Design of a Total Revenue Forecasting Tool to Estimate the Economic Output of Hardwood Logs

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Abstract

This article introduces a total revenue forecasting tool designed for calculating the economic output of visually graded hardwood lumber. The tool integrates Monte Carlo simulation from previous studies' data, providing a pseudoestimation of total board-feet based on log grades. The lumber output from different log groups is modeled using probability distributions for each lumber grade. The estimated volume output is multiplied by the respective price for each grade, leading to an expected amount of economic output for given log-grades. The tool was implemented using Microsoft Excel 2016 and Visual Basic. This work provides hardwood lumber producers with a valuable and simple tool to determine different scenarios of total income from each log, as established by the user with a statistical perspective. This total revenue forecasting tool provides the industry with a way to reduce waste and estimate their potential revenue by maximizing the interaction between the log yield's variables and providing the economic output of log, leading to an improvement of the economy of the hardwood market.

Log yields can be measured and estimated based on historical economic output data of logs. Various physical and morphological wood properties are the major dependent variables that determine the log yield (Thomas 2013). The major contributor of lumber quality output from a log is the quality of the log, which is highly influenced by the defects, dimension, and grain orientation. The nature of defects and dimensional parameters such as diameter and length poses a greater degree of variability, which makes it harder to estimate log yields more precisely (Thomas 2013).

Current mathematical models such as logistic and binary regression, and linear and multiple regression, have been used in an attempt to develop a method of predicting the yield of hardwood lumber from logs (Liu and Zhang 2005, Liu et al. 2007, Øvrum and Vestl 2009, Grushecky and Hassler 2011, Barrette et al. 2013, Auty et al. 2014). Nevertheless, variables such as the number of clear faces, log diameter, and log length tend to make predictions difficult because regression models are limited to studying the interaction effects between the variables (Osborne 2015). Additionally, models tend to overpredict volumes because the sawing optimization technology utilized in commercial sawmills is unable to analyze the internal defects (Zhang and Tong 2005, Lyhykäinen et al. 2009). The use of regression models to estimate hardwood lumber grade yields is limited to constant input values without considering nature's randomness. For example, the logistic regression model proposed by Øvrum and Vestl (2009) is limited to estimating the log yield based only on the log length using average prices, which create a bias across the different grades obtained from the log and leads to an over- or underestimation of the log yield.

Regardless of the mathematical models proposed by the previous authors, there are no documented computer programs based on these models that could provide practitioners with forecast estimates of their total economic output in their log inventory based on historical output data from logs. The log yield estimation tool presented in this article is an application of the research conducted by Quesada et al. (2019), who developed a probability-based model that can precisely estimate log yield from various log-grade groups. This analytical tool would help hardwood lumber manufacturers decide how to best process their logs to increase revenue and measure the economic output of lumber inventory. The tool interface provides a simple way

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to choose the quality of the logs to be processed, as well as to predict possible revenue with multiple scenarios from different log grades, based on potential sales prices.

Data Processing

There is a lack of studies on forecasting the economic impact of log yields on the hardwood lumber industry. The Monte Carlo tool presented in this article is an effort to bridge this gap. This article provides a better understanding of the economic output of lumber and inventory value. In addition, this method allows sensitivity and risk analysis to be conducted to obtain more reliable information, thus enabling better decision-making in the lumber industry. The development of this revenue estimating tool is based on the work conducted by Quesada et al. (2019). This research used a probability-based Monte Carlo simulation to predict lumber grade yields from log groups. The log groups were created based on log grades, diameters, and lengths. The logs were commercially classified as Red Oak logs.

Monte Carlo simulation offers an alternative to analytical mathematics for understanding a statistical sampling distribution and evaluating its behavior in random samples (Mooney 2011). A major advantage of using this method is that the evaluation model uses a random input that provides a better approximation of reality. The mathematical procedure comes with random inputs and random outputs: $y = f(X_1, X_2, ..., X_n)$, where the input values are sampled and the output values are recorded and analyzed (O'Connor and Kleyner 2011). This method obtains a good approximation of the theoretical distribution in all cases, even when there is no analytical solution or the solution is very complex.

For years, the Monte Carlo method provided a variety of uses that work around uncertainty, and it has been a valuable tool for many types of businesses and studies. This method has a large variety of applications that work with reliability, availability, logistics forecasting, risk analysis, load-strength interference analysis, random processes simulation, probabilistic design, and other applications (O'Connor 2011). This method is suitable for the pricing and the hedging of complex path-dependent options, particularly if the number of relevant assets involved is large or if additional randomness is included in the model (Arouna 2004). Other applications include identifying the impact of different approaches on the cost/revenue structure for a typical sawmill in a given evaluation period, identifying the critical factors affecting the profitability of various treatments in irregular softwood stands, and assessing the uncertainty associated with critical factors and profitability (Moore et al. 2011).

