



United States
Department
of Agriculture

Forest Service

**Rocky Mountain
Research Station**

General Technical
Report RMRS-GTR-124

February 2004



Revisiting the Southern Pine Growth Decline: Where Are We 10 Years Later?

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Abstract

This paper evaluates changes in growth of pine stands in the state of Georgia, U.S.A., using USDA Forest Service Forest Inventory and Analysis (FIA) data. In particular, data representing an additional 10-year growth cycle has been added to previously published results from two earlier growth cycles. A robust regression procedure is combined with a bootstrap technique to produce estimates of mean growth with confidence intervals for the fourth, fifth, and sixth inventories of natural pine stands sampled between 1961 and 1990. Results suggest that sixth cycle growth rates of pine stands in Georgia remain fairly constant with rates observed in the fifth growth cycle, though they are not up to the level of growth observed in the fourth cycle. Overall, we conclude that growth in the stands screened for this analysis declined between the fourth and fifth cycles but stabilized in the sixth cycle. Inferences cannot be extended to the entire state of Georgia but only to the unknown population represented by the screened dataset of undisturbed natural pine stands. We highlight some specifics on what can and cannot be inferred from FIA data and recommend future actions to increase the chance of detecting changes and revealing factors that might be associated with the changes. The recent switch in FIA to annualized inventories will make it more likely that changes such as these will be easier to detect and interpret in the future.

Key words: bootstrap, cause-effect, forest inventory and analysis, robust regression

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*Cover: Natural stand of 40-year-old loblolly pine by David J. Moorhead,
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Introduction

A controversial topic related to U.S. forest inventories was the southern pine growth decline issue in the 1980s. The U.S. Forest Service Forest Inventory and Analysis (FIA) program indicated that the growth of natural pines in Georgia and Alabama in the 1970s had decreased significantly from levels reported in the 1960s. In various newspapers articles, this was attributed to pollution.

FIA inventories were never designed to assess true cause and effect (Schreuder and Thomas 1991), just as the linkage between smoking and lung cancer could not be unequivocally confirmed from the numerous survey studies that suggested a connection between the two. Careful experimentation finally conclusively established such a link. Establishing cause-effect from observational survey data is difficult (Gadbury and Schreuder 2003). Although cause and effect is beyond the scope of FIA, the FIA survey is suitable for assessing change in the forest resource over large areas. We document, as well as possible, what can be concluded from FIA data, a new procedure for analyzing FIA data, and a reanalysis that incorporates an additional growth cycle.

Literature Review

The FIA program, initiated in 1928, inventories the forest resources of the United States and regularly produces population estimates such as the total area of forest and timber volume as well as change over time. Until recently, FIA was a periodic inventory where states were visited one at a time every 7-22 years. A decline in growth of natural southern pine timber volume from the fourth cycle (1961-1971) to the fifth cycle (1972-1982) was observed primarily in Georgia and Alabama. Concerns arose regarding the use of FIA data to conclude a growth decline. However, the findings were supported by several researchers (Sheffield and others 1985; Sheffield and Cost 1987). The decline in growth was reported to be as much as 17-23% for natural loblolly pine and 27% for natural shortleaf pine (Zahner and others 1989; Bechtold and others 1991).

Ruark and others (1991) used FIA data to compare the periodic annual increment in basal area of selected naturally regenerated pine stands throughout Alabama

and Georgia. Estimated growth rates between 1972 and 1982 (fifth cycle) were compared with estimated growth rates obtained during the previous 10-year survey cycle (fourth cycle). Separate analyses were conducted for loblolly, longleaf, shortleaf, and slash pine cover types. Comparisons of growth rates yielded reductions ranging from 3% to 31% in both states. All reductions were statistically significant except for the 3% decline in natural loblolly pine in Alabama. Bechtold and others (1991) performed a similar study that focused only on the state of Georgia. Both Bechtold and others (1991) and Ruark and others (1991) developed models that adjusted the observed growth rates for changes in stand structure. T-tests were used to evaluate the significance of mean adjusted growth rates obtained from analysis of covariance models. The conclusion from both papers was that the declines could not be attributed to changes involving the modeled stand structural parameters; however, the agent(s) causing the decline were not identified.

A number of other studies examined possible explanations of a decline in growth. Knight (1987) attributed the decline to four factors: declining area of timberland, inadequate regeneration after harvest on non-industrial private forest lands, increased tree mortality, and a reduction in the rate of tree and stand growth. Zahner and others (1989), collecting tree-ring data on a 10% subsample of FIA field plots across the Piedmont region of Georgia, North Carolina, and South Carolina, developed tree-ring models to interpret the growth decline of loblolly pine. These authors attributed some of the decline to region-wide drought periods between 1950 and 1959 and again between 1980 and 1983. Another important factor identified was the increase in average basal area and number of stems per hectare. This study concluded that the annual growth rate of trees in the early 1980s was about two-thirds that of trees growing in similar conditions 35 years earlier. Moreover, it concluded that a significant portion of the decline could not be attributed to either climatic or stand conditions but speculated that high levels of ozone in the region could have been a significant factor.

Czaplewski and others (1994) used the Georgia FIA data to look at spatial patterns to determine if atmospheric deposition from large metropolitan areas could be a factor in a growth decline. While there was a significant

spatial pattern associated with the growth decline, this pattern could also be explained by an unusually slow-growing cluster of pine plots in the mountains approximately 100 km north of Atlanta. However, after using a regression model to adjust for local stand conditions, no significant spatial autocorrelation existed.

