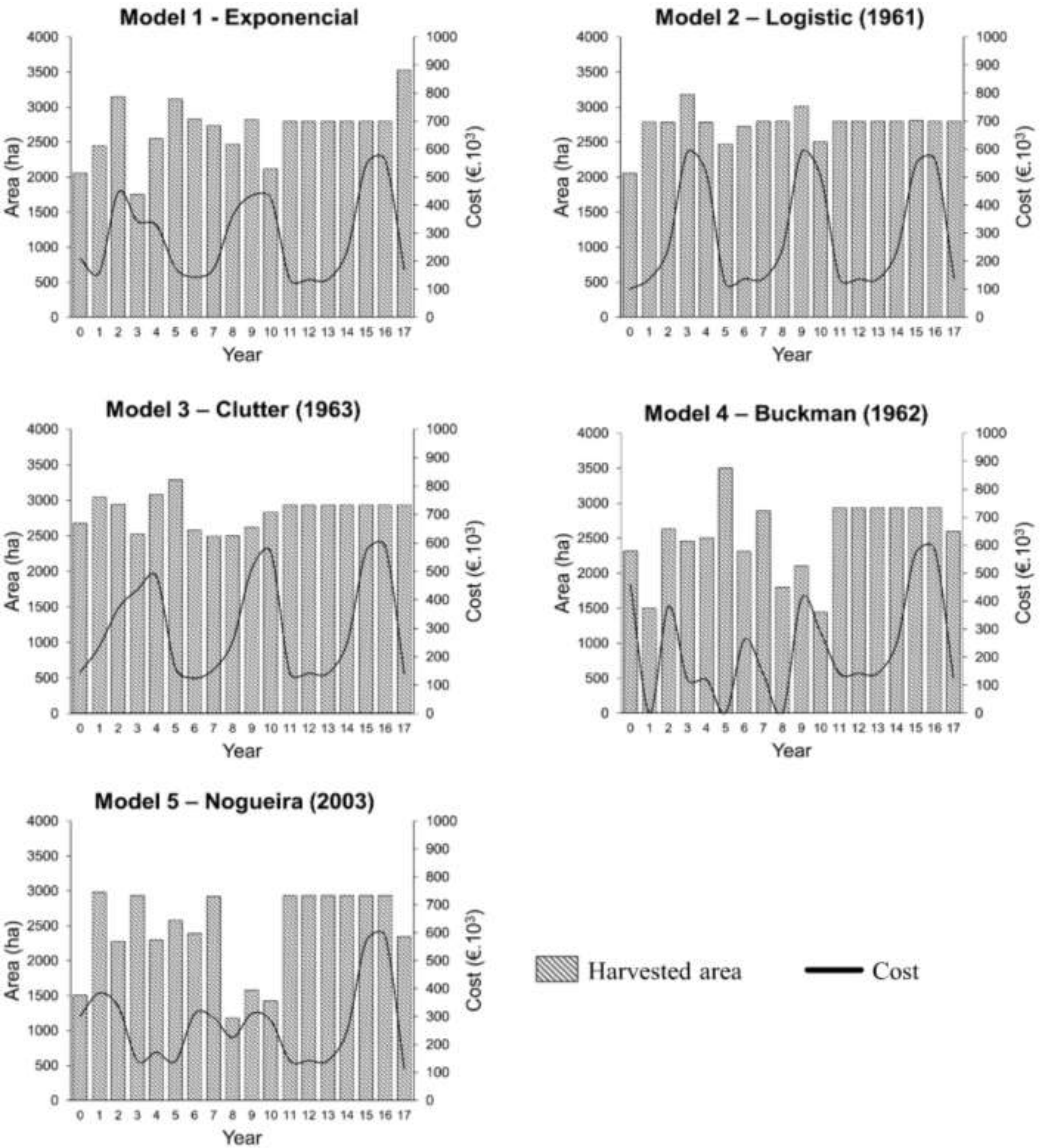

Figure 2. Linear programming model results using data from the five growth and yield models, where: Area (ha) is the annual cut area, represented as bars and Cost (€.10³) is the total cost in that year, represented as the smoothed lines.

2014; Oliveira Neto et al., 2020).

These results demonstrate the consequences of inefficient modelling alternatives. Poor modelling, as shown in Model 4, results to differences in cost, total

NPV, and annual harvesting areas, with similar results found in Silva et al. (2003). Since Model 4 resulted in a strong bias with a yield underestimation, using it would result in a higher probability of failing to meet management objectives during the planning horizon, with a possibility of producing excess wood in the annual cutting.