The data relationships of the Total Revenue Forecasting Tool (TRFT) are displayed in Figure 1, where an entity-relationship model shows how each entity or component in the database is connected to run the interface of the tool or program. The entities or data tables in the program are as follows: Clear Face Codes, Log-Grade Group, Clear Face Prices, Pricing, and Results. Each of the Clear Face Code entities has a one-to-one relationship with the Pricing attribute, by its respective price, from each quality. The Results entity comes from the relationship of Log-Grade group to Pricing, providing the result by multiplying the respective price of the lumber with the number of board-feet obtained in the Log-Grade Group entity.

Input and Output Analysis

An input parametric data model is used to adjust results to predetermined conditions, and random input will provide a better approximation of reality (Biller and Gunes 2010). Each of the 24 log-grade groups in this study had a corresponding probability distribution to model the input parameters as determined by Quesada et al. (2019). The lumber recovered from each log is based on the grading rules defined and managed by the National Hardwood Lumber Association (NHLA) grading system. A summary of the NHLA rules is presented in Table 1.

Historical data are needed to develop an estimation when using Monte Carlo simulation. The first step is to analyze the input data to understand their behavior according to their probability distribution function. In the study conducted by Quesada et al. (2019), an inverse cumulative probability distribution function (ICPDF) was determined based on the behavior of the experimental data. The data used were collected by Grushecky and Hassler (2011). Specifically, the lumber output data were fitted to continuous probability distributions, including Normal, Exponential, Lognormal, Gamma, Weibull, and two of the Johnson Transformations: Johnson Sl and Johnson Su. The ICPDF and their corresponding parameters are used to simulate the number of board-feet obtained from a certain log-grade group. The ICPDF works alongside random numbers in the function, so that every time a run is processed, a new number is generated and stored in the spreadsheet database.

A partial view of the NHLA grading rules and the log groups used in this study is shown in Table 2. In this case, 24 log groups and 10 NHLA grades were used, for 240 total combinations of grades and log groups and their respective prices. The ''A'' value represents the number of board-feet (bf) generated from the simulation on each grade for each group. For example, the cell A_{11} represents the simulated output of ''first and second'' (FAS) graded lumber from the log group 10-0-8. This output will be multiplied by the market value of FAS grade in dollars per board-feet and the number of logs in the log group. The coded price per NHLA grade is shown in Table 3, assigned as ''B''.

Equation 1 shows the formula used to calculate the total revenue. To obtain the economic output value from each board-foot that is extracted from log-grade group *A* from a certain grade; it must be multiplied by its respective price *B*, and *C* is the number of logs for the respective grade.

$$\text{Total revenue} = \sum_{n=1}^{i=24} (A_{i1} \times B_1 \times C_1 + A_{i2} \times B_2 \times C_2 + ... + A_{i10} \times B_{10} \times C_{10})$$

For example, if the log-grade group 14-3.8 generates a simulated value of 5.022 bf of FAS-graded lumber, this volume is then multiplied by the FAS grade price (in this case US$0.91/bf). Therefore the total is US$4.55. This same revenue calculation is conducted for the simulated output of each grade (F1F, SEL, 1 COM) and then their values are added to obtain the total. In general, sawmills have an inventory of different log types (log-grade group), so the revenue per log-grade group must be multiplied by the total number of logs that the sawmill has in the inventory of that group. The simulation is set for 1,000

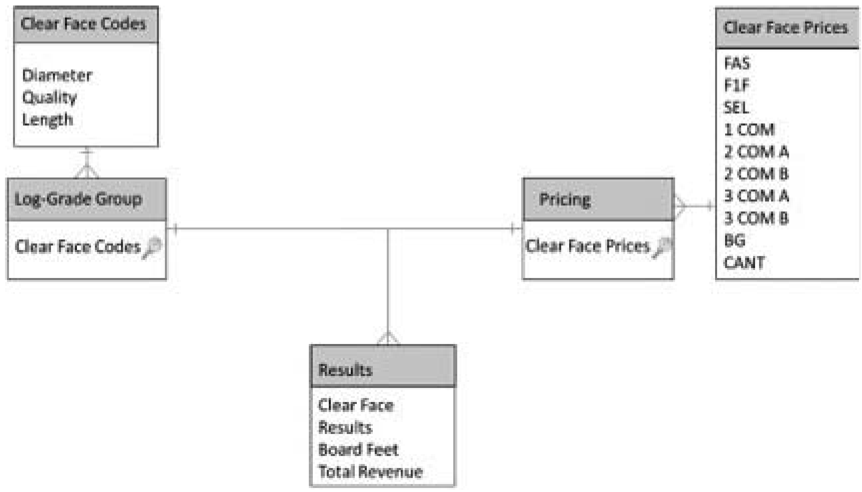

Figure 1.—Entity-relationship model for the Total Revenue Forecasting Tool.

