Compatibilty of Stand Basal Area Predictions Based on Forecast Combination

Xiongqing Zhang, Yuancai Lei, Quang V. Cao

Abstract: Stand growth and yield models include whole-stand models, individual-tree models, and diameter-distribution models. Based on the growth data of Chinese pine (Pinus tabulaeformis Carr.) in Beijing, forecast combination method was used to adjust predicted stand basal areas from these three types of models. The forecast combination method combines information and disperses errors from different models to improve forecast performance. In this study, weights of the three model estimates used in the forecast combination estimator were determined by the optimal weight method. Results showed that the forecast combination method provided overall better predictions of stand basal area than the three types of models. It also improved the compatibility of stand basal area growth predicted from models of different resolutions and provided a method for integration of stand basal area. 

Keywords: compatibility, forecast combination, optimal weight, Pinus tabulaeformis, stand basal area model

In forest management, growth and yield models play a very important role in predicting forest growth and studying its processes. Forest growth and yield models can be broken into three broad categories: whole-stand models, individual-tree models, and diameter-distribution models (Munro 1974). Whole-stand models are models that use a stand as a modeling unit (Curtis et al. 1981, Li et al. 1988, Tang et al. 1993, Wei 2006), whereas individual-tree models consider an individual tree as a study object (Meng and Zhang 1996, Zhang et al. 1997, Cao 2000, Cao et al. 2002). Diameter-distribution models, in contrast, use statistical probability functions, such as the Weibull function (Bailey and Dell 1973, Meng 1988, Liu et al. 2004, Newton et al. 2005), beta function (Gorgoso-Várela et al. 2008), or $S_B$ function (Wang and Rennolls 2005), to characterize stand structure.

There are strengths and weaknesses with each type of model. Whole-stand models can predict stand variables directly and provide accurate predictions of stand growth and yield but lack detailed tree-level information. On the other hand, individual-tree models provide more detailed information, and diameter-distribution models offer stand diameter structure, but stand-level outputs from these two types of models often suffer from an accumulation of errors and subsequently poor accuracy and precision (Garcia 2001, Qin and Cao 2006).

From a commonsense point of view, we expect stand-level outputs from different types of models to be similar. However, these models may still provide numerically inconsistent predictions due to model errors (Meng 1996). Daniels and Burkhart (1988) proposed a framework for an integrated system of forest stand models, in which constraints were applied so that stand outputs from models of different levels of resolution are similar. Recently, researchers have tried to solve problems involving compatibility between different types of models. The disaggregation method was used to maintain compatibility by linking stand-level and tree-level models (Zhang et al. 1993, Ritchie and Hann 1997, Qin and Cao 2006). However, this method assumes that predictions from the stand-level model are superior, and it attempts to adjust outputs from the tree-level model to match those from the stand-level model.

Forecast combination, introduced by Bates and Granger (1969), is a good method for improving forecast accuracy (Newbold et al. 1987). This method combines information generated from different models and disperses errors from these models, thus ensuring consistency for outputs from different models. Yue et al. (2008) used this method to deal with the problem of compatibility between tree-level and stand-level models. The objective of this study was to apply the forecast combination method in linking whole-stand, individual-tree, and diameter-distribution models so that the resulting stand basal area prediction is consistent at various levels of resolution.

Data

The data, provided by the Inventory Institute of Beijing Forestry, consisted of a systematic sample of permanent plots with a 5-year re-measurement interval. The plots, 0.067 ha each, were in Chinese pine (Pinus tabulaeformis Carr.) plantations situated on upland sites throughout northwestern Beijing. The data consisted of 156 measurements, with a 5-year re-measurement interval, obtained in the following years: 1986, 1991, 1996, and 2001. In this study, 106 plots were used in model development and another 50 plots...
were used for validation. Table 1 shows the distribution of plots. Summary statistics for both data sets are presented in Table 2.

