Annual Updating of Plantation Inventory Estimates Using Hybrid Models

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Abstract.—Data for *Pinus radiata* D. Don grown in the Australian Capital Territory (ACT) are used to show that annual indices of growth potential can be successfully incorporated into Schumacher projection models of stand basal area growth. Significant reductions in the error mean squares of the models can be obtained by including an annual growth index derived from estimates of photosynthesis simulated with a detailed process-based model: BIOMASS. In the ACT, it was sufficient to estimate the growth index at a single location within the forest estate.

Predictions made with models containing indices of temporal variation in growth potential were less biased and more accurate than those obtained without including climatic information. The new models improve descriptive power of the models and open up new avenues for forest modeling. They are particularly applicable for making short-term updates of forest inventories.

Builders of management-oriented growth models have shown considerable ingenuity in developing projection equations with additional variables (for example, site index, time, and amount of thinning) to enhance the quality of predictions. Other variables that account for spatial variation in climatic or edaphic factors have not been greatly used partly because of the unavailability of data at sufficient spatial intensity for use with traditional inventory sample plot data. In recent years, many forestry organizations have acquired detailed soil information for their forest estates so that site-specific management regimes can be developed. Moreover, environmental (for example, rainfall, solar radiation) data have become available, through the application of response surface splining programs to climatic data (e.g., BIOCLIM, Nix 1986) from which estimates of long-term climate averages can be made at any chosen location. Woollons *et al.* (1997) were able to show that by including such data an improvement of 10 percent could be obtained in a Schumacher projection model for stand basal area of *Pinus radiata* D. Don grown in the Nelson region of New Zealand.

Representation of temporal variation in growing conditions by year-to-year deviations from climatic averages is rarely included in models to forecast production. However, considerable work has been carried out over many years to relate climatic conditions to the growth of *P. radiata* in the Australian Capital Territory (ACT). In the 1980's, a comprehensive, multidisciplinary, field experiment studying the effects of water and nutrients on the growth of *P. radiata* was carried out in the ACT. One of the key results was the development of a detailed process-based model (BIOMASS) for the growth of *P. radiata* (McMurtrie *et al.* 1990). It was noted that a great deal of work would be required before BIOMASS would provide a reliable management tool for forest management and that a serious limitation was the high data input requirements (McMurtrie and Landsberg 1992). One solution to this was obtained by relaxing some of the input requirements for BIOMASS (see below) and by using various outputs from the model as annual growth indices. Such indices have been successfully incorporated into a logarithmic-reciprocal model in its projection or difference form that was used to model height, basal area, and volume increment in a trial in which *P. radiata* was planted at different stocking rates (Snowdon *et al.* 1998a).

In this paper, the results of Snowdon *et al.* (1998a) are summarized and extended by including annual variation in climatic-based factors into projection models for annual basal area increment of *Pinus radiata* grown in the ACT. It is shown that temporal variation in the growth indices need only be estimated at a single site. A Monte Carlo method is used to compare bias, precision, and accuracy of predictions made with the various models.

METHODS

Growth Data and Site Information

Three sets of data from *Pinus radiata* grown in the ACT are used: (a) height, basal area, and volume data from 4 to 16 years of age in an experiment testing six spacing densities (Snowdon *et al.* 1998a); (b) 444 observations of

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annual basal area increment in stands from 5 to 50 years of age from 20 permanent sample plots (PSP) during 1936 to 1984 (Snowdon *et al.* 1998b); and (c) 1,728 observations of annual basal area increment by combining set (b) with data from 42 additional PSP. The plots were located at 600 to 800 m altitude at about latitude 35° 20' S. Average annual rainfall varied from 645 to 1,120 mm. For each plot in data sets (a) and (b), a detailed soil characterization was made including an estimation of field capacity, wilting point, and plant available water in the soil.

Estimation of Annual Growth Index

Daily records taken of rainfall, maximum temperature, and minimum temperature were available from four meteorological stations each representing a local plantation working circle. The systematic differences in annual climatic averages between the nearest meteorological station and each of the permanent sample plots in the data set were estimated from regional climatic surfaces (BIOCLIM, Nix 1986) based on latitude, longitude, and altitude. These differences were then applied to the measured meteorological data to estimate daily rainfall and temperatures at each plot.

