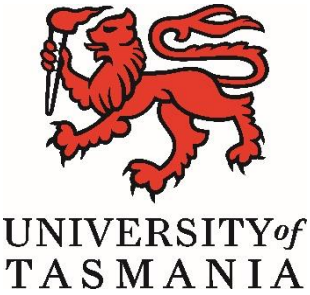


Methods to increase the efficient utilization of hardwood lumber to produce high value products

by

Kent Jason Davis

B.S. Botany and Plant Ecology, Oregon State University

M.S. Botany and Plant Ecology, Oregon State University

Submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy

Architecture and Design,

School of Technology, Environments & Design,

College of Science and Engineering,

University of Tasmania

July 9, 2021

Statements and Declarations

Candidate Name: Kent Jason Davis

Bachelor of Science (Summa Cum Laude)

Master of Science

Subject: Ph.D. Architecture and Design

Supervisors: Professor Gregory Nolan

Professor Dr. Scott Leavengood

Dr. Nathan Kotlarewski

Declaration of Originality

This thesis contains no material which has been accepted for a degree or diploma by the University or any other institution, except by way of background information and duly acknowledged in the thesis, and to the best of my knowledge and belief no material previously published or written by another person except where due acknowledgement is made in the text of the thesis, nor does the thesis contain any material that infringes copyright.

Authority of Access

This thesis may be made available for loan and limited copying and communication in accordance with the Copyright Act 1968.

Kent Jason Davis, Candidate

Signed:

Date: 09/07/2021

We the undersigned agree with the above declarations and approve the submission of the final corrected version of this thesis:

Professor Gregory Nolan
Supervisor
ARC Centre for Forest Value and School of Technology, Environment, and Design
University of Tasmania

Signed:

Dr. Nathan Kotlarewski
Supervisor
University of Tasmania, CLTP Tasmania
Tasmania, Australia

Signed:

Date: 23/04/2021

Professor Dr. Scott Leavengood
Wood Science and Engineering
Oregon State University

23/04/2021

Acknowledgments

This study was conducted under the Australian Research Council, Industrial Transformation Training Centre for Forest Value, University of Tasmania, Tasmania, Australia (Grant Reference: IC150100004). Many thanks to ARC CFV director Professor Mark Hunt and manager Dr. Mark Neyland who were supportive of this research project. The author is also grateful for the support from Forico Pty Ltd. in providing the logs and Britton Brothers Pty Ltd. for milling the logs and seasoning the boards. Personnel from Neville-Smith Forest Products also provided advice and insight to the hardwood lumber market in Tasmania.

The author is also grateful for the support from the University of Queensland and Oregon State University. Both Universities provided short-term desk space while I was under transition from Tasmania to Oregon in 2018.

I would like to sincerely thank the following for guidance, advice, and support with this Ph.D. research project.

Industry and Academic:

Professor Dr. Urs Buehlmann - Virginia Tech University, Virginia, United States

Nick Clark – Nick Clark Design, Oregon, United States

Professor Dr. David DeVallance - InnoRenew CoE, Slovenia, Europe

Patrick S. Freeman - Lucidyne Technologies Inc., Oregon, United States

Dr. Trevor Innes - Timberlink, Tasmania, Australia

Michael Lee – Centre for Sustainable Architecture with Wood, University of Tasmania, Tasmania, Australia

Professor Dr. Joe Gattas - University of Queensland, Queensland, Australia

Dr. Adam Haley - Oregon State University, Oregon, United States

Mark Jones - Allegheny Wood Products, West Virginia, United States

Dr. Nathan Kotlarewski - CLTP Tasmania, Tasmania, Australia

Marlin Langworthy - Cascade Hardwoods, Washington, United States

Ross Larkin - Parkside Timber, Queensland, Australia

Professor Dr. Scott Leavengood - Oregon State University, Oregon, United States

Michael Lee – Centre for Sustainable Architecture with Wood, University of Tasmania, Tasmania, Australia

Arial Muldoon - Oregon State University, Oregon, United States

Professor Gregory Nolan - University of Tasmania, Tasmania, Australia

Dr. Kirsten Orr - New South Wales Architects Registration Board, New South Wales, Australia

Erik Owen – Erik Owen Design, Oregon, United States

Dr. Jakub Sandak - InnoRenew CoE, Slovenia, Europe

Dana Spessert - National Hardwood Lumber Association, Tennessee, United States

Geoff Stringer - Hyne Timber, Queensland, Australia

Ed Thomas - Untied States Department of Agriculture, Northern Research Station, West Virginia, United States

Jeff Wirkkala - Hardwood Industries Inc., Oregon, United States

Undergraduate Students:

Two summer intern students funded by the United States Department of Agriculture and the Department of Wood Science at Oregon State University assisted with MATLAB applications used in this project.

Kathy Hu developed the script that was used in Chapter 3 to determine correctly identified knots and calculate the false positive and false negative rates of the automatic knot detection script. Kathy also performed image markup used for validation.

Harper Swenson developed scripts to determine cutting area distributions and to produce the heatmaps presented in Chapter 5. She also contributed to a presentation at the 2019 Western Hardwood Association Annual Convention in Portland, Oregon.

It was a joy to work with both Kathy and Harper during their summer REEU internships at Oregon State University. I appreciate the Department of Wood Science and Engineering for supporting these students to assist with my Ph.D. research project.

Supervisors:

I wish to thank my supervisors, Professor Gregory Nolan, Dr. Nathan Kotlarewski, and Professor Dr. Scott Leavengood for their assistance and insight. Greg Nolan provided in-depth knowledge about the forest products industry in Australia, solid guidance on thesis structure and organization, and valuable comments at all stages of the project. Dr. Nathan Kotlarewski provided insight into the overall thesis structure, editorial feedback on early drafts, and was an excellent traveling companion to several international conferences. Dr. Scott Leavengood provided background information about the hardwood industry of North America. I also appreciate many long conversations about the technical aspects of the work, his untiring editorial pen on drafts of the thesis, and the support for his efforts from the Department of Wood Science and Engineering at Oregon State University.

Proofreading assistance:

Dr. Mark Neyland-University of Tasmania, Tasmania, Australia

Dr. Neyland proofed this thesis for grammar, spelling, and basic flow; he had no advice or input on the content or structure of the thesis.

Family and friends:

On a personal note, there are many friends, family members, and colleagues that have supported this journey; a journey that has taken my family across the world and back. First, my wife, Tara, and children, Asa, Carmen, and Nico, thank you for your patience, encouragement, and for giving me the time and space to pursue this degree. Asa provided insight on several of the tricky programming problems. Carmen and Nico provided a steady supply of inspirational notes. Tara became the sole parent on many occasions and single-handedly moved the family from Oregon to Tasmania in 2016 so that I could pursue this degree, which I gratefully appreciate. The people that we met and the amazing adventures we had in Tasmania made lasting impressions on all of us. Lastly, we were fortunate to host friends at Freycinet National Park for Christmas in Tasmania—an experience our family and friends will never forget.

I am also incredibly thankful for the support (sometimes financial; other times emotional) from my mom and dad, Ken and Dixie, and my in-laws, Bert and Toni Putney. They were unwavering in their support and belief that I would finish this degree.

I would especially like to thank Mohammad Derikvand for the countless conversations about the project and the other Centre for Forest Value Ph.D. candidates for their comradery during this journey. A special thanks to Erik Owen, John Dixon and Nick Clark for lending an ear to my ramblings when I needed a fresh perspective. I would also like to acknowledge the work of others before me; the topics in this thesis have been encountered by many people at different scales, whether it be the craftsman carefully considering how to cut each board to achieve the perfect match in color, grain, and so further, or the academic researching the relationship between yield and lumber grade, or an industry member just trying to make the best cutting decisions under pressure on the job.

This thesis is dedicated to Chantel Davis, a person that loved to write.

Works Related to This Thesis

Davis, K. 2021. Utilization of hardwood lumber from un-thinned, un-pruned plantation-grown resources for high-value appearance applications – a simulated yield perspective. 2021 Forest Products Society International Virtual Conference, June 15-17. Invited talk. [conference extract]

Davis, K., Nolan, G., Kotlarewski, N., Leavengood, S. 2020. Optimized use of lumber produced from a fiber-managed, short-rotation hardwood resource in Tasmania, Australia. 2020 Forest Products Society International Virtual Conference, July 27-30, Portland, Oregon, USA. Invited talk. [conference extract]

Davis, K., Leavengood., S. 2019. Optimized utilization of low-grade hardwood. Western Hardwood Association Annual Convention. September 11-12. Portland, Oregon, USA. Invited talk. [conference extract]

Davis, K., N. Kotlarewski, K. Orr, G. Nolan, and S. Leavengood. 2018. Optimizing perception-oriented classification of sawn board from a fiber-managed plantation resource. 2018 Society of Wood Science and Technology (SWST) and The Japan Wood Research Society (JWRS) International Convention, November 5-9, Nagoya, Japan. [conference extract]

Davis, K. 2018. Adding value to Australia's plantation hardwood. Wood Science and Technology, School of Natural Resources, Davis College of Agriculture, Natural Resources and Design, West Virginia University, USA. Invited talk.

Davis, K., N. Kotlarewski, K. Orr, and G. Nolan. 2018. Characterization of fiber-managed plantation *Eucalyptus globulus* for non-structural applications from Tasmania, Australia. Forest Products Society, 72nd International Convention, June 11-14, Madison Wisconsin, USA. [conference extract]

Davis, K., G. Nolan, N. Kotlarewski, and K. Orr. 2017. What is the Potential for Australia's plantation hardwoods in appearance applications? 2017 IUFRO Division 5 Conference, 12-16 June, Vancouver, Canada [conference extract]

Table of Contents

Statements and Declarations ii

Acknowledgments iv

Works Related to This Thesis viii

List of Figures xviii

List of Tables xxxiii

List of Equations xl

Abstract xli

Research Setting xliv

1 Chapter One - Thesis Introduction 1

1.1 Perspective 1

1.2 Problem Statement 9

1.3 Aim 9

1.4 Research Question 10

1.5 Scope 16

1.6 Assumptions 17

2 Chapter Two - Justification and Context 19

2.1 Changing Resources 19

2.2 Manufacturing Sector 23

2.3 Hardwood Lumber Grading 29

2.4 Character-marked Products 33

2.5 Lumber Optimization 38

3 Chapter Three - A Method to Characterize Knots Found on Hardwood Lumber 42

3.1 Purpose....42
3.2 Objectives....42
3.3 Background....43
3.4 Vision Inspection....46
3.4.1 Automatic Detection Approach....50
3.4.1.1 Characterization Model Accuracy....50
3.5 Methods and Materials....53
3.5.1 Harvesting, Sawing, and Drying of Material....53
3.5.2 Sample Material....54
3.6 Image Acquisition....57
3.6.1 Image Processing....57
3.6.2 Image Analysis....63
3.6.2.1 Object Detection....65
3.6.2.2 Object Description....66
3.6.2.3 Object Classification....70
3.6.3 Comparison of the Validation and Comparison Datasets....70
3.6.4 Visualization of the Characterization Model....72
3.6.5 Alternate Approaches....73
3.7 Results....74
3.7.1 Characteristics of Validation Knots....74
3.7.2 Classification Model Performance....82
3.7.3 Characterization Model Performance....84
3.7.4 Comparison Between Validation and CI Datasets....85
3.7.5 Characteristics of False negative Detections....93
3.8 Discussion....95

3.8.1 Characteristics of Validated Knots 95
3.8.2 Classification Model Performance 97
3.8.3 Characterization Model Performance 99
3.8.4 Comparison Between the Validation and CI Datasets 99
3.8.5 Characteristics of False negative Detections 102
4 Chapter Four - A Method to Improve the Selection and Specification for Size and Appearance of Knots in Wood Panels 103
4.1 Purpose 103
4.2 Objectives 103
4.3 Background 104
4.3.1 Abstraction 104
4.3.2 Selection 105
4.3.3 Specification 108
4.3.4 Engaging with Visual Attributes 108
4.4 Methods 111
4.4.1 Datasets and Terms 111
4.4.2 Board-scale information 112
4.4.3 Unsorted Panels 112
4.4.4 Board Segments 112
4.4.4.1 Locating Segments 112
4.4.4.2 Panel Assembly 116
4.4.5 Cutting Area 117
4.4.5.1 Locating Cutting Areas 117
4.4.6 Digital Modeling 119
4.5 Results 119

4.5.1 Board Segments Panel Production 119
4.5.1.1 Unsorted Panel 119
4.5.1.2 Definition One 121
4.5.1.3 E. globulus Images 125
4.5.1.4 E. nitens Images 128
4.5.1.5 Definition Two 131
4.5.1.6 E. globulus Images 135
4.5.1.7 E. nitens Images 139
4.5.2 Cutting Area Panel Production 143
4.5.2.1 Definition One 143
4.5.2.2 Definition Two 145
4.5.2.3 Definition Three 149
4.5.2.4 Definition Four 151
4.5.2.5 Yield and Knot Density 153
4.5.3 Digital Modelling 155
4.6 Discussion 156
4.6.1 Board Segment Panels 158
4.6.2 Cutting Area Panels 159
4.6.3 Considerations of the Method 161
4.6.4 Specification 162
5 Chapter Five- A Method to Group Boards by User Specification 164
5.1 Purpose 164
5.2 Objectives 164
5.3 Background 165
5.4 Hardwood Grading 167

5.4.1.1 Board as a Whole 167
5.4.1.2 Cutting Area 169
5.4.1.2.1 Character-Marked Cuttings 177
5.4.2 Machine Grading 179
5.5 Materials and Methods 185
5.5.1 Datasets and Terms 185
5.5.2 Board-scale Knot Distribution Patterns 185
5.5.3 Board Classification 186
5.5.3.1 Board Segments 186
5.5.3.2 Cutting Area 189
5.5.4 NHLA Grades 192
5.6 Results 193
5.6.1 Board-scale Knot Distribution Patterns 193
5.6.1.1 Validated Boards 193
5.6.2 Board Segments 197
5.6.2.1.1 Validated Boards 197
5.6.2.1.2 Comparison Between the Validated and Automatic Detection Boards 204
5.6.3 Board Classification 206
5.6.3.1 Segmenting Method 206
5.6.3.1.1 Segment Definition 1 206
5.6.3.1.2 Segment Definition 2 221
5.6.3.2 Cutting Area Method 226
5.6.3.2.1 Cutting Area Definition 1 226
5.6.3.2.2 Comparison of the Two Species 233
5.6.3.2.3 Cutting Area Definition 2 233

5.6.3.2.4 Cutting Area Definition 3 238
5.6.3.2.5 Cutting Area Definition 4 242
5.6.3.2.6 Comparison to NHLA Graded Lumber 247
5.6.3.2.7 Comparison Between Validated and Automatic Datasets 248
5.6.4 NHLA Grades 249
5.6.4.1.1 Validated Boards 249
5.7 Discussion 250
5.7.1 Board-scale Knot Distribution Patterns 251
5.7.2 Board Segments 252
5.7.2.1 Validated Dataset 252
5.7.2.2 Comparison Between the Validation and Automatic Detection Datasets 254
5.7.3 Board Classification 255
5.7.3.1 Segmenting Method 255
5.7.3.2 Cutting Area Method 256
5.7.4 NHLA Grades 260
5.7.5 Further work 261
6 Chapter Six - A Method to Match Board Classes to Product Requirements 263
6.1 Purpose 263
6.2 Objectives 263
6.3 Background 264
6.3.1 Introduction 264
6.3.2 Rough Mill Operations 264
6.3.3 Cutting Efficiency 271
6.3.4 Simulation of Yield 273

6.3.5 Character-Marked Parts....273
6.3.6 Suitability Index....275
6.4 Material and Methods....276
6.4.1 Datasets and Terms....276
6.4.2 Dimension Parts....276
6.4.2.1 Board Data Files....278
6.4.2.2 ROMI Settings....279
6.4.2.3 Board Value....279
6.4.3 Panel Production....282
6.4.3.1 Panel Cutting Bills....282
6.4.3.2 Simulation....284
6.4.4 Suitability Index....285
6.4.4.1 Property indices....286
6.4.4.2 Panel cutting bill development....289
6.4.4.3 Board Data Files....290
6.4.4.4 Simulation....291
6.5 Results....291
6.5.1 Dimension Parts....291
6.5.2 Panel Production....296
6.5.2.1 Definition 1....296
6.5.2.2 Definition 2....298
6.5.2.3 Definition 3....299
6.5.2.4 Definition 4....300
6.5.3 Suitability Index....301
6.6 Discussion....307

6.6.1 Dimension Parts 309
6.6.1.1 Limitations to the Method 314
6.6.2 Panel Production 315
6.6.2.1 Definition 1 316
6.6.2.2 Remaining Definitions 319
6.6.3 Suitability Index 320
7 Chapter Seven – Thesis Discussion 323
7.1 Contribution to Knowledge 327
7.1.1 Industry 327
7.1.2 Academic 329
7.1.2.1 Characterization of Knots 329
7.1.2.2 Selection and Specification 331
7.1.2.3 Classification of Boards 331
7.1.2.4 Matching Lumber to Applications 333
7.2 Implementation 334
7.3 Future Research Areas 336
8 Appendix 1 338
8.1 Image Acquisition and Processing 338
8.1.1 Object Detection 346
8.1.2 Object Description 357
8.1.3 Object Classification 363
9 Appendix 2 367
9.1 UGRS System Rules 367
9.2 NHLA Grades for Automatic Dataset 368
10 Appendix 3 370

10.1 Cutting Bills Used for Dimension Parts Study 370

10.2 Simulation Results of Panel Production 374

11 References 379

List of Figures

Figure 1-1. Simplified representation of a supply chain (Stiess, 2010) 2

Figure 1-2. A concept diagram of the research explored in this thesis. 13

Figure 1-3. The research outline proposed to address the research question. 14

Figure 2-1. Actual and forecast annual average plantation log availability in Australia (ABARES, 20016) 21

Figure 3-1. Different ways to define the boundary of a knot. 45

Figure 3-2. Different ways to determine the size of a knot. The size could be expressed as a diameter, or calculated from the measurements of a and b, x and y, or x' and y' (Lycken, 2006a). 45

Figure 3-3. Common characteristics found in sawn North American hardwood not allowed within clear area cuttings under NHLA grading rules (American Hardwood Export Council, 2008). 48

Figure 3-4. Schematic of a machine vision system for lumber inspection (Conners et al., 1997). 49

Figure 3-5. Width distribution of the boards in the validation set (n=136 for E. nitens and n=159 for E. globulus). 55

Figure 3-6. Length distribution of boards in the validation set. Note that the maximum x-axis value is 6000 mm for E. nitens. 56

Figure 3-7. The general process for knot characterization. 56

Figure 3-8. An image of a board before and after white balance transformation. Note distortion due to resizing images. 58

Figure 3-9. The results of intensity adjustment on two boards based on dynamic thresholding. The mean red intensity of the top two boards for each pair is 129 and 102. The bottom two boards of each pair are the result of the adjustment. 60

Figure 3-10. Contrast adjustment because of dynamic adjustment for the top image in Figure 3-9. The left panel shows a histogram of the original image; the right panel shows the resulting histogram. 60

Figure 3-11. Contrast adjustment because of dynamic adjustment for the bottom image in Figure 3 20. The left panel shows a histogram of the original image; the right panel shows the resulting histogram.....61

Figure 3-12. An example of an image of the top board in Figure 3-9 transformed into a multi-channel binary image.....62

Figure 3-13. Results of the first opening, then closing the example used in Figure 3-12. 62

Figure 3-14. An example of an image of the top board in Figure 3-9 transformed to HSV color space. 63

Figure 3-15. An example of an image of the top board in Figure 3-9 transformed to greyscale. 63

Figure 3-16. An example of an image of the top board in Figure 3-9 with extreme contrast.63

Figure 3-17. An example of a validation board with knots marked as red.....64

Figure 3-18. An example of an image indicating the location of knots with a transparent mask. 64

Figure 3-19. The process used to create the validation knot data. 64

Figure 3-20. The process used to create the knot classifier. 65

Figure 3-21. The process used to create the automatic knot dataset.....65

Figure 3-22. An example of a complete thresholded binary image. 66

Figure 3-23. Examples of the automatic detection method results plotted against validation images. Black box outlines indicate a dark knot; yellow box outlines indicate dark knots; green box outlines indicate light knots.....73

Figure 3-24. Distribution of the bound box area of knots from both species in the validation set. The right y-axis indicates the combined percentage of knots from 0 to 10,000 mm^2. There were 88 E. globulus knots larger than 10,000 mm^2 and 25 E. nitens knots above 10,000 mm^2. The bin size is 100 mm^2 and the maximum x-axis is 10,000 for E. nitens.....75

Figure 3-25. Distribution of the knot color classes from board surfaces in the validation set. 75

Figure 3-26. Distribution of knot locations. Knot locations are combinations of the top, middle, and bottom thirds of the board. these locations can be all thirds (AT), top two thirds (TTT), bottom two thirds (BTT), top one third (TOT), the middle one third (MOT), and the bottom one third (BOT). 76

Figure 3-27. Distribution of the red ratio of knots from both species in the validation set. ..76

Figure 3-28. Distribution of the tone of knots from both species in the validation set. Note: the maximum x-axis value for E. nitens is 150. 77

Figure 3-29. Distribution of the eccentricity of knots from both species in the validation set. Note: the maximum x-axis value for E. nitens is 1.....78

Figure 3-30. Area of the fit ellipse as a function of the eccentricity from both species in the validation set. Note: the maximum x-axis value for E. nitens is 1.....78

Figure 3-31. Distribution of the orientation of the major axis of knots from both species in the validation set. Zero orientation indicates the major axis is parallel to the long axis of the board; perpendicular knots are indicated by an orientation near -90 or 90. Note: the maximum x-axis value for E. nitens is 90. 79

Figure 3-32. Area of a fit ellipse as a function of orientation. Note: the maximum x-axis value for E. nitens is 90.....80

Figure 3-33. Eccentricity as a function of orientation for both species in the validation set. Data is yellow indicates values between -15 and 15. Note: the maximum x-axis value for E. nitens is 90. 80

Figure 3-34. Distribution of the distances between knot centroids from the validation set. The bin length is 100 mm. Note: the maximum x-axis value for E. nitens and E. globulus is 6000 mm. 81

Figure 3-35. Distribution of the length of board segments free of knots from the validation set. The bin length is 100 mm. The right y-axis indicates the combined percentage of segments in each length class.....82

Figure 3-36. Confusion matrix for the Ensemble Bagged prediction model for both species in the validation image set. 1 indicates non-knots; 2 indicates true knots. 83

Figure 3-37. Confusion matrix of the results of the Ensemble Bagged classifier for E. globulus. 1 indicates non-knots; 2 indicates true knots. 83

Figure 3-38. Confusion matrix of the results of the Ensemble Bagged classifier for E. nitens. 1 indicates non-knots; 2 indicates true knots. 84

Figure 3-39. Distribution of the differences between corresponding knot centroids for both species in the study. The bin size is 5 mm. The right y-axis indicates the combined percentage of differences from 0 to 80 mm. Note: the maximum x-axis value for E. nitens is 80. 86

Figure 3-40. The distribution of the percentage of differences in the area between corresponding knots. The bin size is 20 percent. Differences below zero indicate detected knots smaller than validated ones, while those values above 0 indicate detected knots larger than the corresponding ones. The right y-axis indicates the combined percentage of differences from -100 to 1000. Note: the maximum x-axis value for E. nitens is 1000. 87

Figure 3-41. The distribution of the percentage of overlap in the area between corresponding knots. The bin size is 10 percent. The right y-axis indicates the combined percentage of differences from 100 to 0. Note: values above 100 percent overlap are the observations that are 100 percent overlapped. 88

Figure 3-42. The percentage of overlap of bounding boxes between the detected and the corresponding validated knots. Data in yellow indicate values between -50 and 50 percent. Note: the maximum x-axis value for E. nitens is 800. 89

Figure 3-43. Differences in the frequency of board segments free of knots. The bin size is 100 mm. The right y-axis indicates the combined frequency differences from 6000 mm to zero. Note: the maximum x-axis value for E. globulus is 6000 mm. 90

Figure 3-44. Confusion matrix indicating the prediction performance of size classes of bounding boxes of correctly identified knots for E. globulus. See Table 3-3 for categories... 91

Figure 3-45. Confusion matrix indicating the prediction performance of color classes of correctly identified knots for E. globulus. See Table 3-4 for categories. 92

Figure 3-46. Confusion matrix indicating the prediction performance of size classes of bounding boxes of correctly identified knots for E. nitens. See Table 3-3 for categories. 92

Figure 3-47. Confusion matrix indicating the prediction performance of color classes of correctly identified knots for E. nitens. See Table 3-4 for categories. 93

Figure 3-48. Distribution of size classes of false negative (FN) knots for the two species. Note: the maximum x-axis value for E. nitens is 10000. 94

Figure 3-49. Distribution of size classes in the false negative (FN) knots from the two species. 94

Figure 3-50. Distribution of the red ratio values of the false negative knots from the two species. Note: the maximum x-axis value for E. nitens is 1.2. 95

Figure 3-51. An example of dark grain in an E. globulus board. 98

Figure 4-1. A screenshot of the slider interface available to customize shelving units. 107

Figure 4-2. Flow chart of the process used to determine board segments. 114

Figure 4-3. An example of a segmented board. The colored lines indicate the location of each of the different segment types. Note: a segment must be at least 500 mm to be identified. The image has also been distorted longitudinally to better illustrate the segment locations. 116

Figure 4-4. Flow chart of the process used to create virtual images of panels constructed from board segments 117

Figure 4-5. Flow chart of the process used to produce panels from cuttings. 118

Figure 4-6. A panel made from random E. globulus segments. The red line indicates 1 m. .120

Figure 4-7. A panel made of random E. nitens segments. The red line indicates 1 m. 121

Figure 4-8. Length distribution of different segment types produced under definition 1. 122

Figure 4-9. The parallel plot of the proportion of different segment types ranked by the proportion of clear segments for each board. 124

Figure 4-10. A panel assembled from E. globulus clear segments using definition 1. The red line indicates 1 m. 125

Figure 4-11. A panel assembled from E. globulus type 1 segments using definition 1. The red line indicates 1 m. 126

Figure 4-12. A panel assembled from E. globulus type 2 segments using definition 1. The red line indicates 1 m. 126

Figure 4-13. A panel assembled from E. globulus type 3 using definition 1. The red line indicates 1 m. 127

Figure 4-14. A panel assembled from E. globulus type 4 segments using definition 1. The red line indicates 1 m. 127

Figure 4-15. A panel assembled from E. nitens clear segments using definition 1. The red line indicates 1 m. 128

Figure 4-16. A panel assembled from E. nitens type 1 segments using definition 1. The red line indicates 1 m. 129

Figure 4-17. A panel assembled from E. nitens type 2 segments using definition 1. The red line indicates 1 m. 130

Figure 4-18. A panel assembled from E. nitens type 3 segments using definition 1. The red line indicates 1 m. 131

Figure 4-19. A panel assembled from E. nitens type 4 segments using definition 1. The red line indicates 1 m. 131

Figure 4-20. Length distribution of different segments produced under definition 2. 132

Figure 4-21. The parallel plot of the proportion of different segment types ranked by the proportion of clear segments for each board. 134

Figure 4-22. A panel assembled from E. globulus clear segments using definition 2. The red line indicates 1 m. 135

Figure 4-23. A panel assembled from E. globulus type 1 segments using definition 2. The red line indicates 1 m. 136

Figure 4-24. A panel assembled from E. globulus type 2 segments using definition 2. The red line indicates 1 m. 137

Figure 4-25. A panel assembled from E. globulus type 3 segments using definition 2. The red line indicates 1 m. 137

Figure 4-26. A panel assembled from E. globulus type 4 segments using definition 2. The red line indicates 1 m. 138

Figure 4-27. A panel assembled from E. nitens clear segments using definition 2. The red line indicates 1 m. 139

Figure 4-28. A panel assembled from E. nitens type 1 segments using definition 2. The red line indicates 1 m. 140

Figure 4-29. A panel assembled from E. nitens type 2 segments using definition 2. The red line indicates 1 m. 141

Figure 4-30. A panel assembled from E. nitens type 3 segments using definition 2. The red line indicates 1 m. 142

Figure 4-31. A panel assembled from E. nitens type 4 segments using definition 2. The red line indicates 1 m. 143

Figure 4-32. An example of a 2 m by 916 mm E. globulus panel assembled from cuttings produced from definition 1.....144

Figure 4-33. An example of a 2 m by 916 mm E. nitens panel assembled from cuttings produced from definition 1.....144

Figure 4-34. An example of a 2 m by 1829 mm E. globulus mixed panel from cuttings produced from definition 2.....145

Figure 4-35. An example of a 2 m by 1829 mm E. globulus knotty panel from cuttings produced from definition 2.....146

Figure 4-36. An example of a 2 m by 1829 mm E. nitens mixed panel from cuttings produced from definition 2. 147

Figure 4-37. An example of a 2 m by 1829 mm E. globulus knotty panel from cuttings produced from definition 2.....148

Figure 4-38. An example of a 2 m by 914 mm E. globulus mixed panel from cuttings produced from definition 3.....149

Figure 4-39. An example of a 2 m by 914 mm E. globulus knotty panel from cuttings produced from definition 3.....149

Figure 4-40. An example of a 2 m by 914 mm E. nitens mixed panel from cuttings produced from definition 3.....150

Figure 4-41. An example of a 2 m by 914 mm E. nitens knotty panel from cuttings produced from definition 3.....150

Figure 4-42. An example of a 2 m by 914 mm E. globulus mixed panel from cuttings produced from definition 4.....151

Figure 4-43. An example of a 2 m by 914 mm E. globulus knotty panel from cuttings produced from definition 4.....151

Figure 4-44. An example of a 2 m by 914 mm E. nitens mixed panel from cuttings produced from definition 4.....152

Figure 4-45. An example of a 2 m by 914 mm E. nitens knotty panel from cuttings produced from definition 4.....152

Figure 4-46. A parallel plot of yield for each of the definitions used to produce panels from cuttings.....154

Figure 4-47. An example of wood flooring and wainscoting produced from E. globulus board knotty segments and clear cuttings.....156

Figure 4-48. An example of wood flooring and wainscoting produced from E. nitens clear segments and knotty panels.....156

Figure 5-1. Summary of the different types of sawn timber grading (Davies and Watt, 2005).....166

Figure 5-2. Examples of Select (top), Standard (middle), and High-Feature (bottom) Tasmanian Oak boards graded under AS 2796.....169

Figure 5-3. Examples of FAS, #1C, and #2AC, American red oak graded under the National Hardwood Lumber Association grading standards (American Hardwood Export Council, 2008).....172