**Methods**

**Stand-Level and Tree-Level Models**

Cao (2002) developed a variable-rate method to predict annual diameter growth and survival for an individual tree. This method accounts for the fact that rates of survival and diameter growth vary from year to year. Stand-level growth and survival were also treated in a similar manner (Ochi and Cao 2003). The variable-rate method was used in this study. Annual changes in stand variables (dominant height, stand survival, arithmetic mean diameter, stand basal area, diameter SD, and minimum diameter), and tree variables (dbh and survival probability) were described in a recursive manner (Ochi and Cao 2003, Nord-Larsen 2006, Qin et al. 2007, Cao and Strub 2008). Table 3 lists the stand-level and tree-level growth equations.

Estimates of stand basal area from the tree-level model at age \( t + q \) were obtained by summing up the basal area per ha represented by each tree from the individual-tree diameter growth model (Equation 1g) and survival model (Equation 1h). Because cross-equation correlations existed among error components of the above models, a method suggested by Borders (1989) was used to simultaneously estimate parameters of the regression system (Equations 1a–1g). The fitting procedure involved the use of option SUR (seemingly unrelated regression) of the SAS Procedure Model. Parameters of the tree survival equation were separately estimated by use of the NLIN procedure.

**Diameter Distribution Model**

The Weibull function has been extensively applied in forestry because of its flexibility in describing a wide range of unimodal distributions and the relative simplicity of parameter estimation (Bailey and Dell 1973, Kangas and Maltamo 2000, Mabvurira et al. 2002, Lei 2008). The Weibull probability density function is expressed as

\[
 f(x; a, b, c) = \left( \frac{c}{b} \right) \left( \frac{x-a}{b} \right)^{c-1} \exp \left[ -\left( \frac{x-a}{b} \right)^c \right], \\
 (a \leq x \leq \infty)
\]  

(2)

where \( x \) is dbh, \( a \) is the location parameter, \( b \) is the scale parameter, and \( c \) is the shape parameter.

Moment estimation is one of the widely used parameter recovery methods for estimating Weibull parameters (Liu et al. 2004, Lei 2008). Considering that the location parameter \( a \) must be smaller than the predicted minimum diameter \( (\hat{D}_{\text{min}}) \) in the stand, we set \( a = \hat{D}_{\text{min}} \) because Frazier (1981) found that this value produced minimal errors in terms of goodness of fit. A straightforward method to recover \( b \) and \( c \) involves predicted values of arithmetic and quadratic mean diameters (\( \hat{D}_m \) and \( \hat{D}_g \), respectively). A possible problem is that \( \hat{D}_g \) might be too close to or too far from \( \hat{D}_m \) and can even be smaller than \( \hat{D}_m \) if not properly constrained. Based on our experience with this data set and other data sets, we found that the resulting Weibull parameters are sensitive to the difference between \( \hat{D}_m \) and \( \hat{D}_g \) and therefore might result in unstable estimation of \( b \) and \( c \). An alternative method is to use the predicted arithmetic mean diameter \( (\hat{D}_m \) and diameter variance \( (\hat{D}_\text{var} \) instead of \( \hat{D}_m \) and \( \hat{D}_g \) (Dieguez-Aranda et al. 2006, Qin et al. 2007). The Weibull parameters \( b \) and \( c \) are solutions of the system

\[
 b = (\hat{D}_m + v - a)\Gamma_1 \\
 (\hat{D}_\text{var} + v^2) - b^2\Gamma_1 = 0, \\
 c = \Gamma_1 (1 + 1/c) = \Gamma_1 (1 + 2/c), \\
 (\text{Q}) \\
 b = \hat{D}_g + 2ab\Gamma_1 + a^2, \\
 c = (\pi/40000)(\hat{N} + q)(\hat{D}_g + q). \\
 (6)
\]

**Forecast Combination**

Yue et al. (2008) applied the forecast combination method to combine stand-level and tree-level models. Likewise, predicted stand basal area for our study can be combined from three different models,

\[
 B^C = w_1B^T + w_2B^S + w_3B^D, \\
 (7)
\]

where \( B^C \) is the combined estimator of stand basal area, \( B^T \) is the estimate of stand basal area from the individual-tree model, \( B^S \) is the estimate of stand basal area from the stand-level model, \( B^D \) is the estimate of stand basal area from the diameter-distribution model, and \( w_1, w_2, \) and \( w_3 \) are weight coefficients, with \( w_1 + w_2 + w_3 = 1 \).

