Estimating Tree Grades for Southern Appalachian Natural Forest Stands

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ABSTRACT. Log prices can vary significantly by grade: grade 1 logs are often several times the price per unit of grade 3 logs. Because tree grading rules derive from log grading rules, a model that predicts tree grades based on tree and stand-level variables might be useful for predicting stand values. The model could then assist in the modeling of timber supply and in economic optimization. Grade models are estimated for ten species groups found in the southern Appalachians, using data from several thousand trees and permanent plots in the USDA Forest Service's Forest Inventory and Analysis (FIA) database. The models correctly predicted grades of a majority of trees in both a test and a validation data set, and predictions of grade proportions across a sample of the population were usually within three percentage points of actual grade proportions. But success of models varied across species and diameter groups. Considering several measures of modeling success, the most accurate models were those predicting tree grades for softwoods and larger hardwoods. FOR. SCI. 44(1):73–86.

Additional Key Words: Ordered probit, tree quality, forest value, southern Appalachians, grade distribution.

TIMBER MARKETS, ESPECIALLY FOR HARDWOODS, are notoriously difficult to evaluate because of the influence of log species and grade on value. In the Southern Appalachians, for example, prices for northern red oak range from about \$100 mbf^{-1} for grade 3 logs to more than \$700 mbf^{-1} for grade 1 logs. This range in value reflects a wide variety of end uses, from industrial (e.g., pallets) to aesthetic (e.g., fine furniture, see Luppold 1993). Hardwood markets are therefore not amenable to typical aggregate market analysis. However, while aggregate production quantities hold little meaning, there is no available source of information on timber production by grade. This paper provides a method for estimating sawtimber grade using standard inventory data.

The model developed used data from the United States Forest Service's Forest Inventory and Analysis (FIA) database and related grades of standing timber to tree and stand characteristics. Separate equations were estimated for each of ten species groups found in the southern Appalachians. For all species groups, on a tree by tree basis, equations correctly predicted the grades of over half of the sample trees; in terms of proportions, the models typically predicted correctly the proportion of trees in each grade in a validation data set to within 3% of the actual proportions. Because the models work from the principle of grade probability, this finding indicates that the models would be most useful for informing broad management strategies and for simulation but less useful as predictors of tree grade on a tree by tree basis.

The statistical model presented in the following pages could be useful for incorporating tree grade into stand-level optimization models [e.g., those of Buongiorno and Michie (1980), Bare and Opalach (1988), Haight et al. (1992), and Buongiorno et al. (1995)], enabling more precise predictions of the economic implications of alternative management strategies. Further, the equations imply that different stand structures and species mixes imply different product outputs. If significant differences exist in stand structures and species mixes between private and public forestlands, for example, then we would expect these differences to be expressed in the form of different responses to market stimuli. Such differences would have regional implications: according to the latest set of FIA data, more than 40% of the volume of pine harvested from the northern Blue Ridge mountains came from federal ownerships, whereas only about 10% was obtained from public forestlands in the Ridge and Valley region of the southern Appalachians.

The following pages describe the method used and then present results of empirical estimation. The estimated equations are evaluated using several measures of data fitness,

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permitting a comprehensive view of modeling success. These are followed by conclusions, with a focus on modeling difficulties, and implications of the research.

Methods

Standing sawtimber of all species in the eastern United States is graded in the periodic forest surveys conducted by the USDA Forest Service using the methods described in Schroeder et al. (1968), Brisbin and Sonderman (197 I), and Hanks (1976), usually applying grades of 1 to 5 to sawtimber-sized trees, 1 the highest quality, 5 the lowest. Generally, tree grades were developed from studies of the relationships between the external characteristics of the lower 16 ft (4.9 m) portion (butt log) of the tree's stem and the quality of lumber obtained from that portion upon manufacture; the higher the lumber quality, the better the grade. A grade of 4 in the Forest Service's surveys is assigned to sawtimber-size trees that contain a gradable butt log but do not meet grade 3 standards, and a grade of 5 is given to trees of sawtimber size that do not contain a gradable butt log (Hansen et al. 1992). Hardwood and softwood tree grading procedures differ from each other: hardwood tree grades focus on the minimum top diameter and the amount of defect obtained in the best 12 ft (3.7 m) section of the butt log; softwood tree grades focus on the number of clear (defect-free) cuttings, sweep, and crook in the entire butt log.

These tree grading rules guided development of models to predict tree grades, and these rules required disaggregation of trees by species and diameter group. Grade models were developed for the following species or species groups: southern pine (mainly, *Pinus taeda* L., *P. echinata* Mill., *P. elliottii* Engelm., *P. virginiana* Mill., *P. palustris* Mill.), eastern white pine *(P. strobus* L.), hemlock (*Tsuga* spp.), other softwood (mainly, spruce, *Picea* spp., and eastern redcedar, *Juniper-us virginiana* L.), select white oak (Quercus *alba* L., Q. *bicolor* Willd., Q. *michauxii* Nutt., Q. *muehlenbergii* Engelm.), select red oak (Q. *falcata* Michx., Q. *rubru* L., Q. *shumurdii* Buck].), other oak *(Quercus* spp.), soft maple (mainly, *Acer rubrum* L.), yellow-poplar *(Liriodendron tulipifera* L.), and other hardwood. In FIA, southern pine can be assigned any grade, l-3, while other softwoods generally can be assigned grades 1-4, as long as they meet the minimum dbh (diameter at breast height) requirement, 9 in. (23 cm) dbh, outside bark (Schroeder et al. 1968, Brisbin and Sonderman 1971). Hardwoods are graded slightly differently: grade 1 trees must have a dbh of at least 16 in. (41 cm); grade 2 trees must have a dbh of at least 13 in. (33 cm); and grade 3.4, and 5 trees must meet the minimum grading dbh of at least 11 in. (28 cm) (Hanks 1976). Some trees are not graded in FIA surveys, including trees smaller than sawtimber sizes and others because of sample design. In the analysis presented below, grade 4 and 5 trees were both classified as "grade 4," and ungraded trees were not analyzed.

Little published information was found regarding the relationships between grade and tree and stand variables. One study, by Kärkkäinen and Uusvaara (1982), examined the factors affecting the quality of young Scots pine (*Pinus sylvestris* L.) in Finland. Tree quality was found to be positively related to the tree's dbh and the tree's deviation from the stand average dbh. Tree growth rate also significantly explained tree quality. Belli et al. (1993) used discriminant analysis to predict grades of bottomland hardwoods in Mississippi. Important variables used to explain tree grades were dbh (positively related to tree quality) and various measures of basal area, stand age, and trees per acre. Trees were not divided into diameter classes. Hockman et al. (1990) used discriminant analysis to predict Fraser fir Christmas tree grades. Such grades differ from timber grades in important ways, however.

As implied by the tree grading rules used by FIA, besides species and diameter, tree grade is grossly a function of branching (which can produce defect) and stem form (related to sweep and crook). Both branching and stem form are affected by natural pruning, which is closely related to the degree of competition among trees (Smith 1962). It is widely established that, within species, the denser the stand, the more readily lower branches on a tree will die; some species will then self-prune, although this tendency varies by species. Further, in stands that experience events that substantially lower stand density, the higher light penetration can result in epicormic branching, which would also produce defect. Thus, measures of stand density, such as stand basal area, should help to explain variations in tree grade. On the other hand, stand density may be related to the degree of stress facing a tree and hence the amount of pathogenic and mechanical damage (Smith 1962, Walker 1980).

The rate of natural pruning is also partly determined by tree vigor (Smith 1962). Implicit in this, and considering the results of Kärkkäinen and Uusvaara (1982), site quality should also be related to tree grade: the better the site, the more rapid is height growth, and the sooner lower branches die. One measure of site quality is site index, and this should thus be positively related to tree quality through its influence on self-pruning. On the other hand, it is plausible that a higher quality site may permit a tree to retain more branches with little loss of competitive ability (see Smith 1961).

In this research, I hypothesized that the combination of grading characteristics were related to tree species, diameter, stand density, and site quality. After stratifying by species, these characteristics were measured by dbh in inches, stand average dbh in inches of all trees 5 in. (13 cm) dbh and larger (to account for a tree's deviation from stand average), basal area in square feet per acre, and site index in feet (50 yr base), respectively. While stand age may have been a useful variable to help guide tree grading, it was not consistently reported in FIA. The factors associated with trees per acre were deemed captured well enough by included variables. And because at least the competitive forces associated with trees per acre are highly dependent on the distribution of trees within diameter classes, it was viewed as unnecessarily complicating the model. However, this might be an area for future research.