Figure 5-4. Characteristics allowed in clear area cuttings under NHLA grading rules (American Hardwood Council, 2008).....173

Figure 5-5. Examples of clear cuttings marked out on FAS (top) and #2AC boards (bottom) using NHLA grading rules (NHLA, 2014).....176

Figure 5-6. Flow chart of the process used to classify boards using the segmenting method. 186

Figure 5-7. Flow chart of the process used to find cutting areas in boards. 189

Figure 5-8. Flow chart used to determine board classes using cutting area information.....191

Figure 5-9. The number of knots per board for both species for the validation dataset. Note: the maximum x-axis value is 30 for E. nitens.....194

Figure 5-10. Simpson Index for knot size classes for both species for the validation dataset. Note: the maximum x-axis value is 1 for E. nitens.....194

Figure 5-11. Simpson index for knot color class for both species for the validation dataset. Note: the maximum x-axis value is 1 for E. nitens.....195

Figure 5-12. Scatter plot of minimum bounding box area for each knot for each E. globulus board in green. Red indicates the mean knot size for each board. Note: there were 9 knots above 30,000 mm^2. 196

Figure 5-13. Scatter plot of minimum bounding box area for each knot for each E. nitens board in blue. Red indicates the mean knot size for each board. Note: there were 3 knots above 30,000 mm^2. 196

Figure 5-14. Distribution of the proportion of boards with clear segments greater than 1000 mm for both species. 198

Figure 5-15. Distribution of clear segments across the width classes of boards. Note: the maximum x-axis value is 6000 mm for both species. 199

Figure 5-16. Distribution of type 1 segments across the width classes of boards. Segment lengths are in mm. 200

Figure 5-17. Distribution of type 2 segments across the width classes of boards. Segment lengths are in mm. 201

Figure 5-18. Distribution of type 3 segments across the width classes of boards Segment lengths are in mm. 202

Figure 5-19. Distribution of type 4 segments across the width classes of boards. Segment lengths are in mm. 203

Figure 5-20. Examples of different segment types across boards are coded by different colors. Segments that contain smaller knots are indicated by lines closer to the top of the boards. The top three are E. globulus; the bottom 3 are E. nitens. 204

Figure 5-21. Distribution of the differences in segment types for each board in the validation and automatic detection sets. Negative values indicate that the automatic detection routine underestimates the number of segments. 205

Figure 5-22. Distribution of the differences in the proportion of boards between the validation and automatic datasets. Negative values indicate that the automatic detection routine underestimates the proportion of the board in each segment type. 206

Figure 5-23. Final cluster solution for E. globulus using segmenting definition 1.....207

Figure 5-24. Final confusion matrix for the E. globulus classification model using segmenting definition 1. 208

Figure 5-25. Final cluster solution for E. nitens for segmenting definition 1. 208

Figure 5-26. Final confusion matrix for the E. nitens classification model using segmenting definition 1. 209

Figure 5-27. Distribution of knots per meter of the board for the different board classes determined by the classification model using segmenting definition 1. 211

Figure 5-28. Distribution of the proportion of board containing all segment types above the minimum lengths for the different board classes using segmenting definition 1. The minimum lengths for knotty types are 500 mm and 1000 mm for clear type. 212

Figure 5-29. Distribution of the proportion of board in clear segments for the different board classes using segmenting definition 1. 213

Figure 5-30. Distribution of the proportion of board in type 1 segments for the different board classes using segmenting definition 1. 214

Figure 5-31. Distribution of the proportion of board in type 2 segments for the different board classes using segmenting definition 1. 215

Figure 5-32. Distribution of the proportion of board in type 3 segments for the different board classes using segmenting definition 1. 216

Figure 5-33. Distribution of the proportion of board in type 4 segments for the different board classes using segmenting definition 1. 217

Figure 5-34. Distribution of segment lengths for the board classes determined for E. globulus using segmenting definition 1. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm. 219

Figure 5-35. Distribution of segment lengths for the board classes determined for E. nitens using segmenting definition 1. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm. 221

Figure 5-36. Distribution of segment lengths for the board classes determined for E. globulus using segmenting definition 2. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm. 224

Figure 5-37. Distribution of segment lengths for the board classes determined for E. nitens using segmenting definition 2. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm. 226

Figure 5-38. Cluster solution for E. globulus based on cutting area distribution using cutting area definition 1. 227

Figure 5-39. Confusion matrix for E. globulus classification model based using cutting area definition 1. 228

Figure 5-40. Cluster solution for E. nitens based using cutting area definition 1. 228

Figure 5-41. Confusion matrix for E. nitens classification model using cutting area definition 1. 229

Figure 5-42. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 1 (clear). Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures. 231

Figure 5-43. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 1 (clear). Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear indicated on area proportion figure. 232

Figure 5-44. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 2. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on the area proportion figure. 236

Figure 5-45. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 2. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might occur on the area proportion figure. 237

Figure 5-46. Distribution of cutting areas containing at least 1-knot using cutting area definition 2. 238

Figure 5-47. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 3. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on the area proportion figure. 240

Figure 5-48. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 3. Note that

due to rounding errors, low occurrences may not be indicated on cutting size figures but might be indicated on area proportion figures. 241

Figure 5-49. Distribution of cutting areas that contain at least one-knot using cutting area definition 3. 242

Figure 5-50. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 4. For board class 2, 10 cuttings exceeded the axis range. They were greater than 5300 mm in length. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures. 244

Figure 5-51. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 4. For board class 4, there was 1 cutting that exceeded the axis range. It was 5276 mm in length. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures. 246

Figure 5-52. Distribution of cutting areas that contain at least one-knot using cutting area definition 4. 247

Figure 5-53. Cutting area distribution for NHLA #1C and #3AC graded lumber from the red oak database. The #1 lumber included 1038 boards and the #3AC lumber included 239 boards. All characteristics in the database were used to determine the cutting areas. 248

Figure 5-54. Distribution of missed and extra cuttings found between the validation and automatic detection datasets. 249

Figure 6-1. Approximate value of an increase of 1 BF of lumber as it is processed by the rough mill (Mitchell et al., 2003) 266

Figure 6-2. Various types of multi-blade arbor rip saw types (www.primultini.com). 266

Figure 6-3. The sequence of operations used in a rip-first rough mill to produce parts from lumber (Araman, 1977). 267

Figure 6-4. Influence of cutting bill requirements on yield for #1C lumber in a rip-first configuration (Buehlmann et al., 1998, Buehlmann, 1998). 269

Figure 6-5. Flow chart of the processing steps to determine the total cost of producing dimension parts from E. globulus board classes. 277

Figure 6-6. Flow chart of the process used to produce panels from the standard and special panel cutting bills to determine knot utilization. 282

Figure 6-7. Flow chart of the process used to calculate the Suitability index. 285

Figure 6-8. The distribution of the proportion of area for each panel with class in each cutting bill. 290

Figure 6-9. Radar plots of the indices and the calculate Si for E. globulus. Blue indicates board class 1; red indicates board class 2; yellow indicates board class 3; purple indicates board class 4. Note: X-Cut is used in the figure instead of Cross-Cut, which is used in the text. 304

Figure 6-10. Radar plots of the indices and the calculate Si for E. nitens. Blue indicates board class 1; red indicates board class 2; yellow indicates board class 3; purple indicates board class 4. Note: X-Cut is used in the figure instead of Cross-Cut, which is used in the text.....307

Figure 8-1. An example of an image with a nonuniform background. 339

Figure 8-2. Histogram of intensity values over the entire image (https://www.mathworks.com/help/images/ref/imhist.html).....340

Figure 8-3. The normalized histogram from Figure 8-2.....341

Figure 8-4. Two images and histograms that show poor (left) and good (right) contrast (https://www.mathworks.com/help/images/contrast-adjustment.html). 342

Figure 8-5. Schematic (left) of the RGB color cube showing the primary and secondary colors at the vertices. The RGB color cube (right).....343

Figure 8-6. The HSV color hexagon and HSV color hexagon cone. (http://argos.vu/devnotes-9-16-16-ui-work-initialization-serialization/).....343

Figure 8-7. An example of a median filter applied to an image that contains "salt and pepper" noise. original image (left), filtered image (right). 344

Figure 8-8. An illustration of erosion using a disk structuring element with different radii (Gonzalez et al., 2010). Original image (upper left), radius 10 (upper right), radius 5 (lower left), and radius 20 (lower left). 345

Figure 8-9. Illustration of opening and closing (Gonzalez et al., 2010) original image (upper left), open image (upper right), closed image (lower left), and closing of opened image (lower right). 346

Figure 8-10. A grayscale image containing light objects on a dark background (left) and an accompanying histogram of intensity values(right). 349

Figure 8-11. An example of a grayscale image thresholded using a global value of T (T=140). 350

Figure 8-12. An example of using Otsu's method to determine the threshold value. 350

Figure 8-13. Image of a knot on a piece of veneer (left). Corresponding histograms of the red, green, and blue channels of the image (Funck et al., 2003). 352

Figure 8-14. An example where not all the pixels belonging to the object have been thresholded, but have been labeled as belonging to the same group (Kauppinen, 1999) ...353

Figure 8-15. Examples of common detection mistakes. Uppercase letters indicate actual objects, lowercase letters indicate objects detected by the automatic method (Kauppinen, 1999). 355

Figure 8-16. The minimum bounding box (left) and elliptical fit (right) to an object (knot). 358

Figure 8-17. A confusion matrix indicating classification performance of a k-nearest neighbor classifier of iris species from petal measurements (mathworks.com/help/stats/confusionchart.html). 365

Figure 9-1. Confusion matrix of NHLA grading results from the validation and automatic datasets for E. globulus. 369

Figure 9-2. Confusion matrix of NHLA grading results from the validation and automatic datasets for E. nitens. 369

List of Tables

Table 3-1. Descriptors calculated from the label mask. 67

Table 3-2. Statistics related to detected objects. 68

Table 3-3. Appearance classes of validated knots and objects. 69

Table 3-4. Size classes of knots based on the bounding box area used throughout this thesis. 69

Table 3-5. Performance results of the characterization model developed for this study. 84

Table 3-6. The mean and standard deviations for the difference in distances, the difference in the area, and percent overlap of the correctly identified knots from both species. 86

Table 4-1. Board segmenting definition 1. 115

Table 4-2. Board segmenting definition 2. 115

Table 4-3. Definitions for knot size and type allowed within cutting areas. 118

Table 4-4. The general panel cutting bill used to produce random strip width panels from boards. 118

Table 4-5. Mean proportion of boards in each segment type. The minimum and maximum values are shown in parentheses. Note: total may not equal 100 because segments shorter than the minimum allowed by the definition are not included. 123

Table 4-6. Mean proportion of boards in each segment type. The minimum and maximum values are shown in parentheses. Note: total may not equal 100 because segments shorter than the minimum allowed by the definition are not included. 133

Table 4-7. Yield of cuttings from sample boards using the cutting bill. 153

Table 4-8. Knot density for mixed and knotty panels and the ratio between mixed panel area and knotty panel area for each definition allowing knots to occur in cuttings. 155

Table 5-1. Limits of permissible characteristics in AS 2796 hardwood grades (Australia Standards, 2006). 168

Table 5-2. Permissible characteristics for the main grades of hardwood grown in the UK (Davies and Watt, 2005). 168

Table 5-3. Minimum requirements set out by NLHA grading rules (NHLA, 2014). 170

Table 5-4. Examples of 4/4 southern hardwood lumber grade values in USD per MBF for December 28, 2018, from the Hardwood Market Report (December 28, 2018).....176

Table 5-5. Indicator variables used for the cluster analysis in the board segmenting study. 188

Table 5-6. Indicator variables used for the cluster analysis in the cutting area study. 191

Table 5-7. Current sawmill value (USD) of two comparable North American hardwoods (HMR, 2019). 193

Table 5-8. The number and proportion of boards in each board class for both species using segmenting definition 1. The proportion of board in each board class compared to the total is shown in parentheses (). 207

Table 5-9. Mean proportion of E. globulus boards in the segment types for the different board classes segmenting definition 1. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with second-highest proportion. 210

Table 5-10. Mean proportion of E. nitens boards in the segment types for the different board classes segmenting definition 1. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion. 210

Table 5-11. The number and proportion of boards in each board class for both species using segmenting definition 2. 222

Table 5-12. Mean proportion of E. globulus boards in the segment types for the different board classes using segmenting definition 2. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion. 223

Table 5-13. Mean proportion of E. nitens boards in the segment types for the different board classes using segmenting definition 2. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion. 225

Table 5-14. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 1. 229

Table 5-15. The proportion of cuttings found in each board class and the mean proportion of boards in cutting areas using cutting area definition 1. 229

Table 5-16. The number and proportion of boards in each board class for both species using cutting area definition 2. 234

Table 5-17. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 2. 234

Table 5-18. The number and proportion of boards in each board class for both species using cutting area definition 3. 239

Table 5-19. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 3. 239

Table 5-20. Number and proportion of boards in each board class using cutting area definition 4. 243

Table 5-21. The proportion of cuttings and proportion of board in cuttings in each board class for each species using cutting area definition 4. 243

Table 5-22. The number and proportion (percent) of boards in each NHLA grade for both species from the validated dataset. 250

Table 6-1. Generalized part yield benchmarks for rip and crosscut-first mills and different grades (Mitchell et al., 2003). [a] indicates simulations based on 12 cutting bills from Wiedenbeck and Thomas (1995). [b] indicates simulated yield from 7 cutting bills under rip-first and crosscut-first configurations (Buehlmann et al., 1998, Buehlmann et al., 1999). ..268

Table 6-2. Descriptions of cutting bills ranked from “easy” to “difficult” (hard) (Thomas, 1996). 270

Table 6-3. The Mean number of total (rip and crosscut) required cuts (10 repetitions) from different lumber grades and cutting bills (Steele, 1999). Means with the same capital letter are not significantly different. 271

Table 6-4. Descriptions of the cutting bills used and rank from easiest to the most difficult as determined in this study. 278

Table 6-5. The calculated relative lumber values for E. globulus. 281

Table 6-6. The specialized panel cutting bills used to produce random strip width panels from boards grouped by definitions 2-4. 283

Table 6-7. The panel cutting bills used to examine processing parameters on the 4 groups of boards. D1-D4 indicates the definition used to group boards (refer to 5.5.3.2). A-D indicates which panel bill was used for the simulation. 284

Table 6-8. The Panel cutting bills used to develop the suitability index. The quantities are listed under each panel bill. 289

Table 6-9. Yield and cross-cutting efficiency for E. globulus lumber grouped by definition 1. 292

Table 6-10. Cutting ratio, lumber value, manufacturing costs, and the total cost to manufacture parts from the E. globulus board classes based on an arbitrary value of 1 for board class 4. The proportion of each board class is shown in (). See 6.4.2.3 for an explanation of variables. 293

Table 6-11. Yield and cross-cutting efficiency for NHLA graded lumber. 294

Table 6-12. Cutting ratio, lumber value, manufacturing costs, and the total cost to manufacture parts from NHLA graded lumber. See 6.4.2.3 for an explanation of variables. 295

Table 6-13. Comparative costs to manufacture each cutting bill using E. globulus boards and two NHLA graded lumber. 296

Table 6-14. Processing parameters for E. globulus using the general cutting bill for boards grouped by definition 1. 297

Table 6-15. Processing parameters for E. nitens using the general panel bill for boards grouped by definition 1. 297

Table 6-16. Processing results obtained from the special cutting bills for E. globulus lumber grouped using definition 1. 298

Table 6-17. Processing results obtained from the special cutting bills for E. nitens lumber grouped using definition 1. 298

Table 6-18. Simulation results from the special panel bills for E. globulus lumber grouped by definition 2. 299

Table 6-19. Simulation results from the special panel bills for E. nitens lumber grouped by definition 2. 299

Table 6-20. Simulation results from the special panel bills for E. globulus lumber grouped by definition 3. 300

Table 6-21. Simulation results from the special panel bills for E. nitens lumber grouped by definition 3. 300

Table 6-22. Simulation results from the special panel bills for E. globulus lumber grouped by definition 4. 301

Table 6-23. Simulation results from the special panel bills for E. nitens lumber grouped by definition 4. 301

Table 6-24. Simulation results for the 9 property values developed in this study for E. globulus. 303

Table 6-25. Simulation results for the 9 property values developed in this study for E. nitens. 306

Table 8-1. A confusion matrix indicating detection types. 355

Table 8-2. Descriptions of texture based on intensity histograms (Gonzalez et al., 2010). 360

Table 8-3. Properties calculated from the co-occurrence matrix (see Gonzalez et al. (2010) for further explanation), subscripts r and c refer to rows and columns, subscripts I and j refer to the ith and the jth element of the normalized co-occurrence matrix. 362

Table 9-1. System rules for UGRS based on 1994 NHLA rules with slight modifications. Units of inches are used for width, length, and surface measure. 367

Table 9-2. The number and proportion (percent) of boards in each NHLA grade in both species from the automatic dataset. 368

Table 10-1. Description of Cutting bill 1. 370

Table 10-2. Description of Cutting bill 2. 370

Table 10-3. Description of Cutting bill 3. 370

Table 10-4. Description of Cutting bill 4. 371

Table 10-5. Descriptions of the Buehlmann (B) Cutting bill 5. 371

Table 10-6. Descriptions of Cutting bill 6. 372

Table 10-7. Simulation results using NHLA graded red oak lumber and the cutting bills from this study. 373

Table 10-8. Obtained results from the general cutting bill for E. globulus boards grouped by definition 1. 374

Table 10-9. Obtained results from the general cutting bill for E. nitens boards grouped by definition 1. 374

Table 10-10. Obtained results from the special cutting bill for E. nitens boards grouped by definition 1. 374

Table 10-11. Obtained results from the special cutting bill for E. globulus boards grouped by definition 1. 375

Table 10-12. Obtained pieces from E. nitens boards grouped by definition 2. 375

Table 10-13. Simulation variables obtained from E. nitens boards grouped by definition 2. 375

Table 10-14. Obtained pieces from E. globulus lumber grouped by definition 2. 376

Table 10-15. Processing parameters from E. globulus lumber grouped by definition 2. 376

Table 10-16. Obtained pieces from E. nitens lumber grouped by definition 3. 376

Table 10-17. Processing parameters from E. nitens lumber grouped by definition 3. 376

Table 10-18. Obtained pieces from E. globulus lumber grouped by definition 3. 377

Table 10-19. Processing parameters from E. globulus lumber grouped by definition 3. 377

Table 10-20. Obtained pieces from E. nitens lumber grouped by definition 4 377

Table 10-21. Processing parameters from E. nitens lumber grouped by definition 4. 377

Table 10-22. Obtained pieces from E. globulus lumber grouped by definition 4. 377

Table 10-23. Processing parameters from E. globulus lumber grouped by definition 4.....378

List of Equations

Equation 5-1. Yield determined using a cutting unit method. 175

Equation 5-2. The Simpson Index 186

Equation 6-1. Suitability Index 285

Equation 8-1. Equations to calculate the true positive, false positive, false negative, and true negative rates for an automatic detection method. Adapted from Kohavi and Provost (1998). 356

Equation 8-2. Equation for accuracy and precision of the detection method. Adapted from Kohavi and Provost (1998). 356

Equation 8-3. Centroid location difference 357

Equation 8-4. Difference in the overlapping area 357

Equation 8-5. Area Difference 357

Abstract

This work aims to demonstrate the potential benefits of using board-scale high-resolution digitized information to improve the utilization and description and communication of the visual characteristics and properties of hardwood lumber within the appearance hardwood lumber supply chain. Current practice in the appearance hardwood timber industry is to batch boards according to grading standards that largely disregard the variation caused by natural growth characteristics, such as knots, splits, grain variation, and decay, which largely determined the physical and mechanical properties of boards. These standards describe acceptable characteristics as a boundary condition. There is little assurance that any grade, other than those that contain very few characteristics, can be efficiently and effectively manufactured into high-value products. Often this results in loss of potential utility and value of lumber that contains a high frequency of growth characteristics, such as knots.

The physical and mechanical properties of manufactured homogenous (uniform) materials, such as steel and paint, are described and communicated precisely and accurately within the supply chain. This provides a high level of assurance that material will perform as intended and required. However, this level of assurance is not provided by most grading systems used for natural materials, such as hardwood lumber. This reduces the ability to obtain the best-suited boards and to accurately predict the visual outcome and manufacturing expense for hardwood lumber that contains frequent growth characteristics. The problem occurs largely because of the lack of high-resolution information describing the characteristics of lumber and the absence of a meaningful way to exchange such information between lumber producers and high-value product manufacturers in the appearance hardwood lumber supply chain.

To address this problem, a system was developed to determine ways that the exchange of high-resolution board-scale information describing the size and distribution of growth characteristics within the supply chain would improve the utilization of hardwood lumber. The system involved four areas of research. The first area focused on developing a characterization module to describe knots using digital images. The second area explored methods to improve the ways that an acceptable range of knots could be defined and selected. It also explored the visual outcomes of the effects of different sizes and types of

knots using a wood appearance panel as an exemplary product. The third research area developed a novel lumber sorting approach based on the ways that useable areas of a board were defined by the users. Finally, the fourth area determined ways to match the best-suited group of boards to different product part requirements. User input directed the way the system simulated the batching and processing of boards.

The system's capacity enables greater detail in the communication between producers and manufacturers in the appearance hardwood lumber supply chain. This capacity overcomes the current lumber grading systems by providing the necessary framework to pass and use detailed digital information describing the physical properties among members of the supply chain. The system was built around the occurrence of knots in boards. However, the system could be expanded to include other growth characteristics that allow an even more detailed prediction of the yield of product parts and the potential visual outcomes available from different resources.

The system demonstrated a novel lumber sorting approach that could more effectively differentiate boards into groups, a means to achieve a desired visual outcome from a population of available boards, and a way to determine the manufacturing costs for products. Overall, the system was tested on two short-rotation, fiber-managed, plantation-grown hardwood species from Tasmania, Australia. The system indicated that, despite the common belief that lumber produced from these resources is difficult to utilize for the production of high-value secondary products, a significant proportion (75 percent, and 77 percent for *Eucalyptus nitens* and *E. globulus*, respectively) of the boards from the study produced a high yield of pieces for appearance wood panels that had different visual attributes caused by the inclusion of different sizes and types of knots.

Currently, there are nearly 1 million hectares of plantation hardwood forests in Australia, of which, approximately 92 percent of the volume of harvested timber is exported as low-value fiber for the pulp and paper industry. The findings in this study suggest, that with appropriate technological developments, lumber produced from short-rotation, fiber-managed resources from Australia could be utilized in higher-value appearance products and markets. The system was tested by simulating the potential production of appearance wood panels with differing

visual attributes caused by different sizes and types of knots. It was demonstrated the production of appearance solid wood panels could be viably produced from lumber produced from plantation resources. Because the production of standardized solid wood panels is relatively straightforward, panel products present a means to contribute to local economies, such as the State of Tasmania. The findings also suggest an approach for the uptake of undervalued and underutilized hardwood resources in other regions, such as North America.

Research Setting

This research was conducted within the Australian Research Council's Industrial Transformation Training Centre for Forest Value, based at the University of Tasmania, Australia, but the findings could be applied to appearance hardwood supply chains elsewhere, especially in the United States. The Centre for Forest Value Is a collaboration with partners from all segments of the supply chain, from log harvesting to product design and component fabrication. The Centre aims to assist in the transition from a "traditional resource-driven, low technology base" to an innovative "market-driven, precision manufacturing" industry[1]. This will be done by establishing frameworks to allow precise characteristics of a forest, tree, or piece to be directly matched to product requirements. Within this context, the Centre assumes that current and future markets of wood products and timber processing and manufacturing technologies may be different from the traditional Australian forest sectors. The Australian forest and wood products industry is currently transitioning away from the utilization of native logs towards greater exploitation and value-adding to plantation-grown resources (Ajani, 2008).

This thesis references both North America and Australian hardwood industries. It uses both imperial and metric units, although an attempt was made to use metric units where possible. 1 Australia Dollar (AUD) is equal to 0.72 United States Dollars (USD) at the time of writing. American English is used throughout the thesis.

There are significant differences in the ways that hardwood is described, processed, and marketed between these regions. These include:

- Description
    - In North America, the unit of board foot (BF) is used to describe a volume of lumber that is 144 cubic inches (in.). Notionally, the BF is 12 inches (in.) by 12 in. by 1 in. thick. Value is usually denoted in units of 1000 BF as MBF. The standard-length increment is 1 foot (ft.) between 4 ft. and 16 ft. the standard thickness increment is a ¼ in. for lumber thicker than ¾ in. Thickness is

[1] Referenced from the Centre of Forest Value website (http://www.utas.edu.au/arc-forest-value).

specified in quarters of inches (4/4, 5/4, etc.) For example, a nominal 1 in. board is referred to as 4/4 (“four-quarter”).

- In Australia, cubic meters are used to denote a volume of lumber (‘timber’ in Australia). One cubic meter is equal to 423 BF. Boards are typically supplied in standard widths, thicknesses, and lengths according to a customers’ order.
- Most hardwood is graded according to the National Hardwood Lumber Association rules in North America. In Australia, several standards exist for appearance hardwood grading, however, the most common is AS 2796 Timber—Hardwood—Sawn and milled products, Part 2: Grade description

- Processing
  - In the North American hardwood industry, lumber is sold and graded commercially in random widths, ranging from 3 in. to 12 in. wide. Lumber is usually skip-planed to slightly below nominal thickness to allow assessment of characteristics during grading and processing. Lumber is sold by the unit, which is generally a stack of lumber 3 ft. tall by 4 ft. wide.
  - In Australia, timber is dressed on all 4 sides to exact dimensions and specified as such. Timber is packaged and marketed by the pack, for which there exists no standard unit of measure.
- Market supply
  - The North American hardwood industry is fragmented; small sawmills produce lumber from many regions and species. Lumber is then distributed to the manufacturing sector and is used to produce a variety of low and high-value products, such as pallets, flooring, and furniture.
  - In Australia, hardwood production is largely vertically integrated; sawmills obtain logs and sell products. Timber is processed for a predetermined end application, such as solid or overlay flooring boards (Kotlarewski et al., 2017).

1 Chapter One - Thesis Introduction

1.1 Perspective

The hardwood lumber industry is a segment of the forest products industry. The companies within this industry are different from other material production companies based on the raw materials (hardwood trees), the markets they serve, and the products they produce. The hardwood industry includes companies that produce furniture, flooring, cabinetry, windows, doors, and millwork[2]. These products take advantage of the strength, appearance properties, and visual attributes, and typically add the most value to the raw material (Luppold and Bumgardner, 2004). These products are assembled from elements[3] of various sizes and shapes. Elements result from a series of manufacturing processes that transform raw material into the final product. These processes are performed by a chain of companies that include forestry and harvesting companies, sawmills, component manufacturers, wholesalers and retailers, and result in high-value products in the market that customers desire and are willing to purchase. For a manufacturer to be financially successful, the highest possible return on raw material must be maintained. This requires the conversion of the highest possible volume of material into high-value products, such as furniture and cabinetry.

The wood supply chain describes the processes involved in transforming trees to an end product (Stiess, 2010). It can be represented as a series of events and processes that create a final product from raw materials (Figure 1-1). There are three typical supply chains associated with society's use of hardwood resources. Industrial (sometimes referred to as structural) markets and associated supply chains value the macro-scale strength, fiber/composite markets and supply chains value the micro-scale strength of the material, and appearance markets and supply chains value both the strength and the beauty of the material (Stiess, 2010). The appearance market typically pays more per unit of the recovered board from the log and demands higher quality materials to produce flooring, furniture, cabinets, millwork, and other products where appearance properties and visual attributes are critical.

[2] In Australia, the term 'joinery' is often used to refer to these products.
[3] The term element is used here to denote the smallest possible part of a product, such as the leg of a chair.

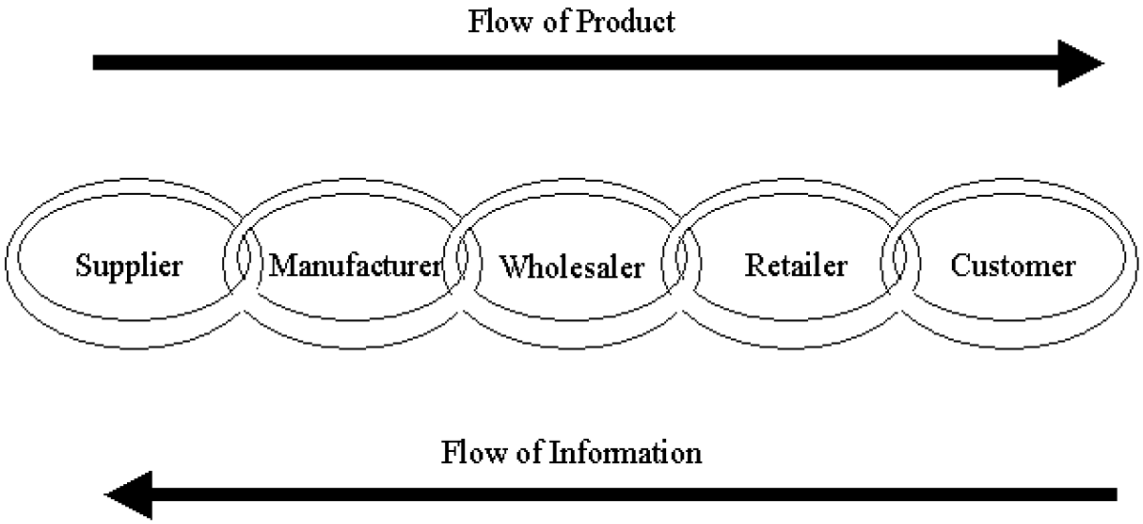


Figure 1-1. Simplified representation of a supply chain (Stiess, 2010)

The appearance supply chain starts with the harvesting of trees from the forest. The logs are then sorted according to log grading standards that are based on shape, size and form, and the presence knots and other growth characteristics for different product lines to maximize the profit of the available resource. The best logs are sent to veneer mills. Logs meeting the requirements of sawmills are processed into lumber[4], and the remaining logs are sent for low-value/low-cost products, such as chips for the pulp and paper industries (Luppold and Bumgardner, 2004). This process results in lumber typically produced from logs that contain numerous knots.

