Is There a Better Metric Than Site Index To Indicate the Productivity of Forested Lands?

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Abstract.—The Forest Service, U.S. Department of Agriculture's Forest Inventory and Analysis (FIA) program selects site trees for each plot that are used to measure site productivity. The ability of a site to produce wood volume is indicated indirectly by comparing total tree height with tree age. This comparison assumes that the rate of height growth is strongly related to site quality and is insensitive to basal area, species composition, and stand structure. Research indicates that stand age is often difficult to determine, especially in uneven-aged stands. Furthermore, stands with mixed species compositions and less than full stocking cause problems when using site index as a predictor of site growing capacity. Now that the FIA program has thousands of plots in which volume has been remeasured, other metrics for site quality can be evaluated by noting the observed past growth of the trees on the plot and comparing it with the height-age relationship. This study describes the first steps of this effort.

Introduction

The productivity of forests lands is largely defined in terms of site quality as an indicator of the potential of the site to produce wood given a particular species or forest type. Considerable interest has long existed in developing ways to predict potential forest productivity directly without using forest variables (diameter at breast height (d.b.h.), height, and so on), trees, or other vegetation as indicators.

The indirect approaches for estimating site quality (Jones 1969) include site index, vegetation, and environment. Site index is the height to which a tree would grow under forest conditions in a specified number of years, the index age (50 years for inventory plots in Pennsylvania), or the height of a dominant tree at a particular diameter (Bickford *et al.* 1957). Site index determinations require the availability of height-age curves for a particular area and species. Areas without suitable trees may not be accurately classified. Site index is normally associated with even-aged, single species and fully stocked stands. In mixed hardwood forests, such as those often found in Pennsylvania, these conditions are uncommon. Many studies have developed predictive mechanisms in the form of multiple regression equations in which site index is determined from a number of independent site variables (Armson 1977). The FIA program in Pennsylvania currently uses site productivity classes derived from site index, based on fully stocked stands at the age of culmination of mean annual increment, to indicate site quality (Scott and Voorhis 1986). Because of the known difficulties associated with using site index as an indirect metric for site quality, we hypothesize that site productivity classes are not well correlated with actual stand growth. Problems associated with using site index to estimate the potential productivity on FIA plots have been documented before. Only 12 percent of 65 remeasured plots in Vermont retained a constant classification over three surveys. Several of the plots varied by up to three site classes gained or lost (Beattie 1979). The FIA program now offers thousands of remeasured plots per year using the same plot design. This abundance enables the comparison and evaluation of site quality metrics with actual growth rates.

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Objective

The objective of this article is to test two hypotheses: (1) site productivity class measured on FIA plots is unrelated to actual growth and (2) no other metrics attributed to FIA plots work better than site productivity class. Furthermore, if we can reject either of these hypotheses, we would like to use geostatistical methods to map site quality over the landscape. It is important to understand that we are not trying to predict growth per se; instead, we want to find a metric that predicts site quality or potential wood productivity.

Methods

For this study, site productivity class was compared with growth. The environmental approach for assessing site quality was used in locations where factors affecting site quality, such as climatic factors (temperature, precipitation, humidity, and solar radiation) and topographic factors (slope, aspect, elevation, longitude, and latitude), were evaluated. Stocking, stand size, and age were used to stratify the plots to eliminate confounding growth competition factors. Remeasured growth on FIA plots is the response variable that was used as an indicator of site quality.

