

NOTE / NOTE

Effects of height imputation strategies on stand volume estimation

Sean M. Garber, H. Temesgen, Vicente J. Monleon, and David W. Harm

Abstract: Subsampling and subsequent imputation of tree heights can improve the predictive performance of stand volume estimation but may also introduce biases. Using coastal Douglas-fir data from southwest Oregon, USA, the predictive performance of several height imputation strategies for estimating stand volume was evaluated. A subsample of 1-15 trees was randomly selected per stand, and missing heights were imputed using a regional Chapman-Richards function with diameter only and diameter plus stand density measures, fitted using a nonlinear least-squares model (NFEM) and a nonlinear mixed-effects model (NMEM). Missing heights were imputed using the regional height-diameter equation and by adjusting the equation with a correction factor (NFEM) or with predicted random effects (NMEM) to calibrate the height-diameter relationship to each stand. Differences in actual stand volumes, calculated with measured heights, and predicted stand volumes, calculated using measured heights for the subsampled trees and predicted heights for those with missing heights, were used to compare the alternative height imputation methods. Precision and bias were poorest for the regional models, especially NMEM, and best for the adjusted models also using NMEM. Results suggest that a similar subsample of heights ($n = 4$) is required for precise stand volume estimation as has been reported for height.

Resume: Le sous-échantillonnage et l'imputation subséquente de la hauteur des arbres peut améliorer la performance prévisionnelle de l'estimation du volume d'un peuplement, mais peut aussi introduire des biais. À l'aide de données sur le douglas de Menzies du sud-ouest de l'Oregon (Etats-Unis), nous avons évalué la performance prévisionnelle de plusieurs stratégies d'imputation de la hauteur pour estimer le volume des peuplements. Un sous-échantillon de un à 15 arbres a été sélectionné aléatoirement pour chaque peuplement et les hauteurs manquantes ont été imputées en utilisant une fonction régionale de Chapman-Richards basée soit sur des mesures de diamètre seules soit sur des mesures de diamètre et de densité du peuplement. Cette fonction a été ajustée à l'aide des moindres carrés non linéaires (NFEM) et d'effets mixtes non linéaires (NMEM). Les hauteurs manquantes ont été imputées en utilisant l'équation régionale hauteur-diamètre qui a été ajustée avec un facteur de correction (NFEM) ou avec des effets aléatoires de prévision (NMEM) pour étalonner la relation hauteur-diamètre de chaque peuplement. Pour comparer ces méthodes d'imputation de la hauteur, nous avons utilisé les différences de volume de peuplement entre les valeurs réelles, calculées à partir des hauteurs mesurées, et les valeurs prédites, calculées à partir des hauteurs mesurées du sous-échantillon d'arbres et des hauteurs prédites pour les arbres dont la hauteur était manquante. Les moins bonnes valeurs de précision et de biais ont été obtenues avec les modèles régionaux, particulièrement NMEM, alors que les meilleures valeurs ont été obtenues avec les modèles qui utilisaient aussi NMEM. Les résultats indiquent qu'un sous-échantillon similaire de hauteur ($n = 4$) est requis pour une estimation précise du volume d'un peuplement comme il a déjà été rapporté pour la hauteur.

[Traduit par la Rédaction]

Introduction

Imputation of values for selected tree- and stand-level attributes is a necessary component of forest inventory. The estimation of tree and stand volumes generally requires an estimate of tree height. Likewise, individual tree growth

models require an estimation of height for each tree in the tree list. For stands without height measurements, the common practice is to impute tree heights using regional equations, which are a function of diameter (Curtis 1967; Wykoff et al. 1982; Huang et al. 1992; Lappi 1997; Temesgen et al. 2007) and perhaps of other tree or stand variables (Curtis

Received 8 August 2008. Accepted 21 November 2008. Published on the NRC Research Press Web site at cjfr.nrc.ca on 14 February 2009.

S.M. Garber,¹ H. Temesgen, and D.W. Hann. Department of Forest Engineering, Resources, and Management. Oregon State University, Corvallis, OR 97331-5703, USA.

V.J. Monleon. Forest Inventory and Analysis, Pacific Northwest Research Station, USDA Forest Service, 620 SW Main Street, Suite 400, Portland, OR 97205, USA.

¹Corresponding author (e-mail: sean.garber@oregonstate.edu).

1967; Larsen and Harm 1987; Hanus et al. 1999; Temesgen and von Gadow 2004; Temesgen et al. 2007). Often heights are sampled in the field using a double sampling approach where a subset of sample trees is also measured for height. This subsample can be used to develop local height-diameter equations; however, adequate subsample sizes tend to be fairly high (Houghton and Gregoire 1993). Likewise, subsampled heights can be used to calibrate an existing regional equation for a stand, using a ratio estimator or a correction factor (Temesgen et al. 2008). This is the dominant technique used in current inventory programs and growth models (e.g., Harm 2006).

Regional height equations are estimated using either linear or nonlinear fitting techniques, such as least squares, that often do not account for the hierarchical nature of the data (i.e., trees within plots within stands). That is, the observed trees are assumed to be independent and the parameters of the equation are assumed to be fixed. It follows that these parameter estimates also provide unbiased height predictions for a new sample of trees from the same population. However, they do not necessarily give the most precise (lower variance) height predictions (Temesgen et al. 2008) because of the nature of height subsampling. It is likely that trees within a given stand are more similar than trees from different stands. Moreover, the assumption that the parameters are fixed, meaning that they take the same value in all stands, may not hold if there are subtle differences among stands. More recently, modeling techniques have been utilized in forestry that account for this hierarchical data structure. Instead of fitting the models with the assumption that the parameters are fixed, random effect fitting techniques allow one or more parameters to vary by some hierarchical grouping variable (e.g., by stand). To date, these so-called mixed-effects models have been used to fit models for a number of forestry applications (Biging 1985; Gregoire et al. 1995; Garber and Maguire 2003; Weiskittel et al. 2007), including height imputation equations (Calama and Montero 2004; Castedo et al. 2006; Temesgen et al. 2008).

Despite the attractive nature of mixed-effects models, problems have surfaced with regard to the use of these equations for predicting and imputing missing values in a new stand (i.e., a stand that is not a member of the original modeling data set). Several studies have found the poorest prediction performance (bias and variance) using nonlinear mixed-effects models (NMEM) (Monleon 2003; Robinson and Wykoff 2004; Temesgen et al. 2008). Since the random effect for a new stand is not known, the fixed-effect portion of the model is the only part used for prediction (the random effect is assumed to be zero). Unlike ordinary least squares or linear mixed-effects models, predictions from NMEMs are biased when the random effect is nonlinear in its parameterization and assumed to be zero. Techniques are available for estimating the random effect by using a best linear unbiased predictor (BLUP) (Goldberger 1962; Temesgen et al. 2008) and a subsample of tree heights in the new stand. A number of studies have reported the prediction performance from these models to be superior to that of other techniques (Monleon 2003; Robinson and Wykoff 2004; Temesgen et al. 2008). Moreover, a large subsample of heights is not required (Temesgen et al. 2008).