Lumber is a naturally variable heterogeneous material that contains an assortment and distribution of different characteristics and properties. As a biological material, the occurrence and frequency of growth characteristics, such as knots, color, grain variation, and mechanical properties, such as density and strength vary considerably for many species in and between individual pieces of lumber (Filipescu et al., 2018, Machado et al., 2014). This variation results from complex interactions between the environment and genetics during the growth of the tree. The extent of variation differs widely among tree species, age, location, and forest management strategies. Most breeding programs have focused on signals from intended markets, the requirements of final utilization, site characteristics and management regimes(Burdon, 2010). The occurrence of natural growth characteristics and properties

[4] Here, the term lumber is used to refer to a batch of boards. Unlike the word timber, used in Australia and the UK, it specifically refers to solid-sawn boards from hardwood trees.

largely determines the potential value and utility of boards as they progress through the current appearance hardwood supply chain. Because high-value elements are usually processed from boards that do not contain most of these characteristics, boards with greater variation and a higher occurrence of characteristics are typically more difficult to effectively transform into high-value products; hence such material generally has a lower market value in the hardwood supply chain than does lumber that does not contain as many growth characteristics. This market structure is clearly evidenced by the differential in cost for different so-called quality classes (grades) of hardwood lumber in Australia (Mr. Michael Lee, CSAW, pers. comm., 2016) and North America (HMR, 2019). In general, boards that contain the highest occurrence of knots and other growth characteristics (lower grade lumber) are used to produce lower-value products, such as pallets, crates, and railroad ties; while higher grade material is used for furniture, flooring, and millwork (Bowyer et al., 2007).

Most appearance hardwood supply chains are more complex than the simplified model shown above. Each company could be part of any number of other supply chains each with its customers requiring different types of materials and information (Stiess, 2010). The appearance hardwood supply chain can be notionally divided into two segments. The production segment includes producers and suppliers that process the raw materials (logs) into primary products, such as lumber. The manufacturing segment includes manufacturers[5], fabricators, and designers who convert lumber to secondary high-value appearance products, such as furniture, flooring, cabinetry, windows, doors, wall panels, and millwork for wholesalers, retailers, and the end consumer. Hardwood lumber is the main constituent of these products; other products such as metal, finish, fabric, and leather are produced by other supply chains and are minimal in comparison to the volume of hardwood lumber (Stiess, 2010).

The efficient recovery of product components from lumber plays a major role in the success of a high-value manufacturing operation (Buehlmann, 1998, Buehlmann et al., 2011b, Huber et al., 1985, West and Hansen, 1996). Depending on the product manufactured, the cost of

[5] Here, manufacturing refers to making goods systematically at a commercial scale. Manufacturing differs from fabrication in that fabrication refers to assembling parts or pieces into an object. Fabrication is one operation or set of operations within the greater process of manufacturing high-value wood products.

lumber can account for between 40 percent and 70 percent of the cost to produce raw dimension parts (Buehlmann et al., 2011b); therefore, the industry takes considerable effort to minimize the volume of lumber used. In general, the manufacturer is concerned with producing and selling products while optimizing the use of each board. The resources of the manufacturer are materials, equipment, facilities, money, and people (Prak and Myers, 1981). Processes are complex and include drying lumber, machining parts, assembly of parts, finishing, and packing during manufacturing (Prak and Myers, 1981). The initial stages of lumber breakdown and conversion are known as "rough mill" operations and take place at what is known as the rough mill or rough end (Prak and Myers, 1981).

In the hardwood appearance supply chain, materials and products flow through producers, suppliers, manufacturers, wholesalers, retailers, and finally to the customer (Stiess, 2010). Information is exchanged within and between members of the manufacturing segment and other associated supply chains. This information describes product requirements, customer specifications, desired quantities for materials, and manufacturing operations. It flows easily and readily and is typically generated and communicated digitally by various types of inventory, order, scheduling, and manufacturing software. It is used to manage the manufacture and flow of products and sharing information between companies has been identified as one key to successful supply chain logistics and operation success (Stiess, 2010). Effective information management allows for companies to respond to changing markets and customer desires (Um, 2017). There is also detailed information flow within the production segment. This information is used to maximize the value of each log by directing it to its highest value product (i.e., veneer, lumber, or chips). Improvement in manufacturing and supply chain performance can be achieved with increased information sharing among the various members (Stiess, 2010).

To a lesser degree, information also flows between the production and manufacturing segments. This information provides a means to describe the properties of lumber produced by the production segment and a means for the manufacturing segment to obtain lumber that meets certain requirements. Compared to the information transferred within the two segments, the information communicated between the production and manufacturing

segments is rudimentary. This often results in underutilization and undervalueation of a significant proportion of boards.

The definitions included in timber grading systems are used to produce information that is exchanged between producers and manufacturers. This information describes the perceived quality of the lumber in different grades and provides some level of assurance that it will perform as required (see 5.4 for an in-depth discussion of hardwood lumber grading). Producers batch boards according to established quality classification standards, or other assessment and sorting agreements between producers and manufacturers. This is called grading (Nolan, 1998). It seeks to classify boards that contain an acceptable range in the variation of form and numerous other properties and the expected proportion of the material that can be used as intended into groups (Bowyer et al., 2007). A grade name is given to a group of boards and a grade definition lists the acceptable limits of form and properties admissible to the grade (Nolan, 1998). The form describes the size, shape, straightness, and other physical dimensions, and the properties describe the type, level, and frequency of natural growth characteristics, such as knots, splits, grain variation, and decay. Grading standards vary across regions, available resources, and intended uses, but most appearance hardwood lumber grading strategies focus on describing minimum utility[6] or a maximum number of certain types of characteristics that can be expected from any individual board within the batch (APECF, 2009, Australia Standards, 2006, NHLA, 2014).

Grading is performed by comparing the form and properties of the board against the requirements of the first, or highest, grade. If the board does not meet the requirements of form and properties, the next grade requirements are examined. This continues until the board meets or exceeds the minimum requirements for a certain grade. In most appearance hardwood supply chains, grades that allow more variation in the characteristics are perceived to be lower quality, lower value, and less desirable to produce high-value products. For example, the Hardwood Market Report (HMR, 2019) lists the price for the highest (FAS) grade of hard maple as USD 1725, while the lowest (#2AC) grade is listed at USD 920.

[6] Utility is used here as a reference to the proportion of the board that can be used to produce elements of products.

A grade standard or grading agreement provides a means to describe and select batches of lumber with similar properties. The end-user selects and specifies a grade of lumber that contains the properties required for different applications. The act of specification is how the user defines the required material properties. Manufacturers specify different grades of lumber assuming the lumber within a selected grade will contain the desired range of characteristics, properties, and level of utility that they require. The aim is to specify a grade of lumber at a cost that will enable the manufacturer to produce higher-value products at a price that the customer will accept. This is achieved by obtaining the optimal or sub-optimal yield[7] of elements to reduce lumber and labor expenses.

Grading systems for uniform manufactured materials, such as steel and paint, function differently to those designed for variable natural materials, such as lumber. For these systems, grading is used to specify materials designed and produced with a combination of the physical and mechanical properties required by the application. Steel grading systems allow producers to communicate the properties of different types of steel with great specificity, which guide manufacturers to the proper processing and application procedures. For example, the SAE steel grading system uses codes of letter and number combinations to indicate different formulations (proportion of other elements), mechanical properties (within a permissible range of variation), and recommended application (i.e., steel for reinforced concrete). Different grades of steel are priced according to supply and demand, cost of raw materials, and energy and labor necessary to produce them. Companies readily supply different types of products to customers and provide documentation that certifies the minimum performance the user can expect. However, the system can also be used by the end-user to specify formulations with properties that meet demanding and unique requirements. Although the exact systems vary by region, all of them convey the necessary information required by the user.

Coatings are another example. Any coating, such as a specific color of paint, can be manufactured consistently and reliably from batch to batch. The color is identified with a name, which refers to a standard by which that color can be manufactured, supplied, and

[7] Here, yield refers to the ratio between the surface area of parts and the surface area of lumber consumed during the production of products.

specified in the market. Different companies offer a range of in-house colors and sample coupons are used to communicate the visual attributes to the users. Unique colors can be specified using systems that allow the specification of the exact attributes of different colors, such as the hue, chroma, and brightness. Companies regularly update color offerings in response to changing customer desires and fashion tastes. Such a system provides a highly accurate way to define and select any imaginable color.

Steel and paint are examples of uniform, homogenous (macroscale) materials with properties that can be replicated and modified to meet different application requirements (i.e., strength in steel and color in paint). The grading systems for these materials provide a means to describe and specify for an almost endless combination of material properties. In the case of steel, a user can choose from supplied products or specify the strength properties required by the application. In the case of paint, the user can also choose from the supplied colors or use the established system to request a unique color that can be manufactured by the suppliers.

These systems provide two important functions. The first is that they provide a means to communicate information about the products by both the producers and the users. That is, producers can communicate detailed information about the products they supply, and the user can use the same system to request special products that a producer can supply by request. The other important function is that these systems provide a means to communicate the physical and mechanical properties and their variation with a high degree of accuracy and precision. They provide a high level of assurance that the material will meet the application requirements. These are high-resolution systems of description and specification that provide information in digital format that can be utilized along the supply chain.

In contrast to manufactured materials, grading systems for natural materials provide far less resolution to the degree of information describing the physical and mechanical properties of the material. These systems lump material into broad categories with names such as “standard”, “common”, and “choice”. Grading systems for natural materials are based on the concept of how much of the material can be utilized or the perceived quality. For example, leather skins that contain numerous defects are considered lower quality and lower value

(Aslam et al., 2019). One industry-accepted standard grades leather skins on a maximum number of marks and patterns (Aslam et al., 2019). Although this system provides a reasonable idea of the potential utility of skins, it does not provide any information as to the distribution, size, or type of pattern or marks in individual skins. Meat provides another example of a typical grading system used for natural materials. United States Department of Agriculture (USDA) beef grading is based on the minimum expected yield of lean, edible meat, and the degree of marbling, a measure of customer preference. Other examples are wool fleece and stone slabs. As mentioned, lumber grading is based on similar principles.

Unlike the systems used for manufactured materials, those developed for natural materials require the user to have a level of knowledge and experience to select the desired grade that will most likely meet their expectations. The systems are typically based on a few key parameters (e.g., the proportion of utility), which are conveyed at low-resolution and packaged into a format that does not enable the exchange of information describing other physical and mechanical properties along the supply chain. They are examples of "paper-based" systems—systems where high-resolution data are converted to and communicated by paper documents. Different grades of lumber are purchased largely based on previous experience in hopes that a given grade can be processed at a profit. Grading systems for natural materials typically do not provide a means to utilize both the physical material and the information that describes the properties of the material along the supply chain.

Each grade of hardwood lumber contains boards with a range of physical and mechanical properties, due to the random distribution of natural growth characteristics. The grade standards do not describe the material in enough detail to allow the user to match the best-suited grade or mix of grades to achieve the best yield of elements while reducing the cost of lumber and satisfying visual and processing requirements. This is an example of a cutting stock problem encountered in other industries, such as paper, glass, and metal (Buehlmann et al., 2011b). However, because lumber is a variable material supplied in random sizes and is usually processed to avoid the randomly distributed growth characteristics, there is limited ability to predict the results of rough mill processing. The problem is further complicated

when certain sizes and types of natural growth characteristics can occur or are desired in the final product[8].

Although the visual attributes of manufactured materials can be accurately communicated, precise grade description techniques have not been developed for lumber. High-resolution information describing the variation in the size, shape, and frequency of growth characteristics found in hardwood lumber is not commonly exchanged between producers and manufacturers. This information could be useful in several ways. First, it could be used to describe and specify unique batching of lumber such that it contains an acceptable and perhaps desired, range of certain characteristics. Second, it could be used to customize the visual attributes of products. Third, it could be used during processing operations to reduce the amount of lumber consumed. This research attempts to advance these areas of the appearance hardwood lumber supply chain and to allow these improvements in the processing of hardwood lumber.

1.2 Problem Statement

The efficient utilization of hardwood lumber is a two-part problem faced by the timber industry. One part of the problem is the lack of an adequate method to communicate the variation of the size, shape, color, and distribution of growth characteristics and to supply the best-suited lumber to end-users. The other side of the problem is the inability of end-users to define and describe a range for certain types of growth characteristics that are acceptable or desirable in lumber. The absence of these mechanisms results in a restricted ability to match boards to different visual requirements and to optimize the processing of lumber to obtain the highest yield from the best-suited boards available.

1.3 Aim

To address this problem, this thesis aims to develop effective digital methods to communicate the potential utility and visual attributes at the board scale along the supply chain between producers and users of hardwood lumber.

[8] The term character-marked is used to denote a category of products where certain types and sizes of characteristics are allowed or desired to occur.

The underlying assumption during this research is that this enhanced communication could lead to improved methods to select, specify, and process lumber into high-value products, especially for lumber that contains an elevated occurrence of growth characteristics, such as knots.

The focus of this thesis is to develop mechanisms to communicate digital information describing the distribution, frequency, and appearance of growth characteristics found in hardwood lumber. These mechanisms are packaged into an automated expert system that enables greater yield from hardwood lumber and improved selection of characteristics during the production of dimension parts used to manufacture high-value products. This requires:

- developing the techniques and tools to assess the characteristics of boards;
- developing procedures to refine selection and specification procedures based on the available resources;
- establishing interfaces for flexible sorting processes;
- creating methods to sort boards into batches with an acceptable distribution of visually desirable areas, and;
- developing procedures to optimize the processing of boards into products.

1.4 Research Question

Research gap:

Despite technological advancements in the production of lumber (scanning and optimization of log breakdown) and the manufacturing sectors (digital design and manufacturing), very little research has addressed the way that the characteristics of lumber are communicated along the supply chain. The research gap identified here are the techniques necessary to collect, format, transmit and use high-resolution board-scale information along the timber supply chain to increase the detail to which sorted lumber can be described, specified, and utilized to manufacture high-value products.

Research question:

This thesis argues that by describing the arrangement, size, and type of characteristics found in lumber, digital workflows and systems can be developed that accommodate the variation in the properties found in lumber and communicate it along the supply chain in order to provide a level of assurance that such material can be viably and efficiently used to manufacture high-value products. The research question investigated here is:

Can high-resolution board-scale digital information describing the size, shape, appearance, and distribution of knots be used to increase the utilization efficiency of lumber that contains an elevated frequency of natural growth characteristics?

Knots are the focus of this work. This is justified because knots are common in most grades of hardwood lumber produced from short-rotation resources, such as the two species of plantation grown Eucalyptus used in this study (Derikvand et al., 2018b, Derikvand et al., 2018a, Derikvand et al., 2019, Jiao et al., 2019). Knot distribution within boars also greatly influences the proportion of the material that is useable for the intended application. In addition, this study was limited to knots because no commercial lumber scanning equipment was available at the University of Tasmania during the research project and therefore, a lab-scale system was designed and built to collect information about the distribution of knots in the sample material. Advanced lumber scanning systems are commercially available and are typically used to assign grades to structural products; few such systems are in use to grade hardwood lumber. Once a grade is assigned, the high-resolution information describing the material is not available to other members of the supply chain. In the future, such advanced scanning systems could be used to assess and describe other types of growth characteristics, such as grain patterns, gum vein, mineral streak, figure, or spalting[9] zone lines, and the digital information would be transmitted to down-stream users.

Research approach:

To address the research question, the research considers knots found on the surface of the hardwood boards. This assumes that knots are the most frequent characteristics and there is an existing body of research that utilizes knots to grade based on visual attributes (Berglund

[9] Spalting is defined as any coloration of wood due to the colonizaiton of fungi. It results in irregular discolorations appearing as dark zone lines throughout the lumber.

et al., 2014, Breinig et al., 2014, Nordvik and Broman, Olofsson et al., 2019, Riekkinen et al., 2004). Substantial visual differences and customer preferences have been found between panels with and without knots (Broman, 2001, Bumgardner et al., 2009, Donovan and Nicholls, 2003). Indeed, research on so-called character-marked products has shown preferences for certain sizes, arrangements, and types of knots and that in some cases customers are willing to pay more for such products. Therefore, because of the high occurrence, diversity, and potential uses, this work focuses on knots.

Figure 1-2 shows a concept of how users and producers could more effectively communicate and deliver material better suited for specific requirements. The concept is based on a four-step process. Theoretically, the processes would occur along the supply chain, bridging the gap between producers/suppliers and manufacturers.

1. Producers provide high-resolution information about the characteristics of lumber that a producer can supply to users. This information would include details about the visual attributes and other information about geometric forms of the material. This process can be symbolized using this icon . This icon indicates how different types of data are processed, organized, and structured to become useful information describing boards in a way that is relevant for users.
2. Users would then explore this information to select and specify the types of characteristics that are desired. This process would require a purpose-built software application. This process can be symbolized with this icon . This icon represents the common slider interface used to control choices made by users. It is useful in this context because the selection of knot size and type is essentially the act of choosing a minimum and maximum range of different characteristics.
3. Producers would then translate these definitions into classification systems to supply the market with appropriate board classes and board-scale information that describes the material. This process can be symbolized with this icon . It is the process

by which producers inspect and certify that batches of lumber meet the user's expectation at an agreed-upon standard.

4. Lastly, the expert user would create digital, transferable cutting solutions based on design and product requirements that optimize the breakdown of boards. This process can be symbolized with this icon . Optimization is an iterative process by which outcomes are simulated using different values of criteria and constraints associated with the breakdown and processing of lumber.

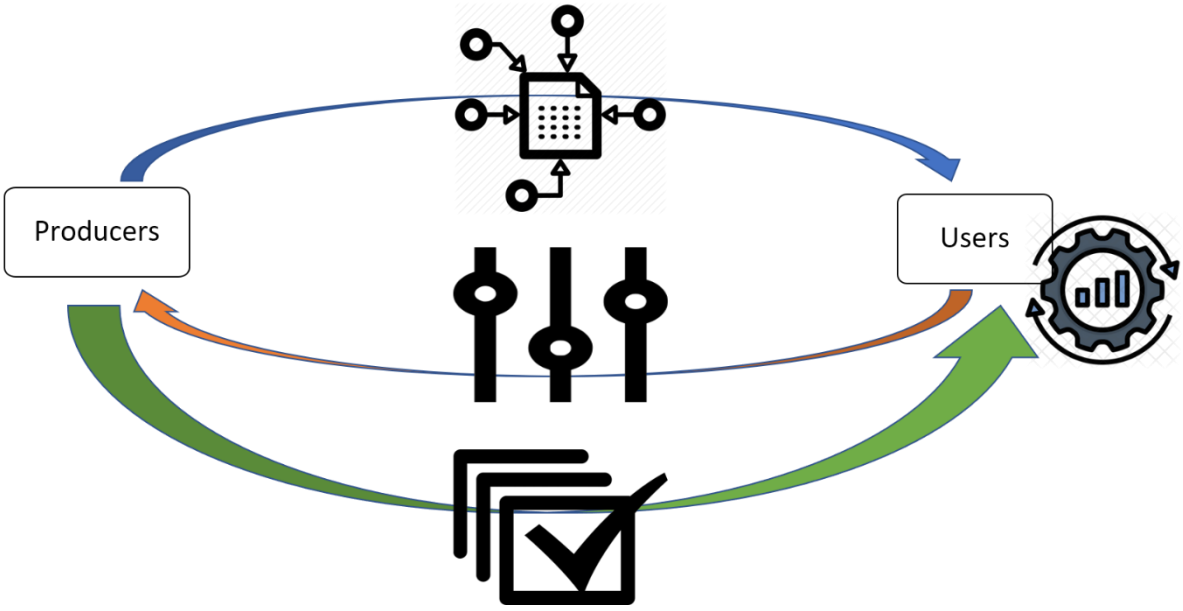


Figure 1-2. A concept diagram of the research explored in this thesis.

The icons presented above are used as visual aids for each chapter. They help the reader to recall the purpose of each chapter.

Research objectives:

To address the research question, this thesis documents the development of the procedures to collect, format, and use high-resolution board-scale digital information to increase the resolution at which the properties of hardwood lumber are communicated between producers/suppliers and users in the appearance hardwood lumber supply chain. The work postulates that such an approach would increase the utilization, and by proxy, the market value of lumber that contains moderate to high levels of growth characteristics, such as knots. This may occur in part because the information could be used to predict the useable

proportion of each board, processing requirements, and enable realistic visualization of potential out comes more accurately from different groups of boards.

Figure 1-3 shows the outline of the project. The process starts with physical lumber. The characteristics are digitized with a custom-built image analysis application. The output from this application provides high-resolution board-scale information describing the size, distribution, and appearance of knots. Users provide a definition of the allowed and desired size and type of knots, which is then used to sort and supply lumber along with high-resolution information that can be utilized to optimize board processing. The thesis demonstrates the principles needed to provide both material and information describing that material along the appearance hardwood lumber supply chain.

Figure 1-3. The research outline proposed to address the research question.

The project can be broken down into four objectives:

1. To develop a means to digitally characterize and describe the knot population found in short-rotation plantation-grown Eucalyptus hardwood lumber from Tasmania, Australia;
2. to develop a means to select and specify different sizes and types of knots in appearance panels;
3. to develop and demonstrate a novel lumber classification based on the distribution of areas within boards that contain a defined range of knots, and;
4. to understand the relationship between the cutting requirements, manufacturing costs, and desired outcomes to determine the best-suited board groups for different product requirements.

Thesis structure:

This thesis is organized into 7 chapters. Chapter 1 introduces the research perspective and the research question. Chapter 2 provides a justification and research context. Chapters 3-6 present the aims, background, methods, and results of each of the objectives. Chapter 1 and

2 introduce several topics that are then elaborated on in Chapters 3-6. Although they some material is repetitive, these chapters are intended to stand alone; a reader should be able to understand the content without referring to the introductory chapters. Because of the length of this thesis, it was decided that this format would be earlier to read and follow, then positioning a complete literature review at the beginning of the thesis. To address each objective, computational modules were developed that automatically-collect data from digital images, transform it to describe the key selected characteristic (knots), provide a means to select and specify the appearance of panel surfaces, and to determine manufacturing parameters. Figures and diagrams are used to illustrate the conceptual framework and the achievements of the systems developed during this research. The modules are as follows:

1. Module one (Chapter 3) uses a visual inspection approach to characterize the knot population in sample boards. The input is color images of board surfaces and the output is size, frequency, appearance type, and description of the properties of knots found in the sample lumber. The module uses data from the individual pixel level and produces knot-scale information.
2. Module two (Chapter 4) uses the output from module one to allow the user to select and specify the appearance of panels produced from board segments that contain a defined size and appearance type of knots.
3. Module three (Chapter 5) uses the user-specified definitions to classify boards into the best-suited groups to achieve the desired appearance of panels containing various sizes and types of knots. This module uses knot-scale information combined with knot location data to create board-scale information that describes the arrangement of the knots within each board. It then uses board-scale information combined with a board classification system to create batch scale information describing the size distribution of useable areas within the batch.
4. Module four (Chapter 6) simulates the potential utilization of lumber according to a selected level of knots. The input is the actual properties of boards in the different groups and design requirements (cutting bills). The output is the simulated yield and manufacturing costs, given an assumed lumber value and parts production costs.

Chapter 7 summarizes the operation of the expert system, the outcomes of the system for hardwood lumber produced from a short-rotation, fiber-managed resource in Tasmania, and presents ideas about the implementation of the work.

1.5 Scope

The scope of this thesis is limited to demonstrating an expert system that describes knots found in Tasmanian grown *E. globulus* and *E. nitens* lumber, the use of this information to visualize the potential visual attributes, and sorting of lumber so that the best-suited batch can then be chosen to achieve the desired design outcomes. The results of the system are used to demonstrate that lumber from these resources could viably[10] be used to produce high-value products. These results demonstrate the potential to add value to lumber that is currently considered undervalued and underutilized due to the inability to provide a level of assurance that the material can be efficiently used to produce high-value products. After the surfaces of lumber were digitized, the remaining research was entirely accomplished within the digital environment.

It is outside the scope of this work to discuss the practice or history of design or designers. In this thesis, design as a discipline is only discussed in terms of the geometric and appearance requirements for an application. Additionally, this is not a study of peoples' preferences of wood surfaces.

This research is limited to the data that can be detected from color images. It is also limited to the production of appearance panels. For such a system to be implemented into the industry, additional systems of information transfer, material handling and sorting, and end-user applications would need to be developed.

This research is not a business case or an assessment of the economic potential to produce appearance solid wood panels for in-state production. However, the research does present a means to estimate the costs of producing rough parts for solid wood panels. To determine the feasibility of producing panels for export would require a detailed study that includes a

[10] This research assumes that drying induced checking and other processing defects can be minimized with future research such that they are not the limiting factors in the conversion of lumber into high-value products.

business plan, capital investment, and market analysis to determine the potential financial benefits of such products.

Although hardwood lumber contains avoidable and unavoidable[11] characteristics that influence the physical and mechanical properties, to keep the scale of the project manageable and for the reasons mentioned previously, the research was limited to knots. The techniques explored in this work could be expanded to include other characteristics as the research area matures. Current technology is capable of highly detailed characterization and subsequent lumber grading; however, the current state of industry does not usually make detailed board-scale information available to down-stream operations and most manufacturers are not capable of integrating such information into existing processes.

1.6 Assumptions

This project is based on several assumptions that help to contextualize and frame the research problem. They are:

- There is lost opportunity and value in lumber that contains a high occurrence of natural growth characteristics compared to lumber with few characteristics;
- there is a desire within the industry to develop more sophisticated methods to describe, classify, and process hardwood;
- the boards in the sample set are representative of lumber produced from the plantation Eucalyptus resources in Tasmania and to greater Australia;
- the sensing technologies used will be able to detect and describe the knot population at a resolution and accuracy necessary to reasonably classify the detected objects (knots);
- there will be enough diversity within the population of knots found in these resources to allow them to be divided into different groups based on size, shape, and appearance;
- boards can be classified into meaningful groups based on the distribution of knots across the sample set;

[11] Avoidable characteristics are those caused during lumber production and transportation, while unavoidable ones are those that result from the natural growth of trees.

- this framework could be generalized to other resources and characteristics, and;
- there are other attributes such as drying induced defect, stability, and hardness that also influence utilization of these resources in high-value products.

2 Chapter Two - Justification and Context

2.1 Changing Resources

Over the last several decades, supplies of mature hardwood logs have decreased while young, immature hardwood supplies have increased (Zobel, 1984). In part, this is due to decades of intensive forestry practices, unbalanced age classes of trees and economic pressures to harvest young and small-diameter trees from plantation-grown resources (Kojima et al., 2009, Walker, 2013, Zobel, 1984, Zobel and Sprague, 2012). These resources typically produce wood with different mechanical, physical, appearance, and manufacturing properties than material harvested from old, large, mature forests of the same species (Kojima et al., 2009, Nolan et al., 2005). The differences in these properties are due to the increased occurrence of natural growth characteristics and different proportions of types of wood (juvenile and mature), found in the younger, managed resources (Zobel and Sprague, 2012). Most timber plantations are managed as investments aimed at achieving the greatest possible return that can be achieved by investors. Currently, most plantations are managed as lower-risk investments with faster returns for the pulp and paper industry (Kelly et al., 2005). While there has been extensive efforts to improve plantation grown softwoods for solid-wood products (Ivković et al., 2006b, Ivković et al., 2006a), however, there has been little similar research on eucalypt hardwoods (Blackburn et al., 2010, Blackburn, 2012b). For example, widespread research has been conducted on improvement or Eucalyptus nitens for the pulp and paper industry, however, the opportunities for genetic improvement of this species for the use in solid-wood applications less clear (Blackburn, 2012b).

The physical and mechanical properties of lumber produced from these younger trees are significantly different from lumber produced from older, mature hardwood trees. Hardwood lumber from short-rotation and plantation produced resources are often undervalued and underutilized. Worldwide, the timber industry is facing the question of how to efficiently and effectively utilize the increasing supplies of undervalued and underutilized hardwood resources produced by plantations and managed trees in higher-value products (Luppold and Bumgardner, 2003, Nicholls and Bumgardner, 2015). Conventional markets and supply chains have not responded adequately to this change in available resources and are not currently set up to provide the economic incentive to remove (harvest), process, distribute and

manufacture end-user products from resources that produce elevated levels of characteristics (Reynolds, 1979). There are some exceptions to this situation, innovation within the hardwood lumber supply chain is needed to utilize the material produced by younger trees (Nicholls and Bumgardner, 2007, Nicholls and Bumgardner, 2015, Nicholls and Bumgardner, 2018).

Although reported in 1979, this long-term problem remains largely unchanged in 2020. Specific to this research project, market structures and grading have lagged behind significant changes in other areas of the supply chain. As introduced in 1.1, one major impediment is the inability to communicate detailed information describing the proportion of a board that could be used for different applications. This is the result of lumber grading systems that do not provide a means to pass or use digital information about the variation in physical and mechanical properties present in hardwood lumber. Such information may be useful to increase the utilization and respond to customer desires for unique visual attributes to occur in end products.

Monocultures of even-aged stands are produced under plantation silvicultural practices. Plantations are managed to produce wood volume in short-rotations. In the tropics and subtropics, there are about 20 million hectares of plantation-grown *Eucalyptus* species under various forms of silvicultural management practices. Until the mid-1990s almost all the wood was utilized as pulp, however, the concept to use wood from eucalypt plantations for solid wood products has been discussed and promoted (Tepper, 2007).

In Australia, there are about 1 million hectares of hardwood plantation forests (ABARES, 2016). The plantation hardwood estate is composed of approximately 50 percent *Eucalyptus globulus* (Tasmanian blue gum), 26 percent *Eucalyptus nitens* (shining gum), with a handful of other species making up the remaining area (Downham and Gavran, 2020). Approximately 89 percent of the *E. nitens* plantations occur in Tasmania (Downham and Gavran, 2020). More than 8 million m^3 of plantation hardwood was produced during 2014-2015 and it is forecast that production will continue to increase per annum over the next 40 years (ABARES, 2016). In 2018-2019, approximately 18 percent of hardwood eucalypt plantations were managed (pruned and thinned) to produce sawlog (Downham and Gavran, 2020), however, these

plantations produce less than 5 percent of the total plantation hardwood volume (ABARES, 2016) and less than 8 percent of the total harvest was in the form of a sawlog during 2017-18 (ABARES, 2019) (most of that was as veneer logs). Plantation sawlog harvest makes up about 5 percent of the total hardwood (plantation and native) log harvest (ABARES, 2019), which results in very little plantation-grown hardwood lumber being supplied to the market.