Thus, for a particular tree within a species group,

$$\begin{aligned}&Grade = \\ &f\,(dbh,\ stand\ average\ dbh,\ basal\ area,\ site\ index)\end{aligned} \tag{1}$$

Because a tree's grade is really one dimension of its phenotype, tree grade can be considered a combination of environmental and genetic factors. Genetic factors might heavily influence tree form, but they are not obvious from inventory data. Further, they would be extremely difficult to accurately quantify. Combined with similarly hard to quantify stand and tree histories, they might comprise the bulk of what statisticians refer to as the stochastic elements associated with an empirical estimate of the relationships implied by (1). If genetic and tree and stand history factors are randomly distributed across all stands, then a statistical estimate of the relationships implied in Equation (1) would be unbiased (Goldberger 1991, p. 189-191).

However, there may be a way to account for systematic genetic variability. Anecdotal information suggests that private stands in the southern Appalachians have been high-graded, leaving the poorer phenotypes to reproduce, inferring that one means of accounting for genetic quality would be to control for ownership status. Thus, a dummy, equal to 1 if a stand was private and nonindustrial and 0 otherwise (including government land, forest industry land, and other private lands managed by forest industry), was included in (1). A negative sign on the dummy would mean that, other things equal, the probability of finding better grades of trees was lower in private nonindustrial stands.

While FIA data do not include entire histories of stands, stretching back several decades, each FIA survey includes information on more recent cutting. The most recent cutting could be high-grading, and (or) it could be associated with substantial reductions in basal area and stand average dbh. In order to control for these potential effects on tree grade, a second dummy variable was included, equaling 1 if any cutting was observed between previous and current FIA surveys (about 8 yr), 0 otherwise. In estimation, a negative sign on this dummy might mean that high-grading had occurred, or it might indicate the effects of recent basal area reductions or stand average dbh changes on grade probabilities.

Including these two dummies, Equation (1) becomes:

$$\textit{Grade} = f\,(\textit{dbh, stand average dbh, basal area, site index, NIPF, recently cut}) \qquad (2)$$

where "NIPF" is the dummy for private nonindustrial ownership status of the tree, and "recently cut" indicates whether or not cutting in the stand occurred between surveys.

Important features of the dependent variable in (2) are that it is discrete and that it could be characterized as ordered—that is, grade 1 has fewer branches and is straighter and less defective than grade 2, grade 2 has fewer branches and is straighter and less defective than grade 3, etc. These features suggested for this research the use of the ordered probit model (see Greene 1990, p. 703-706) as a structure for evaluating the relationship between characteristics and grade. The ordered probit has been used in a wide variety of studies. Examples of empirical applications include Broomhall and Johnson (1994) for identifying significant factors determining educational performance in Kentucky and Virginia school districts, Hausman et al. (1991) for analyzing price changes in the New York Stock Exchange, and Orazem et al. (1989) for identifying agriculture policy preferences of farmers in Iowa. Here, the model required the specification of a latent variable, y^*, which was related to explanatory variables shown in (2), contained in a vector x. The value of y^* determined the region of maximum frequency in the normal distribution of each tree grade. That is,

$$y^* = f(x, \beta) + \varepsilon \qquad (3)$$

and

$$\begin{aligned} &\textit{grade} = 4 && \textit{if } y^* = 0 \\ &\textit{grade} = 3 && \textit{if } 0 \le y^* < \mu_1 \\ &\textit{grade} = 2 && \textit{if } \mu_1 \le y^* < \mu_2 \\ &\textit{grade} = 1 && \textit{if } y^* \ge \mu_2 \end{aligned} \qquad (4)$$

The μ's in (4) were estimated using a maximum likelihood technique along with the parameters, β, in Equation (3). Assuming that the unexplained variations around grades were normally distributed, grade probabilities were calculated using the following formulas:

$$\begin{aligned} &\textit{Prob}\ [\textit{grade} = 4] = \Phi(-\beta' x) \\ &\textit{Prob}\ [\textit{grade} = 3] = \Phi(\mu_1 - \beta' x) - \Phi(-\beta' x) \\ &\textit{Prob}[\textit{grade} = 2] = \Phi(\mu_2 - \beta' x) - \Phi(\mu_1 - \beta' x) \\ &\textit{Prob}[\textit{grade} = 1] = 1 - \Phi(\mu_2 - \beta' x) \end{aligned} \qquad (5)$$

and

$$0 < \mu_1 < \mu_2 \qquad (6)$$

where $\Phi(\bullet)$ symbolized the value of the standard normal cumulative distribution function.

The top curve in Figure 1 is a representation of the ordered probit model as it relates to tree grades. Given a particular tree's characteristics, a normal distribution of probability of tree grade corresponds. The bottom curve shows how a change in one of the tree's characteristics (e.g., a dbh increase) could affect the probabilities of that tree being of different grades. In Figure 1, the change in the tree characteristic causes the probability of a grade 4 tree to decline, that of grade 1 tree to increase, and the probabilities of intermediate grades to change indeterminately. This figure also illustrates how the sum of the changes in probabilities caused by a change in an explanatory variable must be zero. Note that only the changes in probabilities of the lowest grade and the highest grade are definitely of opposite sign.

A natural extension of the ordered probit model is to evaluate the marginal effects of changes in explanatory variables on tree grade probabilities. The equations of marginal effects corresponding to (3)-(6) were:

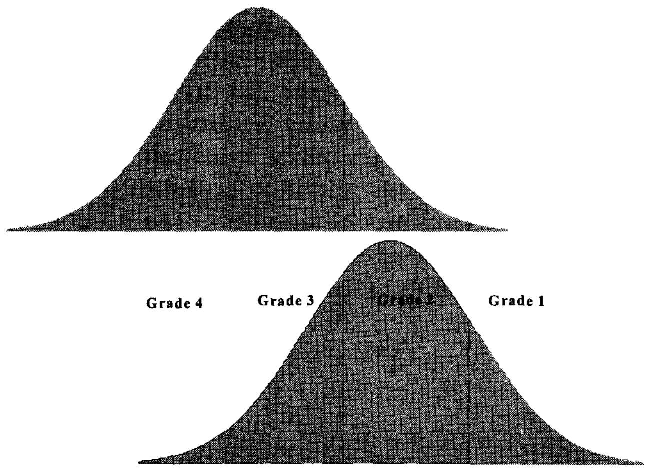

Figure 1. Grade distributions and changes in grade probabilities resulting from a change in a grade determinant.

$$\begin{aligned}
\frac{dProb(grade=4)}{dx} &= -\phi(\beta' x)\beta \\
\frac{dProb(grade=3)}{dx} &= [\phi(-\beta' x)-\phi(\mu_1-\beta' x)]\beta \\
\frac{dProb(grade=2)}{dx} &= [\phi(\mu_1-\beta' x)-\phi(\mu_2-\beta' x)]\beta \\
\frac{dProb(grade=1)}{dx} &= [\phi(\mu_2-\beta' x)]\beta
\end{aligned} \tag{7}$$

Maximum likelihood techniques were used to estimate the β's and μ's in (3)-(6). The true functional form of the right-hand side of (2) was unknown. Aside from the minimum dbh requirements in meeting grades, there was potential for conflicting influences of several of these variables on tree grade. Accordingly, where possible, included in the list of explanatory variables were squared dbh, squared stand average dbh, and squared basal area. Because site index was reported as a discontinuous (in intervals of 10 ft (3 m), 50 yr base) variable, a set of dummies was used. Individual dummies werecreated for site index 30–50, 60, 70, 80, 90, and 100 and larger (called throughout, site index 99). Site indices 30, 40, and 50 were combined because of the infrequency of 30 and 40 (no more than a total of 2% of forested sites). To avoid the dummy variable trap, the dummy corresponding to these three site indices was dropped, making the effect of site indices 30, 40, and 50 combined with the intercept term in the equation estimate.

In parameter estimation, a perceived balance had to be struck between statistical accuracy and empirical practicality. First, heteroscedasticity in the distribution of the error term in (3) was a possibility. In maximum likelihood estimation of the probit model, heteroscedastic disturbances in the underlying regression produces inconsistent parameter estimates and an inappropriate covariance matrix estimate (Yatchew and Griliches 1985). Thus, the covariance matrix of (3) was assumed to be an exponentially linear function of the right-hand variables. But initial attempts at estimation for species-diameter groups with few observations sometimes failed to converge in iterative maximum likelihood estimation, in which case a homoscedasticcovariance was imposed. Further, a paucity of observations contributed to a lack of convergence in iterative maximum likelihood estimation for smaller diameter groups and data sets. Therefore, for trees smaller than 16 in. (41 cm) dbh and for the "other softwood" species group, squared terms were not included in (3).

