Assessing model performance in forecasting long-term individual tree diameter versus basal area increment for the primary Acadian tree species

Matthew B. Russell, Aaron R. Weiskittel, and John A. Kershaw, Jr.

Abstract: Tree basal area (ba) or diameter at breast height (dbh) are universally used to represent tree secondary growth in individual tree based growth models. However, the long-term implications of using either ba or dbh for predictions are rarely fully assessed. In this analysis, Δba and Δdbh increment equations were fit to identical datasets gathered from six conifer and four hardwood species grown in central Maine. The performance of Δba and Δdbh predictions from nonlinear mixed-effects models were then compared with observed growth measurements of up to 29 years via a Monte Carlo simulation. Two evaluation statistics indicated substantial improvement in forecasting dbh using Δdbh rather than Δba. Root mean squared error (RMSE) and percentage mean absolute deviation (MAD%) were reduced by 14% and 15% on average, respectively, across all projection length intervals (5–29 years) when Δdbh was used over Δba. Differences were especially noted as projection lengths increased. RMSE and MAD% were reduced by 24% when Δdbh was employed over Δba at longer projection lengths (up to 29 years). Simulations found that simulating random effects rather than using local estimates for random effects performed as well or better at longer interval lengths. These results highlight the implications that selecting a growth model dependent variable can have and the importance of incorporating model uncertainty into the growth projections of individual tree based models.

Résumé : La surface terrière de l'arbre (G) ou le diamètre à hauteur de poitrine (D) sont universellement utilisés pour représenter la croissance secondaire dans les modèles de croissance d'arbre individuel. Cependant, les implications à long terme de l'emploi de G ou D pour les prédictions sont rarement pleinement évaluées. Dans cette analyse, les équations d'accroissement ΔG et ΔD ont été ajustées à des ensembles de données identiques recueillies à partir de six conifères et quatre feuillus dans le centre du Maine. La performance des prédictions de ΔG et ΔD à l'aide des modèles non linéaires à effets mixtes a été comparée aux mesures de croissance prises sur une période de 29 ans en utilisant une simulation de Monte Carlo. Deux statistiques d'évaluation indiquent une amélioration substantielle de la prédiction de D en utilisant ΔD plutôt que ΔG. Lorsque ΔD a été utilisé à la place de ΔG, l'écart type résiduel et l'écart moyen absolu en pourcentage ont été réduits respectivement de 14 et 15 % en moyenne pour tous les horizons de projection (5–29 ans). Ces différences étaient particulièrement marquées lorsque les horizons de projection s'allongeaient. En effet, l'écart type résiduel et l'écart moyen absolu en pourcentage ont été réduits de 24 % lorsque ΔD a été employé au lieu de ΔG pour les horizons de projection plus longs (jusqu'à 29 ans). Les simulations ont montré que la simulation des effets aléatoires performe aussi bien sinon mieux que les estimations locales des effets aléatoires lorsque les horizons sont longs. Ces résultats mettent en évidence, d'une part, les impacts causés par la sélection de la variable dépendante pour un modèle de croissance et, d'autre part, l'importance d'intégrer l'incertitude des modèles dans les projections de croissance par des modèles d'arbre individuel.

[Traduit par la Rédaction]

Introduction

Diameter (at breast height, dbh) or basal area (ba) can be used to predict secondary growth of individual trees in forest growth models. The circumference of the tree at breast height is commonly measured in the field using diameter tapes, and this value is then converted into corresponding diameter or basal area. Because basal area increment measures the increase in geometric area of the bole at breast height measured at two time periods, it represents individual tree increment differently than does the linear distance measure of diameter.

Given that a significant portion of the variability in basal area increment (Δba) can be attributed to initial tree diameter, Δba will generally display a higher correlation with initial tree diameter than will diameter increment (Δdbh; West 1980). Employing basal area as the dependent variable in tree increment models is also appealing because basal area is directly related to silvicultural practices (Peng 2000). Despite the relative importance of these assumptions, relatively little work has been done quantitatively comparing effectiveness of Δdbh or Δba as the dependent variable in growth modeling.

In a study directly comparing performance of Δdbh and Δba equations developed for even-aged *Eucalyptus* forests in

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southern Tasmania and northern hardwood stands in southern Ontario, Canada, West (1980) concluded that prediction of future diameters using a Δdbh or Δba equation did not differ appreciably. Using equations that predicted maximum potential growth followed by a modifying function, Shifley (1987) similarly found no difference in precision of Δdbh or Δba equations developed for 22 different species growing in three states across the US Midwest. However, these analyses were limited in terms of the projection lengths used, as West (1980) only examined intervals of 3 to 6 years, whereas Shifley (1987) studied 10-year intervals.

Using Δba as the unit of prediction has some important limitations. Hann and Larsen (1991) found that transforming ba to dbh resulted in unreasonable predictions for trees with small diameters. This is likely because basal area assumes that trees are circular and noneccentric. Although stem eccentricity is relatively small in conifers, it can still vary significantly between species, regions, and dbh classes (Tong and Zhang 2008). The importance of the noneccentric assumption would seemingly increase as growth projection lengths increase, which could lend to additional error compounding. In addition, Vanclay (1995) hypothesized that differences between Δdbh and Δba equations could be due to error structures of the equations and their implied functional relationships. The choice of which dependent variable to employ is fundamental, as the error in one prediction equation can be compounded in subsequent equations within a growth and yield system (e.g., Fortin and DeBlois 2010).

