Canadian Journal of Forest Research

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Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2019-0171.R2
Manuscript Type:	Article
Date Submitted by the Author:	09-Aug-2019
Complete List of Authors:	Cao, Quang; Louisiana State University
Keyword:	individual-tree model, least squares, loblolly pine, logistic regression, maximum likelihood
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

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A Method to Derive a Tree Survival Model from Any Existing Stand Survival Model

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Acknowledgement

This project was supported by the National Institute of Food and Agriculture, U.S. Department of Agriculture, McIntire-Stennis project LAB94379.

A Method to Derive a Tree Survival Model from Any Existing Stand Survival Model

Abstract

This study addresses a situation when a forest manager has been using a whole-stand model that seems to predict well for his/her stands, and now wants to derive an individual-tree model from it to form an integrated system that can perform well at both stand and tree levels. A simple method was developed to derive tree survival models from three existing stand-level survival models. The derived tree survival models were based on the difference between diameter of the tree in question and the diameter where tree and stand survival probabilities are equal. For stand survival prediction, each stand model performed less adequately than its derived tree model, and one of the derived tree survival models was the best overall. For prediction of tree survival, the same derived tree model also performed best overall. Even though only three stand-level survival models were considered in this study, the method presented here should be applicable to any stand survival model. When no tree survival data are available, an attempt of deriving tree models from stand survival models resulted in models, albeit the lowest ranked in terms of performance, that produced acceptable evaluation statistics for predicting tree-level survival.

Keywords: individual-tree model; least squares; loblolly pine; logistic regression; maximum likelihood.

23 Introduction

24 Contemporary forest managers make decision partly based on forecasts provided by
25 growth and yield models. Depending on the level of detail, or resolution, of their outputs, these
26 models are often broadly classified as whole-stand models, size-class models, or individual-tree
27 models (Burkhart and Tome 2012). The problem is that outputs from these models of different
28 resolutions might be inconsistent with one another. One type of model might be better in terms
29 of reliability of estimates, whereas the other type might be preferred because it offers more
30 details.

31 In this paper, stand survival refers to the number of surviving trees per unit area, whereas
32 tree survival is the status (dead or alive) of the tree in question. Cumulative survival at the stand
33 level has been predicted by use of regression models. These models are either empirical (Zhang
34 et al. 1993; Diéguez-Aranda 2005; Zhao et al. 2007; Gonzalez-Benecke et al. 2012), or derived
35 from biological principles (Garcia 2009, 2011; Tewari et al. 2014; Stankova 2016). On the other
36 hand, logistic regression has generally been used to predict individual tree-level survival
37 (Hamilton 1974; Monserud 1976; Buchman 1979; 1983, Zhang et al. 1997; Monserud and Sterba
38 1999), even though other approaches have also been used (Glover and Hool 1979; Amateis et al.
39 1989; Guan and Gerner 1991a, 1991b).

40 Growth and yield models have been traditionally modeled separately at stand and tree
41 levels. A revolutionary concept of developing a unified mathematical structure for modeling tree
42 and stand growth, which can be applied at any level of resolution, was introduced by Daniels and
43 Burkhart (1988). The result is an integrated system that can provide consistent growth and yield
44 estimates at various levels of resolution. Cao (2017) applied this concept and experimented with
45 two approaches: deriving a stand-level survival model from a tree-level survival model, and

deriving a tree survival model from a stand survival model. He obtained satisfactory results from the second approach.

A likely scenario arises, in which a forest manager has been using a whole-stand model that seems to predict well for his/her stands, and now wants to derive an individual-tree model from it to form an integrated system that can perform well at both stand and tree levels. The advantage of this integrated system versus an independent tree survival model is that both stand-level and tree-level models have the same mathematical structure, even though they might not be numerically compatible. This study, which is an extension of the work by Cao (2017), widens the scope of the original research by allowing the tree survival model to be derived from any existing stand survival model, whether or not tree survival data are available.

The objectives of this study were to (1) develop a method to derive an individual-tree survival model from any existing stand-level survival model, and (2) evaluate the tree survival models derived from such stand survival models.

