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Deriving a Tree Growth Model from Any Existing Stand Growth Model

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Deriving a Tree-Level Growth Model from Any Existing Stand-Level Growth Model

Abstract

In this study, a new method was developed to derive a tree survival and diameter growth model from any existing stand-level model, without the need for individual-tree growth data. Predictions from the derived tree model are constrained to match number of trees and basal area per ha as outputted by the stand model. The tree models derived from three different stand models were evaluated against a tree model, in both unadjusted and disaggregated forms.

For the same stand-level model, the derived tree model outperformed its counterpart, the disaggregated tree model. Furthermore, except for one stand model with poor performance, the tree models derived from the remaining two stand models delivered comparable results to those obtained from the unadjusted tree model. The tree model derived from one stand model even performed slightly better than the unadjusted tree model. This is significant because the coefficients of the unadjusted and disaggregated tree models had to be estimated from tree-level growth data, whereas the derived tree model required no tree growth data at all. The methodology presented in this study should be applicable when there is no ingrowth or recruitment.

Keywords: disaggregation; individual-tree model; least squares; seemingly unrelated regression.

1. Introduction

Growth and yield models have been extensively used by forest managers in order to make informed decisions on managing forest resources. These models can produce outputs that ranged from high-resolution (individual-tree simulation models), to medium-resolution (size-class models), to low-resolution (whole-stand models) (Burkhart and Tomé 2012).

Whole-stand models are relatively simple models that provide information for the entire stand. The predicted stand attributes can be stand survival (Zhang et al. 1993, Diéguez-Aranda et al. 2005, Tewari et al. 2014, Stankova 2016), basal area per unit area (Cao and Durand 1991, Barrio Anta et al. 2006, Naing 2020), or both (Somers and Farrar 1991, Erikäinen 2002, Garcia 2011, Dean et al. 2013).

Size-class models deal with diameter classes. These models can be stand table-projection models that projects the number of trees in each diameter class into the future (Clutter and Jones 1980, Nepal and Somers 1992, Cao and Baldwin 1999, Allen et al. 2011), or diameter-distribution models that use a probability density function (pdf) to model the frequency of tree diameters (Smalley and Bailey 1974, Matney and Sullivan 1982, Jiang and Brooks 2009, Carretero and Alvarez 2013).

Individual-tree models deliver detailed information for each tree. This information can be tree survival (Guan and Gerner 1991a, 1991b, Monserud and Sterba 1999, Kjell and Lennart 2005, Cao 2006, 2017), tree diameter growth (Andreassena and Tomter 2003, Sánchez-González et al. 2006, Subedi and Sharma 2011, Bohora and Cao 2014), or both tree survival and diameter growth (Cao 1994, 2000, Palahía et al. 2003, Coble et al. 2012, Sun et al. 2019).

Because outputs from models of different resolutions might be inconsistent with one another, linking models having different levels of resolution have recently received a lot of attention. Bridges have been established to connect a whole-stand model to a diameter-distribution model (Matney and Sullivan 1982; Baldwin and Feduccia 1987), to a stand table projection model (Clutter and Jones 1980, Nepal and Somers 1992, Cao and Baldwin 1999, Cao 2007, Allen et al. 2011), or to an individual-tree model (Yue et al. 2008, Zhang et al. 2010, Hevia et al. 2015, Cao 2014, 2017). The latter is called the disaggregation approach (Ritchie and Hann 1997), in which information obtained from the tree model is used to disaggregate stand growth (predicted by a whole-stand model) among trees in the tree list. Recently, Cao (2019) showed how one can derive a tree survival model from any existing stand survival model; the level of accuracy and precision depended on the stand model performance and on whether or not tree-level survival data were available.

The objective of this study was to develop a method to derive a tree-level growth model for tree survival and diameter growth predictions from stand survival and basal area values predicted from any existing stand-level model.

2. Data

Data used in this study were from the Southwide Seed Source Study, which included 15 loblolly pine (*Pinus taeda* L.) seed sources planted at 13 locations across 10 southern states (Wells and Wakeley 1966). A total of 200 plots were randomly selected from this data set; each 0.0164 ha plot consisted of 49 trees, planted at a 1.8 m × 1.8 m spacing. Only one 5-year growth period was randomly selected for each plot to avoid correlation problems caused by repeated measurements. Measurements for growth periods 10-15, 15-20, and 20-25 years were randomly divided into two groups of 100 plots each. The distribution of number of plots for each growth period is presented in Table 1. Table 2 shows the means and standard deviations of stand-level and tree-level attributes.