The process-based model BIOMASS (McMurtrie *et al.* 1990) requires input of seasonal measurements of leaf area index (LAI) and other canopy characteristics. Here, a simplified non-varying canopy structure in the simulations is used: complete canopy closure, a fixed LAI of 5.0, and a crown depth of 10.75 m. Physiological parameters appropriate for *Pinus radiata* and soil moisture characteristics determined for each site were used. The simulations were carried out using daily data for rainfall, maximum temperatures, and minimum temperatures. Annual photosynthetic carbon fixation (P) was then used as a climatic index.

Climatic Indices

As shown by Snowdon *et al.* (1998a), each of the annual observations of a climatic index (CI_i) such as annual rainfall or estimated annual carbon fixation can be regarded as being composed of two components: a long-term average value ($\underline{CI}$) and an annual deviation (Δ_i) from that value. Thus

$$CI_i = \underline{CI} + \Delta_i \qquad (1)$$

These terms can all be scaled by dividing by the mean ($\underline{CI}$) to give a scaled climatic index (SCI_i):

$$SCI_i = 1 + \Delta_i / \underline{CI} \qquad (2)$$

The sum of the scaled climatic index from the planting until a given plantation age is given by

$$\begin{aligned} \Sigma\, SCI_i &= \Sigma\,(1 + \Delta_i / \underline{CI}) \\ &= Age + \Sigma\, \Delta_i / \underline{CI} \end{aligned} \qquad (3)$$

Both scaled deviations ($\Delta_i / \underline{CI}$) and their sum ($\Sigma\, \Delta_i / \underline{CI}$) are used in the models described below. Note that within the data set used to define the mean ($\underline{CI}$) the scaled deviations have a mean of zero and their sum tends to zero.

In the following discussion, the symbol CI will be used to refer to the scaled deviations of a growth index while S CI will refer to their sum from planting until the year of observation.

Schumacher Growth Model

The basic model used in this study was the modified Schumacher log-reciprocal model of forest growth (Clutter *et al.* 1992) in its projection or difference form:

$$Y_2 = \exp(\log(Y_1)(T_1/T_2)^b + a(1 - (T_1/T_2)^b)) \qquad (4)$$

where Y_1, Y_2 are current and future stand size corresponding to ages T_1, T_2 respectively, a is estimated maximum yield parameter, and b is a shape parameter. The basic equation can be extended by exchanging the constants a, b with functions A, B and by replacing (T_1/T_2) with (C_1/C_2), where the denominator and numerator have the same functional form $C_i = T_i + q_j X_j$, with i taking the value 1 or 2, and q_j being functions of X_j additional predictive variables (Snowdon *et al.* 1998a).

In this paper we investigate four classes of equations in which:

1. the basic Schumacher model in which the asymptote, A, is a constant; B is a constant; and $C_i = T_i$;

2. A and B as in 1., but with the time function, C, now augmented with the sum of the deviations of the climate index since plantation establishment, i.e., $C_i = T_i + a\,\Sigma\, CI$ where a is a constant;

3. A, B, and C as in 1. but with the additional incorporation of scaled deviations of the climatic indices, (CI), into the asymptote function, i.e., A = c + d CI;

4. A as in 3., C as in 2., and B as a constant.

These basic models are also examined after the asymptote function has been augmented with continuous variables representing spatial variation in plot elevation (data set a) or site index (data set c). In data set (a), shape function, B, is also a function of stocking; and the time function, C, incorporates a constant that represents the time delay until trees have a measurable breast high diameter.

The study is restricted to annual increments, that is, cases where T_2-T_1=1.

Simulated Sampling Study

A Monte Carlo re-sampling method was used to test the ability of the various models to predict stand increment. This was achieved by constructing samples that contained one randomly chosen measurement from each plot. One hundred samples were constructed. The data in each sample were used to estimate parameters in each of the equations developed above. Each equation within each sample set was used to predict increment for the whole data set. The results from these enable three criteria to be used to compare the models. Bias was estimated by the mean difference between estimates of total annual increment obtained by simulation and its known true values. Precision, or the size of deviations from the biased mean obtained by repeated application of the sampling procedure, was estimated by the standard deviation of the estimates. Accuracy, a measure of the size of deviations from the true mean, was estimated by the formula (Cochran 1963):

$$\text{accuracy}^2 = \text{bias}^2 + \text{precision}^2 .$$

For convenience all three measures are expressed here as percentages. Both precision and accuracy are said to increase when their associated numerical values decline.

