A Comparison of Forest Growth and Yield

Models for Inventory Updating

by

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(ABSTRACT)

A system of loblolly pine growth and yield models was developed which used database files as input. Using database files as direct input created a compatible link between the growth and yield models and a Geographic Information System (GIS). Since growth and yield models can be used to update forest inventories and a GIS is a common method for maintaining forest inventory data, this compatibility provided a method to rapidly update past forest inventory records.

This system was used to evaluate four different loblolly pine growth and yield models. The growth and yield models examined were: a whole stand, a diameter distribution - parameter prediction, a diameter distribution - parameter prediction, and an individual tree. Three different validation approaches were used to create fitting and validation data sets from permanent plot remeasurement data, and evaluate each of the four growth and yield models at varying projection periods. The periods used were zero, three, six, and nine years. Evaluations were based solely on

the capability of each to model to predict merchantable volume.

In terms of root mean square error of prediction, the individual tree and whole stand models performed superior than the diameter distribution models. At shorter projection periods the individual tree model performed better than the whole stand model, but the whole stand was superior at the nine year period. The parameter recovery models performed better for shorter periods than the parameter prediction model, but this difference diminished with longer periods.

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Introduction

The most important commercial tree species in the Southern United States is the loblolly pine. Due to its many desirable properties, this species has the capability to be used for a variety of wood products. As a result it has become the most managed tree species within the region, Detailed predictive information for stand volume yield is required in order to make prudent management decisions. Such decisions are often based on forest inventories of each management unit. This information is obtained at one point in time, and current measurements are not always available. Because of cost reduction and efficiency, inventory updating with growth models is often the most efficient means of obtaining current stand level information.

Many tools are available to forest managers to aid in decision making. Two of these are geographic information systems (GIS) and computerized growth and yield models. GIS systems not only provide for the displaying of geographic data, but also contribute to the analysis of such information. Computerized growth and yield models provide a means to rapidly obtain estimates of present stand values from inventory records. Much would be gained by using both tools together. Both are available to resource managers, but presently very little work has been done in joining two such systems. Linking GIS capabilities with the predictive abilities of growth and yield models would provide an automated means for the display and analysis of predicted information.

Objectives:

There were two primary objectives of this thesis. The first was to create an automated inventory updating system by integrating various loblolly pine growth and yield models with a geographic information system. Many questions remain as to the proper expectations, use, and limitations of the various statistical models available to the land manager. Each model has certain requirements and produces varying levels of predicted information. Therefore, the second objective of this thesis was to analyze the behavior of the three major classes (whole stand, diameter distribution, and individual tree) of growth and yield models for updating forest inventory data. This was done for different projection periods by using the integrated inventory system with remeasured permanent plot data.

In the course of examining model behavior another objective developed. This was to study the effectiveness of various validation techniques for verifying model adequacy.

Literature Review

Forest Inventory Updating:

In the classical sense the term "inventory" refers to "a detailed descriptive list of articles with number, quantity and value of each item" (Loetsch and Haller 1973). Spurr (1952) explains that a forest inventory deals with methods used to obtain information on volume and growth of trees within forested areas. A forest inventory is an attempt to provide a detailed description of an area of forest land and the tree species which comprise the forest growing on this land. Therefore, a forest inventory must include both size of areas and features of growing stock within these areas (Loetsch and Haller 1973).

An inventory is representative of a forest at the moment the inventory was performed. Forests are not static, but dynamically changing structures. Therefore, inventories taken at any given time may become outdated rather rapidly. One solution is to constantly perform reinventories on lands where current information is needed for proper management decisions. This method is extremely time consuming and very costly (Birdsey 1990), and therefore often not an efficient method to provide such information. Inventory updating (estimating current or future forest inventories based on past inventories and growth expectations) becomes a very promising alternative for cost effective management (Burkhart 1993).

There are many tools available which can accomplish this task. Birdsey (1990) reviews the many techniques applicable to updating forest inventories. These are trend extrapolation and time series analysis, transition probability matrices, timber supply models, growth and yield models, sampling methods, remote sensing and geographic information systems, and combinations of these. Birdsey (1990) notes that growth and yield modeling displays particular promise because it not only allows for inventory updating, but also for making future projections. There exists a wide array of well documented growth and yield modeling techniques which provide for many levels of input and output information. This permits the growth and yield modeling approach to inventory updating to be tailored specifically for many different situations.

Growth and Yield Models:

The prediction of growth and yield on forested lands generally requires three forms of input. The simplest of these is time or length of growth period. Growth rate is then based on the remaining factors which are "the innate productive capability of the site" and "the amount and composition of the growing stock present in the stand"

(Clutter, et al. 1983). Although there are a variety of methods to estimate the productivity of a site, the most common method is site index. Site index is generally defined as the average dominant and codominant height of a stand at a given base age. The commonly used base age for loblolly pine plantations is twenty five years. For examples of site index curves for loblolly pine see Amateis and Burkhart (1985). Stand composition is judged by several factors including species, size class distribution, and spatial distribution (Clutter, et al. 1983). This thesis involves only stands which are considered to be homogeneous and comprised of only even-aged loblolly pine which greatly simplifies stand composition. There exists a large body of literature involving the many approaches and attempts of modeling forest growth and yield; because of this, this literature review will focus primarily on the development of loblolly pine growth and yield models chosen to be most appropriate for the integration and testing stage of this thesis.

There are two general categories under which growth and yield models fall; these are stand level and tree level models. The difference arises in the method of modeling and the level of stand information needed as input coupled with the level of information capable of being provided as output.

The stand level models are the simplest type and accordingly were the first to be developed. The concept of whole stand growth and yield modeling originated with the formation of normal tables. These tables were based on stands which were said to have "normal" stocking levels. Graphical techniques were usually used to analyze yields for different age and site combinations (Anon. 1926).

Further refinement in yield prediction was obtained through the use of multiple regression techniques. Schumacher (1939) derived such a regression equation based on geometric relationships of yield with respect to a desirable growth curve. Normal stocking was assumed and yield predicted from site index and stand age. A general model form was presented as well as a specific model fit to longleaf pine data. MacKinney and Chaiken (1939) used this same approach to develop variable density yield tables for loblolly pine. These tables were derived using multiple regression techniques instead of the previous graphical techniques and covered a wide range of stocking levels.

The previously-described regression techniques for modeling growth and yield were used extensively with little modification until Clutter (1963) developed compatible growth and yield models. He stated that past studies treated growth and yield almost entirely as "independent phenomenas," which is not an appropriate approach. Therefore, Clutter developed an approach which produced compatible growth and yields models. Many models were scrutinized and a modified version of the original Schumacher form was chosen for the analysis. The modification to the Schumacher form was the addition of a density variable in terms of basal area. This yield model was then differentiated with respect to age. The differentiated form required a basal area growth component. This component was obtained through graphical analysis of work performed by Schumacher and Coile (1960). The end results were equations to predict cubic-foot yield, basal area growth, cubic-foot growth, basal area projection, and cubic-foot volume projection.

Two primary difficulties in this modeling approach arise when applied to actual plot data. First, because the parameters of each model are not independent, the fitted models (based on algebraically consistent model forms) will not be numerically consistent. This mean that a basal area derived from the yield projection equation will not be the same as a basal area predicted from the basal area projection equation. Secondly, successive remeasurement data are not independent observations and should not be treated as such (Sullivan and Clutter 1972). These problems were addressed by Sullivan and Clutter (1972) in a study which developed a single model relating projected stand volume to initial stand age, projected age, site index, and initial basal area. This was done in such a way as to provide a standard yield equation. With this approach, when initial stand age equals projected stand age, projected stand volume equals initial stand volume and therefore the model was termed a simultaneous growth and yield model.

In the method previously described, the coefficients for the basal area projection equation are not estimated, but derived from those estimated from the volume projection fit. An alternative approach to obtaining parameter estimates for both basal area and volume projection was presented by Burkhart and Sprinz (1984). Their method defines a loss function where both volume and basal area projection were included with equal weights assigned to both equations. An iterative process was used to produce parameter estimates which minimized this loss function.

Diameter distribution models are another form of whole stand models. These models require only whole stand input information but produce output information which includes details of the size class distribution likely to be found in the predicted stand. The size classes used are almost exclusively diameter class. Because there is a significant difference in the output information provided by these models they are often classified into a completely separate class of growth and yield models from previously discussed whole stand models.

Information with respect to the way in which stem diameters are distributed is generally obtained by the use of some common probability density function. Given a probability density function which is assumed to accurately model a stands diameter distribution, the proportion of stems in any diameter class can be estimated by integrating the function from the diameter class lower limit to the corresponding upper limit. This proportion is then multiplied by a the total number of trees per acre to obtain the number of trees within the class of interest. The mid-point of the diameter class in question is then assumed to adequately represent all trees within the class. Depending on requirements of the volume equation, average height either is or is not predicted from the mid-point diameter. Using the "average" diameter and perhaps also height of a class, volume is then calculated using a tree volume equation. Total volume within the class is then determined by multiplying the number of tree within a class by the average volume per tree of that class. Finally, total volume per acre is obtained by simply summing the volume within each class across all diameter classes of interest. Detailed descriptions of this approach can be found in Frazier (1981) and Knoebel et al. (1986).

Another method involving diameter distribution volume prediction was presented by Strub and Burkhart (1975). This method removes the bias created by using the mid point of the class interval to represent all trees within the interval and is referred to as class-interval-free estimation of volume for any upper and lower merchantability limits for a product class in question. This method involves integrating both the function describing the probability density function of the diameter distribution and a local volume equation, from the lower to upper merchantability levels. This removes any use of diameter as discrete units.

The primary difference with diameter distribution modeling is the probability density function chosen to represent stand structure. Most initial modeling attempts were performed using the beta probability density function. Although this function often fits data well, the beta distribution is cumbersome to implement because the cumulative density function does not exist in closed form (Cao et al. 1982).

Almost all of the recently developed diameter distribution models for even-aged stands have used the Weibull probability density function. Knoebel et al. (1986) note the advantages of using the Weibull p.d.f. as: flexible shape, easily estimatable parameters, it exists in two or three parameter forms, and its cumulative distribution function exists in closed form (a primary advantage over the beta p.d.f.).

Bailey and Dell (1973) first proposed the use of the Weibull function for representing diameter distributions. Since their publication, the Weibull function has been used by many others to describe the structure of loblolly pine plantations (Smalley and Bailey 1974, Feduccia et al. 1979, Cao et al. 1982, Amateis et al. 1984). Burk and Burkhart (1984) also used the Weibull function to model natural stands of loblolly pine.

Initially, the parameters of the Weibull function were related to stand level attributes. Using data from sample plots, the parameters of the Weibull function were estimated for each plot using maximum likelihood procedures. Regression equations were then fit to relate each parameter in the distribution to stand characteristics like age, site index, and number of trees per acre. This procedure is referred to as parameter prediction. The main problem with this technique is that these equations typically explain very little of the variation associated with the parameters and have r-square values ranging from .1 to .3 (Frazier 1981).

Based on the class-interval-free method of estimating yield (Strub and Burkhart 1975), Hyink suggested another approach where the parameters of the Weibull function are solved for, based on the stand average attributes gained by using traditional whole stand models. This technique was termed "parameter recovery". Frazier (1981) fully developed this method using both the beta and Weibull function for unthinned stands of loblolly plantations. This was done by acknowledging the fact that many stand level attributes can be treated as non-central moments (or some function of a particular non-central moment) of the function which represents the diameter distribution. For example, average diameter is the estimated first non-central moment and basal area per acre is a function of the estimated second non-central moment of any diameter distribution. By obtaining the first k moments, then k unknown parameters can be solved for using the method of moments technique for p.d.f. parameter estimation. Complete details of this procedure can be found in Frazier (1981). This method provides a completely compatible system between stand average models and diameter distribution models for the attributes used to solve for the p.d.f. parameters.

Another approach to modeling growth and yield has been used which bases the growth element, not on the entire stand, but on the individual tree. These models have been appropriately labeled individual tree models. Individual tree growth is simulated on an annual or other periodic basis. Stand level attributes are determined by summing the individual tree simulations and expanding these values to a per acre basis.

There are two primary classifications of individual tree models. These are distance-independent and distance-dependent models. This classification is based on whether the particular model requires the spatial location of each individual tree. Individual tree models provide for the greatest detail of information about stand growth and yield.

Distance-independent models are generally used to either update stand table estimates or individual tree lists. Individual tree growth is usually based on the size of each tree in relation to that of the stand level average. These models are generally made up of two central components. These are a diameter growth component and an individual tree mortality component (Amateis et al. 1989).

A distance-independent model has been produced for plantation grown loblolly pine on cutover, site-prepared lands (Amateis et al. 1989). This model first calculates each tree's survival rate based on crown ratio and competitive status (quadratic mean stand diameter divided by current individual stem diameter). This value is used empirically to determine the proportion of trees within a given diameter class which will remain living in the next given year. Dominant stand height growth is determined through the use of site index equations. This height is used to calculate the potential diameter at breast height of an open grown tree. This value is appropriately adjusted based on each individual tree's crown ratio and stand quadratic mean diameter to individual tree diameter ratio. It is also noted that this method should be very useful for projecting stand tables for inventory updating purposes (Amateis et al. 1989). A similar approach has been taken by Belcher et al. (1982) to model individual tree growth for tree species in the Lake States and by Harrison et al. (1986) to model individual tree growth of Appalachian mixed hardwoods after thinning.

Distance-dependent models base growth not only on individual tree values such as diameter, height, and crown ratio, but also on the individual location of each tree being simulated. The growth components for distance-dependent models are similar to distance-independent models. The primary difference between the two types is the method employed to determine an individual tree's competitive status. Distance-independent models base competitive status on individual tree size compared to the size of the stand average tree. Distance-dependent models, on the other hand, base individual competitive status on some function of distance to and size of neighboring trees which may influence the individual tree's growth. The distance of influence is generally based on the individual tree size. Determining competitive status in this manner is the element of the model which requires knowledge of each tree's exact location. The main advantage of distance-dependent models is that they are most useful in predicting growth under various silvicultural treatments, especially those where exact tree location is a factor, as is the case under many thinning regimes (Clutter et al. 1983).

Similar to the distance-independent model by Amateis et al. (1989) a distance-dependent model has been created for loblolly pine on cutover, site-prepared lands (Burkhart et al. 1987). This model is based on principles first developed by Daniels and Burkhart (1975) for old-field loblolly pine plantations. Distance dependent models are less suited to inventory updating because inventory data generally do not include tree locations, these models are most complex, and they have not shown to more accurately predict growth than distance-independent models (Clutter et al. 1983). Therefore this modeling procedure will not be examined any further in the course of this thesis.

Geographic Information System Integration:

Aronoff (1989) defines geographic information systems (GIS) as, "computer based systems that are used to store and manipulate geographic information." He further adds that "the power of the system is most apparent when the quantity of data involved is too large to be handled manually." Such an application in forestry could be the process of maintaining accurate stand level inventories for a large region. This would require not only managing detailed records containing stand and possibly tree level information, but also keeping track of each stand's geographic characteristics such as size, shape, location, grade, soil type, distance to roads, or inclusion of streams.

Birdsey (1990) discusses the promise of GIS involvement to aid in updating forest inventories by pointing out that such a system has enormous potential for updating stand level features for specific tracts of land or sample points. Burkhart (1993) recognizes that much work has been applied to developing techniques for the inventory of forests, but little effort has been applied to the integration of growth and yield models with forest inventories. The data management systems associated with most any GIS would be extremely appropriate for managing inventory records. Though presently very little work exists which studies integration of a GIS with growth and yield models for inventory updating, much could be gained by work in this area. Ek (1990) describes the obvious benefits associated with such a system as: 1.) data manipulation such as sorting, querying, selecting, and modifying; 2.) the direct ties created between management systems and a GIS; 3.) reduction of time spent in writing and formatting input and output screens and queries for growth simulators since most management systems already include such options; and 4.) the use of growth models becomes straight forward when used with operational data which is stored in a common data base. In reference to GIS integration with growth and yield models, Ek (1990) states "If we do not take this step now, ten years from now people will have nice maps, but they will still not be able to project growth on the forest."

