Application of Monte Carlo Simulation to Harwood Lumber Yields

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Introduction

- Current hardwood production is 9.3 billion board feet
- Majority of hardwood lumber is manufactured by small to medium-size sawmills (Luppold 2015)
- Export and industrial hardwood lumber market share is 77%
- Volume of low-grade lumber has increased (Cumbo et al. 2003)
- Lack of models to accuraterly predict lumber grade yields (Grushecky 2011)

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Hardwood log grades

- Main variables impacting lumber yield are (Denig et al. 1984):
  - Knots
  - Stains
  - Knobs
  - Holes
  - Length
  - Diameter
- Log quality is the most important factor in predicting log yields
- Clear cuttings by USFS
  - Second worst face of the log
- Clear face
  - Defect-free faces

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Criteria for Hardwood Lumber Grades and Prices per Grade

- Hardwood lumber grades and prices per grade

Grade	Trade Name	Min. Board Width	Min. Board Length	Min. Cutting Size	Min. Area of Clear Cuttings Required	Revenue ($/bf)
Firsts and Seconds	FAS	6 in	8 ft	4 in × 5 ft or 3 in × 7 ft	83⅓%	0.91
FAS One Face	F1F	6 in	8 ft	4 in × 5 ft or 3 in × 7 ft	83⅓%	0.89
Select	SEL	4 in	6 ft	4 in × 5 ft or 3 in × 7 ft	83⅓%	0.9
No. 1 Common	1C	3 in	4 ft	4 in × 2 ft or 3 in × 3 ft	66⅔%	0.58
No. 2A Common	2AC	3 in	4 ft	3 in × 2 ft	50%	0.46
No. 2B Common	2BC	3 in	4 ft	3 in x 2 ft	50%	0.41
No. 3A Common	3AC	3 in	4 ft	3 in x 2 ft	33⅓%	0.385
No. 3B Common	3BC	3 in	4 ft	1½ in × 2 ft	25%	0.3
Below Grade	BG	Lumber with lower quality than 3BC				0.35
CANTS	CANTS	Logs with slabs taken off each of the four sides				-

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Lumber yield prediction models

- Strength and weaknesses of prediction techniques

Method	Strength	Weakness
Regression model to use the artificial neuron network model, lumber volume, lumber value, chip volume, and total product value	Was able to predict the lumber yields, assess them from multiple aspects, and develop confidence in yield prediction	Only two out of the five equation models were able to accurately predict for this study
Logistic regression/binary logistic regression	Better than other regression models and more accurate prediction	Model is compromised when prices change
Poisson regression	Able to produce an optimized log yield	Does not relate to economic income
Monte Carlo simulation	Capacity to adopt variation in inputs, ease of continuous improvement, and follows the theorem of large numbers, which improved the prediction precision	Assumes that all of the parameters vary independently, so excludes potential correlations among variables

Objectives of the study

- To conduct Monte Carlo simulation and develop a Multiple Linear Regression (MLR) equation based on existing log yield data
- To analyze log yield output based on visual grading of hardwood logs
- To compare the results with actual yield to measure the effectiveness of the purposed method.