A number of concerns were raised regarding these findings. Hyink (1991), in a response to Bechtold and others (1991), was concerned about the differences in the distributions of age and site classes in data screened from the two growth cycles. He also noted that there was a troubling number of plots with atypically high growth rates in the fourth cycle in Georgia and that there is a lack of knowledge regarding what constitutes a “normal” growth rate for natural pine stands in the region.

Gertner (1991) commented on the analysis techniques used by Bechtold and others (1991) by noting that there are likely to be large amounts of error in some of the independent variables when a calibrated model is used to adjust mean logarithmic growth. He concludes that while there may have been a real reduction in growth rates, the possibility that the reduction may have resulted from biases caused by sampling errors and data transformations could not be ruled out.

Some of these concerns were addressed in subsequent studies. Ouyang and others (1991) used bootstrap and jackknife methods for inference since distributions of residuals from fitted models were often “heavy tailed.” Ueng and others (1997) used a robust regression technique to minimize the influence of outlying residuals from fitted models. Gadbury and others (1998, 2002) used classification and regression tree methods to account for possible complex nonlinear relationships among variables describing growth, mortality, and stand structure. The results of each of these studies agreed with the results of Bechtold and others (1991) and Ruark and others (1991). Thus, some of the earlier concerns over the methods of analyses did not invalidate the findings.

Zeide (1992) performed an extensive analysis of data from the third to sixth cycles and pointed out that the reported changes were puzzling in light of the fact that the decline occurred only for naturally regenerated pines, but was unobserved in pine plantations. He suggested that either there was a growth decline before 1961, or more likely that there was no evidence of a growth decline and that the data were deficient for several reasons: (1) a drastic change from the fixed area plot sampling to variable radius plot sampling, (2) the presence of numerous outliers, and (3) inconsistencies in relationships between variables.

As noted in Schreuder and Thomas (1991) and affirmed in comments to that article by Clutter and Hyink

(1991), screening of the data as done in both the Georgia and Georgia/Alabama studies make it difficult to assess the actual population for inference. So, was there a decline in growth in natural pine stands in the period from the 1960s to the 1970s? We believe there was for the screened data analyzed, but extension of these results to the entire population of natural pine stands in Georgia and Alabama is not warranted. What should be done to maximize the possibility of identifying and assessing meaningful hypotheses of change in the future and possible causes for them? We address that in the section on recommendations at the end of the paper.

Where Are We Today?

Some things have changed. First and foremost is the addition of the sixth cycle to the FIA inventory. From these data, the growth rate between the fifth and sixth cycle can be estimated and compared to that of the fourth. There are also new analytical techniques. Recently FIA procedures have changed drastically by going from a cyclical inventory to an annualized inventory where 20% of the plots will be measured in each state each year. FIA has also integrated with the Forest Health Monitoring (FHM) program and has dedicated a systematic subset of its plot network to investigating issues related to forest health (Stolte 2001). Ten years of research into cause-effect issues with FIA data has improved our understanding of the problem and going to an annualized inventory has provided us with improved ability to assess change. The goals of this study are to:

- Introduce robust methods for analyzing data from periodic surveys.
- Compare the growth rates between the fourth, fifth, and sixth cycles of the inventory to see whether perceived declines continued into the sixth cycle.
- Recommend possible methods to analyze such data in the future.
- Identify issues that arise when attempting to use observational data to attribute an observed change to potentially “causal” factors.
- Identify what can and cannot be accomplished with FIA-type observational data.

Data Description

Three types of naturally regenerating pine stands were studied and were designated by their dominant species: loblolly (*Pinus taeda*), shortleaf (*Pinus echinata*), and slash pine (*Pinus elliotii*). The data

represent growth rates and stand structure of forest plots in Georgia over three 10-year periods spanning the years 1961-1990. The three periods are referred to as the fourth, fifth, and sixth growth cycles. The data for cycles prior to the fourth were not suitable for assessing changes in growth rates. Additional information about the data can be found in Bechtold and others (1991).

Each growth cycle uses an independent sample of forest plots because the time lapse between samples and drastic changes in stand structure and disturbances made it unrealistic to follow the same plots over the three growth cycles. A total sample size of 692 loblolly plots was obtained, 235 from the fourth cycle, 104 from the fifth cycle, and 353 from the sixth, of which 11 were common to all three cycles. A total sample size of 258 shortleaf plots was obtained, 127 from the fourth cycle, 45 from the fifth, and 86 from the sixth, of which three were common to all three. Finally, a total sample size of 401 slash pine plots was obtained, 84 from the fourth cycle, 83 from the fifth, and 234 from the sixth, of which seven were common to all three. The plots common to all three growth cycles represented a small fraction of the total sample, and so they too were treated as independent observations across the three cycles.

The variables of interest are: GG = gross annual basal area growth per acre (survivor growth + ingrowth); S = site index representing volume growth potential (S represents a relation between age and height of dominant and co-dominant pines in each stand (base 50 years); A = stand age (midpoint of 10 year class); N = number of stems per acre; P = ratio of yellow pine basal area per acre to basal area of all species; M = annual basal area mortality per acre of trees alive at initial inventory that die from natural causes prior to terminal inventory; net growth denoted NG , equal to $GG - M$. GG , N , M , and NG are all based on trees 1.0 inches dbh and larger at the time of the initial inventory.