Little work exists which specifically involves GIS integration with growth and yield models for inventory updating, but there are some examples of model integration for other objectives. Covington et al. (1988) describe such a system referred to as TEAMS-Terrestrial Ecosystem Analysis and Modeling System. This system involves integration of a GIS (Arc/Info), a data base (R:Base 5000), an ecological management simulation system, a recreation evaluation program, and a commercial linear programming package (LINDO). The system was designed to aid forest managers in developing site-specific management plans. Another example of an integrated system is INFORMS-Integrated Forest Resources Management System (Buyoff et al. 1988 and Hunter et al. 1988). This system is described as "a decision support system that integrates spatial data, tabular data, and resource models" (Hunter et al. 1988). This system includes a spatial data base (MOSS), a tabular component, and a model library including models for: forest stand structure, sedimentation, fish response, effect on elk, wildlife cover changes, mountain pine beetle spread, economic evaluation, and visual sensitivity. These are all controlled by and accessed through a software management system called the central control module. Although these systems have made great advances in GIS, data management, and model integration, they are not intended to be used to make accurate predictions which are required for inventory updating. These systems are more specifically designed as tools to aid in decision making.

The only work found to be similar to growth and yield model integration and GIS for inventory updating is a project currently under study by Pro-West and Associates (1992). This work deals with "running readily available existing resource data through a reliable growth and yield modelling framework to produce a geographically oriented prediction of future responses." This work is still under study and presently no details or formal publication exists.

Methods

Model Selection:

To study the behavior of different loblolly pine growth and yield models for inventory projection, three categories of models were recognized: whole stand, diameter distribution, and individual tree. Each approach differs by the detail of information required as input, the level of information provided as output, and the methodology employed to make predictions.

Whole Stand:

Whole stand models require only whole stand variables as input, typically these are: stand age, a measure of site quality, and a measure of stand density. Similarly the output from such a model is in the form of stand level averages. Although many models of this type have been developed, most are quite similar in overall approach. The specific form chosen in this study was that developed by Sullivan and Clutter (1972) which was an extension of Clutter (1963). This form was based on the original Schumacher form developed in 1939. The specific model used is the following.

$$\ln Y_2 = b_0 + b_1 A_2^{-1} + b_3 (A_1/A_2) \ln B_1 + b_4 (1 - A_1/A_2) + b_5 (1 - A_1/A_2) S$$

where,
Y_2 = projected yield in volume per acre
A_1 = initial stand age in years
A_2 = projected stand age in years
B_1 = initial basal area per acre
S = site index
b_i = parameters to be fit, where i is the parameter number

For the purpose of site index estimation an external equation was used without fitting to data to maintain independence. The equation used was taken from Burkhart et al. (1987). The site index equation is common to all models, not just the whole stand model and is the following.

$$\ln(H_d) = \ln S (25/A)^{-.02205} e^{-2.83285 (A^{-1} - 25^{-1})}$$

where,
H_d = average stand height of dominant/codminant trees
A = stand age
other as previously defined

Diameter Distribution:

The diameter distribtuion class of models produce whole stand information which is divided by frequency into diameter classes. This is performed using only whole stand data as input, and done by basing the shape of the diameter distribution on some function. Then one of two common techniques is used to estimate the values of the function parameters for the particular stand. The two techniques used to estimate parameters are parameter prediction and parameter recovery. Although several functions have been used to represent the distribution of diameter at breast height (DBH) values, presently the most common function is the Weibull, which is defined as follows.

$$f_x(x;a,b,c) = \begin{cases} \left(\frac{c}{b}\right)\left(\frac{x-a}{b}\right)^{c-1}\exp\left[-\left(\frac{x-a}{b}\right)^{c}\right] & a,b,c>0 \\ 0,\ otherwise & x>a \end{cases}$$

where,
a = location parameter
b = scale parameter
c = shape parameter
x = random variable
Γ = gamma function

Because the two methods of estimating the parameters are both in common practice and out of the interest of comparison, one parameter prediction model was chosen as well as one parameter recovery model.

The parameter prediction model estimates the three parameters by developing a series of regression equations where each parameter is predicted using whole stand variables.

The specific set of basic equations used in this study are those developed by Smalley and Bailey (1972).

$$a = b_0 + b_1 H_d$$

$$a + b = b_0 + b_1 N + b_2 \log H_d + b_3 / N$$

$$c = b_0 + b_1 A + b_2 \log N$$

where,
N = number of trees per acre
others as previously defined

The other diameter distribution technique investigated was parameter recovery. The system used was based on the method of moments and the specific model was developed by Frazier (1981). In this model the *a* parameter is specified outside the system and then a simple transformation is used to obtain the two parameter Weibull function from the three parameter. Using the first and second moments (average diameter and quadratic mean diameter squared) of the diameter distribution the two remaining parameters can be solved for. The following regression equations are used to predict the necessary whole stand information from which the parameters of the diameter distribution are recovered.

$$\overline{D} = b_0 + b_1 H_d + b_2 A (N/1000) + b_3 H_d / N$$

$$\ln(\overline{D}_q^2 - \overline{D}^2) = b_0 + b_1 \ln H_d + b_2 1/A + b_3 \ln N$$

$$D_{\min} = b_0 + b_1 H_d + b_2 A(N/1000) + b_3 H_d/N$$

where,
$\overline{D}$ = average diameter at breast height
D_q = quadratic mean diameter at breast height
D_{min} = minimum diameter at breast height
others as previously defined

Using predicted minimum diameter the *a* parameter is determined by:

$$a = .5(D_{\min})$$

where,
all variables as previosly defined

Once the *a* parameter is set the coefficient of variation is:

$$c.v. = \frac{[\overline{D}_q^2 - 2\overline{D} + a^2 - (\overline{D} - a)^2]^{1/2}}{(\overline{D} - a)}$$

where,
$c.v.$ = the coefficient of variation
others as previously defined

Given the coefficient of variation the *c* parameter can be iteratively solved for using the following relationship.

$$c.v. = \frac{[\Gamma(1+2/c) - \Gamma^2(1+1/c)]^{1/2}}{\Gamma(1+1/c)}$$

where,
all varaibles as previously defined

Given a value for the *a* and *c* parameters the *b* parameter can be determined by the following.

$$b = \frac{(\overline{D}-a)}{\Gamma(1+1/c)}$$

where,
all varaibles as previously defined

Once the p.d.f. of the distribution is defined, whether using parameter prediction or parameter recovery, the frequency within each diameter class of interest is determined by integrating the function from the lower bound of the class to the upper bound. This frequency is then multiplied by the number of trees in the stand to determine the number of trees within the class. For projection purposes this required a mortality function. One common function developed by Clutter (1984) was chosen for both systems. The significance of site index in this model was questioned. Therefore, two models were fit, one with and the other without site index. A test for significance of the site index variable was then performed. Because site index was found to be significant it was retained and the following model chosen.

$$N_2 = \left[N_1^{b_1} + (b_2 + b_3/S)\ (A_2^{b_4} - A_1^{b_4})\right]^{1/b_1}$$

where,
N_1 = initial number of trees per acre
N_2 = projected number of trees per acre
others as previously defined

Total tree volume within a class is determined by estimating the volume of a single tree at the midpoint of the class; this estimate is then multiplied by the estimated number of trees within the class. Total stand volume is then calculated by summing the volumes within each diameter class of interest. This required an individual tree height equation and an individual tree volume equation. The individual tree height model used was originally developed by Burkhart, et. al. (1987) and follows.

$$\log(H_d/H) = b_0 + (D^{-1} - D_{\max}^{-1})\ (b_1 + b_2 \log N + b_3 A^{-1} + b_4 \log H_d)$$

where,
H = individual tree height
D = indivdual tree diameter at breast height
D_{max} = stand maximum diameter at breast height
others as previously defined

The volume equation was treated as an external equation and therefore was not fit to any data. Previously published parameters were used. This equation was developed by Amateis and Burkhart (1987) and follows.

$$V_{ob}=(.18658+.00250D^2H)(1-.54583(4^{3.22011}/D^{3.03262}))$$

where,
V_{ob} = individual tree volume (outside bark) in cubic feet to a 4 inch top (dob)
others as previosly defined

Individual Tree:

The individual tree model differs from other approaches in that it requires actual diameter distribution information in the form of a diameter list using all the trees in a plot. This set of trees is actually "grown" on an individual tree basis, volume estimated for each tree, then summed to obtain stand volume. This is done by first employing an external equation to determine maximum diameter growth potential without the influence of competition. This equation comes from Amateis, et al. (1989).

$$\Delta D_p=.286583\Delta H+.209472$$

where,

ΔD_p = potential diameter at breast height increment
ΔH = height of dominant/cominant tree increment

Crown ratio is then estimated and used as a modifier to potential diameter increment to determine actual diameter increment. The crown ratio model used was developed by Dyer and Burkhart (1987) and the diameter increment model was developed by Amateis, et al. (1989). These models are:

$$C_r = 1 - e^{(-(b_0 + b_1 A^{-1}) D/H)}$$

$$\Delta D = \Delta D_p b_1 C_r^{b_2} e^{b_3 (1 - \bar{D}_q / D)}$$

where,
C_r = crown ratio
ΔD = actual diameter at breat height increment
others as previosly defined

The probability of individual tree survival is used to adjust each trees relative frequency; the model used was developed by Amateis, et al (1989).

$$P = b_1 C_r^{b_2} e^{b_3 (\bar{D}_q / D)^{b_4}}$$

where,
P = probability of survival over the following year
others as previously defined

The process of incrementing tree diameter and adjusting tree frequency based on survival is performed on an annual basis until the desired projection year is reached. Then individual tree height and individual tree volume equations, presented under diameter distribution models, are employed to determine each tree's volume. This number is reduced by the tree's final relative frequency to account for mortality. Each of these volumes is then summed to determine stand volume.

Data Set and Model Fitting:

A large data set was available for use in this study. This data set exists due to the efforts of a thinning study funded by the Loblolly Pine Growth and Yield Research Cooperative. The study consists of 186 locations at various loblolly pine plantations, each containing three permanent study plots. The locations were chosen to encompass most of the natural range of loblolly pine. Although each location contains a control, a light thinned, and a heavy thinned plot, this thesis dealt only with data collected on the unthinned or control plots.

The three plots at each location were chosen to minimize any difference in site and stand structure within and between the plots. Each plot was established within already existing stands. The plots were chosen to encompass a wide range of stand ages, densities, and site values. The installation of the plots was performed during the dormant seasons of 1980 through 1982. Each of the unthinned plots were designed to be approximately .1 acre in size.

Initially, precise stem maps were constructed for each plot and measurements were taken at each tree, these included DBH, total height, and height to base of live crown. Many characteristics were also noted, such as species, crown class, stem quality, tree vigor, and merchantability class. At the time of this study three subsequent remeasurements had been made at each location at three year intervals.

The described data set contains information for all trees found on each plot, regardless of species and size. For the purpose of this study only loblolly pine trees were used for model fitting. Only plots which were greater than or equal to age ten at the onset of the study and plots which remained undamaged during all four measurements were used. This reduced the total number of plots available for the study to 135 and the total number of trees to 8001. A summary of the plot data with respect to time is provided in Table 1.

Of the many different models which were fit using this data set, each had one of three requirements for data sampling

Table 1. Plot mean information of data set used for fitting and validtion.

Variable*	Time	N	Mean	Standard Deviation	Minimum	Maximum
AGE	0	135	15.47	3.83	10.00	24.00
AGE	3	135	18.47	3.83	13.00	27.00
AGE	6	135	21.47	3.83	16.00	30.00
AGE	9	135	24.47	3.83	19.00	33.00
HD	0	135	40.95	9.93	19.88	66.59
HD	3	135	46.79	9.42	25.30	71.57
HD	6	135	52.03	9.13	31.33	79.00
HD	9	135	57.10	9.12	36.68	85.09
BA	0	135	109.33	31.38	31.49	183.72
BA	3	135	126.07	27.80	45.75	198.53
BA	6	135	137.35	25.94	63.29	203.81
BA	9	135	146.21	26.75	80.89	205.96
TPA	0	135	580.10	136.23	270.00	1020.00
TPA	3	135	555.92	131.20	270.00	1020.00
TPA	6	135	522.23	125.59	260.00	930.00
TPA	9	135	484.64	123.94	200.00	860.00
DBH	0	135	5.75	1.02	3.49	8.79
DBH	3	135	6.35	1.02	4.05	9.54
DBH	6	135	6.87	1.06	4.54	10.16
DBH	9	135	7.38	1.10	5.03	10.94
DMIN	0	135	2.71	1.02	0.60	6.00
DMIN	3	135	3.08	1.06	0.70	6.20
DMIN	6	135	3.48	1.13	0.70	7.70
DMIN	9	135	3.93	1.20	0.70	8.00
YIELD	0	135	1716.27	1032.71	45.96	5418.18
YIELD	3	135	2341.93	1059.95	275.00	5993.22
YIELD	6	135	2912.36	1087.70	696.18	6250.09
YIELD	9	135	3459.35	1098.75	1158.49	6753.49

* where,

AGE - stand age since planting in years
HD - average height of dominant/codominant trees in feet
BA - basal area per acre for all trees in square feet
TPA - number of trees per acre
DBH - diameter at breast height in inches
DMIN - minimum observed tree diameter in inches
YIELD - merchantable volume in cubic feet per acre

intervals to time. These interval requirements were either: a single point in time, an annual increment, or a varying projection length. Data sets with these requirements were created and will be referred to as single, annual, and varying. The overall data set contains four measurements at three year intervals, these will be referred to as time one, two, three, and four.

The multiple observations at each plot imposed a problem of maintaing indepence in observations. To maintain independence, only one possible data selection with respect to time was made to contribute to each data set. For the single data set, observations associated with one of the four points in time were randomly selected. For the annual data set, one of the first three measurements were randomly selected and paired with the next consecutive measurement and then the difference between observation values was divided by three to obtain an average annual values. For the varying data set, the first measurement data was randomly paired with either the second, third, or fourth measurement. In fitting the equations, independence between observations was a primary concern. Therefore data not selected was disregarded. All Parameters were estimated in the most appropriate manner for each model being used, which generally involved some form of least squares procedure.

For fitting the parameter prediction models, values of *a*, *b*, and *c* for each stand were required. These were obtained by fitting the three parameter Weibull function to diameter class frequencies using a maximum likelihood procedure. In some cases convergence could not be met because the *a* parameter was driven negative. Since this case is not of interest because the *a* parameter is a function of the minimum diameter of a stand, the *a* parameter was set to zero and the two parameter Weibull was used for fitting these stands.

Validation Schemes:

The primary data set was randomly divided into fitting and validation sets based on different validation schemes. The size of the fitting versus the validation set depended on the validation approach being employed. Three separate procedures were used to validate model behavior. The first was a 50/50 data split which was double-cross validated. Under this scheme all the plots and associated data were randomly divided into two nearly equal data sets (the total number of available stands was odd). One data set was used for model fitting while the other was used for validation. The validation procedure was then repeated with the roles of each data set being reversed, the fitting data set was used for validation and the validation set was used for fitting. This provided two sets of results.

The second scheme involved a 70/30 data split which was repeated. The data was randomly divided so that 70 percent of the plots and associated information were placed into a fitting data set and the remaining 30 percent were placed into a validation data set. This approach was repeated after changing all random number seeds so that a second independent validation could be performed.

The last scheme involved a PRESS type approach. One at a time, all the information associated with a single plot was temporarily removed. Then all the models were fit to the remaining plot data. These fitted models were then used to make predictions about the single plot which had been removed before fitting. This process was repeated for all 135 plots. Fitting the linear equations was performed by invoking the SAS matrix programming language IML. The remaining nonlinear equations required hand editing 135 times a SAS file designed to fit the nonlinear equations to eliminate the unwanted data from each run. The projections for validation were actually performed by creating separate data files for each model which contained the 135 sets of parameter estimates associated with each plot. During program execution, the appropriate parameters were read in from a data file for each plot and used by the correct model.