Data

Data used in this study were from 270 plots randomly selected from the Southwide Seed Source Study, which include 15 loblolly pine (*Pinus taeda* L.) seed sources planted at 13 locations across 10 southern states (Wells and Wakeley 1966). Each plot had an area of 0.0164 ha and consisted of 49 trees (approximately 3,000 trees per ha), planted at a 1.8 m × 1.8 m spacing. Tree survival varied greatly from plot to plot, ranging from 610 to 2,929 trees/ha at age 10, with an average of 2,102 trees/ha.

The data were randomly divided into three groups of 90 plots each (Table 1). Each group consisted of 30 plots with measurements of tree diameters and survival for each of three growth periods: 10-15, 15-20, and 20-25 years.

Methods

Stand-level survival models

Three stand survival models were selected for this study because of their successful applications in the past. Their coefficients were estimated from the above data.

Clutter and Jones (1980)

$$\hat{N}_{2i} = 100 \left\{ \left(\frac{N_{1i}}{100} \right)^{a_1} + a_2 \left[\left(\frac{A_{2i}}{10} \right)^{a_3} - \left(\frac{A_{1i}}{10} \right)^{a_3} \right] \right\}^{1/a_1} \tag{1}$$

Baldwin and Feduccia (1987)

$$\hat{N}_{2i} = 100 \left\{ \left(\frac{N_{1i}}{100} \right)^{a_1} + (a_2 + a_3/S_i) \left[\left(\frac{A_{2i}}{10} \right)^{a_4} - \left(\frac{A_{1i}}{10} \right)^{a_4} \right] \right\}^{1/a_1} \tag{2}$$

Cao (2006)

$$\hat{N}_{2i} = \frac{N_{1i}}{1 + \exp\{a_1 + a_2 H_{1i} + a_3 RS_{1i} + a_4 (N_{1i}/A_{1i}) + a_5/A_{1i}\}} \tag{3}$$

where A_{1i} and A_{2i} are stand age (years) at the beginning and end of the growth period, respectively; N_{1i} , H_{1i} , and RS_{1i} are stand density (number of trees/ha), dominant height (meters), and relative spacing at age A_{1i} , respectively; $RS_{1i} = \frac{(10000/N_{1i})^{0.5}}{H_{1i}}$ (Wilson 1946); S_i is site index

(meters) at base age 25 years; $\hat{N}_{2i}$ is predicted stand density at age A_{2i} ; a_k 's = regression coefficients; and subscript i refers to plot i .

Tree-level survival models

Considered in this study were two scenarios that depend on the presence or absence of tree survival data.

Having tree survival data

The tree survival data were used to estimate coefficients of the individual-tree survival model.

Method 1

The logistic regression model by Cao (2017) was employed to predict tree survival probability (p_{ij}) of tree j in plot i during a 5-year growth period:

$$p_{ij} = \frac{1}{1 + \exp(b_0 + b_1 H_{1i} + b_2 RS_{1i} + b_3 N_{1i}/A_{1i} + b_4/A_{1i} + b_5 d_{1ij})}, \quad (4)$$

where d_{1ij} = diameter at breast height (cm) of tree j in plot i at age A_{1i} ; and b_k 's = regression coefficients.

The disaggregation method (Cao 2010, 2014) was also applied to compute the adjusted tree survival probability ($\tilde{p}_{ij}$) as follows:

$$\tilde{p}_{ij} = p_{ij}^{\alpha} \quad (5)$$

where α is the adjustment coefficient used to match the sum of the adjusted tree survival probabilities to predictions from each of the above three stand survival models (Equations 1-3).

Methods (1a) and (1b) denote the unadjusted and disaggregated models, respectively.

Method 2

The tree survival model from the integrated system by Cao (2017) is:

$$p_{ij} = \frac{1}{1 + \exp[c_0 + c_1 H_{1i} + c_2 R S_{1i} + c_3 N_{1i}/A_{1i} + c_4/A_{1i} + c_5(d_{1ij} - D_{S1i})]} \quad (6)$$

where D_{S1i} is the tree diameter that would yield a tree survival probability equal to the stand survival prediction, or $\hat{N}_{2i}/N_{1i}$, the proportion of surviving and starting number of trees.