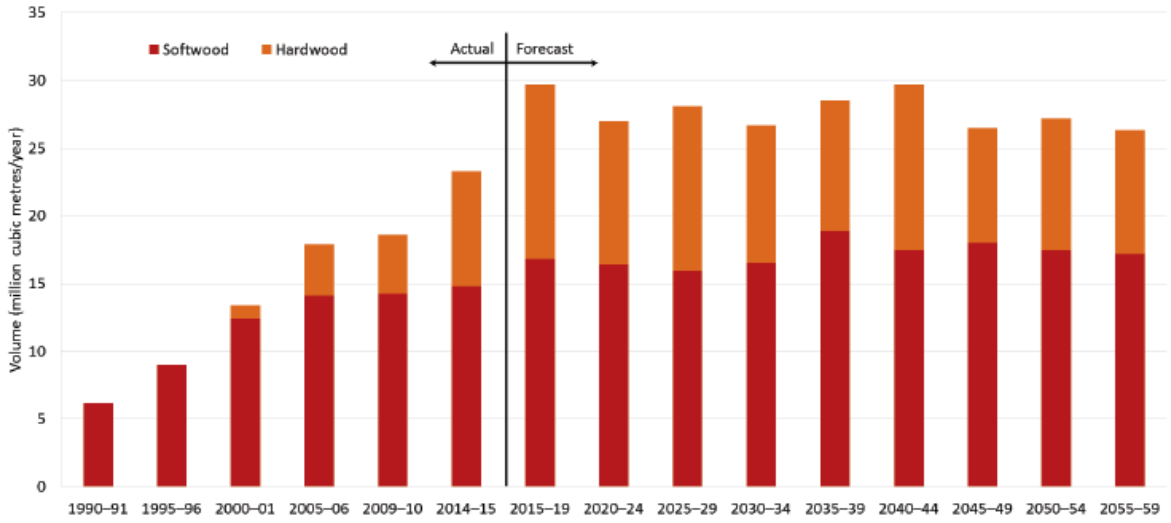


Figure 2-1. Actual and forecast annual average plantation log availability in Australia (ABARES, 20016)

In Australia, research has focused on improving the characteristics of plantation hardwood for use in the pulp industry (Lott and Gooding, 2007); however, very little emphasis has been placed on improving the properties required for solid wood products (Lott and Gooding, 2007). This is primarily because of the uncertain returns on investments over 20 years required to produce sawlogs for lumber and veneer as compared to shorter periods for a pulp managed estate (Blackburn, 2012a).

In Australia, approximately half of the 4 million m^3 of the native forest harvest was sawlog and veneer logs during 2017-18 (ABARES, 2019). This represents a 36.2 percent decrease in the volume of the harvest of native forest logs over 10 years (ABARES, 2019). Sawnwood production has also decreased by 35.9 percent to 711,000 m^3 over the same period (ABARES, 2019). This demonstrates a declining supply of native hardwood which could be replaced with solid wood from plantation resources. Such a replacement requires understanding the properties and potential uses of this new resource (Belleville et al., 2016, McGavin et al.,

2015). However, in the current appearance industry, lumber produced from these resources are undervalued and underutilized because of the significant downgrading to low-value grades due to increased knots and other defects found in unpruned and unthinned logs (Nolan et al., 2005, Washusen et al., 2004). There appears to be a disconnect between forest managers and manufacturers; foresters manage for volume, while manufacturers figure out how to best use the available resources.

Australia currently runs an annual wood and wood products trade deficit of about AUD 2 billion (ABARES, 2019) and imports approximately AUD 451 million of lumber annually (ABARES, 2019). Providing it could be done profitably, processing plantation hardwood to replace imported wood could offset a portion of this deficit (Ozarska, 1998). This could be especially true as the supply of higher quality (but inexpensive) hardwood lumber decreases from other tropical regions. Australia has historically had a small but significant furniture manufacturing industry of more than 3,000 firms (Ozarska, 1998). However, many are craft-based and small (less than 4 employees). Undoubtedly, expectations of the available lumber supply among members of the industry are based on the use of native resources. For the industry to transition to new and different resources, new technologies that increase the utilization of such resources will need to be developed and implemented (Ozarska, 1998).

Given the quantity, available plantation hardwood also has the potential to produce solid-wood products for export markets into neighboring countries with strong secondary-products manufacturing industries, such as China, Taiwan, and Vietnam (Nicholls and Bumgardner, 2018). These markets would require a consistent volume and supply of prepared (dried) and graded lumber that could be integrated and used in the manufacturing sectors in these regions. China currently imports sized quantities of high-quality, high-value hardwood lumber from North America (Wheiler, 2019). For example, North American exports of hardwood in 2007 where about 2.5 million m^3 and increased to about 4.5 million m^3 by 2017 (Wheiler, 2019). During 2017, this accounted to just over 50% of the U.S. hardwood lumber exports (Wheiler, 2019).

The volume of hardwood sawlogs in the eastern United States has been expanding and was approaching 1.3 trillion BF[12] (3 billion m^3) in 2013 (Luppold and Pugh, 2016). Meanwhile, the production of sawn hardwood has decreased to 8.5 billion BF (19 million m^3) in 2018 (Howard and Liang, 2019). Approximately 31 percent of the volume of eastern forests are considered low-quality or cull trees that are typically used for industrial products, oriented strand board, or a source for pulp (Luppold and Pugh, 2016). Lumber from these resources would certainly contain frequent growth characteristics and have a current low market value. Nicholls and Bumgardner (2015) argue that such material could be used in high-value niche specialty markets that utilize small irregularly shaped pieces. They also note that one significant challenge is to maintain consistency within product offerings and for producers to understand consumer preferences for products made from lumber that is different than that of historical supplies. As noted elsewhere in this thesis, the authors of the above-mentioned studies also make a strong case to produce character-marked products from lumber produced from these resources.

The industrial transformation in the forest products industry occurring in Australia and elsewhere presents opportunities to develop innovative technologies and information systems to assist in the value-adding process (Ozarska, 1998), potentially creating jobs locally and abroad. The Tasmanian Wood Encouragement Policy (Department of State Growth, 2017) inspires the building and construction procurement process to take advantage of the opportunities provided by current forest management practices in areas including structural and visual/decorative applications. Observing this policy will ultimately contribute to local economies, industry development, and new products from underutilized resources, however, it will require the creation of efficient and innovative ways to match characteristics of the resource to specific manufacturing processes and requirements.

2.2 Manufacturing Sector

As stated, the purpose of the manufacturing segment in the appearance hardwood supply chain is to produce and assemble elements into complete high-value solid-wood products. The manufacturing of these products typically requires a series of complicated cutting,

[12] Notionally a board foot (BF) is 12 inches by 12 inches by 1 inch. There are approximately 423 BF in one cubic meter.

planing, sanding, and finishing operations which are widely considered to add the most value to lumber (Xiao, 1998). The size and quantity of these elements vary greatly among different types of high-value products. Most high-value products are made up of systems of components assembled from elements. Two common components are panels and structural framework systems. Panels are assembled from strips, or elements, of lumber to create large flat surfaces. Examples are tabletops, doors, flooring, and wall panels. Panels make use of relatively narrow strips to form large surfaces, increasing the utilization rate of lumber that contains narrow useable areas. Panels can be assembled from random length strips of the same width or random width strips of the same length. The two approaches are appropriate for different applications and produce different visual outcomes. Framework systems include the structural components of furniture. An example would be the leg and apron system holding the tabletop the correct distance from the floor.

Specific to the North American secondary wood manufacturing industry, the term cutting[13] is used to replace the term element. The initial step in manufacturing products from hardwood lumber is to produce the required solid dimensional[14] cuttings at the rough mill from quality hardwood lumber (Prak and Myers, 1981). The level of sophistication of processes and equipment in the rough mill varies greatly between companies and regions. For example, for small and medium (less than 100 employees) operations, the rough mill may consist of only a bandsaw and crosscut saw for cutting with and across the grain of the board (Prasetyo et al., 2019). This is sometimes known as piecework and takes different forms depending on available resources, technology, tools, and expertise of the local workforce (Prasetyo, 2018). Large companies process lumber using gang ripsaws to produce multiple strips in a single pass (Gatchell, 1996b). The purpose of the rough mill is to process boards into slightly oversized dimensional parts, or cuttings which are used to produce the end product. In some cases, the rough mill may be separated from other operations, or the rough mill operations are integrated into the operations of the company. In certain situations, rough mill operations are dominated by cutting across the grain. These are known as docking-only operations and are found in countries, such as Australia, where lumber is supplied in standard widths and is

[13] Almost all yield studies use the terms cutting, cutting area and cutting bill.
[14] Dimension parts, in this case, refer to all solid wood parts used in furniture, cabinet and other dimension parts industries. The terms dimension part, dimension part industries or dimension producers applies to all industries listed.

intended to undergo less initial processing. Such operations should be considered a form of the rough mill concept.

Most appearance hardwood lumber breakdown operations use conventional practices based on the sawing limitations discussed above. Few appearance hardwood operations use computer-controlled routers or robots at the rough mill. However, CNC (computer numeric controlled) overhead routers may be able to perform rough mill operations with the proper modifications. Such practices would undoubtedly result in new ways of grading and processing lumber (see 5.4 for an in-depth discussion of current hardwood lumber grading practices).

Dimension parts, or cuttings, are slightly oversized rectangle pieces[15] removed from useable areas of lumber. Here, a useable area[16] is defined as an area of a board that contains an acceptable range of visual attributes[17]. Most research about hardwood lumber processing refers to the usable area as the cutting area. A list of the needed pieces, referred to as the cutting bill, describes the size and the acceptable range of visual attributes of parts required during a rough mill production run for a group of products. The rough mill yield[18] of parts is the ratio between the area of parts produced and the area of lumber processed. Yield is the efficiency of the rough mill[19], and can also be expressed as the amount of lumber processed during a given timespan[20] (Prak and Myers, 1981).

Yield can also be examined in terms of the ratio between the volume of lumber consumed and the volume of finished products, which takes into account operations after the rough mill (Prasetyo et al., 2019). However, yield at the rough mill remains an important aspect because of the strong influence of species, lumber quality, and cutting bill requirements (Prasetyo et al., 2019). The theoretical maximum yield represents the best fit between the cutting bill

[15] Dimension parts are also called blanks, cuttings, component parts, or product elements.
[16] Useable areas may be segments of boards or rectangle areas arranged around unacceptable visual attributes.
[17] Visual attributes may consist of 'clear' (no growth characteristics), grain pattern, color, and other growth characteristics.
[18] Yield is used as a productivity measure.
[19] Rough mill productivity is typically measured as parts-volume/hour, value or volume/employee, value or volume/$ of equipment, or value of parts produced/$ spent on material.
[20] Known as the rough mill production rate in this work.

requirements and the usable areas in the lumber. The goal of the operation is to minimize the cost of the lumber while maximizing the yield of parts at the rough mill. Despite research aimed to develop tools to predict yield from different cutting bills and grades of lumber (Buehlmann and Thomas, 2001, Buehlmann et al., 2004, Buehlmann, 2008, Buehlmann et al., 2008a, Buehlmann et al., 2008b, Buehlmann et al., 2011b, Englerth and Dunmire, 1966, Englerth and Schumann, 1969, Gatchell et al., 1997, Mitchell et al., 2003, Nordvik et al., 2009, Ramage et al., 2017, Schumann and Englerth, 1967, Silk et al., 2015, Stern and McDonald, 1978, Teischinger, 2006, Thomas and Buehlmann, 2002, Thomas and Buehlmann, 2003, Thomas and Weiss, 2006, Thomas and Buehlmann, 2015, Thomas and Buehlmann, 2016, Wiedenbeck et al., 2004). However, the relationship between the cutting bill requirements and the properties of lumber from different quality classes or grades is poorly understood (Buehlmann, 1998, Thomas and Buehlmann, 2016), especially for lumber that contains an abundance of growth characteristics (Buehlmann et al., 1998, Buehlmann et al., 1999, Bumgardner et al., 2000, Nicholls and Bumgardner, 2015, Wiedenbeck and Buehlmann, 1995). This, in turn, limits the ability to accurately predict the cost of materials and labor to produce a given cutting bill.

In 1966 C. D. Dosker was reported to have stated (Englerth and Dunmire, 1966):

> "Wood is missing out as a raw material in thousands of usages simply because the industry has no information on which a designer, or a user, can determine in advance what the refining costs of wood as raw material will be."

In this context, C. D. Dosker was referring to the cost of manufacturing high-value products by the manufacturing segment of the appearance hardwood lumber industry. This sentiment is echoed by more contemporary researchers (Buehlmann et al., 1998, Buehlmann et al., 1999, Bumgardner et al., 2000, Nicholls and Bumgardner, 2015, Wiedenbeck and Buehlmann, 1995) that discuss the uncertainties and feasibility of processing boards that contain a high occurrence of growth characteristics into high-value, character-marked products. Because lumber costs account for approximately 70 percent of the manufacturing costs and up to 50 percent of the total cost of production, it is an important factor in the efficient conversion of lumber to end-user products (Buehlmann et al., 1998, Buehlmann et al., 2011a, West and Hansen, 1996).

Total costs to produce dimension parts are the cost of the lumber and the processing costs[21] incurred during lumber breakdown. Due to the large amount of lumber used in a typical rough mill and the price of lumber, the yield of dimension parts is crucial to the profitability of the overall production of high-value products. The goal is to minimize the expense of raw material and processing costs while producing the maximum area of required parts from the lumber processed. To achieve this, the best-suited lumber needs to be matched to individual cutting bill requirements. The best-suited batch of lumber would contain a distribution of cutting areas that closely meet, but do not exceed the cutting bill requirements. For example, a chair manufacturer could utilize boards that contain shorter and narrower cutting areas, reserving boards with long and wide cutting areas for the manufacture of items that require these sizes of parts. Another example of the best-suited lumber would be a batch of boards with a high proportion of cutting areas that contain an acceptable range of certain characteristics. These cuttings removed from these areas would produce products with specific desired visual outcomes.

The production of dimension parts from lumber is a unique manufacturing process unknown in most other industries. Lumber must be cut in such a way as to obtain all the required parts listed in the cutting bill, maximize yield from each board, and reduce the number of unnecessary parts (Buehlmann, 1998). Also, the process is limited to straight cuts either along the length (with the grain) of the board or across the board (across the grain). Cutting along the length of boards is called ripping and cutting across the boards is called chopping. This limitation is due to the design of machines used in the rough mill. These machines are designed to cut in straight lines either parallel or perpendicular to the grain direction of the board. This limitation requires that parts of similar width be aligned within the board. Cutting solutions to produce the desired quantity of the different sizes of pieces often result in an excess inventory of certain sizes, which is both inefficient and can lead to lumber waste (Prak and Myers, 1981). Ideally, the rough mill avoids waste and inventory to achieve the greatest efficiency.

As introduced in 1.1, the process is also complicated because lumber is a heterogeneous material produced from logs. Lumber is supplied by producers (sawmills) in various sizes and

[21] Includes labor and other associated business costs.

it contains a range of unavoidable natural growth characteristics, such as knots, more or less randomly spread throughout the boards (Brunner et al., 1990a), although certain management and log sorting strategies can result in more uniform distributions and sizes of growth characteristics. The heterogeneous nature is due to the size, type, and frequency of knots and many other characteristics produced during tree growth. The proportion and size of available cutting areas within an individual board or a batch of lumber is directly related to the frequency and distribution of these characteristics. The perceived quality of lumber is largely based on the frequency and distribution of these characteristics and this concept is reinforced by the current hardwood lumber grading systems.

The cutting bill requirements largely determine the maximum yield achievable from a batch of lumber. Many studies have examined the relationship between cutting bill requirements and yield of cuttings from lumber of different quality classes/grades (Buehlmann, 1998, Gatchell, 1996a, Gatchell and Thomas, 1997, Wiedenbeck and Buehlmann, 1995). In general, cutting bills calling for a mix of short and narrow parts mixed with some long parts increase yield, while cutting bills calling for wide and long parts decrease yield (See 6.3.2 for a detailed discussion of this topic). Studies have put forward yield estimation models to predict yield from different grades of lumber for different cutting bills (Buehlmann, 1998, Buehlmann et al., 2003). However, these studies have mostly used lumber graded under the National Hardwood Lumber Association grading rules (see, 5.4.1.2 for more detail about these rules), a database of boards from 1998, and a set of standard cutting bills from products thought to represent the range of what the industry typically manufactures. The results are not particularly relevant for today's lumber supply because boards of the same grade undoubtedly contain a different distribution of cutting area sizes. Also, these studies do not offer a way to understand the relationship for unique cutting bills that might contain a mix of character-marked and clear parts from the lumber available today.

Rough mills lag behind other manufacturing sectors in adopting technology to improve yield. Presently, most cutting decisions are made by human operators with little technical help (Buehlmann, 1998). This practice often results in the yield of clear cuttings below the level that could be achieved using computer simulation of more sophisticated rough mill equipment (Kline et al., 1997). While machine vision systems, computer-assisted simulation

of lumber breakdown, and automated cutting machines become more available and widespread in the rough mill, optimal cutting decisions could occur such that the theoretical maximum yield could be achieved for each board.

Cutting decisions are relatively straightforward for lumber that contains few characteristics within the board, but when boards contain many different sizes and types of characteristics that must be worked around, the decisions about where to cut boards to produce the required parts becomes more complicated. Due to the complexity of the lumber breakdown process, the viable, reliable, and consistent production of parts that contain a defined range of characteristics would be a challenge, if not impossible, for most saw operators given that they have a few seconds to decide how best to cut boards in commercial settings (Buehlmann and Thomas, 2002).

However, an additional challenge occurs during the selection and definition of an acceptable range of characteristics that can occur within cuttings. This challenge largely exists because of the lack of detailed information available to the user describing the variation in the size, shape, and color of different characteristics within the boards. As introduced in 1.1, lumber grading systems do not provide the digital data by which lumber breakdown could be simulated and optimized for different cutting bill requirements. Greater resolution at which lumber is described could provide a means to select or to specify a batch of lumber that would be better suited to produce a certain cutting bill, which may include that specify different levels of characteristics for different parts, over another to achieve the desired visual outcomes, which may or may not include a specific level and type of growth characteristic. Such an ability would enable the user to obtain the best-suited lumber and be able to understand the potential visual outcomes before products where manufactured. As discussed in 2.4, strong markets clearly exist for character-marked products, however consistency in production remains a key limitation in bringing these types of products to market.

2.3 Hardwood Lumber Grading

Grade standards universally segregate lumber based on the form and the perceived quality of the material (Kretschamann and Hernandez, 2006) (see 5.4 for more detail on this topic). The basic concept behind wood quality states that the better the match between the material

characteristics and the product requirements, the higher the quality—regardless of value. Wood quality is a *classification* concept directly related to the suitability of wood for different purposes (Bowyer et al., 2007). Wood quality can be defined as "a measure of the relative characteristics of wood that influence properties of products made from it" (Bowyer et al., 2007) and "… in relation to the usefulness of wood in service to humanity" (Barnett and Jeronimidis, 2003).

The quality of wood is defined in terms of material properties and product requirements, it can be subjective; the perceived quality is determined by the requirements of the application. As an example, imagine a cutting bill that calls for knots of a certain size to occur in parts. A board containing those knots would produce a higher yield of parts than a board without. The knotty board would, therefore, be considered of higher quality than the board without, despite the quality determination of the established grading systems.

Various approaches to lumber grading have evolved for different regions, resources, and industry demands (Kretschamann and Hernandez, 2006). Under both the North American and Australian grading systems, a theoretical value hierarchy emerges between grades of material that contain high levels of characteristics and those that do not. The established grading protocols provide a low-resolution description of the lumber for each grade. That is, the grade definitions do not provide provisions to define and describe the complex arrangement, size, shape, and appearance of the various growth characteristics that could occur within a board or a group of boards. Historically, the technology did not exist to provide high-resolution information and market demand was probably focused on material with few growth characteristics. However, consumer demands change rapidly in contemporary culture, but these changes are not easily accommodated by current lumber grading standards (Nolan, 1998).

In North America, hardwood lumber is graded according to the Rules for the Measurement and Inspection of Hardwood and Cypress issued by the National Hardwood Lumber Association (NHLA). These rules grade lumber according to the minimum potential yield, the minimum size of the board, and the minimum size of all the potential cutting areas[22]; it does

[22] Recently provisions have been added to the standard to accommodate character-marked cutting areas.

not provide size information about the other clear cuttings. It provides 7 quality classes each with progressively lower minimum potential yield and smaller cutting areas size. The NHLA standard assumes cuttings will be removed from clear cutting areas with preference over character-marked cutting areas.

In Australia, hardwood appearance grade lumber is graded according to AS 2796-Timber-Hardwood-Sawn and Milled Products Part 2: Grade Description (Australia Standards, 2006). This standard provides limits to the maximum amount of different avoidable and unavoidable characteristics permitted across the entire piece and the form of the board. It provides 3 quality classes; Select, Standard, and High-Feature. More variation of the frequency and type of characteristics occurs in High-feature lumber than for Select. The accuracy and consistency of grading are considered one of the most important factors for wood buyers (Weinfurter and Hansen, 1999) and both standards provide a means to resolve disputes between suppliers and users that have agreed to use the standards.

These approaches use a conforming and deliberate set of rules that operate on principles of exclusion that are difficult to customize for a different product or consumer need (Olofsson et al., 2019). The rules exclude boards from grade classes based on the defined minimum property[23] for the grade. As mentioned above, cutting area grading only provides information about the smallest cutting area available from a board; it provides no information as to the sizes of the other cutting areas or the distribution of the sizes available from a group of boards. Such an approach implies that there is little indication as to what the maximum potential properties could be for certain boards within the batch. It follows from the discussion on the wood quality that the current grading approaches are at odds with the way that lumber quality is defined for different users and applications. The standards make the universal assumption that quality is associated with large clear cutting areas and boards that do not contain frequent characteristics or for boards that contain few and small growth characteristics overall. The user has limited means to define a group of boards that contain a significant proportion of cutting areas that contain acceptable, and perhaps even desired, visual attributes. Furthermore, suppliers have a limited means to sort lumber consistently and

[23] Properties include cutting area dimensions for NHLA graded lumber, and the amount and group and characteristics permitted within a board for lumber graded using AS 2796.

reliably such that the best-suited boards can be delivered to a user desiring these characteristics.

Lumber grading is part of a marketing strategy designed to ensure users obtain the lumber appropriate for their needs and lumber producers receive the highest possible price for each board. Unfortunately, these objectives are at conflict and can be described as a best attempt to bring order into what would otherwise be a chaotic situation due to the enormous variability in the material (Kretschamann and Hernandez, 2006). Because grading is largely driven by producers and suppliers, it can be seen as a "push" market where the end-user is encouraged to purchase particular grades made available by producers (Shupe and Vlosky, 2010). The current approach is based on the belief that producers understand how the end-users would like lumber to be sorted.

Grading can be accomplished using human vision, machine vision, or a combination of both. In theory, trained personnel should be able to visually grade at, or near, 100 percent accuracy. However, the human inspection process is laborious, inconsistent, error-prone, and subjective (Xiao, 1998). The ability to recognize, locate, and identify different characteristics have been assessed with varying levels of accuracy ranging from roughly 45 percent to 75 percent (Huber et al., 1985, Kline et al., 2003, Pham and Alcock, 1998). Low accuracy is attributed to challenging repetitive mental calculations, difficulty identifying and classifying characteristics, and worker fatigue (Gazo et al., 2018). Assessment and grading inaccuracies can lead to underutilization and do not maximize the value of each piece (Buehlmann, 1998, Gatchell and Thomas, 1997, Gazo et al., 2018).

Commercially available machine vision and associated image analysis software are now capable of accurately detecting and characterizing most growth characteristics and dimensional forms of lumber. Machine grading systems are commonly used for softwood structural commodity products but have only recently been introduced into appearance hardwood lumber production (Gazo et al., 2018). The machines are universally used to assign a grade to boards according to industry-accepted standards, after which the high-resolution information collected by the machines that precisely describes the boards is lost to the low-resolution of the grading standards.

Advances in vision systems, information management, and digital design and manufacturing present an opportunity to match design requirements more precisely (or explore novel design requirements) to the actual supply of timber resources. A better understanding of the relationship between the useable areas and the cutting bill requirements from these areas could lead to greater value return from low-value resources. Investigating this relationship requires a flexible and dynamic means to best match the distribution of useable areas to the cutting bill requirements.

Knowledge of the cutting bill-yield relationship could be used when designing products. Buehlmann et al. (2003), suggested that by utilizing shorter and narrow parts, better yields could be achieved, and that this relationship could be dynamically understood while designing products. The authors state,

> "In the end, smart software should be developed for designers that can be linked to production planning in order to create the individual cutting bills according to part requirements, due dates, and yield interactions."

They argue that these developments and understanding could be used to save money at the rough mill by processing less lumber and in turn, could reduce the pressure on timber resources required to produce quality lumber. Also, a better understanding of yield could result in increased utilization of resources producing lower-quality lumber.

The high-resolution information produced by machine vision systems captures the variation of size, shape, appearance, and distribution of growth characteristics found in hardwood lumber. This information can be used to improve lumber processing in two fundamental areas: the selection of achievable visual attributes and to improve yield by delivering the best-suited lumber for various product requirements. To achieve such a state, technological advancements and transformations in the way digital information that describes the size, shape, appearance, and distribution of characteristics within lumber are required along the supply chain.

2.4 Character-marked Products

Consider the situation where a consumer discusses their desire for visual attributes influenced by certain levels and types of growth characteristics with a design consultant. To

some degree, the consumer can express that they want “knots” or “color” variation in their flooring, for example. However, the consultant has a very limited ability to visualize macro-level changes in the appearance with subtle changes in the composition of size and type of knots. As discussed in 1.1, this is a problem encountered for most naturally heterogeneous materials.

The use of character-marked cuttings has also been shown to provide value-added alternatives for certain species that produce a large portion of character-marked lumber (Nicholls et al., 2009). Nicholls and Bumgardner (2015) note that a remaining challenge is to “use character mark features (characteristics) at strategic levels that consumers’ desire”. If consumers would desire different sizes and combinations of characteristics, manufacturers would be facing a question of yield from the available lumber. Currently, there exists no commercial standard or mechanism to deliver lumber such that different batches would contain the best-suited lumber for products requiring different visual attributes.

The market acceptance and production of character-marked products have been examined in numerous studies. Many studies have examined consumer opinions for different timber species and levels of characteristics, and several have focused on identifying higher value markets for lumber that contain the increased frequency of characteristics (Nicholls et al., 2004c, Nicholls and Bumgardner, 2015). Beyond determining if people like these characteristics, several researchers have reported on people’s perceptions and preferences for differing levels of visual attributes. In the 1990s Masuda (Masuda and Nakamura, 1987, Masuda, 1992, Nakamura et al., 1994, Nakamura and Masuda, 1995, Nakamura et al., 1999) and others investigated simple descriptors, such as ‘novel’ and ‘natural’ used by people to describe different timber surfaces.

Broman (Broman, 1995a, Broman, 1995b, Broman, 1996, Broman, 2000, Broman, 2001) pioneered methods to measure peoples’ preferences for different surfaces containing varying types and frequencies of knots. Broman (2001) found that people’s preference for different levels of wood characteristics was related to harmony and activity and the most important factor was to avoid a state of disharmony. These studies (Broman, 1995a, Broman, 1995b, Broman, 1996) define disharmony as a “bad overall blend of wood features (characteristics)

and …. Divergent features that mismatch on the surface". A bad overall blend could contain too much of some characteristic or a "bad" mismatch of knot shapes. A mismatched surface could contain parts with a wide range of texture or color or knots clustered together. Fell (2004) found that color was a good indicator of consumer preferences for timbers native to Canada. More recently, Breinig et al. (2015), Manuel et al. (2015), and Manuel et al. (2016) suggested that different groups of people prefer timber surfaces that contain a range of different characteristics (i.e. one group may prefer small light knots, while a different group may prefer large dark knots).

Although general conclusions are difficult to draw, there appears to be a preference for homogeneous feature sets, such as knot size and appearance (i.e. black, dark, light, round, elliptical) type (Broman, 2000, Høibø and Nyrud, 2010) and that consumers will readily accept character-marked timber products, and in some cases are willing to pay more for such products (Donovan and Nicholls, 2003, Nicholls and Barber, 2010, Wang et al., 2004).

Despite the growing body of evidence that character-marked products may result in increased utilization of lumber and that significant markets exist for such products, few companies have made specific efforts to produce and market such furniture (Bumgardner et al., 2000). Numerous strategies to increase the success of such furniture have been developed by adventuresome companies looking for something new to attract attention within a competitive industry (Bumgardner et al., 2000). Bumgardner et al. (2000) found the ability to dynamically adjust the level of character-marks based on feedback from retailers and consumers and educating salespeople and retailers that character-marked furniture is produced at the same level of quality emerged as focus areas for successful firms. However, product consistency (knots were not the same in the store as the knots on the furniture delivered) has emerged as a particularly troublesome challenge (Bumgardner et al., 2000). Manufacturers find it difficult to replicate certain visual outcomes between production runs of furniture sets and to estimate yield from the batches (grades) currently available.

Fundamentally, character-marked furniture is a form of customization. The ability to specify certain sizes of knots, splits, checks, and bark during the design phase may be a key component to successful product diversification and development. Nicholls and Bumgardner

(2018) suggest that mass customization strategies need to be adopted that allow rapid response to consumer demands for character-marked furniture. Mass customization gives producers that are “close to the customer” a competitive advantage (Moreira et al., 2008) and has been put forward as a way for the North American furniture industry to stay globally competitive (Bumgardner et al., 2000). Indeed, several models already exist that allow the consumers to participate in the later design stages of furniture manufacturing by choosing from general categories of products, such as ‘naturally blemished’ and “character-marked wood” (Nicholls and Bumgardner, 2018). This approach provides a rudimentary means to define and select the visual outcomes and provides little or no indication as to the manufacturing expenses associated with a users’ choice.

The high-value wood product industry is fashion-conscious; product quality and innovation are highly important considerations (Bumgardner et al., 2001a) as is the ability for rapid product development and production (Leslie and Reimer, 2003). Products often have short lifecycles driven by changing consumer preferences and demands for different styles and colors. Leslie and Reimer (2003) suggest that demand could be increased by shifting the perception of furniture from a commodity to a fashion item. Indeed, the concept of character-marked products and their relationship to the fashions of the day are not new. In 1928, Aldo Leopold, an American philosopher, scientist, ecologist, forester, and conservationist mused about the limitations placed on the use of natural growth characteristics of wood (as referenced in Nicholls and Bumgardner (2015)).

“Take, for instance, our universal insistence on clear hardwoods for furniture and interior woodwork… is it too much to hope that fashion may someday lift the ban against sound knots in places where they enhance the beauty of the wood and do not injure strength (properties).”