Computer Coding:

After obtaining the specific models to be used, each model was computer coded as a generic master subroutine made up of a set of small subroutines needed to apply each model. The master subroutines for each model were coded so that basic stand attributes were available and the appropriate level of predicted information was produced. This assured that each model could be used with relative ease given it is provided the minimum amount of required information. These routines were coded using the C programming language primarily because of its highly structured nature.

A computer coded "shell" was then created around all the models which accessed files of stand and tree level information for all stands of interest, where this number could only be restricted by hardware limitations. This created a batch environment under which the models were run. This form of model coding which allows the computer to make predictions about more than one stand at a time is not new, but surprisingly uncommon. Most computerized stand prediction models require constant user input for each stand, which quickly becomes a laborious task for more than just a few stands.

Of the models which do provide for batch processing, almost all exclusively require ASCII files for input with extremely strict specifications on the data values and formats of the files. This requires unique ASCII files for each model. Applying these models to current stand inventories, even with computer models which provide for batch processing, would require a separate file of with specific information and format for each model used.

Text files require some form of formatting process before they can be used in any way. Many research and industrial applications using data in text or ASCII files require many man-hours to produce files usable for specific systems. This generally involves properly "informing" the software how the data appears in the file, determining how it will be used, and manipulating the data into usable form, which ultimately leaves much room for error. Misspecifying the format of an ASCII file is a common error and one which can be difficult to locate. If data were stored in files which also included formatting information, many hours of repeated processing could be eliminated by performing the task only once and this file used regardless of the software employed.

For these reasons, an existing data format was adopted for the purpose of storing data for this study. One of the more common methods of data file formatting beginning to arise in the IBM-PC environment is that used by the Dbase series of data base software packages. A file in this format is commonly denoted by the DBF extension on DOS files. It is this simple file format which easily allows the computer growth and yield models to be integrated with a Geographic Information System.

The entire data set used in this project now exists as an ASCII file. This file requires much work each time it is used for any purpose. The observations grouped into validation data sets were treated as an inventory of stands, where each plot represents a separate stand. These data sets were used to create working databases instead of generic text files. It is these database files which were used as input for the computer models, not the ASCII file which is the present method of storage. By using Codebase, a library of C functions for database management, the batch processing procedure was easily added to the coded growth and yield models. Using these functions, the program containing all model subroutines is able to access the Dbase files of stand inventories and make future stand predictions for each record in the database.

Also using the various Dbase related functions, the predicted values will not only be simply displayed on the screen, but will be outputed in the form of a Dbase file. This file will be directly usable by Dbase, without any formatting, from which various analyses can be done, reports may be generated, or any other Dbase features used.

One of the primary purposes of this thesis was to produce a method by which growth and yield models can be integrated with a Geographic Information System. To do this, a proper system had to be chosen for this project. Because of data structure, analytical features, availability, and common use, the vector based system Arc/Info was chosen. Arc info stores all its point, line, and polygon related information in Dbase format, therefore an easily establishable link exists between Arc/Info and Dbase formatted data. It is through this link that the integration between the growth and yield models and Arc/Info exists since both will readily access and create Dbase files. This allows for the updating of stand inventories, as well as displaying and spatially analyzing such data.

Analysis:

Once the integrated system was completed, it was be used to evaluate the time-related response of each growth and yield model used under the various validation schemes. This process involved using fitting data sets to obtain estimates of model parameters and converting the validation data sets into Dbase files. The database files were then used as input for the growth and yield models. The system was designed with the intent that one model would be used at a time. This was not convenient for validation, so another option was added which allowed all models to run simultaneously on each stand record. Output from the multi-model runs was produced in the form of on ASCII file. This was done to maintain compatibility with the original data for comparison purposes. This output contained a row of data for each stand, consisting of a stand ID number and an estimate of cubic foot volume per acre from each model.

Every time a validation data set was run through the system, the parameter estimates from its paired fitting data set were used for making predictions. For the 50/50 double cross scheme this involved making two runs using separate parameter estimates on validation data sets containing 67 and 68 stands using two different sets of estimated parameters. For the 70/30 split repeated scheme, two runs using separate parameter estimates were made on 40 stands each. Lastly, the PRESS approach used 135 different sets of parameter estimates for 135 runs each using only a single stand as input. This process was repeated at four times using different projection periods. These were zero years, three years, six years, and nine years. This corresponded with the original data set which contains observed values at each of these time periods.

The output from each of these runs was merged with a data set containing observed volume yields at each time period. A new data set for each run was created which contained predicted volumes minus observed volume for each stand in the validation set, each of the four models, and each of the projection periods. Statistics about these differences were calculated for each model at each time period. These were the mean, standard deviation, minimum, and maximum. The mean of the differences was treated as an estimate of model bias and the standard deviation as an estimate of variability of prediction. The values were squared and added to obtain an overall estimate of mean square error of prediction for each model for each time period.

Results and Discussion

Model Validation:

Three different approaches were used to validate the effectiveness of the four different growth and yield models discussed. These validations were a 50/50 double cross validation, a 70/30 split repeated, and a PRESS approach. The procedures for each were discussed briefly in the methods section. One evident problem exists when applying standard data splitting procedures which does not exist using the PRESS procedure. With data splitting, sacrifices must be made in favor of either the amount of data used for model fitting, or the amount used for model validation. This does not happen under a PRESS approach. The two data splitting procedures produce separate sets of results. This can become a large complication when trying to interpret results. Another consideration is that the results from these procedures are dependent on the random splitting of the data. Therefore the procedures can be replicated with entirely new and possibly very different sets of results being obtained. This is the case for the PRESS procedure.

It is important to realize that certain trade-offs exist for using different modeling approaches. These are the levels of required input and predicted output which can be obtained, versus the reliability of the predictions coupled with the computer time required to produce them. Because of this, it is not appropriate to simply state one model performs better than another. For example, the reason one model performs better than another may be that it requires greater amounts of input, which means it may be more costly to implement. One should take into consideration the costs involved in obtaining data needed as input when determining the value of a particular model. This study judged model performance solely on the basis of predicted total merchantable volume versus observed, with no consideration for the other types and/or levels of output produced. Obviously a model that produces yields by diameter could be more useful than a model which only produces single yields. However, if these diameter class yields are produced using a technique with large error, the numbers may be useless in a practical sense. It should be apparent that the process of choosing an appropriate model is not easy, and the results presented should be weighted appropriately.

PRESS Approach:

The PRESS procedure uses n-1 data points for fitting and n points for validation (where n is the number of plots in the data set). This provides for maximum utilization of data, because nearly all the data is used for fitting and at the same time all the data is used for validation. The results from this procedure are not dependent on random splitting and therefore, one and only one set of results, can be generated. Because of these reasons, the results from the PRESS run will be the primary focus of this discussion. It should be noted that the PRESS procedure may be intuitively appealing, but it was much more computationally expensive. Considering the speed of modern computers, this concern is becoming much less prevalent.

Each modeling approach uses different procedures to obtain an initial estimate of yield. The estimate of yield derived from a stand level model (referring to diameter distribution models as well as whole stand models) is not assumed to be correct, though the expected amount of error of this estimate is assumed to be zero. Since the variance associated with the amount of error is greater than zero, initial stand estimates will always contain some error and initial stand estimates of volume will be different from observed volume.

The opposite is true for tree level models. Since these models are provided with exact tree lists where volume is assumed to be measured without error (in actuality volume is estimated using tree volume equations), the initial volume determined by the stand level model is considered to be correct. This assumption, although very close, is not entirely correct for the individual tree model used. In this study, the actual plot volumes were determined using a standard volume approach (using both tree diameter and height), while the model estimates were based on a local volume approach (using only actually measured diameters). Therefore, slight differences from observed volume will be noticed at time zero. To summarize, whole stand and diameter distribution models estimate initial yields with some error, while individual tree models determine initial yield without error.

Some of the questions evolving from these assumptions which warranted investigation are: of the models which inherently produce initial estimates with error, which methods do so with the highest accuracy; what happens to the error in the projected volumes in comparison with increasing projection length. To answer these questions, projections were made using the four different models using the three different validation approaches. The estimates at zero years, three years, six years, and nine years, were computed and compared to actual observed plot values.

The difference statistics between the predicted and observed values were examined. Because the PRESS approach is most easily interpreted, these results have been summarized first (Table 2). These results are the following difference (predicted minus observed) statistics: mean, standard deviation, root mean square error, minimum, and maximum. The

Table 2. Summary of Difference Statistics in Cubic Feet per Acre for Each Growth and Yield Modeling Approach at 0,3,6, and 9 Year Projection Periods Under the PRESS Validation Scheme.

Model	Time	N	Mean (Bias)	Standard Deviation	RMSE	Minimum	Maximum
Whole Stand	0	135	5.63	300.16	300.21	-547.60	1795.84
Whole Stand	3	135	-23.20	302.73	303.62	-742.97	1505.41
Whole Stand	6	135	-3.92	381.75	381.77	-1103.48	1148.29
Whole Stand	9	135	10.05	587.64	587.72	-1466.90	2617.67
Parameter Prediction	0	135	188.97	449.74	487.83	-1761.57	1275.02
Parameter Prediction	3	135	-19.19	532.56	532.90	-2114.11	1066.04
Parameter Prediction	6	135	-255.87	646.60	695.38	-2353.23	1008.01
Parameter Prediction	9	135	-542.77	790.23	958.67	-2806.47	1601.20
Parameter Recovery	0	135	15.71	374.21	374.54	-834.89	1770.79
Parameter Recovery	3	135	-73.12	478.88	484.43	-1154.65	1999.49
Parameter Recovery	6	135	-147.45	649.48	666.01	-1824.83	2345.65
Parameter Recovery	9	135	-255.40	945.12	979.02	-2440.10	3646.47
Individual Tree	0	135	-3.74	53.48	53.61	-171.07	181.93
Individual Tree	3	135	-138.01	176.54	224.08	-621.44	382.93
Individual Tree	6	135	-235.90	309.47	389.13	-1187.65	377.16
Individual Tree	9	135	-417.96	521.03	667.95	-1563.95	1705.18

root mean square error is estimated as the square root of the squares of the mean and standard deviation. The mean, standard deviation, and root mean square error (RMSE), of each model have been graphed over time to emphasize these results (Figure 1).

It is the RMSE which is most representative of the total variability within each model. At time zero the model with the smallest RMSE of predicted yield is the individual tree model. The only reason this is not exactly zero is that the model determines volumes from only diameter, while the plot observed values were calculated using measured diameter and height. Therefore for all practical purposes this value is zero, or the model is free of error at time zero. The model with the most error is the diameter distribution - parameter prediction. This is not unexpected, because the equation used to estimate the Weibull parameters under this method, have traditionally, as well as in this study, had very poor fits to data. One reason for this is the high variance of the maximum likelihood estimators of the Weibull distribution parameters. Roughly midway between these models is the whole stand model and roughly midway between the whole stand model and the parameter prediction model is the parameter recovery model. These results are not unexpected because previous work has shown that the parameter recovery approach is slightly better then than parameter prediction approach. The logic behind this is that a Weibull distribution can be determined by

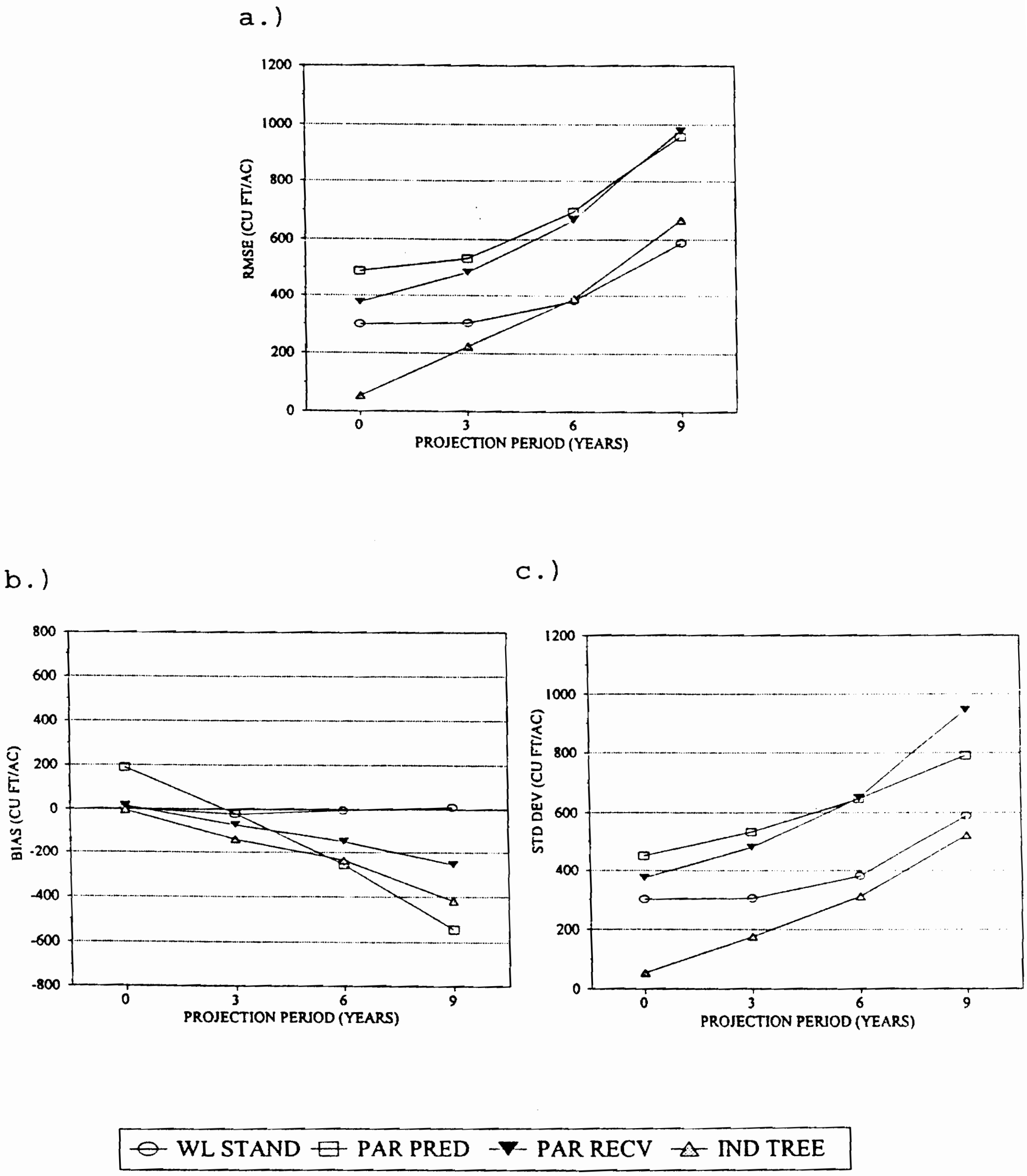

Figure 1. Graphed Results from PRESS Validation by model type: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

either knowing certain moments of the distribution or parameters used to define the function, and that the moments of the distribution can be estimated with much higher confidence then the function parameters. The whole stand model providing median results are also expected because this model is least demanding in terms of input, and most limited in terms of output.

As each model predicts yield under increasing projection lengths, certain trends became apparent. The first is that the diameter distribution models consistently remain the most variable (in terms of RMSE) and that the difference between the two becomes less evident, almost as if the error in the parameter recovery system approaches that of the parameter prediction. At the shortest projection period (three years) the individual tree model still outperforms all other models, but the prediction error for this model increases very rapidly. This is the nature of this type of model. Because the model annually evaluates the tree list and bases each new prediction on previous prediction, the error in each new annual estimate is multiplicatively increased by each previous estimate. This results in exponentially increasing error with increasing projection length.

At the six year projection period the error in all models rapidly increases, but very little difference exists between the diameter distribution models. The whole stand model first slightly outperforms the individual tree model. The RMSE in the diameter distribution models is much greater than the other models.