Variables GG , N , M , (and consequently NG) have separate data available for pine only and for all trees, denoted by the subscripts p and t respectively. These are represented as GG_p and GG_t for gross pine growth or gross total growth, respectively. Similarly, we use N_p and N_t , M_p and M_t , and NG_p and NG_t , the latter being net pine growth and net total growth. Summary statistics and sample sizes for the sixth growth cycle are shown in table 1. The corresponding results for the fourth and fifth growth cycles are reported in Bechtold and others (1991, page 708). Extreme data points at either of the fourth, fifth, or sixth growth cycles are handled with the method described below. In particular, variable transformations,

Table 1. Sample size and summary statistics (mean and standard error) for variables from the sixth FIA growth cycle.

Variable	Loblolly n = 353		Shortleaf n = 86		Slash n = 234	
	mean	SE	mean	SE	mean	SE
GG_p	3.05	0.10	2.64	0.22	2.77	0.11
GG_t	4.17	0.11	3.76	0.24	3.69	0.13
M_p	1.04	0.06	0.90	0.13	0.52	0.06
M_t	1.24	0.07	1.13	0.14	0.66	0.06
N_p	442.8	20.1	437.2	36.7	345.1	19.2
N_t	834.9	24.4	858.2	46.3	688.7	32.0
A	28.7	0.7	27.4	1.4	30.4	0.8
S	73.0	0.5	67.0	1.1	71.4	0.6
P	0.79	0.01	0.77	0.02	0.83	0.01

diagnostic procedures, and robust fitting procedures should minimize the effect of extreme data values on any conclusions from the following analyses.

Methods

The statistical methods discussed earlier have different strengths and limitations. We focus on a method that incorporates some of the advantages in Ueng and others (1997), Gadbury and others (1998, 2002), and Ouyang and others (1991). A linear model is fit relating a function of growth variables (i.e., response variables) to functions of covariates. We also explore more complex nonlinear relationships between covariates and the response in a second model and include these nonlinear terms if appropriate. The results then are a linear and a nonlinear model. The models are fit to the FIA data using a robust fitting algorithm to minimize the influence of large residuals, and interval estimates of growth are obtained using the bootstrap to minimize parametric assumptions. Results from inference using each of the two models are compared in order to evaluate the effect, if any, of the higher order nonlinear terms on conclusions from the analyses. The details of the method are described below.

Selecting a Model

Initially, the range of each covariate, i.e., A , P , S , and N_k , $k = p, t$, was studied to determine if transformations were necessary (Weisberg, 1985, p. 156). If, for a data set, the maximum of a covariate divided by its minimum was greater than 10, the natural logarithm was used. For all data sets, this resulted in $\ln(A)$ and $\ln(N_k)$ being used in place of A and N_k , respectively. These transformations helped to stabilize the variance of residuals and to

control for influential observations (outliers in the values of a covariate) in model-fitting algorithms, and both were also used by Bechtold and others (1991) and Ruark and others (1991). Then, a model of the following form was considered:

$$g(Y_k) = b_0 * T_4 + b_1 * T_5 + b_2 * T_6 + b_3 * \ln(A) + b_4 * \ln(N_k) + b_5 * S + b_6 * P + \epsilon \quad [1]$$

where $T_i = 1$ if a plot was sampled from the i th growth period and zero otherwise ($i = 4, 5, 6$), $k = p$ or t for pine growth or total growth, Y is either GG or NG , and ϵ represents a random error term that need not be normally distributed for the method proposed here. Box-Cox transformations (Box and Cox 1964) were used with this model to determine a suitable transformation $g(\cdot)$ for Y_k , the goal being stabilization of variances of residuals. Because NG_k values were occasionally negative, a location transformation, $NG_k^* = NG_k + |\min(NG_k)| + 1$, $k = p, t$, was used when applying the natural logarithm transformation.

Since relationships between the predictor variables and the response variable appeared to be quite complicated, even after transformations, higher order terms were evaluated in a second model. In addition to the terms in model 1, two-way interactions and quadratic terms were selected using stepwise regression (Neter and others 1990, chapter 12). The objective of this step was to determine if any second order terms were important for capturing the complex relationship between covariates and response. There were, then, 22 additional terms in the pool of covariates that could be selected in this step. This model will be referred to as model 2.

Cook's distance (Cook and Weisberg 1982) was used to identify any influential points in the models. These points may not only exert excessive influence on the fit of the model, but also the selected form for the model, i.e., they may suggest curvature in the model that is not really there. If such points were detected, they were investigated further to determine if they were valid and to assess their effect on conclusions from a model. Diagnostic plots were also used to evaluate equal variance of residuals and to identify any possible data points with high leverage.

A Robust Method for Fitting the Models

There were still outlying residuals in a model fitted by the usual least squares. To deal with this issue, both models 1 and 2 were fit to the data using iteratively re-weighted least squares (Holland and Welsch 1977). The function to do this is available in the statistical analysis software S-Plus and is called *rreg*. We used a bi-square

weighting function given by $(1 - (u/c)^2)^2$ if $u < c$ and zero otherwise, where u is the residual scaled by a factor proportional to the median of the absolute deviations from the median of the residuals. The constant c was set equal to 4.685, the default value (Holland and Welsch 1977), indicating that an observation with a scaled residual bigger than 4.685 received a weight of zero (i.e., it is removed from the data set), and is otherwise weighted by $(1 - (u/c)^2)^2$. After the observations are weighted, the model was fitted again to the data and the observations were re-weighted as described above. Eventually the model converged (i.e., there is negligible change in the regression coefficients).

