Accelerated statistical prediction of lumber grades and part yields

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Abstract

Assignment of lumber grades by lumber scanning followed by computer grading requires faster hardware and/or software. This study explored the potential for determining lumber grades by a linear discriminant analysis model. Designating lumber grades by applying a discriminant analysis model will dramatically increase software execution speed. Development of special lumber grades would be much easier if they were described by a discriminant analysis model. Quantitative variables expected to discriminate between lumber grades were tested for significance. Eight of 15 variables tested were found to be significant. The best four-variable model was chosen to reduce the amount of data collection and computation. The model successfully classified 92.8, 75.0, 66.3, and 74.1 percent of sample lumber in the lumber grades FAS, 1C, 2AC, and 3AC, respectively. Overall accuracy for all four lumber grades was 74.3 percent. Parts yields from the lumber graded by the discriminant analysis model were nearly identical to the lumber graded by National Hardwood Lumber Association grading rules for the three cutting orders involved in this study. The discriminant analysis software assigned lumber grades 77,000 percent faster than the lumber grading software tested in this study.

Considerable research is currently being conducted to develop the technology required to provide machine vision for lumber processing systems. Various types of sensors have been investigated for machine vision systems to detect defects in lumber. Detection methods tested have been ultrasonics (McDonald 1978, Szymani and McDonald 1981), x-ray (Szymani and McDonald 1981, Kenway 1989), light diffraction (Matthews 1987), laser (Szymani and McDonald 1981, Juvonen 1985, Soest 1985, Soest and Matthews 1987), microwave (Szymani and McDonald 1981, King et al. 1985), electrical field (McLaughlan et al. 1973, Samson 1984, Steele et al. 1991, 2000), and video scanning devices (Szymani and McDonald 1981; McMillin 1982; McMillin et al. 1984; Conners et al. 1987; Forrer et al. 1988, 1989; Butler et al. 1989; Koivo and Kim 1989; Conners et al. 1991). For many of these sensors, research continues to improve their capabilities. X-ray and solid-state camera systems are being marketed for scanning both softwood and hardwood lumber (Saul 1989).

The large effort underway to improve machine vision capabilities has not been matched by programs to increase software performance. Increased execution speed has been largely a function of improved hardware execution speed. An alternative, which is generally less expensive, is to develop software that executes at faster speeds, which is the solution pursued in this study.

Existing software systems for grading hardwood lumber simulate the performance of a lumber grader applying the National Hardwood Lumber Association (NHLA) grading rules (Franklin 1986, Klinkachorn et al. 1988, Moody et al. 1998). These rules are relatively complex and have numerous exceptions to the primary rules. In addition, cuttings must be laid out in many alternative ways to insure that the optimum selection of cuttings has been achieved. While this optimization process appears to be fairly simple when performed by a human grader, it is actually very complex. The complexity involved in the application of NHLA lumber grades (NHLA 2003) becomes very apparent when the process is reduced to a computer model.

One method of reducing the complexity of a computer solution is to substitute it with a simpler model. Such substitu-

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tion generally sacrifices some precision to achieve increased solution speed, but the degree of precision provided by the simpler model may be acceptable for the process involved.

In addition to a potential need to develop less complex models for the NHLA lumber grades, is the need to develop special grades. Some manufacturers develop special grades for their hardwood lumber buyers to satisfy their special requirements. Studies have also indicated that lumber for which NHLA rules do not exist such as character-marked (Buehlmann et al. 1999) and short lumber have potential as a marketable resource. Rational trade of new lumber types requires newly developed lumber grades. A simple, rapidly applied method to develop such grades would be desirable.

Objective

The objective of this project was to develop software to simulate the NHLA grading of hardwood lumber with a discriminant analysis model resulting in faster software execution speed.