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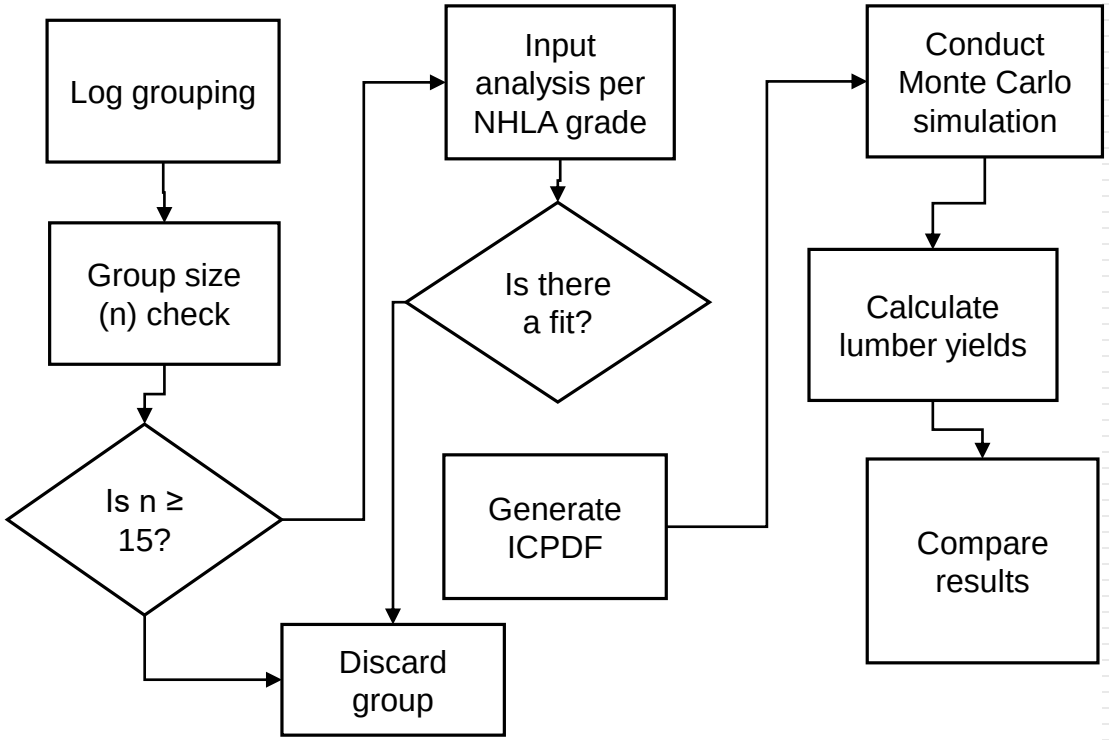
Methodology

- 1. Materials
  - Lumber yield database from Red Oak (Quercus) from the Appalachian Hardwood Center at West Virginia University
- 2. Fit to probability distributions
- 3. Obtain inverse probability distributions
- 4. Simulate results and compare to MLR
  - 1000 replicas



