Improving tree survival prediction with forecast combination and disaggregation

Xiongqing Zhang, Yuancai Lei, Quang V. Cao, Xinmei Chen, and Xianzhao Liu

Abstract: The tree mortality model plays an important role in simulating stand dynamic processes. Past work has shown that the disaggregation method was successful in improving tree survival prediction. This method was used in this study to forecast tree survival probability of Chinese pine (*Pinus tabulaeformis* Carrière) in Beijing. Outputs from the tree survival model were adjusted from either the stand-level model prediction or the combined estimator from the forecast combination method. Our results show that the disaggregation approach improved the performance of tree survival models. We also showed that stand-level prediction played a crucial role in refining outputs from a tree survival model, especially when it is a very simple model. Because the forecast combination method produced better stand-level prediction, we prefer the use of this method in conjunction with the disaggregation approach, even though the performance gain in using the forecast combination method shown for this data set was modest.

Résumé : La modélisation de la mortalité des arbres joue un rôle important dans la simulation des processus dynamiques de la croissance forestière. Les travaux antérieurs ont montré que la méthode de désagrégation pouvait améliorer la prédiction de la survie des arbres. Cette méthode a donc été utilisée ici pour prédire la probabilité de survie du pin de Chine (*Pinus tabulaeformis* Carrière) à Pékin. Les extrants du modèle de survie des arbres ont été ajustés à partir soit de la prédiction du modèle à l'échelle du peuplement, soit de l'estimateur combiné de la méthode de combinaison des prédictions. Nos résultats montrent que l'approche de désagrégation a amélioré la performance du modèle de survie des arbres. Nous avons également montré que la prédiction à l'échelle du peuplement a joué un rôle crucial dans le raffinement des extrants du modèle de survie des arbres, surtout lorsque le modèle est très simple. Comme la méthode de combinaison des prédictions prédit le mieux les attributs du peuplement, nous préférons l'utiliser conjointement avec la méthode de désagrégation, même si le gain de performance était modeste pour l'ensemble de données considéré.

[Traduit par la Rédaction]

Introduction

Tree mortality, one of the main components of forest succession, is a complex process affected by environmental, pathological, and physiological factors, as well as random events (Franklin et al. 1987; Yang et al. 2003). Tree mortality is very difficult to predict accurately because the causes of tree mortality are variable. Vanclay (1994) made a distinction between regular (noncatastrophic) mortality, which results from competition for water, nutrients, and light within a stand (Peet and Christensen 1987), and irregular (catastrophic) mortality, which results from random disturbances or hazards such as local fire, wind, snow, or drought (Kneeshaw and Bergeron 1998). Catastrophic wildfires and insect outbreaks reset forest succession at large spatial scales (Turner et al. 1997; Bouchard et al. 2006). In contrast, regular tree mortality occurs at a small, local scale (Kenkel 1988). Because of the uncertainty of the tree mortality process, mortality remains one of the least understood components of natural growth processes (Hamilton 1986; Álvarez González et al. 2004).

The tree mortality model is part of the forest management tools that enable prediction of the development of forest stands (Crecente-Campo et al. 2010). Because of the randomness of irregular mortality and the difficulty in predicting the variability of ecological disturbances in climatic stress, extreme winds, drought, wildfire, and other destructive agents (Stage 1973), most tree mortality models in growth systems are developed only for regular mortality (e.g., Monserud 1976; Lynch et al. 1998; Eid and Tuhus 2001) or for a local type of irregular mortality (Breece et al. 2008; Vega et al. 2011). In growth models used in forest management, individual-tree mortality is often described by empirical models (Monserud and Sterba 1999).