Yue et al. (2008) used the variance-covariance method to calculate weight coefficients for the stand basal area combined model. Theoretically, the best weight coefficients can be obtained on the basis of this approach. However, the weights are often unstable in practice, and thus this method has limitations (Zhang et al. 2006). The optimal weight method, which is the ordinary least-squares estimate of the weights, is an alternative method for solving quadratic programming problems and it yields unbiased combining forecasts (Tang 1992, 1994). We used the optimal weight method in this study to calculate the weight coefficients of the combined stand basal area. The objective was to minimize

\[
 Z = \sum_{i=1}^{n} [B_i - (w_1B^T_i + w_2B^S_i + w_3B^D_i)]^2, \\
 (8)
\]
subject to the constraint,

\[ w_1 + w_2 + w_3 = 1, \tag{9} \]

where \( B_i \) is stand basal area of plot \( i \) and \( B^k_i \) is stand basal area of plot \( i \) predicted from method \( k \).

Equations 8 and 9 can be written in matrix notation as

\[
\text{minimize } Z = W^T E W \quad \text{subject to } R^T W = 1, \tag{10}
\]

where \( W = (w_1 + w_2 + w_3)^T \), \( R = (1, 1, 1)^T \),

\[
E = \begin{pmatrix} e_1^T \\ e_2^T \\ e_3^T \end{pmatrix} = \begin{pmatrix} e_1^T e_1 \\ e_2^T e_2 \\ e_3^T e_3 \end{pmatrix},
\]

\( e_k = (e_{k1}, e_{k2}, \ldots, e_{kn}), e_{ki} \) is the forecast error of observation \( i \) from method \( k \), and \( n \) is numbers of plots.

Function 10 can be written as

\[
Z = W^T E W + \lambda(R^T W - 1), \tag{11}
\]

where \( \lambda \) is a Lagrangian multiplier. By taking the first partial derivative of \( Z \) with respect to \( W \) and setting it equal to 0, the optimum weight is obtained,

\[
W = E^{-1} R R^T E^{-1} R. \tag{12}
\]

The optimum weights can be computed by use of the Forstat statistical package (Tang et al. 2009) or a spreadsheet with matrix capabilities such as Microsoft Excel.

### Model Evaluation

Performance of the three growth models and the combined estimator was evaluated based on the fit and validation data sets. The following evaluation statistics were calculated:

**Mean Difference:**

\[
\text{MD} = \frac{1}{n} \sum (y_i - \hat{y}_i)
\]

**Mean Absolute Difference:**

\[
\text{MAD} = \frac{1}{n} \sum |y_i - \hat{y}_i|
\]

**R-square:**

\[
R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}
\]

where \( y_i \) is observed value at age \( A_{t+q} \) of stand variables (stand basal area, arithmetic mean diameter, diameter SD, minimum diameter, and stand survival) or tree variables (diameter and survival probability of tree \( i \)). \( \hat{y}_i \) and \( \bar{y} \) are predicted value and average, respectively, of \( y_i \) and \( n \) is number of observations.

### Results and Discussion

The estimates and standard errors of parameters of the different growth models are presented in Table 4. All of the parameters were significant (\( P < 0.0001 \)). Equation 12 was used to calculate the weight coefficients of the basal area.

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fit data (n = 106)</th>
<th>Validation data (n = 50)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>Age (years)</td>
<td>11</td>
<td>55</td>
</tr>
<tr>
<td>Dominant height (m)</td>
<td>0.4</td>
<td>17.4</td>
</tr>
<tr>
<td>Stand survival (trees ha(^{-1}))</td>
<td>254</td>
<td>2,284</td>
</tr>
<tr>
<td>Stand basal area (m(^2) ha(^{-1}))</td>
<td>0.80</td>
<td>33.10</td>
</tr>
<tr>
<td>dbh (cm)</td>
<td>5</td>
<td>36.8</td>
</tr>
</tbody>
</table>

**Table 3. List of recursive stand-level and tree-level growth equations at year \((t + j), j = 1, 2, \ldots, q\), where \( q \) is length of growth period in years**

**Stand-level**

\[ H_{t+q} = \exp((A_{t+q} - A_{t+q})(A_{t+q} + A_{t+q})(A_{t+q} - A_{t+q})) + (A_{t+q} - A_{t+q})(A_{t+q} - A_{t+q})(A_{t+q} - A_{t+q}) \]