The two-fold evaluation scheme was applied in this study. Parameters of both stand and tree models were estimated from the fit data (group 1), and then used to predict for the validation data (group 2). The same procedure was repeated with group 2 being the fit data and group 1 the validation data. Predictions from both groups were finally pooled to compute evaluation statistics for the different methods.

3. Methods

3.1 Tree-Level Prediction

3.1.1 Method 1: Deriving a Tree Model

In this method, an individual-tree model was derived from an existing stand-level model, assuming that no tree survival and growth data was available. For this purpose, Cao (2019) employed the cumulative distribution function (CDF) of the negative exponential distribution to replace the often-used logistic function to model tree survival probability.

$$p_{ij} = 1 - exp(\alpha_1 d_{1ij}) \ , \qquad (1)$$

where p_{ij} is the survival probability of tree j in plot i having diameter d_{1ij} (in cm) at time 1 (beginning of the growth period); and α_1 is a coefficient to be determined so that the number of surviving trees sum up to the stand-level output.

In this study, preliminary analysis showed that better results were obtained when a location parameter (a) was added to the CDF function as follows:

$$p_{ij} = 1 - exp[\alpha_1 (d_{1ij} - a)] \ , \qquad (2)$$

where $a = 0.95\ Dmin_{1i}$; and $Dmin_{1i}$ = minimum diameter (cm) in plot i. The coefficient 0.95 above ensures that a is less than $Dmin_{1i}$. A sensitivity analysis evaluating different coefficient values from 0.90 to 0.99 revealed that 0.95 produced best results.

Future tree diameter ($\hat{d}_{2ij}$) was predicted from current diameter (d_{1ij}) by use of the following simple function:

$$\hat{d}_{2ij} = d_{1ij}\, exp(\alpha_2 d_{1ij})\ , \tag{3}$$

By use of SAS proc MODEL (SAS Institute Inc. 2004), the parameters α_1 and α_2 in equations (2) and (3) were solved such that

$$\hat{N}_{2i} = \sum_{j=1}^{n_{1i}} p_{ij}/s\ , \text{ and} \tag{4}$$

$$\hat{B}_{2i} = \sum_{j=1}^{n_{1i}} K p_{ij} d_{1ij}^2/s\ , \tag{5}$$

where $\hat{N}_{2i}$ and $\hat{B}_{2i}$ are stand survival (number of trees per ha) and basal area (m^2/ha) of plot i at time 2, respectively, predicted from any existing stand growth model; $K = \pi/40000$; and s = plot size in ha.

3.1.2 Method 2: Unadjusted Tree Model

The tree model form used in this study consisted of the survival function by Cao (2014) and the tree diameter growth function by Cao (2021):

$$p_{ij} = [1 + \exp\{1 + \exp(b_0 + b_1 RS_{1i} + b_2 H_{1i} + b_3 d_{1ij}/Q_{1i})\}]^{-1}, \tag{6}$$

$$\hat{d}_{2ij} = d_{1ij}\{1 + exp[b_4 + b_5 N_{1i}/A_{1i} + b_6/A_{1i} + b_7 Q_{1i} + b_8(d_{1ij}^2 - Q_{1i}^2)]\}\ , \tag{7}$$

where $\hat{d}_{2ij}$ is predicted diameter at time 2 (end of the growth period); A_{1i}, H_{1i}, N_{1i}, and Q_{1i} are, respectively, age (years), dominant height (m), number of trees per ha, and quadratic mean diameter (cm) for plot *i* at time 1; $RS_{1i} = \frac{\sqrt{10000/N_{1i}}}{H_{1i}}$ = relative spacing; and the *b*'s are regression coefficients.