Although many functions have been used to predict the probability of a tree dying during a growth period due to regular mortality, e.g., the Weibull function (Somers et al. 1980), Richard's function (Buford and Hafley 1985), gamma function (Kobe and Coates 1997), or exponential function (Moser 1972), logistic regression seems to be the preferred choice for tree mortality models and has been widely adopted (e.g., Vanclay 1995; Cao 2000; Yao et al. 2001; Zhao et al. 2004; Hartmann et al. 2007; Zhang and Lei 2009). Most independent variables in the logistic function such as age, tree

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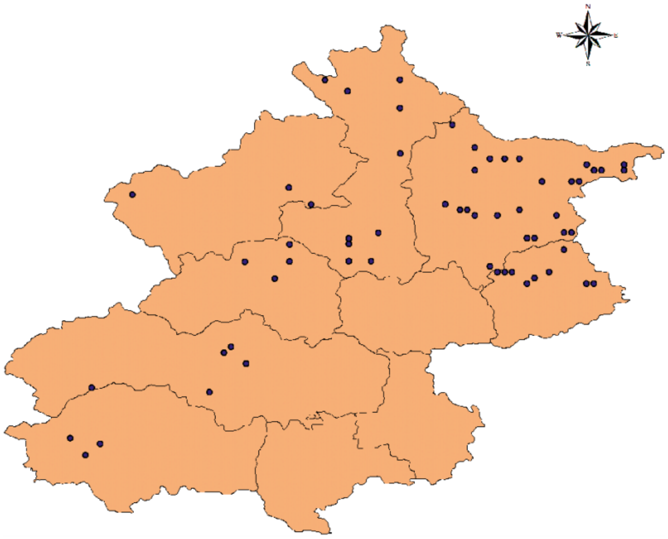
Fig. 1. The spatial location of Chinese pine (*Pinus tabulaeformis*) in Beijing.



size, and measures of competition and tree vigor are easily obtainable (Crecente-Campo et al. 2009).

Disaggregation is a good method for improving prediction of tree growth and survival (Cao 2006, 2010; Qin and Cao 2006). In this method, individual-tree growth and survival predictions are adjusted so that the resulting sums would match outputs from a stand-level model. Cao (2010) believed that the success of the disaggregation method depends largely on the reliability of the stand-level predictions. When different types of models (tree-level, stand-level, and diameter distribution) are used, stand-level predictions (stand basal area, stand density, etc.) can be improved by combining estimates from these models (Yue et al. 2008; Zhang and Lei 2010; Zhang et al. 2010*a*, 2010*b*) using a method called forecast combination (Bates and Granger 1969).

The objective of this study was to investigate the improvement of the tree survival model by disaggregation from either a stand-level model estimate or a combined estimate from both tree- and stand-level models.

Data

The data, collected by the Inventory Institute of Beijing Forestry, consisted of a systematic sample of permanent plots with a 5-year remeasurement interval. The plots (squared plots, 0.067 ha each) were in Chinese pine (*Pinus tabulaeformis* Carrière) plantations situated on upland sites of Beijing (Fig. 1). The data consisted of measurements from 155 plots obtained between 1986 and 2001. In this study, 105 plots were used in model development and the remaining 50 plots were withheld for validation. The distribution of plots is presented in Table 1. Summary statistics of stand- and tree-level variables are presented in Table 2 for both data sets.

Methods

The disaggregation approach often requires two steps. The first step involves the development of a tree survival model and a stand survival model. In the second step, outputs from the tree survival model are then adjusted so that the sum of tree survival probabilities matches the output from the stand survival model. The term "disaggregation" is used here because the stand survival estimate appears to be split into individual-tree components. Merging the disaggregation and forecast combination methods involves an extra step to combine the stand-level survival predictions from these two models before disaggregation begins (Fig. 2).

Table 1. Distribution of plots.

Measurement time	Fit data	Validation data	Total
1986–1991	27	12	39
1991–1996	36	17	54
1996–2001	42	21	63
Total	105	50	155

Development of stand survival and tree survival models

We modified Cao and Strub's (2008) survival model by including relative spacing, which is a function of dominant height and stand density:

$$[1] \qquad \widehat{N}_2 = \exp\{\ln(N_1)(A_1/A_2) + (1 - A_1/A_2)(\alpha_1 + \alpha_2 \mathrm{Rs}_1 + \alpha_3 N_1)\}$$

where Rs_1 is the relative spacing at age A_1 (calculated as $(10\ 000/N_1)^{0.5}/H_1$), where H_1 is dominant height (in metres) at age A_1 and N_1 is the number of trees per hectare at age A_1; $\exp(x) = \mathrm{e}^x$; $\ln(x)$ is the natural logarithm of x; and α_is are the parameters to be estimated.