Equation (6) can be simplified as follows:

$$p_{ij} = \frac{1}{1 + \exp[b_0 + b_1(d_{1ij} - D_{S1i})]} \quad (7)$$

where D_{S1i} is expressed as $D_{S1i} = b_2 D_{q1i}^{b_3}$, with D_{q1i} being the quadratic mean diameter of plot i at the beginning of the growth period. In other words, when $d_{1ij} = D_{S1i}$,

$$\frac{\hat{N}_{2i}}{N_{1i}} = \frac{1}{1 + \exp(b_0)} \quad (8)$$

Combining Equations (7) and (8) gives:

$$p_{ij} = \frac{1}{1 + \left(\frac{N_{1i} - \hat{N}_{2i}}{\hat{N}_{2i}}\right) \exp[b_1(d_{1ij} - b_2 D_{q1i}^{b_3})]} \quad (9)$$

Equation (9) is therefore a tree survival model derived from $\hat{N}_{2i}$, which is the output of a stand survival model for plot i . $\hat{N}_{2i}$ can be obtained from one of the above-mentioned stand survival models by use of equations (1-3), or from any other stand-level survival model. Although the derivation method is demonstrated only for these three stand models, it should be applicable to any existing stand survival model. The disaggregation method mentioned above was then used to adjust the tree survival model. The resulting methods were referred to as (2a) for unadjusted models and (2b) for disaggregated models.

Figure 1 shows the relationship between tree survival probability and tree diameter for three different plots. Note that when diameter is equal to D_{S1} , tree survival probability is equal to stand survival rate.

No tree survival data

When no tree survival data are available, a simple function can be used to describe tree survival and then disaggregated to match stand survival estimates (method 3b). The cumulative distribution function (cdf) of the negative exponential distribution (Johnson and Kotz 1970) was used here because its shape is similar to that of a logistic function while it has only one coefficient:

$$p_{ij} = 1 - \exp(-\beta d_{1ij}) . \quad (10)$$

The coefficient β was solved such that:

$$\sum_j p_{ij} = s_i \hat{N}_{2i} , \quad (11)$$

where s_i = size of plot i , and $\hat{N}_{2i}$ = output of a stand survival model, obtained either from one of the equations (1-3), or from any existing stand-level survival model.

Evaluation

A three-fold evaluation scheme (Table 2) was used in this study. This scheme simulated the case of deriving a tree model from an existing stand survival model, by ensuring that separate data were used for (1) developing the stand survival models, (2) deriving the tree survival models, and (3) evaluating the models. Predicted values from all three groups were then pooled to compute evaluation statistics.

152 **Stand survival prediction**

153 The following statistics were computed for stand-level evaluation:

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$$\text{Mean difference: } MD = \frac{1}{m} \sum_i (N_{2i} - \hat{N}_{2i}), \quad (12)$$

$$\text{Mean absolute difference: } MAD = \frac{1}{m} \sum_i |N_{2i} - \hat{N}_{2i}|, \quad (13)$$

$$\text{Fit index: } FI = 1 - \frac{\sum_i (N_{2i} - \hat{N}_{2i})^2}{\sum_i (N_{2i} - \bar{N}_2)^2}, \quad (14)$$

where m = number of plots; N_{2i} and $\hat{N}_{2i}$ = observed and predicted number of surviving trees per hectare for plot i at age A_{2i} ; $\bar{N}_2$ = average number of surviving trees per hectare at age A_{2i} ; and $\sum_i$ denotes the sum for i from 1 to m . For tree-level models, stand survival prediction is the sum of predicted tree survival probabilities, scaled by plot area.

MD and MAD are measures of accuracy and precision, respectively, whereas FI is a measure of both.