RESULTS

Variation in the Growth Index

The 48-year average for the climatic index derived from BIOMASS ranged from 17.3 to 29.9 tonnes of carbon per hectare (t C ha^{-1}) between sites (PSP). On the best site, annual variation was in the range +/- 15 t C ha^{-1}, while on the poorest it was about +/- 9 t C ha^{-1}. Variations of this magnitude would be expected to result in large variations in growth between sites and between growing seasons.

Growth in a Spacing Trial

The functions in the complete model for volume increment, which included a growth index in both the asymptote functions, took the form

$$A = a + d\,CI + f\,Elevation$$
$$B = b + g\,Stock$$
$$C = T - (c + h\,Stock) + k\,\Sigma\,CI$$

where a, b, c, d, f, g, h are constants, and Elevation is local plot elevation (range 14 m) and Stock is planting density (1,000s stems ha^{-1}). Volume increment observed in three treatments from the experiment is illustrated in figure 1a. Annual increments predicted by the basic Schumacher model (in which d=k=0, EMS=9.91) are shown in figure 1b, while those predicted by the complete model with a growth index in the time and asymptote function (EMS=5.30) are shown in figure 1c. The improvement in fit can be judged by the reduction in EMS. Table 1 summarizes the percentage reduction in mean squares obtained by including the growth index into the basic models (including elevation where appropriate) for annual increments in height, basal area, and volume. Including the climatic index in the asymptotic function was always better than including it in the time function, but the best models had expressions of the indices in both functions.

Comparison of Climatic Indices

Models including a term for site index in the asymptote were developed for annual basal area increment in 20 PSP in the region. A test was made to determine if a climatic index P evaluated at a single representative site could be used as the index for all sites. The PSP chosen was close to one of the meteorological stations (Uriarra) and was close to the averages of all plots with respect to annual rainfall and climatic index P. Correlations of the growth index obtained at this site with 19 other sites were between 0.87 and 1.00 with an average of 0.94. Application of a single index resulted in only a small inflation of the EMS for the various classes of models (table 2). This is a key result because it eases the burden of large and detailed data requirements necessary as input to process-based models such as BIOMASS, which has precluded their use for day-to-day forest management applications.

Bias, Precision, and Accuracy of Predicted Annual Basal Area Increment

The finding above allowed the larger data set to be used in conjunction with a growth index estimated at a single site. The sample was sufficiently large so that a Monte Carlo re-sampling method could be used to avoid problems arising from correlated errors in the data. Percentage bias, precision, and accuracy for annual basal area increments predicted by the various models are given in table 3. Average annual basal area increment was 1.9 m^2ha^{-1}.

None of the models produced predictions that were significantly ($p<0.05$) biased. These results were obtained with the complete data set, which contained observations for which the growth index varied markedly from year to year, i.e., they are an index of average performance over a wide range of growing conditions. To determine the effectiveness of the models to predict basal area increment in different climatic circumstances, five subsets of the data based on increasing magnitudes of the growth index