At the greatest projection period examined (nine years) the parameter prediction model actually performed slightly better than the parameter recovery model. At this projection length the whole stand model has most obviously become the model with the least error, and the individual tree model error has greatly increased.

To summarize, the diameter distribution models begin with the greatest error with a zero projection period. The parameter recovery method performs better than the parameter prediction, but this difference diminishes as time increases. Over all projection periods examined, diameter distribution models maintain considerably more error than either the whole stand or individual tree types. The individual tree model begins with essentially no error at time zero, but begins to produce estimates with rapidly increasing error so that for a six year projection period its error exceeds that of the whole stand model, with this trend only becoming much more prevalent at the nine year projection period.

The overall mean square error is a combination of two error components, bias and standard deviation. These components were also graphed with respect to projection period so that each could be examined as to its contribution to the overall error in these models (Figure 1).

The mean bias graph displays several trends. The first and most obvious is that the whole stand model appears to be essentially unbiased. This result is not unexpected. This model requires the fitting of only one equation and the error of this fit is minimized with respect to volume. When considering the other models it is important to realize that each of these models require fitting of many equations and these equations generally have dependent variables other than volume, and therefore the error minimization of these equations is not performed on volume but on some other variable of interest, such as whole stand mortality.

These arguments lead one to conclude that the whole stand model should be relatively free from bias provided that the fitting data is reflective of the data from which predictions are being made. In contrast, the remaining models can be assumed to have bias and that as more is expected from the initial data (or in other words, the longer the projection period) the greater this bias can be expected to get. Indeed this can be seen from the graph of bias over time (Figure 1). Each model appears to have distinctive rate of bias increase. It is important to note the model order from lowest to highest bias is: whole stand; parameter recovery, individual tree, and parameter prediction.

The minimum and maximum values in Table 2 further augment the bias results. For models which are unbiased and have normally distributed error, it would be expected that the minimum and maximum difference in prediction would be a similar distance from zero. This is rarely the case with any model. It can be seen that the width between the minimum and maximum values increases with projection period, most dramatically for the diameter distribution models.

In comparison with the root mean square error (RMSE), some slightly different trends exist with the standard deviation of the differences over time. The first is that the individual tree model consistently has the smallest standard deviation. The whole stand model remain between the individual tree and diameter distribution models though it approaches the individual tree model as projection period increases. Since the individual tree model actually crosses the whole stand in overall root mean square error it can be reasoned that increasing bias of the individual tree model forces this to happen in later years. Therefore bias plays a significant role in the comparison of these two models. The standard deviation of the diameter distribution models begins very similarly to that of the RMSE, which implies that the bias plays little role in overall RMSE. Since the standard deviation increases more rapidly for the parameter recovery model than the RMSE, the reduced bias of this model over the parameter prediction in later years becomes more significant.

Model improvement for inventory updating should be of primary concern to all foresters. The overall error in prediction can be divided into two components, these being bias and standard deviation of error. It is these components that must be reduced to improve the overall RMSE of prediction. Assuming specific models are fixed, the only means to reduced the standard deviation is to increase the sample size.

Study results indicate that the whole stand model seems to be absent of bias. This is most likely because the model was fit so as to minimize squared error in terms of merchantable volume while the other models were not. It stands to reason that a similar approach to fitting could be developed for the other models, in order to reduce or eliminate their respective bias as well. Because these models are complex, this would require simultaneous equation fitting in which the error of each individual model equation would not be minimized, but instead the error in overall prediction of merchantable volume would be minimized. Each of these models produces a wide variety of other stand descriptive estimates as output. This approach of minimizing overall volume error would do so at the cost of reduction of model performance in other stand and tree level predictions.

Fifty-Fifty Double Cross:

The fifty-fifty double cross approach was the first to be used for validation of the four growth and yield models. It was believed that by splitting the data in half, with one half for fitting and the other for validation and then reversing the roles, that the two separate results would provide sounder conclusions. Instead, it showed that sample size is indeed an important factor to consider when fitting and validating growth and yield models.

Under this scheme two different runs were performed interchanging the roles of the split data. The first run and any associated results will be referred to as Set 0 and the second run as Set 1. More important than the results and trends from each run are the comparison of the trends between the runs. The results from Set 0 and Set 1 have been summarized in numerical form (Table 3) and in graphical form (Figures 2 and 3).

The RMSE graphs display different results when comparing the diameter distribution models or the whole stand and individual tree models. In Set 1, the diameter distribution models first show almost no difference at the first two projection periods with the parameter prediction model diverging and outperforming the parameter recovery model in projection periods three and four. This is not the case for Set 0. The parameter recovery produces better results for the

Table 3. Summary of Difference Statistics in Cubic Feet per Acre for Each Growth and Yield Modeling Approach at 0,3,6, and 9 Year Projection Periods Under the 50/50 Double Cross Validation Scheme: a.) Results from set 0, b.) Results from Set 1.

a.)

Model	Time	N	Mean (Bias)	Standard Deviation	RMSE	Minimum	Maximum
Whole stand	0	67	-11.88	185.83	186.21	-476.70	476.48
Whole stand	3	67	-75.19	260.87	271.49	-674.01	529.97
Whole stand	6	67	-84.81	379.71	389.07	-1142.23	793.97
Whole stand	9	67	-89.29	690.63	696.38	-1550.70	2500.77
Parameter Prediction	0	67	88.55	455.69	464.21	-677.11	2059.90
Parameter Prediction	3	67	95.11	565.46	573.40	-1167.68	2261.73
Parameter Prediction	6	67	93.16	698.91	705.09	-1714.45	2204.17
Parameter Prediction	9	67	41.55	982.16	983.04	-2202.16	3004.38
Parameter Recovery	0	67	31.08	388.76	390.00	-800.54	1673.94
Parameter Reccvery	3	67	-59.29	510.14	513.57	-1158.54	1960.49
Parameter Recovery	6	67	-98.05	694.36	701.25	-1801.61	2166.93
Parameter Recovery	9	67	-127.43	1066.97	1074.55	-2360.52	3733.23
Individual Tree	0	67	-4.51	55.60	55.78	-147.50	178.23
Individual Tree	3	67	-154.18	176.14	234.09	-610.24	239.10
Individual Tree	6	67	-232.53	328.93	402.83	-1162.64	533.58
Individual Tree	9	67	-345.42	643.41	730.27	-1525.32	2183.26

b.)

Model	Time	N	Mean (Bias)	Standard Deviation	RMSE	Minimum	Maximum
Whole stand	0	68	95.72	273.96	290.20	-421.80	1272.16
Whole stand	3	68	77.03	285.22	295.44	-644.35	1209.09
Whole stand	6	68	64.24	362.88	368.52	-966.93	940.11
Whole stand	9	68	11.30	468.43	468.56	-1436.78	1437.78
Parameter Prediction	0	68	-13.56	369.80	370.05	-1194.44	1059.46
Parameter Prediction	3	68	-81.67	443.41	450.87	-1440.47	1171.22
Parameter Prediction	6	68	-193.62	580.64	612.07	-1636.24	1599.25
Parameter Prediction	9	68	-392.83	732.33	831.03	-2345.13	2356.35
Parameter Recovery	0	68	28.04	358.86	359.95	-912.97	1106.42
Parameter Recovery	3	68	-104.88	439.73	452.07	-1107.22	1460.61
Parameter Recovery	6	68	-246.45	607.65	655.73	-1837.54	2174.09
Parameter Recovery	9	68	-432.31	830.12	935.95	-2467.16	3343.35
Individual Tree	0	68	-2.52	50.60	50.67	-175.82	182.30
Individual Tree	3	68	-134.84	188.48	231.75	-733.43	308.43
Individual Tree	6	68	-286.13	334.31	440.03	-1150.55	396.37
Individual Tree	9	68	-581.70	472.81	749.61	-1813.43	495.31

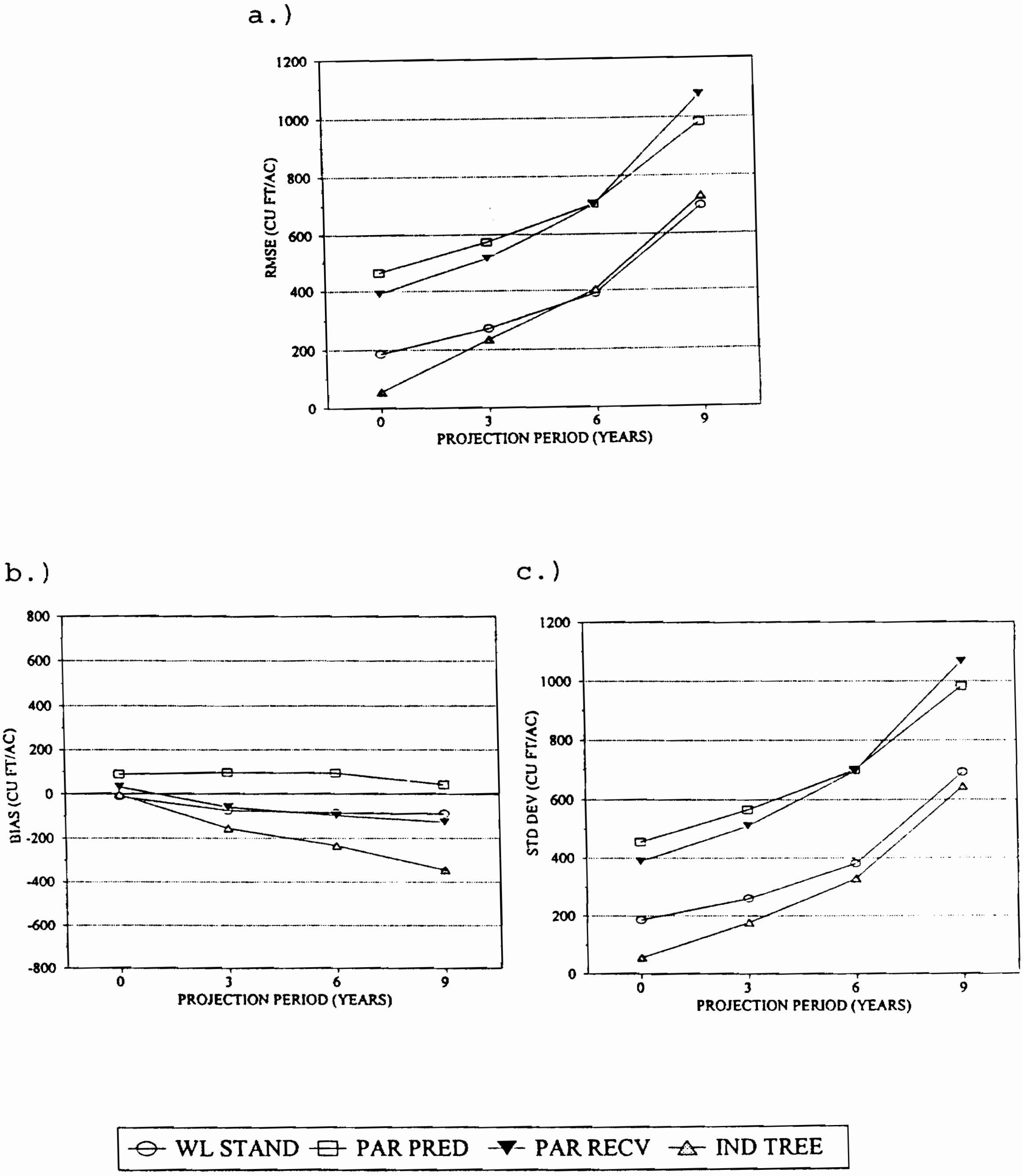

Figure 2. Graphed Results from 50/50 Double Cross Validation by model type for set 0: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

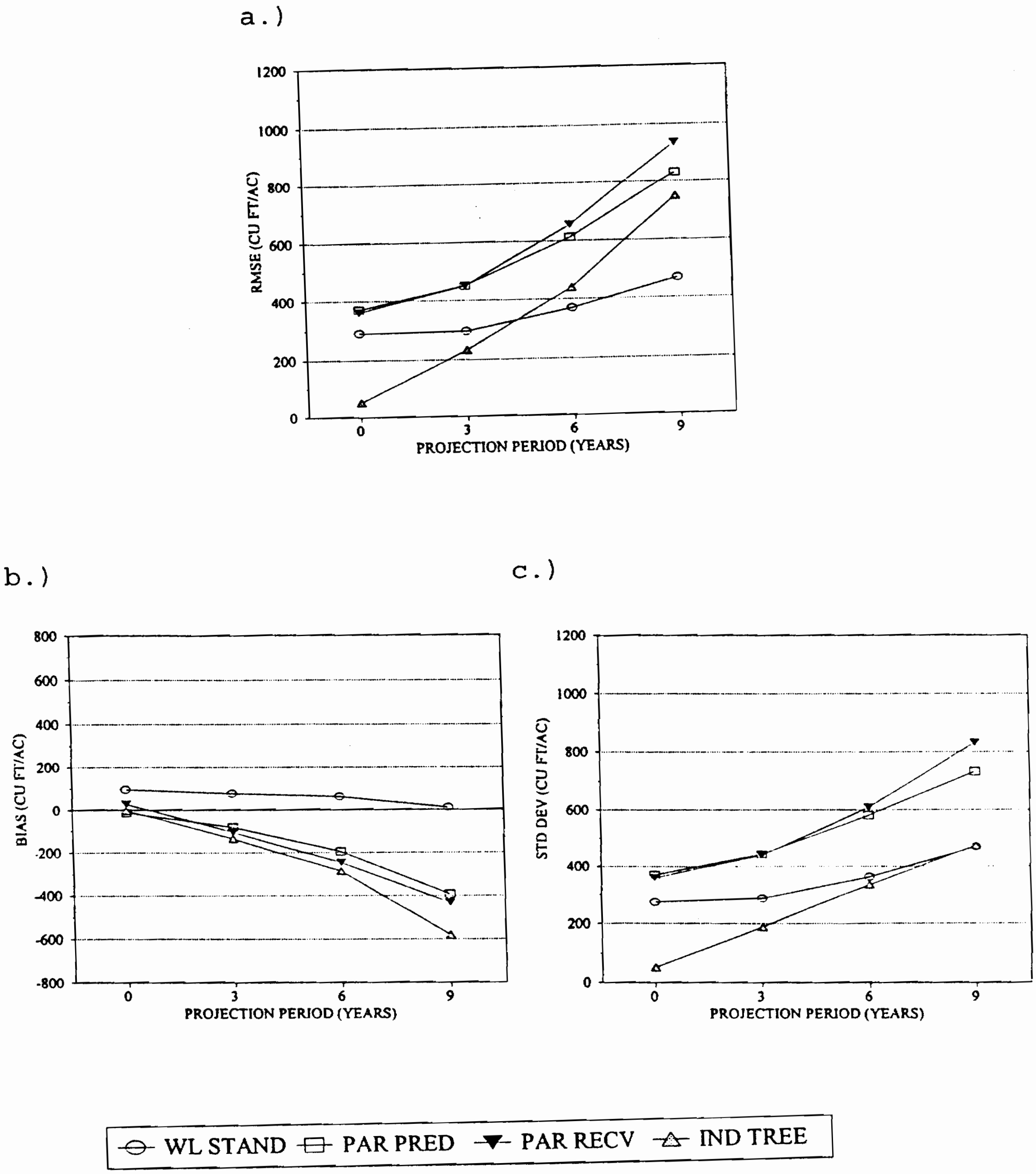

Figure 3. Graphed Results from 50/50 Double Cross Validation by model type for set 1: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

first two projection periods, then similar results at the third, and only at the fourth period is it outperformed by the parameter prediction model. The whole stand model and individual tree models perform quite similarly with Set 0, but display drastically different results in Set 1.