Table 1.—Standard grades of hardwood lumber. Source: Grushecky and Hassler (2011).

Classification	Characteristics	April 13, 2018 prices (US$/bf)[a]
FAS: First and Seconds	The best and most expensive grade. Boards 6″ and wider, 8′ and longer. Yields 83-1/3 percent of clear face cuttings with minimum sizes of 4″ × 5′, or 3″ × 7′. Board graded from better face.	1.225
F1F: FAS One Face	Same as FAS except the board is graded from the better face.	1.215
SEL: Selects	Boards are 4″ and wider, 6′ and longer. Yields 83-1/3 percent clear face cuttings with minimum sizes of 4″ × 5′, or 3″ × 7′. A cost-effective substitute for FAS when only one good face is required or smaller cuttings are acceptable.	1.205
1C: No. 1 Common	Boards are 3″ and wider, 4′ and longer. Yields 66-2/3 percent clear face cuttings with minimum sizes of 4″ × 2′, or 3″ × 3′. Provides good value, especially if relatively small pieces can be used.	0.93
2AC: No. 2A Common	Boards are 3″ and wider, 4′ and longer. Yields 50 percent clear face cutting 3″ and wider by 2′ and longer.	0.625
2BC: No. 2B Common	Suitable for some paneling and flooring applications.	0.575
3AC: No. 3A Common	Boards are 3″ and wider, 4′ and longer. Yields 33-1/3 percent clear face cuttings 3′ and wider by 2′ and longer. Economical choice for rough utility applications.	0.565
3BC: No. 3B Common	Boards are 3″ and wider, 4′ and longer. Yields 25 percent clear face cuttings 1-1/2′ and wider by 2′ and longer. Applications same as No. 3A Common.	0.515
BG: Below Grade	Lumber poorer in quality than 3BC and all above.	0.48
Cants	Log with slab taken off each of four sides.	0.45

[a] bf = board-feet.

repetitions, as suggested by the Monte Carlo simulation procedure. The tool automatically aggregates the calculations based on the price and number of logs selected by the end user. The tool then provides a set of graphs that display the minimum, maximum, average, and median values of the simulated revenue, as well as the number of board-feet that can come from the logs in each grade.

Limitations

1. The outcomes were limited to the output data analyzed by Quesada et al. (2019).
2. This study was limited to a database that only used the classification rule of Clear Faces grading of logs.
3. The outputs provided by the tool were the gross values of the product.

Table 2.—Board-feet matrix for each log-grade group with clear face. See Table 1 for definitions.

	Grade (bf)									
Log-grade group	FAS	F1F	SEL	1 COM	2A COM	2B COM	3A COM	3B COM	BG	CANT
10-0,8	$A_{1\ 1}$	$A_{1\ 2}$	$A_{1\ 3}$	$A_{1\ 4}$	$A_{1\ 5}$	$A_{1\ 6}$	$A_{1\ 7}$	$A_{1\ 8}$	$A_{1\ 9}$	A_{110}
10-1,8	$A_{2\ 1}$	$A_{2\ 2}$	$A_{2\ 3}$	$A_{2\ 4}$	$A_{2\ 5}$	$A_{2\ 6}$	$A_{2\ 7}$	$A_{2\ 8}$	$A_{2\ 9}$	$A_{2\ 10}$
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17-4,12	$A_{24\ 1}$	$A_{24\ 2}$	$A_{24\ 3}$	$A_{24\ 4}$	$A_{24\ 5}$	$A_{24\ 6}$	$A_{24\ 7}$	$A_{24\ 8}$	$A_{24\ 9}$	$A_{24\ 10}$