3.1.3 Method 3: Disaggregating a Tree Model

Cao (2010) suggested the following method to adjust the predicted tree survival probability (p_{ij}) and diameter at the end of the growth period ($\hat{d}_{2ij}$) such that the resulting aggregated values match predicted number of trees per ha ($\hat{N}_{2i}$) and basal area per ha ($\hat{B}_{2i}$) from any existing stand model, respectively:

$$p_{ij}^{*} = p_{ij}^{\beta_{1i}}, \text{ such that } \sum_j p_{ij}^{*} = s_i \hat{N}_{2i}, \tag{8}$$

$$d_{2ij}^{*\,2} = d_{1ij}^{2} + \beta_{2i}\left(\hat{d}_{2ij}^{2} - d_{1ij}^{2}\right), \text{ where } \beta_{2i} = \frac{(s_i \hat{B}_{2i}/K) - \sum_j \left(p_{ij}^{*} d_{1ij}^{2}\right)}{\sum_j \left[p_{ij}^{*}\left(\hat{d}_{2ij}^{2} - d_{1ij}^{2}\right)\right]}, \tag{9}$$

3.2 Stand-Level Models

3.2.1 Model *a*: Cao (2021)

The growth model by Cao (2021) has components to predict stand survival (*N*, number of trees per ha) and quadratic mean diameter (*Q*, cm) as follows:

$$\hat{N}_{2i} = N_{1i}/[1 + exp\{a_0 + a_1 RS_{1i} + a_2 H_{1i} + a_3 N_{1i}/A_{1i} + a_4/A_{1i}\}], \tag{10}$$

$$\hat{Q}_{2i} = Q_{1i}\{1 + exp[a_5 + a_6 N_{1i}/A_{1i} + a_7/A_{1i} + a_8 Q_{1i}]\}, \tag{11}$$

and
$$\hat{B}_{2i} = K \hat{N}_{2i} \hat{Q}_{2i}^{2}, \tag{12}$$

where $\hat{N}_{2i}$, $\hat{B}_{2i}$, and $\hat{Q}_{2i}$ are, respectively, predicted number of trees and basal area (m^2) per ha and quadratic mean diameter (cm) for plot *i* at time 2; and the *a*'s are regression coefficients.

3.2.2 Model *b*: Clutter and Jones (1980)

Clutter and Jones (1980) predicted stand survival and basal area as follows:

$$\hat{N}_{2i} = 1000\left\{\left(\frac{N_{1i}}{1000}\right)^{a_1} + a_2\left[\left(\frac{A_{2i}}{10}\right)^{a_3} - \left(\frac{A_{1i}}{10}\right)^{a_3}\right]\right\}^{1/a_1} , \tag{13}$$

and

$$\hat{B}_{2i} = exp\left\{\left(\frac{A_{1i}}{A_{2i}}\right)^{a_4} \ln\,(B_{1i}) + a_5\left[1 - \left(\frac{A_{1i}}{A_{2i}}\right)^{a_4}\right]\right\} . \tag{14}$$

Note that models *a* and *c* (below) predict future stand attributes for defined time intervals (5 years in this case) and therefore do not need the future projection age (A_{2i}). On the other hand, model *b* can be used for any projection length and consequently requires A_{2i}.

3.2.3 Model *c*: New model

A new stand-level growth model was developed in this study to predict stand survival and quadratic mean diameter as follows:

$$\hat{N}_{2i} = N_{1i} - exp[1 + exp\{a_0 + a_1RS_{1i} + a_2H_{1i} + a_3N_{1i}/A_{1i} + a_4A_{1i}\}] , \tag{15}$$

$$\hat{Q}_{2i} = Q_{1i} + exp[a_5 + a_6N_{1i}/A_{1i} + a_7A_{1i}] . \tag{16}$$

and

$$\hat{B}_{2i} = K\hat{N}_{2i}\hat{Q}_{2i}^2 , \tag{17}$$

The Seemingly Unrelated Regressions (SUR) method (SAS proc MODEL, SAS Institute Inc., 2004) was used to estimate parameters of the systems of equations listed in the three stand models.

3.3 Evaluation

After the coefficients were obtained from one group, they were used to predict for the other group. Predicted values from both groups were then pooled for the computation of evaluation statistics.

3.3.1 Stand-level prediction

The following statistics were computed for evaluation of the three stand models:

Mean difference: $$MD = \frac{1}{m}\Sigma_i(y_{2i} - \hat{y}_{2i}) \ , \tag{18a}$$

Mean absolute difference: $$MAD = \frac{1}{m}\Sigma_i|y_{2i} - \hat{y}_{2i}| \ , \tag{18b}$$

Fit index: $$FI = 1 - \frac{\Sigma_i(y_{2i} - \hat{y}_{2i})^2}{\Sigma_i(y_{2i} - \bar{y}_2)^2} \ , \tag{18c}$$

where m = number of plots; y_{2i} and $\hat{y}_{2i}$ are, respectively, observed and predicted values of N, Q, or B of plot i at the end of the growth period; and $\bar{y}_2$ = average of y_{2i}.