The following logistic model that included age, stand density, tree size, and a competition measure was selected because it was widely used to simulate tree survival (Vanclay 1995; Cao 2000):

$$[2] \qquad \widehat{P}_i = \{1 + \exp(\beta_1 + \beta_2/A_1 + \beta_3 d_{i,1}/\mathrm{Dg}_1 + \beta_4 A_1/N_1)\}^{-1}$$

where $\widehat{P}_i$ is the survival probability of tree i during the period between ages A_1 and A_2; $d_{i,1}$ is the diameter (in centimetres) of tree i at age A_1; Dg_1 is the quadratic mean diameter (in centimetres) at age A_1; and β_is are the parameters to be estimated. Number of trees per hectare at age A_2 was calculated from $\widehat{N}_2^T = \sum_{i=1}^{n_1} \widehat{P}_i/s$, where n_1 is number of trees in a plot at age A_1 and s is plot size (in hectares).

Forecast combination

Yue et al. (2008) and Zhang et al. (2010*b*) applied the forecast combination method to combine stand- and tree-level models for basal area. Similarly, predicted stand survival for our study can be combined from these two types of models:

$$[3] \qquad \widehat{N}_2^{\mathrm{C}} = w_1 \widehat{N}_2^{\mathrm{T}} + w_2 \widehat{N}_2^{\mathrm{S}}$$

where $\widehat{N}_2^{\mathrm{C}}$ is the combined estimator of stand survival; $\widehat{N}_2^{\mathrm{T}}$ is the estimate of stand survival from the tree survival model; $\widehat{N}_2^{\mathrm{S}}$ is the estimate of stand survival from the stand survival model; and w_1 and w_2 are weight coefficients, with $w_1 + w_2 = 1$.

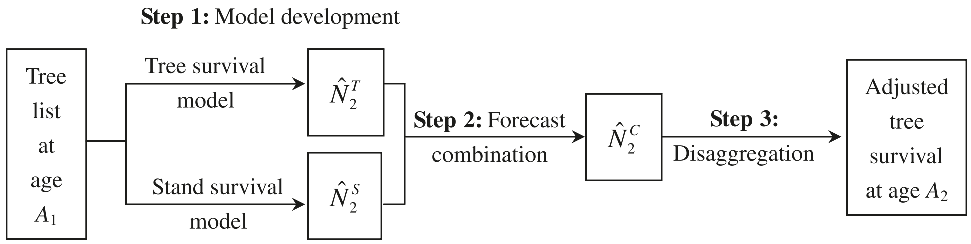
The variance–covariance method used by Yue et al. (2008) to calculate the optimal weight coefficients was found unstable by Zhang et al. (2006). We used the following formula

Table 2. Summary statistics of stand- and tree-level variables by data set.

	Fit data (n = 105)				Validation data (n = 50)			
Variables	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
Age (years)	11	66	31	8.54	12	52	30	7.65
Dominant height (m)	4	17.4	6.8	2.5	2.5	17.4	7.3	3.2
Stand survival (trees·ha^{-1})	238	2284	1190	503	284	2089	1010	462
Stand basal area (m^2·ha^{-1})	0.80	33.10	11.20	6.05	0.80	28.15	10.72	6.58
Quadratic mean diameter (cm)	6.0	17.3	10.8	2.5	5.8	17.9	10.9	2.8
Diameter at breast height (cm)	5.0	36.8	10.4	3.9	5.0	29.7	10.6	4.0

Note: Min., minimum; max., maximum; SD, standard deviation.