The study followed these steps:

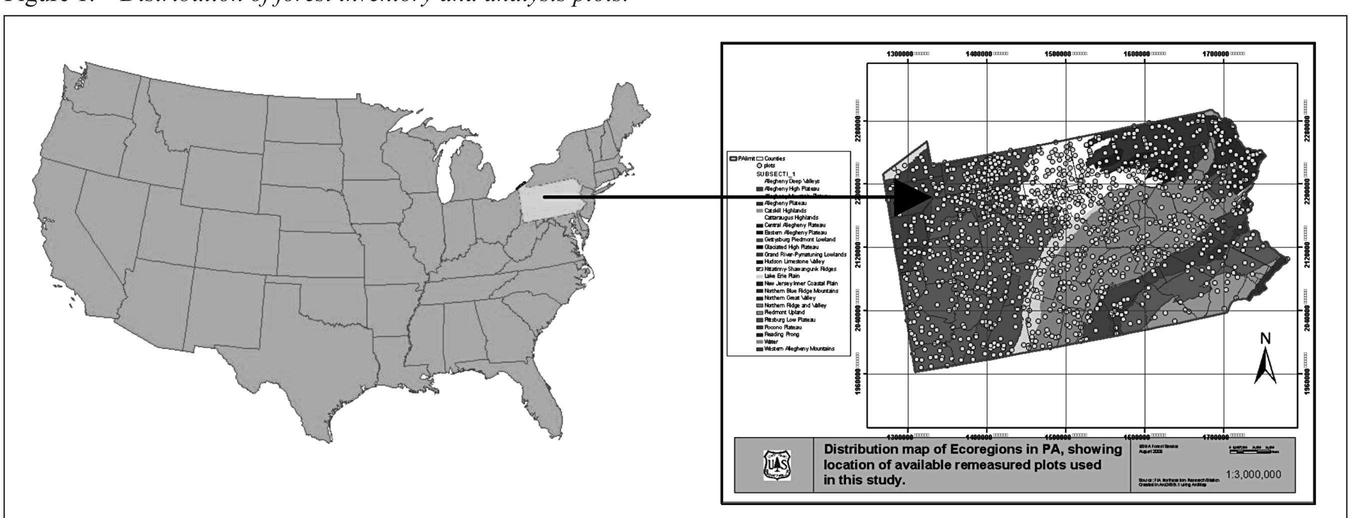
- Compare plot site productivity class with actual growth.
- Identify other site factors that might accurately predict site quality.
- Develop multiple regression models to map areas of different site quality in Pennsylvania as a result of the integration of these nonbiological factors.

The data used in this research were collected from the Forest Service's Northern Research Station, FIA unit. Under this federally mandated program, sampling is based on an interpenetrating panel design at an intensity of 1 plot per approximately 6,000 acres. Data were collected from the periodic survey conducted in 1989 and compared with annual plots collected from 2000 to 2004 in the State of Pennsylvania. The time interval between plot remeasurement was used to calculate annual growth.

On each sample plot, data were summarized by joining the tree and plot tables, considering only the remeasured plots with trees having a d.b.h. of 5.0 in or larger and plots with no removals or mortality. Condition-level variables were assigned to each plot based on the largest condition area. Finally, the subplot-level table was added to the summary to include topographic factors measured directly by the crew in the field. The number of plots that met the criteria was 558 (11.5 percent). The plot distribution and study areas are shown in figure 1.

FIA data provided the following metrics for each plot: stand size and age, site productivity class, forest type, aspect, eleva-

Figure 1.—*Distribution of forest inventory and analysis plots.*



tion, latitude, longitude, and slope. Temperature, precipitation, solar radiation, and humidity were provided by the DAYMET U.S. Data Center. This resource provides daily surface weather data and climatological summaries of the United States, at a 1-km resolution, from ground-based meteorological stations over a 9-year period (1989 through 1997).

The aspect metric was transformed into a linear variable ranging from 0.00 to 2.00 using the transformation of Beers *et al.* (1966) (i.e., A′ = cos (Amax − A) + 1, where A′ = transformed aspect, Amax = 45°, and A = the measured aspect.

Growth for each plot was analyzed in terms of accretion, considering three components: (1) basal area, (2) sound volume, and (3) gross volume; see equations (1), (2), and (3).