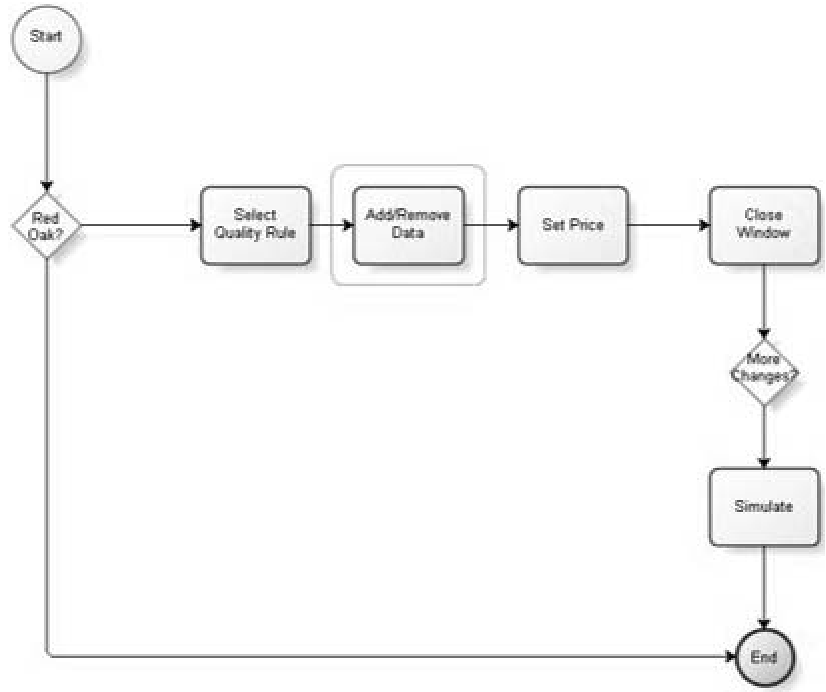


Figure 2.—Flowchart for the use of the Total Revenue Forecasting Tool.

4. This tool is limited to only Red Oak commercial logs and related species.

Total Revenue Forecasting Tool: Overview

The following is a description of the main functions integrated into the TRFT. A summary of the steps used in the tool is presented in Figure 2.

To initiate the program, the user has to click on the button ''Total Revenue Forecasting Tool'' as shown in Figure 3.

When the user clicks the button, the interface in Figure 4 is shown. The log-grade group is the combination of the diameter of the log, quality of the log, and length of the log. The user can select a log-grade group that is in the table shown on the right side of the figure. To select a log-grade group in the tool, the user must click on the list box in section A, as presented in Figure 4. Section B in Figure 4 displays a table with all the groups that the user has selected to be simulated.

In Figure 5, an example is displayed in which the user wants to change the number of logs in the log-grade group ''13-2, 8'' (Diameter-Quality, Length). The program has zero logs for this group already established because of a previous iteration, but the user has 25 logs in inventory.

To make the necessary changes in the inventory in the program, the user must update the number of logs by typing the correct amount in the box next to ''Number of Logs'' and then hit the button ''Add Data,'' and the table will automatically update. In Figure 6, the change was made from zero logs to 25 logs. The user can check the total number of logs at the end of the table to make sure that the changes were made.

The user also has the option to adjust the prices of the NHLA grades. To make changes for each grade's price, the user must press the ''Pricing'' button. A window will open with the prices that were recently used. These can be modified by typing the new price and pressing the ''Set Price'' button as shown in Figure 7.

Once all the changes are made, the window must be closed, and the user can hit the button ''Simulate,'' to start the program, which might take several seconds. When the simulation is ready, a new sheet will open with a bar graph that represents the range of total profits that can be obtained based on the logs and price typed, displaying the average, minimum, and maximum revenue, as shown in Figure 8. The tool also will display the economic output from each

Table 3.—Price matrix for the lumber grade. See Table 1 for definitions.

Grade	Price (US$/bf)
FAS	B1
F1F	B2
SEL	B3
1 COM	B4
2A COM	B5
2B COM	B6
3A COM	B7
3B COM	B8
BG	B9
CANT	B10

Figure 3.—Total Revenue Forecasting Tool button.

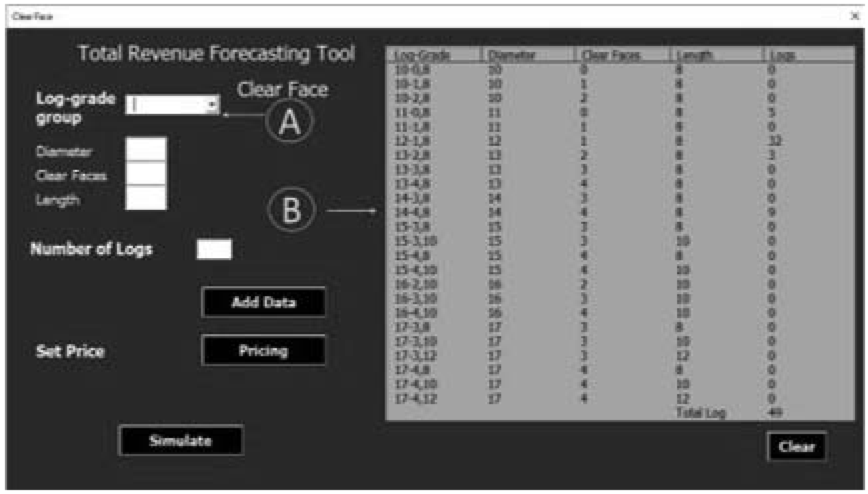


Figure 4.—Simulator interface.