Fig. 2. Flow chart depicting the three steps used in this study.



for computing the optimal weight coefficients based on the ordinary least-squares method (Zhang et al. 2010*a*):

$$[4] \qquad W = \frac{E^{-1}R}{R^{\mathrm{T}}E^{-1}R}$$

where $W = (w_1, w_2)^{\mathrm{T}}$; $R = (1, 1)^{\mathrm{T}}$;

$$E = \begin{pmatrix} e_1^{\mathrm{T}}e_1 & e_1^{\mathrm{T}}e_2 \\ e_2^{\mathrm{T}}e_1 & e_2^{\mathrm{T}}e_2 \end{pmatrix}$$

$e_k = (e_{k1}, e_{k2}, \ldots, e_{kn})$; and e_{ki} is the forecast error of observation i from method k, where $i = 1, 2, \ldots, m$, with m being the number of plots.

Disaggregation

Four methods were used to adjust the tree survival in this study.

Method 1: power function

In this method, the adjusted tree survival probability at age A_2 was expressed as a simple power function of the unadjusted probability (Cao 2006):

$$[5] \qquad \widetilde{P}_i = P_i^{\lambda}$$

where λ is the adjusting coefficient to be iteratively solved such that

$$[6] \qquad \sum_{i=1}^{n_1} \widetilde{P}_i = s\widehat{N}_2$$

$\widehat{N}_2$ is estimate of stand survival either from the stand-level model ($\widehat{N}_2^{\mathrm{S}}$) or from the combined estimator ($\widehat{N}_2^{\mathrm{C}}$).

Method 2: proportional mortality

The tree survival probability at age A_2 was adjusted based on the ratio of dead and alive probabilities (Qin and Cao 2006):

$$[7] \qquad \widetilde{P}_i = \frac{\widehat{P}_i}{\widehat{P}_i + \lambda(1 - \widehat{P}_i)}$$

where λ, the adjusting coefficient, is iteratively solved in the same manner as in method 1.

Method 3: coefficient adjustment

Using the approach by Qin and Cao (2006), an adjusting coefficient λ was added to tree survival:

$$[8] \qquad \widetilde{P}_i = \{1 + \exp(\beta_1 + \beta_2/A_1 + \lambda\beta_3 d_{i,1}/\mathrm{Dg}_1 + \beta_4 A_1/N_1)\}^{-1}$$

where λ is iteratively solved to satisfy eq. 6.

Method 4: addition

Cao (2010) developed the addition method (see Supplementary data for SAS code)[1] for adjusting tree survival as follows:

$$[9] \qquad \widetilde{P}_i = \widehat{P}_i + \lambda(1 - \widehat{P}_i)$$

The adjustment coefficient λ in the first three methods was iteratively solved for each plot such that $\sum_{i=1}^{n_1} \widetilde{P}_i = s\widehat{N}_2$. In method 4, λ is given by

$$\lambda = \frac{s\widehat{N}_2 - \sum_{i=1}^{n_1} \widehat{P}_i}{n_1 - \sum_{i=1}^{n_1} \widehat{P}_i}$$

$\widehat{N}_2$ in the four methods above is predicted stand survival at

[1]SAS code for the addition method is available as supplementary data with the article through the Journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/x11-109.

Table 3. Parameter estimates and standard errors (SEs) of the stand- and tree-level survival models.

Attribute	Parameter	Estimate	SE	Fit statistics
Eq. 1	α_1	5.8803	0.2530	0.9062 (R^2)
	α_2	3.8351	1.1090	
	α_3	0.0007	0.0002	
Eq. 2	β_1	1.2276	0.3663	2466.43 (–2 lnL)
	β_2	–46.9434	6.7486	
	β_3	–2.2894	0.2408	
	β_4	–17.2342	3.8579	

Table 4. Evaluation statistics for predicted stand survival from the tree survival model, stand survival model, and forecast combination method.

Statistic	Tree survival	Stand survival	Forecast combination
MD	9.67	–5.26	**–1.44**
MAD	95.52	91.07	**90.41**
R^2	0.8973	0.9062	**0.9074**

Note: MD, mean difference between observed and predicted values; MAD, mean absolute difference. Value in bold denotes the best statistics among the three models.

age A_2, either directly from the stand survival model or adjusted by use of the forecast combination method.