Despite the superior height prediction of NMEMs when the random effect is predicted, tree heights are generally not an end unto themselves but rather a means to some other end, such as the estimation of tree and stand volume. Relative performance of the alternative height imputation techniques does not necessarily translate for stand volume, since they are optimized for height prediction. Therefore, the primary objective of this study was to evaluate several height imputation techniques on stand volume prediction. Specifically, two model forms found to be superior by Temesgen et al. (2007) and assessed for height prediction by Temesgen et al. (2008) were compared for their ability to predict stand volume using the following four strategies: (i) nonlinear fixed-effects models (NFEM) were fit to a regional data set using least-squares regression and then applied to a new stand without a correction factor, (ii) NMEMs were fit to a regional data set and then applied to a new stand without calculating the BLUP, (iii) NFEMs were fit to a regional data set and then applied to a new stand with a correction factor based on subsampled heights, and (iv) NMEMs were fit to a regional data set and then applied to a new stand with the BLUP calculated using the subsampled heights.

Methods

Data

The data were collected in two studies associated with the development of southwestern Oregon variant of the ORGANON growth model (SWO-ORGANON) (Hann 2006). The first set of data was collected during 1981, 1982, and 1983 as part of the southwest Oregon Forestry Intensified Research Growth and Yield Project. This study included 391 plots in an area extending from near the California border (42°10'N) in the south to Cow creek (43°00'N) in the north, and from the Cascade crest (122°15'W) on the east to approximately 15 miles (1 mile = 1.609 344 km) west of Glendale (123°50'W). Elevation of the sample plots ranged from 250 to 1600 m. Selection was limited to stands under 120 years of age and with 80% basal area in conifer species. The second study covered approximately the same area but extended the selection criteria to include stands with trees over 250 years in age and to younger stands with a greater component of hardwoods. An additional 138 plots were measured in this second study. Stands treated in the previous 5 years were not sampled in either study.

In both studies, each stand was sampled with 4-25 sample points spaced 45.73 m apart. The sampling grid was established in a manner such that all sample points were at least 30.5 m from the edge of the stand. At each sample point, trees were sampled with a nested plot design composed of four subplots: (i) trees with ≤ 10.2 cm diameter at breast height (d) were selected on a circular subplot with a fixed 2.37 m radius, (ii) trees with 10.3-20.3 cm d were selected on a circular subplot with a fixed 4.74 m radius, (iii) trees with 20.4-91.4 cm d were selected on a 4.592 basal area factor (BAF) variable radius subplot, and (iv) trees with >91.4 cm d were selected on a 13.776 BAF variable radius subplot.

Measurements of total tree height (h) and d were taken on all sample trees. Diameter was measured to the nearest 0.25 cm, rounded down, with a diameter tape. Height was

measured either directly with a 7.6-13.7 m telescoping fiber glass pole or, for taller trees, indirectly using the pole-tangent method (Larsen and Hann 1987) and was recorded to the nearest 0.03 m. For trees with broken or dead tops, *h* was measured to the top of the live crown. All trees were assessed for type and severity of damage. Time since last cutting was determined on all previously treated plots.

A total of 30 tree species was found on 529 plots. The number of species found on a single plot ranged from 1 to 12 and averaged almost five species. Coastal Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) was the most common species, found on 339 plots, and was the focus of this study. From each untreated plot, height and diameter of undamaged trees were extracted to evaluate selected height prediction strategies on stand volume estimation. Since one of the main objectives of this study was to evaluate the predictive performance of the models as a function of the number heights subsampled from the stand, only stands with at least 25 coastal Douglas-fir sample trees were included. This resulted in a total of 4948 trees on 142 plots. The data set covered a wide array of stand densities with the basal area (BA) ranging from 8.1 to 101 m²·ha⁻¹, the crown competition factor (Krajicek et al. 1961) ranging from 112.2% to 490.4%, *d* ranging from 0.3 to 178.9 cm, and *h* ranging from 1.4 to 62.1 m (Table 1).

Models and prediction strategies

In this paper, we examined four model-based strategies. While the first two strategies fill in the missing height using preestablished coefficients, the last two strategies fill in the missing height by using the subsample tree data to adjust the height-diameter equations.

Strategy 1-NFEMs without correction

Two Chapman-Richards based model forms found to be superior model forms in fit statistics (Temesgen et al. 2007), a base model that was a function of *d* only (eq. 1) and an enhanced model that was a function of *d* and additional tree and stand variables (eq. 2) were fitted by nonlinear least squares and thus are NFEMs.

$$[1] \quad h_{ij} = 1.37 + \beta_0(1 - e^{\beta_1 d_{ij}})^{\beta_2} + \varepsilon_{ij}$$

$$[2] \quad h_{ij} = 1.37 + (\beta_{00} + \beta_{01} \text{CCFL}_{ij} + \beta_{02} \text{BA}_i)(1 - e^{\beta_1 d_{ij}})^{\beta_2} + \varepsilon_{ij}$$

where $\beta_0, \beta_{00}, \beta_{01}, \beta_{02}, \beta_1,$ and β_2 are the parameters to be estimated by the data; d_{ij} is the diameter at breast height of tree *j* in stand *i*; h_{ij} is the height of tree *J* in stand *i*; CCFL_{*ij*} is the crown competition factor in trees of larger than *d_{ij}* for tree *j* in stand *i*; BA_{*i*} is the basal area of stand *i*; and ε_{ij} is an error term assumed to independent between observations and $N(0, \sigma_\varepsilon^2)$. Equation 2 was motivated by the assumption that the height-diameter relationship depends on tree position within the stand and stand density. CCFL was calculated by summing the maximum crown area of all trees in the stand with a *d* greater than that of the subject tree. Maximum crown areas were calculated using the maximum crown width equations of Paine and Hann (1982).

Table 1. Summary of tree- and stand-level attributes used in the study.

	Min.	Mean	Max.	SD
Tree level				
Diameter (cm)	0.3	35.7	178.9	21.5
Height (m)	1.4	25.9	62.1	11.9
Crown competition factor in larger trees (%)	0.0	112.4	485.6	79.1
Volume (m ³)	0.01	1.73	44.73	2.45
Stand level				
Basal area (m ² ·ha ⁻¹)	8.1	51.4	101.0	15.8
Crown competition factor (%)	112.2	277.1	490.4	65.9
Site index (m)	12.6	29.9	43.5	5.6
Volume (m ³ ·ha ⁻¹)	16.8	313.5	1107.8	188.7

Note: The number of trees used in the study was 4948 on 142 stands.