Nicholls and Bumgardner (2018) provide an in-depth discussion connecting the concepts of supply chain agility and the ability to respond to changing consumer desires. The authors note that agility is required for high-level product customization such as manufacturing innovations and fashion products. Agile enterprises are the “furniture enterprises of the future” and adopt technology that matches the customization strategies of the firm (Azouzi et al., 2009). Agility is enabled by the introduction of new technology that outlives the products which it was developed to produce. According to Um (2017), supply chain agility

includes the ability to rapidly reduce product development cycle time, manufacturing lead times, increase product customization, and improve responsiveness to changing market needs. Agility and customization strategies have been shown to increase the competitiveness of U.S. furniture and cabinet industries (Lihra et al., 2008). Successful internal strategies include involving the customer in the later stages of production, such as the customization of finishes. External strategies include developing close linkages between producers and customers (Um, 2017). Supply chains can be designed and managed to match unique (and changing) customer demands to special products, materials, and information flow. This thesis addresses the challenge of agility by improving the flow of information describing the variation of hardwood lumber between producers and users.

The work presented here uses a solid-wood architectural appearance panel as an exemplar product to illustrate the capabilities of the procedures developed within the thesis. Wood panels represent a significant product and provide an excellent opportunity for the wood industry to compete in international markets (Deaver, 2006). It is a lower-cost alternative to conventional mills and an opportunity to utilize lumber from species that are sometimes underutilized and undervalued (Lamb et al., 1990). In 2001 solid wood panels accounted for 13 percent of the wood components market in the US (McDaniel, 2003). Panelized products are marketed towards other manufacturers of furniture, doors, and various other solid wood products. They can serve as an intermediary product and be processed into other products or be produced in specific sizes as components to products. Deaver (2006) provides an in-depth discussion of the economic considerations and past research on the production of wood appearance panels but also notes the difficulty in producing and maintaining consistent visual attributes (uniform color) during the production of panels using clear[24] strips. The in-state production of standard-sized wood appearance products represents a potential export product for the State of Tasmania. Such panels could be processed into parts in ways similar to other sheet goods such as plywood and composite materials.

[24] Clear strips refer to strips that are not allowed to contain growth characteristics such as knots.

The construction of these panels typically involves assembling strips processed from areas of boards. This result promotes a commercially viable product manufactured from the lumber studied and demonstrates the tangible value of the approach presented here.

2.5 Lumber Optimization

To fully exploit the concept of character-marked customization, limitations in the way that high-resolution information describing the visual outcomes and processing costs are collected, packaged, and passed between suppliers and users need to be addressed. Users require information formatted in such a way that it can be digitally integrated into design procedures and manufacturers need information formatted such that it can be used to determine which boards should be used to produce different cutting bills. Lumber needs to be batched in such a way that the best-suited lumber can be specified for different cutting bill requirements.

Within the digital environment, design elements are represented by abstract geometric shapes. The visual attributes of these elements can be observed by assigning information describing the properties, such as color, within the digital representation. The assumption of material uniformity is built into most computer-aided design (CAD), computer-aided manufacture (CAM), and stock cut-up optimization software, which has led to a situation that attempts to treat non-uniform materials with the same techniques as uniform ones. For example, the representation of wood surfaces is generally limited to generic color and grain patterns. In the current industry, seldom is the selection for or against various visual attributes produced from the distribution of growth characteristics found in hardwood lumber considered during design and manufacturing operations.

Many industries use computer algorithms to reduce waste during cutting operations. The process of arranging the required parts within the supplied cutting stock is known as nesting. Nesting consists of simulating the cutting of irregularly shaped master surfaces (cutting areas for lumber) into many smaller shaped pieces (cuttings). The resulting layout could be required to satisfy constraints concerning the arrangement of acceptable characteristics, cutting bill requirements, and cutting technology and capabilities. The objective is to minimize waste of the master surfaces while adhering to the required constraints. Stock cut-up simulation and

nesting are common in industries that work with uniform manufactured products, such as metal sheets, paper, and standard sizes of composite boards (e.g., plywood, MDF). Information describing the dimensions of the stock and the required parts are supplied to the optimizing software to derive the optimal cutting solution. Nesting is often built into CAD/CAM software such that cutting directions can be sent directly to computer-controlled cutting machines (CNC).

When the size of the master surfaces varies, it is termed the irregular multiple stock-size cutting problem (Baldacci et al., 2014). This problem occurs in the leather and garment industries where pieces must be arranged around unacceptable characteristics found on the master surfaces. This problem can be applied to lumber because of the variation in the available cutting areas. Optimal solutions for these problems can be found algorithmically using computer simulations of the lumber breakdown process (Thomas et al., 2014). The results of these solutions can be passed to cutting machines to achieve the best possible yield of parts from the available supply of lumber (Conners et al., 1997b, Kline et al., 1997, Lu et al., 1997). Simulation can be used to predict the yield of both clear cuttings and character-marked cuttings by defining an acceptable range of size, color, or shape of characteristics that parts can contain, and therefore, an estimate of the raw material costs needed to satisfy the cutting bill. The results not only optimize the cut-up problem but also provide a means to determine the best-suited batch of lumber that satisfies the cutting bill requirements. Despite the ability to optimize the cut-up of lumber, it is uncommon for rough mills to use simulation to predict the match between cutting bill requirements and different batches of lumber (Grueneberg et al., 2012).

Methods and techniques used to optimize cut-up and selection for specific properties for uniform products could be adapted for non-uniform materials. However, information that defines and describes the physical properties and distribution of growth characteristics within individual boards and batches of lumber is largely unavailable to the manufacturing sector. This is due to the antiquated lumber grading methods that do not describe the variation and distribution of growth characteristics of lumber or communicate high-resolution board-scale information that could be used to achieve a better yield of parts. Furthermore, the topics under considerations in this thesis may be new within the context of the industry. It is

reasonable to assume that companies will respond and fill the role to provide the equipment and protocols to fulfill the research gaps addressed in this work.

Optimizing the use of lumber requires special considerations and techniques which have not been fully developed. Technologically advanced log breakdown and CAD/CAM optimization software are commonly used by the production and manufacturing segments. This technology relies on detailed geometric data describing the material to be cut, the market value of different products and the parameters of the pieces to be produced to determine the optimized cutting patterns. However, there is little digital information exchanged between the production and manufacturing segments to inform the sorting and delivery of lumber that could result in the optimized processing of lumber along the supply chain. As mentioned in 1.1, it is very difficult to predict the finished appearance and the manufacturing costs of wood products on a commercial scale. The availability of such information for lumber would allow detailed selection for or against certain visual attributes during design, the development of flexible grading methods that could more effectively deliver the best-suited batch of lumber for different cutting bill requirements and would improve rough mill performance. Such a system may overcome the current limitations by determining the processing costs and predicting the visual attributes available from different batches of lumber.

As Industry 4.0 technology is developed and adapted to suit the needs of the industry, the forest products industry is under transition (Müller et al., 2019). Within the smart wood supply chain, information describing products, including lumber, would be stored in a cloud-based network. The information would provide the capacity to value-add for all stakeholders within a given supply chain (Müller et al., 2019). One benefit of such a system would be fewer disruptions and information conversion (i.e., paper-based systems to digital systems). These benefits would support the effective allocation and processing of lumber in the hardwood supply chain.

The research presented in this thesis provides a framework for advanced analytics of sorting and grading lumber that improves the match between harvested (available) timber resources and customer requirements. This is done by enabling high-resolution communication of the

characteristics of hardwood lumber between producers and manufacturers within the appearance hardwood lumber supply chain. This could potentially change the supply from a push market to a pull market, an important transition for the development of agile and responsive supply chains that combine the physical and digital world (Müller et al., 2019). Such a system could provide the advancements necessary to utilize the characteristics of the available hardwood resources more effectively.

3 Chapter Three - A Method to Characterize Knots Found on Hardwood Lumber

3.1 Purpose

This chapter presents the procedures that were developed to detect and classify knots from images of the sample boards. This information was then used to create a novel knot classification model and characterization technique that enhanced the resolution at which knots are described and at which knots, and other characteristics can be specified by end-users. It also presents a validation method that indicates the performance of the model and characterization methods.

3.2 Objectives

Knots are one of the most frequent characteristics that influence manufacturing properties and greatly influence visual attributes (Breinig et al., 2014, Broman, 1995b, Broman, 1996, Buehlmann et al., 2008a). Most vision system research has focused on classifying the natural wood characteristics into industry-accepted classes, such a live knot, dead knot, wane, and so forth. This information is used to grade lumber according to established industry grading standards. This thesis seeks to describe knots at a greater resolution to develop a lumber characterization strategy that provides the ability to match the cutting areas more accurately to different cutting bill requirements. This chapter addresses objective one, which describes the development of a means to digitally characterize and describe the knot population of lumber in greater detail then is available from current lumber grading standards. This requires developing a means to:

- automatically detect and characterize knots from digital images;
- validate the automatically collected data, and;
- develop descriptive variables that describe knot size, color, and orientation.

The method should have the following detection targets:

- true positive rate of detection greater than 80 percent;
- the false positive rate of detection less than 10 percent;

- the false negative rate of detection less than 20 percent;
- accuracy of detection greater than 80 percent;
- a precision greater than 80 percent, and;
- the true positive rate for size and color classification greater than 50 percent.

Initially, these criteria may seem low compared to other results found in the literature (Bond et al., 2002, Xiao, 1998). Those studies were largely driven by the endeavor to grade boards according to specific quality and grading standards, which require accurate detection and classification of growth characteristics. In this study, the goal was to collect digital information about the sample lumber. This was necessary because there is very little publicly available digitized information describing the distribution of knots and other growth characteristics of lumber produced from the resources used in this work. To the author's knowledge, there has been no large-scale machine vision work done on the species examined in this research, however, commercial lumber scanning machines exist that could be used to collect this information at speeds and accuracy necessary for an industrial application of the work presented in this thesis.

3.3 Background

The rational trade of resources that differ from those historically supplied requires a new grading and assessment approach. This is because the utilization and value of these new resources are challenged by the traditional concepts of wood quality and wood utilization, and specification procedures. To fully capture the potential value from these new resources, producers must batch material such that it can be processed effectively and efficiently according to different product cutting bill requirements. Undoubtedly, methods of assessment, description, and processing will differ from conventional practice. Technological advances adaptable from Industry 4.0 will improve how the performance requirements and the material properties are communicated and used within the supply chain.

To achieve these improvements, tools and techniques that account for and communicate the expected cutting areas achievable from individual pieces and batches of material and a way to integrate high-resolution material description into processing and manufacturing operations need to be developed and utilized. Neither Australian nor North American

hardwood grading standards provide the resolution to delineate groups of boards in this way or into user-configurable batching of materials. An alternate approach would effectively group boards according to size, frequency, and distribution of cutting areas containing user-defined properties. Although some manufacturers develop special grades for such applications, studies have indicated that lumber for which no industry standard grade exists has potential as a marketable resource (Boden et al., 2005, Buehlmann et al., 1999). A flexible, simple, and rapidly applied method to develop such a system is desired (Boden et al., 2005). A reasonable approach would involve a visual inspection system that automatically detects; describes and classifies characteristics and determines the available areas where cuttings of the required appearance could be removed.

Any assessment approach requires a consistent methodology to define and measure the characteristics found in the material. Consider a knot; the initial challenge is to determine the boundaries of the knot. From a technical point of view, a knot is a characteristic that occurs in logs. It is the consequence of branch formation in trees. In branches, the angle of the water transporting cells change from largely vertical to largely horizontal. Therefore, a knot is defined at a cellular level as a dramatic change in fiber and vessel angle, which can happen gradually or abruptly, depending on species and many other factors. Visually, this gives rise to the grain pattern on board surfaces. A knot edge could be defined at the beginning of any irregularity of the surrounding grain, or in terms of a distinct change in color or wood density from the surrounding area (Figure 3-1), but often cannot be definitively demarcated and is subject to personal judgment and manufacturing requirements. Knots can be measured in two perpendicular directions (a, b or x, y or x', y'), or size can be expressed in terms of the diameter (Figure 3-2).

Figure 3-1. Different ways to define the boundary of a knot.

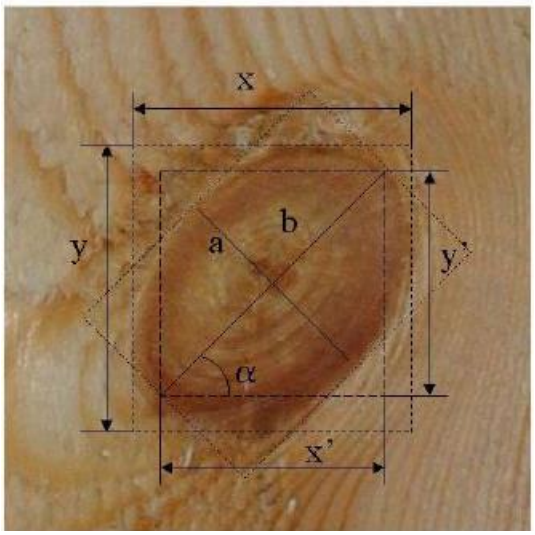


Figure 3-2. Different ways to determine the size of a knot. The size could be expressed as a diameter, or calculated from the measurements of a and b, x and y, or x' and y' (Lycken, 2006a).

The problem of how to describe the appearance of a knot also needs to be addressed. Typical terminology, such as '*sound*' or '*unsound*', provides little detail into the visual characteristics. Often the words such as '*dead knot*' and '*live knot*' are used, which provide only the knowledgeable user with a basic idea of appearance. The term '*black knot*' is a bit better; it provides a clue that the knot is darker than the surrounding wood. Describing the 'grain' of a piece of lumber provides yet another example of the complexity of the lumberman's vernacular. Hoadley (2000) lists more than 50 ways that the word 'grain' is used to describe the visual attributes of the "direction of the dominant longitudinal cells in a tree".

Modern vision inspection technology provides a solution to standardize both the measurement and the definition of certain characteristics and to help clarify the visual appearance of certain features. For example, the definition of a black knot might be based on the percentage of pixels below a specified threshold within a region defined as a knot. Such an approach may liberate segments of the industry from the homogenization and standardization of the grading of lumber, which treats the unique characteristics of wood as unwanted defects (Hubbe and Buehlmann, 2010).

3.4 Vision Inspection

Automated vision-based inspection systems can be used to identify and describe the variation and type of characteristics found in lumber produced by different hardwood resources (Buehlmann et al., 2007b, Conners et al., 1992, Conners et al., 1997a, Kline et al., 1997, Kline et al., 1998a, Kline et al., 2003, Lu et al., 1997). Visual inspection is defined as the process by which pictorial information is perceived from human or machine vision sensation (Kauppinen, 1999). Therefore, automated visual inspection is defined as an inspection process performed by a machine vision system using pictorial information from optical sensors (color or gray-scale camera), ultrasonic, laser-range profiling, or X-ray imaging, or a fusion of several sensor types (Boden et al., 2005, Hashima et al., 2015, Xiao, 1998). Such systems are used extensively to differentiate defective products from acceptable ones, measure product properties to control a manufacturing process, and to gather statistics on a manufacturing process (Kauppinen, 1999). Visual inspection systems should not be considered a testing procedure as they do not examine the performance or operational function of a product. Grading inspection, a hybrid type of inspection, is based on the process of grouping products into classes with defined limits of certain properties.

Visual inspection is primarily concerned with describing the objects found in an image. The disciplines of machine learning and image analysis provide terms to describe the process (Kohavi and Provost, 1998). After an object has been described, it is considered an instance in a dataset. Instances are described by attributes. An attribute is a measurable quantity, such as color and size, that describes a single object. Attributes can be categorical, such as large, medium, small, or continuous, and provide a means to describe a measurable difference in

value. A feature specifies the attributes and their value. Certain attributes with multiple *dimensions*, such as size and location, require several features to fully describe. These are commonly referred to as dimensions of the attribute. For example, the attribute of size requires the dimensions of width, height, and depth. The attribute of location requires, for example, a set of x and y coordinates from an origin. An instance is fully described by its feature vector—a list of the specifications of attributes that characterize the object.

An instance is classified, or labeled, to a discrete class by a classifier. A classifier is a mathematical function implemented by an algorithm. For this work, the term instance refers to an object that has been described by a feature vector that can be classified. It follows then, an instance refers to objects of various scales. This chapter uses the instance to refer to objects found on the surface of boards, but Chapter 5 uses the instance to refer to the boards themselves.

Knots and other natural growth characteristics are produced in a variety of colors, sizes, shapes, and frequency. In the wood products industry, common classes of these characteristics include different knot types, checks, bark pockets, gum vein, wane, wormholes, decay, and pith (Figure 3-3). Defining and specifying the feature vector of individual growth characteristics is a multiple-step operation. The objects of interest must first be detected, then described, then classified according to a classification structure. For this research, object detection is a procedure that determines the location of an object in an image of a board's surface. Object description is the process by which the attributes of each object are described. The result is a feature vector for each instance in the image. Object classification is the process by which an instance is assigned to a discrete and defined class of characteristics. The domain defines the range of characteristics of interest to the problem at hand. Therefore, an inspection *process* is concerned with the rate of detection, the accuracy of the characterization of the object, and the mapping of objects to a specific domain. The domain of this study are knots produced by two plantation hardwoods from Tasmania, Australia. The classes in this domain are designed to increase the resolution of information that describes a knot.

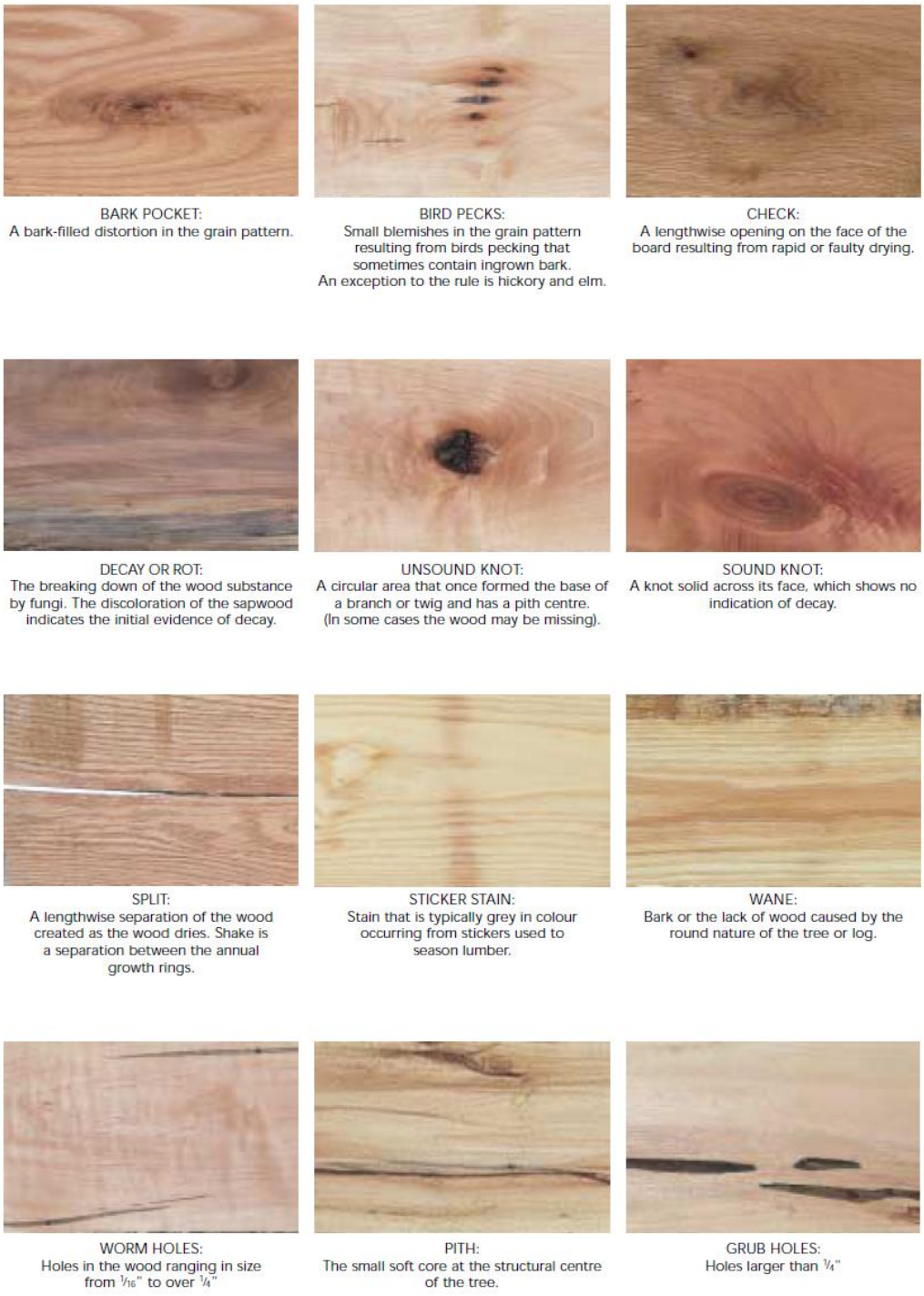


Figure 3-3. Common characteristics found in sawn North American hardwood not allowed within clear area cuttings under NHLA grading rules (American Hardwood Export Council, 2008).

The literature on machine vision systems applied to industrial inspection problems is extensive, however, each application requires unique adaptations of existing approaches or the development of new methods to locate objects for further examination. Automatic

detection of the characteristics of hardwood has been an active area of research for decades and has been suggested to be an effective means to grade boards and to increase processing efficiency (Boden et al., 2005, Buehlmann et al., 2007b, Hashima et al., 2015, Kline et al., 1998a, Kline et al., 1998b, Kline et al., 2003, Luo and Sun, 2019, Xiao, 1998). Machine vision systems are composed of hardware and software components (Figure 3-4) (Conners et al., 1997a). Hardware includes one or more image sensors, lighting, and image acquisition components. The software usually consists of image processing, user interface, and graphical and equipment control modules.

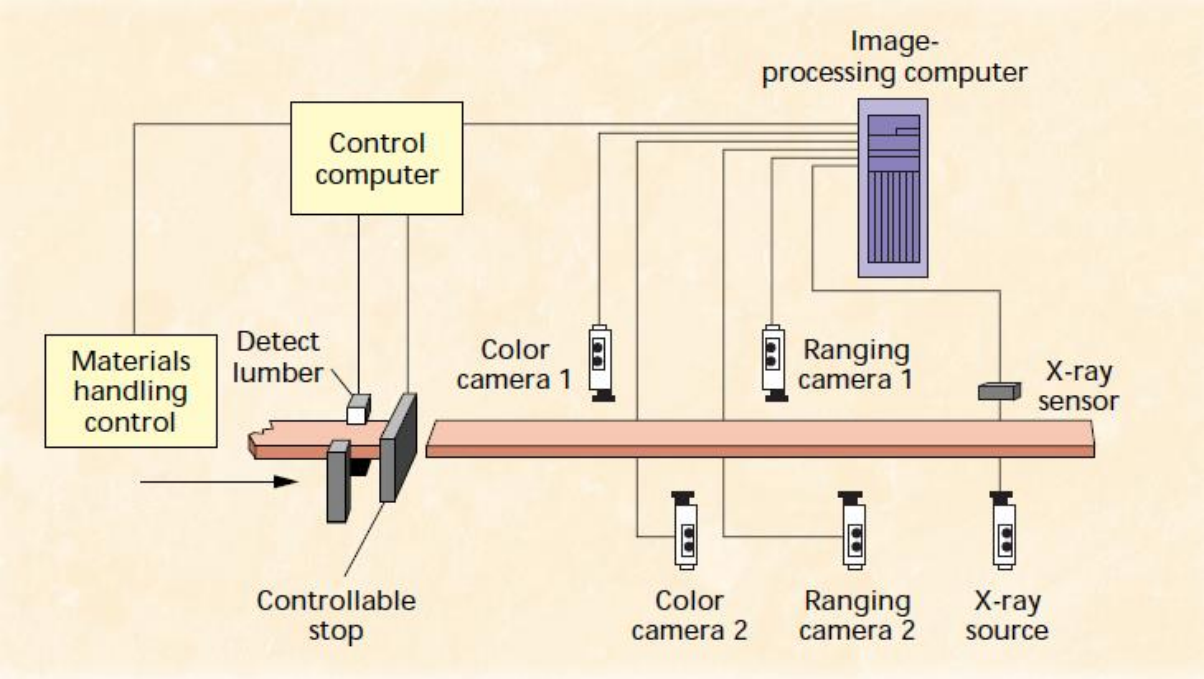


Figure 3-4. Schematic of a machine vision system for lumber inspection (Conners et al., 1997).

Such machines are commercially available and universally used to grade materials to existing commercial grading standards. Most systems are used in conjunction with other machines to improve sawmilling processes and to increase the value of the sawmilling process. Examples of commercially available systems include the GradeScan available from Lucidyne Technologies (https://www.lucidyne.com/), the WoodEye available from WoodEye (https://woodeye.com/), and complete scanning, optimization, and process control systems available from USNR (https://www.usnr.com/) and Microtec (https://www.microtec.eu). These systems are mostly used to optimize the production of high-value lumber. However, due to the wide diversity of growth characteristics among different species, the parameters

of the system need to be tuned to each new species (Gazo et al., 2018). Detailed information is collected at a board scale and used to assign a grade from a grading standard. Judged against human graders, on-grade accuracy exceeds 92 percent (Gazo et al., 2018). The high-resolution board-scale information collected during lumber production is typically not used in further lumber conversion operations and there does not appear to be a mechanism to move this information along the supply chain, despite the potential to use it. However, there are examples of docking line systems that scan lumber just before processing. Despite optimizing the incoming lumber, that approach does not provide the ability to sort lumber before distribution.

3.4.1 Automatic Detection Approach

Because of the wide variation in the features of wood attributes, different methods are required to successfully classify the characteristics present in the sample material. However, the general approach is composed of three components: image acquisition, image processing, and object classification. Image acquisition consists of exposing the sensor(s) of a camera to a sample and digitizing the image. Poor or uneven lighting, resolution, and focus will cause problems in further processing. Once an image is recorded, information lost during image acquisition cannot be recovered. Image processing consists of various operations to correct, calibrate, and manipulate the image to detect objects. Object classification seeks to determine the feature vector of detected objects and map these objects to classes. Therefore, a general visual inspection system consists of image acquisition, image processing, and image analysis sub-modules. Image analysis consists of object detection, object description, and object classification sub-modules. Various methods are used during these processes depending on the detail required for the application and the attribute type of interest (Kohavi and Provost, 1998, Nisbet et al., 2018, Tan et al., 2018). For a detailed presentation of the techniques used during image acquisition, image processing and object classification see Appendix 1.

3.4.1.1 Characterization Model Accuracy

Many types of classifiers have been developed for various purposes, data, and classification problems. There has been a long-standing interest in the forest products industry to develop

a machine vision system to improve the processing and grading of lumber (Conners et al., 1997b, Gazo et al., 2018, Kline et al., 1997). This is because value is lost on boards that are downgraded to lower value classes, which is a better outcome for the end-user, but lowers overall profit for producers (Kauppinen, 1999). The overall goal of using an automatic classification system is to detect the characteristics of timber faster and more accurately than the human grader. This is important during grading and processing operations because grading accuracy determines a board's market value, effects profitability of sawmilling and provides greater assurance to end-users that they will receive lumber of the grade specified. Automatic feature detection in research settings report rates of feature detection and classification exceeding 70 percent and near 100 percent has been achieved, for both softwood and hardwood using various approaches (Conners et al., 1983, Conners et al., 1992, Conners et al., 1997b, Conners et al., 1997a, Funck et al., 2003, Hashima et al., 2015, Kline et al., 1997). Performance varies according to both the classifier method and attributes used during model development.

Classification methods based on color information work well for dry and bark-ringed knots, pitch pockets, and color defects because of the large difference in color values between the feature and the surrounding backgrounds (Kauppinen, 1999). Shape information is more useful to detect and classify splits and many types of knots, than the deviation in grain and color defects (Kauppinen, 1999). Sound knots and splits are ranked among the most difficult to detect, while rotten knots and grain deviation are the most difficult to classify (Kauppinen, 1999). Therefore, it follows, different techniques and scanning technology are necessary to detect and classify different types of wood characteristics. For example, both color and grayscale images produced from cameras are useful to detect knots, while laser produced images are more suitable for determining the shape and form of boards.

Classifiers such as fuzzy logic (fuzzy matching), artificial neural networks (ANN), and rule-based classifiers, self-organizing maps (SOM), and decision trees have been used to classify timber characteristics (Hashima et al., 2015, Pham et al., 2005, Xiao, 1998). Other studies have proposed linear discriminant models (Kim, 1985, Koivo and Kim, 1989), support vector machines (SVM), and bagging (Gu et al., 2009, Hittawe et al., 2015, Niskanen et al., 2001, Venkatachalapathy, 2012) to classify characteristics such as knots, pith, shake, and pitch

pockets. An Ensemble Bagged classifier was used in this chapter. This type of classifier combines several decision trees to produce better predictive performance. The performance of various classifiers has generally been above 70 percent. Non-supervised methods such as SOM have also been tested (Niskanen et al., 2001). Various classifiers have also been used to determine grades of boards (See 5.4.2). Many authors have referred to this as quality grading.

Various image processing and image analysis approaches have been developed to aid in the description of the characteristics. Early work proposed characteristics could be adequately detected and described using simple color channel intensity levels (Brunner et al., 1990b, Brunner et al., 1992, Butler et al., 1989, Conners et al., 1983, Kauppinen et al., 1999, Niskanen et al., 2001, Silven et al., 2003, Sobey and Semple, 1989, Todoroki et al., 2010). Others investigated the use of geometric features to detect characteristics (Cho et al., 1990c, Conners et al., 1992), while many others have used both color information and geometry (Astrand, 1996, Bond et al., 1998, Hu et al., 2004, Kline et al., 2003, Yang et al., 2017). Texture measures, (both histogram-based and relative position) have also been used by several researchers (Conners et al., 1983, Estevez et al., 1999, Kim and Koivo, 1994, Niskanen et al., 2001, Rinnhofer et al., 2005, Silven et al., 2003, Wang et al., 2010, Weidenhiller and Denzler, 2014, Ziadi et al., 2007a).

Due to the complex and variable surfaces of wood, tonal (intensity-based) measures have limitations (Kauppinen, 1999). However, the use of color images improves the ability to detect features that blend into the background and has been shown to increase the accuracy of detection of some types of features by as much as 20 percent (Butler et al., 1989). Textural information increases detection and classification accuracy. Rinnhofer et al. (2005) argue that the characteristics of hardwood are best described using textural attributes. Wang et al. (2010) state that the choice of parameter analysis (e.g. x and y) during the implementation of the co-occurrence matrix requires consideration, but likely provides a useful solution in further wood characteristic classification.