Tree survival prediction

Tree-level survival predictions were evaluated from:

$$\text{Mean difference: } MD = \frac{\sum_i \sum_j (y_{ij} - p_{ij})}{\sum_i n_{1i}}, \quad (15)$$

where $y_{ij} = 1$ if tree j in plot i was alive and 0 if it was dead; $\sum_i$ denotes the sum for i from 1 to m ; $\sum_j$ denotes the sum for j from 1 to n_{1i} ; and n_{1i} = number of trees in plot i at age A_{1i} .

$$\text{Mean absolute difference: } MAD = \frac{\sum_i \sum_j |y_{ij} - p_{ij}|}{\sum_i n_{1i}}, \quad (16)$$

AUC: area under the ROC (Receiving Operating Characteristic) curve. The range for AUC is between 0.5 (worst) and 1 (best). The AUC has been used as a measure of predictive accuracy of survival models in medical research (Heagerty and Zheng 2005) and forestry research (Weiskittel et al. 2016).

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Relative ranking system

The relative ranking system, introduced by Poudel and Cao (2013), was used in this study to determine the relative position of each method for each evaluation statistic. The relative ranking of method i (R_i) is defined as

$$R_i = 1 + \frac{(m-1)(S_i - S_{\max})}{S_{\max} - S_{\min}}, \quad (17)$$

where S_i is the evaluation statistics produced by method i ($i = 1, 2, \dots, m$), and $S_{\min}$ and $S_{\max}$ are minimum and maximum values of S_i , respectively.

In this ranking system, the best method receives a relative rank of 1 and the worst method a rank of m . Ranks of the remaining methods are presented as real numbers between 1 and m , reflecting both the magnitude and order of the evaluation statistic, and therefore should provide more information than the traditional consecutive/sequential integer-based ordered ranking systems. An overall rank was calculated based on the sum of all relative ranks for each method.

Results and Discussion

Table 3 shows evaluation statistics for stand-level survival prediction. The tree model derived from Cao (2006) (method 2a), performed best in predicting stand survival, whereas the stand-level model by Baldwin and Feduccia (1987) ranked last among the seven alternatives.

For tree survival prediction (Table 4), method (2a) derived from Cao (2006) was also best, followed closely (rank of 1.11) by the unadjusted tree model (method 1a). Method (3b), derived from different stand-level models using no data, produced ranks ranging from 10.53 to 13.00. The models from method (3b) formed a group at the bottom, separate from the remaining methods.

These results show that tree survival model derived from Cao’s (2006) stand survival model (method 2a) provided best prediction not only at the tree level, but also at the stand level, surpassing the stand model from which it was derived. It is impressive that the summation of individual tree probabilities from method (2a) did outperform the direct prediction of stand survival from Cao’s (2016) model.

Table 5 shows parameter estimates and their standard errors from Cao’s (2006) stand survival model and its derived tree survival model (method 2a), based on the pooled data.

Stand-level survival prediction

Stand-level survival models

Among the three stand-level survival models, the Cao (2006) model received the best overall ranking, mainly based on better values of MAD and FI (Table 3). The Baldwin and Feduccia (1987) model, which was derived from the Clutter and Jones (1980) model (modified by the addition of a site index variable, turned out to be slightly inferior to the Clutter and Jones (1980) model.

Stand-level models versus tree-level survival model

The sum of predicted tree survival probabilities from the tree-level model (method 1a) were used for stand survival prediction. Surprisingly, this tree model ranked better than the Cao (2006) stand-level model (2.57 versus 5.27), even though it produced worse values of MAD and FI than the Cao (2006) model (Table 3). These results suggest that stand-level models are not necessarily better than tree-level models in predicting stand survival, contrary to some findings

in the literature (Qin and Cao 2006, Cao 2014, Hevia et al. 2015), which favor the direct prediction of stand models to the extra summation step of tree models. Consequently, disaggregation, which adjusts outputs from tree-level models to match those from stand-level models, is not justified in these cases.

Stand-level models versus derived tree models

Method (2a) involved deriving a tree survival model from each of the three stand-level models. The sum of predicted tree survival probabilities from each tree model provided better stand survival prediction in terms of MAD and FI than did the stand-level model from which it was derived. These findings were true for all three stand survival models (Table 3). Stand survival predictions from the tree models derived from Clutter and Jones (1980) and Baldwin and Feduccia (1987) were more biased (higher absolute MD values) as compared to their stand-level model counterpart, but method (2a) from Cao (2006) yielded better MD value than did the Cao (2006) model, which produced the worst MD value of -19.71 trees/ha.