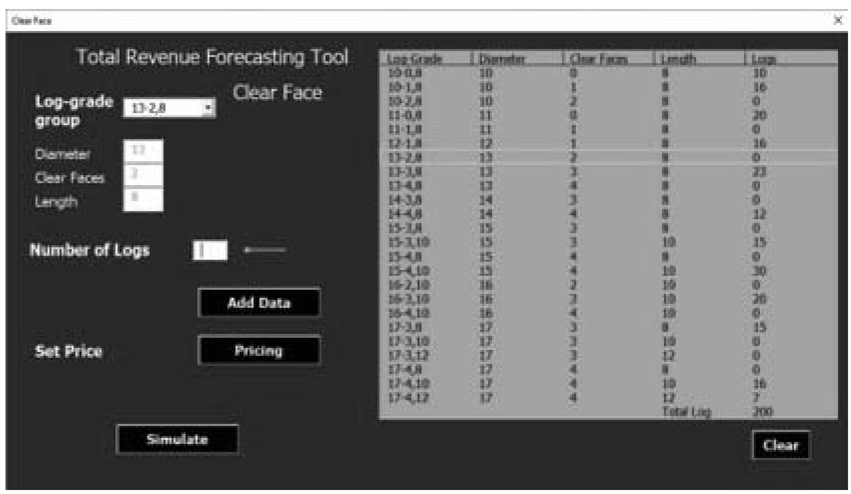


Figure 5.—Number of logs.

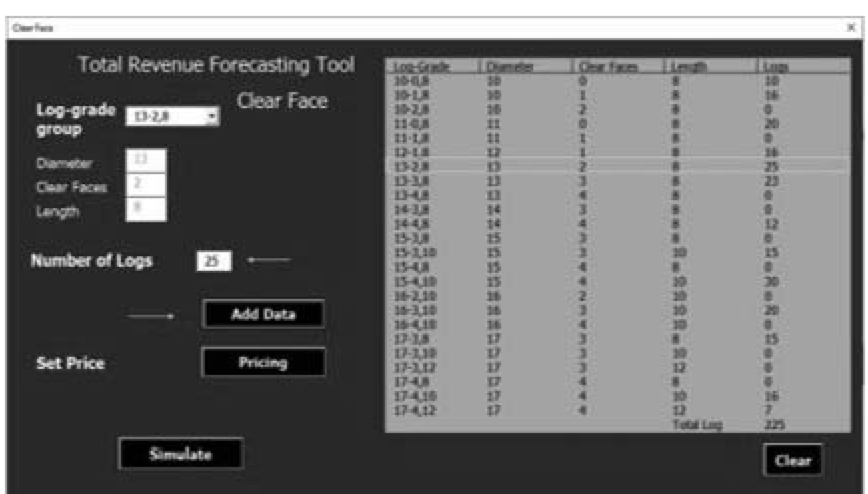


Figure 6.—Updating logs.

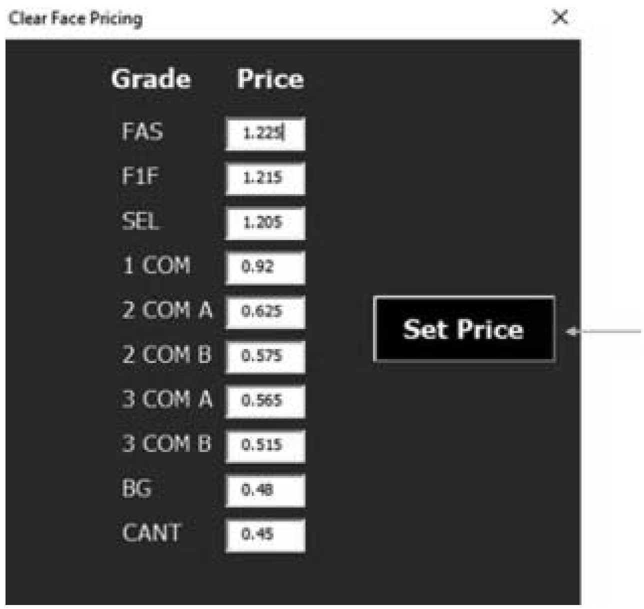


Figure 7.—Pricing.

Table 4.—Example of supplier's inventory.