The bias graph shows even more varying results. In Set 0, the whole stand model appears to have a negative bias, while in Set 1 the bias appears to be positive. As discussed earlier, this model should be approximately unbiased if the fitting data is representative of the validation data. From this it can be assumed that the fitting data set is too small. The number of observations used in fitting were 67 and 68. These may be too small to accurately model whole stand volume. The parameter prediction model also displayed very different trends. In Set 0, the bias is positive and approximately constant, and in Set 1 the bias is negative and is increasingly negative. Though the trends within the parameter recovery model and individual tree model were similar between runs, the actual numbers were quite different. The graphs of the standard deviations between Sets 0 and 1 (Figures 2 and 3), were different though not as drastic as the bias results. The diameter distribution trends and comparisons are nearly identical to those found in the RMSE. Though the trends in the whole stand and individual tree models were not quite the same as RMSE trends. The standard deviation from the whole stand and individual tree models never truly cross. In Set 0 the two perform similarly and only gradually come together, while in Set 1 the begin further spread apart then meet by the fourth measurement.

Seventy-Thirty Replicated Split:

Differences in the fifty-fifty double cross results indicated that the sample size of the fitting data set may be too small to draw any conclusions about model behavior. This should emphasize to others the importance of using appropriately sized data sets. It was from these results that the seventy-thirty split was deemed necessary, to provide more data for model fitting. This procedure was replicated to determine the stability of results. To make a replicate, all random number seeds used to select data for fitting and validation were changed to obtain the second set of results. The first set is referred to as Seed 1 and the second as Seed 2. The numerical data from each run is summarized in Table 4.

It was encouraging to find that the RMSE trends (Figures 4 and 5) appeared to be more consistent with the seventy-thirty splits than those of the fifty-fifty splits (Figures 2 and 3). The trends in both of the seventy-thirty graphs were the same. The diameter distribution models performed poorer than the whole stand and individual tree models, with the parameter recovery performing better than the parameter

Table 4. Summary of Difference Statistics in Cubic Feet per Acre for Each Growth and Yield Modeling Approach at 0,3,6, and 9 Year Projection Periods Under the 70/30 Repeated Validation Scheme: a.) Results from seed 1, b.) Results from Seed 2.

a.)

Model	Time	N	Mean (Bias)	Standard Deviation	RMSE	Minimum	Maximum
Whole Stand	0	40	3.55	193.48	193.51	-328.18	343.12
Whole Stand	3	40	-61.73	270.26	277.21	-631.15	408.19
Whole Stand	6	40	-129.13	401.65	421.90	-1034.72	602.65
Whole Stand	9	40	-199.33	530.96	567.14	-1237.40	1240.33
Parameter Prediction	0	40	249.94	518.28	575.40	-1104.51	1353.74
Parameter Prediction	3	40	18.36	617.39	617.66	-1569.93	1131.82
Parameter Prediction	6	40	-266.58	785.39	829.40	-2266.65	1107.46
Parameter Prediction	9	40	-613.64	932.51	1116.30	-2816.52	1386.88
Parameter Recovery	0	40	138.87	438.24	459.72	-685.68	1799.15
Parameter Recovery	3	40	15.47	560.91	561.13	-1088.76	1931.88
Parameter Recovery	6	40	-147.58	744.69	759.17	-1750.01	2013.74
Parameter Recovery	9	40	-343.63	955.31	1015.23	-2169.21	3067.78
Individual Tree	0	40	-2.81	54.69	54.76	-121.54	180.67
Individual Tree	3	40	-177.20	158.48	237.73	-583.23	150.78
Individual Tree	6	40	-368.46	316.70	485.86	-1031.49	210.19
Individual Tree	9	40	-658.53	485.98	818.44	-1621.91	461.31

b.)

Model	Time	N	Mean (Bias)	Standard Deviation	RMSE	Minimum	Maximum
Whole Stand	0	40	-11.71	192.41	192.76	-551.94	331.17
Whole Stand	3	40	15.39	241.80	242.29	-681.03	513.38
Whole Stand	6	40	47.62	285.07	289.02	-714.95	509.37
Whole Stand	9	40	63.55	408.72	413.64	-963.13	890.66
Parameter Prediction	0	40	140.50	401.21	425.09	-912.81	851.90
Parameter Prediction	3	40	-33.01	468.38	469.54	-1122.23	820.70
Parameter Prediction	6	40	-267.96	561.23	621.91	-1603.82	758.98
Parameter Prediction	9	40	-556.55	656.14	860.39	-2052.75	607.43
Parameter Recovery	0	40	-8.40	372.22	372.31	-904.36	640.63
Parameter Recovery	3	40	-101.21	444.02	455.41	-1114.82	662.39
Parameter Recovery	6	40	-209.74	561.76	599.64	-1795.25	997.56
Parameter Recovery	9	40	-347.39	736.50	814.31	-2199.91	1451.51
Individual Tree	0	40	-13.97	48.03	50.02	-105.24	176.11
Individual Tree	3	40	-86.83	179.19	199.12	-597.60	266.08
Individual Tree	6	40	-165.45	282.25	327.17	-862.15	403.30
Individual Tree	9	40	-342.09	417.81	539.99	-1276.14	435.43

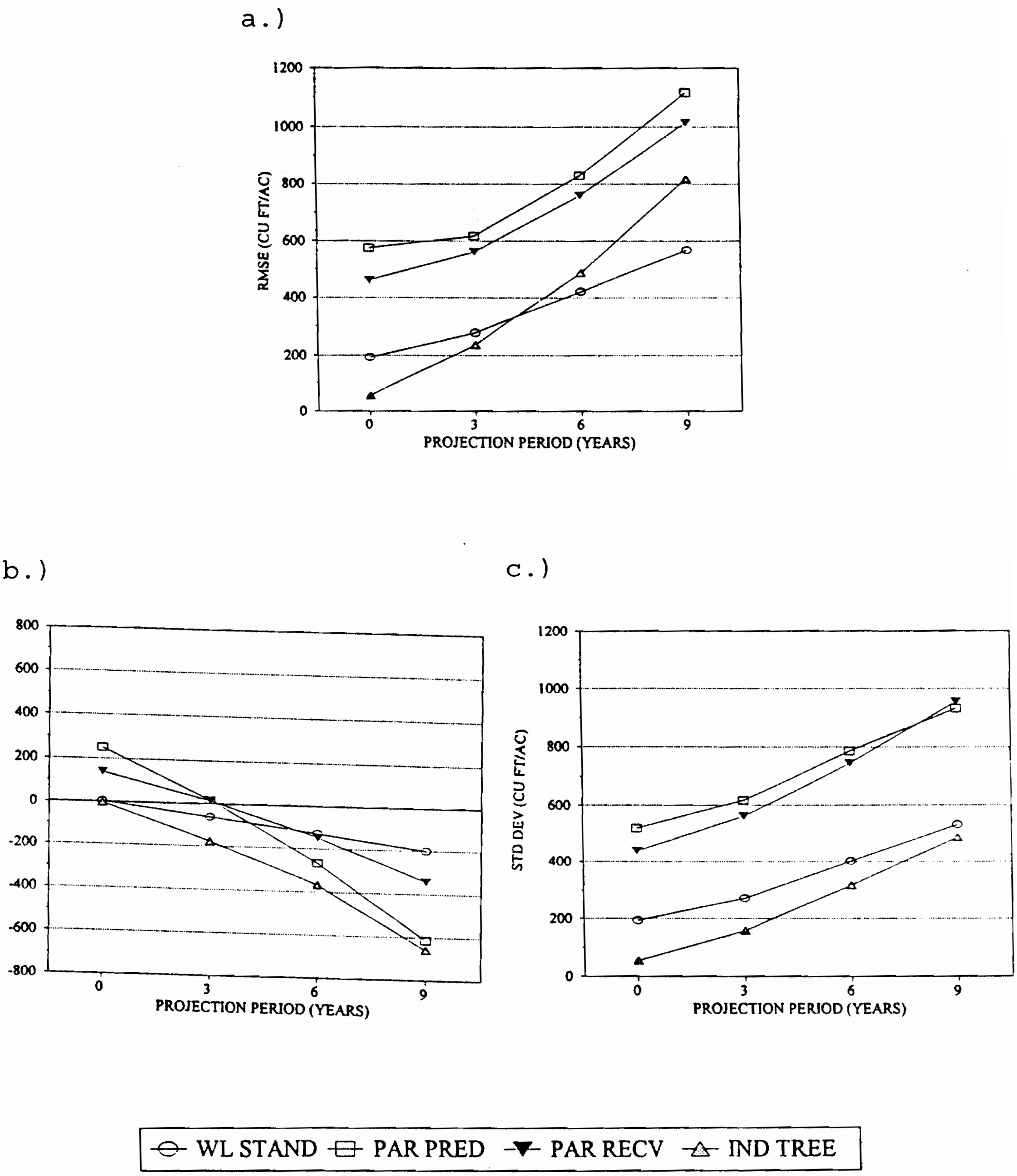

Figure 4. Graphed Results from 70/30 Repeated Validation by model type for seed 1: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

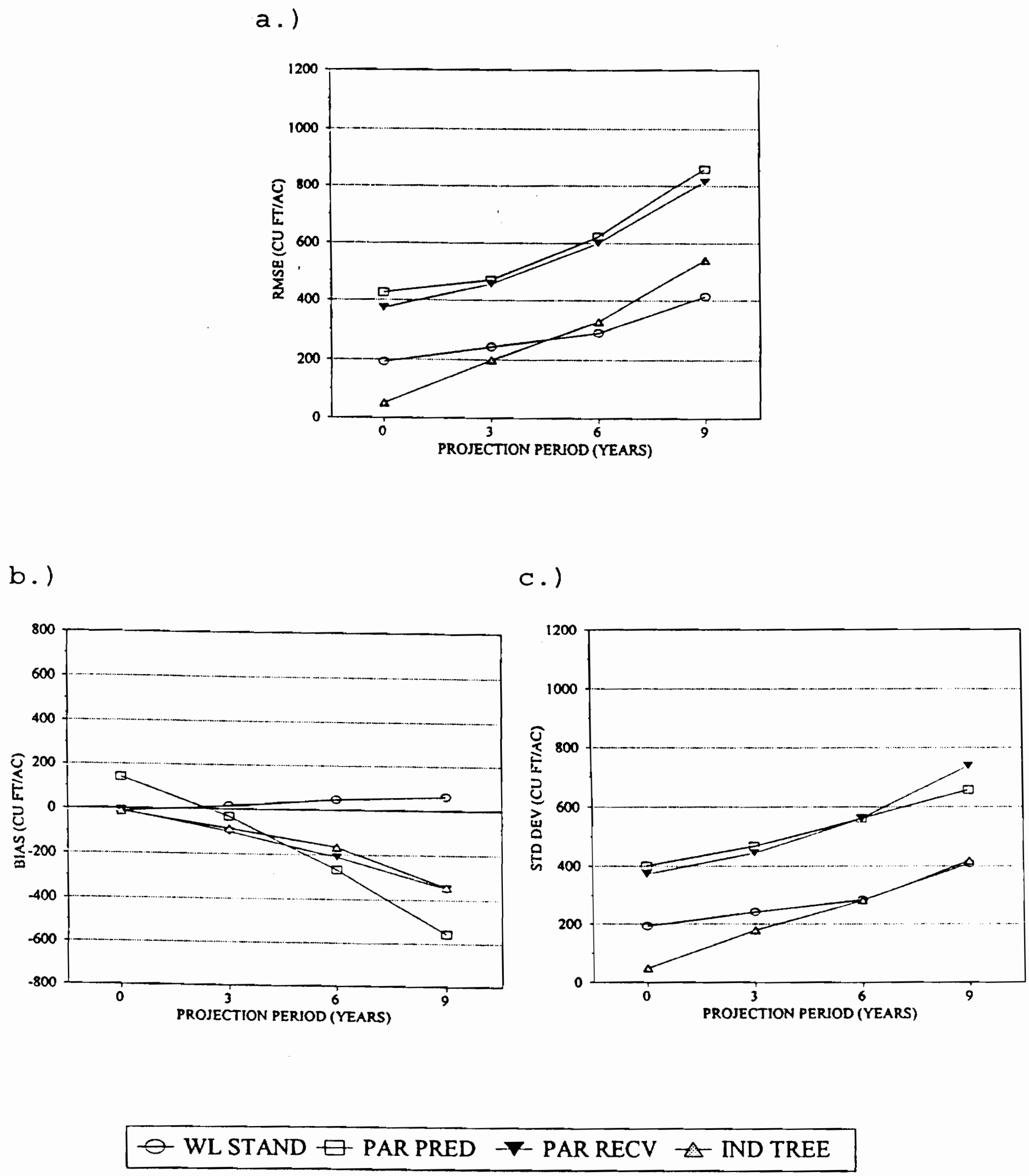

Figure 5. Graphed Results from 70/30 Repeated Validation by model type for seed 2: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

prediction. Also in both graphs, the individual tree model begins with smaller RMSE than the whole stand, maintains this to the second projection period, and crosses before reaching the third. At the fourth, the whole stand model begins to substantially perform better than the individual tree model in both graphs.

Most of the obvious differences between the two runs appear in the components of the RMSE, bias and standard deviation. The most noticeable difference exists in the bias graphs (Figures 4 and 5). The whole stand model appears to only have a slight positive bias with longer projection periods with the Seed 2 results, but quickly obtains a strong negative bias with Seed 1. The trend in the individual tree appear similar, but the actual numerical values are considerably different. The trend and data values are very similar for the parameter prediction model, but the bias results in the parameter recovery have shifted in the early projection periods. With Seed 2 the parameter recovery begins with almost no bias then goes negative, while with Seed 1 the initial projection period is positively biased, and does not go negative until just after the second period. These results are indicative of data sets (fitting and validation) that are not truly representative of each other, at least in terms of detecting model bias.

The graphs of standard deviation of the differences (Figures 4 and 5) are not truly alike, but similarities do exist. Primarily, the diameter distribution models perform worse than the other two models. The parameter recovery model begins with less variation than the parameter prediction version, then near or after the third projection period the lines cross. The individual tree model begins with much less variation than the whole stand model, then the results approach each other with the longer projection periods, though this is more pronounced with Seed 2 than with Seed 1.

These results show improvement in stability over the fifty-fifty double cross validated results. The data sets used for fitting contained 95 elements each. By comparing the standard deviations produced by the seventy-thirty runs with those of the fifty-fifty runs (Figures 2-5), it can be seen that those with the seventy-thirty runs on average have smaller standard deviations than those from the fifty-fifty runs. These smaller deviations from the seventy-thirty runs were calculated from validation sets which were smaller than those of the fifty-fifty runs. Smaller data sets producing less variation would seem to imply that large improvements have been made in parameter estimates by sacrificing data from the validation set in favor of data into the fitting set.

Yield Projection versus Basal Area & Yield:

The press results indicated that the whole stand model was unbiased and it was believed this was due to fitting the model totally with respect to minimizing error in volume prediction. To test this hypothesis, a second model fitting procedure was used, where a basal area projection equation was fit separately from the yield model. In the original model only one yield projection model was fit to data without regard to basal area projection. These models were identical in terms of yield projection, only the emphasis in parameter estimation was shifted.