3.2.2 Tree-level prediction

The seven methods (1a, 1b, 1c, 2, 3a, 3b, and 3c) were evaluated for tree-level prediction. Method 2 is independent of the stand models used. The remaining methods are combinations of tree-level and stand-level prediction methods. For example, method 3b refers to the tree model disaggregated from the Clutter and Jones (1980) model.

Evaluation statistics for tree diameter predictions were similar to those presented in equations (18a–18c). Tree-level survival predictions were evaluated from:

Mean difference: $$MD = \frac{\Sigma_i\Sigma_j(y_{ij} - p_{ij})}{\Sigma_i n_{1i}} \ , \tag{19a}$$

where y_{ij} = 1 if tree j in plot i was alive and 0 if it was dead; Σ_i denotes the sum for i from 1 to m; Σ_j denotes the sum for j from 1 to n_{1i}; and n_{1i} = number of trees in plot i at the beginning of the growth period.

Mean absolute difference: $$MAD = \frac{\Sigma_i\Sigma_j|y_{ij} - p_{ij}|}{\Sigma_i n_{1i}} \ , \tag{19b}$$

AUC: area under the ROC (Receiver Operating Characteristic) curve. The range for AUC is between 0.5 (poorest fit) and 1 (perfect fit).

Poudel and Cao's (2013) relative rank system was used to describe the relative position of each method for stand- and tree-level prediction. The best and worst methods received relative ranks of 1 and *m*, respectively, in this ranking system for *m* methods. The remaining methods were ranked as real numbers between 1 and *m*. Because the magnitude as well as the order of each evaluation statistic were taken into consideration, this ranking system should provide more information than the traditional ordinal ranks.

4. Results and Discussion

Table 3 shows parameter estimates by group for each of the three stand-level models. Parameter estimates of the individual-tree model for each group were also presented (Table 4). All parameter estimates were significant at the 5% level. Evaluation statistics are shown for predicting attributes at the stand level for the stand models (Table 5). After a relative rank was computed separately for each statistic of each method, an overall rank was calculated based on the sum of all ranks for each method. Based on the overall ranks, the new stand model (*c*) was first, achieving the best statistics in all categories but two (MD for *N* and *B*). Model *a* (Cao 2021) was second with a rank of 1.80, and model *b* (Clutter and Jones 1980) was a distant third (Table 5).

Table 6 presents evaluation statistics for predicting tree diameter and survival probability, for each of the seven methods. Method 1*c* had the best overall rank (1.00), followed closely by method 2 (1.68) and method 1a (1.77). The bottom methods include method 1*b* (4.89) and method 3*b* (7.00), both associated with stand model *b* (Clutter and Jones 1980).

4.1 Method 2 versus method 3

Method 2 is the unadjusted tree model, whereas method 3 is the disaggregated tree model. The success of disaggregation depends largely on how well the stand attributes are predicted. Using observed stand attributes (to simulate a perfect stand model) for adjustment resulted in improvement of tree-level predictions (Cao 2010). On the other hand, disaggregation from a poor stand-level model might hurt rather than help the performance of the tree model (Cao 2017). The tree model (method 3*b*) that was disaggregated from the worst stand model in this study (Clutter and Jones 1980, Table 5) also ranked last among the seven tree models (Table 6).

The disaggregated tree models over-predicted tree survival, which is a direct result of over-prediction by the stand survival models (negative MD for both tree and stand levels). The fact that method 2 was better than method 3 in terms of MD for tree survival (Table 5) is consistent with findings from Cao (2017). He stated that tree survival MDs was better for the disaggregated tree models if the FI from the stand survival model exceeded 0.93, which was not the case for any of the three stand survival models tested in this study. Cao (2017) also found through simulation that the disaggregated tree models produced better tree survival MADs and AUCs if the FI from the stand survival model exceeded 0.81. From Table 5, this was true for models *a* and *c* (FI = 0.85 and 0.86, respectively), whereas the reverse was true for model *b* (FI = 0.74).