Basal area accretion:

$$ACCBA = \frac{\sum (BA_{ij2} - BA_{ij1})}{r_i} \qquad (1)$$

Gross volume accretion:

$$ACCGROS = \frac{\sum (GV_{ij2} - GV_{ij1})}{r_i} \qquad (2)$$

Sound volume accretion:

$$ACCSOUND = \frac{\sum (SV_{ij2} - SV_{ij1})}{r_i} \qquad (3)$$

where BA_{ijk} = basal area (ft^2) of tree *i* on plot *j* at measurement *k* (K=1,2), GV_{ijk} = gross volume (ft^3/acre) of tree *i* on plot *j* at measurement *k* (K=1,2), SV_{ijk} = sound volume (ft^3/acre) of tree *i* on plot *j* at measurement *k* (K=1,2), and r_i = remeasurement period (year) for plot *i*.

SAS 9.1 was used to summarize the data, perform statistic analyses, and develop models. ArcGIS 9.1 and ArcInfo Workstation were used to generate maps based on the models.

Data Analysis Techniques

The data analysis techniques included the following:

Frequency Analysis

This technique was used to determine how the plots should be grouped into different categories of tree species, stand age, and stocking. The frequency distributions of these variables were evaluated and appropriately sized intervals were selected. Because growth rates can be strongly influenced by differences in these three variables, it is necessary to remove these sources of confounding growth variation as much as possible. Consider that a fully stocked stand of older trees on a poor site will most likely have a greater growth rate than that of a poorly stocked stand of young trees on a good site. Obviously, forest type group is already divided. The variables of age and stocking were grouped as follows: Age class ranges from 1 (youngest) to 4 (oldest) age (0 to 30, 31to 60, 61to 90, and older than 90 years, respectively); stocking class ranges from 1 (lowest) to 3 (highest) percent (0 to 60 percent, 61 to 80 percent, and more than 80 percent, respectively).

Dependence Analysis

Analysis of variance (ANOVA) was carried out to test for differences among the means of the levels of the categorical variables (forest-type group, stand age, stand size, stocking, and site productivity).

The assumptions are that the observations are independent and randomly selected from normal populations with equal variances. These assumptions were assessed by examining plots of the residuals. A statistical comparison of site productivity and growth was made by using ANOVA and scatterplots. Tukey's test was used to determine if any of the tree species, stand age, and stocking groups were statistically different from one another.

Correlation Study

This study, which was completed for quantitative explanatory variables, used Spearman's rank correlation method to discard highly correlated variables. All variables were considered.

Estimating Site Quality by Multifactorial Analysis

Multiple linear regression (MLR) was used to help select the independent variables to predict the quantitative dependent accretion variables. Modeling site quality, from environmental factors using accretion as the quality metric, was carried out using SAS 9.1 to perform MLRs. The following relationship was assumed:

$$SQ = \beta_0 + \beta_1 * X_1 + \dots\dots\dots + \beta_n * X_n + \varepsilon$$

where SQ is site quality, expressed in terms of accretion, $X_1 \ldots\ldots X_n$ are the vectors corresponding to site variables, $\beta_1 \ldots \beta_n$ represent model coefficients, and ε is the additive error term.

The assumptions were that the expected value of the residuals is 0, or E[e] = 0, which implies that the relationship is linear in the explanatory variables, the errors are distributed with equal variance (homoscedasticity), the errors are independent, the predictors are not correlated, and the errors are normally distributed.

Regarding MLR, the normality of the metrics was checked by using the standardized skewness Z-score test, which examined the lack of symmetry in the data. Of all the variables, it was necessary to transform the variable slope to $\log_{10}$(slope) and the variable aspect to sqrt($\log_{10}$(aspect)) to normalize them. Within the site factor variables, it was necessary to select the ones that could be used to model the site quality variation. The analysis began by examining the variables available in terms of their relationship with accretion in basal area and volume. Simple plots of accretion and growth versus potential predictor variables were analyzed in an attempt to understand the relationship between the variables and growth (e.g., suggesting linear or nonlinear relationships).

Stepwise regression was used because it is considered the best method of automated variable selection (Draper and Smith 1998). This automatic procedure for statistical model selection was used because no underlying theory exists on which to base the selection model. A model that is a result of an automated variable selection process may not be biologically sensible, however, and needs to be evaluated on biological grounds.