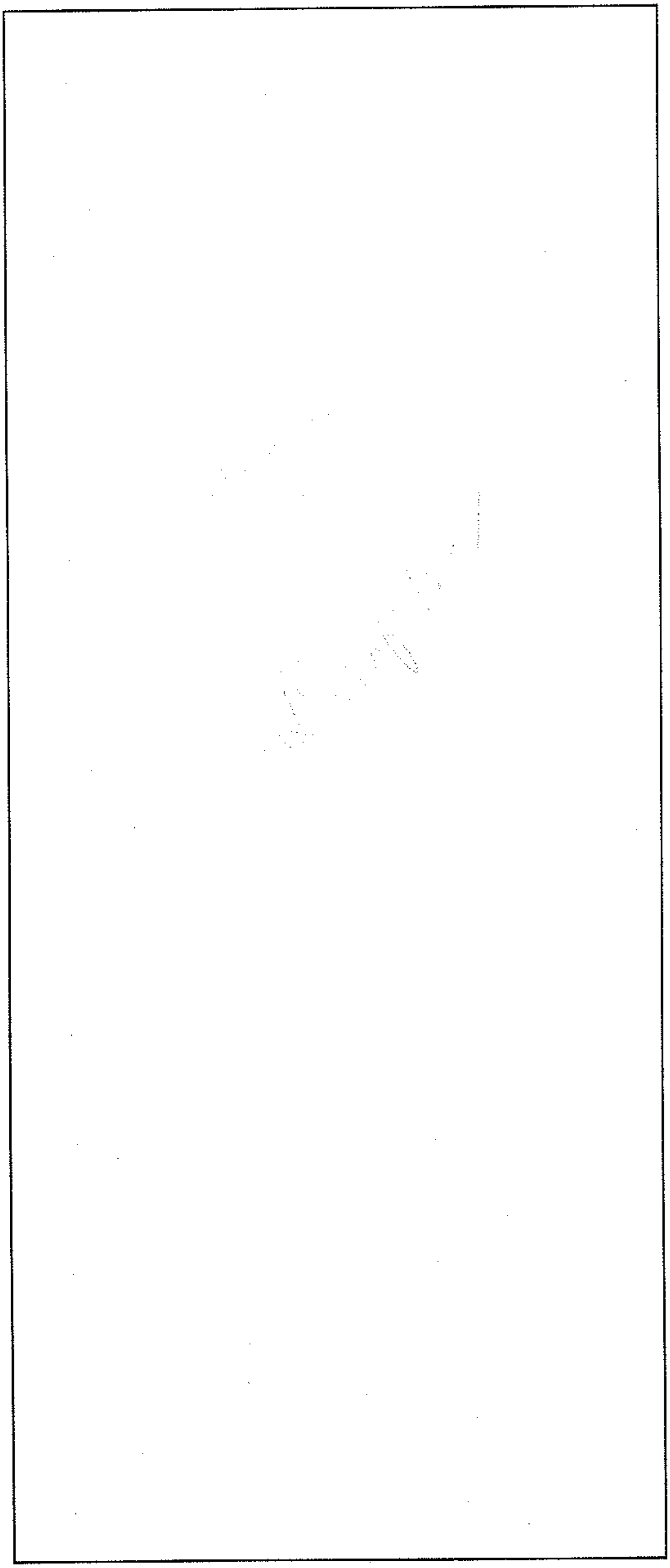


Figure 1.—*Observed annual volume increment of* Pinus radiata *grown at different stockings* (**A**), *and predictions made with the basic Schumacher model* (**B**), *and the modified model* (**C**) *containing climatic indices in the asymptote and time functions.*

Table 1.—*Percentage reduction in error mean squares obtained by including the growth index obtained from BIOMASS into the time and asymptote functions of the Schumacher equation*

Function	Height	Basal area	Volume
Time	6.8	12.3	25.8
Asymptote	7.7	28.7	32.7
Time and asymptote	21.4	38.6	46.5

Table 3.—*Bias, precision, and accuracy of various models used to predict annual basal area increment in 62 permanent sample plots of* P. radiata

Model	Bias	Precision	Accuracy
a) Basic	-0.61	3.17	3.23
b) Asymptote	-1.80	2.38	2.98
c) Time	-1.65	2.25	2.79
d) Complete	-1.80	2.52	3.10

were derived. The values of bias, precision, and accuracy for predictions made with the basic model and those containing temporal components are illustrated in figure 2. The basic model greatly overestimated ($p < 0.01$) annual increment when the growth index was low and greatly underestimated ($p < 0.01$) increment when the index was high. There was only a small region, between + 5 and - 5 percent predicted bias, where bias was not significantly different from zero. Thus, the small bias in the estimates of increment obtained with the basic model using the complete data set arise from compensatory balances between overestimates and underestimates. The biases for models containing temporal parameters were only significantly biased for the central subset of the data.

Precision for all models tended to take a parabolic form with their minimal values near the average value of the growth index. The precision for the predictions from the basic model tended to have a flatter parabolic form than those obtained with models containing temporal variables. Accuracy of models containing temporal variables was relatively constant throughout the whole range of the growth index, but comparable levels of accuracy were obtained with the basic model only when the growth index approached average values.