The PRESS approach was used to evaluate the difference in behavior between the two different fitting approaches. The results of the difference statistics for volume prediction are displayed graphically in Figure 6. Examining the graph of RMSE, it can be seen that the fitting procedure involving basal area projection has produced more variable (in terms of RMSE) estimates then the fitting procedure only to yield projection. The component graphs, bias and standard deviation also support this. The standard deviation is nearly identical to RMSE. The bias graph shows that the basal area projection fit model is consistently biased, but since the standard deviation and RMSE values are so similar, this indicates that bias plays a small role in overall error. It is important to recognize that bias and increased variable were induced in the

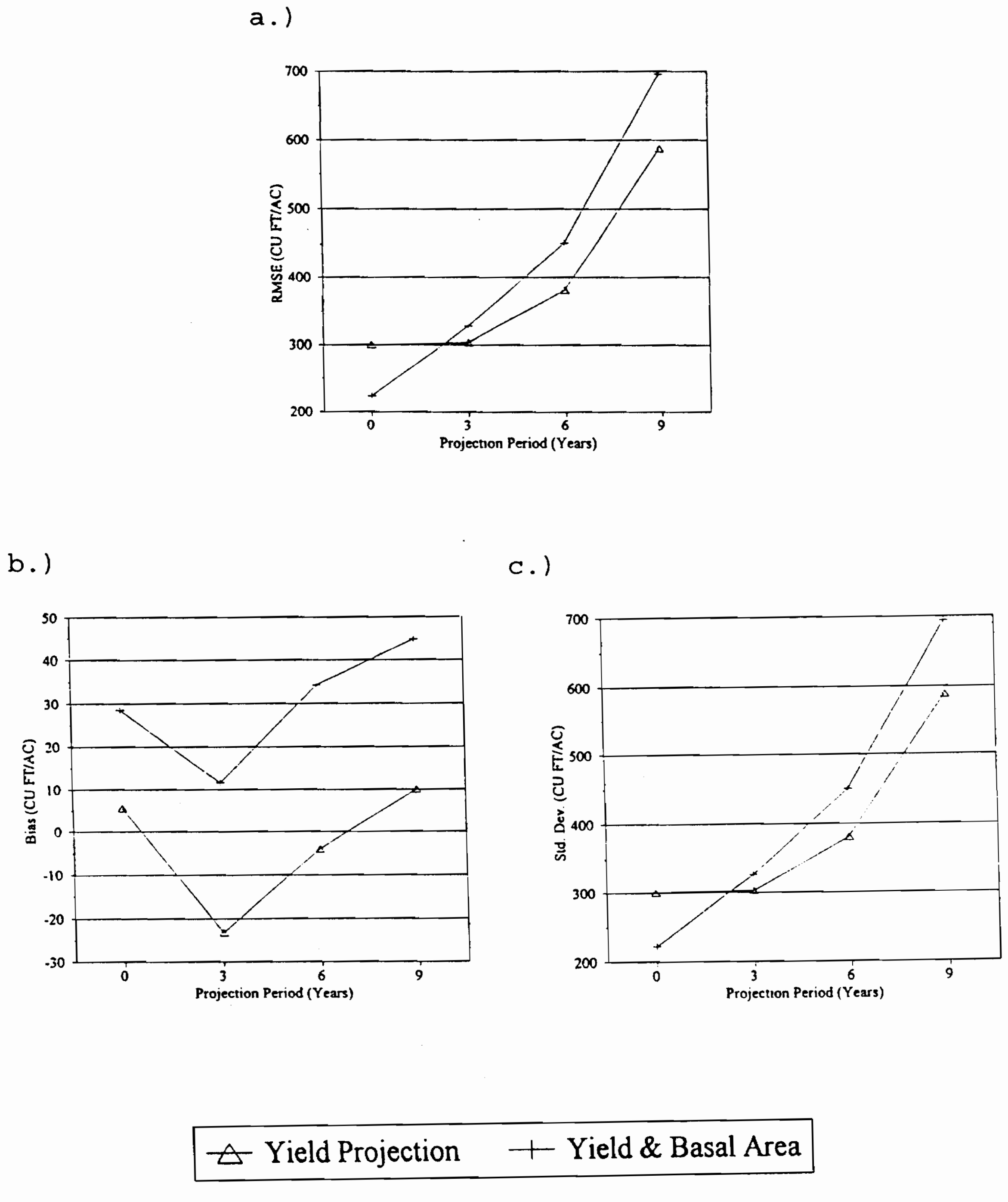

Figure 6. Graphed Results from Whole Stand Yield Analysis by Parameter Estimation Procedure: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

model by simply shifting the emphasis in model fitting away from volume. This evidence supports the reasoning that other approaches in model fitting which emphasize volume may be warranted with such models as the diameter distribution and individual tree models.

Both whole stand models are capable of predicting basal area. This was also examined, and the results are graphed in Figure 7. The graphs truly show that by fitting the model only to yield projection, sacrifices were made in terms of basal area projection. The separate basal area fit model produces basal area estimates with smaller RMSE than yield projection model. The trend is similar for standard deviation. The bias graph shows that the basal area fit model is essentially unbiased while the other displays rapidly increasing bias. If a model to predict both volume and basal area is desired, these results indicate that a simultaneous fitting procedure may more appropriate.

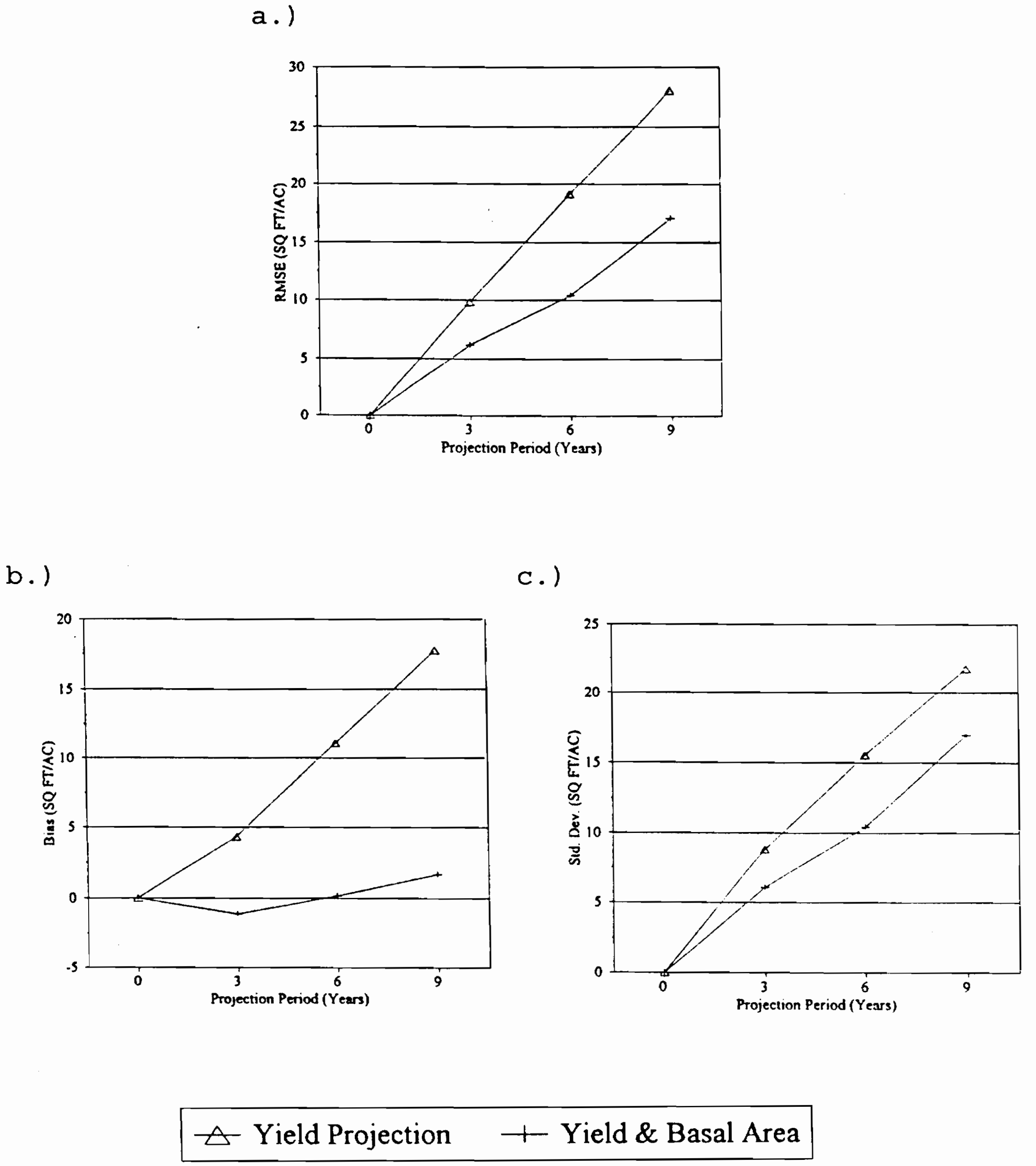

Figure 7. Graphed Results from Whole Stand Basal Area Analysis by Parameter Estimation Procedure: a.) RMSE versus Projection Period, b.) Bias versus Projection Period, c.) Standard Deviation versus Projection Period

Conclusions

The objectives of this thesis was to develop a system of growth and yield models which was compatible with a GIS, and to use this system to evaluate the behavior of different growth and yield models with increasing projection period. In this manner their effectiveness for inventory updating was determined. Four different models were evaluated ranging from the very simple to the extremely complex. These models were a whole stand model, diameter distribution - parameter prediction model, diameter distribution - parameter recovery model, and an individual tree model. Model performance was judged on error in prediction of merchantable volume per acre with increasing projection length.

The diameter distribution models performed consistently worse than the whole stand and individual tree models. For projection periods less than or equal to six years the parameter recovery model performed better than the parameter prediction model. Over the projection periods examined, the difference between the two diameter distribution methods diminished until age nine, where the results were nearly identical. The individual tree model produced the best results until around a six year period, at which time it was approximately equal to the whole stand model. After six years, it is the whole stand model that produced the most reliable results. Of the models examined only the whole stand model appears to be unbiased. All models display rapidly increasing standard error of prediction with increasing projection length.

Within this thesis three different validation procedures were explored. It was found that the standard fifty-fifty data splitting procedure was unreliable and not a wise way to use data. Results were highly dependent on the way in which the data was randomly split. The seventy-thirty split produced sounder results, but it did not appear that these results were stable enough to base decisions about model behavior. The PRESS approach used the data to the fullest, both for fitting and predicting. This approach was very pleasing because it was not dependent on random splitting and it produced results which were highly interpretable.

With this technique of growth and yield model integration with GIS compatible data, new fields of study are open for exploration. This type of system could be used to examine the topic of optimality of inventory projections periods with respect to various growth and yield models, given various constraints. Another application would be the integration of growth and yield models with spatially oriented models such as wildlife habitat or harvest scheduling.