Log-grade group	No. logs
Supplier 1	
10-0,8	10
10-1,8	16
10-2,8	20
11-0,8	20
11-1,8	15
12-1,8	16
13-2,8	25
13-3,8	23
13-4,8	17
14-3,8	11
14-4,8	12
15-3,8	15
15-3,10	15
Total	215
Supplier 2	
13-2,8	25
13-3,8	23
13-4,8	20
14-3,8	15
14-4,8	12
15-3,8	15
15-3,10	15
15-4,8	10
15-4,10	30
16-2,10	5
16-3,10	20
17-3,8	15
17-3,10	5
Total	210

grade for the two rules and a chart with the number of board-feet that can be extracted for each grade.

As previously discussed, the tool works with only Red Oak commercial species and a certain number of log-grade groups, limiting sawmills from estimating the economic output coming from other species. The availability of log yield studies in the hardwood industry that provide further data on other species continues to be a problem. However, if the data are available, they can be added to this forecasting tool. The main purpose of this tool is to achieve an expected total economic output quickly and easily using statistical parameters. If the user is not interested in the economic

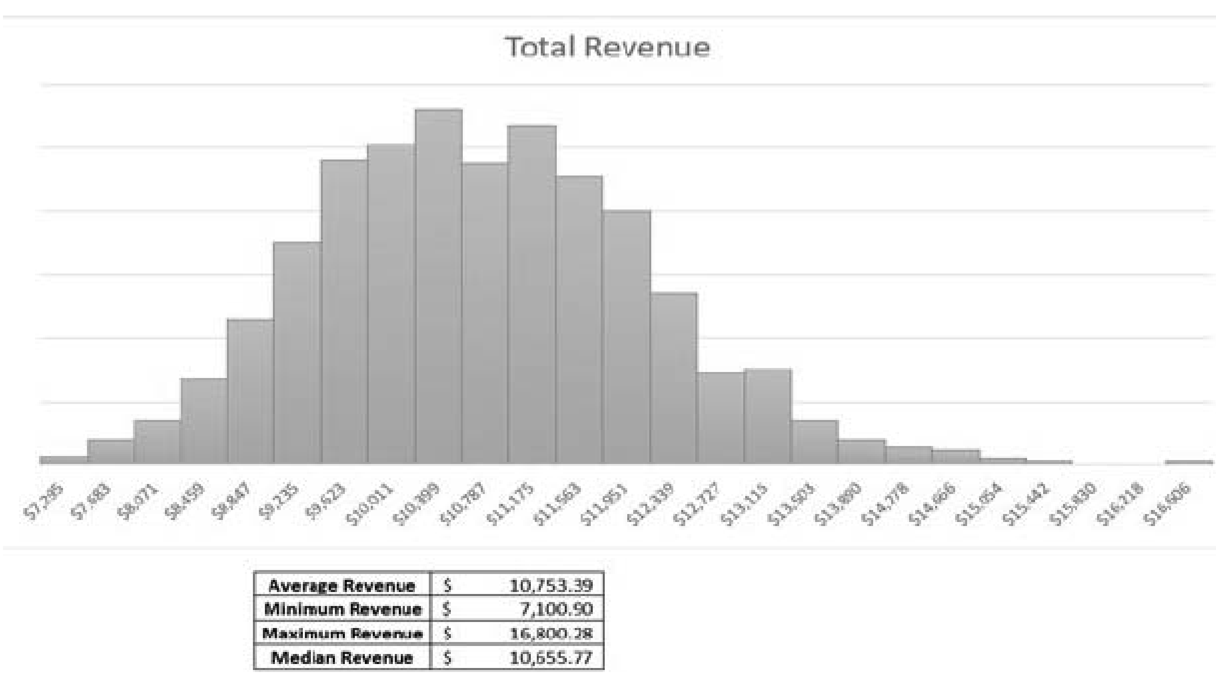


Figure 8.—Total revenue range.