The goal of this analysis was to evaluate the performance of individual tree diameter versus basal area increment models using long-term growth records for 10 species common to the Acadian forest region. The specific objectives of this project were (*i*) to fit species-specific equations using Δdbh and Δba as dependent variables, (*ii*) to use a Monte Carlo simulation study to assess the performance of nonlinear mixed-effects models in forecasting the Δdbh and Δba equations; and (*iii*) to evaluate the influence of short-term (<10 years) and long-term (>25 years) projection intervals on the effectiveness of using Δdbh or Δba as the dependent variable.

Methods

Study area

The 1619 ha United States Forest Service (USFS) Penobscot Experimental Forest (PEF) is located in the towns of Bradley and Eddington, Maine (44°52′N, 68°38′W). Mean temperatures in February and July are –7.1 °C and 20.0 °C, respectively, and mean annual precipitation is 107 cm. Soils in this area are typically thin, often wet, and somewhat poorly to poorly drained.

Located within the Acadian forest ecotype, the PEF is characterized by a mixture of northern conifer and hardwood species that dominate its forest cover. Conifer species include balsam fir (*Abies balsamea* (L.) Mill.), red spruce (*Picea rubens* Sarg.), black spruce (*Picea mariana* (Mill.) B.S.P.), white spruce (*P. glauca* (Moench) Voss), eastern hemlock (*Tsuga canadensis* (L.) Carr.), northern white-cedar (*Thuja occidentalis* L.), and eastern white pine (*Pinus strobus* L.). Common hardwood species include red maple (*Acer rubrum* L.), paper birch, (*Betula papyrifera* Marsh.), gray birch (*B. populifolia* Marsh.), and quaking aspen (*Populus tremuloides* Michx.).

Ten contrasting silvicultural treatments were applied between 1952 and 1957 by the USFS. These treatments, each with two replicates, were located in a ~170 ha area of the PEF. Twenty managed stands resulted from the various silvicultural treatments that included selection systems based on 5-, 10-, and 20-year harvest cycles, an unregulated commercial harvest, a modified and flexible diameter limit harvest, a two- and three-stage uniform shelterwood treatment, a three-stage shelterwood treatment with precommercial thinning, and an unmanaged natural area (Sendak et al. 2003).

Data

A network of permanent sample plots was established along transects nested within each stand at the start of the study. Plots consisted of a nested design with 0.081 and 0.020 ha circular plots sharing the same plot center. All trees ≥ 11.43 cm dbh were measured in the 0.081 ha plot, whereas trees with dbh ≥ 1.27 cm and < 11.43 cm were measured in the 0.020 ha plot. Beginning in 1974, individual trees were numbered in these plots, and stand, plot number, tree number, species, dbh, and live or dead status were recorded. Tree dbh measurements were made with a diameter tape. Plots were initially measured and then remeasured at 5-year intervals. Beginning in 2000, a 0.008 ha plot was nested within the plot, and trees ≥ 6.35 cm dbh were measured on the original 0.020 ha plots and trees ≥ 1.27 cm dbh were measured in the new 0.008 ha plots. The remeasurement interval was changed from 5 years to 10 years.

Stands were selected from treatments containing individually numbered trees with consecutive dbh measurements and where harvesting did not occur during the growth interval. Growing period length of the stands ranged from an average of 3.6 to 6.6 years, and cumulative years of diameter measurement reached 29 years (Table 1).

Observed individual tree dbh increment (Δdbh; cm) was defined as the difference between two consecutive dbh measurements. These dbh measurements were converted to basal area to compute tree basal area increment (Δba; m^2). Because of their abundance at the PEF and their ecological and commercial importance to the Acadian forest region, the following conifer species were chosen to develop species-specific increment equations: balsam fir, red spruce, white spruce, northern white-cedar, and eastern white pine. Similarly, equations for the following hardwood species were developed: red maple, paper birch, gray birch, and quaking aspen (Fig. 1). Because red and black spruce hybridize extensively at the PEF (Saunders and Wagner 2008), no distinction between the two species is made in the field. Hence, these species are grouped and are referred to as red spruce throughout. The number of growth observations varied between species (Table 2).

Model development

The Wykoff (1990) model form was selected for use in this analysis:

$$[1] \qquad \Delta gr = \beta_1 \, dbh^{\beta_2} \exp\left(\frac{\beta_3 \, dbh^2}{100}\right)$$

Table 1. Silvicultural treatments and stand information for diameter growth data from Penobscot Experimental Forest, Bradley and Eddington, Maine.

				Length of growing period (years)		
Treatment	Code	Stands	Count of stand measurements	Mean	Range	Cumulative
Unharvested control	NAT	2	6	5.8	4–10	29
Two-stage shelterwood	SW2	2	5	5.0	4–10	20
Three-stage shelterwood	SW3	2	6	5.5	3–6	24
Three-stage shelterwood with precommercial thinning	SW3PCT	1	6	3.6	2–6	18
Commercial clearcutting	URH	2	5	6.6	5–10	21

Fig. 1. Annual (*a*) diameter at breast height (Δdbh) and (*b*) basal area (Δba) increments versus initial tree dbh with loess regression line for conifers (broken line) and hardwoods (solid line) for long-term data obtained from Penobscot Experimental Forest, Bradley and Eddington, Maine.