Model evaluation

Stand survival predictions from the stand survival model (eq. 1), the tree survival model (eq. 2), and the forecast combined estimator were evaluated. The evaluation statistics included MD (mean difference between observed and predicted values), MAD (mean absolute difference), and R^2.

For tree survival, we evaluated unadjusted predictions against those adjusted from the stand-level model and from the combined estimator. The following statistical criteria were examined: root mean squared error (RMSE) = $\sqrt{\sum(y_i-\widehat{y}_i)^2/n}$; loglikelihood (–2 lnL) = $-2\{\sum\widehat{P}_i\ln(\widehat{P}_i) + \sum(1-\widehat{P}_i)\ln(1-\widehat{P}_i)\}$, and AUC, the area under the ROC (receiver operating characteristic) curve. The ROC analysis has been applied in various areas ranging from medicine to ecology (Zweig and Campbell 1993; McPherson et al. 2004) and was used as a criterion to evaluate tree mortality by Saveland and Neuenschwander (1990). The AUC value reflects the performance of the model: the larger the value of AUC, the better the model performs (Fielding and Bell 1997). AUC values range from 0.5 (unacceptable) to 1 (perfect prediction). A rough guideline for AUC follows the traditional academic point system: 0.9–1 = excellent (A); 0.8–0.9 = good (B); 0.7–0.8 = fair (C); 0.6–0.7 = poor (D); and 0.5–0.6 = fail (F).

Results and discussion

The parameter estimates and their standard errors for the stand-level and tree-level survival models are listed in Table 3. All parameters were significant at the 5% level. The weight coefficients of the combined estimator for stand survival, calculated for the fit data using the optimal weight method (Zhang et al. 2010*a*), were $w_1 = 0.26$ and $w_2 = 0.74$.

Table 5. Evaluation statistics for the unadjusted and adjusted predictions of tree survival based on the validation data.

Method	RMSE	–2 lnL	AUC
Unadjusted tree survival model			
Unadjusted	0.1903	901.78	0.756
Adjusted from stand survival model			
Method 1	0.1875	779.14	0.892
Method 2	0.1875	779.45	0.892
Method 3	0.1895	823.62	0.837
Method 4	0.1875	778.83	0.892
Adjusted from forecast combination			
Method 1	0.1874	771.69	0.896
Method 2	0.1873	771.94	0.896
Method 3	0.1893	816.19	0.848
Method 4	**0.1873**	**771.46**	**0.896**

Note: RMSE, root mean squared error; –2 lnL, –2 loglikelihood; AUC, area under the ROC (receiver operating characteristic) curve. Value in bold denotes the best statistics among all methods.

Prediction of stand survival

The evaluation statistics for predicted stand survival from the stand- and tree-level models and from the combined estimator, computed for the validation data are presented in Table 4. The mean difference for the combined estimator was –1.44 as compared with 9.67 and –5.26 for the tree- and stand-level models, respectively; the mean absolute difference was 90.41 compared with 95.52 and 91.07, respectively; and R^2 was 0.9074 compared with 0.8973 and 0.9062, respectively. These results confirmed findings by Yue et al. (2008) and Zhang et al. (2010*b*) that the forecast combination method performed better than either of the other two models in predicting stand attributes. Forecast combination, introduced by Bates and Granger (1969), is a good method for improving forecast accuracy (Newbold et al. 1987). The forecast combination method efficiently utilized information generated from different models to improve prediction by reducing errors from a single model (Zhang et al. 2010*a*). The implicit assumption in forecast combination is that the relationship between observed values and outputs from different models is stable. If this relationship remains relatively unchanged from the sample data to the population, then the combined estimator should provide predictions that are closer to the true values than those by any model alone.