Classification accuracy varies considerably with differences in the characterization model, species, and the wood character of interest. Because knots are a very common characteristic and important in both structural and appearance grading, this class of characteristics has been

the focus of many studies. Funck et al. (2003) reported 95 percent and 90 percent accuracy for loose and tight knots in Douglas-fir veneer, while Todoroki et al. (2010) reported a rate of 96 percent on the same type of material. Both studies used a variety of image processing analysis procedures but not texture measurements. Sobey and Semple (1989) and Conners et al. (1983) used a Bayes Decision tree classifier to achieve 88 percent accuracy for knots found in southern red oak and achieved a 58 percent increase by incorporating texture measures into the classifier. Estévez et al. (2003) reported an accuracy of 82 percent for knots using a combination of multicolor thresholding and segmentation and 3 neural network classifiers on ponderosa pine boards. Hu et al. (2004) claimed 92 percent and 94 percent accuracy for live and dead knots using a non-segmenting approach to detect knots and a rule-based classifier for Sugi (Japanese Cedar). Koivo and Kim (1989) and Kim (1985) obtained 97 percent detection and classification accuracy using discriminant functions based on the mean and variance of the grey levels of features as inputs. Their technique was further improved by Iwasaki and Sadoh (1991) to determine knot size and achieved accuracies between 90 percent and 100 percent. Established industrial equipment vendors are claiming nearly 100 percent accuracy for a wide range of characteristics (e.g. https://www.lucidyne.com/products/gradescan/), however, it is widely assumed that 100 percent detection is generally not possible for hardwood lumber (Buehlmann et al., 2007b).

3.5 Methods and Materials

3.5.1 Harvesting, Sawing, and Drying of Material

This study uses *Eucalyptus nitens* and *E. globulus* board milled from logs harvested from northwestern Tasmania, Australia. Boards of *E. nitens* were selected from 44 logs harvested from a 15-year-old unthinned, unpruned plantation site located in the Woolnorth region of Tasmania. *E. globulus* boards milled from 26-year-old logs harvested from a nearby estate under similar management were also selected for this study. The logs were originally harvested in 2016 for a research project examining the potential of such material for structural applications at the University of Tasmania (Derikvand et al., 2019). Trees were harvested using conventional processes for pulplog production, and as such ungraded, un-bucked logs were delivered to the sawmill for processing. After harvest, logs were processed using the conventional plain sawing method, which produced mostly flat sawn board with a

limited amount of quarter sawn lumber[25]. Boards were dried according to industry standards of the area and processed to a finished thickness of 35 mm and finished widths of 70 mm, 90 mm, 120 mm, and 140 mm. The un-graded boards contained numerous avoidable and unavoidable characteristics.

3.5.2 Sample Material

Images were acquired from 152 unique *E. globulus* boards and 110 unique *E. nitens* boards. From these boards, both sides of 8 *E. globulus* and 26 *E. nitens* were imaged, for a total of the 159 images of *E. globulus* and 136 images for *E. nitens*. The distribution of width and length of the validation set is shown in Figure 3-5 and Figure 3-6.

[25] To reduce drying induced defects (collapse), lumber produced from large older trees is typically quarter-sawn. Quater-sawn results in a board with its broad face more or less in the radial plane of the growth rings. Flat sawn refers to boards with a board face more or less tangential to the growth rings. In Australia, the term backsawn is often used to refer to flat sawn boards.

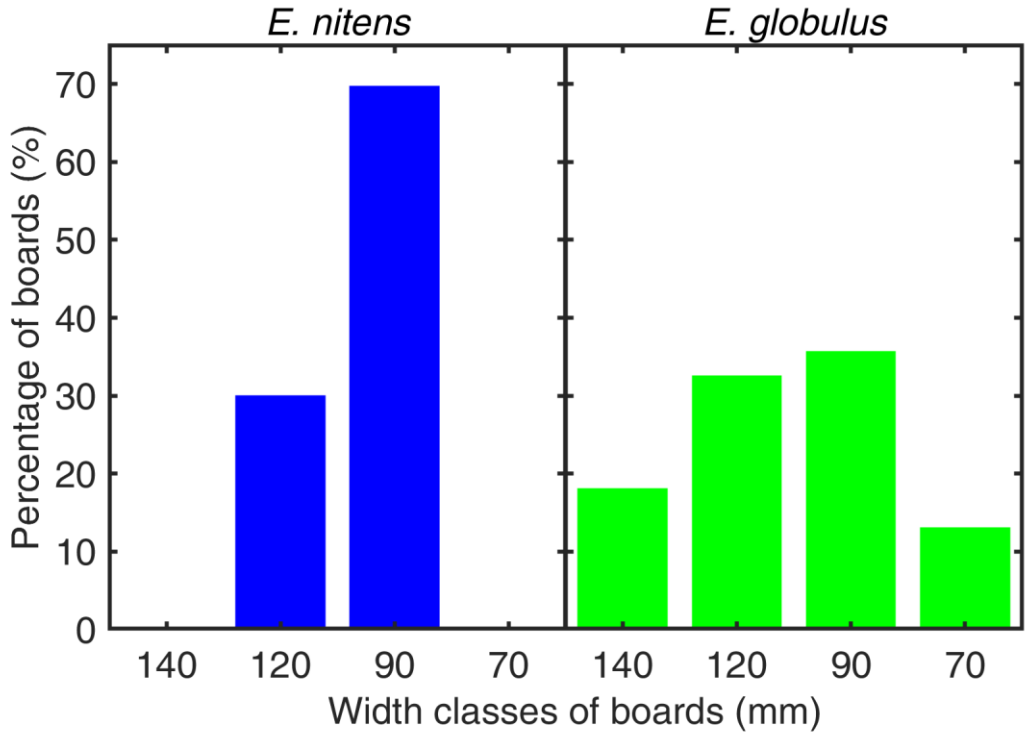


Figure 3-5. Width distribution of the boards in the validation set (n=136 for E. nitens and n=159 for E. globulus).

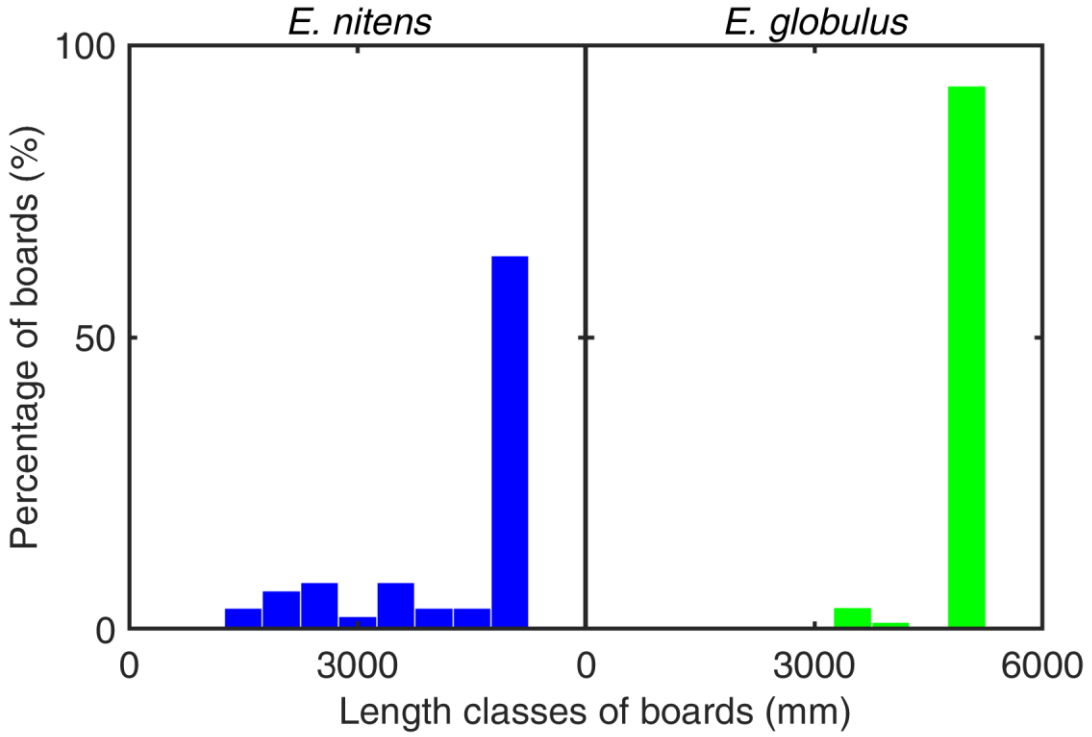


Figure 3-6. Length distribution of boards in the validation set. Note that the maximum x-axis value is 6000 mm for E. nitens.

The knot characterization model developed in this work is shown in Figure 3-7. It consists of image acquisition and a processing module, an image processing module, and an image analysis module. Although accuracy is important for industry-focused grading activities, it is not the primary focus of this work. Rather, the primary importance was to demonstrate the principle that such a system could provide board-scale information that describes the distribution of knot size and appearance type.

Figure 3-7. The general process for knot characterization.

The focus of this project was to develop methods to automatically detect knots found in lumber from these two resources and to use this information to create ways to describe the physical properties of these characteristics in more detail than is currently available in lumber gradings standards. Color images have been used extensively for similar detection problems

(Abbott and Kline, 2003, Conners et al., 1997b, Lu et al., 1997). The photographic procedures used for this work are based on high-resolution digital images (24-bit, RGB).

3.6 Image Acquisition

The hardware components used to acquire the images consisted of a Nikon D3100 CMOS color camera, two 500w Halogen bulbs mounted 3.1 m from the board surface, and a laptop running DigicamControl (http://digicamcontrol.com/) to store images to the laptop hard drive. The camera was fitted with an 18-55 Nikon AF-S lens set to a focal length of 35 mm. Images of 1.8 m sections of boards were captured with the camera mounted 3.1 m from the boards. To completely capture the full length of boards, after the first image was captured, the board was moved 1.8 m to expose the next section to the camera. This process was repeated until the full length of the board was captured. Images were captured over 5 different sessions. Lighting varied slightly between sessions, which resulted in variation in image quality.

3.6.1 Image Processing

The software components of the automatic detection system consisted of various image processing and image analysis MATLAB algorithms custom-built for this project. Image processing consisted of cropping, straightening, background removal, and stitching images together to create one image for each board surface. Illumination inconsistencies across the surface of the complete image were color balanced using an automatic white balance procedure written in MATLAB (Garud et al., 2014, Suveer, 2015). This MATLAB function is available at the MathWorks File Exchange (https://www.mathworks.com/matlabcentral/fileexchange/51087-auto-white-balance-correction). An example of a color-balanced image is shown in Figure 3-8. The purpose of white balance is to transform the image into an appearance closer to how it is perceived by the human eye. This image is referred to as the 'original image' in the rest of this thesis.

Figure 3-8. An image of a board before and after white balance transformation. Note distortion due to resizing images.

Additional image transformation procedures included board edge defining, image sharpening, median filtering, and contrast adjustment to improve edge detection and image noise in the final image. Image sharpening was performed using the MATLAB function `imsharpen`, with the arguments '*Radius*' set to 1, '*Amount*' set to 1, and '*Threshold*' set to 0. Edge defining was accomplished by replacing all pixels in each of the R, G, and B channels with an intensity value of less than 30 within 20 pixels of the top and bottom edge with the average of that channel. Image noise was reduced using the `medfilt` function with a '*Neighborhood*' size of 5 pixels on each channel. Contrast adjustment was accomplished by using a multi-step process. The first step used the function `adaptthresh` with arguments '*Neighborhood*' of 7 x 1111, '*ForegroundPolarity*' set on, '*Bright*' set to on, '*Statistic*' set to on, and '*Gaussian*' set to on to calculate the normalized intensity values, T, for the R, G, and B channels. The argument '*Sensitivity*' was calculated as the linear function:

$$Sensitivity = -0.0111(meanred) + 2.044$$

where:

$meanred$ is the mean intensity level of the red channel pixels and

$$0 \leq Sensitivity \leq 1$$

The second step adjusted T according to the $meanred$ of the image. For images with $meanred$ above 115, the factor, F, was added to T. F is given by the equation:

$$F = -0.0124(meanred) + 1.826$$

where:

$$1 \leq F \geq -.25$$

and

$$if\ F \leq -.25$$

then

$$F = 0$$

then

$$T = |T + F|$$

For images with $meanred$ below or equal to 115, F is given by:

$$F = -0.034(meanred) + 3.930$$

where:

$$1 \leq F \geq -.15$$

and

$$if\ F \leq -.15$$

then

$$F = 0$$

then

$$T = |T + F|$$

In either case, every pixel of each channel in the original image is divided by the resulting T. This process serves to both reduce the intensity differences among the sample set of boards

and increase the contrast of the images. Examples of two boards from each $meanred$ class are shown in Figure 3-9, Figure 3-10, and Figure 3-11 show the same 2 boards before and after the dynamic adjustment methods developed in this thesis.

Figure 3-9. The results of intensity adjustment on two boards based on dynamic thresholding. The mean red intensity of the top two boards for each pair is 129 and 102. The bottom two boards of each pair are the result of the adjustment.

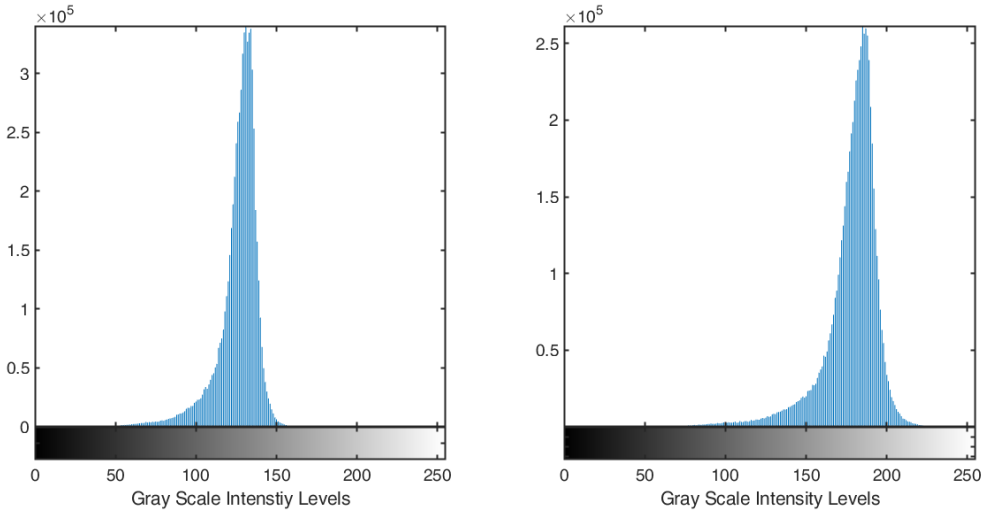


Figure 3-10. Contrast adjustment because of dynamic adjustment for the top image in Figure 3-9. The left panel shows a histogram of the original image; the right panel shows the resulting histogram.

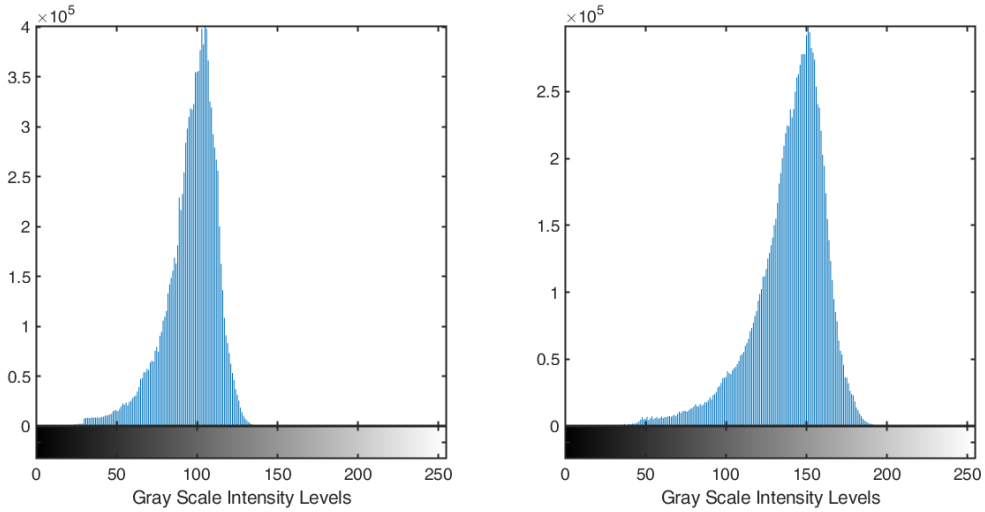


Figure 3-11. Contrast adjustment because of dynamic adjustment for the bottom image in Figure 3 20. The left panel shows a histogram of the original image; the right panel shows the resulting histogram.

The last transformation of the image produced a binary color image. This type of image is created by producing a binary (0 or 1) for each of the color channels. This produces an image with 8 possible colors – white [1 1 1], black [0 0 0], red [1 0 0], green [0 1 0], blue [0 0 1], yellow [1 1 0], magenta [1 0 1], cyan [0 1 1]. The assignment is based on value, T. As above, T was determined by using the `adaptthresh` function with arguments '*Neighborhood*' set to 7 x 1111, '*ForegroundPolarity*' set on, '*Bright*' set on, '*Statistic*' set on, and '*Gaussian*' set on. For boards with a $meanred$ above 115[26], the argument '*Sensitivity*' was calculated as the linear function:

$$Sensitivity = 0.000322(meanred) + 0.8209$$

where:

$$0 \leq Sensitivity \leq 1$$

For boards with a $meanred$ below or equal to 115, $Sensitivity$ was calculated as:

[26] The value of 115 was determined by trial and error to provide a good boundary for the different methods of transformation.

$$Sensitivity = -0.006(meanred) + 1.57$$

where:

$$0 \leq Sensitivity \leq 1$$

Once T had been determined, it was used as the threshold value to produce a multichannel binary image. An example of the effects of this transformation is shown in Figure 3-12, as one can see, dark areas of the original image are transformed into black or red.

Figure 3-12. An example of an image of the top board in Figure 3-9 transformed into a multi-channel binary image.

A series of morphological operations made up the final step to prepare the images for analysis. In this work, two operations were used to remove small areas and to connect objects. The first operation used the `imopen` function operating with a 20-pixel '*disk*' on each of the color channels. This operation was followed with a closing using the function `imclose` with a '*rectangle*' of 3 x 15 pixels. The results are shown in Figure 3-13.

Figure 3-13. Results of the first opening, then closing the example used in Figure 3-12.

Three other transformations were performed on the original image (before the initial transformation). An HSV image (Figure 3-14) was created using the `rgb2hsv` function and a grey-scale (Figure 3-15) image was created using `rgb2gray` function. The third more complex transformation mapped a subset of pixels from each channel of the original image to the full scale [0 1]. The subset consists of a range of 7 intensity levels from the original image. The high value of this range is determined by:

$$High_{in} = -0.0132(meanred)^2 + 4.35(meanred) - 245.43$$

where:

$meanred$ is the mean red intensity levels, and

The low value of the range is given by:

$$Low_{in} = High_{in} - 7$$

This procedure gives an image with extreme contrast; most intensity values are 1, with the target range occupying dark pixel intensity values (Figure 3-16). This image is referred to as the contrast stretched image hereafter.

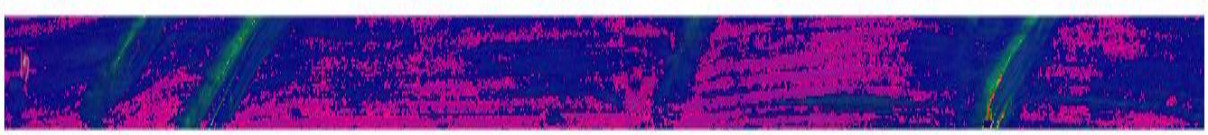


Figure 3-14. An example of an image of the top board in Figure 3-9 transformed to HSV color space.

Figure 3-15. An example of an image of the top board in Figure 3-9 transformed to greyscale.

Figure 3-16. An example of an image of the top board in Figure 3-9 with extreme contrast.

3.6.2 Image Analysis

After images have been acquired and processed, objects are detected, described, and classified from them. Two image sets were created. One was the validation image set. It consisted of all the images for both species but is used here as the benchmark. Validation images were produced by manually marking knots in red [255, 0, 0]. This created an image where knots could be easily detected with a thresholding procedure set to label red pixels in the red channel as those belonging to the domain of knots (Figure 3-17). The validation images were marked by an undergraduate at Oregon State University studying mechanical

engineering and checked by the author. In cases of disagreement, the areas were discarded from the analysis. For the 295 boards, this process located 2236 knots.

Figure 3-17. An example of a validation board with knots marked as red.

The second set of validation images were created from the original images by locating the hand-marked knots as indicated by red and then adding 40 to the red channel, 10 to the green channel, and 20 to the blue channel intensity values in those areas of the original images. This created an image with a slight reddish tone that indicated the location of the knots marked by hand. This provides a transparent mask, or shadow, over the knot. See Figure 3-18 for an example of this process.

Figure 3-18. An example of an image indicating the location of knots with a transparent mask.

The second image set is referred to as the automatic images. They are also the same images as the validation set but provide the input for the vision system developed in this research. The validation dataset was used to train and assess the performance of the automatic method. The process is shown in Figure 3-19. Here, the image analysis module shown in Figure 3-7 has been split into object detection, object description, and object classification sub-modules. Each sub-module is explained in the next section.

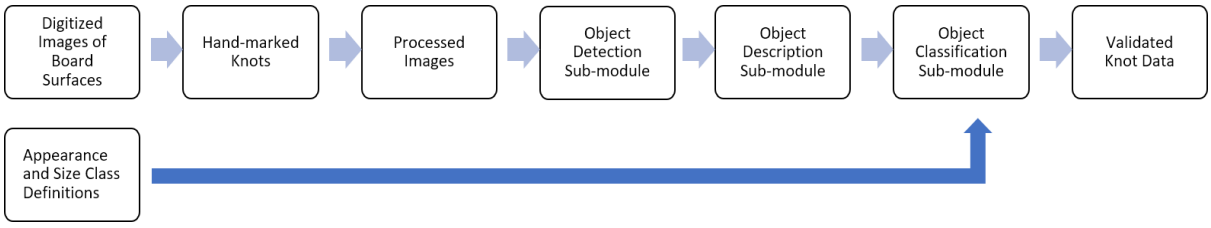


Figure 3-19. The process used to create the validation knot data.

The process for automatic detection of knots is shown in Figure 3-20 and Figure 3-21. Here the image analysis module has been split into three sub-modules as in the validation method. However, in the automatic method, a knot classifier is created by comparing detected knots to validated knots. This classifier is then used to determine if a detection by the automatic method is a knot or non-knot in the automatic knot dataset as shown in Figure 3-21. The process is explained in more detail below.

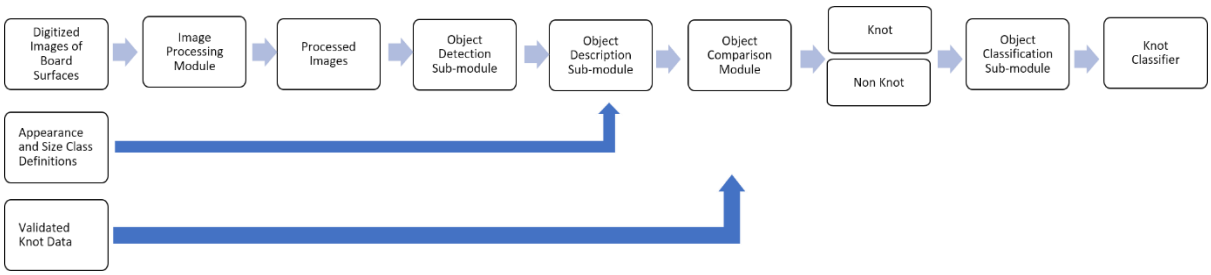


Figure 3-20. The process used to create the knot classifier.

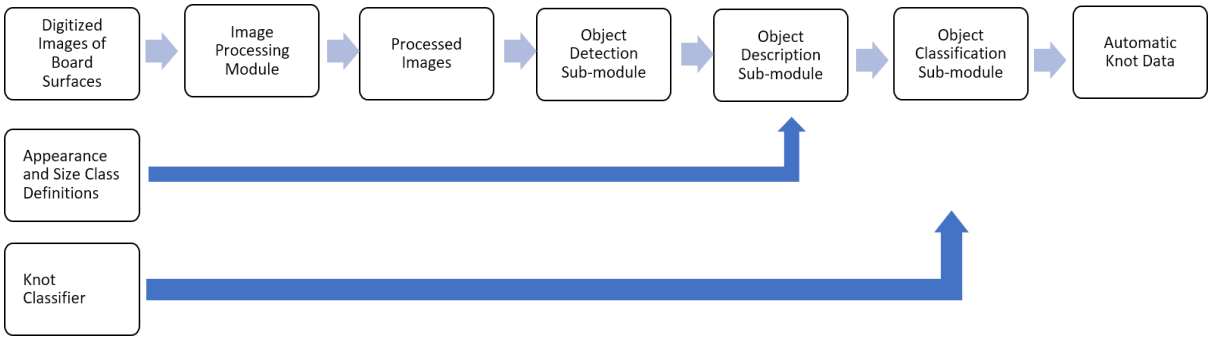


Figure 3-21. The process used to create the automatic knot dataset.

3.6.2.1 Object Detection

The first step in the image analysis phase is to segment the image into foreground and background pixels (See Appendix 1). Color segmentation was used to threshold foreground and background pixels. This was performed using the `colorseg` function configured to use '*Euclidean*' distance (Gonzalez et al., 2010). The argument 'T' was set to 1 and 'M' was set to [1 1 1]. This operation produces a single channel binary image with dark objects appearing as black background pixels. Because the remaining analysis examines foreground pixels (white), the complement of the image was produced (Figure 3-22). This image serves as the segmentation mask that is used to label each pixel to either the class foreground or background.

Figure 3-22. An example of a complete thresholded binary image.

The label matrix was created by using the `bwlabel` function set to 8-connected component. Because not all pixels of objects are classified correctly (see 8 Appendix 1), components within 10 pixels were joined together to represent meaningful objects in the segmentation mask. Using the centroids and major and minor axis lengths, an ellipse was fitted to each object in the segmentation mask. The object mask was created that included all pixels inside the ellipse for each object.

Detection of marked up validation objects from the validated images was based on a simpler process of thresholding pixels from the red channel. The threshold was set to pixels about 220 to create the object mask for validated knots.

3.6.2.2 Object Description

Using the original image, board-scale statistics were calculated using a conversion factor. The conversion to real units was based on the relationship between the number of pixels in the image that represented a real-world unit of length and was calculated by dividing the number of pixels across the width of a board by the known width. The average conversion was 2.3 pixels/mm. The length of the board was calculated using this conversion factor. The mean red intensity value and the standard deviation were also calculated for the entire board.

Objects were described in terms of location, geometry, and texture. Geometric attributes were calculated directly from the label mask using the `regionprops` function and converted to real-world units using the conversion factor. The descriptions of these attributes are listed in Table 3-1.

Table 3-1. Descriptors calculated from the label mask.

Descriptors	Explanation	Real-world units
Upper left corner x	The upper left corner x coordinate of the smallest rectangle box that contains the object	mm
Upper left corner y	The upper left corner y coordinate of the smallest rectangle box that contains the object	mm
Width	The width of the rectangle in the x-direction	mm
Height	The height of the rectangle in the y-direction	mm
Centroid x	The x coordinate location of the centroid of the object	mm
Centroid y	The y coordinate location of the centroid of the object	mm
Length of the major axis	The length of the major axis of an ellipse that has the same second moment as the thresholded pixels in the segmentation mask	mm
Length of the minor axis	The length of the minor axis of an ellipse that has the same second moment as the thresholded pixels in the segmentation mask	mm
Area	The area of pixels in the object from the segmentation mask	mm^2
Box area	The area of the minimum bounding box	mm^2
Ellipse area	The area of an ellipse fit to the pixels in the object from the segmentation mask	mm^2
Axis ratio	The ratio between the major and minor axes	NA
Eccentricity	The ratio of the distance between the foci of the ellipse and its major axis length. 0 for a circle, 1 for a line	NA
Solidity	The proportion of the pixels in the convex hull that is also in the object	NA
Orientation	The angle between the horizontal (x-axis) and the major axis of the object.	Degrees

Basic object statistics were calculated using the pixels from within the ellipse fitted to the object pixels. These statistics are listed in Table 3-2.

Table 3-2. Statistics related to detected objects.

Statistic	Explanation	Source
Percent black	Percentage of pixels below 60	Red channel
Red ratio	The ratio between red channel pixels inside the fitted area and outside the fitted area but inside the bounding box	
Tone	Mean of pixels above 60	Red channel
Red mean	The mean of the intensity values of the red channel	Original image red channel
Red mean std	The standard deviation of the intensity values of the red channel	Original image red channel
Green mean	The mean of the intensity values of the green channel	Original image green channel
Blue mean	The mean of the intensity values of the green channel	Original image blue channel
H mean	The mean of the intensity values of the H channel	HSV transformed image
Grey mean	The mean of the intensity values	Greyscale image

Statistical properties of objects were calculated by mapping the pixel locations within the fitted ellipse to the original image arrays that contain the information of interest. The attributes listed in Table 8-2 were calculated from the greyscale image, the R, G, and B channels of the original images, and the H, S, and V channels from the HSV transformation, and the red channel of the contrast stretched image using the `statxture` function (Gonzalez et al., 2004).

Additional texture and object attributes were calculated for each object by mapping the minimum bounding box to images. The attributes relating the appearance of the pixels within an object compared to the immediate surroundings and the overall appearance of the board was calculated. The local ratio was calculated by dividing the mean red intensity value of the object by the mean red intensity of the pixels outside of the object, but still inside the bounding box. The global ratio was calculated by dividing the mean of the object red

intensities by the mean of the red intensity of the entire board. Using the object mask based on the bounding box, a co-occurrence matrix and corresponding attributes listed in Table 8-3 were calculated from the greyscale image, red, green, and blue channels of the original image. This resulted in 112 variables describing each object.

The same set of attributes were calculated from the validation images.

Knots from the validation set and objects resulting from automatic detection were assigned to three appearance classes and 5 size classes. The appearance classes were based on the percentage of pixels in the red channel within an object that was below 60. This was a rule-based classification method—it only considers a calculated variable to assign the class. These classes are believed to represent live, transitional, and dead knots—classes common in lumber grading standards. The classes are listed in Table 3-3. The size classes were based on the area of the fitted ellipse. These size classes are somewhat arbitrary but are primarily chosen to differentiate knot size with higher resolution for smaller knots. It is thought that smaller sized knots are more important from a manufacturing perspective because smaller knots are more likely to survive milling operations than larger ones, which are more likely to disintegrate under the stresses of planning and sawing. The size classes are listed in Table 3-4.

Table 3-3. Appearance classes of validated knots and objects.