Each stand-level model and its derived tree model (method 2a) were conceptually compatible because they formed an integrated system of equations, but were not numerically compatible. The fact that a derived tree model actually produced better prediction of stand survival than its corresponding stand model was an unexpected result, because stand survival models have been found to outperform tree models in predicting stand survival (Qin and Cao 2006, Cao 2014, Hevia et al. 2015). A plausible reason for this result is that the tree survival model from method 2 consists of the Cao's (2016) stand model with the least squares parameter estimates, plus extra tree information that, thanks to the D_s constraint, appeared to help improve stand survival prediction.

Tree-level model versus derived tree models

Table 3 shows that the tree survival model (method 1a) was least biased (yielding the best MD value) in predicting stand survival when compared to the three derived tree models (method 2a). In terms of MAD and FI values, it did better than the tree models derived from Clutter and Jones (1980) and Baldwin and Feduccia (1987), but worse than the one derived from Cao (2006). These results were similar to those obtained by evaluating method (1a) against the three stand-level survival models (described earlier in section 4.1.2).

Tree-level survival prediction

Without disaggregation

The tree survival model (1a) produced better MD value than did the three derived tree models (method 2a). However, the tree model derived from Cao (2006) was better in terms of MAD and AUC values (Table 4).

Among the three stand survival models, the best stand model (Cao 2006) did produce the best derived tree model (overall rank of 1.00), which edged out method (1a) (rank of 1.11) in terms of predicting tree-level survival.

Disaggregation

Method 1a vs. 1b

The unadjusted tree survival model (1a) produced the best AUC value (0.7624) as compared to the three disaggregated models (AUC values ranging from 0.7309 to 0.7447). Its

MAD and MD values were in the middle of the statistics from the three disaggregated models. Overall, model (1a) produced a much higher rank (1.11) than did the tree disaggregated models (ranks varied between 4.31 and 6.86).

Method 2a vs. 2b

For the derived tree survival models, the unadjusted models (2a) ranked better than the disaggregated models (2b) in predicting tree survival, except for the tree model derived from Clutter and Jones (1980) (Table 4). Zhang et al. (2011) showed that disaggregation from observed stand survival resulted in much better tree survival prediction than did an unadjusted tree model. The logical conclusion was that a tree model disaggregated from an excellent stand model should perform well. Because the tree models outperformed the stand models in predicting stand survival as discussed above, it makes sense that disaggregation was not only unnecessary but also detrimental in terms of predictive accuracy.

Disaggregation: with versus without data

When it is desired that a tree survival model yields the same stand survival as predicted from a given stand model, disaggregation can be carried out either from a tree survival model with parameters estimated from a tree-survival data set (1b and 2b), or from a simple function that requires no data (3b). Even though all methods (1b, 2b, and 3b) yielded identical MD value for each stand survival model, methods (1b) and (2b), as expected, consistently produced better MAD and AUC values than did method (3b) (Table 4). Because Cao (2006) was the best among the three stand survival models for this data set, the tree model derived from Cao (2006) was also the best tree survival model among the three models from method (3b). Considering that method

(3b) requires no survival data, it is surprising that this tree model from method (3b) approached method (1b) in terms of AUC (0.7212 versus 0.7447) and MAD (0.2772 versus 0.2534). The reason might be that the negative exponential cdf used in method (3b) was sufficient to model the general trend of tree survival, whereas the tree survival models in other methods were more sensitive to plot variations.

Conclusions

In this study, methods were developed to derive tree survival models from three existing stand-level survival models. For stand survival prediction, each stand model performed worse than its derived tree model, and the tree survival model derived from Cao (2006) was the best overall. For prediction of tree survival, the same tree survival model derived from Cao (2006) also performed best overall. Even though only three stand-level survival models were considered in this study, the method presented here should be applicable to any stand survival model.

Without tree survival data, as expected, the derived tree models were at the bottom in terms of performance and did produce decent evaluation statistics for predicting tree-level survival. The fact that the actual magnitude of the error metrics for Method 3b are not consequentially different from those for other methods shows that this could be a viable approach if a tree survival model is needed when no tree survival data are available.