Methods

The simulation of the NHLA grading rules with rapidly executing algorithms requires the development of alternative methods for measuring the area of clear cuttings available on lumber faces. It was considered important that the new methods eliminate the need to test numerous alternative patterns of cuttings layout. The numerous cuttings layout steps consume large amounts of computer solution time. The emphasis of the NHLA rules on the examination of clear areas is the reason for the need to lay out cuttings in multiple ways. Existing NHLA grading software systems correctly model this concentration on clear areas. However, a more direct and faster method of measuring available clear areas was hypothesized to be the consideration of the presence of defects on both lumber faces as indicators of the magnitude of available clear areas. This approach differs from the concentration of the NHLA lumber grading rules on only clear areas to assign a grade. Rather, the focus of our method is restricted to the size, location, and dispersion of the defects. Because defect types, sizes, and distributions vary by species, it is possible that the algorithms developed for each may differ somewhat. This may require a separate analysis and algorithm development for each species.

Clear areas available on a board surface are a function of defect number, size, and dispersion. It was hypothesized that accurate determination of this function would allow a more rapidly computed measure of clear areas and thereby accurately mirror the NHLA grading rules.

A measure that influences dispersion but is not directly related to the measurement of defect characteristics is board size. Obviously, all else equal, boards with the same numbers, sizes, and measured dispersion of defects will differ in relative clear area available if the relative board dimensions differ significantly. For this reason, variables indicating board size were considered.

Fifteen quantitative variables were formulated based on board size, number of defects, defect size, and defect dispersion. These variables were hypothesized to have potential influence on the available areas of clear cuttings. Information for the NHLA's First and Seconds (FAS), No. 1 Common (1C), No. 2A Common (2AC), and No. 3A Common (3AC) lumber grades (NHLA 2003) was obtained for each of these variables and the significance of each variable was tested at the 0.05 significance level to determine the extent to which it makes a unique contribution to the predication of grade membership. Selects and First and Seconds One-Face lumber grades were not analyzed in this study. They are not graded in the same manner as the remaining grades and were not included in order to simplify the analysis. Both Selects and First and Seconds One-Face grades are graded on the best board face while the grades employed in our study are graded on the poorest board face.

Table 1. — Volume and number of boards per NHLA lumber grade used in this study.

Grade	Volume (BF)	No. of boards
First and Seconds (FAS)	977	137
Number 1 Common (1C)	2,284	312
Number 2 Common (2C)	2,251	344
Number 3A Common (3AC)	1,514	215
Total	7,026	1,008

Description of the database

A discriminant analysis model for predicting the FAS, 1C, 2AC, and 3AC lumber grades was developed based on a digitally described database of red oak lumber. The lumber database is a component of the RIP-Xcut (Steele and Harding 1997, Steele et al. 2001) rough mill simulation software, which consists of 1,008 digitally described southern red oak boards. Fifty percent of the boards in the database were randomly selected for gathering information on each quantitative variable by lumber grade. The remaining 50 percent of the boards were used for testing the accuracy of the resulting model. **Table 1** gives the volume of the boards and the number of boards contained in each lumber grade of the RIP-Xcut lumber database.

Description of quantitative variables

Fifteen quantitative variables were tested for correlation with the available clear area on lumber surfaces. Six variables were based on board size, four were based on the number of defects, two were based on defect size, and three were based on defect dispersion.

Three of the variables chosen to indicate board size were board length (BOARDL), board width (BOARDW), and board area (BOARDA). These variables were expected to be positively correlated with lumber grade.

The number of defects in a board (ND) was presumed to be negatively correlated with lumber grade because the lumber grade should decrease as the number of defects increases. A measure of the number of defects relative to board size was also considered important. To measure the number of defects relative to board size, three variables were created. The first, NDWID, gave the ratio of the number of defects to the board width; the second, NDLEN, gave the ratio of the number of defects to the board length; and the third, NDARE, gave the ratio of the number of defects to the board area. These variables were expected to be negatively related to the lumber grade.

The size of defects was also expected to be of importance. Two variables were created to relate defect size to lumber grade. The first variable, ADEF, gave the ratio of the total area

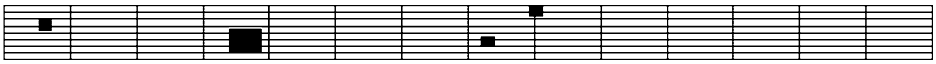

Figure 1. — Two-dimensional grid superimposed on a 140-inch board for the variable RATARE.