Similar to the stand survival component, the three stand-level models over-predicted basal area per ha (negative MD, Table 5), leading to over-prediction of tree diameters by the disaggregated tree models (Table 6). On the other hand, except for method 3*b*, the disaggregated tree models (methods 3*a* and 3*c*) outperformed the unadjusted tree model (method 2) in terms of MAD and FI.

4.2 Method 1 versus method 3

The derived tree survival function (Equation 1) was revised from the one by Cao (2019) by adding a location parameter ($a = 0.95\ Dmin_{1i}$). This simple modification improved the AUC range from 0.70 – 0.72 (Cao 2019) to 0.76 – 0.81 in this study (Table 6). The coefficients (α_1 in Equation 1 for tree survival and α_2 in Equation 2 for tree diameter) were solved such that the tree-level predictions summed up to outputs obtained from the stand models.

Methods 1 and 3 are similar in that their individual tree predictions summed up to the predictions from the stand-level models. In this respect, the derived tree models (method 1) can be considered a form of disaggregated tree models. However, the main difference between the two methods is that method 3 requires individual tree growth and survival data whereas method 1 does not.

For the same stand-level model, the derived tree models (method 1) always fared better than the disaggregated models (method 3): overall rank of 1.77 vs. 2.83 for Cao (2021), 4.89 vs. 7.00 for Clutter and Jones (1980), and 1.00 vs. 2.02 for the new stand model. Similar to the disaggregated models, the performance of the derived tree models depended on the quality of the corresponding stand models.

4.3 Method 1 versus method 2

With the exception of method 1*b* (derived from Clutter and Jones 1980), the derived tree model compared favorably with the unadjusted tree model (method 2). The overall rank of method 2 (1.68) was sandwiched between methods 1*a* (1.77) and 1*c* (1.00). It is amazing that the derived tree models did that well, considering that they required no tree-level growth data, and were completely based on existing stand models. In fact, method 1*c*, which was derived from the best-ranked stand model (*c*), even outperformed method 2. Figure 1 shows 5-year survival probabilities and future diameters, derived from method 1*c*, for current diameters of trees in three different plots.

5. Summary and Conclusions

In this study, a new method was developed to derive a tree survival and diameter growth model from any existing stand-level model, without the need for individual-tree growth data. Predictions from the derived tree model are constrained to match number of trees and basal area per ha as outputted by the stand model. The tree models derived from three different stand models were evaluated against a tree model, in both unadjusted and disaggregated forms.

For the same stand-level model, the derived tree model outperformed its counterpart, the disaggregated tree model. Furthermore, except for one stand model with poor performance, the tree models derived from the remaining two stand models delivered comparable results to those obtained from the unadjusted tree model. The tree model derived from one stand model even performed slightly better than the unadjusted tree model. This is significant because the coefficients of the unadjusted and disaggregated tree models had to be estimated from tree-level growth data, whereas the derived tree model required no tree growth data at all. The methodology presented in this study should be applicable when there is no ingrowth or recruitment.

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Table 1. Distribution of 200 plots, by starting age and group.

Starting age	Ending age	Group 1	Group 2
		- - - Number of plots - - -	
10	15	33	33
15	20	33	33
20	25	34	34
Total		100	100

Table 2. Means (and standard deviations) of stand and tree attributes, by group and age at the beginning of the growth period.

Group	Age	Dominant height (m)	Number of trees/ha	Basal area (m^2/ha)	Tree diameter (cm)
1	10	9.3 (1.1)	2063 (646)	22.9 (5.7)	11.6 (2.7)
	15	13.2 (1.9)	1713 (714)	31.7 (9.2)	14.8 (3.9)
	20	16.3 (2.1)	1256 (370)	33.5 (8.2)	17.9 (4.4)
2	10	9.2 (1.5)	2065 (608)	22.4 (7.2)	11.4 (2.7)
	15	13.3 (1.7)	1631 (463)	30.9 (5.9)	15.1 (3.8)
	20	16.8 (1.7)	1337 (326)	34.5 (7.0)	17.7 (4.2)

Table 3. Parameter estimates (and standard errors), by stand model and group.