Obtaining Estimates of Growth

The adjusted mean growth at each growth cycle was estimated at the mean value of the covariates over all three growth cycles. This is arbitrary, but some value of covariates or combination of values was necessary to obtain predictions from the models and the mean value of covariates is a reasonable choice (c.f., Bechtold and others 1991). Moreover, differences of estimated mean growth between cycles will be the same when using model 1 regardless of the choice of covariate values since no covariate by cycle interactions are included. If such interactions were included in model 2, the model coefficients would be less interpretable and estimated differences of growth between cycles would depend on the choice of covariate values. Thus, to compare growth rates between models 1 and 2, estimates were computed at the mean of the covariates over all three cycles. Some of the interactions that were included in model 2 may have been spurious, primarily due to the large sample sizes. An advantage of reporting results from both models is to determine if any interaction terms in model 2 could alter conclusions obtained from the simpler model 1.

A disadvantage to the robust model fitting procedure is that certain features of classical parametric inference are not available. So to obtain confidence intervals, a bootstrap routine (Efron 1982) was conducted as follows. Suppose there are n_1 , n_2 , and n_3 observations from growth cycle 4, 5, and 6, respectively. A bootstrap sample was obtained by sampling n_1 observations with replacement from growth cycle 4, n_2 observations with replacement from growth cycle 5, and n_3 observations with replacement from growth cycle 6. Iteratively re-weighted least squares was used to fit a model to the bootstrap sample data, and the adjusted mean growth was estimated using each fitted model. This resampling technique was repeated 1000 times, thereby producing a

sampling distribution of adjusted mean growth estimates for each growth cycle and for each model. A family of three 95% confidence intervals was constructed for the mean growth at each growth cycle using a Bonferroni correction so that each individual interval had a 98.3% confidence level, i.e., since we are simultaneously estimating mean growth at three growth cycles, an individual confidence interval will have a confidence level of $100(1 - 0.05/3) = 98.3\%$ (c.f., Christensen 1996, section 6.2). Using the bootstrapped sampling distribution, the eighth and 992nd sorted values represent the bootstrapped lower and upper confidence limits. See Efron and Tibshirani (1993, chapter 13) for more details on percentile bootstrap confidence intervals. Growth estimates from both models were transformed back to the original arithmetic units.

Results

Estimated coefficients for model 1 are shown in table 2. With either gross growth or net growth as the dependent variable in the model, Box-Cox transformation analysis suggested that the natural logarithm transformation be used for most stand types. For some stand types, a square root transformation was suggested for net growth models, but the uncertainty in the maximum of the Box-Cox likelihood also indicated the logarithm would suffice. Thus, the dependent growth variable was transformed using the natural logarithm for all stand types for consistency. The signs and relative magnitudes

of the coefficients generally agree with those of Bechtold and others (1991), who analyzed the natural logarithm of gross growth for the fourth and fifth cycles, but included mortality as a covariate in a standard analysis of covariance model. The coefficients for T_4 , T_5 , and T_6 in the net growth models appear different from those of the gross growth models due to the location transformation required in $g(NG_k)$, $k = p, t$. It is the differences between the coefficients for T_4 , T_5 , and T_6 that show differences in estimated growth between growth cycles because there are no covariate by cycle interactions in model 1.

Quadratic terms that commonly appeared in model 2 for the different data sets were $(\ln A)^2$ and $(\ln N_k)^2$. An interaction between S and $\ln(A)$ and between S and $\ln(N_k)$ was commonly detected as was an interaction between $\ln(A)$ and $\ln(N_k)$. It was also not unusual to see S interacting with a growth cycle variable in some of the models. The other second order terms for model 2 varied with the data set and, for the sake of brevity, we do not list the details. Instead, the estimated mean growth using both models is shown in tables 3, 4, and 5. Estimates using model 2 are always slightly greater than those using model 1 with the exception of net pine growth for slash pine (growth cycle 4) and gross growth shortleaf pine (growth cycle 5). However, the estimates are close enough that the interval estimates using model 1 and model 2 easily overlap, indicating no significant difference between estimates obtained from the two models. Though significant interaction terms may be of biological interest and may suggest future studies to verify their significance, we focus on estimates from model 1 for a key reason. Estimated

Table 2. Details of model 1 fitted by robust regression. The response variable, $Y = GG_k$ or NG_k ($k = p$ for pine growth and t for total growth), was transformed to $g(GG_k) = \ln(GG_k)$, and $g(NG_k) = \ln[NG_k + |\min(NG_k)| + 1]$, respectively, for gross growth or net growth analyses.