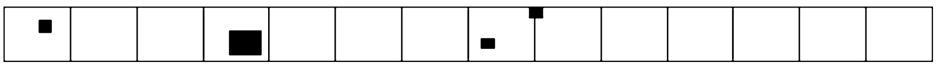

Figure 2. — Fourteen 10-inch length-wise sections superimposed on a 140-inch board for variables ADJSEC and DISP.

of defects to the board area. This variable was expected to provide an indication of the available clear area. Because NHLA grading rules restrict the amount of wane allowed on an FAS board, the second variable was based on wane defect size. This variable, AWANE, gave the ratio of the total area of wane defects to board area. These two variables were hypothesized to correlate negatively with lumber grade.

Defect dispersion was also considered to be a highly influential predictor of lumber grade. One important measure of defect dispersion is the approximate amount of clear area separating defects. To obtain a measure of dispersion, one variable, RATARE, was created by superimposing a two-dimensional grid on each board. The two-dimensional grid was constructed by dividing the board into 10-inch sections along the length and 1-inch sections along the width. The choice of the size of grid elements was arbitrary. **Figure 1** shows an illustration of this two-dimensional grid superimposed on a board.

RATARE gave the approximate percentage of available clear area by computing the percentage of the area occupied by grid sections that were completely defect free. RATARE was defined as the ratio of the total area of clear grid sections to the board area. RATARE was expected to have a positive correlation with lumber grade.

Although RATARE gave the percentage of the area of clear grid sections, a limited amount of information regarding defect dispersion was given by this measure. For example, a board that has defects grouped in a single region will have many contiguous clear grid sections and should have more available clear cutting area than an equally sized board with the same area of defects distributed throughout the board.

To measure defect dispersion along the board length, the 1-inch width-wise grid sections were eliminated, and two variables, ADJSEC and DISP, were created that measured the available clear contiguous 10-inch length-wise sections. **Figure 2** shows an illustration of the 10-inch length-wise sections superimposed on a board.

ADJSEC gave the ratio of the maximum number of clear contiguous length-wise sections to the board length. This variable was intended to indicate the approximate length of the longest clear cutting obtainable. DISP related clear blocks of length-wise sections to board area. This variable was intended to indicate the amount of clear area available for medium-to-long cuttings. DISP was computed by summing the lengths of clear blocks of 10-inch sections whose lengths exceeded a specified threshold value and dividing this sum by the board length. The threshold value was defined to be a given percentage of the board length. Clear blocks of 10-inch sections whose length did not exceed the threshold value were not counted in the computation of the DISP variable. Values of 5, 10, 15, 20, 25, 30, 35, and 40 percent of the board length were tested to determine the best threshold value. Twenty percent was found to yield the highest coefficient of determination value (r^2) for the DISP variable and was selected for inclusion.

To explain the computation of the DISP variable more clearly, consider the board shown in **Figure 3**. This board has a length of 140 inches and is thus divided into 14, 10-inch length-wise sections. The threshold value used for the computation of the DISP variable for this board is 28 inches (20% of 140 in). As can be seen, there are three separate blocks of clear length-wise sections for this board. The length of the first clear block (sections 2 and 3) is 20 inches. Because this length is less than the 28-inch threshold value, it will not be counted in the computation. The lengths of the second clear block (sections 5, 6, and 7) and the third clear block (sections 10 through 14) are 30 inches and 50 inches, respectively. Because these lengths exceed the threshold value, both will be counted in the computation. The computation of the DISP variable for this board is thus given by: DISP = (30 in + 50 in)/140 in = 0.571. ADJSEC and DISP were expected to have a positive relation with lumber grade.

Examination of the accuracy of an initial model revealed that the predicted grade of many boards containing defects on the ends or along the edges was also lower than expected. Apparently, defects on board edges and ends fail to prevent clear cuttings from being obtained to a lesser degree than if these defects were randomly dispersed over the board surface. To compensate for this, the board ends and/or edges containing defects were trimmed away before the values of the variables were computed. The "end" of the board was considered to be 2.5 percent of the board length measured from the board end, while the "edge" was considered to be 10 percent of the board width measured from the board edge. Because this trimming process caused a reduction in board area, three other variables based on board size were added. These variables included the board width after trimming (TBOARDW), the board length after trimming (TBOARDL), and the board area after trimming (TBOARDA). These three variables were expected to positively correlate with lumber grade.