Equations specified for eastern white pine, eastern hemlock, and hardwoods with a dbh of at least 16 in. (41 cm) were exactly as described in Equations (3)-(6). For southern pine, no grade 4 trees were contained in the sample, and for the group "other softwood," no grade 1 trees were contained in the sample. Further, for hardwoods in the 13 to less than 16 in. (33 to less than 41 cm) dbh grouping, no grade 1 trees were possible. For these species-diameter groups, the ordered probit model was abbreviated to allow for only three grades. Finally, for hardwoods with dbh greater than or equal to 11 in. but less than 13 in. (28 to less than 33 cm) dbh, a simple binary choice (probit) model applied (either grade 3 or grade 4).

Several measures of data fitness were applied to evaluate data fitness to the estimated equations (see Maddala (1983), Judge et al. (1985), and Greene (1990) for descriptions of a few). One measure was the percentage of correct predictions, or C_m. Once the β's and the μ's were estimated, the resulting ordered probit model for a species-diameter group was used to predict the grade of each sample tree in that species-diameter group. The grade predicted for each sample tree was the one with the highest calculated probability, as given by (5). The C_m was calculated for each species-diameter group:

$$C_m = \frac{100}{n} \times \sum_{i=1}^{n} [\textit{Actual grade of tree } i = \textit{Predicted grade of tree } i] \tag{8}$$

Because randomly assigning grades to trees according to sample grade frequencies, without regard to equation estimates, would always result in a certain percentage of correct predictions, C_m was judged to be an incomplete measure of modeling success. To better gauge success, C_m was compared with what was called the "naive" model of correct predictions, C_0, the percentage of correct predictions that would have been obtained by simply predicting grade by applying sample proportions:

$$C_0 = \frac{100}{n^2}\sum_{j=1}^{J} n_j^2 \tag{9}$$

where n was the total number of trees in the sample of the species-diameter group, n_j was the actual number of trees in the sample of the species-diameter group that are of gradej, and J was the number of possible grades. A comparison of the estimated and the naive model was called the fitness improvement index *(FII):*

$$FII = 100\frac{(C_m - C_0)}{C_0} \tag{10}$$

Other measures of success in estimation of the relationships described in (3)–(6) involved maximum likelihood statistics. These included the likelihood ratio statistic and the likelihood ratio index. The likelihood ratio statistic (LRS) uses the criterion of the likelihood ratio, distributed chi-squared (k-l), suggesting whether the right-hand variables significantly explained any variation in the dependent variable:

$$LRS = 2(\ln L_0 - \ln \hat{L}_m) \tag{11}$$

where $\hat{L}_m$ was the log-likelihood of the estimated equation and L_0 was the log-likelihood of a model with only the intercept on the right-hand side. The likelihood ratio index *(LRZ)* was (Greene 1990, p. 682-683):

$$LRI = 1 - \frac{\ln \hat{L}_m}{\ln L_0} \tag{12}$$

The LRI is analogous to the R^2 of OLS, being bounded between zero and one, with higher values meaning a better fit of the data to the predicted values.

The last way used to evaluate modeling success was based on the expected grade rather than on the predicted grade. Instead of predicting a grade for each sample tree based on the single grade of maximum probability, each tree was apportioned to the probabilities of each grade. That is, if, upon estimation of the parameters, calculated probabilities as given in (5) showed that the estimated probability of a grade 1 tree was 0.15, then 15 one-hundredths of that tree was assigned a grade 1. Other grades were apportioned similarly. Differences between the expected proportions and the sample proportions hint at possible biases in estimated equations. Mathematically, for thejth grade, probabilities, $Prob[grade = j] = p_j$, were summed across the n trees in the sample:

$$Proportion\ [Grade_j] = \frac{\sum_{i=1}^{n} p_{ij}(x_i)}{\sum_{j=1}^{J}\sum_{i=1}^{n} p_{ij}(x_i)} \tag{13}$$

C_m, *FII*, *LRS*, and the *LRI*, were calculated using the test data set. In addition, the C_m, the *FII*, and the expected grade proportions comparisons were applied to a validation data set by applying the estimated species-diameter group model estimates to a set of data not used in model estimation. Taken together with the significance of the estimated parameters, these fitness criteria provided a comprehensive overview of the estimated models.

Data

Data were obtained from tree and plot records gathered from the natural forest stands in the southern Appalachians during the FIA state surveys of 1986–1992. Only trees that were graded and had complete data on dbh and associated plots with measured basal area, site index, and ownership status were used here. Overall, 21,382 tree records and 3,063 associated plot records were included in the sample. [1]

In estimation, tree data were divided into two groups, 70% randomly assigned to a test data set, used in parameter estimation, with the remaining 30% set aside in a validation data set. Division was accomplished by assigning to each tree in a species group a rectangularity distributed random variable between zero and one.

Results

Empirical results are shown in Tables 1-4. Table 1 reports estimates for softwood groups, and Tables 2-4 report estimates for the various hardwood species-diameter groups. These tables show parameter estimates and several measures of data fitness to test and validation data sets.

Only a portion of the included variables were statistically significant in explaining variations in tree grades. In most models where squared terms were included, at least one squared term was statistically different from zero at 10% significance. That is, it appears that the relationships between the stand and tree variables with tree grade were more complex than linear. Across all species, in the case of diameter at breast height, the probability of a tree being of the higher quality grades (higher quality meaning a lower grade number) either increased at a decreasing rate or was maximized at intermediate diameter classes. For example, maximum grade 1 probability for select red oak was found in the 31-35 in. (79-89 cm) dbh range. This increase and then, for several species, decrease in probabilities for the best grades perhaps reflected the cumulative effects on larger trees of damage caused by environmental factors. Alternatively, this intermediate maximization might reflect human intervention in the past, when the lowest grade trees were left to grow old, while the best grade trees were cut. Thus, dbh typically carried a positive sign and dbh-squared carried a negative sign. The relationship of dbh to grade probabilities, other included variables being equal, is illustrated for a few species in Figures 2a–2c.

Stand average dbh was estimated to be positively related to tree quality for low stand average dbh, and negatively related to tree quality at higher stand average dbh. But its effect varied substantially by species group. Figures 3a and 3b illustrate its effect for southern pine, where its influence was mild, and select white oak, where its effect on grade probabilities was substantial and had a curvilinear relationship with tree quality.

Basal area also had a curvilinear relationship with tree quality, showing the same trends as dbh and stand average dbh (Figures 4a and 4b). Where site indices were statistically significant (southern pine, eastern white pine, and oaks), it appeared that site quality, as measured using this variable, had a complex relationship to tree grade (e.g., Figures 5a and 5b).

[1] Summary tables of these data are available from the author.

Table 1. Estimation results for test data set: softwoods.

Variable		Southern pine	E. white pine	E. hemlock	Other softwood
Constant	Estimate	-2.38	-2.40	-0.99	3.65
	Standard error	0.89***	1.02***	2.13	10.58
Dbh	Estimate	0.22	0.17	0.16	0.30
	Standard error	0.07***	0.04***	0.07***	0.17**
Dbh^2	Estimate	–4.76E-03	–2.43E-03	–1.82E-03	
	Standard error	2.56E–03**	1.02E-03***	1.36E-03*	
Basal area	Estimate	6.67E-03	7.53E-03	9.07E-03	-3.578-03
	Standard error	4.06E-03*	4.87E-03*	1.22E-02	2.91E-02
(Basal area)*	Estimate	–3.00E-05	–2.34E-05	-2.518-05	
	Standard error	1.84E-05*	1.76E-05*	4.60E-05	
Stand ave. dbh	Estimate	-0.17	0.47	0.15	-0.57
	Standard error	0.16	0.18***	0.34	1.14
(Stand ave. dbh)^2	Estimate	9.92E-03	–1.97E-02	–8.46E-03	
	Standard error	8.25E-03	8.21E-03***	1.30E-02	
SI 60 dummy	Estimate	0.42	-0.36	-0.59	0.73
	Standard error	0.09***	0.18**	0.43*	4.60
SI 70 dummy	Estimate	0.13	-0.21	-0.21	-0.92
	Standard error	0.09*	0.18	0.37	3.23
SI 80 dummy	Estimate	0.13	-0.11	-0.40	n.a.[a]
	Standard error	0.11	0.18	0.37	
SI 90 dummy	Estimate	0.05	-0.30	-0.03	1.06
	Standard error	0.13	0.19*	0.38	5.15
SI 99 dummy	Estimate	-0.34	-0.16	-0.76	2.36
	Standard error	0.26*	0.20	0.40**	3.59
NIPF dummy	Estimate	-0.16	0.13	–0.27	-0.15
	Standard error	0.06***	0.09*	0.17*	3.74
Recent cut dummy	Estimate	0.27	0.17	-0.02	-1.54
	Standard error	0.09***	0.14	0.33	3.89
μ_1	Estimate	0.83	2.97	2.50	4.40
	Standard error	0.04***	0.14***	0.17***	2.22**
μ_2	Estimate		4.22	3.57	
	Standard error		0.15***	0.20***	
Test observations		2,408	1,026	254	32
Test LRS		148***	153***	74***	14
Test LRI		0.04	0.08	0.14	0.41
Test C_m		74.0	58.8	63.3	87.5
Test FII		15.4	13.1	17.6	15.0
Validation C_m		73.7	61.7	64.4	75.0
Validation FII		15.27	15.71	18.00	-3.65
Proportions differences[b]					
Expected-actual	Grade 4	n.c.[c]	-0.10	0.43	-2.09
	Grade 3	0.01	-2.47	-1.06	1.79
	Grade 2	-0.28	4.63	-1.29	0.30
	Grade 1	0.27	-2.06	1.92	n.c.[c]
Predicted-actual	Grade 4	n.c.[c]	-0.93	-4.44	-7.69
	Grade 3	26.16	17.29	23.70	7.05
	Grade 2	-18.79	-6.07	-17.78	0.64
	Grade 1	-7.55	-10.28	-1.48	n.c.[c]