Stand type	Response variable	Estimated coefficients						
		T_4	T_5	T_6	$\ln(A)$	$\ln(N_k)$	S	P
Loblolly	$g(GG_p)$	-0.343	-0.528	-0.480	-0.315	0.293	0.003	0.746
	$g(GG_t)$	-0.025	-0.133	-0.090	-0.308	0.284	0.002	0.480
	$g(NG_p)$	2.015	1.933	1.882	-0.179	0.063	-0.001	0.282
	$g(NG_t)$	2.214	2.129	2.100	-0.159	0.072	-0.001	0.137
Shortleaf	$g(GG_p)$	-1.008	-1.271	-1.222	-0.282	0.347	0.005	0.704
	$g(GG_t)$	0.018	-0.246	-0.162	-0.268	0.262	0.003	0.312
	$g(NG_p)$	1.587	1.461	1.470	-0.137	0.092	0.001	0.198
	$g(NG_t)$	1.990	1.834	1.868	-0.167	0.066	0.001	0.123
Slash	$g(GG_p)$	-0.746	-1.064	-0.910	-0.216	0.399	0.003	0.140
	$g(GG_t)$	-0.523	-0.788	-0.691	-0.258	0.346	0.004	0.332
	$g(NG_p)$	1.798	1.705	1.721	-0.089	0.094	-0.001	0.095
	$g(NG_t)$	1.452	1.319	1.317	-0.137	0.13	-0.002	0.146

growth at each cycle depends on the chosen values for the covariates at which the estimates are computed. However, differences in growth between cycles will be constant for any chosen values of covariates when using model 1, but not necessarily for model 2. In other words, in model 1 the “slopes” of the fitted robust regression surfaces are the same for the three growth cycles.

Tables 3, 4, and 5 show the same decrease in growth from the fourth to the fifth cycle for all data sets and all analyses as was seen in Bechtold and others (1991). However, the family of three 95% confidence intervals based on the Bonferroni correction suggest the decrease is, at most, marginally significant after accounting for

sampling variability. For most stand types and most analyses, the estimated growth for the 6th cycle represented a slight increase from the fifth cycle. An exception was loblolly net growth, which continued to decrease, though not significantly so, from the fifth cycle. Comparing the sixth cycle summary statistics in table 1 with those for cycles 4 and 5 given in Bechtold and others (1991, page 708), one would observe that loblolly unadjusted gross growth for the sixth cycle was only slightly lower than that of the fifth, but mortality for the sixth cycle was higher than either the fourth or fifth cycles. This combination might explain the apparent continued estimated decline of loblolly net growth into the sixth cycle.

Table 3. Loblolly pine stands. Growth estimates from models 1 and 2. Estimates are given in original arithmetic units and they include a point estimate for mean adjusted growth for each growth cycle, $\hat{\mu}$, and a family of three 95% confidence intervals (L, U). Interval estimates are computed with the bootstrap technique.

Growth type	Growth cycle	Model 1	Model 2
		$\hat{\mu}, (L, U)$	$\hat{\mu}, (L, U)$
Gross pine growth	4	3.31,(3.07, 3.55)	3.59,(3.27, 3.92)
	5	2.75,(2.44, 3.08)	3.03,(2.68, 3.41)
	6	2.89,(2.71, 3.06)	3.19,(2.92, 3.44)
Gross total growth	4	4.47,(4.16, 4.84)	4.63,(4.22, 5.09)
	5	3.81,(3.45, 4.22)	3.95,(3.52, 4.40)
	6	3.98,(3.80, 4.19)	4.22,(3.92, 4.54)
Net pine growth	4	2.99,(2.65, 3.31)	3.15,(2.75, 3.59)
	5	2.42,(1.97, 2.81)	2.67,(2.28, 3.09)
	6	2.09,(1.83, 2.34)	2.40,(2.06, 2.71)
Net total growth	4	3.98,(3.58, 4.38)	4.18,(3.64, 4.74)
	5	3.19,(2.67, 3.69)	3.40,(2.78, 3.95)
	6	2.94,(2.68, 3.21)	3.24,(2.81, 3.66)

Table 4. Shortleaf pine stands. Growth estimates from models 1 and 2. Estimates are given in original arithmetic units and they include a point estimate for mean adjusted growth for each growth cycle, $\hat{\mu}$, and a family of three 95% confidence intervals (L, U). Interval estimates are computed with the bootstrap technique.

Growth type	Growth cycle	Model 1	Model 2
		$\hat{\mu}, (L, U)$	$\hat{\mu}, (L, U)$
Gross pine growth	4	2.77,(2.47, 3.05)	2.99,(2.64, 3.37)
	5	2.13,(1.69, 2.61)	2.04,(1.60, 2.63)
	6	2.23,(1.95, 2.56)	2.39,(2.06, 2.79)
Gross total growth	4	3.98,(3.65, 4.33)	4.30,(3.88, 4.77)
	5	3.05,(2.47, 3.72)	3.14,(2.50, 3.89)
	6	3.32,(2.96, 3.70)	3.57,(3.08, 4.14)
Net pine growth	4	2.63,(2.22, 3.01)	2.76,(2.33, 3.24)
	5	1.79,(1.31, 2.39)	1.86,(1.29, 2.55)
	6	1.84,(1.38, 2.24)	2.09,(1.56, 2.67)
Net total growth	4	3.51,(3.05, 3.95)	4.12,(3.43, 4.85)
	5	2.33,(1.54, 3.26)	2.68,(1.61, 3.82)
	6	2.57,(2.08, 3.11)	3.12,(2.50, 3.83)

Table 5. Slash pine stands. Growth estimates from models 1 and 2. Estimates are given in original arithmetic units and they include a point estimate for mean adjusted growth for each growth cycle, $\hat{\mu}$, and a family of three 95% confidence intervals (L , U). Interval estimates are computed with the bootstrap technique.