Conclusions

Choosing an inefficient modelling alternative, results in profound changes and uncertainties in the forest management plan. That is, the successful implementation of a management plan is dependent on the quality of the yield tables used. In this study, the management plan is more consistent when using the Clutter et al. (1983) model, fitted using the genetic material strata.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Araujo CA, Mendes JB, Cabacinha CD, Assis AL, Matos LMA, Leite HG (2018). Meta-heuristic clonal selection algorithm for optimization of forest planning. Revista Árvore 41(6):2-10.

Bachmatiuk J, Garcia-Gonzalo J, Borges JG (2015). Analysis of the performance of different implementations of a heuristic method to optimize forest harvest scheduling. Silva Fennica 49(4):1-18.

Bettinger P, Boston K, Siry JP, Grebner DL (2017). Forest management and planning. Academic press. 362p.

Bouchard M, D'Amours S, Rönnqvist M, Azouzi R, Gunn E (2007). Integrated optimization of strategic and tactical planning decisions in forestry. European Journal of Operational Research 259(3):1132-1143.

Buckman RE (1962). Growth and yield of red pine in Minnesota. Washington, D.C: USDA, (Techical Bulletin, 1272). 50p.

Buongiorno J, Gilles JK (2003). Decision methods for forest resource management. San Diego, CA: Academic Press 439p.

Burkhart HE, Tomé M (2012). Modeling forest trees and stands. Springer Science and Business Media.

Carvalho KHA, Silva ML, Leite HG, Binoti, DHB (2015). Influência da taxa de juros e do preço da madeira em modelos de regulação florestal. Pesquisa Florestal Brasileira 35(82):143-151.

Carvalho KHA, da Silva M, Leite HG, Binoti DHB, da Silva LF (2016). Influência de diferentes funções objetivo em modelos de regulação florestal. Revista Agro@ mbiente On-line 10(4):371-380.

Casas GG, Villanueva JRB, Leite HG, de Albuquerque Santos AC, Júnior CAA, de Alcántara AEM (2018). Regulación de la producción forestal con pronósticos de modelación Clutter y redes neuronales artificiales en plantaciones de eucalipto del Estado de Minas Gerais–Brasil. Revista Científica UNTRM: Ciencias Naturales e Ingeniería 1(1):55-59.

Campos JCC, Leite HG (2017). Mensuração florestal: Perguntas e respostas. 5. ed. rev. e ampl. Viçosa: UFV. 636p.

Castro RVO, Soares CPB, Martins FB, Leite HG (2013). Crescimento e produção de plantios comerciais de eucalipto estimados por duas categorias de modelos. Pesquisa Agropecuária Brasileira 48(3):287-295.

Castro RVO, Araújo RAA, Leite HG, Castro AFNM, Silva A, Pereira RS, Leal FA (2016). Modelagem do crescimento e da produção de povoamentos de Eucalpytus em nível de distribuição diamétrica utilizando índice de local. Revista Árvore 40(1):1-11.

Clutter JL, Fortson JC, Pienaar LV, Brister GH, Bailey RL (1983). Timber Management: A quantitative approach. New York, J. Wiley, 333p.

Davis LS, Johnson KN (1987). Forest management. 3rd ed. New York: MacGraw-Hill Book Company 790p.

Draper NR, Smith H (1998). Applied regression analysis. New York: John Willey e Sons. 3rd ed., 706p.

Duvemo K, Lämas T (2006). The influence of forest data quality on planning processes in forestry. Scandinavian Journal of Forest Research 21(4):327-339.

Dykstra DP (1984). Mathematical programming for natural resource management. New York: McGraw-Hill, 318p.

European Central Bank (2019). https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/ [Cited 29 April 2019]

Fahlvik N, Elfving B, Wikström P (2014). Evaluation of growth functions used in the Swedish Forest Planning System Heureka. Silva Fennica 48(2):1-17.

Härkönen S, Pulkkinen M, Duursma R, Mäkelä A (2010). Estimating annual GPP, NPP and stem growth in Finland using summary models. Forest Ecology And Management 259(3):524-533.

Heinonen T, Pukkala T (2007). The use of cellular automaton approach in forest planning. Canadian Journal of Forest Research 37(11):2188-2200.