[a] Not applicable because no trees sampled in this group were growing in site index 80 stands.
[b] Differences in percentage of trees in each grade, expected from estimated model minus actual, using the validation data set.
[c] Not calculated because no trees of this grade were contained in the sample.
NOTE: one asterisk indicates significance at 10%, two at 5%. and three at 1%.

Table 2. Estimation results for test data set: hardwoods of 16 in. (41 cm) dbh and laraer.

Variable		Sel. white oak	Sel. red oak	Other oak	Soft maple	Yellow-poplar	Other hardwoods
Constant	Estimate	-2.92	-1.24	-1.02	-2.68	-1.42	1.78
	Standard error	1.20***	0.99	0.61**	4.02	1.16	1.12*
Dbh	Estimate	-0.01	0.11	0.09	0.12	0.18	-0.08
	Standard error	0.07	0.05**	0.03***	0.36	0.08**	0.09
Dbh^2	Estimate	–9.27E-05	–1.78E-03	–1.78E-03	–2.48E-03	–3.78E-03	2.38E-03
	Standard error	1.52E-03	1.01E-03**	6.25E-04***	8.63E-03	1.76E-03**	1.91E-03
Basal area	Estimate	4.56E-03	1.29E-02	-5.11E-03	6.79E-03	1.79E-03	7.81E-03
	Standard error	6.47E-03	6.76E-03**	4.19E-03	9.84E-03	5.24E-03	5.11E-03*
$(\text{Basal area})^2$	Estimate	-2.21E-05	–4.94E-05	3.26E-05	–1.49E-05	–5.76E-06	–2.99E-05
	Standard error	2.99E-05	2.62E-05**	1.85E-05**	4.12E-05	2.07E-05	2.15E-05*
Stand ave. dbh	Estimate	0.67	0.07	0.20	0.25	0.19	-0.03
	Standard error	0.15***	0.12	0.07***	0.30	0.10**	0.07
$(\text{Stand ave. dbh})^2$	Estimate	–2.51E-02	–2.19E-03	–7.04E-03	–6.92E-03	–6.85E-03	1.45E-03
	Standard error	5.97E-03***	4.58E-03	2.96E-03***	1.21E-02	3.73E-03**	2.65E-03
SI 60 dummy	Estimate	0.18	0.46	0.33	-0.21	-0.29	-0.26
	Standard error	0.17	0.14***	0.09***	0.50	0.48	0.19*
SI 70 dummy	Estimate	0.42	0.49	0.31	0.03	–0.50	0.09
	Standard error	0.17***	0.14***	0.08***	0.47	0.47	0.19
SI 80 dummy	Estimate	0.46	0.66	0.27	-0.47	–0.31	0.53
	Standard error	0.19***	0.15***	0.09***	0.48	0.47	0.19***
SI 90 dummy	Estimate	0.50	0.62	0.61	0.02	–0.29	0.37
	Standard error	0.23**	0.16***	0.11***	0.52	0.46	0.19**
SI 99 dummy	Estimate	0.25	0.69	0.60	0.13	-0.17	0.31
	Standard error	0.26	0.19***	0.12***	0.48	0.47	0.20*
NIPF dummy	Estimate	-0.14	-0.02	-0.23	-0.05	0.02	-0.30
	Standard error	0.11*	0.09	0.06***	0.22	0.11	0.08***
Recent cut dummy	Estimate	-0.09	-0.06	0.06	0.06	0.02	-0.22
	Standard error	0.16	0.24	0.10	0.50	0.14	0.11**
μ_1	Estimate	1.38	1.47	1.43	1.49	1.11	1.45
	Standard error	0.08***	0.10***	0.05***	0.12***	0.08***	0.06***
μ_2	Estimate	2.40	2.64	2.46	2.85	2.19	2.53
	Standard error	0.09***	0.11***	0.05***	0.24***	0.08***	0.07***
Test observations		563	760	1,746	216	972	972
Test LRS		49***	53***	85***	17	27**	82***
Test LRI		0.03	0.03	0.02	0.04	0.01	0.03
Test C_m		41.5	41.2	43.8	51.9	44.2	44.8
Test FII		10.6	8.0	11.3	14.9	10.9	12.2
Validation C_m		36.8	37.5	45.9	54.5	41.8	47.1
Validation FII		5.58	4.92	12.34	16.27	8.47	14.61
Proportions differences”							
Expected-actual	Grade 4	0.09	-1.84	2.01	10.30	0.46	-2.04
	Grade 3	-0.69	-1.94	-1.67	-3.52	-0.15	-1.32
	Grade 2	-1.39	1.36	-2.42	4.36	2.05	2.20
	Grade 1	2.00	2.42	2.08	-2.42	-2.37	1.16
Predicted-actual	Grade 4	-6.88	-4.47	–6.79	-7.58	-3.13	-11.22
	Grade 3	6.48	-18.21	36.95	42.42	-20.43	29.02
	Grade 2	18.62	43.99	-17.50	-28.79	29.57	-5.37
	Grade 1	-18.22	-21.31	-12.67	–6.06	–6.01	-12.44

[a] Differences in percentage of trees in each grade, expected from estimated model minus actual, using the validation data set.
NOTE: one asterisk indicates significance at 10%, two at 5%. and three at 1%.

Table 3. Estimation results for test data set: hardwoods of 13 in. (33 cm) dbh to less than 16 in. (41 cm) dbh.

Variable		Sel. white oak	Sel. red oak	Other oak	Soft maple	Yellow-poplar	Other hardwoods
Constant	Estimate	-3.67	4.50	-2.16	-1.07	-2.68	-1.48
	Standard error	1.09***	1.45***	0.62***	1.54	0.93***	0.76**
Dbh	Estimate	0.31	0.44	0.22	0.05	0.26	0.17
	Standard error	0.07***	0.10***	0.04***	0.10	0.06***	0.05***
Basal area	Estimate	3.48E-03	-3.49E-04	3.74E-03	2.91E-03	-2.728-04	1.75E-03
	Standard error	1.97E-03**	2.62E-03	1.16E-03***	2.99E-03	1.44E-03	1.16E-03*
Stand ave. dbh	Estimate	1.06E-02	6.01E-03	-1.57E-02	2.31E-02	4.86E-02	-4.39E-03
	Standard error	3.64E-02	4.10E-02	1.95E-02	4.03E-02	2.60E-02**	1.90E-02
SI 60 dummy	Estimate	-0.14	0.34	0.04	0.62	-0.35	0.27
	Standard error	0.20	0.30	0.11	0.69	0.49	0.20*
SI 70 dummy	Estimate	-0.16	0.17	0.02	0.50	0.25	0.12
	Standard error	0.19	0.29	0.11	0.68	0.47	0.18
SI 80 dummy	Estimate	0.01	0.15	-0.01	0.44	0.00	0.04
	Standard error	0.23	0.31	0.13	0.69	0.47	0.19
SI 90 dummy	Estimate	-0.14	-0.06	0.39	0.32	0.37	0.08
	Standard error	0.30	0.50	0.15***	0.70	0.47	0.21
SI 99 dummy	Estimate	-0.08	0.80	0.04	0.30	0.15	0.38
	Standard error	0.33	0.35**	0.20	0.76	0.47	0.22**
NIPF dummy	Estimate	-0.03	-0.06	-0.12	0.17	-0.14	0.02
	Standard error	0.17	0.17	0.08*	0.22	0.13	0.09
Recent cut dummy	Estimate	0.29	-0.12	0.07	0.46	-0.12	-0.06
	Standard error	0.20*	0.49	0.11	0.26**	0.15	0.13
μ_1	Estimate	1.56	2.19	1.82	1.82	1.65	1.79
	Standard error	0.10***	0.18***	0.06***	0.13***	0.08***	0.07***
Test observations		400	259	1,138	229	649	766
Test LRS		28***	30***	53***	9	49***	23***
Test LRI		0.04	0.07	0.02	0.02	0.04	0.02
Test C_m		55.8	66.5	60.7	62.8	58.3	59.9
Test FII		15.1	19.0	15.1	16.7	13.6	14.6
Validation C_m		54.3	64.9	60.7	63.6	58.3	53.1
Validation FII		13.3	13.8	15.5	14.4	14.0	11.2
Proportions differences[a]							
Expected-actual	Grade 4	2.05	2.74	-0.44	5.09	-0.72	-3.77
	Grade 3	1.60	-4.48	0.32	-12.97	0.61	-8.42
	Grade 2	-3.65	1.73	0.12	7.88	0.11	12.20
Predicted-actual	Grade 4	-12.20	-0.90	-12.82	-15.91	6.55	-15.43
	Grade 3	36.5	94.50	37.67	31.82	-1.03	16.00
	Grade 2	-24.39	-3.60	-24.85	-15.91	7.59	-0.57