Parameter estimate	Model *a* (Eq. 10 – 11) Cao (2021)		Model *b* (Eq. 13 – 14) Clutter and Jones (1980)		Model *c* (Eq. 15 – 16) New model	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
a_0	21.9167 (2.2756)	18.4259 (2.3563)			6.1444 (0.4326)	6.3533 (0.5284)
a_1	-58.8599 (6.5739)	-53.0888 (6.9893)	-0.9715 (0.3473)	-0.5457 (0.3698)	-9.7324 (0.7245)	-9.6260 (0.9511)
a_2	-0.8944 (0.0959)	-0.7785 (0.0951)	0.0650 (0.0228)	0.0902 (0.0365)	-0.1475 (0.0115)	-0.1380 (0.0130)
a_3	-0.0254 (0.0044)	-0.0262 (0.0044)	2.0236 (0.4175)	1.2577 (0.4394)	-0.0032 (0.0005)	-0.0037 (0.0006)
a_4	37.8062 (12.0869)	51.5813 (11.9887)	1.3479 (0.2361)	0.8344 (0.1386)	-0.0283 (0.0088)	-0.0472 (0.0099)
a_5	-1.7207 (0.2855)	-1.3051 (0.2815)	3.8760 (0.0818)	4.2214 (0.1267)	2.8552 (0.1358)	2.8173 (0.1454)
a_6	-0.0028 (0.0005)	-0.0033 (0.0004)			-0.0032 (0.0003)	-0.0033 (0.0004)
a_7	17.8976 (1.6905)	16.2977 (1.8217)			-0.0970 (0.0074)	-0.0918 (0.0076)
a_8	-0.0602 (0.0114)	-0.0744 (0.0111)				

Table 4. Parameter estimates of the individual-tree model (Eq. 6 – 7), by group.

Parameter estimate	Group 1	Group 2
b_0	10.2765 (0.9423)	12.1540 (0.7658)
b_1	-0.2256 (0.0311)	-0.2773 (0.0261)
b_2	-21.9825 (2.5434)	-25.5995 (2.0180)
b_3	-5.0864 (0.3482)	-5.9253 (0.3098)
b_4	-2.6091 (0.1325)	-1.3919 (0.1373)
b_5	-0.0029 (0.0002)	-0.0038 (0.0002)
b_6	23.7870 (0.8111)	19.0524 (0.7664)
b_7	-0.0455 (0.0056)	-0.0954 (0.0056)
b_8	0.0011 (0.0001)	0.0013 (0.0001)

Table 5. Evaluation statistics for stand-level prediction, by variable and model.

Variable[1/]	Evaluation Statistic[2/]	Cao (2021)	Clutter and Jones (1980)	New model
N	*MD*	-13.115	***-8.080***	-10.239
	MAD	148.649	195.740	***145.034***
	FI	0.8545	0.7439	0.8581
B	*MD*	-0.3354	***-0.1994***	-0.2502
	MAD	3.2008	3.7804	***3.0246***
	FI	0.7674	0.6222	***0.7854***
Q	*MD*	0.0422	-0.0625	***0.0119***
	MAD	0.5519	0.6366	***0.5435***
	FI	0.9577	0.9467	***0.9594***
Sum of the ranks		15.53	23.00	***10.61***
Overall rank		1.80	3.00	***1.00***

[1/] N = number of trees per ha; B = basal area (m^2/ha); Q = quadratic mean diameter (cm).

[2/] *MD* = mean difference; *MAD* = mean absolute difference; *FI* = fit index.

For each evaluation statistic, a bold, italic number denotes the best statistic, and an underlined number denotes the worst.

Table 6. Evaluation statistics[1/] for tree-level prediction, by method and variable.

Method	Tree diameter			Tree survival			Sum of the ranks	Overall ranks
	MD	*MAD*	*FI*	*MD*	*MAD*	*AUC*		
1*a*	-0.0152	0.8576	0.9416	-0.0078	0.2030	0.8027	16.21	1.77
1*b*	***0.0007***	0.8935	0.9376	-0.0048	0.2174	0.7608	29.62	4.89
1*c*	-0.0095	***0.8537***	0.9420	-0.0061	***0.2020***	0.8078	***12.91***	***1.00***
2	0.0022	0.8695	0.9420	***0.0005***	0.2202	0.7929	15.83	1.68
3a	-0.0958	0.8608	0.9431	-0.0078	0.2090	0.7992	20.79	2.83
3*b*	-0.1277	0.9009	0.9384	-0.0048	0.2284	0.7566	38.71	7.00
3*c*	-0.1020	0.8553	***0.9438***	-0.0061	0.2094	***0.8093***	17.28	2.02

[1/] For each evaluation statistic, a bold, italic number denotes the best statistic, and an underlined number denotes the worst.