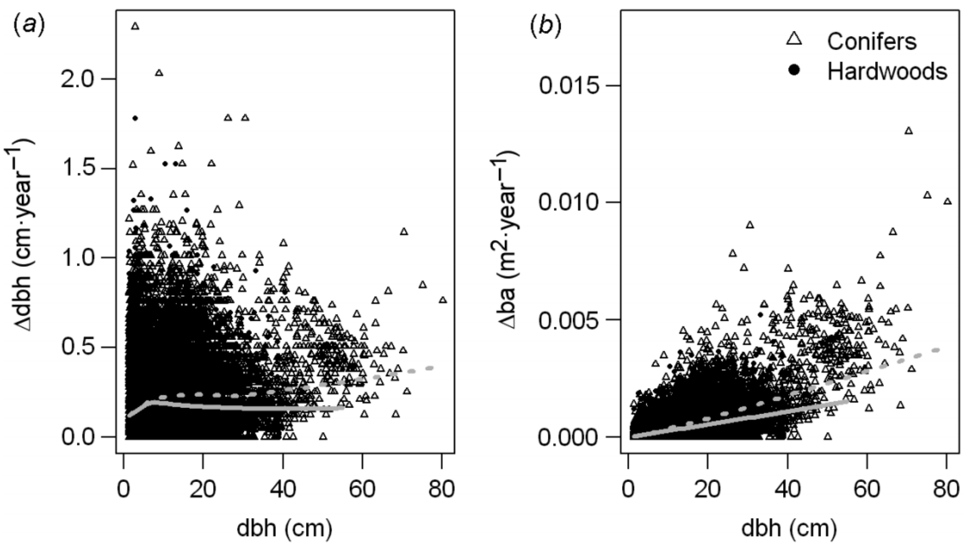


Table 2. Tree diameter statistics including number of observations used in model development (*n*), initial tree diameter (dbh), and Pearson's correlation coefficients of dbh with diameter (Δdbh) and basal area (Δba) increments, by species.

		dbh (cm)		Pearson correlation	
Species	*n*	Mean (SD)	Range	$r_{\text{dbh},\Delta\text{dbh}}$	$r_{\text{dbh},\Delta\text{ba}}$
Conifers					
Balsam fir	25 111	5.5 (4.9)	1.3–50.3	0.238	0.664
Red spruce	7 477	6.8 (6.0)	1.3–48.5	0.049	0.557
Eastern hemlock	4 423	11.2 (11.2)	1.3–56.6	0.279	0.699
Eastern white pine	2 079	14.0 (14.8)	1.3–80.0	0.148	0.789
Northern white-cedar	1 696	16.9 (6.1)	1.3–53.3	0.128	0.490
White spruce	820	9.2 (9.6)	1.3–46.7	0.070	0.537
Hardwoods					
Red maple	8 374	6.7 (6.6)	1.3–54.9	0.066	0.618
Paper birch	3 941	4.7 (5.1)	1.3–38.9	0.138	0.562
Quaking aspen	2 191	6.5 (6.1)	1.3–45.0	0.196	0.744
Gray birch	1 887	3.5 (2.4)	1.3–25.2	0.161	0.509

where Δgr is tree diameter (Δdbh; cm) or basal area (Δba; m^2) increment and dbh (cm) is initial tree diameter at breast height. In terms of general performance and magnitude of parameter estimates, preliminary analyses indicated that eq. 1 fit the data well for the species examined.

Using a nonlinear mixed-effects modeling approach (Pinheiro and Bates 2000), eq. 1 was structured in a manner that took into account both fixed and random parameters:

$$[2] \qquad \Delta \mathrm{gr}_{ijk} = (\beta_1 + b_i + b_{ij})\mathrm{dbh}_{ijk}^{\beta_2} \exp\left(\frac{\beta_3\, \mathrm{dbh}_{ijk}^2}{100}\right) + \varepsilon_{ijk}$$

where $\Delta \mathrm{gr}_{ijk}$ is the annual observed increment of the kth tree found in the jth plot in the ith stand, β_1, β_2, and β_3 are population-level fixed effect parameters, b_i and b_{ij} are random effect parameters for the ith stand and the jth plot, respectively, and ε_{ijk} is the model error term, where $\varepsilon_{ijk} \sim \mathrm{N}(0, \mathbf{R}_{ijk})$ and $\mathbf{R}_{ijk}$ is the variance–covariance matrix for the model error term.

To test whether or not ba would serve better as an independent variable than dbh in predicting Δba, initial tree basal area (ba$_{ijk}$) was used in place of dbh$_{ijk}$ on the right-hand side of eq. 2.

A variance power function of initial diameter was used to represent the nonhomogeneous variance observed in the growth data. This function took the form $\mathrm{Var}(\varepsilon_{ijk}) = \sigma^2 \mathrm{dbh}_{ijk}^{\delta}$, where σ^2 was the residual sums of squares and δ was the variance function coefficient. A first-order continuous autoregressive correlation structure (CAR1) is defined as $\mathrm{Corr}(\varepsilon_{it}, \varepsilon_{is}) = \rho^{|\lambda_{is} - \lambda_{it}|}$, where ρ is the autocorrelation parameter between two growth observations on tree i and $\lambda_{is} - \lambda_{it}$ is the interval length between observation t and s. The CAR1 structure allows fitting of unbalanced data that are spaced irregularly (Gregoire et al. 1995).