Growth type	Growth cycle	Model 1	Model 2
		$\hat{\mu}$, (L , U)	$\hat{\mu}$, (L , U)
Gross pine growth	4	2.91,(2.47, 3.38)	3.03,(2.62, 3.61)
	5	2.12,(1.74, 2.56)	2.38,(1.96, 2.86)
	6	2.47,(2.27, 2.68)	2.68,(2.42, 2.97)
Gross total growth	4	3.84,(3.33, 4.42)	4.32,(3.72, 5.05)
	5	2.96,(2.49, 3.52)	3.41,(2.82, 4.09)
	6	3.26,(3.01, 3.52)	3.68,(3.30, 4.10)
Net pine growth	4	2.83,(2.43, 3.32)	2.79,(2.38, 3.33)
	5	2.16,(1.73, 2.61)	2.38,(1.78, 2.91)
	6	2.27,(2.01, 2.54)	2.39,(2.10, 2.73)
Net total growth	4	3.66,(3.14, 4.20)	3.96,(3.45, 4.59)
	5	2.87,(2.31, 3.38)	3.14,(2.52, 3.81)
	6	2.86,(2.58, 3.16)	3.14,(2.72, 3.59)

A visual comparison of estimated growth for the three cycles can be seen in figures 1, 2, and 3. These are box-plots of an estimated bootstrapped sampling distribution of estimated mean growth. There are four subfigures in each figure and three boxplots in each subfigure for

each of the three growth cycles. Each individual box-plot represents 1000 bootstrap estimates of adjusted mean growth from model 1 at a particular growth cycle. The lower and upper lines of the shaded region of a box are the first ($Q1$) and third ($Q3$) quartiles of the

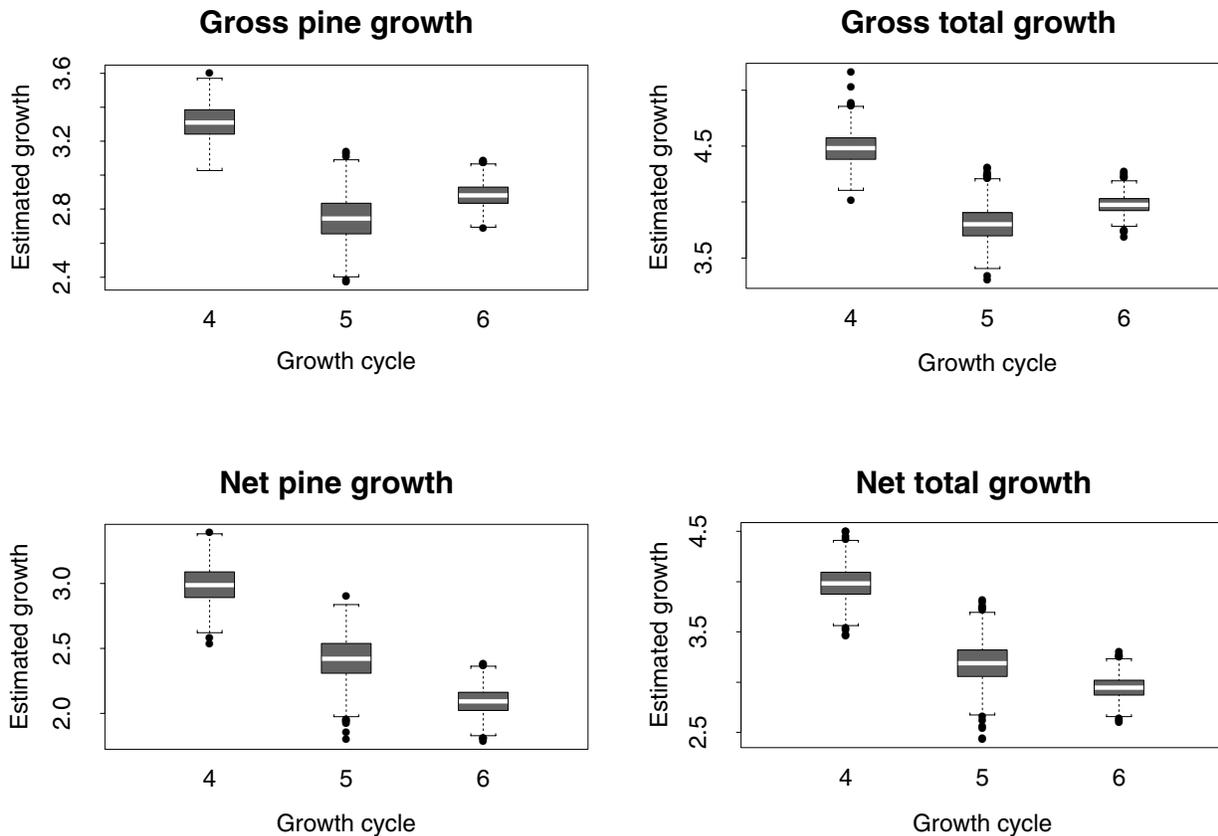


Figure 1. Loblolly pine: Box plot of a bootstrapped sampling distribution of estimated mean growth at each of the three growth cycles. Each box plot contains 1000 bootstrap estimates at each growth cycle.