[a] Differences in absolute percentages of trees in each grade.
NOTE: one asterisk indicates significance at 10%. two at 5%, and three at 1%.

Generally, the dummy variables for private nonindustrial ownership and for a recent history of cutting were not statistically significant. Even for those species-diameter groups in which their coefficients were estimated as significantly different from zero, the practical effects of ownership and cutting on grade probabilities were small. However, where the NIPF dummy was significant, the effect was negative, implying that, other things being equal, a tree growing on private, nonindustrially owned land was probably of lower quality, lending tentative support to a hypothesis of poorer genetic quality on these lands. The cutting dummy, where significant, varied in sign. Further, statistical significance was rare in estimation, hinting that the few cases of significance were merely random sampling extreme events.

Measures of goodness of fit generally indicated that the estimated models were better than naïve models in predicting tree grades. The percentage of correct predictions in both the test and validation data sets were high, usually in the 60–85% range. But these statistics hide the fact that most of the correct predictions were in the grade 3 cat-

Table 4. Estimation results for test data set: hardwoods of 11 in. (28 cm) dbh to less than 13 in. (33 cm) dbh.

Variable		Sel. white oak	Sel. red oak	Other oak	Soft maple	Yellow-poplar	Other hardwoods
Constant	Estimate	-1.91	-2.32	-1.92	-1.72	5.04	-2.35
	Standard error	1.80	3.40	1.09**	2.22	39.11	1.33**
Dbh	Estimate	0.23	0.37	0.12	0.21	-0.01	0.17
	Standard error	0.16*	0.28*	0.09*	0.17	0.15	0.11*
Basal area	Estimate	6.29E-03	1.05E-03	4.79E-03	6.18E-04	−1.77E-03	−1.38E-03
	Standard error	3.02E-03**	5.15E-03	1.94E-03***	2.52E-03	2.41E-03	1.61E-03
Stand ave. dbh	Estimate	4.12E-03	−9.10E-03	9.41E-02	-3.1 1E-02	−8.00E-03	6.93E-02
	Standard error	5.85E-02	7.73E-02	3.29E-02***	4.74E-02	4.81E-02	3.26E-02**
SI 60 dummy	Estimate	−0.42	-0.84	-0.19	0.65	-3.34	0.15
	Standard error	0.35	0.54*	0.14*	0.41*	39.07	0.24
SI 70 dummy	Estimate	-0.71	-0.49	0.08	0.19	-2.77	0.60
	Standard error	0.35**	0.55	0.14	0.36	39.07	0.23***
SI 80 dummy	Estimate	−0.85	-0.50	0.22	0.16	-3.18	0.31
	Standard error	0.39**	0.60	0.19	0.39	39.07	0.23*
SI 90 dummy	Estimate	−0.87	-0.85	0.17	0.40	-2.03	0.14
	Standard error	0.45**	0.63*	0.28	0.44	39.07	0.24
SI 99 dummy	Estimate	−0.97	2.78	0.20	0.08	-2.85	0.37
	Standard error	0.53**	68.29	0.32	0.44	39.07	0.31
NIPF dummy	Estimate	−0.13	-0.16	-0.13	0.03	-0.38	0.16
	Standard error	0.24	0.33	0.11	0.23	0.26*	0.15
Recent cut dummy	Estimate	0.43	3.63	0.29	0.27	-0.26	0.15
	Standard error	0.29*	67.87	0.20*	0.42	0.24	0.21
Test observations		269	158	852	220	451	606
Test LRS		13	8	35***	7	8	19**
Test *LRI*		0.05	0.08	0.04	0.03	0.03	0.03
Test C_m		79.7	92.0	80.4	79.3	90.4	81.5
Test FII		12.1	6.7	11.9	12.1	7.7	11.7
Validation C_m		86.4	96.2	82.6	81.3	92.8	84.3
Validation FII		9.9	3.6	11.3	11.7	6.2	10.3
Proportions differences”							
Expected-actual	Grade 4	7.68	3.72	2.58	2.80	-0.17	11.53
	Grade 3	-7.68	-3.72	-2.58	-2.80	0.17	-11.53
Predicted-actual	Grade 4	-13.64	-3.85	-17.40	-18.69	-7.22	-14.96
	Grade 3	13.64	3.85	17.40	18.69	7.22	14.96

[a] Differences in percentage of trees in each grade, expected from estimated model minus actual, using the validation data set.
NOTE: one asterisk indicates significance at 10%. two at 5%, and three at 1%.

egory, and fewer were in the grades I, 2, or 4 categories. The Fitness Improvement Index was usually in the 10–15% range for the test data set, important gains over the naive model. These gains were maintained using the validation data set as well, especially for softwoods, indicating model robustness. Likelihood ratio statistics (*LRS*'s) were statistically significant for the largest and intermediate species-diameter groups and for only two of six of the smallest species-diameter groups. On the other hand, *LRI*'s were usually low across all groups.

While the percentage of correct predictions varied by grade across all species-diameter groups when tree grade was predicted as the grade of maximum probability, this effect was not present when evaluated from the perspective of expected grades (the last rows of Tables I-4). Using the validation data set, expected grade proportions were very precisely predicted. This precision was replicated across all species groups, except soft maple, with predicted percentages in each grade deviating from actual percentages typically by less than three percentage points, compared with deviations typically in the 10 to 30% range using predicted probabilities.

Before continuing, an example may be helpful to understand the model. Table 5 describes calculations for tree grade probabilities for three select red oak trees from the validation data set. The table shows grade probabilities [calculated using equations in (4)], actual tree grades, predictions of grades using maximum probabilities, and