The adjusted R-squared selection method was chosen and Akaike's Information Criterion (AIC) (Akaike 1974) statistic was used as the criterion, or the measure, of the goodness of the fit for selecting models. AIC is calculated from

$$AIC = 2\ln(RMSE) + \frac{2c}{n}$$

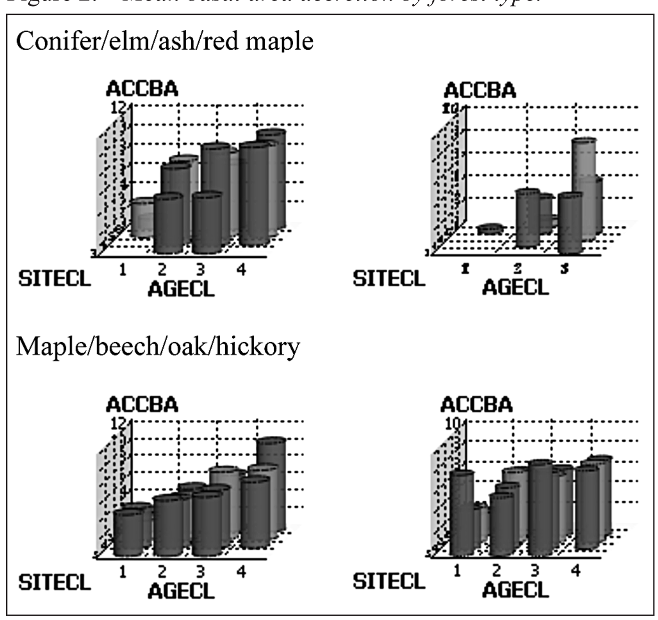
where *RMSE* is the root mean squared error during the estimation period, *c* is the number of estimated coefficients in the fitted model, and *n* is the sample size used to fit the model.

Results

Site productivity classes, based on site index, were plotted against actual growth. In figure 2, mean basal area accretion is presented versus site productivity class and age class for four forest types. The closest site class on the x axis is associated with the highest site productivity class. Notice that the conifers plots show the lowest growth occurring on the best sites. The same pattern of high variability of site productivity classes occurs for sound and gross volume accretion.

According to Tukey's test for ANOVA, growth means were not significantly different (P-value greater than 0.05) among the five productivity classes. Surprisingly, the same observation

Figure 2.—*Mean basal area accretion by forest type.*



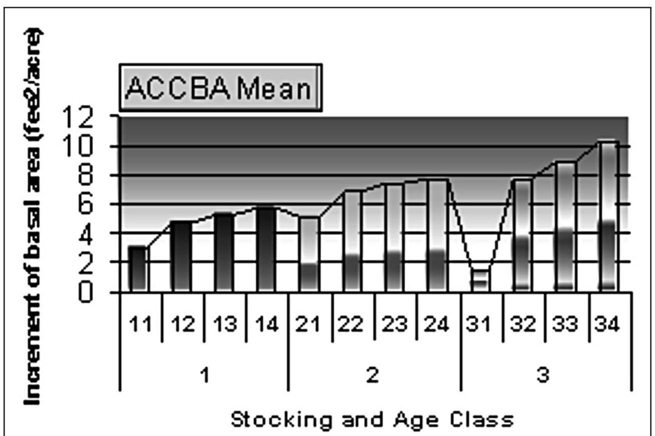
ACCBA = mean basal area accretion. AGECL = age class. SITECL = site class.

was true for forest types. Significant differences (P-value less than 0.05) were found when stocking, size, and age class were analyzed against growth.

Therefore, after analyzing the frequency distributions of both age class and stocking classes, these classes were used to divide the data set of 558 plots into logical compositional growth groups. Figure 3 shows the histogram of increment of basal area for the stocking and age class groups. Within each increase of stocking class, basal area increment rises with the increasing of stand age. Mean sound and gross volume increment follow the same pattern as basal area increment. This result led us to consider 12 different subpopulations by stocking class and stand age to model growth.