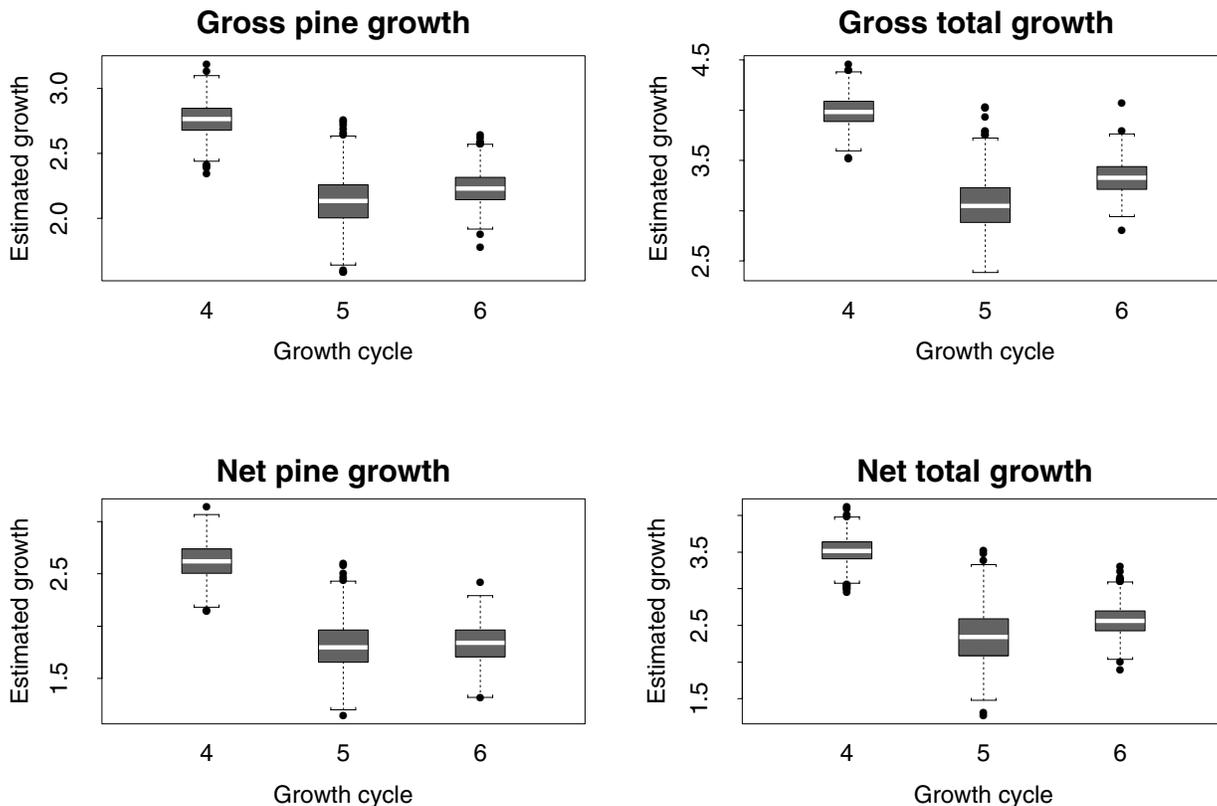


Figure 2. Shortleaf pine: Box plot of a bootstrapped sampling distribution of estimated mean growth at each of the three growth cycles. Each box plot contains 1000 bootstrap estimates at each growth cycle.