This study shows that the integrated system of stand- and tree-level survival models is a better alternative to separate stand- and tree-level models. Furthermore, the study suggests a reasonable method of constructing a tree survival model, even when no tree survival data are available.

References

- Amateis, R.L., Burkhart, H.E., and Walsh, T.A. 1989. Diameter increment and survival equations for loblolly pine trees growing in thinned and unthinned plantations on cutover, site-prepared lands. *South. J. Appl. For.* 13:170-174.
- Baldwin, V.C., Jr., and Feduccia D.P. 1987. Loblolly pine growth and yield prediction for managed West Gulf plantations. *USDA For. Ser. Res. Pap. SO-236.* 27 p.
- Buchman, R.G. 1979. Mortality functions. P. 47-55 in *A generalized forest growth projection system applied to the Lake States region.* *USDA For. Serv. Gen. Tech. Rep. NC-49.*
- Buchman, R.G. 1983. Survival predictions for major Lake States tree species. *USDA For. Serv. Res. Pap. NC-233,* 7 p.
- Burkhart, H.E., and Tome, M. 2012. *Modeling forest trees and stands.* Springer Netherlands. 458 p.
- Cao, Q.V. 2006. Predictions of individual-tree and whole-stand attributes for loblolly pine plantations. *For. Ecol. Mgt.* 236:342-347.
- Cao, Q. V. 2010. Adjustments of individual-tree survival and diameter growth equations to match whole-stand attributes. P. 369-373 in *Proc. of the South. Silv. Res. Conf.* *USDA For. Serv. Gen. Tech. Rep. SRS-121.*
- Cao, Q.V. 2014. Linking individual-tree and whole-stand models for forest growth and yield prediction. *For. Ecosys.* 2014, 1:18.
- Cao, Q. V. 2017. An integrated system for modeling tree and stand survival. *Can. J. For. Res.* 47:1405-1409.
- Clutter, J.L., and E.P. Jones, Jr. 1980. Prediction of growth after thinning of old-field slash pine plantations. *USDA For. Serv. Res. Pap. SE-217,* 14p.

- 338 Daniels, R.F., and Burkhardt, H.E. 1988. An integrated system of forest stand models. For. Ecol.
339 Mgt. 23:159-177.
- 340 Diéguez-Aranda, U., Castedo Dorado, F., Álvarez González, J.G., and Rodríguez Soalleiro, R.
341 2005. Modelling mortality of Scots pine (*Pinus sylvestris* L.) plantations in the northwest of
342 Spain. Eur. J. For. Res. 124:143-153.
- 343 Garcia, O. 2009. A simple and effective forest stand mortality model. Math. Comp. For. & Nat.
344 Res. Sci. 1:1-9.
- 345 Garcia, O. 2011. A parsimonious dynamic stand model for interior spruce in British Columbia.
346 For. Sci. 57:265-280.
- 347 Glover, G.R., and Hool, J.N. 1979. A basal area ratio predictor of loblolly pine plantation
348 mortality. For. Sci. 25:275-282.
- 349 Gonzalez-Benecke, C.A., Gezan, S.A., Leduc, D.J., Martin, T.A., Cropper, Jr., W.P., and
350 Samuelson, L.J. 2012. Modeling survival, yield, volume partitioning and their response to
351 thinning for longleaf pine plantations. Forests 3:1104-1132.
- 352 Guan, B.T., and Gertner, G. 1991a. Using a parallel distributed processing system to model
353 individual tree mortality. For. Sci. 37:871-885.
- 354 Guan, B.T., and Gertner, G., 1991b. Modeling red pine tree survival with an artificial neural
355 network. For. Sci. 37:1429-1440.
- 356 Hamilton, D.A. 1974. Event probabilities estimated by regression. USDA For. Serv. Res. Pap.
357 INT-152, 18 p.
- 358 Heagerty, P.J., Zheng, Y. 2005. Survival model predictive accuracy and ROC curves.
359 Biometrics 61:92-105.