Because measurement intervals ranged from 2 to 10 years, an annualization technique was employed to make full use of all growth measurements and to provide a finer resolution of individual tree increment predictions (Weiskittel et al. 2007). Individual tree dbh was assumed to transition linearly during the growth interval, so that annual growth was computed as the average increment over the interval (Cao 2000). Hence, the β_i coefficients in eqs. 1 and 2 are annualized coefficients that can be used to simulate tree increment to any desired projection length. Model parameters were estimated in R using the nonlinear mixed-effects (nlme) package (R Development Core Team 2009).

Simulation system

Data from the PEF ranged from a total of 18 to 29 years of measurements, depending on the stand of interest (Table 1). Not all trees, individually tagged at the initial measurement, survived this entire period, and ingrowth was considerable in some plots. To compare simulated increment with observed values, trees that survived all measurements in a plot were used as the tree list for the simulation. Simulated data were considered a subset from the data used in model development. This resulted in simulating growth for 3784 trees from 110 plots across the nine different stands. The most abundant species that composed the simulation dataset were (number of observations in parentheses) balsam fir (1448), red maple (726), eastern hemlock (471), northern white-cedar (319), red spruce (246), and paper birch (229). To compare the baseline performance of the fixed-effects equation (eq. 1) with simulated predictions, a deterministic prediction was made using the developed equations with the simulation data.

Variability within the Monte Carlo simulation was assigned in various ways (Fortin et al. 2009): random numbers from a normal probability density function were drawn to account for errors associated with model coefficients, i.e., ~N(β_i, SE(β_i)) and model error terms, i.e., ~N(0, ε_{ijk}). Annual variability in dbh increment was also assigned in a manner consistent with other regions: as dbh increment can deviate ±25% from expected growth in a given year (Kangas 1998), predicted annual growth was multiplied by a uniform random variable drawn from U(–0.25, 0.25), then added to the previous year's tree size. During the same Monte Carlo run, random error terms and model error terms were held constant throughout the entire length of the simulation. Annual variability was assigned at each annual time step. Predicted Δdbh and Δba occurred within the same growth step, so variability attributed to climate would increase or decrease by the same relative amount for both Δdbh and Δba. Because correlations between equation parameters were relatively low, it was assumed to have no influence on model predictions.

Two sets of simulations were run to test the influence of the model random effects on the Δdbh and Δba predictions. In one simulation, the local random effects for each stand (b_i) and plot (b_{ij}) were extracted from model output and used throughout the simulation. In the other, random effects were simulated. The b_i and b_{ij} random effects were simulated from a normal distribution assuming a mean of 0 with their associated standard error obtained from model output, i.e., ~N(0, SE(b_i)) and ~N(0, SE(b_{ij})).

For each of the 110 plots used in the simulation, a 1000-run Monte Carlo simulation was performed. Equations provided annual predictions, and simulations were run up to the maximum observed cumulative growing period length (29 years). Simulations were carried out using R (R Development Core Team 2009).

Evaluation statistics

Uncertainty in future predictions includes both systematic and random variation. Mean bias (MB) and percentage mean absolute deviation (MAD%) measure systematic variation, whereas root mean squared error (RMSE) measures both types (Kangas 1999). These measures were computed in this analysis as follows:

$$[3a] \qquad \mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 / n}$$

$$[3b] \qquad \mathrm{MB} = \sum_{i=1}^{n} (y_i - \hat{y}_i) / n$$

$$[3c] \qquad \mathrm{MAD}\,\% = 100 \times \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{\sum_{i=1}^{n} y_i}$$

where y_i is the observed diameter, $\hat{y}_i$ is the mean predicted tree diameter from the simulations, and n is the number of observations.

Table 3. Parameter estimates and standard errors for eq. 2 for predicting diameter (Δdbh) and basal area (Δba) increments using initial tree diameter (dbh) for various species using an annualized nonlinear mixed-effects fitting technique.