For each of the 12 subpopulations and for each dependent variable, simple regression was applied to make models to explain the variability of each one of the accretions. The importance was ranked by the highest R-square obtained. (see tables 1, 2, and 3). Models with the minimum or lowest AIC had R-squares of about 0.3. This observation indicates high variability of the data.

Figure 3.—*Mean basal area increment by stocking class and stand age class.*



The following is an example of a site quality model (using stepwise regression) based on gross volume accretion, created for the subpopulation consisting of stocking class of 3 and age class of 3. To further test the importance of the different factors influencing site quality, we separately compared the correlations between gross accretion and each one of the site factors. The correlation coefficients are listed in table 4. The major factors influencing gross accretion are latitude and slope, with P-values of 0.0063 and 0.0112, respectively.

Table 1.—*Rank of the major factors influencing site quality, by simple regression according to the highest R-square, for mean basal area accretion.*

ACCBA	Variable	Ranking
	Latitude	1
	Longitude	2
	Elevation	3
	Aspect	4
	Temperature	5

Table 2.—*Rank of the major factors influencing site quality, by simple regression according to the highest R-square, for gross volume accretion.*

ACCGROS	Variable	Ranking
	Temperature	1
	Latitude	2
	Precipitation	3
	Longitude	4
	Aspect	5
	Slope	6

Table 3.—*Rank of the major factors influencing site quality, by simple regression according to the highest R-square, for sound volume accretion.*

ACCSOUND	Variable	Ranking
	Latitude	1
	Longitude	2
	Precipitation/Slope	3
	Aspect	4
	Elevation	5

Table 4.—*Pearson correlation coefficients.*

	Independent variable							
Dependent variable	ASPECT	ELEVATE	LAT	LON	SLOPE	P	T	VPD	SRAD
ACCGROS	– 0.15	– 0.04	– 0.34	– 0.08	– 0.32	– 0.07	0.01	0.14	0.02
Prob > |r|	0.23	0.74	0.01	0.51	0.01	0.61	0.94	0.28	0.86

Notes: N = 64

MLR provided the following model:

Dependent variable: ACCGROS; independent variables: SLOPE, LAT, VPD, and T; R-square = 39.9711 percent; R-squared = 35.6054 percent; standard error of estimate = 36.93; mean absolute error = 26.5597; Durbin-Watson statistic = 2.10416; P = 0.6069; Lag 1 residual autocorrelation = -0.0532975.

The output (see table 5) shows the results of fitting an MLR model to describe the relationship between ACCGROS and the independent variables SLOPE, LAT, T, and VPD. The equation of the fitted model is as follows:

ACCGROS = 99.0402 - 0.756874*SLOPE - 0.00015621*LAT - 17.0289*T + 0.60851*VPD

Because the P-value in the ANOVA table (table 6) is less than 0.05, a statistically significant relationship exists between the variables at the 95.0-percent confidence level.

The R-square statistic indicates that the model, as fitted, explains 40 percent of the variability in ACCGROS. The adjusted R-squared statistic, which is more suitable for comparing models with different numbers of independent variables, is 35 percent. The standard error of the estimate shows the standard deviation of the residuals to be 36.93. The mean absolute error of 26.5 is the average value of the residuals.