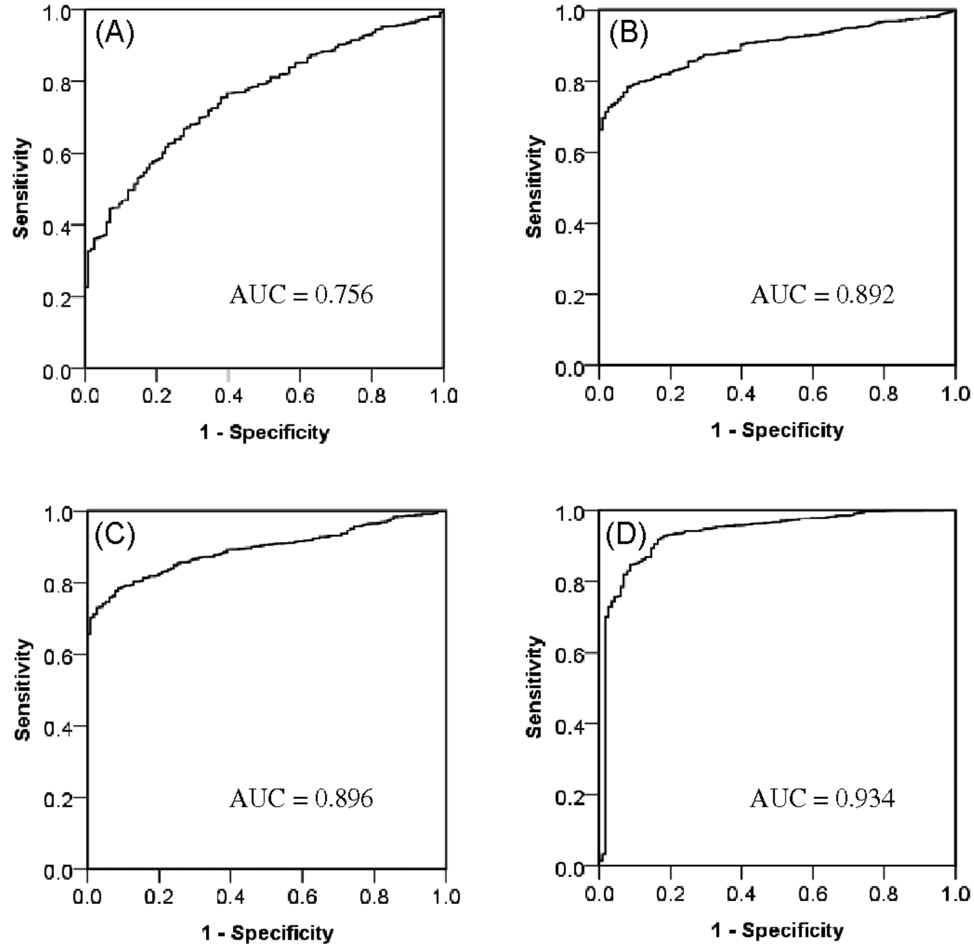
Prediction of tree survival

Evaluation results for the adjusted and unadjusted predictions of tree survival are presented in Table 5. The ROC curves of unadjusted and adjusted tree survival are displayed in Fig. 3.

Disaggregation methods

Statistics from the four disaggregation methods were similar when the tree survival was adjusted from the stand survival model. The addition method (method 4) performed slightly better than the remaining three disaggregation methods. An advantage of the addition method is that it allowed direct computation of the adjusting coefficient λ (Cao 2010), whereas the other methods required that λ be resolved in an iterative manner (Qin and Cao 2006; Cao 2010). Disaggrega-

Fig. 3. ROC curves for unadjusted and adjusted tree survival prediction: (A) unadjusted; (B) adjusted from stand survival model; (C) adjusted from forecast combination model; and (D) adjusted from observed stand survival. AUC, area under the ROC (receiver operating characteristic) curve.



tion methods have also been used to adjust individual trees for diameter (e.g., Leary et al. 1979; McTague and Stansfield 1995; Ritchie and Hann 1997), basal area (e.g., Campbell et al. 1979; Moore et al. 1994), and volume (e.g., Dahms 1983; Zhang et al. 1993). Similar results were found when the adjustment came from the combined estimator. The following discussion will be based on results from the addition method.