Strategy 2-NMEMs without BLUP

Since eqs. 1 and 2 do not account for the hierarchical structure of the data, these same model forms were also refitted to incorporate a random asymptote that varies by stand.

$$[3] \quad h_{ij} = 1.37 + (\beta_0 + b_i)(1 - e^{\beta_1 d_{ij}})^{\beta_2} + \varepsilon_{ij}$$

$$[4] \quad h_{ij} = 1.37 + (\beta_{00} + \beta_{01} \text{CCFL}_{ij} + \beta_{02} \text{BA}_i + b_i)(1 - e^{\beta_1 d_{ij}})^{\beta_2} + \varepsilon_{ij}$$

where b_i is the random effects for the *i*th stand and is assumed to be independent among stands and distributed $N(0, \sigma_{b_i})$; all other variables are defined above.

Strategy 3-NFEMs with correction

A subsample of *h* collected from a new stand (*m*) can be used to calculate stand-level correction factors to adjust eqs. 1 and 2 for imputation. The technique described by Draper and Smith (1998, p. 225) and implemented by Temesgen et al, (2008) was used in this study.

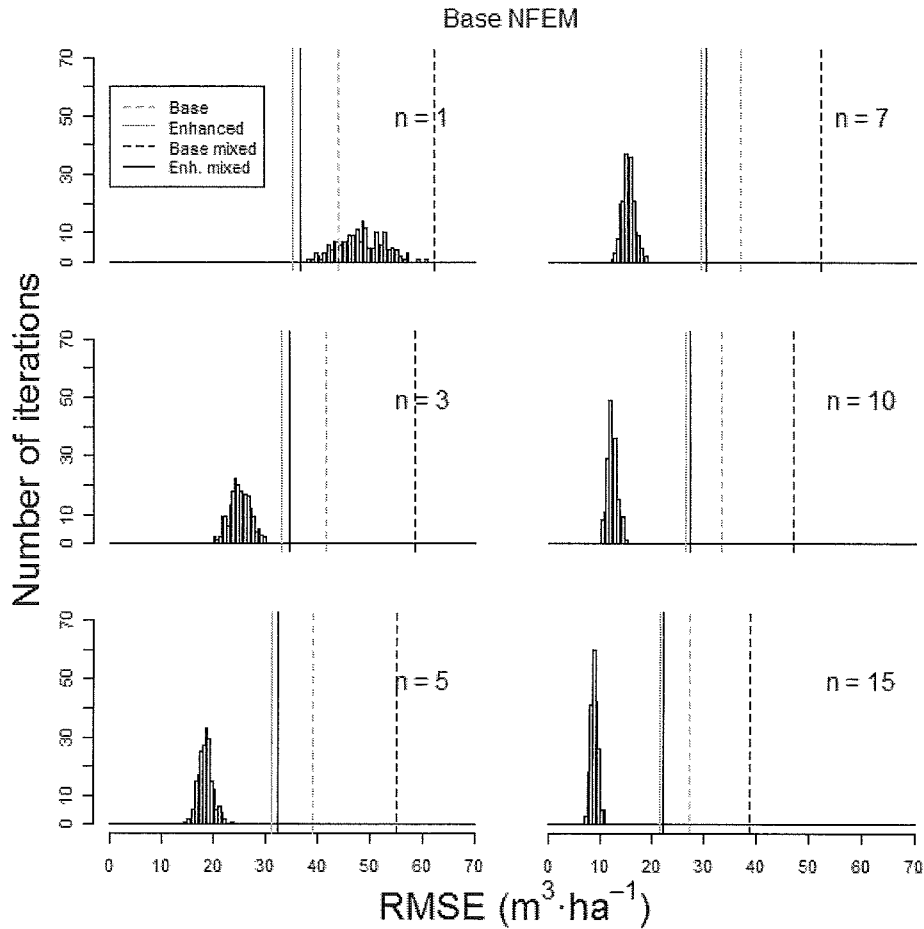
Suppose again that the *h* of a subsample of n_m trees from a new stand is known. Let \mathbf{h}_m and \mathbf{X}_m be the *h* and matrices of covariates from those trees. Then, the *h* of another tree from the same stand can be adjusted with the following ordinary least-squares correction factor on the regional hand *d* equations (Draper and Smith 1998, p. 225):

$$k_m^* = \frac{\sum_{j=1}^{n_m} [(\hat{h}_{mj} - 1.37)(h_{mj} - 1.37)]}{\sum_{j=1}^{n_m} [(\hat{h}_{mj} - 1.37)^2]}$$

where \hat{h}_{mj} is the predicted *h* from eq. 1 or 2 and h_{mj} is the observed *h*. Then, the adjusted predicted *h* for a tree from the new stand can be calculated as

$$\hat{h}_{m_{new}} = 1.37 + k_m^* \hat{\beta}_0 (1 - e^{\hat{\beta}_1 d_{m_{new}}})^{\hat{\beta}_2}$$

Fig. 1. Frequency distribution of the root mean square error (RMSE) of the estimated stand volume after 200 simulations for the nonlinear least-squares model (NFEM) with a correction factor (strategy 3) base model. as a function of the number of randomly selected heights used to predict the random effect. For comparison, the RMSEs from the fits of Temesgen et al. (2008) to all trees for the following models are shown as vertical lines: the base NFEM without the correction factor (broken grey line), the enhanced NFEM without the correction factor (solid grey line), the base nonlinear mixed-effects model (NMEM) without a best linear unbiased predictor (BLUP) (broken black line), and the enhanced NMEM without a BLUP (solid black line). The base models include just diameter and the enhanced models include diameter, crown competition factor in larger trees, and stand basal area.



For the enhanced equation, the adjustment is

$$\hat{h}_{m_{new}} = 1.37 + k_m^* (\hat{\beta}_{00} + \hat{\beta}_{01} CCFL_{mj} + \hat{\beta}_{02} BA_m) (1 - e^{\hat{\beta}_1 d_{m_{new}}})^{\hat{\beta}_2}$$

Strategy 4-NMEMs with BLUP

For a new stand, the random effects were approximated using a BLUP (Goldberger 1962). The closed-form BLUP for a single random effect presented by Temesgen et al. (2008, p. 557) was used in this study.

$$\hat{b}_m = \hat{\sigma}_b^2 \hat{Z}'_m (\hat{\sigma}_\epsilon^2 \mathbf{I}_m + \hat{\sigma}_b^2 \hat{Z}'_m \hat{Z}_m)^{-1} \times \begin{bmatrix} h_{m1} - 1.37 - \hat{\beta}_0 (1 - e^{\hat{\beta}_1 d_{m1}})^{\hat{\beta}_2} \\ \vdots \\ h_{mm} - 1.37 - \hat{\beta}_0 (1 - e^{\hat{\beta}_1 d_{mm}})^{\hat{\beta}_2} \end{bmatrix}$$

where β_m is the predicted random effect for stand m ; $\beta_0, \beta_1, \beta_2, O^2_b$ and O^2_ϵ ; are parameters estimated from the training data set; \mathbf{I}_m is the $n \times n$ identity matrix; and \mathbf{Z}_m is a vector of transformed co variates with the j th element defined as