Table 5.—*Multiple regression fits.*

Parameter	Estimate	Std error	T- statistic	P-value
CONSTANT	99.0402	99.8446	0.991943	0.3256
SLOPE	– 0.756874	0.237175	– 3.1912	0.0023
LAT	– 0.0001562	4.895E–05	– 3.19122	0.0023
VPD	0.60851	0.204799	2.97126	0.0044
T	– 17.0289	9.45356	– 1.80132	0.0771

LAT = latitude. T = temperature. VPD = vapor pressure deficit

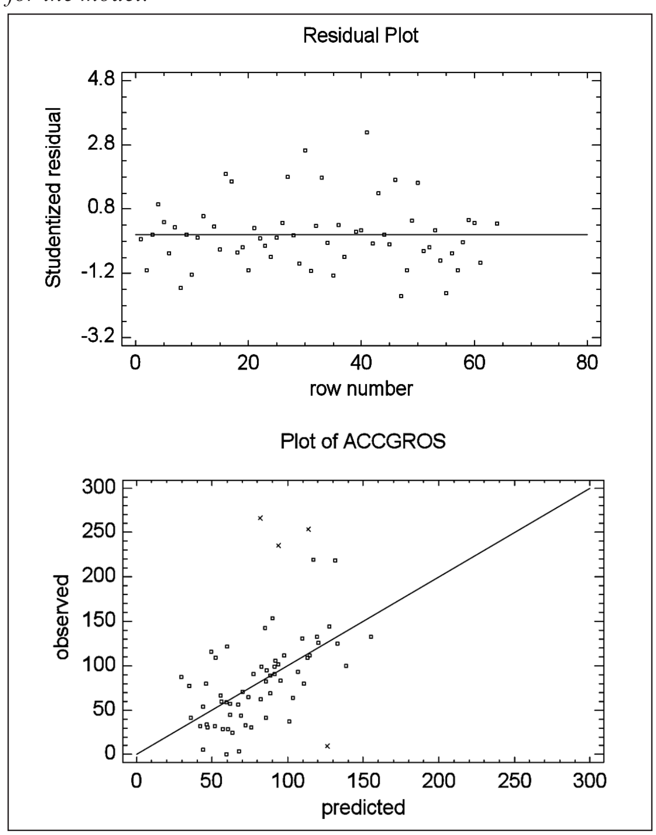
Table 6.—*Analysis of variance table.*

Source	Sum of squares	Degrees of freedom mean square	F-ratio	P-value
Model	49946.7	12486.7	9.16	<0.0001
Residual	75010.3	1363.82		
Total (Correlation)	124957.59			

In determining whether the model can be simplified, we chose a 90-percent confidence level as the basis for retaining predictor variables. The highest P-value on the independent variables is 0.0771, belonging to T. Because the P-value is not greater or equal to 0.1, that term is still statistically significant at the 90.0-percent or higher confidence level. Predicted versus observed data and residual plots are shown in figure 4. Residuals follow a normal distribution, are randomly distributed in figure 4, and have a mean of 0.

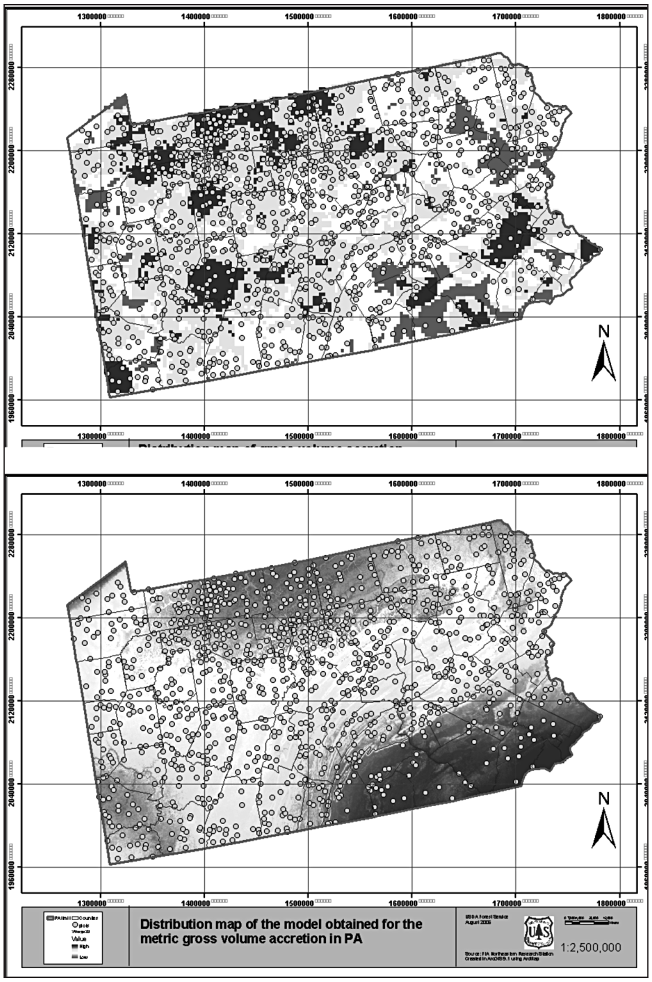
A map of site quality was produced for Pennsylvania by applying the model to the values of the predictor variables, representing each 250-m pixel, in an array of pixels covering the State (fig. 5). This map was compared with a map of actual growth (gross accretion (ft^3/acre/year) for the stocking and age class block 33 (stocking > 80 percent and age from 61 to 90 years). This map was produced by using a GIS moving window that statistically summarized groups of plot data and displayed the

