NRC Research Press

ARTICLE

A method to derive a tree survival model from any existing stand survival model

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Abstract: This study addresses a situation in which a forest manager has been using a whole-stand model that seems to predict well for their 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 the diameter of a given tree and the diameter at which 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 tree survival prediction, 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 were available, tree survival models derived from stand survival models ranked lowest in terms of performance but produced acceptable evaluation statistics for predicting tree-level survival.

Key words: individual-tree model, least squares, loblolly pine, logistic regression, maximum likelihood.

Résumé : Cette étude aborde la situation où un gestionnaire forestier utilise un modèle de peuplement qui semble fonctionner adéquatement pour ses peuplements et qui souhaite maintenant utiliser ce modèle pour dériver un modèle d'arbre individuel afin d'obtenir un système intégré qui fonctionne bien à l'échelle de l'arbre et du peuplement. Une méthode simple a été développée pour dériver trois modèles de survie des arbres à partir de trois modèles de survie à l'échelle du peuplement. Les modèles de survie des arbres ont été dérivés sur la base de la différence entre le diamètre d'un arbre donné et le diamètre de l'arbre dont la probabilité de survie est égale à celle du peuplement. Dans le cas de la prédiction de la survie du peuplement, chaque modèle de peuplement avait une moins bonne performance que le modèle d'arbre correspondant et un des modèles de survie des arbres qui a été dérivé était globalement le meilleur. Pour la prédiction de la survie des arbres, le même modèle d'arbre qui a été dérivé avait aussi globalement la meilleure performance. Même si on a utilisé seulement trois modèles de survie du peuplement dans cette étude, la méthode présentée ici devrait être applicable peu importe le modèle de survie du peuplement. Lorsqu'aucune donnée de survie des arbres n'est disponible, les modèles de survie des arbres dérivés des modèles de survie du peuplement se classaient derniers en terme de performance mais étaient tout de même statistiquement acceptables pour prédire la survie à l'échelle des arbres. [Traduit par la Rédaction]

Mots-clés : modèle d'arbre individuel, moindres carrés, pin à encens, régression logistique, maximum de vraisemblance.

Introduction

Contemporary forest managers make decisions partly based on forecasts provided by growth and yield models. Depending on the level of detail, or resolution, of their outputs, these models are often broadly classified as whole-stand models, size-class models, or individual-tree models (Burkhart and Tomé 2012); however, outputs from these models of different resolutions might be inconsistent with one another. One model might provide better reliability of estimates, whereas another model might provide more details.

In this paper, stand survival refers to the number of surviving trees per unit area, and tree survival refers to the status (dead or alive) of a given tree. Regression models have been used to predict cumulative survival at the stand level. These models are either empirical (Zhang et al. 1993; Diéguez-Aranda et al. 2005; Zhao et al. 2007; Gonzalez-Benecke et al. 2012) or are derived from biological principles (Garcia 2009, 2011; Tewari et al. 2014; Stankova 2016). In contrast, logistic regression has generally been used to predict survival at the individual-tree level (Hamilton 1974; Monserud 1976; Buchman 1979, 1983, Zhang et al. 1997; Monserud and Sterba 1999), even though other approaches have also been used (Glover and Hool 1979; Amateis et al. 1989; Guan and Gertner 1991*a*, 1991*b*).

Growth and yield models have traditionally been modeled separately at stand and tree levels. Daniels and Burkhart (1988) introduced a revolutionary concept of developing a unified mathematical structure for modeling tree and stand growth, which can be applied at any level of resolution. The result is an integrated system that can provide consistent growth and yield estimates at various levels of resolution. Cao (2017) applied this concept and experimented with 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. The latter approach delivered satisfactory results.

This study addresses a likely scenario in which a forest manager has been using a whole-stand model that seems to predict well for their 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 over an independent tree survival model is that both stand-level and

Received 9 May 2019. Accepted 14 August 2019.

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Published at www.nrcresearchpress.com/cjfr on 3 October 2019.

Table 1. Stand and tree attributes at the beginning of each growth period by group.

	Age of growth period		
Attribute	10–15 years	15–20 years	20–25 years
Group 1			
Dominant height (m)	9.5 (1.3)	13.4 (1.5)	17.1 (2.0)
Density (trees·ha^{-1})	1875 (586)	1450 (630)	1074 (412)
Basal area (m^2·ha^{-1})	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)
Group 2			
Dominant height (m)	8.9 (1.1)	13.2 (1.7)	16.4 (2.0)
Density (trees·ha^{-1})	1912 (720)	1576 (627)	1200 (420)
Basal area (m^2·ha^{-1})	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)
Group 3			
Dominant height (m)	9.4 (1.0)	13.3 (1.5)	17.3 (1.7)
Density (trees·ha^{-1})	1857 (653)	1684 (723)	1182 (416)
Basal area (m^2·ha^{-1})	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)

Note: Values are means, with standard deviations in parentheses. There were 30 plots in each growth period of each group.