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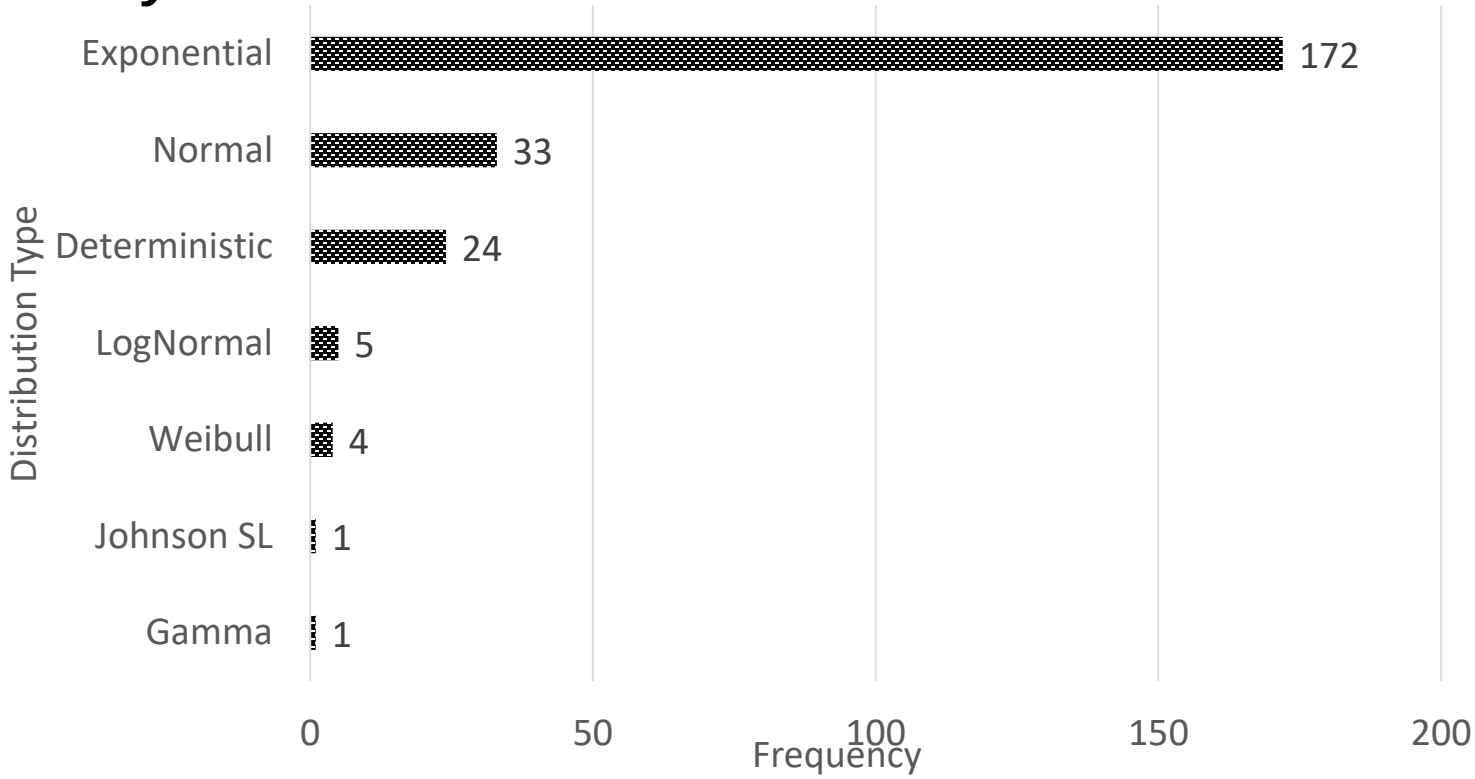
Results: Average log yields by grade

- 214 log groups (n)
- Only n>15
- 240 combinations

Log Group	N	Yield by Grade (bf)										Total BF	$/log
		F1F	FAS	SEL	1 COM	2A COM	2B COM	3A COM	3B COM	BG	CANT		
10-0,8	16	0.00	0.25	0.00	2.19	2.06	0.00	3.69	0.13	0.94	22.82	32.07	12.17
10-1,8	25	0.00	0.16	0.00	2.16	3.84	0.32	2.12	0.32	0.16	20.46	29.54	11.43
10-2,8	19	0.42	0.63	0.00	3.37	5.26	0.00	2.32	0.21	0.32	17.34	29.87	12.45
11-0,8	18	0.22	0.22	0.00	3.00	6.00	0.50	4.50	1.56	2.11	21.18	39.29	15.41
11-1,8	17	0.00	0.24	0.00	6.18	5.00	0.00	6.88	1.59	1.41	18.01	39.30	16.00
12-1,8	18	1.64	0.64	0.00	4.39	6.33	0.11	3.39	0.89	3.61	28.88	49.88	20.36
13-2,8	18	1.94	3.17	0.00	10.67	8.89	0.22	4.50	3.61	1.33	23.79	58.12	26.65
13-3,8	22	3.78	6.65	0.18	13.55	8.86	0.00	5.18	5.00	1.09	13.14	57.43	30.12
13-4,8	20	12.90	9.08	0.30	9.06	6.60	0.00	3.95	0.50	1.65	17.26	61.29	36.69
14-3,8	19	9.22	5.49	0.21	15.58	9.84	0.00	5.32	7.84	0.21	11.53	65.24	35.86
14-4,8	20	13.45	10.60	0.95	12.96	8.35	0.00	4.45	3.25	2.00	13.73	69.74	42.19
15-3,8	15	10.40	12.03	0.73	11.67	10.93	0.13	5.60	9.47	1.20	14.76	76.92	43.65
15-3,10	17	11.79	11.09	0.76	18.62	16.24	0.00	8.47	7.71	2.24	22.97	99.88	54.21
15-4,8	16	24.20	16.44	1.44	13.73	7.84	0.25	4.19	1.63	0.69	12.94	83.35	56.67
15-4,10	16	24.44	12.09	0.50	18.08	8.19	0.00	4.88	1.88	2.00	28.19	100.23	60.79
16-2,10	16	11.27	18.27	0.19	27.03	14.56	0.81	3.44	2.63	2.19	33.84	114.22	64.27
16-3,10	23	24.80	15.85	0.39	20.87	10.26	0.00	6.48	4.70	2.87	23.84	110.06	67.28
16-4,10	20	40.06	17.54	0.35	19.84	8.10	0.10	3.70	2.40	2.00	26.11	120.20	79.79
17-3,8	23	25.43	18.88	0.83	23.79	21.22	0.70	8.09	9.04	1.91	12.02	121.91	75.64
17-3,10	21	53.71	13.69	0.29	30.26	21.29	0.43	6.38	9.43	1.81	19.61	156.90	102.00
17-3,12	18	54.03	25.58	0.00	36.11	20.78	0.00	9.17	6.06	1.28	33.50	186.50	120.36
17-4,8	29	49.57	21.23	1.90	20.69	11.47	0.33	4.30	3.53	1.57	14.53	129.11	91.71
17-4,10	31	72.47	21.43	0.77	37.54	11.90	0.48	4.68	4.48	1.29	22.92	177.97	125.08
17-4,12	15	65.17	34.37	0.00	37.93	18.80	0.00	11.47	5.60	0.40	24.99	198.72	136.04