DISCUSSION

Applications

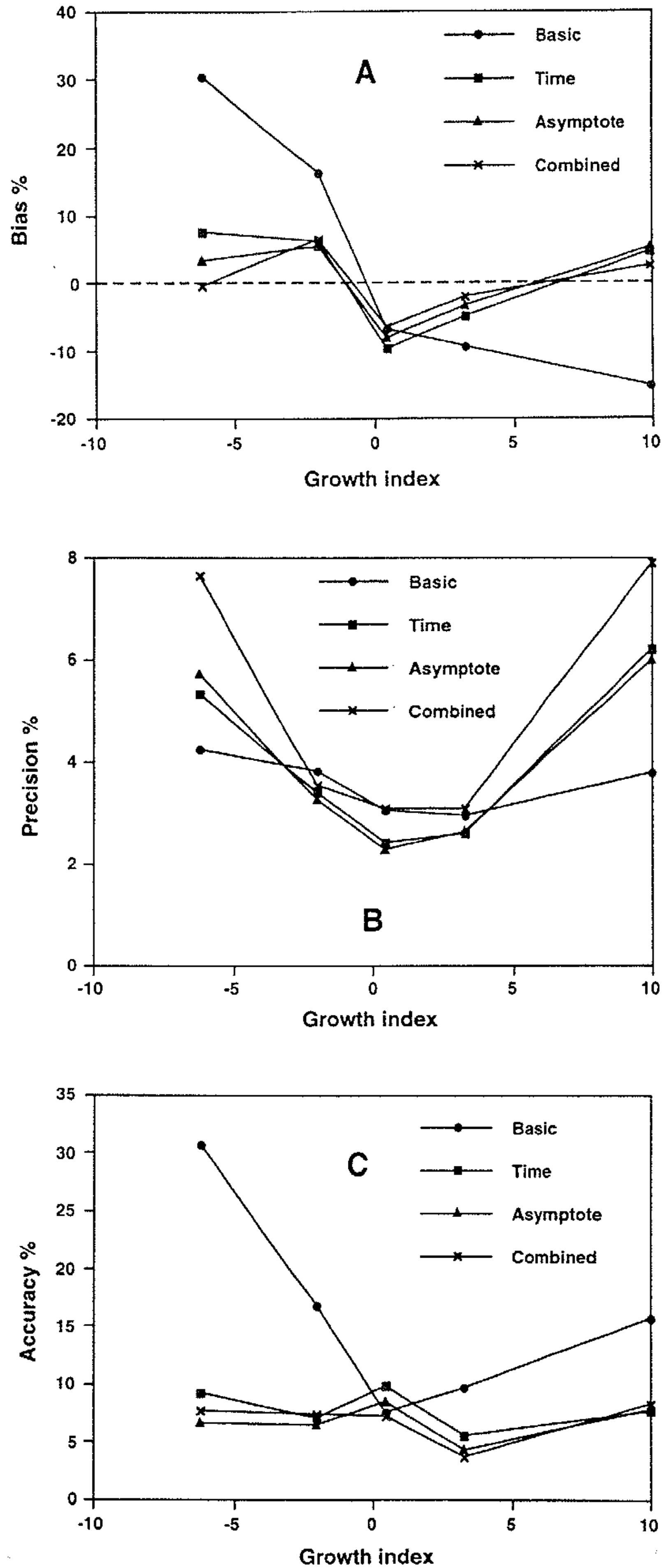
Forest managers need accurate and timely information to make decisions. Considerable research has been directed at refining models for this purpose with emphasis placed on those in projection form. It is particularly important that the models should provide unbiased predictions. As shown above (fig. 2), the basic Schumacher model can be seriously biased when it is used for specific short-term predictions in regions where there are large year-to-year differences in growing conditions.