Experimental discriminant analysis model

To determine which quantitative variables contributed the most to the discrimination between lumber grades, stepwise discriminant analysis was performed using the Statistical Analysis System (SAS) software (SAS 1989 to 2004). The significance level specified for the stepwise selection method was 0.05.

The distribution within each lumber grade was assumed to be approximately normal and the within-grade covariance matrices were shown to be unequal. Therefore, a parametric method was used in the SAS software to derive a quadratic discriminant analysis model for classifying each board into one of the four lumber grades on the basis of the most significant quantitative variables. The discriminant analysis model consists of a discriminant function and a probability distribution function. The discriminant function is based on a measure of generalized squared distance (Rao 1973) and the probability distribution function gives a membership probability for

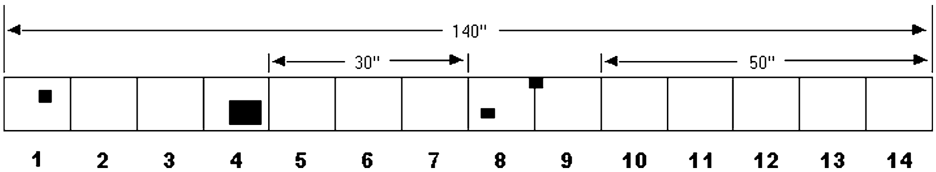

Figure 3. — Using the board in Figure 2 as an example, DISP is computed first by determining the threshold value based on 20 percent of the board length or 0.2 × 140 inches = 28 inches. Two clear lengths (30 in and 50 in) comprised of 10-inch sections exceed the 28-inch threshold for this example and are therefore summed to give a total clear length of 80 inches. DISP is then computed as the ratio of this 80-inch contiguous clear length to the total board length. Therefore, DISP = 80 inches / 140 inches = 0.571 in this example.

Table 2. — Easy cutting bill (referred to as "cabinet" by the USDA Forest Service [Gatchell and Walker 1997]).[a]

	Width						
Length	1.75 in.	2.00 in.	2.25 in.	3.75 in.	4.50 in.	5.00 in.	5.25 in.
(in.)							
10.00	100 (1,1)	0	0	0	0	0	0
12.25	50 (2,2)	0	0	0	0	0	200 (2,2)
13.00	0	0	200 (3,3)	0	0	0	0
13.50	0	0	0	50 (1,4)	0	0	0
14.50	0	0	75 (2,5)	0	0	25 (2,5)	0
15.00	550 (3,6)	1,000 (3,6)	0	0	0	0	100 (3,6)
18.75	400 (1,7)	200 (1,7)	400 (1,7)	0	0	0	0
20.50	100 (2,8)	50 (2,8)	450 (2,8)	0	0	0	0
21.00	0	0	0	0	150 (3,4)	0	0
22.50	0	0	400 (1,3)	0	0	0	0
24.75	1,150 (2,9)	650 (2,9)	1,150 (2,9)	0	0	0	0
27.75	500 (3,1)	0	0	0	0	0	0
28.25	0	0	700 (1,10)	200 (1,10)	0	0	0
31.50	0	100 (2,2)	0	0	0	0	0

[a]Values given are the number of pieces required for each length-by-width combination; values in parentheses are the individual crosscut and rip saw machine numbers to which these parts were assigned to be cut. Total number of parts: 8,950; average part width: 2.1 inches; average part length: 21.5 inches; approximate part volume: 2,806 BF.

each lumber grade for a given board. The discriminant analysis model is as described by Model [**1**]:

Generalized squared distance function:

$$D_j^2(X) = (X - \overline{X}_j)' COV_j^{-1} (X - \overline{X}_j) + \ln|COV_j| \qquad j = 1, 2, 3, 4 \qquad \text{Model } [\mathbf{1}]$$