**Tree-level:**

\[ D_{i,t+q} = D_{i,t+q} + \exp(\lambda_i + \lambda_j + \lambda_k + \lambda_t + \lambda_s)/\ln(D_{i,t+q} + \lambda_s) \]

**where** \( R_{i,t+q} = ((10.000/R_i) + 1)/H_{i,t+q} \), the relative spacing at age \( A_{i,t+q} \); \( H_{i,t+q} \) = dominant height in m at age \( A_{i,t+q} \); \( N_{i,t+q} \) = number of trees ha\(^{-1}\) at age \( A_{i,t+q} \); \( D_{i,t+q} \) = arithmetic mean diameter in cm at age \( A_{i,t+q} \); \( B_{i,t+q} \) = stand basal area in m\(^2\) ha\(^{-1}\) at age \( A_{i,t+q} \); \( D_{i,t+q} \) = diameter standard deviation in cm at age \( A_{i,t+q} \); \( D_{i,t+q} \) = minimum diameter in cm at age \( A_{i,t+q} \); \( D_{i,t+q} \) = diameter of tree \( i \) at age \( A_{i,t+q} \); \( A_{i,t+q} \) = probability that tree \( i \) is survived the period from age \( A_{i,t+q} \) to \( A_{i,t+q} \), and \( \alpha_1, \alpha_2, \ldots, \alpha_4 \) = parameters to be estimated.
on both fit and validation data. The combined estimator was
ter-distribution models in predicting stand basal area, based
method was slightly better than the stand-level and diame-
basal area for different models for the validation data.

Table 5. Evaluation statistics from the forecast combination method and from models having three levels of resolution

<table>
<thead>
<tr>
<th>Attribute Parameter</th>
<th>Estimate</th>
<th>SE</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant height (m)</td>
<td>α₁</td>
<td>4.0944</td>
<td>0.0889</td>
</tr>
<tr>
<td></td>
<td>α₂</td>
<td>-19.6596</td>
<td>1.4176</td>
</tr>
<tr>
<td></td>
<td>α₃</td>
<td>-0.0955</td>
<td>0.0061</td>
</tr>
<tr>
<td>Stand basal area (m² ha⁻¹)</td>
<td>ϕ₁</td>
<td>7.3429</td>
<td>0.1844</td>
</tr>
<tr>
<td></td>
<td>ϕ₂</td>
<td>0.0303</td>
<td>0.0033</td>
</tr>
<tr>
<td></td>
<td>ϕ₃</td>
<td>-25.0852</td>
<td>1.3085</td>
</tr>
<tr>
<td>Arithmetic mean diameter (cm)</td>
<td>δ₁</td>
<td>3.1948</td>
<td>0.0567</td>
</tr>
<tr>
<td></td>
<td>δ₂</td>
<td>-12.2948</td>
<td>0.3531</td>
</tr>
<tr>
<td></td>
<td>δ₃</td>
<td>1.6756</td>
<td>0.3796</td>
</tr>
<tr>
<td></td>
<td>δ₄</td>
<td>0.0340</td>
<td>0.0081</td>
</tr>
<tr>
<td>Diameter SD (cm)</td>
<td>γ₁</td>
<td>1.4832</td>
<td>0.0989</td>
</tr>
<tr>
<td></td>
<td>γ₂</td>
<td>0.5026</td>
<td>0.0186</td>
</tr>
<tr>
<td></td>
<td>γ₃</td>
<td>-0.0858</td>
<td>0.0140</td>
</tr>
<tr>
<td>Minimum diameter (cm)</td>
<td>κ₁</td>
<td>1.6716</td>
<td>0.1110</td>
</tr>
<tr>
<td></td>
<td>κ₂</td>
<td>-10.6887</td>
<td>0.6792</td>
</tr>
<tr>
<td></td>
<td>κ₃</td>
<td>5.4953</td>
<td>0.7982</td>
</tr>
<tr>
<td>Stand survival (trees ha⁻¹)</td>
<td>β₁</td>
<td>2.0224</td>
<td>0.1740</td>
</tr>
<tr>
<td></td>
<td>β₂</td>
<td>21.0962</td>
<td>0.6869</td>
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<tr>
<td></td>
<td>β₃</td>
<td>0.6388</td>
<td>0.0230</td>
</tr>
<tr>
<td>Diameter growth (cm)</td>
<td>λ₁</td>
<td>15.5015</td>
<td>0.8853</td>
</tr>
<tr>
<td></td>
<td>λ₂</td>
<td>-16.6289</td>
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</tr>
<tr>
<td></td>
<td>λ₃</td>
<td>-0.0351</td>
<td>0.0030</td>
</tr>
<tr>
<td></td>
<td>λ₄</td>
<td>0.1522</td>
<td>0.0165</td>
</tr>
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<td>-1.4820</td>
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<td></td>
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<td>0.9450</td>
<td>0.1604</td>
</tr>
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* Log likelihood: \[-2 \ln L = -2 (\sum P_i \ln(P_i) + \sum(1 - P_i) \ln(1 - P_i))\].