- 360 Hevia, A., Cao, Q. V., Álvarez-González, J. G., Ruiz-González, A. D., and von Gadow, K. 2015.
361 Compatibility of whole-stand and individual-tree models using composite estimators and
362 disaggregation. *For. Ecol. Mgt.* 348:46-56.
- 363 Johnson, N.L., and Kotz, S. 1970. Continuous univariate distributions–1. John Wile & Sons. 300
364 p.
- 365 Monserud, R.A. 1976. Simulation of forest tree mortality. *For. Sci.* 22:438-444.
- 366 Monserud R.A., and H. Sterba. 1999. Modeling individual tree mortality for Austrian forest
367 species. *For. Ecol. Mgt.* 113:109-123.
- 368 Poudel, K., and Cao, Q.V. 2013. Evaluation of methods to predict Weibull parameters for
369 characterizing diameter distributions. *For. Sci.* 59:243-252.
- 370 Qin, J., and Cao, Q. V. 2006. Using disaggregation to link individual-tree and whole-stand
371 growth models. *Can. J. For. Res.* 36:953-960.
- 372 Stankova, T.V. 2016. A dynamic whole-stand growth model, derived from allometric
373 relationships. *Silva Fennica* vol. 50:1-21.
- 374 Tewari, V.P., Álvarez-González, J.G., and García, O. 2014. Developing a dynamic growth model
375 for teak plantations in India. *For. Ecosyst.* 1:9.
- 376 Weiskittel, A., Kuehne, C., McTague, J.P., Oppenheimer, M. 2016. Development and
377 evaluation of an individual tree growth and yield model for the mixed species forest of the
378 Adirondacks Region of New York, USA. *For. Ecosystem* 3:26.
- 379 Wells, O.O., and Wakeley P. C. 1966. Geographic variation in survival, growth, and fusiform
380 rust infection of planted loblolly pine. *For. Sci. Monograph* 11. 40 p.
- 381 Wilson, F.G. 1946. Numerical expression of stocking in terms of height. *J. For.* 44:758-761.
- 382 Zhang, L.; Moore, J.A., and Newberry, J.D. 1993. A whole-stand growth and yield model for
383 interior Douglas-fir. *West. J. Appl. For.* 8:120-125.

- 384 Zhang, S., Amateis, R. L., and Burkhardt, H. E. 1997. Constraining individual tree diameter
385 increment and survival models for loblolly pine plantations. *For. Sci.* 43:414-423.
- 386 Zhang, X., Lei, Y., Cao, Q. V., Chen, X., and Liu X. 2011. Improving tree survival prediction
387 with forecast combination and disaggregation. *Can. J. For. Res.* 41:1928-1935.
- 388 Zhao, D., Borders, B., Wang, M., and Kane, M. 2007. Modeling mortality of second-rotation
389 loblolly pine plantations in the Piedmont/Upper Coastal Plain and Lower Coastal Plain of
390 the southern United States. *For. Ecol. Mgt.* 252:132–143.

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Table 1. Means (and standard deviations) of stand and tree attributes at the beginning of each growth period, by group. There were 30 plots in each growth period of each group.

Group	Attribute	Age (years) of growth period					
		10-15		15-20		20-25	
1	Dominant height (m)	9.5	(1.3)	13.4	(1.5)	17.1	(2.0)
	Number of trees/ha	1875	(586)	1450	(630)	1074	(412)
	Basal area (m ² /ha)	22.0	(6.4)	28.3	(10.7)	30.1	(7.3)
	Tree diameter (cm)	11.9	(2.8)	15.2	(4.1)	18.4	(4.5)
2	Dominant height (m)	8.9	(1.1)	13.2	(1.7)	16.4	(2.0)
	Number of trees/ha	1912	(720)	1576	(627)	1200	(420)
	Basal area (m ² /ha)	19.4	(6.2)	27.8	(6.1)	30.9	(8.7)
	Tree diameter (cm)	11.0	(2.8)	14.5	(3.9)	17.6	(4.1)
3	Dominant height (m)	9.4	(1.0)	13.3	(1.5)	17.3	(1.7)
	Number of trees/ha	1857	(653)	1684	(723)	1182	(416)
	Basal area (m ² /ha)	21.5	(5.9)	31.4	(9.3)	34.3	(9.2)
	Tree diameter (cm)	11.8	(2.7)	15.0	(3.7)	18.7	(4.6)

Table 2. List of groups of data used for fitting and evaluating models. For example, in the first row, coefficients from the stand-level model (group 1) and the tree-level model (group 2) were used to evaluate survival data from group 3. This scheme ensured that data for fitting the stand and tree models and evaluating the models were independent of one another.