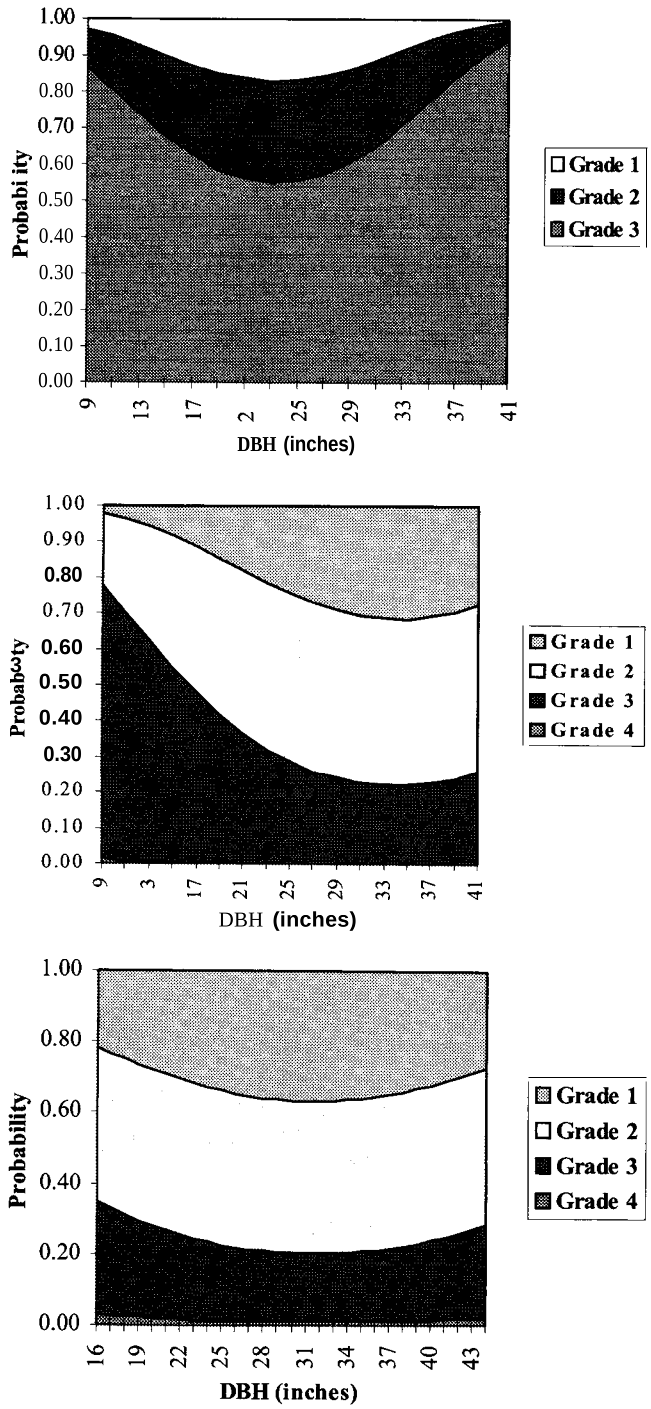

Figure 2. (a) Effect of dbh on grade probabilitiesfor southern pine (1 in.=2.54cm); (b) Effectofdbhongradeprobabilitiesforeastern white pine (1 inch =2.54cm); (c) Effect of dbh on grade probabilities for select red oak, 16 in. (41 cm) dbh and larger.

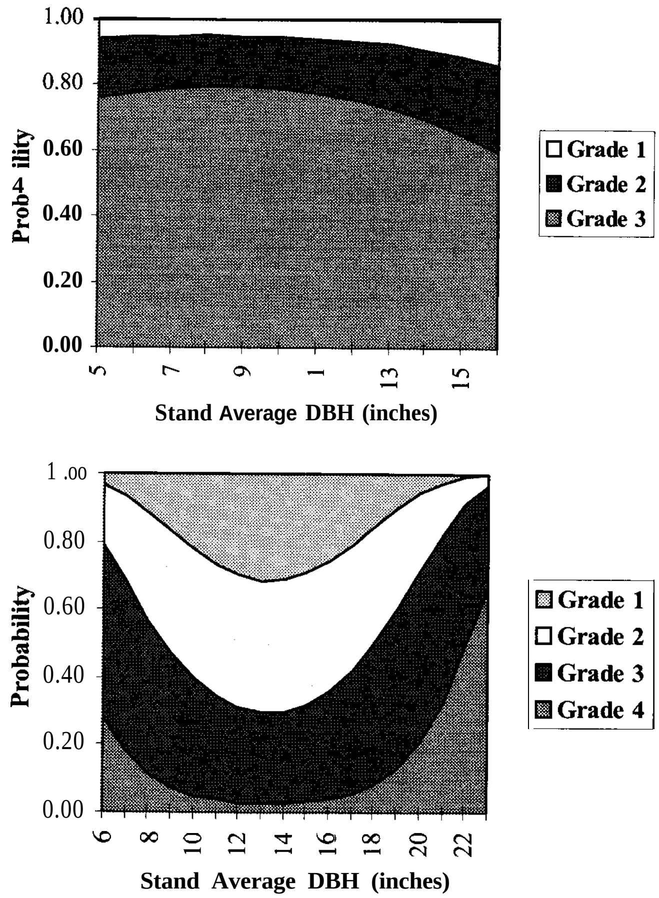

Figure 3. (a) Effect of stand average dbh on grade probabilities for southern pine (1 in. = 2.54 cm); (b) Effect of stand average dbh on grade probabilities for select white oak, 16 in. (41 cm) dbh and larger (1 in. = 2.54 cm).

the effects on grade probabilities of increasing tree dbh by 1 in. (2.5 cm). The table hints at how using maximum probabilities from the estimated model could overpredict certain grades (in this example, tree grade 2) and underpredict others (in this example, 1, 3, and 4). The model also shows how marginal effects (discussed below) of changes in variables were calculated.

Table 6 reports the marginal effects of the chosen explanatory variables on grade probabilities. This table, for conciseness, lists marginal effects for only softwoods and for hardwoods larger than 16 in. (41 cm) dbh. The marginal effects are the change in tree grade probabilities, from (7), caused by shifting the normal distribution (as was illustrated in Figure 1). For dbh, stand average dbh, and stand basal area per acre, the marginal effects shown were the weighted average marginal effects across all trees in the validation data set, expanded to the population using expansion factors. For other variables (site index and dummies), these tables report the marginal effects of deviating from population modes, given the median or modal values of other variables for the population for that species-diameter group. Due to the nonlinear nature of ordered probit models, these marginal effects varied according to the point of evaluation (e.g., see Table 5 for three select red oaks). While this table shows an estimate of the average effect across the entire population of trees, this is only one possible table that could be constructed. For example, a table could be constructed to show the effects on probabilities of changing from a 30 in. (76.2 cm) to a 31 in. (78.7 cm) dbh tree.

Across all species-diameter groups shown (and across hardwoods of smaller diameters), the marginal effects of variables were generally as hypothesized, with dbh, basal area, and site index usually positively related to tree quality.

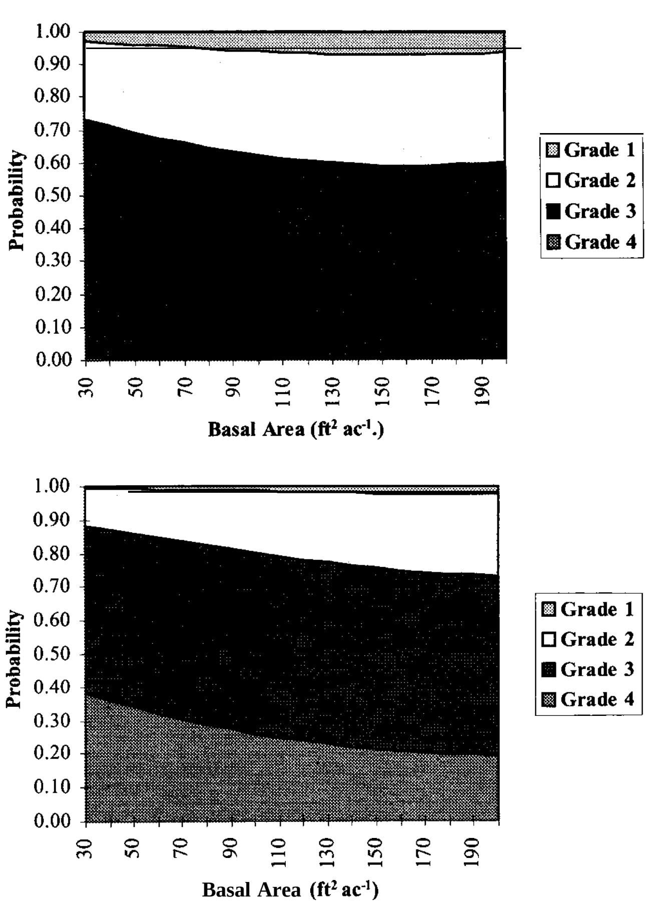

Figure4. (a) Effect of basal area on grade probabilities for eastern white pine (where 1 ft^2 ac^{-1} = 0.23 m^2 ha^{-1}); (b) Effect of basal area on grade probabilities for soft maple, 16 in. (41 cm) dbh and larger (where 1 ft^2 ac^{-1} = 0.23 m^2 ha^{-1}).