combined estimator from the fit data and yielded the follow-
ing weight values: \(w_1 = 0.4369, w_2 = 0.1784\), and \(w_3 = 0.3848\). These weight values were then used in Equation 7
to compute the combined basal area estimators for both fit
and validation data sets.

Table 5 shows evaluation statistics from the combined estimator and the three different types of models. For the
validation data, the mean difference for the combined estimator was \(-0.0478\), compared with \(0.0811, -0.2885\), and
\(-0.0827\) for the tree-level, stand-level, and diameter-distri-
bution models, respectively, the mean absolute difference
was 0.2661 versus 0.0811, \(0.0827\), and \(0.0027\) for the tree-
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results showed that the forecast combination method was
slightly better than the stand-level and diameter-
distribution models in predicting stand basal area, based
on both fit and validation data. The combined estimator was
the most accurate (mean difference) compared with the
other single models but only second best in precision (mean
absolute difference) next to the tree-level model. Finally,
the combined estimator ranked first in R², a common sta-
tistic for measuring goodness-of-fit in regression models.

The optimal weights of the combined estimator were
determined in the study by use of the method employed by
other researchers (Tang 1994, Li et al. 2008). The objective
of this method is to minimize the sum of squares of errors.
That explains why the combined estimator exhibited the
highest R² values for the fit data, because R² is a function of
the sum of squares of errors. Even though the weights were
computed from the fit data, the combined estimator still
produced the best R² value for the validation data compared
with the three single models. We need to note that because
mean square error is expressed as the sum of variance and
the square of bias, a high R² value can be interpreted as

Table 4. Parameter estimates and model evaluation

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</table>

* Log likelihood: \[-2 \ln L = -2 (\sum P_i \ln(P_i) + \sum(1 - P_i) \ln(1 - P_i))\].

Mean difference 0.2661 0.0811 0.0159 0.2885 -0.0285 -0.2211 -0.0827 0.0027 -0.0478
Mean absolute difference 1.1689 1.0312 1.1769 1.1213 1.2693 1.1539 1.1787 1.0698
R² 0.9255 0.9486 0.9282 0.9494 0.9244 0.9466 0.9298 0.9507

Value in bold denotes the best statistic among four models for each of the fit and validation data sets.
into three types: whole-stand, individual-tree, and diameter-distribution models (Munro 1974). Each type has various degrees of success in predicting stand attributes such as basal area per unit area. It makes sense therefore to combine these separate predictions into a single weighted average. The method can be considered an extension of the work by Yue et al. (2008), who combined only tree-level and stand-level models. Another difference was that the work of Yue et al. (2008) minimized the variance of the combined estimator, whereas the sum of squares of error in terms of stand basal area was minimized in this study. The combined estimator provided a consistent prediction of stand basal area at various levels of resolution, thus improving compatibility among these models.

Conclusions

In this study, forecast combination was used to predict stand basal area by combining three different estimators from models having different levels of resolutions. The forecast combination method efficiently uses information generated from different models to improve predictions by reducing errors from a single model. By dealing with inconsistent stand basal area estimates from models with different levels of resolutions, the method provides a feasible integrated system of stand basal area growth models.

Literature Cited