Species	Δgr	β_1 (SE)	β_2 (SE)	β_3 (SE)	SE(b_i)	SE(b_{ij})	ε_{ijk}
Conifers							
Balsam fir	Δdbh	0.129 (0.015)	0.367 (0.0093)	–0.0242 (0.0062)	0.044	0.025	0.67
	Δba	3.55×10^{-5} (4.4×10^{-6})	1.16 (0.008)	—	1.3×10^{-5}	9.2×10^{-6}	3.0×10^{-4}
Red spruce	Δdbh	0.132 (0.020)	0.325 (0.018)	–0.0176 (0.0087)	0.057	0.026	1.2
	Δba	2.85×10^{-5} (4.7×10^{-6})	1.24 (0.026)	–0.0247 (0.0085)	1.3×10^{-5}	8.0×10^{-6}	5.8×10^{-4}
Eastern hemlock	Δdbh	0.0945 (0.011)	0.550 (0.016)	–0.0331 (0.0046)	0.031	0.024	0.61
	Δba	2.43×10^{-5} (3.2×10^{-6})	1.39 (0.018)	–0.0191 (0.0043)	8.6×10^{-6}	8.6×10^{-6}	2.1×10^{-4}
Eastern white pine	Δdbh	0.186 (0.026)	0.432 (0.023)	—	0.069	0.028	2.1
	Δba	3.23×10^{-5} (5.7×10^{-6})	1.42×10^{-5} (0.033)	—	1.4×10^{-5}	6.8×10^{-6}	1.1×10^{-3}
Northern white-cedar	Δdbh	0.070 (0.013)	0.278 (0.047)	—	0.021	2.5×10^{-6}	0.52
	Δba	1.31×10^{-5} (2.4×10^{-6})	1.24 (0.050)	—	3.9×10^{-6}	3.4×10^{-10}	1.3×10^{-4}
White spruce	Δdbh	0.0760 (0.015)	0.481 (0.048)	–0.0258 (0.018)	0.033	0.022	0.77
	Δba	1.32×10^{-5} (2.9×10^{-6})	1.49 (0.059)	–0.0352 (0.019)	6.0×10^{-6}	4.0×10^{-6}	2.4×10^{-4}
Hardwoods							
Red maple	Δdbh	0.105 (0.011)	0.266 (0.013)	—	0.032	0.032	0.79
	Δba	2.69×10^{-5} (3.5×10^{-6})	1.12 (0.014)	—	9.3×10^{-6}	1.2×10^{-5}	2.7×10^{-4}
Paper birch	Δdbh	0.0785 (0.012)	0.675 (0.030)	–0.244 (0.027)	0.034	0.024	0.59
	Δba	1.97×10^{-5} (3.4×10^{-6})	1.49 (0.033)	–0.182 (0.026)	9.2×10^{-6}	7.8×10^{-6}	1.9×10^{-4}
Quaking aspen	Δdbh	0.185 (0.015)	0.292 (0.020)	—	0.030	0.045	0.91
	Δba	4.47×10^{-5} (4.5×10^{-6})	1.17 (0.028)	—	7.4×10^{-6}	1.5×10^{-5}	5.5×10^{-4}
Gray birch	Δdbh	0.159 (0.019)	0.294 (0.040)	–0.130 (0.064)	0.041	0.050	0.79
	Δba	4.81×10^{-5} (6.9×10^{-6})	1.022 (0.047)	–0.127 (0.066)	1.5×10^{-5}	2.3×10^{-5}	3.3×10^{-4}

Results

Model development

For the six conifer species examined, the number of growth observations ranged from 820 for white spruce to 25 111 for balsam fir. For the four hardwood species examined, the number of observations ranged from 1887 for gray birch to 8374 for red maple. Average annual Δdbh was 0.21 and 0.18 for conifers and hardwoods, respectively. The sample Pearson's correlation coefficient between initial tree dbh and Δba ($r_{\mathrm{dbh},\Delta\mathrm{ba}}$) was always higher than the correlation between dbh and Δdbh ($r_{\mathrm{dbh},\Delta\mathrm{dbh}}$). For all species, $r_{\mathrm{dbh},\Delta\mathrm{dbh}}$ ranged from 0.049 to 0.279 and $r_{\mathrm{dbh},\Delta\mathrm{ba}}$ ranged from 0.509 to 0.789 (Table 2). On average, $r_{\mathrm{dbh},\Delta\mathrm{ba}}$ was 0.48 higher than $r_{\mathrm{dbh},\Delta\mathrm{dbh}}$ for all species.

Akaike's and Bayesian information criterions showed that including β_1 as the mixed-effect parameter rather than β_2 resulted in slightly favorable model fits. The β_i parameters were retained such that they displayed biologically appropriate properties, i.e., were of the proper sign and approximate magnitude. Tree dbh alone proved to be an effective predictor of individual tree increment (Table 3).