Probability of membership in each grade:

$$P(j|X) = \frac{e^{-0.5D_j^2(X)}}{\sum_{k=1}^{4} e^{-0.5D_k^2(X)}} \qquad j = 1, 2, 3, 4$$

where j = respective lumber grade, i.e., 1 = FAS, 2 = 1C, 3 = 2AC, and 4 = 3AC; X = vector of quantitative variables for a given board; $\overline{X}_j$ = vector of mean quantitative variables for grade j; COV_j = covariance matrix within grade j; $D_j^2(X)$ = generalized squared distance of board X to grade j; $P(j|X)$ = probability of board X belonging to grade j.

Because the actual purpose of the NHLA grades is to classify lumber such that cutting orders may be produced from them with consistent expectation of the resultant yields, exact replication of the NHLA lumber grades may not be required in a simplified model. The best measure of the efficiency of the discriminant analysis model may be its accuracy in segregating lumber into categories such that part yield does not differ from that of lumber graded by NHLA rules. To test the efficiency of the discriminant analysis model, a comparison was made between the part yield of lumber graded by the NHLA grading rules and the part yield of the lumber graded by the discriminant analysis model.

The CUTSIM rough mill simulation software previously described by Steele et al. (1999) simulated the crosscut-first processing of three cutting orders. CUTSIM is a computer program that simulates a crosscut-first rough mill that employs manually operated crosscut saws and straight-line ripsaws. The three cutting orders used are referred to by the USDA Forest Service (Gatchell and Walker 1997) as "cabinet," "squire," and "tough." The three cutting orders are given in **Tables 2**, **3**, and **4** with a breakdown of the part dimensions and quantities within each cutting order. Numbers indicating the crosscut saw and straight-line ripsaw to which each part was assigned are given in parentheses to the right of the part quantities. The number of parts assigned to each machine directly influences the resulting yield as shown recently by Steele and Aguirre (2004). These researchers have shown that as greater numbers of cutting bill parts are assigned to machines, yields increase because parts fitting within the boards are more easily accomplished.

To generate replications, 20 random lumber samples were selected from each lumber grade from both the lumber database based on the NHLA grading rules and the lumber database based on the discriminant analysis model. For each lumber database, 240 crosscut-first simulation runs were made: 4 lumber grades × 3 cutting orders × 20 replications.

Required sample size for an analysis of variance (ANOVA) was determined by the power approach utilizing tabular values giving direct sample sizes. It was desired to detect a mean difference in yield both between each cutting bill and length class of two standard deviations or more. Further, Type I error was desired to be $\alpha = 0.05$, and Type II error $\beta = 0.10$; and the power of the test was therefore $1 - \beta = 0.90$. Based on these parameters, a tabular sample size value of eight was determined. This sample size is adequate for both factors of a two-factor ANOVA if the sample sizes are not extremely small (Neter et al. 1985). This condition was satisfied, rendering a replication sample size of eight for each factor adequate.

Table 3.— Moderate cutting bill (referred to as “squire” by the USDA Forest Service [Gatchell and Walker 1997]).[a]

Length	Width						
	1.50 in.	2.25 in.	2.75 in.	3.00 in.	3.25 in.	4.00 in.	4.25 in.
(in.)							
19.50	0	0	156 (1,1)	0	0	0	0
21.00	0	0	0	0	0	0	183 (2,2)
22.75	0	100 (3,3)	0	0	0	0	0
23.25	0	0	0	0	0	671 (1,4)	0
28.25	0	0	0	43 (2,5)	0	0	0
30.00	605 (3,6)	203 (3,6)	203 (3,6)	203 (3,7)	405 (3,7)	0	0
48.25	480 (2,8)	240 (2,8)	240 (2,9)	120 (2,9)	120 (2,9)	0	0
56.00	0	0	0	0	617 (3,4)	0	0
64.50	0	67 (1,3)	0	0	0	0	0
80.50	0	67 (2,1)	0	0	0	0	0

[a]Values given are the number of pieces required for each length-by-width combination; values in parentheses are the individual crosscut and rip saw machine numbers to which these parts were assigned to be cut. Total number of parts: 5,421; average part width: 2.8 inches; average part length: 38.3 inches; approximate part volume: 4,037 BF.