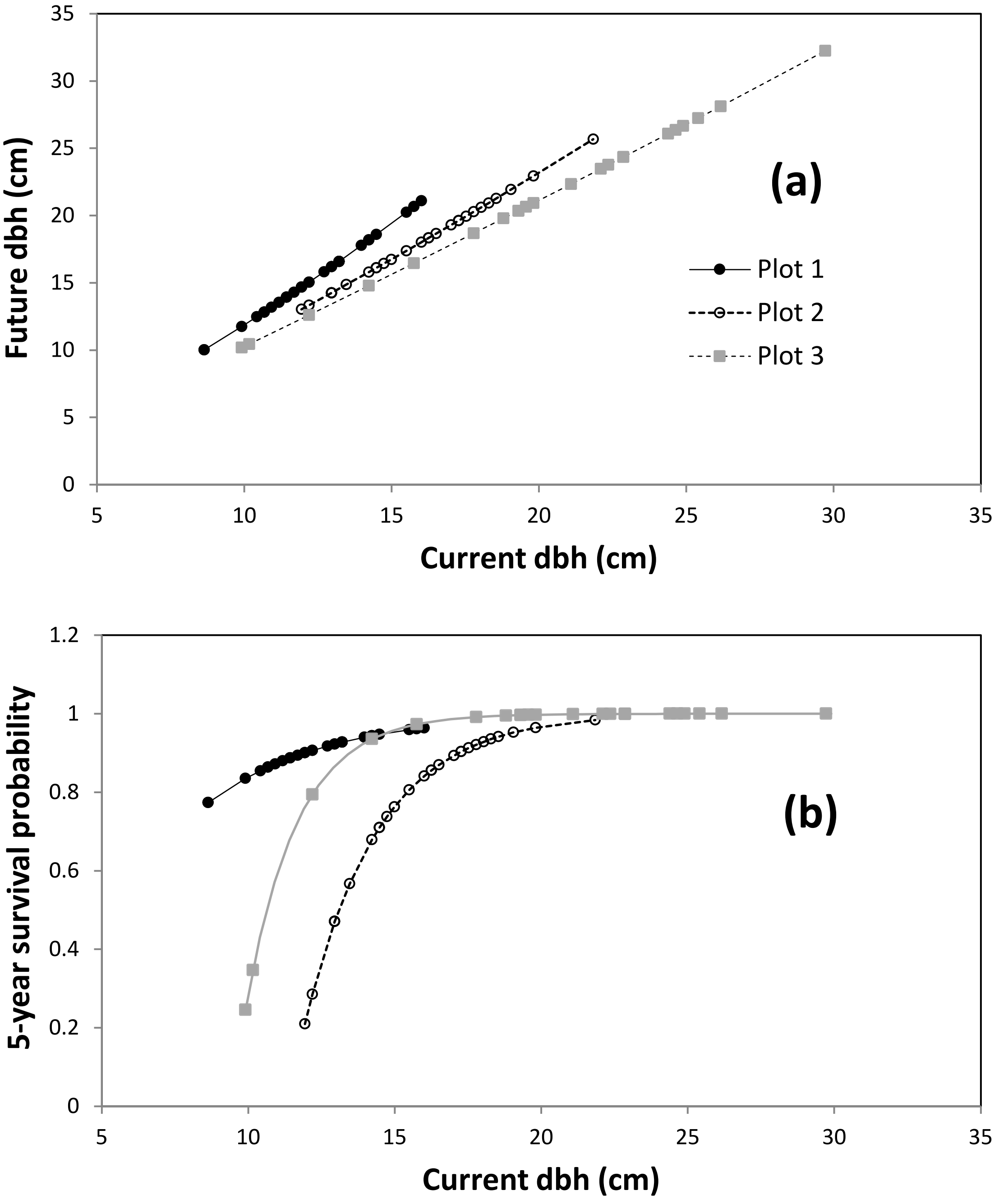
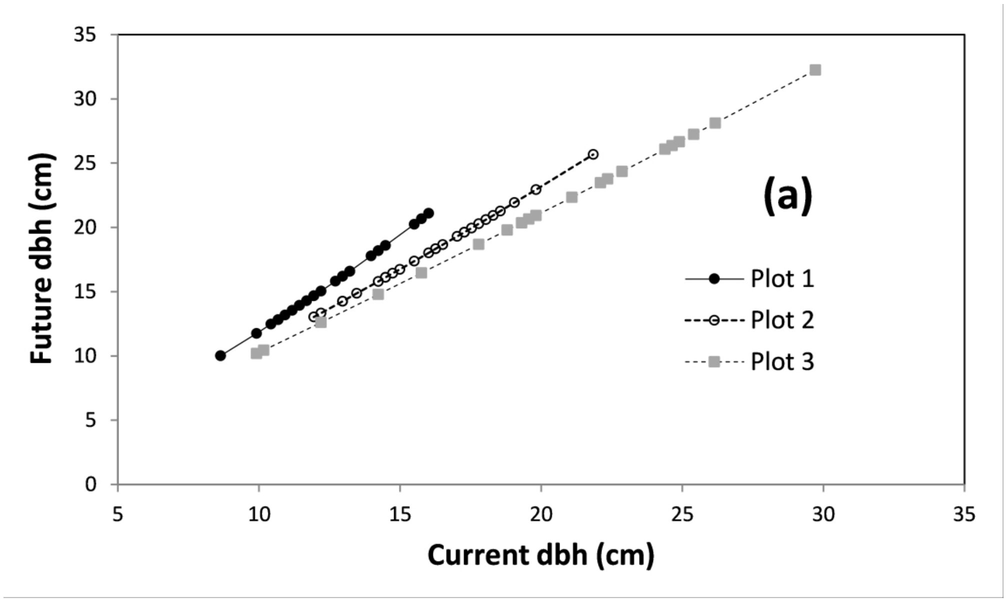
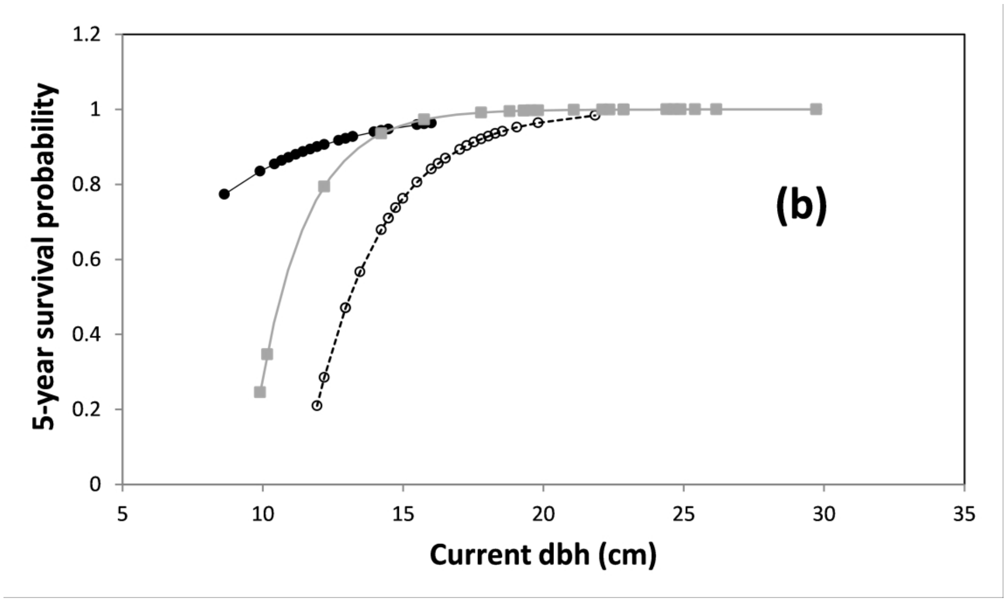


Figure 1. Curves for 5-year diameter growth (a) and survival probability (b), as derived from the new stand model, for trees in
plot 1 (A_1 = 10 yrs; H_1 = 9.2 m; N_1 = 2074 trees/ha; B_1 = 24.5 m^2/ha),
plot 2 (A_1 = 15 yrs; H_1 = 12.3 m; N_1 = 1647 trees/ha; B_1 = 33.9 m^2/ha), and
plot 3 (A_1 = 20 yrs; H_1 = 16.9 m; N_1 = 1342 trees/ha; B_1 = 45.5 m^2/ha).



389x231mm (236 x 236 DPI)



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