Islam MN, Kurttila M, Mehtätalo L, Haara A (2009). Analysing the Effects of Inventory Errors on Holding-Level Forest Plans: The case of measurement error in the basal area of the dominated tree species. Silva Fennica 43(1):71-84.

Johnson KN, Scheurman HL (1977). Techiniques for prescrinbing optmal timber harvest and investment under different objetives - Discussion and synthesis. Forest Science 23(1):1-31.

Leuschner WA (1984). Introduction to forest resource management. New York: John Willey & Sons, 298p.

Martin AB, Richards E, Gunn E (2016). Comparing the efficacy of linear programming models I and II for spatial strategic forest management. Canadian Journal of Forest Research 47(1):16-27.

Mäkinen A, Kangas A, Nurmi M (2012). Using cost-plus-loss analysis to define optimal forest inventory interval and forest inventory accuracy. Silva Fennica 46(2):211-226.

Mccullagh A, Black K, Nieuwenhuis M (2017). Evaluation of tree and stand-level growth models using national forest inventory data. European Journal of Forest Research 136(2):251-258.

Melido RCN (2012). Avaliação técnica e econômica de dois projetos florestais com eucalipto para fins energéticos. Dissertação de Mestrado em Engenharia Florestal, Departamento de Engenharia Florestal, Universidade de Brasília, Brasília, DF,113 p.

Nascimento FAF, Dias AN, Figueredo Filho A, Miranda GM, Arce JE (2015). Sistema de crescimento e produção para povoamento de *Pinus taeda* na região norte de Santa Catarina. Cerne 21(2):235-242.

Novaes DM, Santos ACA, Soares CPB, Paiva HN, Reis GG, Monte MA, Davila FS, Leite HG (2017). Modeling *Tectona grandis* tree and stand growth using stem analysis and permanent plot data. Revista Árvore 41(5):1-10.

Oliveira MLR, Leite HG, Nogueira GS, Campos JCC (2009). Modeling and Prognosis in Nonthinned Stands of Eucalyptus Clones. Revista Árvore 33(5):841-852.

Oliveira Neto RR, Silva S, de Albuquerque Santos AC, Leite RV, Gleriani JM, Leite HG, Fardin LP (2020). Modeling the sensitivity of strategic plans to risks and uncertainties in forest management. 15(2):222-228.

Palahí M, Pukkala T, Miina J, Montero G (2003). Individual-tree growyh and mortality models for Scot pine (*Pinus sylvestris* L.) in north-east Spain. Forest Science 60(1):1-10.

Pereira S, Prieto A, Calama R, Diaz-Balteiro L (2015). Optimal management in *Pinus pinea* L. stands combining silvicultural schedules for timber and cone production. Silva Fennica 49(3):1-16.

Peng C (2000). Growth and yield models for uneven-aged stands: Past, present and future. Forest Ecology and Management 132(2-3):259-279.

Pukkala T (2002). Introduction to multi-objective forest planning in: Pukkala, T. Multi-Objective Forest Planning ed. Kluwer Academic

Publishers, Netherlands, pp. 1-19.
Siipilehto J, Rajala M (2019). Model for diameter distribution from assortments volumes: Theoretical formulation and a case application with a sample of timber trade data for clear-cut sections. Silva Fennica 53(1):1-21.
Silva GFD, Leite HG, Soares CPB, Silva MLD (2003). Influência de estimativas de produção de madeira em processos de regulação florestal utilizando programação linear. Ciência Florestal 13(1):57-72.
Scolforo HF, McTague JP, Burkhart H, Roise J, McCarter J, Alvares CA, Stape JL (2019). Stand-level growth and yield model system for clonal eucalypt plantations in Brazil that accounts for water Availability. Forest Ecology and Management 448:22-33.
Soares CPB, Leite HG, Oliveira MLR, Carvalho A (2004). Especificação de um modelo de crescimento e produção florestal. Revista Árvore 28(6):831-837.
Rode R, Leite HG, Silva ML, Ribeiro CAAS, Binoti DDHB (2014). The economics of optimal management regimes of eucalyptus plantations: A case study of forestry outgrower schemes in Brazil. Forest Policy and Economics 44:26-33.
Troncoso J, D'Amours S, Flisberg P, Rönnqvist M, Weintraub A (2011). A mixed integer programming model to evaluate integrating strategies in the forest value chain - A case study in the Chilean forest industry. Canadian Journal of Forest Research 45(7):937-949.
Vanclay JK (1994). A growth model for North Queensland rainforests. Forest Ecology and Management 27:245-271.