Figure 4.—*Residual plots and predicted versus observed data for the model.*



ACCGROS = gross volume accretion.

Figure 5.—*Map comparison of actual growth (gross volume accretion and site quality based on a model of gross volume growth predicted by slope, latitude, humidity, and temperature). In order of increasing growth, the colors are red, yellow, turquoise, and blue. Plot locations are approximate.*



results spatially. As mentioned previously, a site quality map does not necessarily correspond to a map of actual growth. It is interesting to note that the area of greatest growth potential, southeastern Pennsylvania, is considered a productive agricultural area and is known for productive forest sites.

Conclusions and Discussion

Site quality is not easy to assess using the response variable of growth over about 10 years. The factors of site quality, site history, and the vegetation itself are interacting and interdependent, making it difficult to assign cause-and-effect relationships. This study found no straightforward measure of site quality to be entirely satisfactory.

Lessons learned and ponderings:

- Predicting site quality is more difficult than predicting growth because the effects of stocking and stand age have to be eliminated.
- Our results are consistent with other studies (Beattie 1979) that have found that site quality is not easy to assess because site factors and trees themselves are interacting and interdependent.
- It does appear that the site productivity classes of the plots have a poor correlation to actual growth; however, the hypothesis that states that no relationship exists between FIA site productivity classes and growth deserves to be tested over a greater time period than 10 years before making any definite conclusions.
- Soil type was eliminated in the AVOVA test because of technical difficulties with the GIS layer and concern about the soil map accuracy. Soil type is documented to be a major predictor of site quality and must be included in any follow-on study.
- The model and corresponding map need a proper accuracy evaluation despite the fact that 40 percent of the variability of growth was explained in well-stocked stands of advanced age provides some hope that site quality can be predicted.

Literature Cited

Akaike, H. 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control. 19(6): 716-723.

Armson, K.A. 1977. Forest soils: properties and processes. Toronto, Canada: University of Toronto Press. 390 p.

Beattie, M.H. 1979. An evaluation of the U.S. Forest Service system for predicting the potential productivity of northern hardwoods in Vermont. Burlington, VT: Graduate College of the University of Vermont. 108 p.

Beers, T.W.; Dress, P.E.; Wensel, L.C. 1966. Aspect transformation in site productivity research. Journal of Forestry. 64(10): 691-692.

Bickford, C.A.; Baker, F.S.; Wilson, F.B. 1957. Stocking, normality, and measurement of stand density. Journal of Forestry. 55: 99-104.

Draper, N.R.; Smith, H. 1998. Applied regression analysis. 3rd ed. New York: John Wiley. 706 p.

Jones, J. 1969. Review and comparison of site evaluation methods. Res. Pap. RM-51. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station. 27 p.

Scott, C.T.; Voorhis, N.G. 1986. Northeastern forest survey site index equations and site productivity classes. Northern Journal of Applied Forestry. 3(4): 144-148.