Knot class	Appearance class	The ratio of red channel pixels below pixel value 60
1	Light	≤1percent
2	Dark	>1percent & ≤25percent
3	Black	>25percent

Table 3-4. Size classes of knots based on the bounding box area used throughout this thesis.

Knot class	Size class	Size range (mm^2)
1	Small	≤ 322.6
2	Medium	>322.6 & ≤645
3	Large	> 645 & ≤1290
4	Exlarge	>1290 & ≤1935
5	Ex2large	>1935

3.6.2.3 Object Classification

Classification is the process by which an instance is labeled for a class. A classifier was developed by using the comparison dataset from the validation images and the validated dataset. A separate classifier was developed for each species. The first step was to determine which instances in the automatic dataset correspond to a validated knot in the validated dataset. This was done by comparing the centroid locations of each instance in the comparison dataset to every knot in the validation set for each image. An instance that fell within 75 mm on the longitudinal axis of the board and within 30 mm along the cross-grain axis of the board was a true knot. These values were derived by testing different distances and manually checking to confirm which knots between the two datasets correspond. This resulted in the labels of either 'knot' or 'non-knot' for each instance in the automatic dataset. Using this dataset, different combinations of attributes (variables) and classifiers were explored to develop a classifier to label instances in the automatic dataset.

The classifiers were developed using the MATLAB Classification Learner app. This app allows the user to dynamically explore supervised machine learning, select variables, train models, and assess results quickly without manually coding the tasks. The selected model can be exported and used for prediction with new datasets. For this work, the app was set to 20 splits, 30 learners, and a learning rate of 0.1. Cross-validation was set to 5. The model was used to determine which detections should not be considered a knot in the automatic dataset. This resulted in the automatic knot dataset. Because classification is not perfect, this dataset contained both true positive and false positive detections. To find all corresponding knots between the validated and automatic knot dataset, the centroids of each knot in the automatic knot dataset were compared to each knot in the validated data. This process resulted in a list of corresponding knots (referred to as correctly identified (CI)) for which performance parameters could be calculated.

3.6.3 Comparison of the Validation and Comparison Datasets

Comparisons between the two datasets were calculated in two ways. The first way only involved the CI knots from the comparison and the knots from the validation set. This is necessary because, although the classifier performance is important and provides a means to

compare different classifiers with a given dataset (the labeled data), it does not indicate how well the overall characterization model performs against the validation set. Overall performance is of primary interest. The initial assessment was based on calculating the true positive rate (TPR), false negative rate (FNR), false positive rate (FPR), true negative rate (TNR), accuracy, and precision (Equation 8-1, Equation 8-2). This was accomplished using an algorithm that compared each CI knot in the automatic dataset to each knot in the validation dataset. Each knot was assigned a detection type as presented in Table 8-1. Automatically detected knots within 75 mm in the longitudinal axis and within 30 mm in the transverse axis of each CI knot were considered a true positive detection. Detections in other locations were labeled false positives, and knots occurring in the validation dataset, but not in the labeled set were considered false negative. Detections eliminated by the classification model were labeled as true negatives. The true positive detections were then isolated from the other instances to form a dataset that could be used to assess the quality of each detection.

The second phase was to determine the quality of the detections made by the characterization model for the CI knots. Because the data were highly skewed a log transformation was used and the mean and standard deviation of C, and O_p, and A_r were calculated by comparing the minimum bounding box area of the two datasets using Equation 8-3, Equation 8-4, and Equation 8-5. By subtracting 100 from the area difference percentage, the differences for both smaller and larger automatically detected knots can be described. For example, a comparison knot that is one-half the size of the corresponding validated knot, the value would be -50 percent. However, for a knot that is twice the size, the value would be 100 percent. Results are also presented as a histogram to indicate the distribution of the parameters.

The second set of comparisons utilized all knots from both the automatic and validated datasets. These comparisons involve the distribution of knot size, distribution of distances between knots, board segments free of knots, and differences in classifying knots into size and color classes.

The above process is iterative—that is, the researcher has many parameters that can be adjusted throughout the workflow that influence the performance and quality of the

detections (see next section for more detail). Slight differences in any one parameter can produce significantly different overall performance levels. For this research, the way the images were transformed and thresholded had significant effects on overall results. The knot classifier model also influences the performance parameters. For example, the accuracy of a boosted tree classifier was reported at 82 percent while a bagged tree classifier indicated an accuracy of 81 percent. However, the overall TPR using the boosted tree classifier was 82 percent, while the bagged tree classifier produced an overall true positive rate of 90 percent.

Through many iterations of different combinations of attributes and classifiers, it was found that an ensemble bagged tree model resulted in the highest performance of detection for *E. nitens* and *E. globulus*. These models are based on the AdaBoost, a boosting algorithm that combines multiple weak classifiers into a strong classifier (Freund and Schapire, 1997) and has been used to successfully classify wood characteristics (Jabo, 2011). An ensemble bagged tree model was found to provide the highest performance when species were grouped. The final models all used the same 59 variables describing the instance. They are the:

- mean values of the R, G, B, and H intensity levels.
- the ratio between the major and minor axis.
- eccentricity, solidity, and orientation of the major axis.
- tone, red ratio, and percentage of black pixels.
- smoothness and skewness of the red channel of extreme contrast image.
- intensity, contrast, smoothness, skewness, uniformity, and entropy of the red, green, and blue channels from the original image.
- co-occurrence contrast, correlation, energy, entropy, and homogeneity of the greyscale image.
- co-occurrence contrast, correlation, energy, entropy, and homogeneity of the red, green, and blue channels from the original image.

3.6.4 Visualization of the Characterization Model

To assess how well the automatic detection method performed visually, the location of knots was plotted on the shadow validation image (Figure 3-23). These images were manually inspected to find types of knots that were not being accurately detected by the method, and

then adjustments in the process were made to better locate and describe problem knots. Adjustments included slight changes to many of the image processing parameters and the features used in the knot classification model.

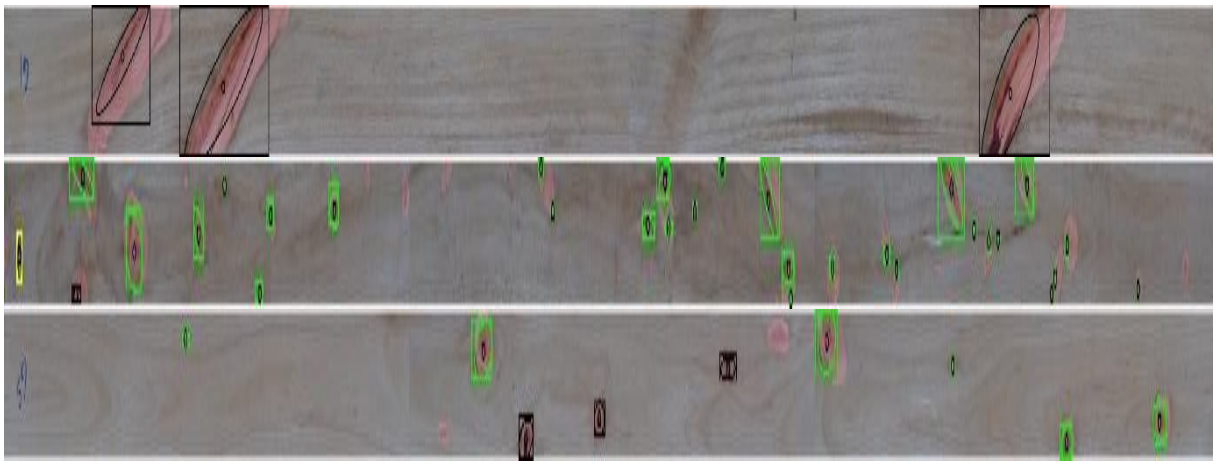


Figure 3-23. Examples of the automatic detection method results plotted against validation images. Black box outlines indicate a dark knot; yellow box outlines indicate dark knots; green box outlines indicate light knots.

3.6.5 Alternate Approaches

Any classification model is only as good as the initial detection procedures—that is if an object is not detected, it cannot be classified later during the classification procedure. Therefore, all possible objects must be detected. However, due to the limitations and complications (see 8 Appendix 1) of the threshold method for wood surfaces, an approach that detects all possible objects of interest also detects a high proportion of unwanted objects, such as grain variation, gum vein, collapse, and wane. The key is to develop a method that detects the maximum number of desired objects while reducing the detection of unwanted objects. The final knot classification model used in this work is the result of many tests with different detection settings. Initial tests used basic thresholding parameters based on single-channel images. This approach produced many false positive objects that could not be eliminated during further processing. More sophisticated attempts examined the potential to transform images into other color spaces to increase the accuracy of detection. These attempts were largely unsuccessful because objects were either undetected or appeared exceptional larger or smaller than the corresponding validated knots. Other methods focused on developing adjustment factors (such as those discussed in 3.6.1). Several rule-based classification methods were also explored with limited success. These approaches filtered out instances

based on geometric relationships that were unlikely to occur for real knots. For example, a large ratio between the major and minor axes of an object. The final characterization model is the result of "fine-tuning" each of the steps leading to the classification of instances and testing several classification models in terms of overall performance.

3.7 Results

3.7.1 Characteristics of Validation Knots

There were 2224 knots above a filtered area of 25 mm^2 detected from the validation images. The minimum bounding box area, color class, location, red ratio, and tone are shown in Figure 3-24, Figure 3-25, Figure 3-26, Figure 3-27, and Figure 3-28. Overall, the knot area distribution was highly right-skewed (towards zero) for both species. However, there were differences in the distribution between the species. There was a higher proportion of smaller knots in *E. nitens* than for *E. globulus*. For example, in *E. nitens*, 51 percent of the knots were less than 600 mm^2, while for *E. globulus*, 52 percent of the knots were less than 1100 mm^2. There was also a higher proportion of knots larger than 10,000 mm^2 for *E. globulus*. Approximately 20 percent of the knots occupied the top two thirds, the bottom two thirds, the top one third, or the bottom one-third of the boards. The proportion of knots in each color class was similar between the species. The distribution of red ratio (see Table 3-2) values differed between the two species. For *E. globulus*, approximately 45 percent of the knots had a ratio of mean red value to the surrounding area greater than 0.925, while only 33 percent of the knots for *E. nitens* had a value higher than 0.925. This indicates that in general, a larger proportion of knots produced by *E. nitens* are darker than the surrounding areas than those found in *E. globulus*. However, the tone (Table 3-2) indicated a higher proportion of knots found in *E. nitens* to be lighter (above 110) than those found in *E. globulus*. This is the result of removing intensities less than 60 from the calculation of the appearance classes of knots.

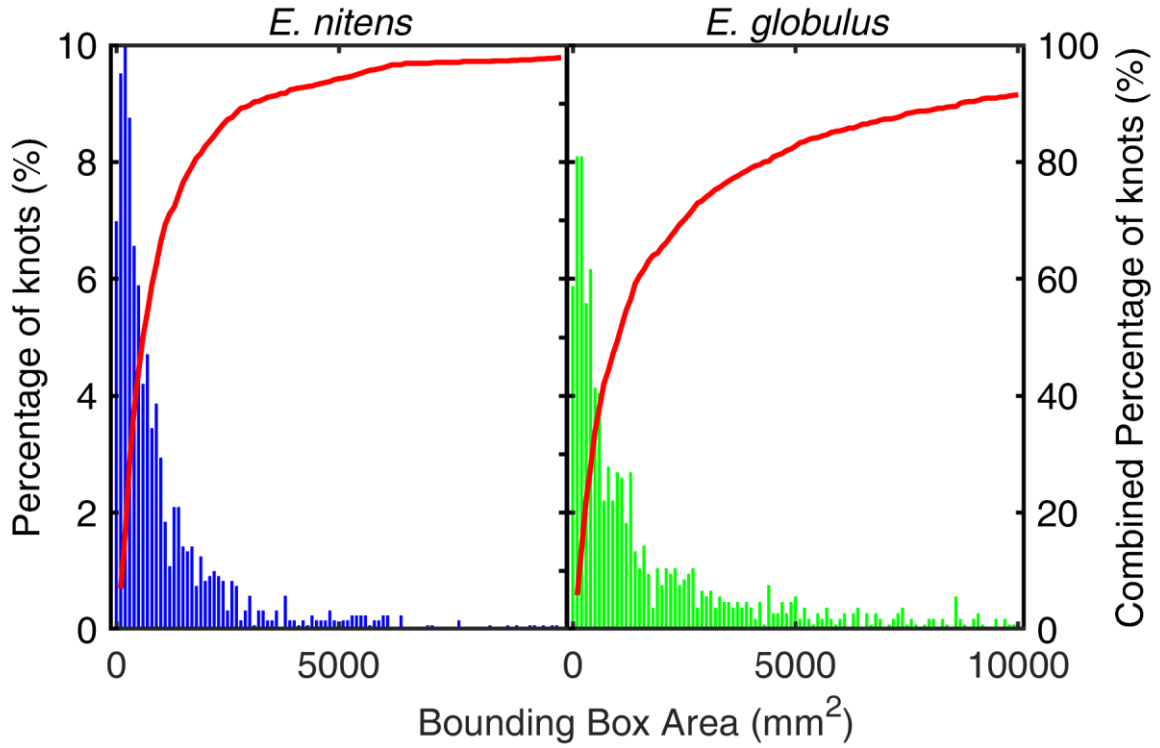


Figure 3-24. Distribution of the bound box area of knots from both species in the validation set. The right y-axis indicates the combined percentage of knots from 0 to 10,000 mm^2. There were 88 E. globulus knots larger than 10,000 mm^2 and 25 E. nitens knots above 10,000 mm^2. The bin size is 100 mm^2 and the maximum x-axis is 10,000 for E. nitens.

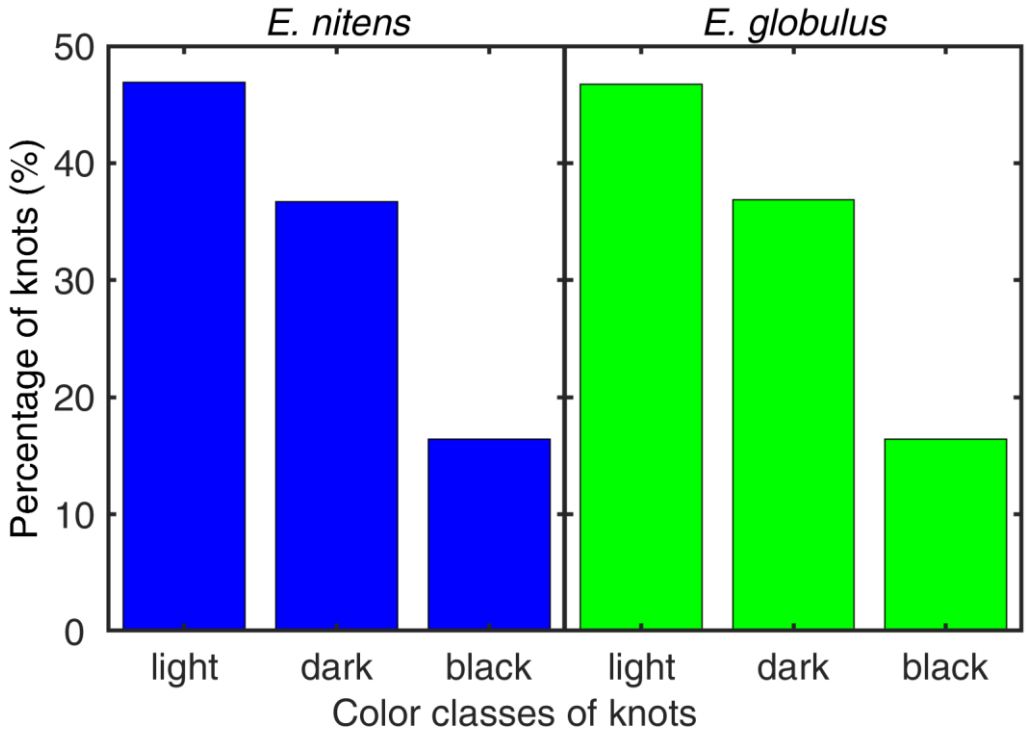


Figure 3-25. Distribution of the knot color classes from board surfaces in the validation set.

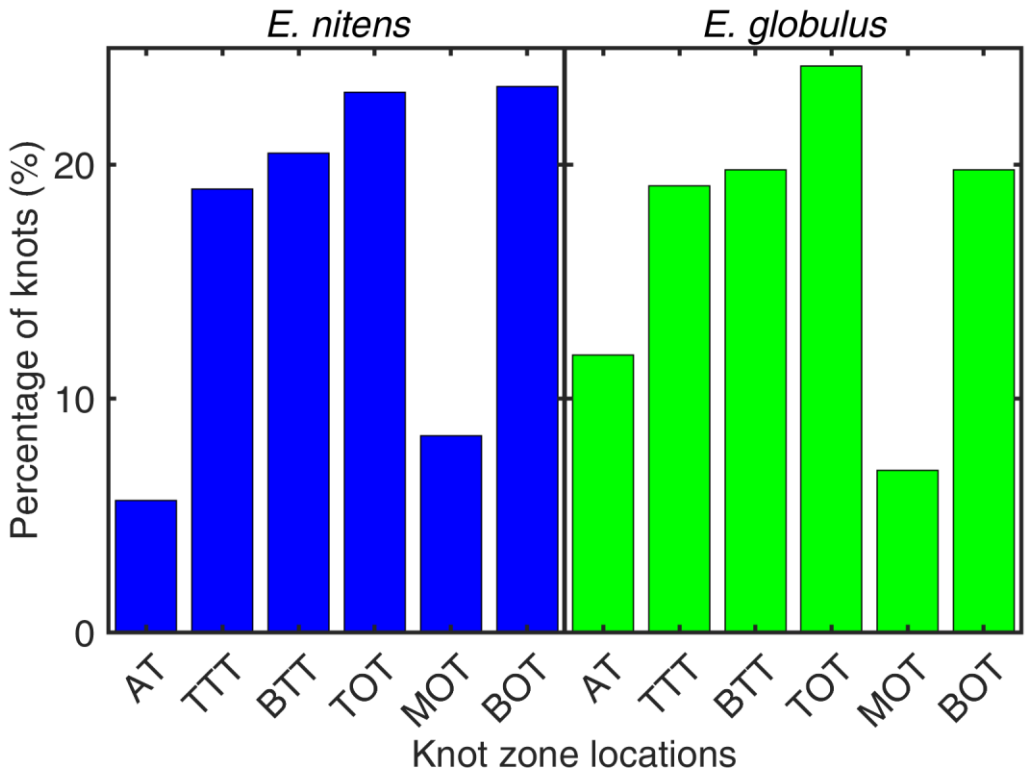


Figure 3-26. Distribution of knot locations. Knot locations are combinations of the top, middle, and bottom thirds of the board. these locations can be all thirds (AT), top two thirds (TTT), bottom two thirds (BTT), top one third (TOT), the middle one third (MOT), and the bottom one third (BOT).

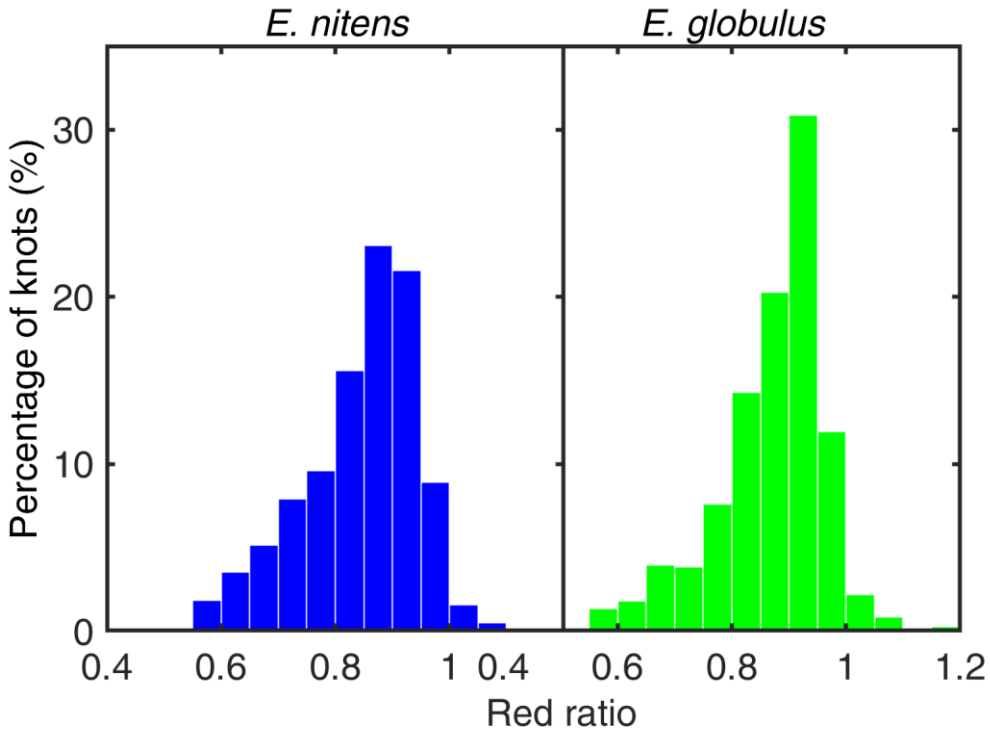


Figure 3-27. Distribution of the red ratio of knots from both species in the validation set.

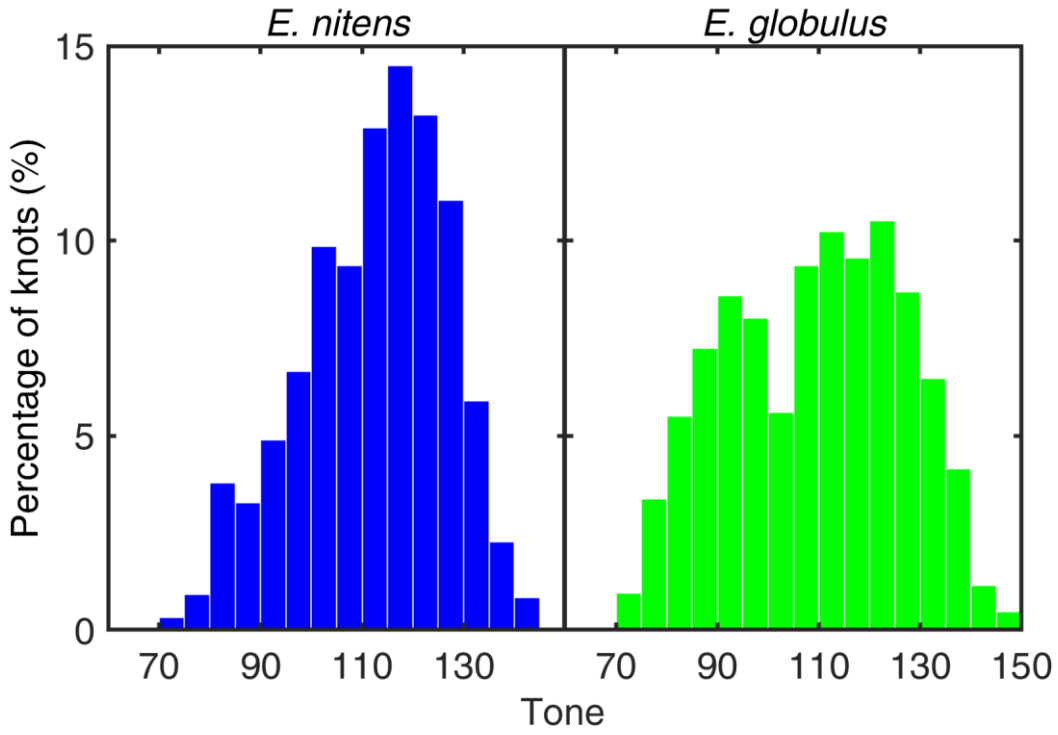


Figure 3-28. Distribution of the tone of knots from both species in the validation set. Note: the maximum x-axis value for E. nitens is 150.

The distribution of the eccentricity of knots is highly left-skewed and similar for both species. This indicates that most knots were elliptical to some degree (Figure 3-29). Indeed, the eccentricity of 72.8 percent of *E. nitens* knots and 78.4 percent of *E. globulus* knots were above 0.6. This indicates a high proportion of elliptical-shaped knots. The degree of eccentricity varied by knot area (Figure 3-30). In general, knots above 2000 mm^2 were more elliptical. However, smaller (less than 1000 mm^2) knots were present across the range of shapes.

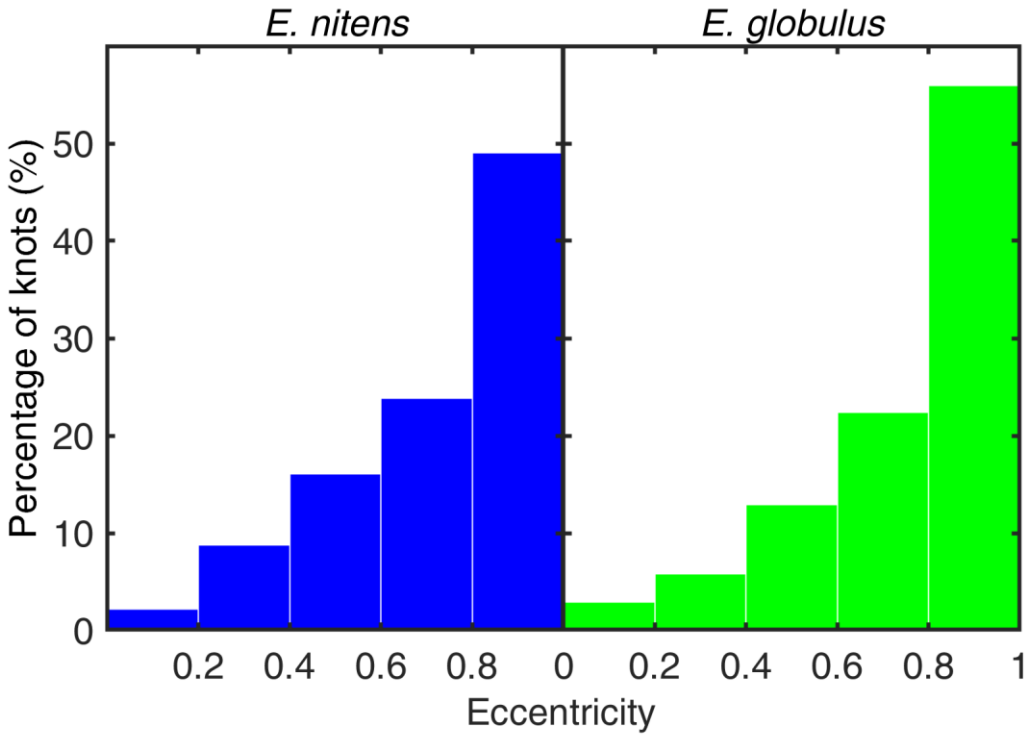


Figure 3-29. Distribution of the eccentricity of knots from both species in the validation set. Note: the maximum x-axis value for E. nitens is 1.

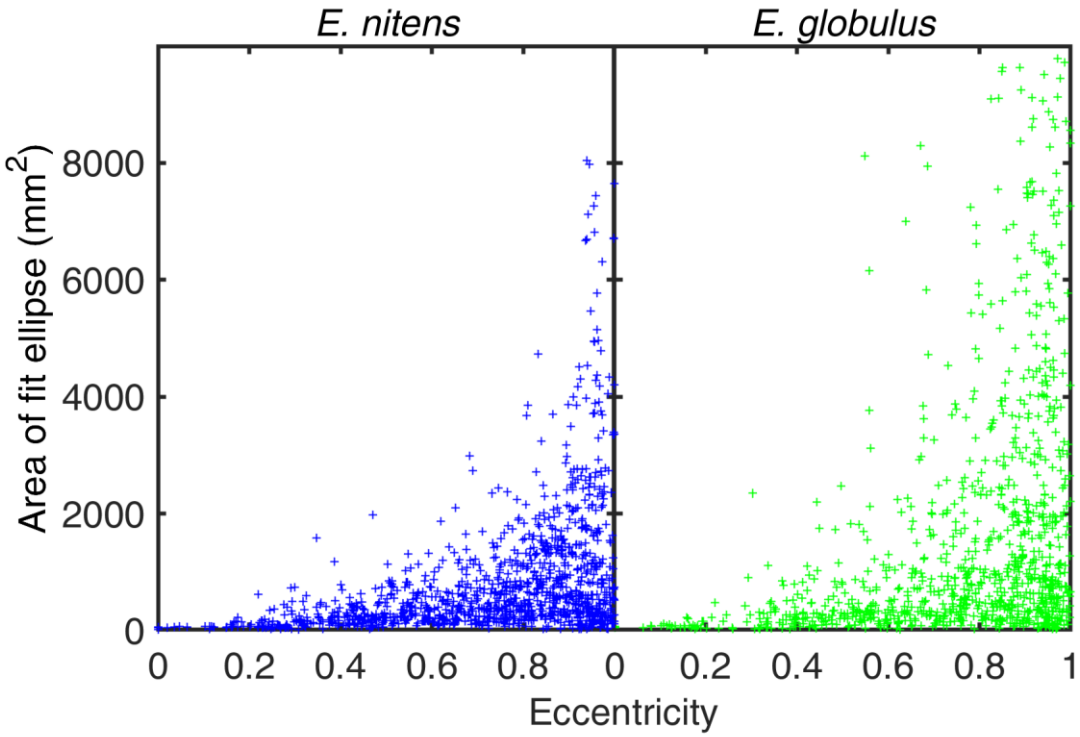


Figure 3-30. Area of the fit ellipse as a function of the eccentricity from both species in the validation set. Note: the maximum x-axis value for E. nitens is 1.

The orientation of knots was right-skewed for both species, but also contained an appreciable proportion over the entire range (Figure 3-29). In general, smaller knots were found for a wider range of orientation than larger knots (Figure 3-30). For *E. globulus* 57 percent of the knots were oriented between -15 and 15, while 55 percent of the knot in *E. nitens* were oriented between this range (Figure 3-33). Within this range, knots were highly skewed towards elliptical shapes (eccentricity close to 1).