Fitting		Evaluation
Stand model	Tree model	
----- Group -----		
1	2	3
2	3	1
3	1	2

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Table 3. Evaluation statistics for stand-level survival prediction. Bold, underlined numbers denote the best method for each criterion. Overall ranks vary from 1 (best) to 7 (worst).

Model	MD*	MAD*	FI	Overall Rank
Clutter and Jones (1980)	-0.72	212.54	0.7423	6.58
Baldwin and Feduccia (1987)	<u>0.42</u>	214.87	0.7394	7.00
Cao (2006)	-19.71	192.36	0.7819	5.27
Method 1a	3.41	193.43	0.7754	2.57
Method 2a -- Clutter and Jones (1980)	12.87	204.66	0.7584	6.97
Method 2a -- Baldwin and Feduccia (1987)	5.14	203.69	0.7547	5.55
Method 2a -- Cao (2006)	-9.01	<u>183.26</u>	<u>0.7970</u>	<u>1.00</u>

* Unit is number of trees/ha.

Table 4. Evaluation statistics for tree-level survival prediction. Bold, underlined numbers denote the best method for each criterion. Overall ranks vary from 1 (best) to 13 (worst).

Method	Model	MD*	MAD*	AUC	Overall Rank
1a	Cao (2017)	0.0022	0.2639	0.7624	1.11
1b	Clutter and Jones (1980)	-0.0005	0.2703	0.7328	4.31
	Baldwin and Feduccia (1987)	<u>0.0003</u>	0.2703	0.7309	4.40
	Cao (2006)	-0.0128	0.2534	0.7447	6.86
2a	Clutter and Jones (1980)	0.0084	0.2668	0.7497	6.08
	Baldwin and Feduccia (1987)	0.0033	0.2638	0.7526	2.69
	Cao (2006)	-0.0059	<u>0.2514</u>	<u>0.7632</u>	<u>1.00</u>
2b	Clutter and Jones (1980)	-0.0005	0.2675	0.7365	3.49
	Baldwin and Feduccia (1987)	<u>0.0003</u>	0.2711	0.7331	4.30
	Cao (2006)	-0.0128	0.2517	0.7498	6.07
3b	Clutter and Jones (1980)	-0.0005	0.2937	0.7079	10.53
	Baldwin and Feduccia (1987)	<u>0.0003</u>	0.2938	0.7017	11.11
	Cao (2006)	-0.0128	0.2772	0.7212	13.00

* Unit is tree survival probability.

Table 5. Parameter estimates and their standard errors of the stand- and tree-level survival models, based on all observations.

Type	Parameter	Estimate	Std Error
Stand-level model ^{1/}	a ₁	13.7321	2.0799
	a ₂	-0.5943	0.0888
	a ₃	-37.5397	5.5936
	a ₄	-0.0205	0.00374
	a ₅	36.5848	10.0493
Tree-level model ^{2/}	b ₁	0.7902	0.0778
	b ₂	1.0657	0.0361
	b ₃	-0.3747	0.0142

$$^{1/} \hat{N}_{2i} = \frac{N_{1i}}{1 + \exp\{a_1 + a_2 H_{1i} + a_3 RS_{1i} + a_4 (N_{1i}/A_{1i}) + a_5/A_{1i}\}}$$

$$^{2/} p_{ij} = \frac{1}{1 + \left(\frac{N_1 - \hat{N}_2}{\hat{N}_2}\right) \exp[b_1(d_{1ij} - b_2 D_{q1}^{b_3})]}$$

Figure 1. Relationship between tree survival probability and tree diameter for three different plots. At each point marked by a circle, diameter is equal to D_{S1} , and therefore tree survival probability is equal to stand survival rate.