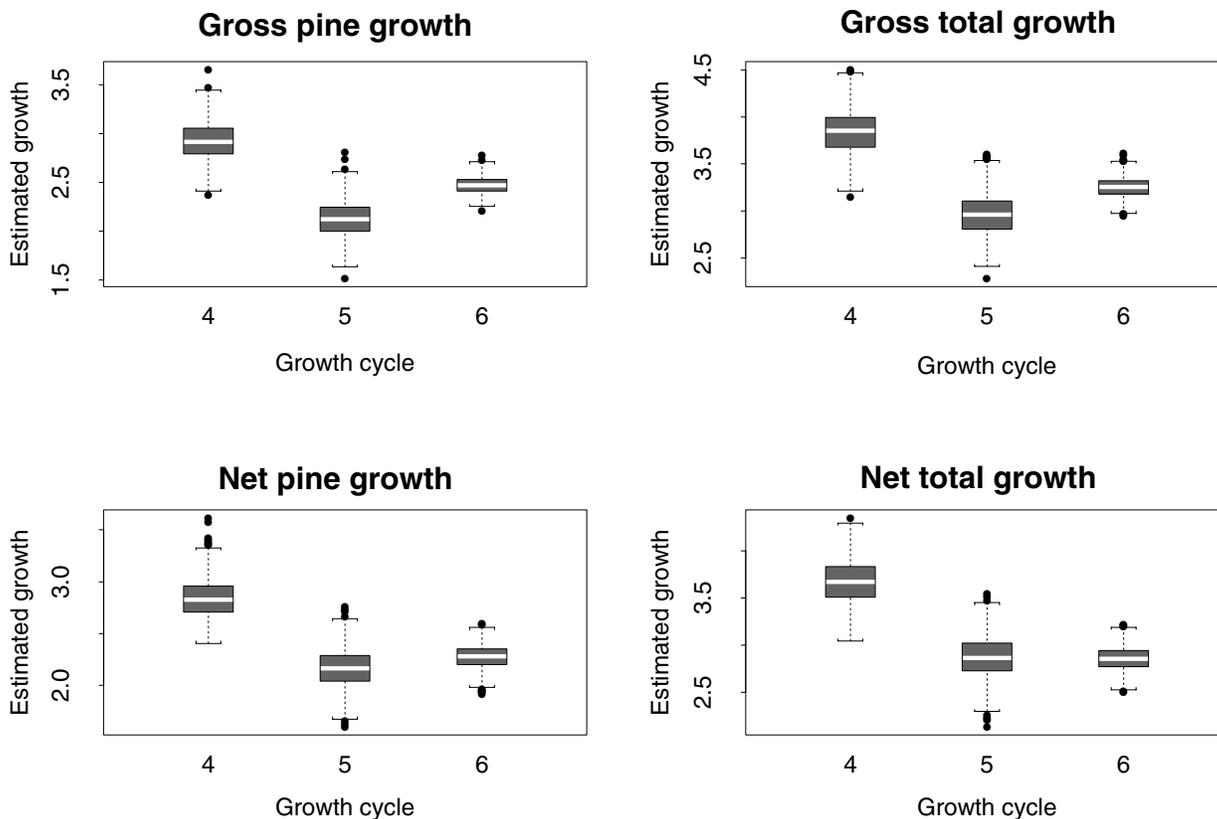


Figure 3. Slash pine: Box plot of a bootstrapped sampling distribution of estimated mean growth at each of the three growth cycles. Each box plot contains 1000 bootstrap estimates at each growth cycle.

1000 estimates, and the middle line in the box is the median. The extended lines stretch to the nearest value within a “step” below $Q1$ and a “step” above $Q3$ where a step is 1.5 multiplied by the interquartile range ($IQR = Q3 - Q1$). Estimates outside the “steps” are plotted as points and are generally considered outside the normal “spread” of the data though this designation is somewhat arbitrary. The figures show that estimated growth for the 6th cycle is slightly higher than the fifth, though not up to the level of growth in the fourth cycle. The exception, again, is loblolly net growth, which shows a continued decline at the sixth cycle, but the two distributions of estimated growth at the fifth and sixth cycles have a fair amount of overlap. As indicated earlier, this continued apparent decline is not significant after accounting for sampling variability.

Summary

Given the analyses performed, a summary of the results is as follows:

1. There is no further significant decrease in either net or gross growth from cycle 5 to 6 as there was from 4 to 5.
2. There is generally an interaction between S and A , S and N , and A and N , as uncovered in model 2, though inclusion of these interactions did not significantly alter estimates of growth at each cycle.
3. With the exception of loblolly net growth, there is a slight increase in growth for both net and gross growth from the fifth to the sixth cycle, but none of the growth differences are significant between any of the three growth periods as determined by a family of 95% confidence intervals.
4. Our inference space is quite limited due to the heavily screened data sets that were used.
5. We are not accounting for a large amount of the variability observed with our models. There may be additional variables that need to be measured to account for this variability.

While the results are of interest in their own right, the more important issue is determining what the implications of the results are in terms of the southern growth decline issue. We conclude the following:

1. Although there was a valid concern about a decline in pine growth in natural pine stands, this decline has not continued.
2. We need to find ways to broaden our capability of inference to more general forest populations of interest.
3. We need to measure additional variables to sharpen the predictive ability of our models.

It should also be noted that the current annualized FIA inventories, although yielding a small sample size for a given year, may eliminate the need for screening the data to achieve comparability of results for each year. Hence, meaningful changes can be detected for a sufficiently large area (see Schreuder and others 2000). In addition, it may be possible to detect or assess changes more immediately by using additional samples of ground plots or by using alternative data sources such as large-scale aerial photography.

Recommendations

The southern growth decline is only one example of how observational survey data can become the focal point of a very contentious issue. Based on what has been learned in the last decade regarding this issue, we make the following recommendations.

1. Maintain clear and consistent sampling protocols as recommended by Zeide (1992).
2. Develop a general analysis and sampling strategy to assess changes of interest from annualized inventories.
3. Protect against results that are difficult to interpret, such as the growth decline in Georgia and Alabama. With the small sample size annually in each state, false alarms will happen, especially since many users will use the data themselves without realizing their limitations. Sampling strategies should be in place to follow up on interesting changes that are detected (see Schreuder and Wardle [1999] for an example related to similar issues).
4. Measure key additional variables on the FIA plots as often as possible. With such variables, considerably improved prediction models could be developed making the detection and assessment of meaningful changes more likely. Though it is not feasible yet to obtain weather data for FIA plots, FIA data can be merged with climatic data to yield rough estimates of climatic influences.
5. Emphasize quality design, analyses, and data collection. As recommended by Zeide (1992), data from forest inventories, such as FIA, need to be as good as research-quality data. It is possible that some of the growth decline detected in the earlier studies may have been due to unusual data points.
6. Develop multiple working hypotheses and innovative analytical approaches. Such approaches are likely to provide the best scientific progress in assessing change or necessary “interventions.”
7. Use a subjective checklist to form an elaborate theory that attempts to consider all possible variables

that could have produced an observed change (Olsen and Schreuder 1997). Remember that in surveys one does not know how “treatments” are assigned to response units, so results could be biased (Gadbury and Schreuder 2003).

8. Have a clear understanding of what can and cannot be done with the data. Observational data are inadequate to establish cause-effect, but they can be used to identify interesting hypotheses.
9. Publish controversial or important findings in refereed journals to ensure such analyses receive appropriate critical review.

Acknowledgments

Though the authors take full responsibility for the content herein, we are grateful to several individuals for their time in reviewing earlier versions of this work, including Tara Barrett, Rudy M. King, Francis A. Roesch, Stan Zarnoch, William Bechtold and Boris Zeide.

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