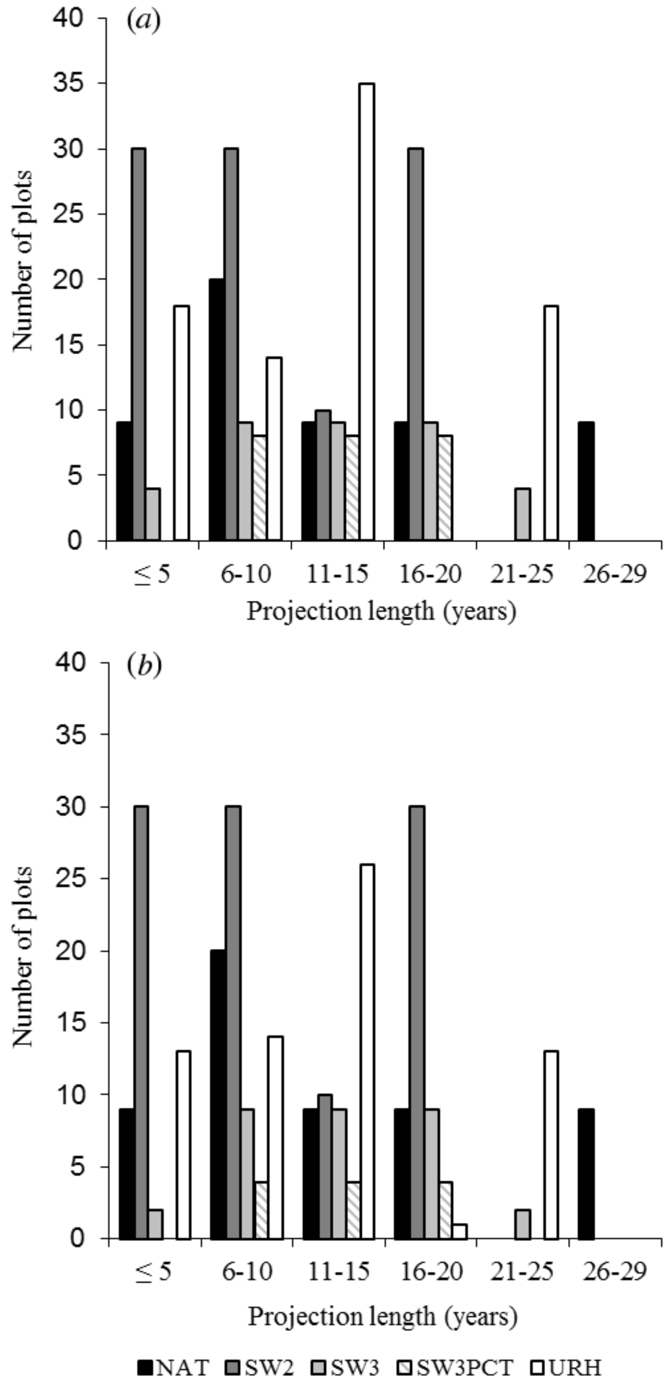
Assessing model prediction uncertainty

Growth observations were grouped into 5-year intervals according to their projection length from the initial measurement year (Fig. 2). The greatest number of plots with growth observations (99) occurred in the 6–10 year projection length interval, and the fewest number of plots (9) occurred in the 26–29 year projection length interval.

Generally, deterministic predictions were similar to stochastic predictions derived from the Monte Carlo simulation (Table 4). For all projection length intervals, evaluation statistics (eq. 3) showed favorable results when predicted Δdbh was used rather than Δba and compared with observed dbh values. Minimum values for these statistics were observed in the ≤5 year projection length interval: for stochastic simulations that used local estimates of random effects, RMSE, MB, and MAD% for Δdbh equations were 1.78 cm, 0.73 cm, and 11%, respectively. Similarly for Δba equations, RMSE, MB, and MAD% were 1.89 cm, 0.84 cm, and 13%, respectively. For simulations that simulated random effects, RMSE, MB, and MAD% for Δdbh equations were 2.10 cm, 0.71 cm, and 13%, respectively. Similarly for Δba equations, RMSE, MB, and MAD% were 2.20 cm, 0.94 cm, and 14%, respectively.

Maximum values for these statistics were observed in the 26–30 year projection length interval: for stochastic simulations that used local estimates of random effects, RMSE, MB, and MAD% for Δdbh equations were 8.66 cm, –7.25 cm, and 31%, respectively. Similarly for Δba equations, RMSE, MB, and MAD% were 10.78 cm, –9.49 cm, and 39%, respectively. For simulations that simulated random effects, RMSE, MB, and MAD% for Δdbh equations were 6.01 cm, –4.62 cm, and 22%, respectively. Similarly for Δba equations, RMSE, MB, and MAD% were 7.91 cm, –6.85 cm, and 28%, respectively. Mean bias showed that models underpredicted tree growth in all but the longest projection intervals. Generally, equations that predicted Δba using ba as the independent variable produced similar evaluation statistics to Δba equations when dbh was used as the independent variable.

Fig. 2. Number of permanent sample plots used in simulation for (*a*) conifer and (*b*) hardwood species according to projection length and silvicultural regime: unharvested control (NAT), two-stage shelterwood (SW2), three-stage shelterwood without (SW3) and with (SW3PCT) precommercial thinning, and commercial clearcutting (URH).



When simulated random effects were used, the RMSE and MAD% were reduced on average by 15% and 16%, respectively, for conifer species across all projection length intervals when Δdbh was used over Δba. Similarly, for hardwood species, both RMSE and MAD% were reduced on average by

Table 4. Comparisons of root mean squared error and mean bias for tree diameter at breast height (Δdbh) and basal area (Δba) increment equations for projections that simulated stand- and plot-level random effects or used local estimates of random effects in a stochastic simulation (eq. 2), or used fixed effects (eq. 1) in a deterministic prediction.

				Projection length (years)					
Dependent variable	Independent variable	Random effects	Prediction	<5	6–10	11–15	16–20	21–25	26–30
Root mean squared error									
Δdbh	dbh	Simulated	Stochastic	2.10	2.94	3.52	3.80	3.15	6.01
Δdbh	dbh	Local	Stochastic	1.78	2.88	3.66	3.93	2.72	8.66
Δba	dbh	Simulated	Stochastic	2.20	3.23	4.04	4.40	3.85	7.91
Δba	dbh	Local	Stochastic	1.89	3.23	4.23	4.65	3.45	10.78
Δba	ba	Simulated	Stochastic	2.21	3.18	3.97	4.31	3.80	6.36
Δba	ba	Local	Stochastic	1.87	3.10	3.99	4.29	3.43	9.50
Δdbh	dbh	Fixed	Deterministic	1.81	2.71	3.51	3.68	3.12	6.95
Δba	dbh	Fixed	Deterministic	1.88	3.07	3.92	4.23	3.58	8.29
Δba	ba	Fixed	Deterministic	1.86	3.08	3.86	4.12	3.52	7.94
Mean bias									
Δdbh	dbh	Simulated	Stochastic	0.71	0.12	0.65	0.52	–0.7	–4.62
Δdbh	dbh	Local	Stochastic	0.73	0.06	0.55	0.59	0.07	–7.25
Δba	dbh	Simulated	Stochastic	0.94	0.42	1.27	1.42	1.44	–6.85
Δba	dbh	Local	Stochastic	0.84	0.18	0.96	0.99	1.52	–9.49
Δba	ba	Simulated	Stochastic	1.00	0.53	1.46	1.59	1.43	–4.97
Δba	ba	Local	Stochastic	0.92	0.35	1.28	1.23	1.54	–7.52
Δdbh	dbh	Fixed	Deterministic	0.86	0.34	1.08	0.98	0.61	–4.90
Δba	dbh	Fixed	Deterministic	0.96	0.40	1.34	1.38	1.45	–6.95
Δba	ba	Fixed	Deterministic	0.97	0.44	1.42	1.45	1.45	–6.11