Unadjusted vs. adjusted tree survival

Overall, the adjustment was better from the forecast combination than from the stand survival model. Both adjustment approaches improved the performance of the unadjusted tree survival model. Compared with predictions from the unadjusted model, the adjustment from the combined estimator lowered RMSE by 1.6% (from 0.1903 to 0.1873) and –2 lnL by 14.5% (from 901.78 to 771.46), and increased AUC by 18.5% (from 0.756 (fair) to 0.896 (good)) (Table 5).

Adjusted tree survival predictions from the combined estimator were consistently better than those from the stand model estimates, but the improvement in terms of evaluation statistics was modest: RMSE decreased from 0.1875 (stand model) to 0.1873 (combined estimator), –2 lnL decreased from 778.83 to 771.46, and AUC increased from 0.892 to 0.896 (Table 5).

Disaggregation as applied to tree survival

To examine the importance of a tree mortality model in the disaggregation method, we developed relatively simple tree survival model:

$$[10] \qquad \widehat{P}_i = \{1 + \exp(\beta_1 + \beta_2 d_{i,1})\}^{-1}$$

Next, we looked at how well eq. 10 performed after being adjusted from the stand survival model, the forecast combined estimator, and the observed stand survival values. In addition, eq. 2 was also adjusted from the observed stand survival values. Results computed from the validation data are presented in Table 6.

As expected, the relatively simple model (eq. 10), when unadjusted, was inferior to eq. 2 based on all three evaluation statistics. The AUC value was 0.591 (fail) for eq. 10 versus 0.756 (fair) for eq. 2. The gap between the two equations was narrowed when they were adjusted from the combined estimator: the AUC values were 0.884 and 0.896, both considered good. This gap was virtually erased when they were adjusted from the observed stand survival: the AUC values were 0.934 and 0.931, both excellent. The ROC method has advantages in assessing model performances in a threshold-independent fashion and comparing several different models (e.g., Manel et al. 2001; Wunder et al. 2007). Common sense

Table 6. Evaluation of unadjusted and adjusted predictions from a tree-level survival model (eq. 2) and a relatively simple model (eq. 10), based on the validation data.

	Eq. 2			Eq. 10		
Method	RMSE	–2 lnL	AUC	RMSE	–2 lnL	AUC
Unadjusted	0.1903	901.78	0.756	0.1924	970.43	0.591
Adjusted from forecast combination	0.1873	771.46	0.896	0.1882	791.28	0.884
Adjusted from observed stand survival	0.1702	516.48	0.934	0.1717	530.84	0.931

Note: RMSE, root mean squared error; –2 lnL, –2 loglikelihood; AUC, area under the ROC (receiver operating characteristic) curve.

dictates that the disaggregation approach should be successful when it involves both a good tree-level model and a good stand-level model. In the tree-level model, we used logistic regression (eq. 2) without considering spatial variations between the plots. A multilevel logistic regression model (generalized linear mixed-effect model) that uses random effects at plot level to incorporate the spatial variation between plots (Jutras et al. 2003; Rose et al. 2006; Mailly et al. 2009) could improve the tree-level model and, consequently, the adjusted tree mortality. Results from Table 6 suggest that the stand-level output plays a more important role than we previously suspected in determining the quality of the adjusted tree survival prediction. Even a very simple tree-level model would suffice if the stand-level prediction used for disaggregation approaches the true values. In this regard, forecast combination, which improves stand-level prediction, should be used in conjunction with the disaggregation method.

Conclusion

Our results show that the different disaggregation methods improved the performance of the tree survival model. Although the four methods evaluated gave similar results, the addition method (Cao 2010) was consistently better and allows direct computation of the adjusting coefficient. We also showed that stand-level prediction played a crucial role in refining outputs from the tree survival model. Disaggregation from an excellent stand estimate could almost erase the gap between a mediocre and a good tree survival model. Because the forecast combination method produced better stand-level prediction, we prefer the use of this method in conjunction with the disaggregation approach, even though the performance gain in using the forecast combination method shown for this data set was modest. Because disaggregation works best when the stand-level prediction is good, the union between disaggregation and forecast combination should provide adequate survival prediction at both tree and stand levels. The union method might be applicable to models for predicting other attributes such as tree diameter, basal area, or volume growth.

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