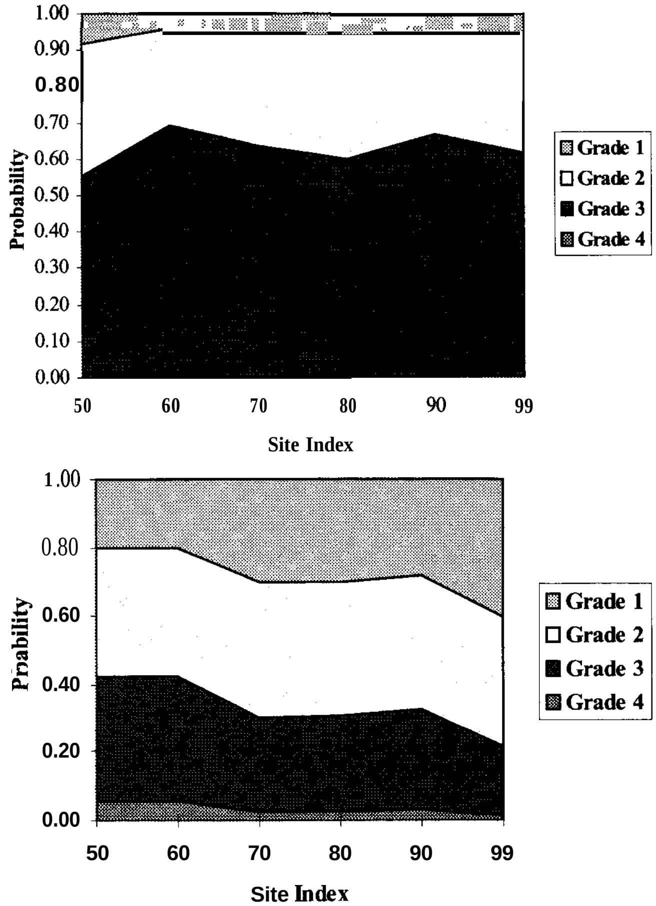

Figure 5. (a) Effect of site index (in feet, 50 yr base, where 1 ft = 0.30 m) on grade probabilities for eastern white pine; (b) Effect of site index (in feet, 50 yr base, where 1 ft = 0.30 m) on grade probabilities for other oak, 16 in. (41 cm) dbh and larger.

Tree dbh was most influential in the smaller diameter groups of hardwoods (not shown[2]), southern pine, yellow-poplar.

An increase by 1 in. (2.5 cm) in stand average dbh was usually associated with an increase in probability that trees were of the top grades and a decrease in probability that trees were of the lowest grades. Ownership status, where statistically significant, was associated with a change in probability of grade 1 tree by -0.015 for eastern white pine to 0.08 for the "other hardwood" group. Where recent cutting was significantly positive (southern pine), it increased grade 1 probability by 0.034; where it was significantly negative (other hardwoods), it decreased grade 1 probability by 0.046.

Discussion

The estimated models were better than naïve models in terms of total percentages of correct predictions, when choosing the grade of maximum probability was used as the criterion for predicting tree grade for individual trees. But the maximum probability approach tended to clump its predictions into just one or two tree grades. Applying data from either the test or validation data sets, predicted proportions deviated substantially from actual proportions. Using expected grade proportions, there was no obvious tendency to under- or overpredict the proportions of trees in the sample in each grade.

On the other hand, given the low *LRI*'s, it might be concluded that a substantial portion of variation was left unexplained. A well-established concept in genetics is that phenotype (e.g., tree grade) is a combination of genotype (unobservable) and environment (to some extent, observable). If there were a way to quantify and systematically measure genotype, then its incorporation in estimation might enable more precise prediction. Further, if there were a way to account for the degree of past high grading in stands, estimated models might also improve their prediction success.

The results suggest that the ordered probit model would permit accurate predictions and projections of expected stand values. By using tree grades to derive the resulting log grades, the models could be used in economic optimization models. Tree grade models could enhance the usefulness of FIA data for tracking harvests in the southern Appalachians, and the techniques developed here could be applied to modeling tree grades for species growing in other physiographic regions.

The models revealed significant relationships between tree and stand variables and tree grade in explaining grade variations. In terms of statistical significance, the variables most commonly significantly related to tree grade across species-diameter groups were dbh and stand aver-

2 These results are available from the author.

Table 5. Example calculations for three select red oak trees (validation data set).

Variable	Estimated coefficients	Tree 1	Tree 2	Tree 3
Constant	-1.24	1	1	1
Dbh	0.1126	19.5	16	19.9
Dbh^2	–1.78E-03	380.25	256	396.01
Stand ave. dbh	6.53E-02	11.69	10.38	13.60
(Stand ave. dbh)^2	–2.19E-03	136.57	107.69	185.07
Basal area	1.29E-02	158	195	143
(Basal area)*	–4.94E-05	24,964	38,025	20,449
SI 60 dummy	0.46	0	1	0
SI 70 dummy	0.49	0	0	0
SI 80 dummy	0.66	0	0	0
SI 90 dummy	0.62	0	0	1
SI 99 dummy	0.69	1	0	0
NIPF dummy	–2.28E-02	1	0	1
Recently cut dummy	–6.21E-02	0	0	1
μ_1	1.47			
μ_2	2.64			
$\beta'x$		2.22	1.65	2.16
Prob(Gr = 4)		0.013	0.049	0.016
Prob(Gr = 3)		0.214	0.379	0.231
Prob(Gr = 2)		0.437	0.411	0.440
Prob(Gr = 1)		0.336	0.161	0.313
Actual grade		4	2	1
Predicted grade		2	2	2
Add 1 in. to dbh				
$\beta'x$		2.26	1.71	2.20
Prob(Gr = 4)		0.012	0.044	0.014
Prob(Gr = 3)		0.203	0.363	0.220
Prob(Gr = 2)		0.434	0.419	0.438
Prob(Gr = 1)		0.351	0.174	0.328
Marginal effects on grades				
dProb(Gr = 4)		-0.001	-0.005	-0.001
dProb(Gr = 3)		-0.011	-0.016	-0.011
dProb(Gr = 2)		-0.003	0.008	-0.002
dProb(Gr = 1)		0.015	0.014	0.014

NOTE: 1 in. = 2.54 cm.

age dbh, with tree basal area, site index, ownership status, and recent cutting history less often significantly related to tree grades. These results largely conformed with the findings of Belli et al. (1993) and Kärkkäinen and Uusvaara (1982) and with the expectations presented in this research. Where statistically significant, the relationships between tree dbh and basal area with tree quality were positive for smaller trees and became less positive and even negative for the largest trees. The positive region of this relationship could be related to trees proceeding through a process of self-pruning and development of clear faces early in life, while the less positive or negative region could be linked to the accumulated effects of natural damage to the tree after many years of growth and the effects of past human intervention. The results, however, indicate that the relationship between tree grade and growth rate or tree vigor (Smith 1962, Kärkkäinen and Uusvaara 1982) was complex and (or) not revealed by using site index as an explanatory variable. Further, while stand average dbh was positively related to tree quality, this relationship was often reversed in stands of large average diameters. Where it was positively related, it was probably most indicative of stand age and density, and a positive sign might have been expected-older and denser stands might be expected to have better quality trees.

Significant negative influence of NIPF status on some species hints that some dysgenic effect of ownership (and hence, historical stand treatment) has occurred on private nonindustrial forested ownerships in the southern Appalachians, lending tentative support to the suspicions of some, or it could also be a simpler, nongenetic selection effect of high-grading. While this effect was not observed across all species-diameter groups, it was significant for all diameters of southern and eastern white pines and hemlock and for larger diameters of select white oak, nonselect oak, and the "other hardwood" species group. Assuming that the included trees and plots were representative of the population, these species-diameter groups comprise more than half of the standing volume in the southern Appalachians. However, nonsignificant signs on the dummy accounting for recent cutting indicates that, for most species-diameter groups, more contemporary cutting has not had any immediately detectable effect on tree quality.

While no causal links between tree quality and the chosen variables were proved in modeling, these results are at least informative. Only time-series studies may be able to definitively address issues of causality. But following Smith (1961, 1962), there are plausible causal links, at least for certain variables. Thus, it may be safe to say that, given proper management, if the right balance can be. struck among tree diameters and stand densities, higher quality trees can result.

Table 6. Marginal effects of changing indicated variables (increasing dbh and average dbh by 1 in., basal area by 1 ft^2/ac, and as changed from population modes for other variables): all gradeable softwoods, hardwoods of dbh greater than or equal to 16 in.