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APPENDIX

Sample coputer code used to create inventory updating system, all models were fit to entire data set.

```
/**************************************************************************/
/*                                                                        */
/*  Loblink 2 version 1                                                   */
/*                                                                        */
/*  Program:     loblink2.c                                               */
/*                                                                        */
/*  Programmer: Jamie Shortt                                              */
/*                                                                        */
/*  Purpose:     This program reads forest stand information which        */
/*               is stored as a DBASE database file.  Each record         */
/*               pertains to a particular stand which may or may not      */
/*               include an individual tree list of stem diameters at     */
/*               breast height.  Growth for each stand is then projected  */
/*               for some set future year.  The projected (or future)     */
/*               stand characteristics for each stand are then stored     */
/*               as a database of future stands.                          */
/*                                                                        */
/*   Input:      File for whole stand models - wllall.dbf                 */
/*                                                                        */
/*               File for individual tree models - illall.dbf             */
/*                                                                        */
/*   Output:     File - xllall.dbf (contains whole stand information)     */
/*                                                                        */
/*   NOTE:       Program written in ANSI standard C, except for Dbase     */
/*               related procedures which require CODEBASE 4.5 librarys   */
/*               to compile                                               */
/*                                                                        */
/**************************************************************************/

#include "stdio.h"
#include "stdlib.h"
#include "math.h"
#include "string.h"
#include "conio.h"
#include "d4all.h"

void   title(void);
void   initial(void);
void   inputw(void);
void   inputi(void);
void   inputm(void);
void   whole(void);
void   weibull1(void);
void   single(void);
void   mort(void);
void   baproj(void);
void   yield(void);
void   diadist(void);
void   weibpara(void);
void   classhgt(void);
void   vol(void);
void   uptree(void);
void   xstand(void);
double qdia(void);
double domhgt(double standage, double site);
double indhgt(double d, double maxd, double t, double age, double h);
double treevol(double d, double h);
void   multi(void);
void   outdbf(void);
void   outputw(void);
void   outputm(void);
double solver(double (*func)(double), double x1, double x2);
double cvfunc(double cpt);
```

```
double gamma(double xx);
void   nerror(char error_text[]);
void   dpredict(void);
void   weibrec(void);
void   weibull2(void);

int    type,              /*  kind of model used                          */
       class,             /*  index each d class                          */
       xyear,             /*  year into future for final predictions      */
       iyear,             /*  year of inventory information               */
       pyear,             /*  year of planting                            */
       stdnum,            /*  id for each stand                           */
       dmin,              /*  minimun diameter for harvesting             */
       dmax,              /*  maximum dia class                           */
       numtree,           /*  number of trees in files                    */
       i;                 /*  tree index                                  */

float  area,              /*  stand size in acres                         */
       dia[106];          /*  diameter of the ith tree on a stand         */

double si,                /*  site index for stand at base age 25         */
       age1,              /*  stand age at inventory date                 */
       age2,              /*  future stand age                            */
       ptpa,              /*  planted trees per acre at year of planting  */
       itpa,              /*  inventory trees per acre                    */
       iba,               /*  inventory basal area per arce               */
       xtpa,              /*  future trees per acre                       */
       aparm,             /*  a parameter for the weibull dist            */
       bparm,             /*  b parameter for the weibull dist            */
       cparm,             /*  c parameter for the weibull dist            */
       xnclass [40],      /*  array for future TPA in each dia class      */
       xmort,             /*  %mort of stand at future year               */
       avghgt,            /*  average stand height                        */
       xahclass [40],     /*  array for future avg height in each d class */
       xvclass [40],      /*  array for future vol in each age class      */
       xah,               /*  future avg height                           */
       xad,               /*  future avg dia                              */
       xba,               /*  future avg basal area per acre              */
       xav,               /*  future avg volume                           */
       ihgt,              /*  height at inventory age                     */
       ht[106],           /*  height of the ith tree                      */
       cr[106],           /*  crown ratio of the ith  tree                */
       freq[106],         /*  individual tree relative frequency          */
       qd,                /*  quadratic mean diameter of the stand        */
       xvol[106],         /*  future volume of each tree                  */
       xwvol,             /*  whole stand volume estimate                 */
       xd1vol,            /*  dia. dist. param. pred. model volume estimate */
       xd2vol,            /*  dia. dist. param. rec. model volume estimate  */
       xivol;             /*  individual tree model volume estimate       */

double cv,                /* coefficient of variation of the dia. dist.   */
       dbar,              /* average stand diameter                       */
       sd2,               /* variance of diameter distribution            */
       mind;              /* minimum predicted diameter                   */

long   recnum;            /*  identifies the current dbf record           */

char   inbasew[80],       /*  whole stand input database file name        */
       inbasei[80],       /*  individual tree input databse file name     */
       outbase[80],       /*  output database file name                   */
       outascii[80];      /*  ascii output file name for multi models     */

/* ascii output file pointer */
```

```
FILE   *outfp;

/* database settings */
C4CODE xcodebase, icodebase, wcodebase;

/* pointers for database files */
D4DATA *ibase,*wbase,*out1;

/* pointers for database fields */
F4FIELD *zstandid, *zpyear, *ziyear, *zptpa, *ztpa, *zsi,
      *zitpa, *ziba, *zarea, *zdbh[106],
      *out1id, *out1xtpa, *out1xh, *out1xd, *out1xv,
      *out1xage, *out1harv, *out1xba;

/* define output database fields */
F4FIELD_INFO out1_fields[] = {
  {"STANDID", 'N', 4, 0},
  {"XTPA", 'N', 8, 2},
  {"XH", 'N', 8, 2},
  {"XDIA", 'N', 8, 2},
  {"XBA", 'N', 8, 2},
  {"XVOL", 'N', 10, 2},
  {"AGE", 'N', 4, 0},
  {0,0,0,0}
};


main()
{
  long int r;

  dmax=1000;

  /* continue loop until exit option is selected */
  for(;;){
    title();
    initial();
    /* count records in input database */
    if(type!=4) r=d4reccount(wbase);
    if(type==4) r=d4reccount(ibase);
    /* process each record */
    for(recnum=1L; recnum<=r; recnum++) {
      switch(type) {
      case 1:
      /* whole stand model */
        inputw();
        whole();
        break;
      case 2:
      /* parameter prediction model */
        inputw();
        weibull1();
        break;
      case 3:
      /* parameter recovery model */
        inputw();
        weibull2();
        break;
      case 4:
      /* individual tree model */
        inputi();
        single();
        break;
```

```
      case 5: /* run all models */
        inputm();
        multi();
        break;
      default: exit(0);
      }
      if(type!=5) {
      /* create screen and database output */
      outputw();
      outdbf();
      }
      if(type==5) {
      /* create multi-model output */
      outputm();
      }
    }
    /* close all datafiles */
    d4close(ibase);
    d4close(wbase);
    d4close(out1);
    fclose(outfp);
    printf("\a\n\n  Press any key to continue...");
    getch();
  }
}

/*************************************************************************/
/*                                                                       */
/*           title, initialization, and input subroutines                */
/*                                                                       */
/*************************************************************************/

void title(void)
{
  /* title screen and user required input */

  int k;

  char response;

  for(k=1; k<=3; k++) printf("\n");
  printf("                                   Loblink...\n\n");
  printf("                the multi forest stand simulator for predicting\n");
  printf("                the growth and yields of Loblolly pine stands\n");
  printf("                accessed through Dbase IV formatted data\n");

  for(k=1; k<=7; k++) printf("\n");
  printf("  Growth and yield model menu:\n\n");
  printf("                1.  Whole Stand\n");
  printf("                2.  Diameter Distribution - Parameter
Prediction\n");
  printf("                3.  Diameter Distribution - Parameter Recovery\n");
  printf("                4.  Individual Tree - Distance Independent\n");
  printf("                5.  Multi-Model Yield Comparison Routine\n");
  printf("                6.  Exit\n\n\n\n");
  printf("  Enter the number of desired approach: ");
  response=getche();
  printf("\n");
  while(!strchr("123456", response)) {
    title();
  }
  if(response=='1') type=1;
  if(response=='2') type=2;
```

```
  if(response=='3') type=3;
  if(response=='4') type=4;
  if(response=='5') type=5;
  if(response=='6') exit(0);
  printf("\n  Enter the projection year for final predictions:    ");
  scanf("%d", &xyear);
}


void initial(void)
{
  /* initialize codebase procedures */

  if(type!=4) {
    /* initialize whole stand input database */

    d4init(&wcodebase);
    wcodebase.open_error=0;

    printf("  Enter the whole stand input DBASE file <wllall.dbf>: ");
    gets(inbasew);
    gets(inbasew);
    if(strlen(inbasew)==0) strcpy(inbasew, "wllall.dbf");
    wbase=d4open(&wcodebase, inbasew);
  }

  if(type==4 || type==5) {
    /* initialize individual tree database */

    d4init(&icodebase);
    icodebase.open_error=0;

    printf("  Enter the individual tree input DBASE file <illall.dbf>: ");
    gets(inbasei);
    if(type==4) gets(inbasei);
    if(strlen(inbasei)==0) strcpy(inbasei, "illall.dbf");
    ibase=d4open(&icodebase, inbasei);
  }
  if(type==5) {
    /* open output ascii file */

    printf("  Enter the multi-model ascii output file <multi.dat>: ");
    gets(outascii);
    if(strlen(outascii)==0) strcpy(outascii, "multi.dat");

    if((outfp=fopen(outascii,"w"))==NULL) {
      printf(" ERROR - output datafile can not be created\n");
      exit(1);
    }
  }
  if(type!=5) {
    /* initilize output database */

    d4init(&xcodebase);
    xcodebase.open_error=0;

    printf("  Enter the name for output DBASE file <xllall.dbf>: ");
    gets(outbase);
    if(strlen(outbase)==0) strcpy(outbase, "xllall.dbf");
    out1=d4open(&xcodebase, outbase);
    if(out1==0) {
      out1=d4create(&xcodebase, outbase, out1_fields,0);
    }
```

```
    else {
      for(d4top(out1); !d4eof(out1); d4skip(out1,1)) d4delete(out1);
      d4pack(out1);
    }
    e4exit_test(&xcodebase);
  }
  e4exit_test(&icodebase);
  e4exit_test(&wcodebase);

  if(type==1 || type==2 || type==3) {
    /* initialize field names for whole stand input database */
    zstandid=d4field(wbase,"STANDID");
    zpyear=d4field(wbase,"PYEAR");
    ziyear=d4field(wbase,"IYEAR");
    zptpa=d4field(wbase,"PTPA");
    zitpa=d4field(wbase,"ITPA"),
    ziba=d4field(wbase,"IBA");
    zsi=d4field(wbase,"SI");
  }
  if (type==4 || type==5) {
    /* initialize field names for individual tree input database */
    if (type==5) {
      /* initialize requires field names for multi model runs */
      zptpa=d4field(wbase,"PTPA");
      zitpa=d4field(wbase,"ITPA"),
      ziba=d4field(wbase,"IBA");
    }

    zstandid=d4field(ibase,"STANDID"); zarea=d4field(ibase,"ACRES");
    zpyear=d4field(ibase, "PYEAR"); ziyear=d4field(ibase, "IYEAR");
    zsi=d4field(ibase, "SI"); zdbh[1]=d4field(ibase, "DBH1");
    zdbh[2]=d4field(ibase, "DBH2"); zdbh[3]=d4field(ibase, "DBH3");
    zdbh[4]=d4field(ibase, "DBH4"); zdbh[5]=d4field(ibase, "DBH5");
    zdbh[6]=d4field(ibase, "DBH6"); zdbh[7]=d4field(ibase, "DBH7");
    zdbh[8]=d4field(ibase, "DBH8"); zdbh[9]=d4field(ibase, "DBH9");
    zdbh[10]=d4field(ibase, "DBH10"); zdbh[11]=d4field(ibase, "DBH11");
    zdbh[12]=d4field(ibase, "DBH12"); zdbh[13]=d4field(ibase, "DBH13");
    zdbh[14]=d4field(ibase, "DBH14"); zdbh[15]=d4field(ibase, "DBH15");
    zdbh[16]=d4field(ibase, "DBH16"); zdbh[17]=d4field(ibase, "DBH17");
    zdbh[18]=d4field(ibase, "DBH18"); zdbh[19]=d4field(ibase, "DBH19");
    zdbh[20]=d4field(ibase, "DBH20"); zdbh[21]=d4field(ibase, "DBH21");
    zdbh[22]=d4field(ibase, "DBH22"); zdbh[23]=d4field(ibase, "DBH23");
    zdbh[24]=d4field(ibase, "DBH24"); zdbh[25]=d4field(ibase, "DBH25");
    zdbh[26]=d4field(ibase, "DBH26"); zdbh[27]=d4field(ibase, "DBH27");
    zdbh[28]=d4field(ibase, "DBH28"); zdbh[29]=d4field(ibase, "DBH29");
    zdbh[30]=d4field(ibase, "DBH30"); zdbh[31]=d4field(ibase, "DBH31");
    zdbh[32]=d4field(ibase, "DBH32"); zdbh[33]=d4field(ibase, "DBH33");
    zdbh[34]=d4field(ibase, "DBH34"); zdbh[35]=d4field(ibase, "DBH35");
    zdbh[36]=d4field(ibase, "DBH36"); zdbh[37]=d4field(ibase, "DBH37");
    zdbh[38]=d4field(ibase, "DBH38"); zdbh[39]=d4field(ibase, "DBH39");
    zdbh[40]=d4field(ibase, "DBH40"); zdbh[41]=d4field(ibase, "DBH41");
    zdbh[42]=d4field(ibase, "DBH42"); zdbh[43]=d4field(ibase, "DBH43");
    zdbh[44]=d4field(ibase, "DBH44"); zdbh[45]=d4field(ibase, "DBH45");
    zdbh[46]=d4field(ibase, "DBH46"); zdbh[47]=d4field(ibase, "DBH47");
    zdbh[48]=d4field(ibase, "DBH48"); zdbh[49]=d4field(ibase, "DBH49");
    zdbh[50]=d4field(ibase, "DBH50"); zdbh[51]=d4field(ibase, "DBH51");
    zdbh[52]=d4field(ibase, "DBH52"); zdbh[53]=d4field(ibase, "DBH53");
    zdbh[54]=d4field(ibase, "DBH54"); zdbh[55]=d4field(ibase, "DBH55");
    zdbh[56]=d4field(ibase, "DBH56"); zdbh[57]=d4field(ibase, "DBH57");
    zdbh[58]=d4field(ibase, "DBH58"); zdbh[59]=d4field(ibase, "DBH59");
    zdbh[60]=d4field(ibase, "DBH60"); zdbh[61]=d4field(ibase, "DBH61");
    zdbh[62]=d4field(ibase, "DBH62"); zdbh[63]=d4field(ibase, "DBH63");
    zdbh[64]=d4field(ibase, "DBH64"); zdbh[65]=d4field(ibase, "DBH65");
```

```
    zdbh[66]=d4field(ibase, "DBH66"); zdbh[67]=d4field(ibase, "DBH67");
    zdbh[68]=d4field(ibase, "DBH68"); zdbh[69]=d4field(ibase, "DBH69");
    zdbh[70]=d4field(ibase, "DBH70"); zdbh[71]=d4field(ibase, "DBH71");
    zdbh[72]=d4field(ibase, "DBH72"); zdbh[73]=d4field(ibase, "DBH73");
    zdbh[74]=d4field(ibase, "DBH74"); zdbh[75]=d4field(ibase, "DBH75");
    zdbh[76]=d4field(ibase, "DBH76"); zdbh[77]=d4field(ibase, "DBH77");
    zdbh[78]=d4field(ibase, "DBH78"); zdbh[79]=d4field(ibase, "DBH79");
    zdbh[80]=d4field(ibase, "DBH80"); zdbh[81]=d4field(ibase, "DBH81");
    zdbh[82]=d4field(ibase, "DBH82"); zdbh[83]=d4field(ibase, "DBH83");
    zdbh[84]=d4field(ibase, "DBH84"); zdbh[85]=d4field(ibase, "DBH85");
    zdbh[86]=d4field(ibase, "DBH86"); zdbh[87]=d4field(ibase, "DBH87");
    zdbh[88]=d4field(ibase, "DBH88"); zdbh[89]=d4field(ibase, "DBH89");
    zdbh[90]=d4field(ibase, "DBH90"); zdbh[91]=d4field(ibase, "DBH91");
    zdbh[92]=d4field(ibase, "DBH92"); zdbh[93]=d4field(ibase, "DBH93");
    zdbh[94]=d4field(ibase, "DBH94"); zdbh[95]=d4field(ibase, "DBH95");
    zdbh[96]=d4field(ibase, "DBH96"); zdbh[97]=d4field(ibase, "DBH97");
    zdbh[98]=d4field(ibase, "DBH98"); zdbh[99]=d4field(ibase, "DBH99");
    zdbh[100]=d4field(ibase, "DBH100"); zdbh[101]=d4field(ibase, "DBH101");
    zdbh[102]=d4field(ibase, "DBH102"); zdbh[103]=d4field(ibase, "DBH103");
    zdbh[104]=d4field(ibase, "DBH104"); zdbh[105]=d4field(ibase, "DBH105");
  }
  if(type!=5) {
    /* initializes fields for the output datadase */

    out1id=d4field(out1,"STANDID");
    out1xtpa=d4field(out1,"XTPA");
    out1xh=d4field(out1,"XH");
    out1xd=d4field(out1,"XDIA");
    out1xba=d4field(out1,"XBA");
    out1xv=d4field(out1,"XVOL");
    out1xage=d4field(out1,"AGE");
  }
}

void inputw(void)
{
  /* assigns current record to values to programs values */

  d4go(wbase, recnum);

  stdnum=f4int(zstandid);
  pyear=f4int(zpyear);
  iyear=f4int(ziyear);
  ptpa=f4double(zptpa);
  iba=f4double(ziba);
  itpa=f4double(zitpa);
  si=f4double(zsi);

  if(xyear>=pyear) age2=xyear-pyear;
  else {
    printf("\n  ERROR - projection year is less than planting year");
    printf("\n  Projection year = %4d    planting year = %4d\n", xyear,
pyear);
    exit(0);
  }
  if(iyear>=pyear) age1=iyear-pyear;
  else {
    printf("\n  ERROR - inventory year is less than planting year");
    printf("\n  Inventory year = %4d    planting year = %4d\n",
      iyear, pyear);
    exit(0);
  }
}
```

```
void inputi(void)
{
  /* assigns current record to values to programs values */

  int j;

  d4go(ibase, recnum);