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 (*i*) develop a method to derive an individual-tree survival model from any existing stand-level survival model and (*ii*) evaluate the tree survival models derived from such stand survival models.

Methods

Data

Data used in this study were from 270 plots randomly selected from the Southwide Seed Source Study, which included 15 loblolly pine (*Pinus taeda* L.) seed sources planted at 13 locations across 10 states in the southern United States (Wells and Wakeley 1966). Each plot had an area of 0.0164 ha and consisted of 49 trees (approximately 3000 trees·ha^{-1}) planted at a spacing of 1.8 m × 1.8 m. Tree survival varied greatly from plot to plot, ranging from 610 to 2929 trees·ha^{-1} at age 10 years, with a mean of 2102 trees·ha^{-1}.

The data were randomly divided into three groups of 90 plots each (Table 1). For each group, tree diameters and survival were measured from 30 plots for each of three growth periods: 10–15, 15–20, and 20–25 years.

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 data in Table 1.

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)

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

Cao (2006)

$$\hat{N}_{2i} = \frac{N_{1i}}{1 + \exp[a_1 + a_2H_{1i} + a_3\mathrm{RS}_{1i} + a_4(N_{1i}/A_{1i}) + (a_5/A_{1i})]} \tag{3}$$

where A_{1i} and A_{2i} are stand ages (in years) at the beginning and end of the growth period, respectively, for plot i; N_{1i}, H_{1i}, and RS_{1i} are stand density (in trees per hectare), dominant height (in metres), and relative spacing at age A_{1i} ($\mathrm{RS}_{1i} = \frac{(10000/N_{1i})^{0.5}}{H_{1i}}$ (Wilson 1946)), respectively; SI is the site index (in metres) at base age 25 years; $\hat{N}_{2i}$ is the predicted stand density at age A_{2i}; and a_k is the regression coefficient.

Tree-level survival models

In this study, two scenarios that depend on the presence or absence of tree survival data were considered.

With 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:

$$p_{ij} = \frac{1}{1 + \exp[b_0 + b_1H_{1i} + b_2\mathrm{RS}_{1i} + (b_3N_{1i}/A_{1i}) + (b_4/A_{1i}) + b_5d_{1ij}]} \tag{4}$$

where d_{1ij} is diameter at breast height (DBH, in centimetres; breast height = 1.30 m) of tree j in plot i at age A_{1i}, and b_k is the regression coefficient.

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

$$\tilde{p}_{ij} = p_{ij}^{\alpha} \tag{5}$$

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

Hereafter, methods 1*a* and 1*b* denote the unadjusted and disaggregated models, respectively.

Method 2

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

$$p_{ij} = \frac{1}{1 + \exp[c_0 + c_1H_{1i} + c_2\mathrm{RS}_{1i} + (c_3N_{1i}/A_{1i}) + (c_4/A_{1i}) + c_5(d_{1ij} - D_{S1i})]} \tag{6}$$

where D_{S1i} is the tree diameter that would yield a tree survival probability equal to that of the stand survival prediction, or $p_{ij} = \frac{\hat{N}_{2i}}{N_{1i}}$ (the proportion of surviving and starting number of trees) and c_k is the regression coefficient. Equation 6 can be simplified as follows:

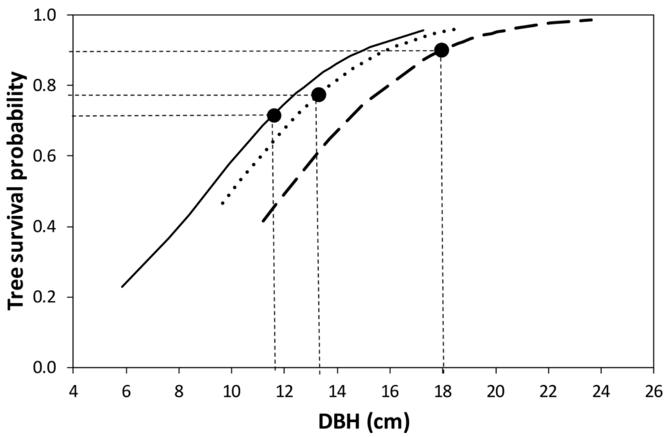
$$p_{ij} = \frac{1}{1 + \exp[b_0 + b_1(d_{1ij} - D_{S1i})]} \tag{7}$$

where D_{S1i} is expressed as $D_{S1i} = b_2D_{q1i}^{b_3}$, with D_{q1i} being the quadratic mean diameter of plot i at the beginning of the growth period. In other words, when $d_{1ij} = D_{S1i}$,