Results

- Probability distribution fit



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Results: Comparison

- Use revenue to compare Monte Carlo against MRL and real inventory
- The higher the quality and diameter, the more accurate the prediction
- Total error of MC was -0.88% and MRL as 3.31%

Grade	Predicted MLR Yield	Predicted MC Yield	Real Inventory (RI)	Error Differences with RI	
				MLR	MC
10-0,8	1.01	12.90	12.17	92%	-6%
10-1,8	2.50	11.21	11.43	78%	2%
10-2,8	4.00	12.03	12.45	68%	3%
11-0,8	11.07	11.32	15.41	28%	27%
11-1,8	12.56	17.19	16.00	21%	-7%
12-1,8	22.62	13.20	20.36	-11%	35%
13-2,8	34.18	27.75	26.65	-28%	-4%
13-3,8	35.67	30.43	30.12	-18%	-1%
13-4,8	37.17	39.41	36.69	-1%	-7%
14-3,8	45.73	39.74	35.86	-28%	-11%
14-4,8	47.23	47.79	42.19	-12%	-13%
15-3,8	55.79	48.15	43.65	-28%	-10%
15-3,10	76.24	60.11	54.21	-41%	-11%
15-4,8	57.29	58.53	56.67	-1%	-3%
15-4,10	77.73	67.78	60.79	-28%	-11%
16-2,10	84.80	66.70	64.27	-32%	-4%
16-3,10	86.30	63.28	67.28	-28%	6%
16-4,10	87.79	78.78	79.79	-10%	1%
17-3,8	75.91	76.32	75.64	0%	-1%
17-3,10	96.36	102.61	102.00	6%	-1%
17-3,12	116.80	120.15	120.36	3%	0%
17-4,8	77.41	92.34	91.71	16%	-1%
17-4,10	97.85	127.64	125.08	22%	-2%
17-4,12	118.30	137.84	136.04	13%	-1%
Average Error				3.31%	-0.88%