Table 4. — Difficult cutting bill (referred to as “tough” by the USDA Forest Service [Gatchell and Walker 1997]).[a]

Length	Width			
	2.00 in.	2.75 in.	3.50 in.	4.25 in.
(in.)				
15.00	325 (1,6)	175 (1,6)	250 (1,6)	0
18.00	100 (2,1)	0	0	0
25.00	250 (3,2)	250 (3,2)	0	0
29.00	0	0	0	400 (1,3)
33.00	300 (2,4)	0	0	0
38.00	0	0	250 (3,3)	0
45.00	0	600 (1,4)	0	0
50.00	400 (2,5)	0	600 (2,5)	200 (2,5)
60.00	0	0	100 (3,1)	0
72.00	0	150 (1,3)	0	300 (1,2)

[a]Values given are the number of pieces required for each length-by-width combination; values in parentheses are the individual crosscut and rip saw machine numbers to which these parts were assigned to be cut. Total number of parts: 4,650; average part width: 3.0 inches; average part length: 39.1 inches; approximate part volume: 3,788 BF.

However, a sample size of 20 was utilized for the sake of convenience.

Model [**2**] was developed to test the influence of the lumber grading method and cutting order on lumber yield.

$$Y_{ij} = \mu + M_i + C_j + M_i \times C_j + \varepsilon_{ij} \qquad \text{Model [2]}$$

where Y_{ij} = lumber yield for lumber grading method i and cutting order j (i = 1,2; j = 1,2,3); μ = population mean lumber yield for all lumber grading method-cutting order combinations; M_i = effect of lumber grading method i (i = 1,2); C_j = effect of cutting order j (j = 1,2,3); $M_i \times C_j$ = effect of lumber grading method i by cutting order j interaction (i = 1,2; j = 1,2,3); ε_{ij} = error term for lumber grading method i and cutting order j (i =1,2; j = 1,2,3).

Results and discussion

Eight of the 15 quantitative variables tested by the stepwise discriminant analysis procedure were significant, including three variables based on defect dispersion (RATARE, ADJSEC, DISP), two variables based on board size (BOARDL, TBOARDW), one variable based on defect size (ADEF), and two variables based on defect numbers (NDLEN, NDWID). The variables not found to be significant consisted of one variable based on wane defect size (AWANE), four variables based on board size (BOARDA, BOARDW, TBOARDL, TBOARDA), and two variables based on defect numbers (ND, NDARE).

The most significant variable was DISP, whose partial r^2 value was 0.70. RATARE was highly significant with a partial r^2 value of 0.31. ADEF’s partial r^2 value was 0.12 and ADJSEC’s partial r^2 value was 0.11. The partial r^2 value for each of the remaining four variables (BOARDL, NDLEN, TBOARDW, NDWID) was less than 0.06.

Because the partial r^2 value of the four least important variables (BOARDL, NDLEN, TBOARDW, NDWID) was small, their contribution to the discriminatory power of Model [**1**] was considered to be insignificant. For this reason, and to reduce the amount of data collection required, these variables were not included in the model.

After the accuracy of Model [**1**] was examined, some FAS boards containing only one small defect on the grading face were being graded as 1C. A method was needed that would lead the model to grade boards such as these as FAS. A rule was adopted that eliminated the defect before grading to allow the model to grade these boards as FAS. To apply this rule, the model had to be able to properly identify these boards. An examination of these boards revealed that the ratio of the grading face defect area to the board area did not exceed 0.025 for most boards. Therefore, during the grading process, if the ratio of the grading face defect area to the board area did not exceed 0.025, the defect was removed. This method allowed the model to grade the majority of these boards as FAS.

The predicted grades of Model [**1**] were compared to the NHLA grades. **Table 5** gives the distribution of the predicted grades for each NHLA grade. The model predicted the FAS grade with 92.8 percent accuracy, the 1C grade with 75.0 percent accuracy, the 2AC grade with 66.3 percent accuracy, and the 3AC grade with 74.1 percent accuracy. The overall accuracy of Model [**1**] for all grades was 74.3 percent. Model [**1**] graded 15.8 percent of the boards above their NHLA grade and graded 9.9 percent below their NHLA grade.