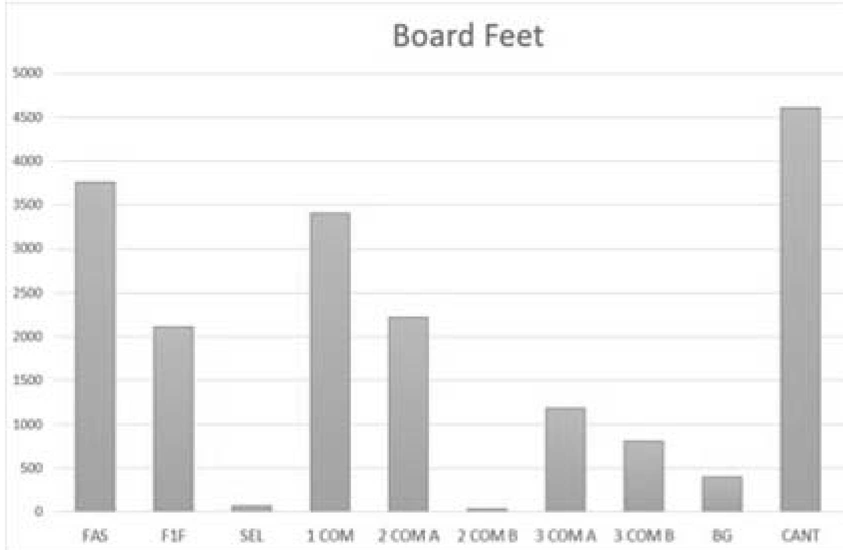
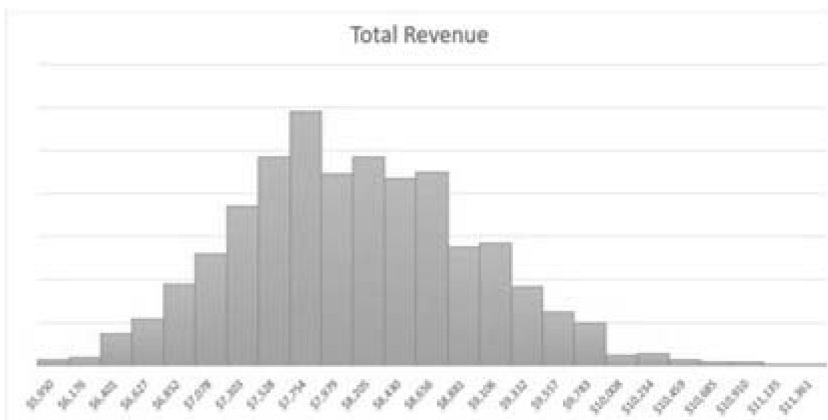


Figure 9.—Board-feet.



Average Revenue	$	8,112.70
Minimum Revenue	$	5,837.61
Maximum Revenue	$	11,473.56
Median Revenue	$	8,052.74

Figure 10.—Total economic output, using raw material from Supplier 1.

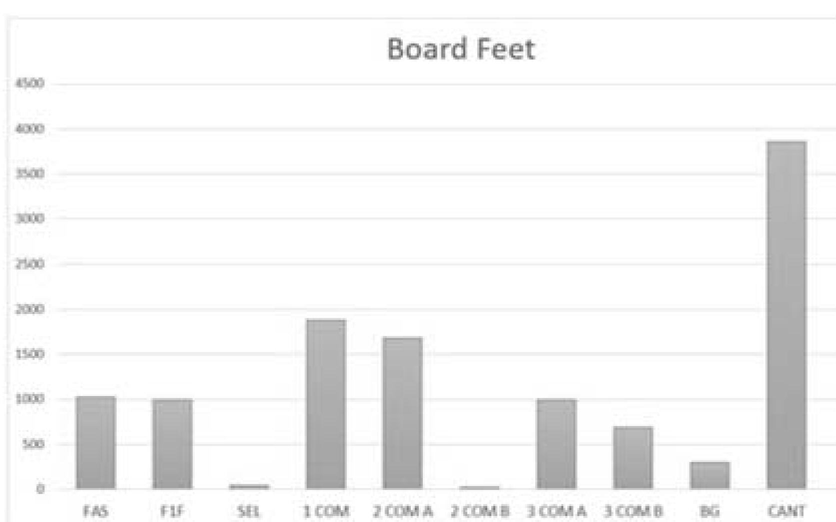
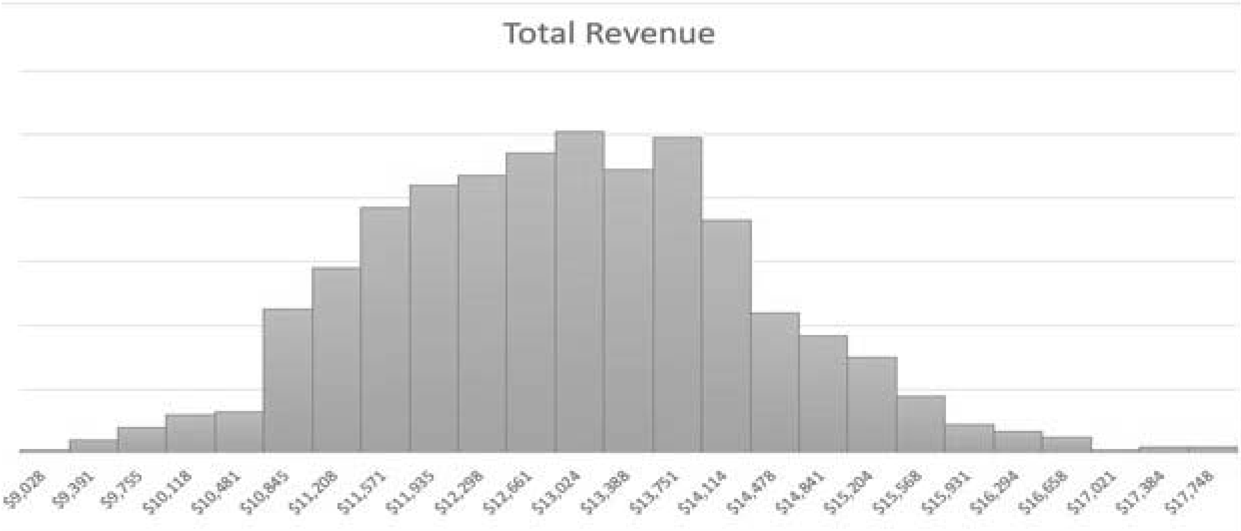