Species group, diameter group	Variable	Grade 4	Grade 3	Grade 2	Grade 1
Southern pine	Dbh		-0.065	0.013	0.051
	Ave. dbh		-0.003	0.001	0.002
	Basal area		0.001	0.000	-0.00 1
	Increase SI by 10		0.001	0.000	0.000
	Decrease SI by 10		-0.09 1	0.054	0.037
	Not NIPF		-0.047	0.029	0.018
	Recently cut stand		-0.083	0.050	0.034
Eastern white pine	Dbh	-0.004	-0.027	0.022	0.008
	Ave. dbh	-0.004	-0.018	0.016	0.005
	Basal area	-0.001	-0.002	0.002	0.001
	Increase SI by 10	0.002	0.069	-0.05	-0.02 1
	Decrease SI by 10	0.001	0.036	-0.026	-0.012
	Not NIPF	0.002	0.048	-0.034	-0.015
	Recently cut stand	-0.001	-0.066	0.042	0.025
Eastern hemlock	Dbh	-0.016	-0.012	0.020	0.008
	Ave. dbh	0.003	0.004	-0.004	-0.002
	Basal area	-0.001	-0.001	0.001	0.001
	Increase SI by 10	0.016	0.038	-0.041	-0.013
	Decrease SI by 10	0.040	0.063	-0.080	-0.023
	Not NIPF	-0.0 16	-0.077	0.064	0.029
	Recently cut stand	0.002	0.006	-0.005	-0.002
Other softwood	Dbh	-0.023	-0.003	0.026	
	Ave. dbh	0.044	0.006	-0.050	
	Basal area	0.000	0.000	0.000	
	Increase SI by 10	-0.041	0.023	0.018	
	Decrease SI by 10	na[a]	na[a]	na[a]	
	Not NIPF	-0.014	0.012	0.002	
	Recently cut stand	0.408	-0.405	-0.003	
Select white oak Dbh ≥ 16"	Dbh	0.001	0.002	-0.001	-0.002
	Ave. dbh	-0.020	-0.030	0.019	0.03 1
	Basal area	-0.001	-0.001	0.000	0.001
	Increase SI by 10	-0.004	-0.013	0.002	0.015
	Decrease SI by 10	0.024	0.065	-0.020	-0.070
	Not NIPF	-0.011	-0.040	0.003	0.048
	Recently cut stand	0.008	0.025	-0.006	-0.028
Select red oak Dbh ≥ 16"	Dbh	-0.003	-0.0 11	0.002	0.012
	Ave. dbh	-0.001	-0.005	0.001	0.005
	Basal area	-0.001	-0.003	0.000	0.004
	Increase SI by 10	-0.007	-0.049	-0.007	0.063
	Decrease SI by 10	0.001	0.007	0.000	-0.008
	Not NIPF	-0.001	-0.007	0.000	0.008
	Recently cut stand	0.003	0.018	-0.001	-0.02 1
Other oak Dbh ≥ 16"	Dbh	-0.004	-0.005	0.004	0.005
	Ave. dbh	-0.008	-0.011	0.009	0.011
	Basal area	0.001	0.001	-0.001	-0.00 1
	Increase SI by 10	0.007	0.009	-0.008	-0.008
	Decrease SI by 10	-0.003	-0.004	0.003	0.004
	Not NIPF	-0.032	-0.059	0.037	0.055
	Recently cut stand	-0.010	-0.015	0.011	0.013

(Table 6 continued next page)

Table 6 (continued)

Species group, diameter group	Variable	Grade 4	Grade 3	Grade 2	Grade 1
Soft maple	Dbh	-0.007	-0.002	0.007	0.002
Dbh ≥ 16"	Ave. dbh	-0.027	-0.006	0.026	0.007
	Basal area	-0.002	0.000	0.002	0.000
	Increase SI by 10	-0.129	-0.037	0.135	0.031
	Decrease SI by 10	-0.129	-0.038	0.135	0.031
	Not NIPF	-0.016	0.001	0.013	0.002
	Recently cut stand	-0.018	0.001	0.014	0.002
Yellow-poplar	Dbh	-0.004	-0.010	-0.002	0.016
Dbh ≥ 16"	Ave. dbh	-0.004	-0.009	-0.001	0.014
	Basal area	0.000	0.000	0.000	0.001
	Increase SI by 10	-0.007	-0.027	-0.013	0.048
	Decrease SI by 10	0.001	0.004	0.001	-0.007
	Not NIPF	0.001	0.004	0.001	-0.006
	Recently cut stand	-0.00 1	-0.004	-0.002	0.007
Other hardwood	Dbh	-0.001	-0.001	0.001	0.001
Dbh ≥ 16"	Ave. dbh	-0.001	0.000	0.000	0.001
	Basal area	0.000	0.000	0.000	0.000
	Increase SI by 10	0.008	0.014	-0.009	-0.013
	Decrease SI by 10	-0.019	-0.045	0.023	0.041
	Not NIPF	-0.032	-0.087	0.036	0.082
	Recently cut stand	0.035	0.055	-0.043	-0.046

[a] Not applicable because the modal site index for this diameter-species group was the lowest site index in the sample range.
NOTE: 1 in. = 2.54 cm.

But questions remain regarding the modeling of tree grades. One major area for future investigation is to develop techniques for linking genetic characteristics and the variables included in the reported models. Further, a precise way of indicating the degree and nature of past human intervention might help explain the effects of human activities on tree quality. In addition, this research did not evaluate the success of tree grade modeling on tree grade distributions of removals. Linking data from previous FIA surveys on tree grades of harvested trees would permit such an analysis.

Literature Cited

BARE, B.B., AND D. OPALACH. 1988. Determining investment-efficient diameterdistributionsforuneven-agednorthemhardwoods. For. Sci. 34(1):243–249.

BELLI, K.L., T.G. MATNEY, J.D. HODGES, R. T. DEEN, AND J.C.G. GOELZ. 1993. Tree grade prediction for Mississippi bottomland hardwoods using discriminant analysis. South. J. Appl. For. 17(3):120–123.

BRISBIN, R.L., AND D.L. SONDERMAN. 1971. Tree grades for eastern white pine. USDA For. Serv. Res. Pap. NE-214. 30 p.

BROOMHALL, D.E., AND T. JOHNSON. 1994. Economic factors that influence educational performance in rural schools. Am. J. Agric. Econ. 76(3):557–567.

BUONGIORNO, J., AND B. MICHIE. 1980. A matrix model of uneven-aged forest management. For. Sci. 26(4):609–625.

BUONGIORNO, J., J-L. PEYRON, F. HOULLIER, AND M. BRUCIAMACCHIE. 1995. Growth and management of mixed-species, uneven-aged forests in the French Jura: Implications for economic returns and tree diversity. For. Sci. 41(3):397–429.

GOLDBERGER, A.S. 1991. A course in econometrics. Harvard University Press, Cambridge, MA. 405 p.

GREENE, W.H. 1990. Econometric analysis. Macmillan Publishing Co., New York. 783 p.

HAIGHT, R.G., R.G. MONSERUD, AND J.D. CHEW. 1992. Optimal harvesting with stand density targets: Managing Rocky Mountain conifer stands for multiple forest outputs. For. Sci. 38(3):554–574.

HANKS, L.F. 1976. Hardwood tree grades for factory lumber. USDA For. Serv. Res. Pap. NE-333. 81 p.

HANSEN, M.H., T. FRIESWYK, J.F. GLOVER, AND J.F. KELLY. 1992. The Eastwide Forest lnventory Data Base: Users manual. USDA For. Serv. Gen. Tech. Rep. NC-151.48 p.

HAUSMAN, J.A., A.W. Lo, AND A.C. MACKINLAY. 1991. An ordered probit analysis of transaction stock prices. NBER Working Pap. No. 3888, Nat. Bur. of Econ. Res., Cambridge, MA. 39 p.

HOCKMAN, J.N., J.A. BURGER, AND D. WM. SMITH. 1990. Classification model to predict Fraser fir Christmas tree grade. For. Sci. 36(1):45–53.

KARKKAINEN, M., AND 0. UUSVAARA. 1982. Nuorten mäntyjen laatuun vaikuttavia tekijöitä (Factors affecting the quality of young pines). Folia Forestalia 515:2–27.

LUPPOLD, W. 1993. Decade of change in the hardwood industry. P. 1 l-24 *in* Proc. of the Twenty-first Annual Hardwood Symp. of the Hardwood Res. Counc. Coping with economic and social changes, Cashiers, N.C. (ed.).

ORAZEM, P.F., D.M. OTTO, AND M.A. EDELMAN. 1989. An analysis of farmers' agricultural policy preferences. Am. J. Agric. Econ. 71(4):837–846.

SCHROEDER, J.G., R.A. CAMPBELL, AND R.C. RODENBACH. 1968. Southern pine tree grades for yard and structural lumber. USDA For. Serv. Res. Pap. SE-40. 15 p.

SMITH, D.M. 1961. Comments on "Relationship between tree spacing, knot size, and log quality in young Douglas-fir stands." J. For. 59:682–683.

SMITH, D.M. 1962. The practice of silviculture. Wiley & Sons, New York. 578 p.

WALKER, L. 1980. The Southern Pine region. P. 231-276 *in* Regional silviculture of the United States, Barrett, J.W. (ed.). Wiley, New York. 551 p.

YATCHEW, A., AND Z. GRILICHES. 1985. Specification error in probit models. Rev. Econ. Stat. 67(1):134–139.