A comparison was made between the computer time required for Model [**1**] to execute to that of the UGRS system developed by Moody et al. (1998), which is a hardwood lumber grading software system that grades hardwood lumber based on NHLA grading rules. On an IBM compatible Pentium 4 PC with a 2.0-GHz processor, UGRS graded the database of 252 boards in 12 minutes and 51 seconds. Model [**1**] graded the boards in approximately 1 second; this includes the computational time required to compute the values of the

*Table 5. — Model [**1**] predicted grade distribution for each NHLA grade.*

NHLA grade	Model [**1**] predicted grade	Distribution
		(%)
FAS	FAS	92.8
	1C	7.2
	2AC	0.0
	3AC	0.0
1C	FAS	9.0
	1C	75.0
	2AC	16.0
	3AC	0.0
2AC	FAS	0.0
	1C	22.1
	2AC	66.3
	3AC	11.6
3AC	FAS	0.0
	1C	0.0
	2AC	25.9
	3AC	74.1

quantitative variables. Hence, Model [**1**] executed approximately 771 times or 77,000 percent faster than UGRS.

Cutting order yield test results

The results of the Model [**2**] ANOVA, which examined the variability in yield for the different lumber grading methods and cutting orders, showed both main effects (grading methods and cutting order) to be significant at the 0.05 significance level. The interaction term $M_i \times C_j$ representing lumber grade and cutting order was not significant. The significance of all terms satisfied Fisher's Protected LSD Tests allowing performance of comparison-of-means tests. Absence of interaction allowed performance of comparison-of-means tests.

Comparison-of-means test results are given in **Table 6**. The discriminant analysis-based grading system's estimates of yield for the FAS and 2AC lumber grades differed significantly from those of the NHLA-graded lumber. However, yields for the 1C and 3AC lumber grades did not differ significantly. The difference between discriminant analysis and NHLA-based yields for FAS and 2AC lumber, while significant, were only 0.73 and 1.3 percent, respectively. These small differences in yield between the discriminant analysis and NHLA graded lumber indicate that, while some errors existed in identifying lumber grades by the discriminant analysis method, little difference in yields existed. This finding indicates that a discriminant analysis model approach for the automated grading of hardwood lumber has potential.

Summary

A discriminant analysis model was developed to predict lumber grades based on lumber defect characteristics in hardwood lumber. The defect characteristics were board size, number of defects, defect size, and defect dispersion. Fifteen quantitative variables were hypothesized to influence lumber grades. Stepwise discriminant analysis showed that 8 of the 15

Table 6. — Mean lumber yield (for 20 replications) for each lumber grade for the three cutting orders. Means with the same capital letter within each grade did not differ significantly.

	Lumber grading method	
Lumber grade	NHLA	Discriminant analysis model
FAS	74.4 A	73.7 B
1C	63.4 A	63.1 A
2AC	53.4 A	52.1 B
3AC	46.4 A	45.6 A

variables contributed to the discrimination between the grades. The best four-variable model was chosen to reduce the amount of data collection and computation. This model predicted the lumber grades FAS, 1C, 2AC, and 3AC with accuracies of 92.8, 75.0, 66.3, and 74.1 percent, respectively. The overall accuracy of the model for all grades was 74.3 percent.

The mean parts yields obtained from the lumber graded by the NHLA grading rules and the lumber graded by the discriminant analysis model were compared by simulating the crosscut-first processing of three cutting orders using a rough mill simulation model. For the 1C and 3AC lumber grades, the yields between lumber graded by the two methods did not differ significantly. A statistical difference was detected for the FAS and 2AC lumber grades but actual yield differences were only 0.73 and 1.3 percent, respectively.

Although the grade estimation success rates of the discriminant analysis procedure indicate that this approach requires improvement, the results in predicting yield percentages indicate some potential. For those who require special grades and for future rapid development of lumber grades, the discriminant analysis approach may be a viable and inexpensive approach.

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