9% across all projection intervals when Δdbh was used over Δba. For conifer species averaged across all diameters classes, RMSE and MAD% were reduced on average by 16% and 17%, respectively, when Δdbh was used over Δba. Similarly, for hardwood species averaged across all diameter classes, both RMSE and MAD% were reduced on average by 17% when Δdbh was used over Δba (Fig. 3).

Discussion

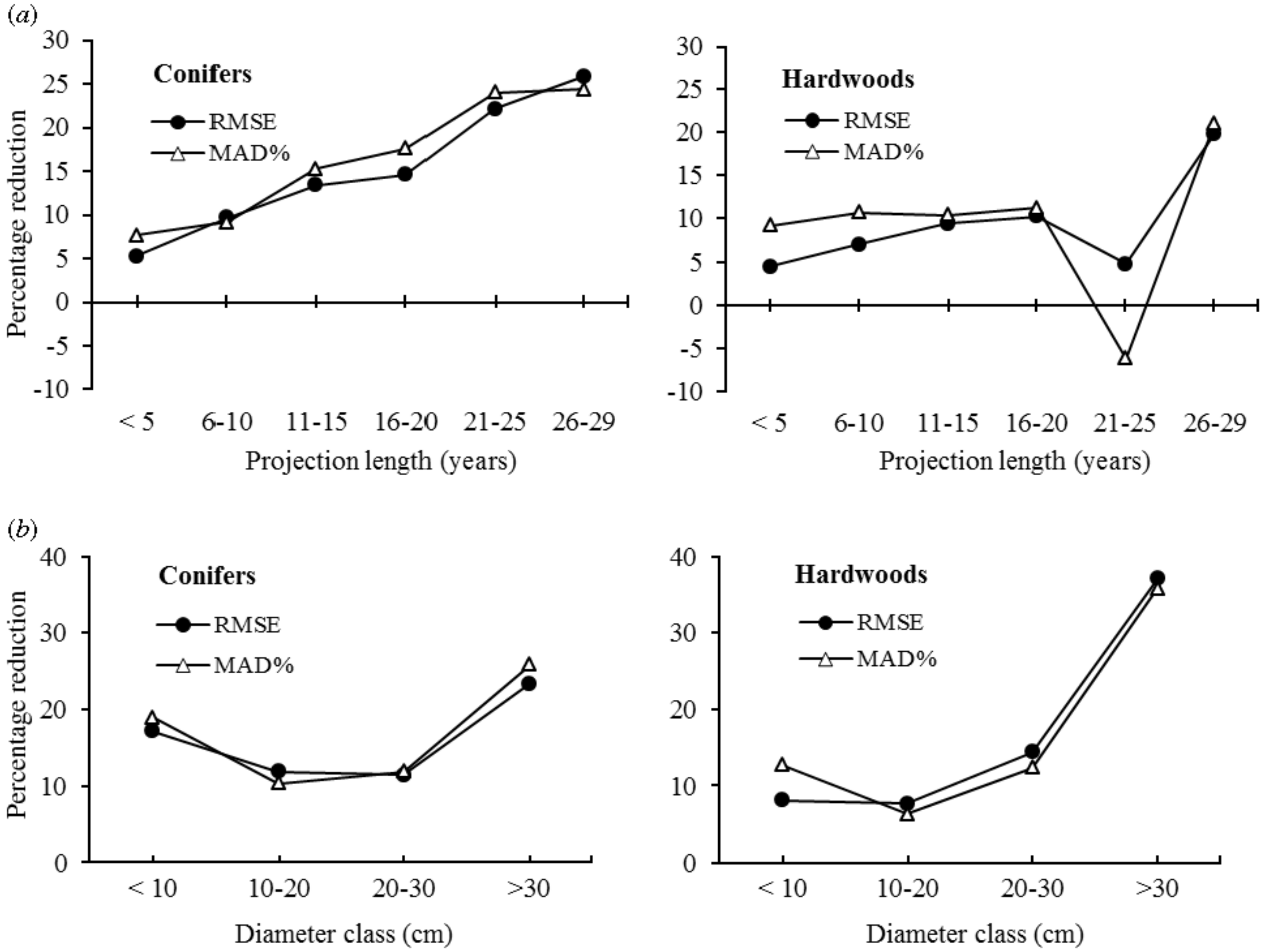
After developing equations for predicting diameter and basal area increment for 10 species common to the Acadian forest, results showed Δdbh equations to be superior to Δba equations when RMSE and MB were computed for up to 29 years of observations. Nonlinear mixed-effects models fitted with stand- and plot-level random effects adequately predicted future growth, as mean bias was generally within 5 cm for up to 29 years using trees growing in a variety of stand types subject to varying silvicultural practices.