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

Combining eqs. 7 and 8 gives

Fig. 1. Relationship between tree survival probability and tree diameter at breast height (DBH; breast height = 1.30 m) for three different plots (denoted by solid, dotted, and dashed lines). At each filled circle, diameter is equal to D_{S1}; therefore, tree survival probability is equal to stand survival rate.



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

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 previously mentioned stand survival models (by use of eqs. 1–3) or 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 previously mentioned disaggregation method was then used to adjust the tree survival model. The resulting methods are hereafter referred to as methods 2*a* and 2*b* for unadjusted models and disaggregated models, respectively.

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.

Without 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 (hereafter referred to as method 3*b*). 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 and it has only one coefficient:

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

The coefficient β was solved such that

$$\sum_j p_{ij} = s_i \hat{N}_{2i} \tag{11}$$

where s_i is the size of plot i, and $\hat{N}_{2i}$ is the output of a stand survival model, obtained either from one of eqs. 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 (*i*) developing the stand survival models, (*ii*) deriving the tree survival models, and (*iii*) evaluating the models. Predicted values from all three groups were then pooled to compute evaluation statistics.

Table 2. Groups of data used for fitting and evaluating models.

Fitting: stand model	Fitting: tree model	Evaluation
Group 1	Group 2	Group 3
Group 2	Group 3	Group 1
Group 3	Group 1	Group 2

Note: 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.

Stand survival prediction

Mean difference (MD), mean absolute difference (MAD), and fit index (FI) were computed for stand-level evaluation:

$$\mathrm{MD} = \frac{1}{m}\sum\nolimits_i (N_{2i} - \hat{N}_{2i}) \tag{12}$$

$$\mathrm{MAD} = \frac{1}{m}\sum\nolimits_i |N_{2i} - \hat{N}_{2i}| \tag{13}$$

$$\mathrm{FI} = 1 - \frac{\sum_i (N_{2i} - \hat{N}_{2i})^2}{\sum_i (N_{2i} - \bar{N}_2)^2} \tag{14}$$

where m is the number of plots; N_{2i} and $\hat{N}_{2i}$ are the observed and predicted numbers, respectively, of surviving trees per hectare for plot i at age A_{2i}; $\bar{N}_2$ is the mean number of surviving trees per hectare at age A_{2i}; and Σ_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 MD, MAD, and area under the receiving operating characteristic (ROC) curve (AUC).

$$\mathrm{MD} = \frac{\sum_i \sum_j (y_{ij} - p_{ij})}{\sum_i n_{1i}} \tag{15}$$

where y_{ij} equals 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} is the number of trees in plot i at age A_{1i}.

$$\mathrm{MAD} = \frac{\sum_i \sum_j |y_{ij} - p_{ij}|}{\sum_i n_{1i}} \tag{16}$$

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).

Relative ranking system

The relative ranking system, introduced by Poudel and Cao (2013), was used in this study to determine the relative position of

Table 3. Evaluation statistics for stand-level survival prediction.

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

Note: Mean difference (MD) and mean absolute difference (MAD) are in terms of number of trees per hectare. FI, fit index. Values in boldface type denote the best method for each criterion. Overall rank varies from 1 (best) to 7 (worst).

Table 4. Evaluation statistics for tree-level survival prediction.

Model	MD	MAD	AUC	Overall rank
Method 1*a*: Cao (2017)	0.0022	0.2639	0.7624	1.11
Method 1*b*				
Clutter and Jones (1980)	−0.0005	0.2703	0.7328	4.31
Baldwin and Feduccia (1987)	**0.0003**	0.2703	0.7309	4.40
Cao (2006)	−0.0128	0.2534	0.7447	6.86
Method 2*a*				
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	**0.2514**	**0.7632**	**1.00**
Method 2*b*				
Clutter and Jones (1980)	−0.0005	0.2675	0.7365	3.49
Baldwin and Feduccia (1987)	0.0003	0.2711	0.7331	4.30
Cao (2006)	−0.0128	0.2517	0.7498	6.07
Method 3*b*				
Clutter and Jones (1980)	−0.0005	0.2937	0.7079	10.53
Baldwin and Feduccia (1987)	**0.0003**	0.2938	0.7017	11.11
Cao (2006)	−0.0128	0.2772	0.7212	13.00