Figure 11.—Board-feet from Supplier 1.



Average Revenue	$	12,925.98
Minimum Revenue	$	8,846.36
Maximum Revenue	$	17,929.19
Median Revenue	$	12,912.88

Figure 12.—Total economic output using raw material from Supplier 2.

output of the log, the tool also provides estimation in board-feet, as displayed in Figure 9. The TRFT will provide sawmills with a structured method to assign batches and gross prices.

Application Example

Next, a brief case is presented to understand how the tool works for forecasting revenue from timber. With two suppliers, the user may be able to estimate which supplier can deliver the greatest revenue from the logs. With the proposed tool, the practitioners will have a better understanding of how much revenue can be obtained from different logs, helping them understand the economic impact of logs. The information on the raw materials brought by the suppliers is displayed in Table 4.

Using the TRFT, total economic output that can be provided by Supplier 1 by selling the lumber for the respective prices of each quality is US$5,837.61 to US$11,473.56, as shown in Figure 10. Most of this revenue comes from the CANT quality, which may be the reason for the low revenue from this set of logs, as shown in Figure 11.

For Supplier 2, the chart provided by the tool (Fig. 12) shows more revenue, with a median of US$12,912.88 and a range between US$8,846.36 and US$17,929.19. By comparing the median outcomes from both suppliers, the best choice is the raw material provided by Supplier 2 because it provides approximately 60 percent more revenue than that provided by Supplier 1.

Grade prices and logs amounts will vary each time new logs arrives and are measured, but this tool provides sawmills with a way to simulate different scenarios regarding the yields from logs. Total economic output from the log can be estimated using characteristics of the log. The ability to change both grade prices and log amounts will enable users to create different scenarios, using a structured method.

Uses for the TRFT vary for different sawmills. These uses can include maximizing the economic output from logs, avoiding low log yield, and most importantly having a standard method to assign prices for batches with mixed grades or for each grade. There also are many differences between big and small sawmills, and difference in the number of logs each can process is significant. Bigger sawmills may care primarily about maximizing economic output from logs, and small sawmills may be more focused on delivering maximum amount of board-feet from individual logs. This tool will help different departments (such as sales or production) in a sawmill because knowing the characteristics of a log before it is transferred to the workplace will affect inventories, production capacities, and even work rhythms.

This tool should be used by top management personnel in the sales department or the production department, but not both, because the tool provides a simulation and every scenario generated is different. If the input parameters are not the same in both departments, this could cause conflicts within the organization. This tool successfully evaluates different scenarios based on supply simulations. Sawmills must know how to maximize their economic output or how can they avoid getting the minimum value, instead of working with information based on the mean value. The next step for this tool is to consider the manufacturing cost of timber because these prices tend to vary with each sawmill. With this approach, sawmills can include their production cost, providing users with an accurate estimate of the total revenue of processing timber.

General Information

Microsoft Excel 2013 (Microsoft Corporation, USA) or later versions for Windows are required to run this tool, which can be obtained at https://sim.sbio.vt.edu/.

Summary

1. This tool provides information on log yield that allows hardwood sawmills to make decisions before processing a log.
2. The use of TRFT can vary for different sawmills. TRFT allows sawmills to simulate maximizing the economic outputs from logs, and most importantly, have a standard method to assign prices for batches with mixed grades or for each grade.
3. This tool facilitates the estimation of log yield with the interaction of length, diameter, and number of clear faces.

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