$$\hat{z}_{mj} = (1 - e^{\hat{\beta}_1 d_{mj}})^{\hat{\beta}_2}$$

The h of a new tree from the m stand is predicted as

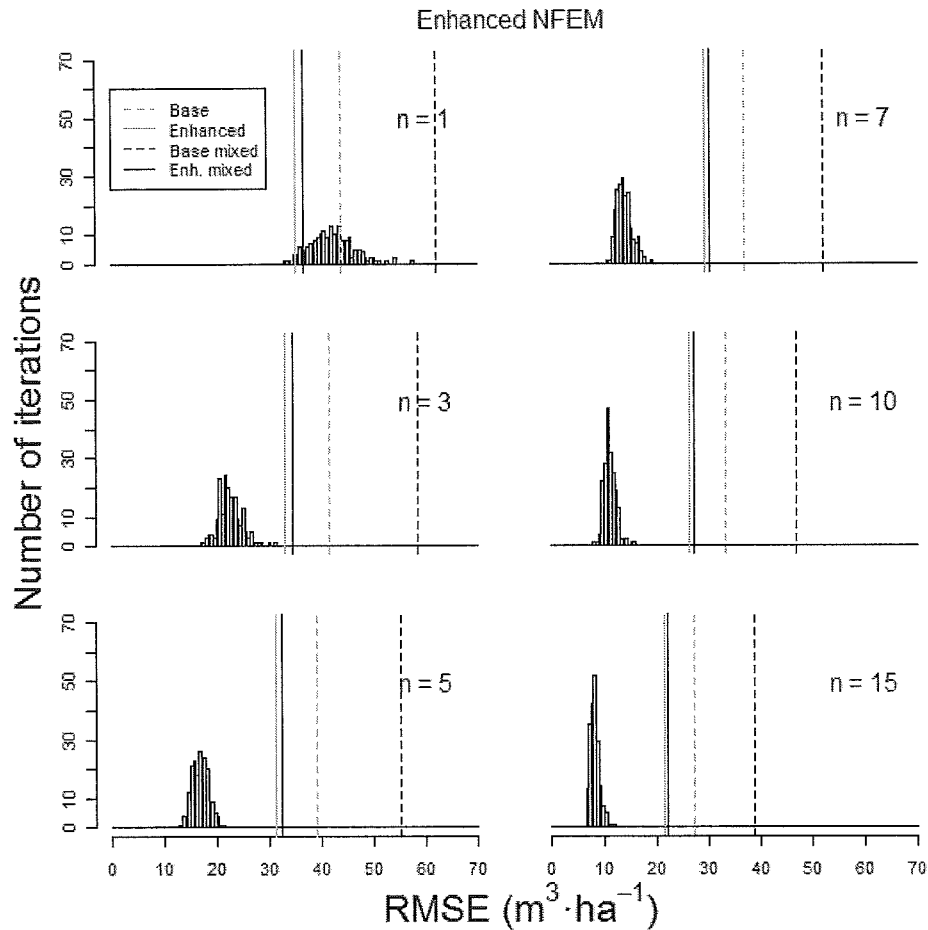
$$h_{m_{new}} = 1.37 + (\hat{\beta}_0 + \hat{b}_m) (1 - e^{\hat{\beta}_1 d_{m_{new}}})^{\hat{\beta}_2}$$

When relative position and stand density variables are included, the closed form will have the same form but with β_0 substituted by $\beta_{00} + \beta_{01} CCFL_{mj} + \beta_{02} BA_m$.

Simulation and prediction performance

The predictive performance of the different strategies was evaluated using the following steps for each of the 142 stands.

Fig. 2. Frequency distribution of the root mean square error (RMSE) of the estimated stand volume after 200 simulations for the nonlinear least-squares model (NFEM) with a correction factor (strategy 3) enhanced model, as a function of the number of randomly selected heights used to predict the random effect. For comparison, the RMSEs from the fits of Temesgen et al. (2008) to all trees for the following models are shown as vertical lines: the base NFEM without the correction factor (broken grey line), the enhanced NFEM without the correction factor (solid grey line), the base nonlinear mixed-effects model (NMEM) without a best linear unbiased predictor (BLUP) (broken black line), and the enhanced NMEM without a BLUP (solid black line). The base models include just diameter and the enhanced models include diameter, crown competition factor in larger trees, and stand basal area.

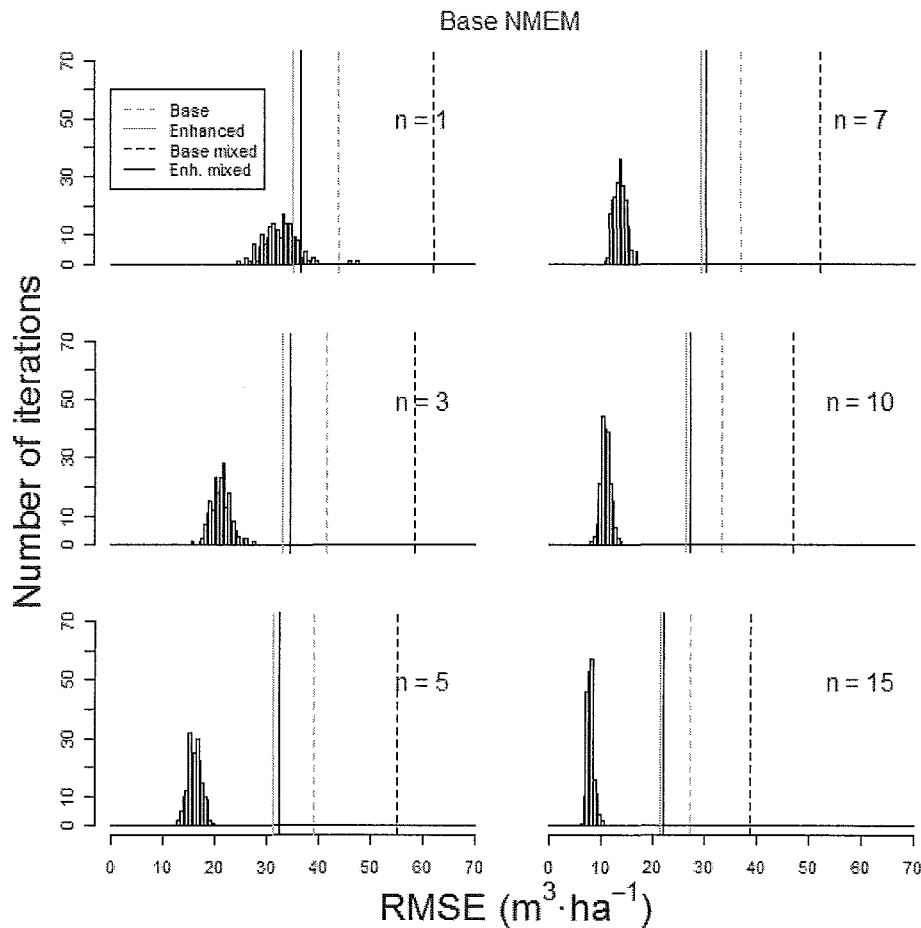


1. Starting with the first stand, parameters were estimated based on strategies 1–4 and by using the data from the remaining 141 stands, using the fitting procedures outlined above.
2. A subsample of 1–15 heights was selected from the stand of interest. The correction factor (strategy 3) and random stand effect (strategy 4) were calculated from this subsample. Since we did not correct for the different inclusion probabilities associated with the use of nested fixed and variable radius subplots, the random-subsampling approach we used will tend to include larger trees from the stand more frequently than smaller trees.
3. The height of the remaining trees in the selected stand was predicted and individual total tree volumes were calculated. The individual total tree volume equation without the crown ratio of Walters et al. (1985) was used in this study. This equation was constructed using many of the plots in this study. Actual tree volumes were estimated using the observed heights and were multiplied by their expansion factors and then summed across the

Douglas-fir trees in the stand to determine actual stand volume (V_j). The predicted stand volumes (\hat{V}_j) were calculated in the same fashion except the tree volumes were predicted using the predicted tree heights for trees not subsampled and the actual tree heights for trees that were subsampled. The prediction error ($V_i - \hat{V}_i$) was calculated for each stand.