Note: Mean difference (MD) and mean absolute difference (MAD) are in terms of tree survival probability. AUC, area under the receiver operating characteristic (ROC) curve. Values in boldface type denote the best method for each criterion. Overall rank varies from 1 (best) to 13 (worst).

each method for each evaluation statistic. The relative ranking of method i (R_i) is defined as

$$R_i = 1 + \frac{(k-1)(S_i - S_{\max})}{S_{\max} - S_{\min}} \tag{17}$$

where S_i is the evaluation statistic produced by method i ($i = 1, 2, \ldots, k$), 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 receives a rank of k. Ranks of the remaining methods are presented as real numbers between 1 and k, reflecting both the magnitude and order of the evaluation statistic, and should therefore provide more information than the traditional ordered ranking systems based on consecutive integers. 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 2*a*) performed best in predicting stand survival, whereas the stand-level model by Baldwin and Feduccia (1987) ranked last among the seven alternatives.

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

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

Table 5 shows parameter estimates and their standard errors from Cao's (2006) stand survival model and its derived tree survival model (method 2*a*), 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 1*a*) were used for stand survival prediction. Surprisingly, this tree model ranked better than the Cao (2006) stand-level model (rankings of 2.57 and 5.27, respectively), 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

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

Parameter	Estimate	SE
Stand-level model		
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		
b_1	0.7902	0.0778
b_2	1.0657	0.0361
b_3	−0.3747	0.0142

Note: The stand-level model is $\hat{N}_{2i} = \dfrac{N_{1i}}{1+\exp[a_1 + a_2H_{1i} + a_3\mathrm{RS}_{1i} + a_4(N_{1i}/A_{1i}) + (a_5/A_{1i})]}$, and the tree-level model is $p_{ij} = \dfrac{1}{1+[(N_1-\hat{N}_2)/\hat{N}_2]\exp[b_1(d_{1ij} - b_2D_{q1}^{b_3})]}$. See Methods for definitions of variables.

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 over 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 2*a* 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 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) than their stand-level model counterparts, but method 2*a* derived from Cao (2006) yielded a better MD value than the original Cao (2006) model, which produced the worst MD value of −19.71 trees·ha^{-1}.

Each stand-level model and its derived tree model (method 2*a*) were conceptually compatible because they formed an integrated system of equations; however, they 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 Cao's (2006) stand model with the least squares parameter estimates and extra tree information that, because of 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 1*a*) was least biased (yielded the best MD value) in predicting stand survival when compared with the three derived tree models (method 2*a*). In terms of MAD and FI values, the tree survival model (method 1*a*) performed 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 1*a* against the three stand-level survival models (previously described in Stand-level models versus tree-level survival model).

Tree-level survival prediction

Without disaggregation

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

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

With disaggregation

Method 1a *versus method* 1b

The unadjusted tree survival model (method 1*a*) produced the best AUC value (0.7624) as compared with the three disaggregated models (method 1*b*; 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, the unadjusted tree survival model (method 1*a*) produced a much higher rank (1.11) than the tree disaggregated models (ranks varied between 4.31 and 6.86).

Method 2a *versus method* 2b

For the derived tree survival models, the unadjusted models (method 2*a*) ranked better than the disaggregated models (method 2*b*) 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 that from 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 previously discussed, it makes sense that disaggregation was not only unnecessary, but also detrimental in terms of predictive accuracy.

Disaggregation: with tree survival data versus without tree survival 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 (methods 1*b* and 2*b*) or from a simple function that requires no data (method 3*b*). Even though all methods (1*b*, 2*b*, and 3*b*) yielded identical MD values for each stand survival model, methods 1*b* and 2*b* consistently produced better MAD and AUC values than those of method 3*b*, as was expected (Table 4). Because the Cao (2006) model 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 3*b*. Considering that method 3*b* requires no survival data, it is surprising that this tree model from method 3*b* approached method 1*b* in terms of AUC (0.7212 and 0.7447, respectively) and MAD (0.2772 and 0.2534, respectively). The reason for this might be that the negative exponential CDF used in method 3*b* 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 tree survival prediction, 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, the derived tree models ranked worst in terms of performance but produced decent evaluation statistics for predicting tree-level survival, as was expected. The fact that the actual magnitudes of the error metrics for method 3*b* 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, this study suggests a reasonable method of constructing a tree survival model, even when no tree survival data are available.

Acknowledgements

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

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