It has not been usual to take account of temporal variation of growth in forestry growth models. Temporal variation in climatic factors cannot be reliably predicted for future years so the inclusion of temporal variables into growth models would seem, at first sight, to be a futile exercise. This is not the case. A complete forest inventory is rarely carried out across the entire forest estate on an annual basis, but timely information on the forest resource may be needed at any time (e.g., Van Deusen 1997). Double sampling, in which some plots are re-measured, is often used, but models are sometimes used to update the previous inventory to the current time. In the latter case the weather conditions during the intervening period are known, so more accurate updates can be achieved by including temporal variables in the model. The inclusion

Table 2.—*Effect of various indices of climatic variation on the reduction of error mean squares of modified Schumacher models of annual basal area increment in 20 permanent sample plots of* P. radiata

	Model			
	Basic	Time	Asymptote	Both
Indices for each plot	0.2693	0.1976	0.1842	0.1800
Single index	0.2693	0.2033	0.1886	0.1789

Figure 2.—*Bias* (**A**), *precision* (**B**), *and accuracy* (**C**) *of predictions of annual basal area increment made with basic and modified Schumacher models at different values of the climatic index.*



of temporal variables opens up the possibility of forecasting growth according to various hypothetical climatic scenarios. If a detailed process-based model has been used, then the effects of important changes, such as increasing atmospheric carbon dioxide concentrations, can be examined.

Properties of the Models

Ideally, models used for estimation of growth and yield in forests should be compatible and path invariant (Clutter *et al.* 1992). As is well known, the projection or difference equations used in this study are all compatible. Those equations that do not include an annually variable growth index in the asymptote function, A, are all path invariant because for each age and stocking there is a unique value for the function C. When an annually variable growth index is included in A, the projections must be iterated annually. This need not be a disadvantage for prediction because such computations can now be easily and rapidly made. Incorporation of temporal factors into the models increases bias in predictions, but these are not statistically significant for predictions of annual growth (table 3). Annual observations of climate-based indices or those derived from processed-based models are required for calibration of the growth models. In the case of path invariant models, these are required so that the sum of the deviations from the long-term average can be calculated. When the temporal variable is included in the asymptote function, annual growth measurements are also required.

Various indices can be used to capture the essence of seasonal differences in growth potential. Good improvement can be obtained by using a simple index such as growth season rainfall (Snowdon *et al.* 1998 a,b) but better results can usually be obtained by using an index derived from a process-based model such as BIOMASS. The superiority of this growth index compared to rainfall can be attributed to the ability of the BIOMASS model to integrate the effects of seasonal differences in climatic factors such as temperature, rainfall, and evaporative demand with changes in soil water storage and thereby the effectiveness of photosynthetic production in different growth periods. Thus, a dry period during winter may have little effect on the growth index while a wet period during summer would have a large effect. Annual rainfall weights each rainfall event equally.

In this study it was sufficient to use a growth index calculated at a single location to capture temporal variability for the entire regional data set. Although there is considerable spatial variability in climatic averages, particularly for rainfall, across the region, the climatic data are highly correlated. Consequently, the relative suitability of conditions for producing stand growth during a growth season is also highly correlated across the region. This is an important property when the models are used to predict growth on plots established for inventory purposes. The number of plots used for inventory usually far exceeds the number of plots used to calibrate the model. Consequently, it is important that the input data for the model (stand age, initial basal area, site factors, growth indices, etc.) be quickly and cheaply estimated. Use of a single, regional index of climatic variation avoids the need for time-consuming calculation of an index for each inventory plot.

The best index in these studies was estimated by using a detailed process-based model of photosynthetic carbon fixation with simplified assumptions about canopy structure. Simplification was necessary because there were no historic data about canopy cover or structure. It is likely that the index could be improved if estimates of leaf area index were available. In the case of existing data, the estimates would need to be made with a mathematical model based on stand and site characteristics. In existing stands, rapid but reliable estimates can be made by eye (Sampson *et al.* 1996). Spatial variables, such as site index, topographic position, spatial averages of climatic and growth indices, geological substrate, and indices of soil development, can also be included in the models to reduce EMS (Snowdon *et al.* 1998 a,b). The effects of spatial and temporal classes of variables are approximately additive.

CONCLUSIONS

Substantial improvement in prediction of annual basal area growth can be achieved for some forests by incorporating annual growth indices derived from detailed process-based models into Schumacher difference equations. Short-term predictions made with these models are more accurate than those obtained with the traditional model and are particularly useful for updating stand inventories. The new models should be most applicable to regions where there is substantial variation in climatic factors from season to season and where the object species is responsive to those factors.

The approach can broaden the scope of forestry modeling and will be of increasing importance as quantification of the forest estate becomes more detailed and forest managers become increasingly reliant upon geographic information systems in making their decisions.

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