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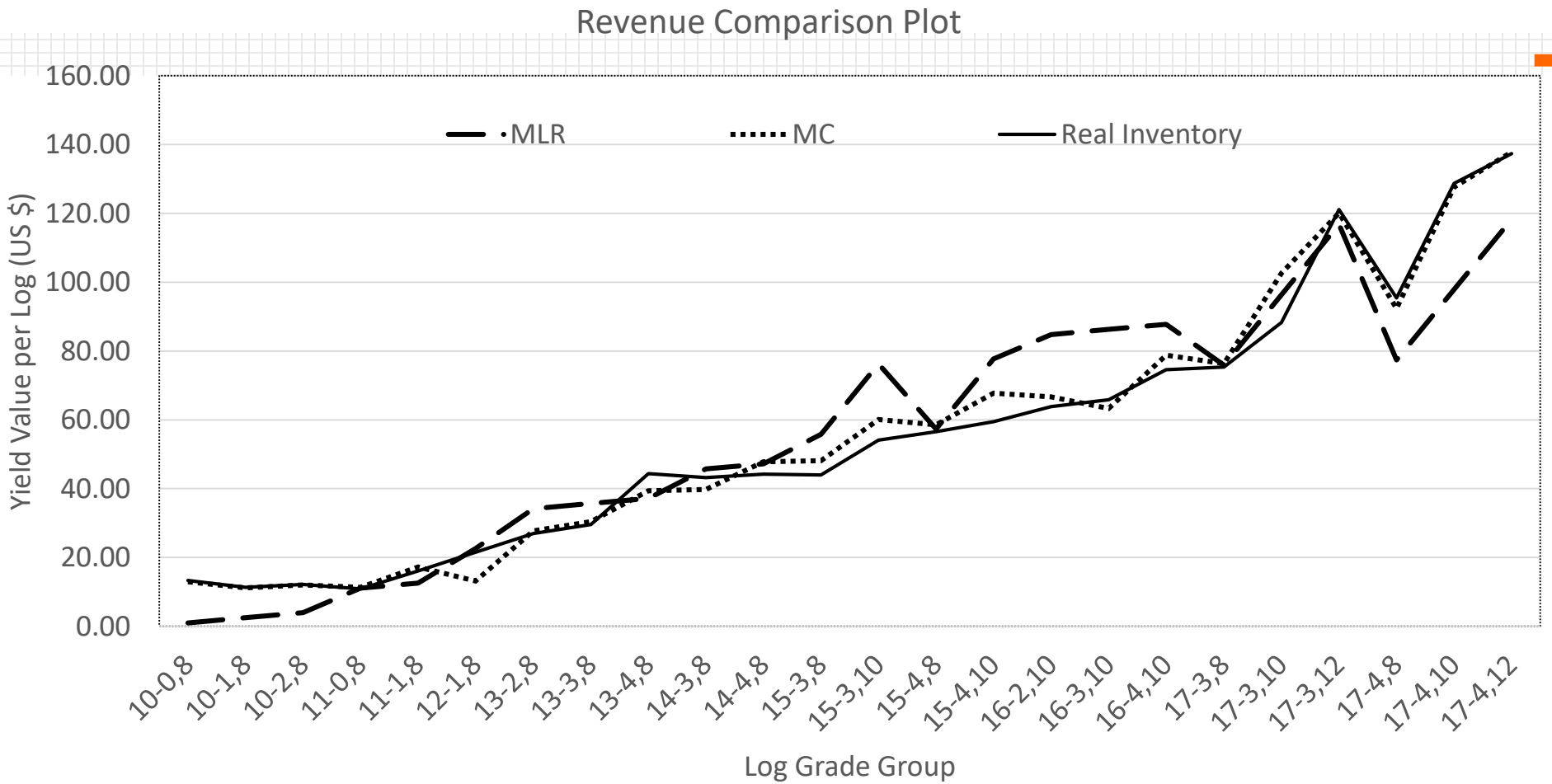
Results: Comparison



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Conclusions

- Most of the grade, length, and diameter log combination fits an exponential distribution (71.7%)
- Monte Carlo simulation is more accurate to predict revenue of an inventory of logs than MLR
- The higher the diameter and the grade, the more accurate results are produced when using Monte Carlo simulation

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