4. The process was repeated for all stands to estimate the prediction RMSE and prediction bias. Note that the true volume of a tree was not known but was predicted from a volume equation. Therefore, in estimating the prediction error, RMSE, and bias, we are actually comparing the volume computed when tree heights are estimated with the volume computed when the true tree heights are known rather than with the actual volume. There would be an additional prediction error associated with use the volume equation. Gertner (1990) found a 6.76% prediction error when a regional volume function was used. The volume equation used in the study is the standard equation used in the region (Hann 2006). Since the

Fig. 3. Frequency distribution of the root mean square error (RMSE) of the estimated stand volume after 200 simulations for the nonlinear mixed-effects model (NMEM) (strategy 4) base model, as a function of the number of randomly selected heights used to predict the random effect. For comparison, the RMSEs from the fits of Temesgen et al. (2008) to all trees for the following models are shown as vertical lines: the base nonlinear least-squares model (NFEM) without the correction factor (broken grey line), the enhanced NFEM without the correction factor (solid grey line), the base NME1vl without a best linear unbiased predictor (BLUP) (broken black line), and the enhanced NMEM without a BLUP (solid black line). The base models include just diameter and the enhanced models include diameter, crown competition factor in larger trees, and stand basal area.



main interest is in predicting stand volume, estimates of the RMSE and bias were averaged over the 142 stands.

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (V_i - \hat{V}_i)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (V_i - \hat{V}_i)^2}$$

- The process was repeated 200 times with the prediction RMSE, and bias was calculated during each iteration. They were then averaged over the 200 iterations to calculate the mean RMSE and mean bias.

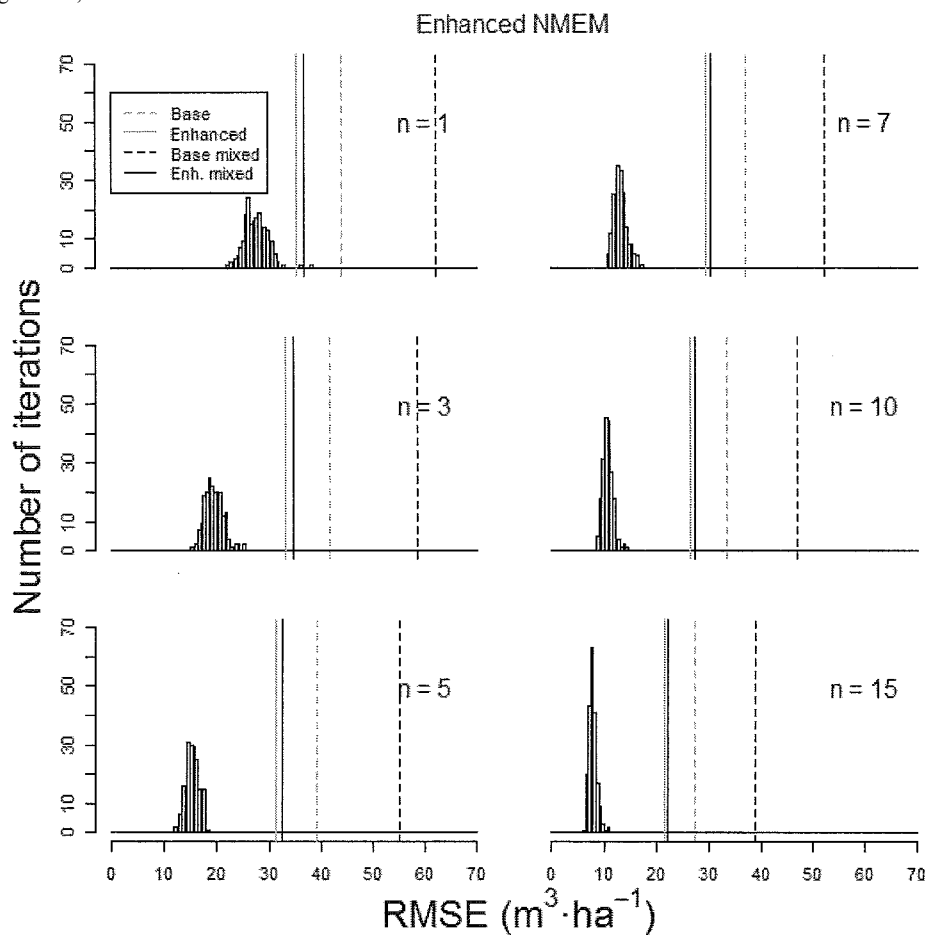
Results

The mean and variance of the distribution of the root mean square errors from the 200 iterations decreased with increasing sample size for the NFEM with correction factor (strategy 3) using the base (Fig. 1) and enhanced (Fig. 2)

models. The pattern was similar for the base (Fig. 3) and enhanced (Fig. 4) NMEM with a BLUP (strategy 4). A subsample of a single tree height resulted in a wide range of RMSE values, primarily ranging from 33 to 61 m³·ha⁻¹ for the base and enhanced NFEMs (Figs. 1 and 2). Large variation was also evident with the base and enhanced NME1vls, though both the RMSE average and range were much smaller (Figs. 3 and 4). For the corrected NFEMs, a subsample of three heights resulted in more than 95% of the RMSE values below the best uncorrected model (enhanced NFEM). A subsample size of only two trees (not shown) was sufficient to accomplish the same result for the NMEMs.

Mean RMSE was lower for the enhanced models fit with either NFEM or NMEM (Fig. 5). Likewise, mean RMSE was lower when subsampled heights were used to calculate an adjustment factor (NFEM) or a BLUP (NMEM). An increase in subsample size showed a large initial reduction in mean RMSE (Fig. 5). A random subsample of just one tree resulted in a lower mean RMSE for the base NMEM with a BLUP than either of the regional base models (Fig. 5(a). A

Fig. 4. Frequency distribution of the root mean square error (RMSE) of the estimated stand volume after 200 simulations for the nonlinear mixed-effects model (NMEM) (strategy 4) enhanced model, as a function of the number of randomly selected heights used to predict the random effect. For comparison, the RMSEs from the fits of Temesgen et al, (2008) to all trees for the following models are show as vertical lines: the base nonlinear least-squares model (NFEM) without the correction factor (broken grey line), the enhanced NFEM without the correction factor (solid grey line), the base NMEM without a best linear unbiased predictor (BLUP) (broken black line), and the enhanced NMEM without a BLUP (solid black line). The base models include just diameter and the enhanced models include diameter, crown competition factor in larger trees, and stand basal area.