  numtree=0;
  stdnum=f4int(zstandid);
  area=f4double(zarea);
  pyear=f4int(zpyear);
  iyear=f4int(ziyear);
  si=f4double(zsi);
  for(j=1; j<=105; j++) dia[j]=0;
  for(j=1; j<=105; j++) {
    dia[j]=f4double(zdbh[j]);
    if(dia[j]>0) numtree=j;
  }

  if(xyear>=pyear) age2=xyear-pyear;
  else {
    printf("\n  ERROR - projection year is less than planting year\n");
    printf("\n  Projection year = %4d    planting year = %4d\n", xyear,
pyear);
    exit(0);
  }
  if(iyear>=pyear) age1=iyear-pyear;
  else {
    printf("\n  ERROR - inventory year is less than planting year\n");
    printf("\n  Inventory year = %4d    planting year = %4d\n",
      iyear, pyear);
    exit(0);
  }
}

void inputm(void)
{
  /* assigns current record to values to programs values */

  int j;

  d4go(wbase, recnum);
  d4go(ibase, recnum);

  numtree=0;
  ptpa=f4double(zptpa);
  iba=f4double(ziba);
  itpa=f4double(zitpa);
  stdnum=f4int(zstandid);
  area=f4double(zarea);
  pyear=f4int(zpyear);
  iyear=f4int(ziyear);
  si=f4double(zsi);
  for(j=1; j<=105; j++) dia[j]=0;
  for(j=1; j<=105; j++) {
    dia[j]=f4double(zdbh[j]);
    if(dia[j]>0) numtree=j;
  }

  if(xyear>=pyear) age2=xyear-pyear;
  else {
    printf("\n  ERROR - projection year is less than planting year\n");
    printf("\n  Projection year = %4d    planting year = %4d\n",
```

```
      xyear, pyear);
    exit(0);
  }
  if(iyear>=pyear) age1=iyear-pyear;
  else {
    printf("\n  ERROR - inventory year is less than planting year\n");
    printf("\n  Inventory year = %4d    planting year = %4d\n",
      iyear, pyear);
    exit(0);
  }
}

/***********************************************************************/
/*                                                                     */
/*           growth and yield model main subroutine calls              */
/*                                                                     */
/***********************************************************************/

void whole(void)
{
  /* whole stand model */

  xtpa=-1.0; /* infers that tpa is not known */
  baproj();
  yield();
}

void weibull1(void)
{
  /* parameter prediction model */

  avghgt=domhgt(age2,si);
  if(itpa>0) ihgt=domhgt(age1,si);
  else ihgt=0;
  mort();
  weibpara();
  diadist();
  classhgt();
  vol();
}

void weibull2(void) {
  /* parameter recovery model */

  avghgt=domhgt(age2,si);
  if(itpa>0) ihgt=domhgt(age1,si);
  else ihgt=0;
  mort();
  dpredict();
  weibrec();
  diadist();
  classhgt();
  vol();
}

void single(void)
{
  /* inidividual tree model */

  uptree();
  xstand();
}
```

```
void multi(void)
{
  /* run all models and maintain different estimates of volume for each */

  whole();
  xwvol=xav;
  weibull1();
  xd1vol=xav;
  weibull2();
  xd2vol=xav;
  single();
  xivol=xav;
}

/************************************************************************/
/*                                                                      */
/*                 Whole stand model subroutines                        */
/*                                                                      */
/************************************************************************/

void baproj(void)
{
  /* project basal area for the whole stand model */
  double c[2] = { 8.1105, -.0408 };


  if(iba<=0) {
    printf("ERROR - inventoried basal areais required\n");
  }
  else {
    xba=(age1/age2)*log(iba)+c[0]*(1-age1/age2)+c[1]*(1-age1/age2)*si;
    xba=exp(xba);
  }
}

void yield(void) {
/* whole stand yield from Sullivan & Clutter 1972 For Sci */
  double b[6] = { .1145, .0313, -11.0490, 1.3110, 10.6325, -.0535 };

    xav=exp(b[0]+b[1]*si+b[2]/age2+b[3]*(age1/age2)*log(iba)
      +b[4]*(1-age1/age2)+b[5]*(1-age1/age2)*si);
}

/************************************************************************/
/*                                                                      */
/*   Diameter distribution - parameter prediction model subroutines     */
/*                                                                      */
/************************************************************************/

void mort(void){
  /*  calculate the predicted number of future tpa  */

  double b[4] = {-1.2563, .000000012, -.000000470, 3.2220 };


  if(itpa>0) {
    /* based on inventory tree count */
    xtpa=pow(itpa,b[0])+(b[1]+b[2]/si)*(pow(age2,b[3])
      -pow(age1,b[3]));
    xtpa=pow(xtpa,(1/b[0]));
  }
  else {
    /* based on planted number of trees, when no inventory available */
```

```
      xtpa=pow(ptpa,b[0])+(b[1]+b[2]/si)*(pow(age2,b[3])-1);
    xtpa=pow(xtpa,(1/b[0]));
  }
}

void weibpara(void)
{
  /*  determine a,b,c parameters using parameter prediction */

  double  b[2] = { .1297, .03262 },
          c[4] = { -.41627, -.00121, 4.20583, 583.09248 },
          d[3] = { 9.54155, -.04167, -1.86873 };

  aparm = b[0]+b[1]*avghgt;
  if(aparm<0) aparm=0.0;
  bparm = (c[0]+c[1]*xtpa+c[2]*log10(avghgt)+c[3]/xtpa)-aparm;
  cparm = d[0]+d[1]*age2+d[2]*log10(xtpa);
}

void diadist(void)
{
  /*  create the diameter distribution */

  double xdperc, /* holds the percent of trees in each class */
      totn;      /* total number of tpa found by summing each class */

  float  lclass, /* the lower limit of the current class */
      uclass;    /* the upper limit of the current class */

  dmax=0;
  class=0;
  totn=0;
  xad=0;
  xba=0;
  dmin=5;

  if(age2>7) {
    do { /* for each diamater class */

      /* determine upper and lower diameter class limits */
      class+=1;
      lclass=class-.5;
      uclass=class+.5;

      /* integrate weibull from lower to upper diameter limit */
      if (lclass<=aparm && uclass>aparm)
     xdperc=1-exp(-pow((uclass-aparm)/bparm,cparm));
      if (lclass>aparm)
     xdperc=exp(-pow(((lclass-aparm)/bparm),cparm))
     -exp(-pow(((uclass-aparm)/bparm),cparm));

      /* calculate the number of trees in diameter class */
      xnclass[class]=xtpa*xdperc;

      /* sum diams, basal areas and number of trees in all classes */
      xad+=class*xnclass[class];
      xba+=.005454*pow(class,2)*xnclass[class];
      totn+=xnclass[class];
    } while(!(xnclass[class]<.5 && totn>5));
  }
  dmax=class;
  if(totn>0) {
    xtpa=totn;
```

```
    xad=xad/xtpa;
  }
}

void classhgt(void)
{
  /*  determines the average height for each class */

  int    d;
  double dia, diamax;

  for(d=1; d<=dmax; d++) {
    dia=d;
    diamax=dmax;
    xahclass[d] = indhgt(dia, diamax, xtpa, age2, avghgt);
  }
  xah=avghgt;
}

void vol(void)
{
  /*  calculates the average tree volume for each diameter class */

  int d;
  double dia;

  xav=0;
  for(d=1; d<=dmax; d++) {
    dia=d;
    xvclass[d]=treevol(dia, xahclass[d]);
    if(d>=dmin) xav=xav+xnclass[d]*xvclass[d];
  }
}

/************************************************************************/
/*                                                                      */
/*     Diameter distribution - parameter recovery model subroutines     */
/*                                                                      */
/************************************************************************/
void dpredict(void)
{
  /* estimate required whole stand variables */

  double dq2,  /* quad. mean dia. squared */
         b[4] = { 2.82052, .064632, -.046799, 10.73593 },
         c[4] = { .28382, .03471, -.005335, 13.68287 },
         d[4] = { 1.0407, .515768, -8.18769, -.287531 };


  dbar = b[0]+b[1]*avghgt+b[2]*age2*(xtpa/1000)+b[3]*(avghgt/xtpa);
  mind = c[0]+c[1]*avghgt+c[2]*age2*(xtpa/1000)+c[3]*(avghgt/xtpa);
  if(mind<0) mind=0;
  aparm = .5*mind;
  sd2 = exp(d[0]+d[1]*log(avghgt)+d[2]*(1/age2)+d[3]*log(xtpa));
  dq2=sd2+pow(dbar,2);
  cv=sqrt(dq2-2*dbar*aparm+pow(aparm,2)-(dbar-aparm))/(dbar-aparm);
}

void weibrec(void)
{
  /* estimate b and c parameters of Weibull function */

  cparm = solver(cvfunc, 1, 12);
```

```
  bparm = (dbar-aparm)/(gamma(1+1/cparm));
}

double cvfunc(double cx)
{
  /* function used to solve for the c parameter */

  return ((sqrt(gamma(1+2/cx)-pow(gamma(1+1/cx),2))/gamma(1+1/cx))-cv);
}

double gamma(double xx)
{
  /* calculate the value of the gamma function */

  double x, tmp, ser;

  static double cof[6]={76.18009173, -86.50532033, 24.01409822,
    -1.231739516, 0.120858003e-2,-0.536382e-5};

  int j;

  x=xx-1.0;
  tmp=x+5.5;
  tmp -= (x+.5)*log(tmp);
  ser=1.0;
  for(j=0;j<=5;j++) {
    x += 1.0;
    ser += cof[j]/x;
  }
  return exp(-tmp+log(2.50662827465*ser));
}

/****************************************************************/
/*                                                              */
/*  Iterative solution solver for one equation with one unknown */
/*                                                              */
/****************************************************************/
double solver(double (*func)(double), double x1, double x2)
{
  int g;
  double f1, f2, solution;

  if(((*func)(x1)>0.0&&(*func)(x2)>0)||((*func)(x1)<0.0&&(*func)(x2)<0.0))
    nerror("Solution exists outside initially provided range");

  for(g=x1; g<=x2; g++) {
    f1=(*func) (g);
    f2=(*func) (g+1);
    if( (f1<0.0 && f2>0.0) || (f1>0.0 && f2<0.0) ) {
      solution=g;
      break;
    }
    if(f1==0.0) return g;
    if(f2==0.0) return g+1;
  }

  for(g=1; g<=10; g++) {
    f1=(*func) (solution + (float) g/10 - 0.1);
    f2=(*func) (solution + (float) g/10);
    if( (f1<0.0 && f2>0.0) || (f1>0.0 && f2<0.0) ) {
      solution += (float) g/10 - 0.1;
      break;
    }
```

```
    if(f1==0.0) return solution + (float) g/10 - .1;
    if(f2==0.0) return solution + (float) g/10;
  }

  for(g=1; g<=10; g++) {
    f1=(*func) (solution + (float) g/100 - 0.01);
    f2=(*func) (solution + (float) g/100);
    if( (f1<0.0 && f2>0.0) || (f1>0.0 && f2<0.0) ) {
      solution += (float) g/100 - 0.01;
      break;
    }
    if(f1==0.0) return solution + (float) g/100 - .01;
    if(f2==0.0) return solution + (float) g/100;
  }

  return solution+.005;
}

void nerror(char error_text[])
{
  /* create error message */

  printf("\nNumerical Recipes run-time error...\n");
  printf("%s\n",error_text);
}


/**************************************************************************/
/*                                                                        */
/*       Individual tree - distance independent model subroutines         */
/*                                                                        */
/**************************************************************************/

double qdia(void)
{
  /*  returns the quadratic mean diameter per acre of trees in list */

  double  quadia,
         tperac,
         qsum;

  qsum=0;
  tperac=0;
  for(i=1; i<=numtree; i++) {
    qsum=qsum+pow(dia[i],2)*freq[i];
    tperac=tperac+freq[i];
  }
  quadia = sqrt(qsum/tperac);
  return quadia;
}

void uptree(void)
{
  /*  updates each tree on an annual basis */

  int    y;              /* current year in updating procedure */

  double dht,            /* average dom/codom height at init. age */
       rnum,           /* random number */
       p[106],         /* prob of surviving over the next year  */
       hinc,           /* height increment over the year */
       dinc,           /* diameter increment over the year */
       dpotent,        /* open growth increment potential */
```

```
        dmax,          /* maximum diameter in the stand */
        hd,            /* avg codom and dom height      */
        ts;            /* total number of surviving stems per acre */

    /* declare and initialize model parameters */
    double r[2] =  { 1.6349, 31.49505 }, /* crown ratio */
        s[4] = { 1.11173, .083403, -.038311, 2.02272 }, /* surv. funct. */
        d[3] = { .43382, .94029, 1.15166 }; /* diam. incr. equ. */

    /* regular initialization */
    dmax=0;
    ts=0;

    for(i=1; i<=numtree; i++) {
      freq[i] = 1/area;
      ts=ts+freq[i];
      if(dia[i]>dmax) dmax=dia[i];
    }
    /* determine height based on diameter  */
    dht=domhgt(age1,si);
    for(i=1; i<=numtree; i++) {
      ht[i]=indhgt(dia[i], dmax, ts, age1, dht);
    }
    for(y=age1; y<age2; y++) {
      ts=0;
      for(i=1; i<=numtree; i++) {
        if(dia[i]>dmax) dmax=dia[i];
        ts=ts+freq[i];
      }

      /* calculate quadratic mean diameter of stand */
      qd=qdia();
      for(i=1; i<=numtree; i++) {

        /* calculate crown ratio of each tree form Dyer & Burkhart 1987 */
        cr[i]=1-exp(-(r[0]+r[1]/y)*(dia[i]/ht[i]));

        /*  calculate probability of survival over next year */
        /*  from Amateis, Burkhart, and Walsh 1989           */
        p[i]=s[0]*pow(cr[i],s[1])*exp(s[2]*pow((qd/dia[i]),s[3]));
        if(p[i]>1) p[i]=1;

        /* adjust frequency of trees by survival function    */
        freq[i]=freq[i]*p[i];

        /* calculate potential increment for open grown tree */
        /* then predict actual increment based on potential   */
        /* from Amateis, Burkhart, and Walsh, 1989            */
        dpotent=.286583*(domhgt(y+1,si)-domhgt(y,si))+.209472;
        dinc=dpotent*d[0]*pow(cr[i],d[1])*exp(d[2]*(1-qd/dia[i]));

        /* update diameters and heights */
        dia[i]=dia[i]+dinc;
        hd=domhgt(y,si);
        ht[i]=indhgt(dia[i], dmax, ts, y, hd);
      }
    }
  }

  void xstand(void)
  {
    /*  calculates final stand variables for individual tree model */
```

```
  xba=0;
  xtpa=0;
  xav=0;
  xad=0;

  for(i=1; i<=numtree; i++){
    /* sums basal area */
    xba+=freq[i]*.005454*pow(dia[i],2);

    /* sums the number of trees per acre */
    xtpa+=freq[i];

    /* calculates and sums merchantable volume */
    if(dia[i]>4.5)
      xvol[i]=treevol(dia[i],ht[i]);
    else
      xvol[i]=0;
    xav+=freq[i]*xvol[i];
    /*  sums diameter diameters */
    xad+=freq[i]*dia[i];
  }
  /* calculates average height of dom/codom trees based on site index */
  xah=domhgt(age2,si);
  /* calculates average diameter */
  xad=xad/xtpa;
}

/**************************************************************************/
/*                                                                        */
/*                Common equations for models                             */
/*                                                                        */
/**************************************************************************/

double domhgt(double standage, double site)
{
/*  site index equation base age of 25                                    */
/*  function returns dom. & codom. height for a given age and site index */

  double    b1 = -.02205,          /* parameter for equation */
          b2 = -2.83285,         /* parameter for equation */
          z,                     /* intermediate variable  */
          height;                /* height of tree         */

  z=log(site)*pow((25/standage),b1)*exp(b2*(1/standage-(float) 1/25));
  height=exp(z);
  return height;
}

double indhgt(double d, double maxd, double t, double age, double h)
{
  /*  determine height based on diameter  */

  double b[5]= {-.032336, -.919045, -.260981, 2.302275, 1.471620 };
  double q1, height;

  q1 = b[0]+(1/d-1/maxd)*(b[1]+b[2]*log10(t)+b[3]/age+b[4]*log10(h));
  height = h/pow(10,q1);
  return height;
}

double treevol(double d, double h)
{
  /*  tree volume equation from Amateis and Burkhart, 1987           */
```

```
  /*  volume is cubic foot outside bark to a 4 inch top              */

  double b[5] = { .18658, .00250, .54583, 3.22011, 3.03262 };
  double volume, topdia;

  topdia=4;
  if(d>=4.5)
    volume =
(b[0]+b[1]*pow(d,2)*h)*(1-b[2]*(pow(topdia,b[3])/pow(d,b[4])));
  else
    volume = 0;
  if(volume<0) volume=0;
  return volume;
}

/*************************************************************************/
/*                                                                       */
/*                Output subroutines, screen and database                */
/*                                                                       */
/*************************************************************************/

void outputm(void)
{
  /*  multi stand level screen and file output  */

  if(recnum==1) {
    printf("\n\n        Multi Growth Model Output for Year %4d\n\n",
xyear);
    printf("                                Vol per Acre in Cubic
Feet\n");
    printf("  Stand  Stand  Site    Whole     Dia. Dist.    Dia. Dist.
Indv.\n");
    printf("   ID     Age   Index   Stand     Par. Pred.    Par. Recv.
Tree\n");
    printf("  -----  -----  -----  ---------  ----------   ----------
---------\n");
  }
  printf("  %4d  %5.0f  %5.0f   %8.2f    %8.2f    %8.2f    %8.2f\n",
   stdnum, age2, si, xwvol, xd1vol, xd2vol, xivol);

  fprintf(outfp, "  %4d   %8.2f   %8.2f   %8.2f   %8.2f\n",
   stdnum, xwvol, xd1vol, xd2vol, xivol);
}

void outputw(void)
{
  /*  whole stand level screen output  */

  if(recnum==1) {
    printf("\n\n\n");
    printf("     Multi Stand Level Summary for the Year %4d\n\n", xyear);
    printf("   Stand     Age    Site                        Vol/AC\n");
    printf("    ID     (Years)  Index    TPA      BA       (CU FT)\n");
    printf("  ------   -------  -----  -------  ------   ----------\n");
  }
    printf("  %5d    %4.0f     %3.0f    %6.2f    %6.2f    %8.2f\n",
    stdnum, age2, si, xtpa, xba, xav);
}

void outdbf(void)
{
  /*  output whole stand info to database */
```

```
  d4append_start(out1,0);

  f4assign_int(out1id,stdnum);
  f4assign_double(out1xtpa,xtpa);
  f4assign_double(out1xh,xah);
  f4assign_double(out1xd,xad);
  f4assign_double(out1xba,xba);
  f4assign_double(out1xv,xav);
  f4assign_double(out1xage,age2);

  d4append(out1);
}
```

Vita

James S. Shortt was born on March 30, 1968 on an United States military base in Würtburg, Germany. He attended Virginia Polytechnic Institute and State University, graduating in December of 1990 with a Bachelor of Science in Forestry. In August of 1991 he continued his education at V.P.I. & S.U. where he earned his Master of Science in Forest Biometrics in August 1993. Upon graduation he accepted employment with Mead Coated Board in Columbus, Georgia.

James Shortt

James Stover Shortt