The data herein support the results that others have found in contrasting forest types, i.e., that higher correlations are observed when Δba is compared with dbh rather than Δdbh (West 1980; Shifley 1987), as noted in Fig. 1. Because accurate prediction of future dbh is the aim of most growth models, these results favor the use of Δdbh over Δba equations because improvements were observed in three evaluation statistics when using Δdbh (Table 4). This was especially true for trees simulated to long projection length intervals and at larger diameter classes. Percentage improvements in RMSE and MAD% for Δdbh versus Δba was always 10% or greater, except for shorter projection length intervals (i.e., <10 years). A sharp decrease in the percentage reduction for RMSE and MAD% in hardwood species at the 21–25 year projection interval is likely due to the relatively smaller numbers of tree observations for hardwoods in that interval (n = 104), the majority of the hardwoods being red maple (n = 91), and the data only being collected from 15 plots within two stands.

Regardless of the dependent variable used, simulations that employed extracted random effects from model output appeared to perform well for shorter projection lengths (i.e., <5 years). For simulations carried out past 5 years, our analyses indicated that simulating random effects rather than using extracted values performed as well or better in three of the five remaining interval lengths for RMSE and two of the five remaining interval lengths for MB. As projections at longer interval lengths contain a greater degree of uncertainty given the influence of previous growth, this analysis indicates that simulating the general error structure of equations performs nearly as well as or better than using precise estimates of random effects for longer projection lengths. Deterministic predictions made with fixed-effects equations generated evaluation statistics in agreement with statistics drawn from stochastic simulations, which highlights the role that fixed-effects parameters can play in making long-term growth projections.

Evaluating the results by species groups, the six conifer species examined tended to be more sensitive to differences in terms of Δdbh versus Δba than hardwood species. For predicting increment across interval lengths, hardwood species showed less drastic improvement in using Δdbh over Δba. In a database compiled with stem taper measurements for conifers across the Acadian region (Li et al. 2011), stem eccentricity (ratio of smaller diameter to larger diameter) for balsam fir, red spruce, and white spruce was 0.98, 0.96, and 0.97, respectively. Although these eccentricity values were

Fig. 3. Percentage reduction in root mean squared error (RMSE) and percentage mean absolute deviation (MAD%) for conifers and hardwoods using tree dbh increment equations over ba increment equations compared with observed dbh (cm), according to (*a*) projection length and (*b*) diameter class.



relatively low, a one-tailed *t* test for each species indicated that the values were significantly different from 1. Tong and Zhang (2008) found that several of the conifers used in this study displayed similar eccentricity values. In a stem analysis of hardwood species found at the PEF (data not published), eccentricity was calculated as 0.93, 0.90, 0.95, and 0.92 for red maple, paper birch, gray birch, and quaking aspen, respectively. Although these hardwood data came from a small sample size for each species ($n \leq 12$) and were of relatively small dbh (up to 12 cm), supplementary data indicate that hardwood species could display more eccentric stems compared with conifer species found throughout the region. Additional data is needed to assess how these values change through time.

The biological differences between tree dbh and ba should be noted as they relate to tree radial increment. As the cross section of trees measured at breast height are rarely perfectly circular, measuring eccentrically shaped boles with diameter tapes is likely to be positively biased (Binot et al. 1995; Avery and Burkhart 2002, p. 144). Much data used in modeling Δdbh come from permanent sample plots where circumference is measured using diameter tapes. Differences in dbh error associated with the type of dendrometer used in measuring diameter exist (Binot et al. 1995); however, from the perspective of monitoring individual tree growth, diameter tapes are preferred over other dendrometers such as calipers because they provide the most consistent measurement of dbh. As circumference is measured with a diameter tape, this value is converted to diameter assuming a circular shape of the tree bole at dbh. Outlined in Husch et al. (2004, p. 89), as the major–minor axes length ratio increases, i.e., as the eccentricity of cross-sectional area at dbh becomes more pronounced, circumference of the tree and associated “diameter” increase. This will tend to overestimate the true diameter at cross section. Converting this value to a measurement of area (basal area) requires the further assumption that the stem is circular at the cross section measured at dbh. Using ba would also be more sensitive to measurement error, as error would propagate as one converted an inaccurate linear measurement (dbh) to an area measurement. We hypothesize that the improved performance of employing Δdbh over Δba could be attributed to (*i*) the extension of the assumption of a circle in modeling tree basal area increment, and (*ii*) the supposition that error is compounding when simulating long-term increment.

Individual tree diameter increment plays a tremendous role in forest growth and yield simulators as dbh predictions are used in subsequent equations such as volume, biomass, and mortality. If a Δba equation is employed within a growth and yield system, predicted ba is generally converted to dbh to be used in subsequent equations. As an example, a 10% bias in tree diameter could cause a 25% error in predicting stand-level basal area (Gertner and Dzialowy 1984). This warrants a thorough assessment of the performance of Δdbh equations as they relate to various sources of error at the level of the individual tree, but also as one scales to the plot and stand levels.

Conclusions

Using up to 29 years of observed growth data for 10 Acadian species grown in a range of stand types, this analysis found that Δdbh equations outperformed Δba equations by up to 16% when averaged across all projection lengths. Fitting nonlinear mixed-effects models that provided annualized output allowed the ability to incorporate model error terms and annual climate variability into a Monte Carlo simulation system to directly assess performance of Δdbh over Δba equations. Although higher correlations in the data were observed between initial tree dbh and the dependent variable Δba, incorporating model error terms into growth simulations showed Δdbh equations to more accurately project future growth. Results showcase the importance of incorporating attributes of model error into projections and assessing the stochastic elements of forest growth and yield models.

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