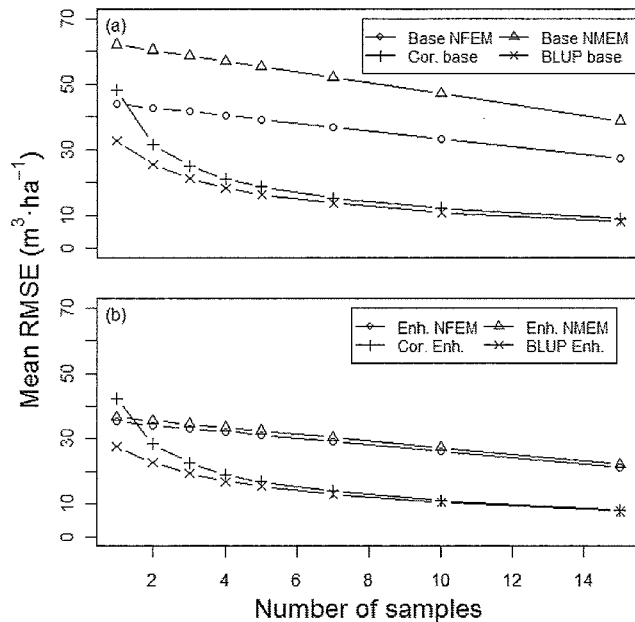
subsample size of two heights was necessary to accomplish the same result for the corrected NFEMs. As subsample size increased, the difference in the mean RMSE between the corrected base and enhanced NFEMs decreased, with the NMEM with a BLUP having greater mean precision than the NFEM with correction. However, the average RMSE for those two scenarios did not quite converge in the range of sample sizes assessed. Results were similar for the enhanced models, except regional enhanced models performed better than the regional base models (Fig. 5b). As with the base models, the enhanced NFEM with correction and NMEM with a BLUP mean precision increased with increasing subsample size, converging somewhere between seven and ten height subsamples.

A bias was evident for all strategies (Fig. 6). A positive bias (observed volume greater than predicted volume) was evident for all strategies and subsample sizes except the NFEM with correction at low subsample sizes. The NFEM regional base model had mean biases less than $4 \text{ m}^3 \cdot \text{ha}^{-1}$

and performed much better than the NMEM base model, which had mean biases greater than $20 \text{ m}^3 \cdot \text{ha}^{-1}$ (Fig. 6a). Using subsampled heights, either through strategies 3 or 4, improved mean bias for the NFEM and NMEM relative to the regional models. Mean bias improved with subsample size, leveling off near a subsample of four trees, though both models improved slightly as subsample size continued to increase. The enhanced models showed similar results, but the bias was smaller in magnitude (Fig. 6b). With a single subsampled height, the NFEM had the lowest mean bias. At larger subsample sizes, the NFEM with a correction factor and NMEM with a BLUP had smaller mean biases than the regional enhanced models. At low subsample sizes, NFEM with a correction factor had slightly less mean bias than the NMEM with a BLUP. Beyond a subsample size of seven, the two models were virtually indistinguishable.

Trends in bias averaged over the 200 iterations showed some small patterns as a function of stand variables. There were no obvious patterns with site index or crown competi-

Fig. 5. Mean root mean square error (RMSE) for the four prediction strategies as a function of the number of tree heights subsampled at random to predict the nonlinear least-squares model (NFEM) with a correction factor or nonlinear mixed effects model (NMEM) with a best linear unbiased predictor (BLUP) for the (a) base model and (b) enhanced model. For comparison, the NFEM without the correction factor and NMEM without a BLUP (b) are shown.



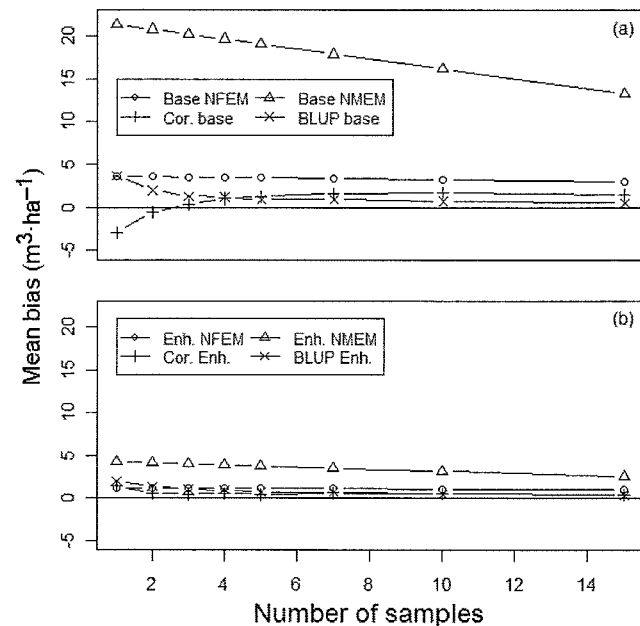
tion factor. Interestingly, there was a positive nonlinear trend in mean bias with stand basal area in the base NFEM and NMEM (Figs. 7a and 7c). This pattern disappeared with the correction factor and a BLUP, respectively (Figs. 7f and 7h).

Discussion

Without subsampling, the NFEM had greater precision and less bias than the NMEM models. In particular, the base NMEM's RMSE and bias were at least 40% and 400% higher, respectively, than any of the other strategies assessed. This result was not completely unexpected, as several studies have reported larger biases in height prediction using NMEM without BLUPs (Monleon 2003; Robinson and Wykoff 2004; Temesgen et al. 2008). Mean percentages of bias and RMSE in height prediction were approximately 3% and 16%, respectively, for NMEM without BLUPs in these stands (calculated from Temesgen et al. 2008). These numbers are well within the 40% the height estimation error tolerance for utilizing a height-based volume equation (Williams and Schreuder 2000), these translated into mean percentages of bias and RMSE of roughly 7% and 20%, respectively, in stand volume estimation.

The incorporation of additional tree and stand competition variables improved stand volume prediction bias and precision. The importance of these variables has been demonstrated in past studies for improving model fits (Ritchie and Hann 1987; Zumrawi and Hann 1989; Hann et al. 2003; Temesgen et al. 2007) and height prediction (Temesgen et al. 2008). Height has generally been considered to be less

Fig. 6. Mean bias for the four prediction strategies as a function of the number of heights subsampled at random to predict the NFEM with correction factor or the nonlinear mixed-effects model (NMEM) with a best linear unbiased predictor (BLUP) for the (a) base model and (b) enhanced model. For comparison, the NFEM without the correction factor and NMEM without a BLUP (b) are shown.



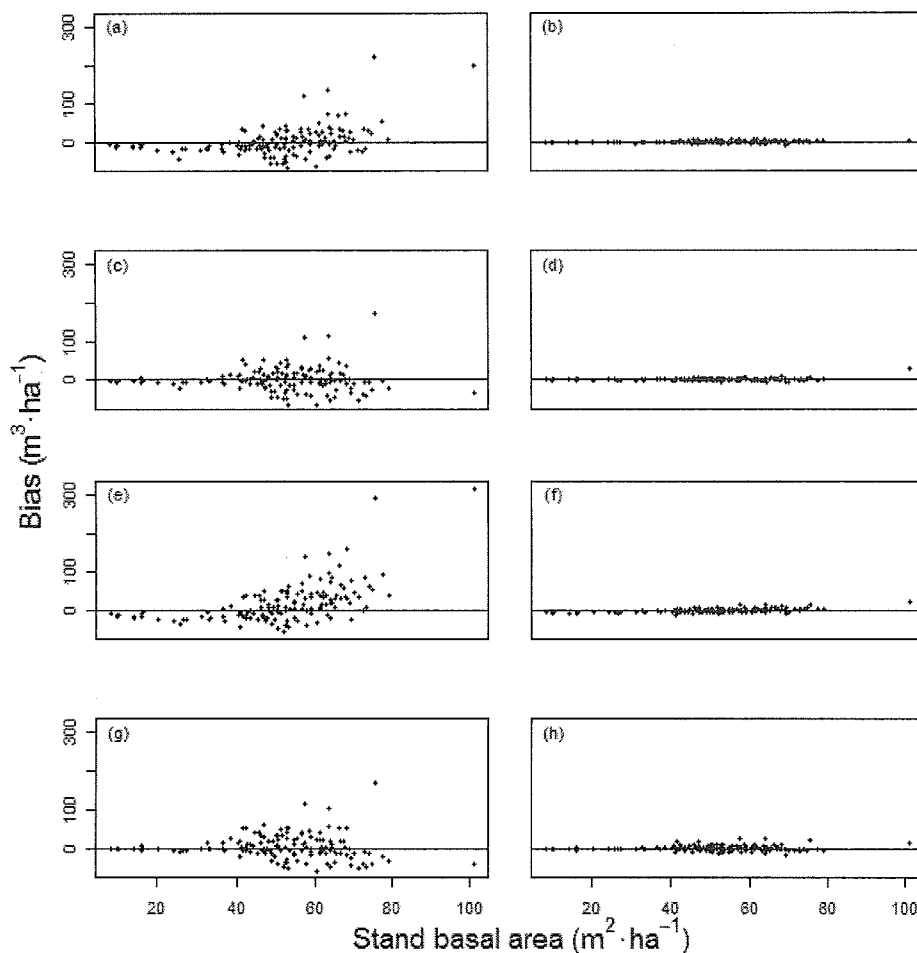
sensitive to density than diameter (Curtis and Marshall 2002). Moreover, tree position in the stand and stand density influence tree crown length and stem form and thus the height-diameter relationship (Larson 1963).

When tree heights were subsampled, the NMEMs (strategy 4) were superior or equal to NFEMs with a correction factor (strategy 3) at all subsample sizes, albeit the difference was negligible for large subsample sizes. Smaller subsample sizes were required to produce smaller RMSE and bias with the NMEM with a BLUP than with the NFEM with a correction factor. A similar result was observed in height prediction using a similar analysis with the same data set (Temesgen et al. 2008). The results presented here suggest that these results carry through to the estimation of stand volume.

Three sources of error have been observed in the estimation of stand volume from a stand inventory: error due to the sample trees selected (sampling error), error due to the volume equation (regression function error), and error associated with measuring the attribute of interest (measurement error) (Gertner 1990). As mentioned above, all attributes are rarely measured on all sample trees for the calculation of tree volume. Therefore, we have introduced two new sources of error: imputation error (error in missing height prediction strategies) and subsampling error (the error associated with the subsampled height trees) (Gregoire and Williams 1992).

Sampling and measurement errors were not addressed in this study and thus are not components of the results presented. Likewise, the regression error associated with the volume equation was not addressed because true tree vol-

Fig. 7. Bias averaged over the 200 simulations for a subsample size of five random tree heights over stand basal area for each of the 142 stands. (a) Base nonlinear least-squares model (NFEM) without the correction factor, (b) base NFEM with the correction factor, (c) enhanced NFEM without the correction factor, (d) enhanced NFEM with the correction factor, (e) base nonlinear mixed-effects model (NMEM) without a best linear unbiased predictor (BLUP), (f) base NMEM with a BLUP, (g) enhanced NMEM without a BLUP, (h) enhanced NMEM with a BLUP.



umes were unknown. Tree volumes calculated using the measured values of h were assumed to be the true tree volumes. Consequently, volume regression function error would not be a component of the results. Regardless, since these equations were developed using trees from these plots and produced very good fits to these data (Walters et al. 1985), the contribution of this error in practice would likely be relatively small (Gertner 1990).

The error associated with the height imputation function and the subsampling error on stand volume were the main focuses of this study. The magnitude of the bias and increased variability demonstrated the effect of error propagated between tree height prediction and stand volume estimation. From the standpoint of volume calculation, the error in tree height prediction is one form of measurement error (Monserud and Ek 1974). If these errors are assumed to have an expectation of zero, then the impact is comparable to sampling error and would likely decrease with increasing sample size of plots (Gertner 1990). However, if the expectation of the error is not zero, then the prediction error would likely be the dominant source of error and

would not decrease with sample size (Gertner 1990; Gregoire and Williams 1992). As previously demonstrated, bias exists to a varying degree during height imputation (Temesgen et al. 2008). The incorporation of stand variables reduces bias and improves precision in height prediction (Temesgen et al. 2008), thus resulting in better stand volume estimates. Likewise, subsampling heights and estimating an ordinary least-squares correction factor or the NMEM best linear unbiased predictor reduce bias and improve precision in height prediction (Temesgen et al. 2008), resulting in better stand volume estimates. These two approaches were comparable as they both utilize stand information to improve prediction. However, the relative error increases from the tree-level height predictions to the stand-level volume predictions because, although less bias still exists (i.e., the expectation of the error is not zero).

Conclusion and recommendations

Temesgen et al. (2008) recommended the use of NFEMs with stand and tree density variables for stands without a

subsample of heights and NMEMs with or without density variables for stands with a height subsample. The results of the present study underscore these recommendations. The use of NMEM is not recommended when a subsample of heights is not available because of extremely high bias and low precision when stand volume will be calculated after imputing tree heights. Results here suggest either approach is applicable when height subsamples are collected and tree and stand volume is of interest. In cases where there are very few tree heights subsampled, such as measurement of site trees for the estimation of site index, the NMEMs appear to have greater precision. Temesgen et al. (2008) recommended a subsample size of around four random trees or fewer if larger trees were subsampled. The results here suggest this number of trees is also adequate for stand volume calculation; however, there does not appear to be an appreciable gain if larger trees were preferentially subsampled.

References

- Biging, G.S. 1985. Improved estimates of site index curves using a varying-parameter model. *For. Sci.* 31: 248-259.
- Calama, R., and Montero, G. 2004. Interregional nonlinear height-diameter model with random coefficients for stone pine in Spain. *Can. J. For. Res.* 34: 150-163. doi:10.1139/x03-199.
- Castedo, F., Diequez-Aranda, M.B., Rodriguez, M.S., and von Gadow, K. 2006. A generalized height-diameter model including random components for radiata pine plantations in northwestern Spain. *For. Ecol. Manage.* 229: 202-213. doi:10.1016/j.foreco.2006.04.028.
- Curtis, R.O. 1967. height-diameter and height-diameter-age equations for second-growth Douglas-fir. *For. Sci.* 13: 365-375.
- Curtis, R.O., and Marshall, D.D. 2002. Levels-of-growing-stock cooperative study in Douglas-fir. Report No. 14-Stampede Creek: 30-year results. USDA For. Servo Res. Pap. PNW-RP-543.
- Draper, N.R., and Smith, H. 1998. Applied regression analysis. 3rd ed. John Wiley & Sons, New York.
- Garber, S.M., and Maguire, D.A. 2003. Modeling stem taper of three central Oregon species using nonlinear mixed effects models and autoregressive error structures. *For. Ecol. Manage.* 179: 507-522. doi:10.1016/S0378-1127(02)00528-5.
- Gertner, G.Z. 1990. The sensitivity of measurement error in stand volume estimation. *Can. J. For. Res.* 20: 800-804. doi:10.1139/x90-105.
- Goldberger, A.S. 1962. Best linear unbiased prediction in the generalized linear regression model. *J. Am. Stat. Assoc.* 57: 369-375. doi:10.2307/2281645.
- Gregoire, T.G., and Williams, M. 1992. Identifying and evaluating the components of non-measurement error in the application of standard volume equations. *Statistician*, 41: 509-518. doi:10.2307/2348917.
- Gregoire, T.G., Schabenberger, O., and Barrett, J.P. 1995. Linear modelling of irregularly spaced, unbalanced, longitudinal data from permanent-plot measurements. *Can. J. For. Res.* 25: 137-156.
- Hann, D.W. 2006. ORGANON user's manual edition 8.2 [computer manual]. Oregon State University, Department of Forest Resources, Corvallis, Ore., USA.
- Hann, D.W., Marshall, D.D., and Hanus, M.L. 2003. Equations for predicting height-to-crown-base, 5-year diameter-growth rate, 5-year height-growth rate, 5-year mortality rate, and maximum size-density trajectory for Douglas-fir and western hemlock in the coastal region of the Pacific Northwest. *Ore. State Univ. For. Res. Lab. Res. Contrib.* 40.
- Hanus, M.L., Hann, D.W., and Marshall, D.D. 1999. Predicting height for undamaged and damaged trees in southwest Oregon. *Ore. State Univ. For. Res. Lab. Res. Contrib.* 27.
- Houghton, D.R., and Gregoire, T.G. 1993. Minimum subsamples of tree heights for accurate estimation of loblolly pine plot volume. *South. J. Appl. For.* 17: 124-129.
- Huang, S., Titus, S.J., and Wiens, D.P. 1992. Comparison of nonlinear height-diameter functions for major Alberta tree species. *Can. J. For. Res.* 22: 1297-1304.
- Krajicek, J., Brinkman, K.A., and Gingrich, S.P. 1961. Crown competition-a measure of density. *For. Sci.* 7: 35-42.
- Lappi, J. 1997. A longitudinal analysis of height/diameter curves. *For. Sci.* 43: 555-570.
- Larsen, D.R., and Hann, D.W. 1987. Height-diameter equations for seventeen tree species in southwest Oregon. *Ore. State Univ. For. Res. Lab. Res. Pap.* 49.
- Larson, P. 1963. Stem form development of forest trees. *For. Sci. Monogr.* 5.
- Monleon, V.J. 2003. A hierarchical linear model for tree height prediction. In Proceedings of the 2003 Meeting of the American Statistical Association. Section on Statistics and the Environment. 3-7 August 2003, San Francisco, Calif., USA. pp. 2865-2869.
- Monserud, R.A., and Ek, A.R. 1974. Plot edge bias in forest stand growth simulation models. *Can. J. For. Res.* 4: 419-423.
- Paine, D.P., and Hann, D.W. 1982. Maximum crown-width equations for southwestern Oregon tree species. *Ore. State Univ. For. Res. Lab. Res. Pap.* 46.
- Ritchie, M.W., and Hann, D.W. 1987. Equations for predicting height to crown base for fourteen tree species in southwest Oregon. *Ore. State Univ. For. Res. Lab. Res. Pap.* 50.
- Robinson, A.P., and Wykoff, W.R. 2004. Imputing missing height measures using a mixed-effects modeling strategy. *Can. J. For. Res.* 34: 2492-2500. doi:10.1139/x04-137.
- Temesgen, H., and von Gadow, K. 2004. Generalized height-diameter models for major tree species in complex stands of interior British Columbia. *Eur. J. For. Res.* 123: 45-51.
- Temesgen, H., Hann, D.W., and Monleon, V.J. 2007. Regional height-diameter equations for major tree species of southwest Oregon. *West. J. Appl. For.* 22: 213-219.
- Temesgen, H., Monleon, V.J., and Hann, D.W. 2008. Analysis and comparison of nonlinear tree height prediction strategies for Douglas-fir forests. *Can. J. For. Res.* 38: 553-565. doi:10.1139/X07-104.
- Walters, D.K., Hann, D.W., and Clyde, M.A. 1985. Equations and tables predicting gross total stem volumes in cubic feet for six major conifers of southwest Oregon. *Ore. State Univ. For. Res. Lab. Res. Bull.* 50.
- Weiskittel, A.R., Garber, S.M., Johnson, G.P., Maguire, D.A., and Monserud, R.A. 2007. Annualized diameter and height growth equations for Pacific Northwest plantation-grown Douglas-fir, western hemlock, and red alder. *For. Ecol. Manage.* 250: 266-278. doi:10.1016/j.foreco.2007.05.026.
- Williams, W.S., and Schreuder, H.T. 2000. Guidelines for choosing volume equations in the presence of measurement error in height. *Can. J. For. Res.* 30: 306-310. doi:10.1139/cjfr-30-2-306.
- Wykoff, W.R., Crookston, N.L., and Stage, A.R. 1982. User's guide to the stand prognosis model. USDA For. Servo Res. Pap. INT-GTR-133.
- Zumrawi, A.A., and Hann, D.W. 1989. Equations for predicting the height to crown base of six tree species in the central western Willamette Valley of Oregon. *Ore. State Univ. For. Res. Lab. Res. Pap.* 52.