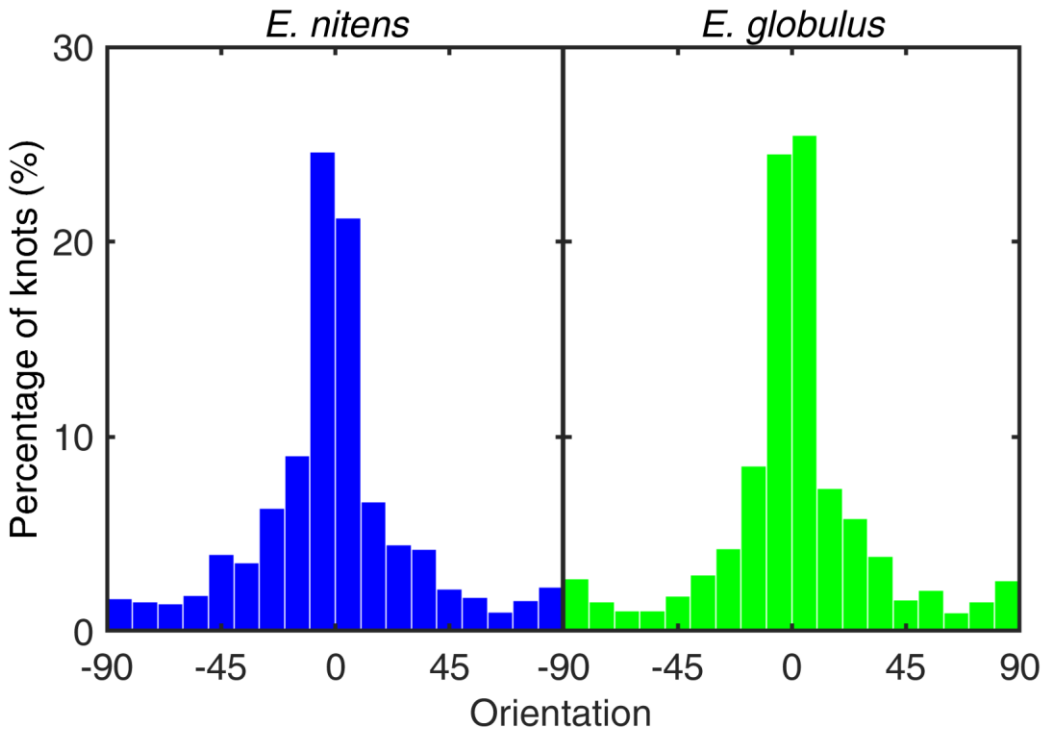


Figure 3-31. Distribution of the orientation of the major axis of knots from both species in the validation set. Zero orientation indicates the major axis is parallel to the long axis of the board; perpendicular knots are indicated by an orientation near -90 or 90. Note: the maximum x-axis value for E. nitens is 90.

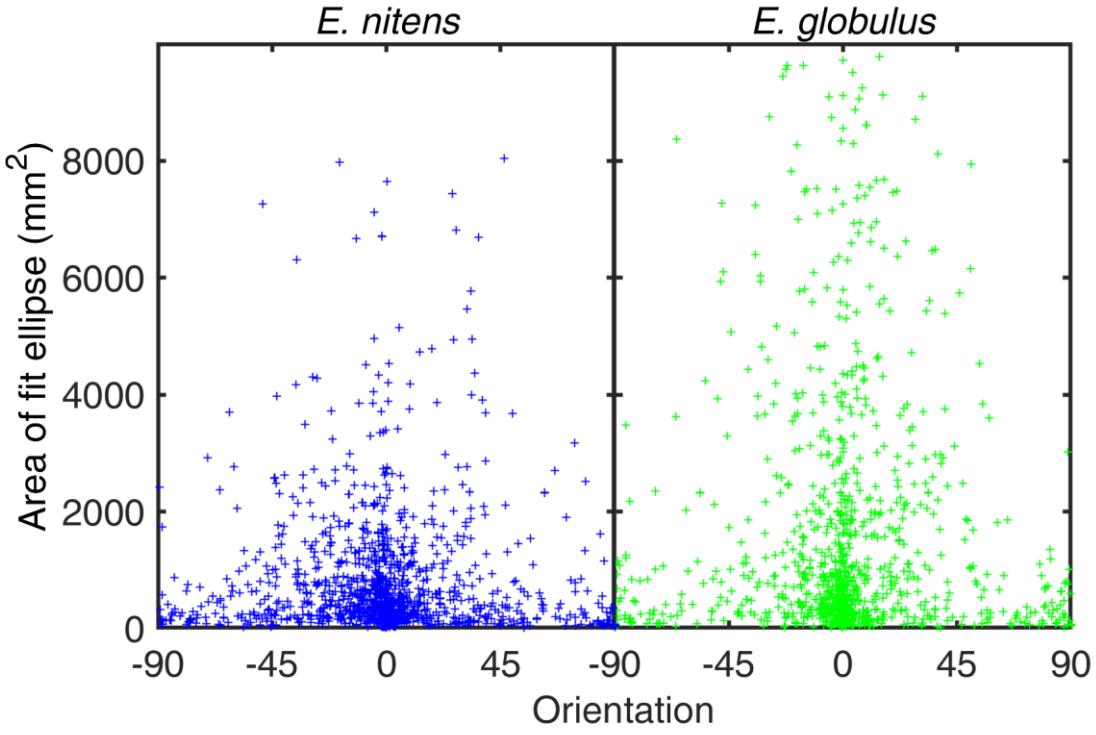


Figure 3-32. Area of a fit ellipse as a function of orientation. Note: the maximum x-axis value for E. nitens is 90.

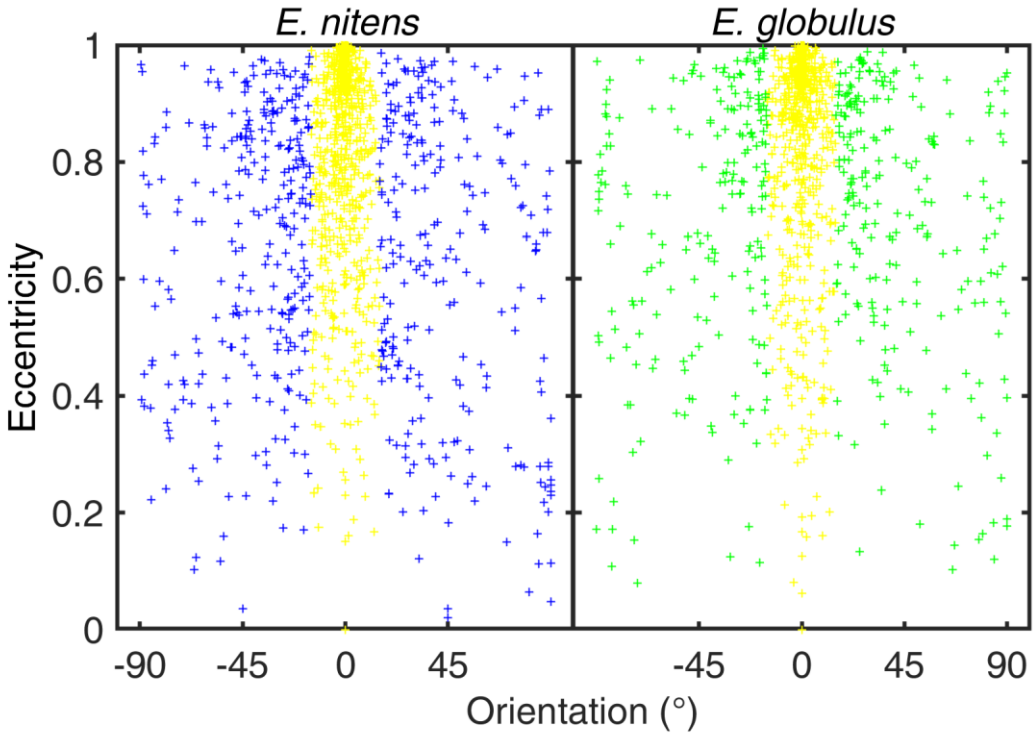


Figure 3-33. Eccentricity as a function of orientation for both species in the validation set. Data is yellow indicates values between -15 and 15. Note: the maximum x-axis value for E. nitens is 90.

The distribution of distances between knots was highly skewed for the two species (Figure 3-34). The mean distance between knots for *E. nitens* was 372 mm and 88 percent of the distances between knots were less than 1000 mm. However, the average distance was 449 mm for *E. globulus* and 80 percent of the distances between knots were below 1000 mm. The length of board segments free of knots was also highly skewed (Figure 3-35). The mean (log-transformed) board segment for *E. globulus* was 315 mm, while it was 246 mm for *E. nitens*. For *E. globulus*, 20 percent of the segments were greater than 1200 mm and for *E. nitens*, 20 percent were greater than 700 mm. There was also a higher proportion of segments over 2000 mm for *E. globulus*. Both distances between knots and knot-free board segment lengths indicate that knots are more frequent in boards produced from *E. nitens* than for *E. globulus* from this sample set.

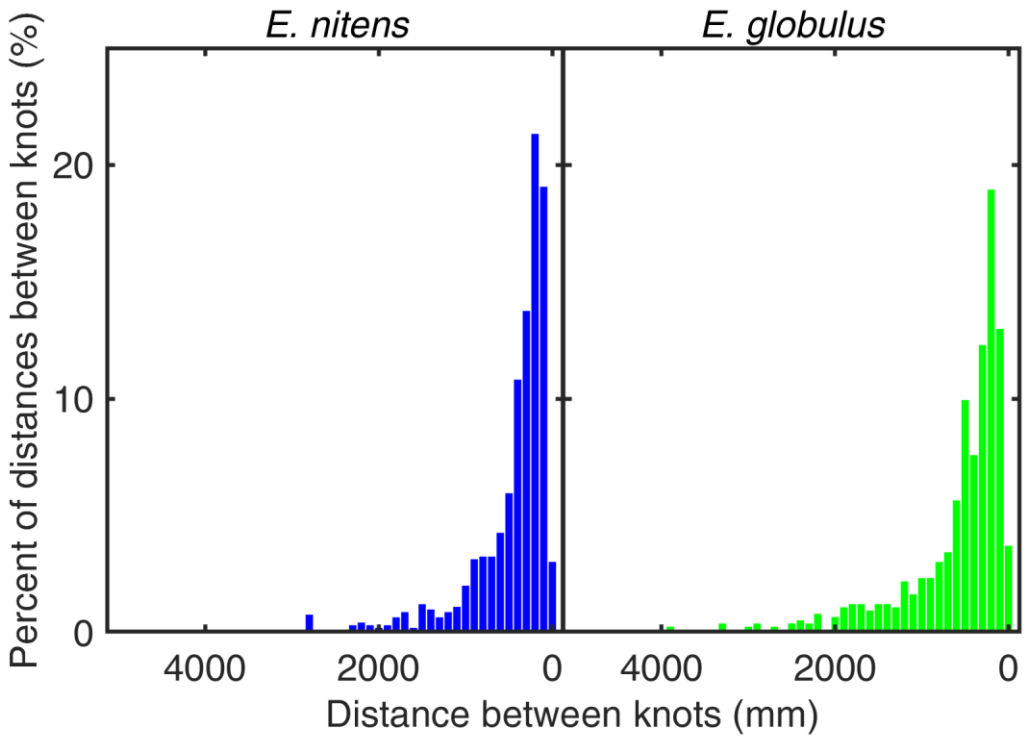


Figure 3-34. Distribution of the distances between knot centroids from the validation set. The bin length is 100 mm. Note: the maximum x-axis value for E. nitens and E. globulus is 6000 mm.

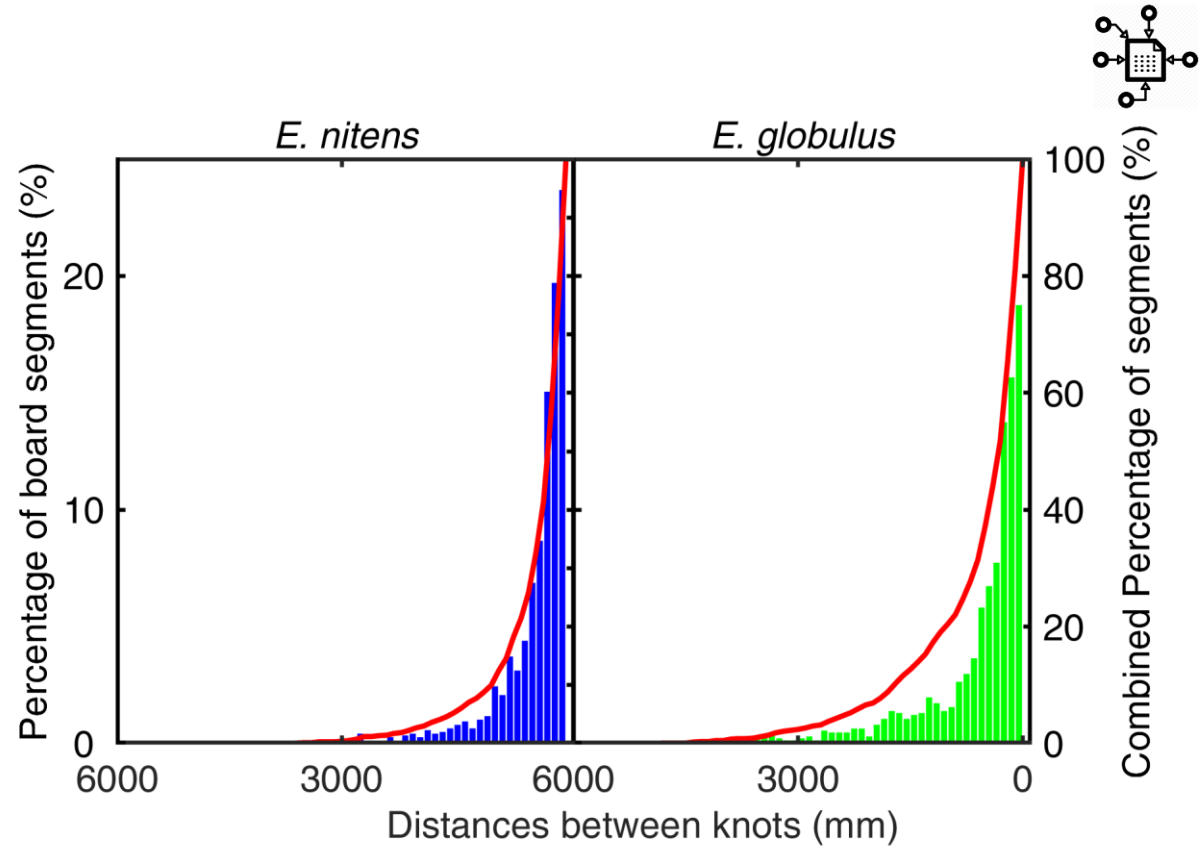


Figure 3-35. Distribution of the length of board segments free of knots from the validation set. The bin length is 100 mm. The right y-axis indicates the combined percentage of segments in each length class.

3.7.2 Classification Model Performance

The automatic detection method detected 4127 objects from the boards in the validation set. It was determined by the classification model that 2190 of these objects were true knots, which contain 2076 knots above 25 mm^2. Using this binary dataset (knot, non-knot), the Ensemble Bagged Tree classifier was 81.6 percent accurate. The true positive and false negative rates are shown in Figure 3-26.

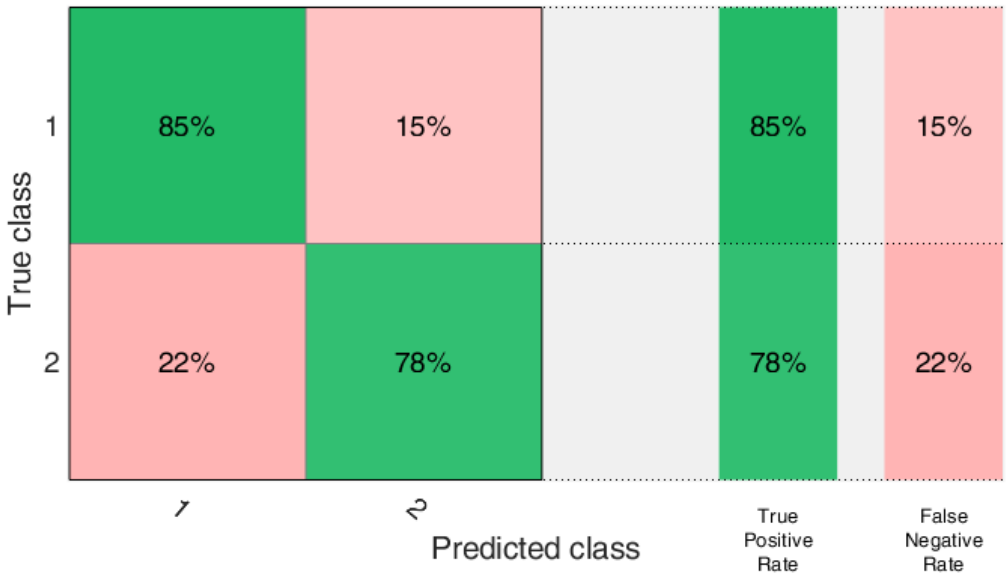


Figure 3-36. Confusion matrix for the Ensemble Bagged prediction model for both species in the validation image set. 1 indicates non-knots; 2 indicates true knots.

There were 1039 knots manually located on the validation images of *E. globulus* boards. The automatic detection routine found a total of 1963 objects from the images. A comparison between the automatic and validated datasets determined that 979 of these objects were true knots above 25 mm^2. Using the binary dataset, the Ensemble Bagged Tree classifier was 79 percent accurate. The true positive and false negative rates are given in Figure 3-37.

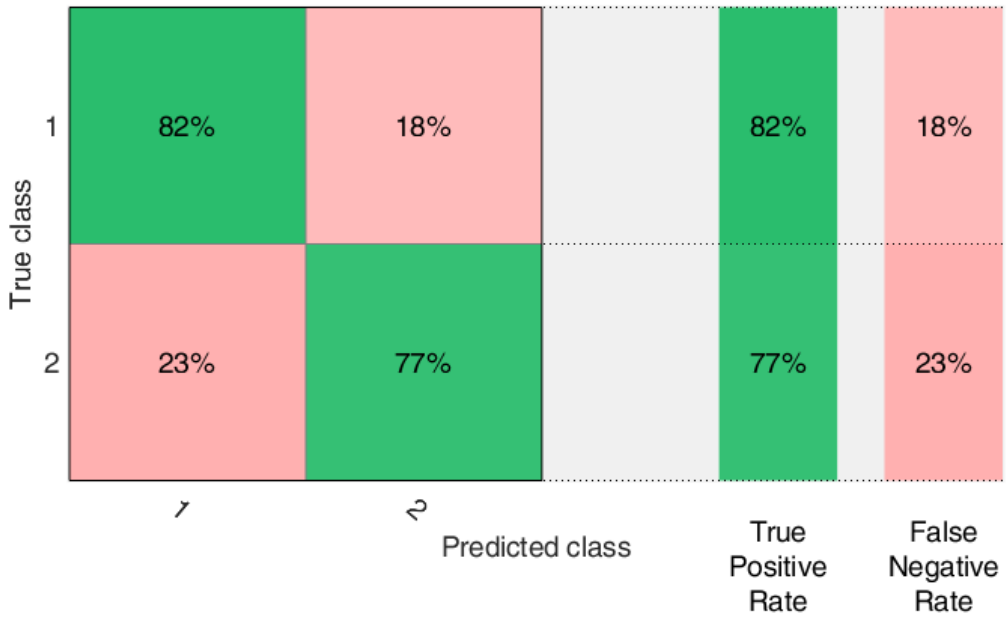


Figure 3-37. Confusion matrix of the results of the Ensemble Bagged classifier for E. globulus. 1 indicates non-knots; 2 indicates true knots.

Manual validation found 1197 knots in the *E. nitens* validation image set. The automatic detection routine located 2164 objects, of which 1142 were determined to be true knots. Of this, there were 1096 greater than 25 mm^2. Using this binary dataset, the Ensemble Bagged classifier performed at an accuracy of 83.8 percent. The true positive and false negative rates are given in Figure 3-38.

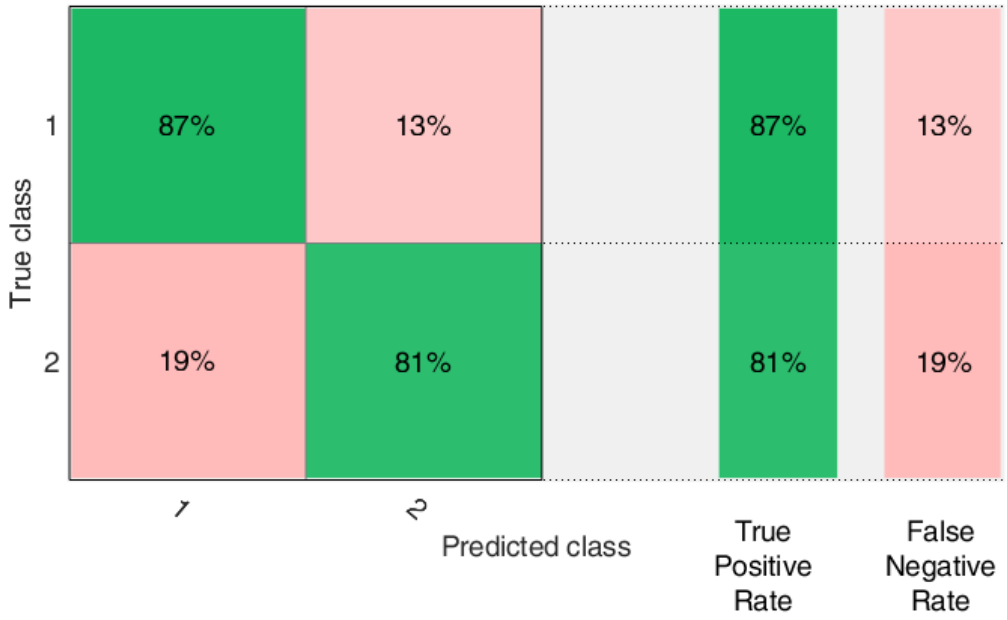


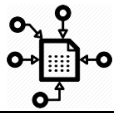
Figure 3-38. Confusion matrix of the results of the Ensemble Bagged classifier for E. nitens. 1 indicates non-knots; 2 indicates true knots.

3.7.3 Characterization Model Performance

Of the 979 knots identified as true knots on the images of *E. globulus* boards, the classifier determined that 949 were true knots. Of the 1096 knots in the *E. nitens* validation set, the classifier determined that 1052 were true knots. This relationship resulted in the performance of the characterization model shown in Table 3-5.

Table 3-5. Performance results of the characterization model developed for this study.

Detection type	Detection performance		
	Overall (%)	*E. globulus* (%)	*E. nitens* (%)
True positive rate (TPR)	90	89	91
False negative rate (FNR)	10	11	9
False positive rate (FPR)	0	0	0
True negative rate (TNR)	100	100	100
Accuracy	95	94	95
Precision	100	100	100



3.7.4 Comparison Between Validation and CI Datasets

The preceding performance results only state how many knots the characterization model correctly detected. It is also informative to understand the quality of the detections. The mean and standard deviations of distances between centroids (C), differences in area overlap (O_p), and the differences in the area (A_r) for knots in both datasets were calculated and are shown in

Table 3-6. The distribution of these variables is shown in Figure 3-39, Figure 3-40, and Figure 3-41. In general, C were less for *E. nitens* than for *E. globulus*. For example, 53 percent of C *E. nitens* were less than 5 mm, while for *E. globulus*, only 40 percent were less than 5 mm. For *E. nitens*, 77 percent of the centroid pairs were within 10 mm, and for *E. globulus*, 60 percent were within this limit. The distribution of O_p varied considerably between the species. For *E. nitens*, 49 percent of the automatic knots overlapped the corresponding validated knot by more than 90 percent. However, this occurred for *E. globulus* for only 30 percent of the knots. For *E. nitens*, 60 percent of the knots overlapped by 80 percent, while 42 percent of the areas overlapped by 80 percent in *E. globulus*. The differences in areas between the validated knots and the automatically detected ones also varied by species (Figure 3-40).

There was a higher proportion of automatically detected knots with values above 200 percent for *E. nitens* than for *E. globulus*. However, there were fewer knots below -50 percent for *E. nitens* than for *E. globulus*. For both species, approximately 50 percent (51 percent for *E. nitens* and 49 percent for *E. globulus*) of the differences occurred between –40 percent and 100 percent (Figure 3-41). This indicates that 50 percent of the automatically detected knots fell between one-half and twice the size of the corresponding validated knot. Knots found for *E. nitens* between -50 percent and 50 percent (one half to one and one-half the size of the corresponding validated knots) made up 46.8 percent, while knots for *E. globulus* in this range composed 39 percent of the sample set.

Table 3-6. The mean and standard deviations for the difference in distances, the difference in the area, and percent overlap of the correctly identified knots from both species.

	E. nitens		*E. globulus*	
Detection statistic	Mean	Std	Mean	Std
Difference in centroids (C)	4.9	2.8	6.9	3.4
Difference in area (A_r)	125.7	2.8	67.4	4.0
Percent overlap (O_p)	172.6	1.2	159.8	1.25

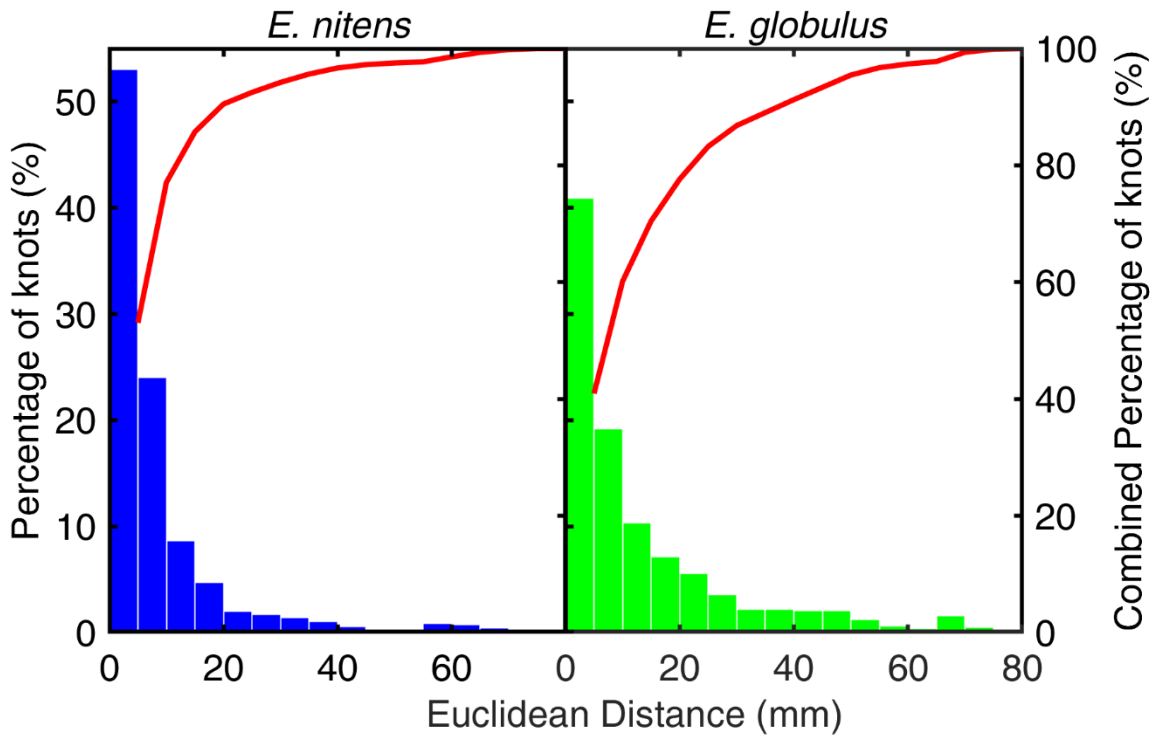


Figure 3-39. Distribution of the differences between corresponding knot centroids for both species in the study. The bin size is 5 mm. The right y-axis indicates the combined percentage of differences from 0 to 80 mm. Note: the maximum x-axis value for E. nitens is 80.

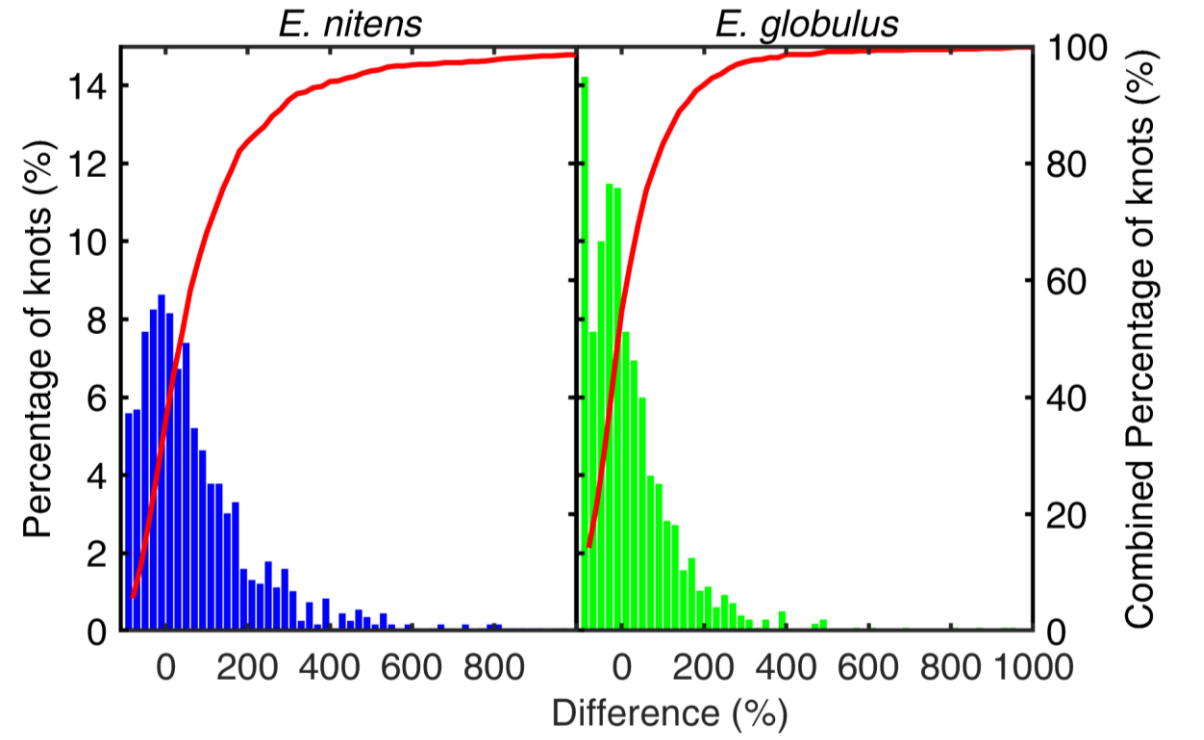


Figure 3-40. The distribution of the percentage of differences in the area between corresponding knots. The bin size is 20 percent. Differences below zero indicate detected knots smaller than validated ones, while those values above 0 indicate detected knots larger than the corresponding ones. The right y-axis indicates the combined percentage of differences from -100 to 1000. Note: the maximum x-axis value for E. nitens is 1000.

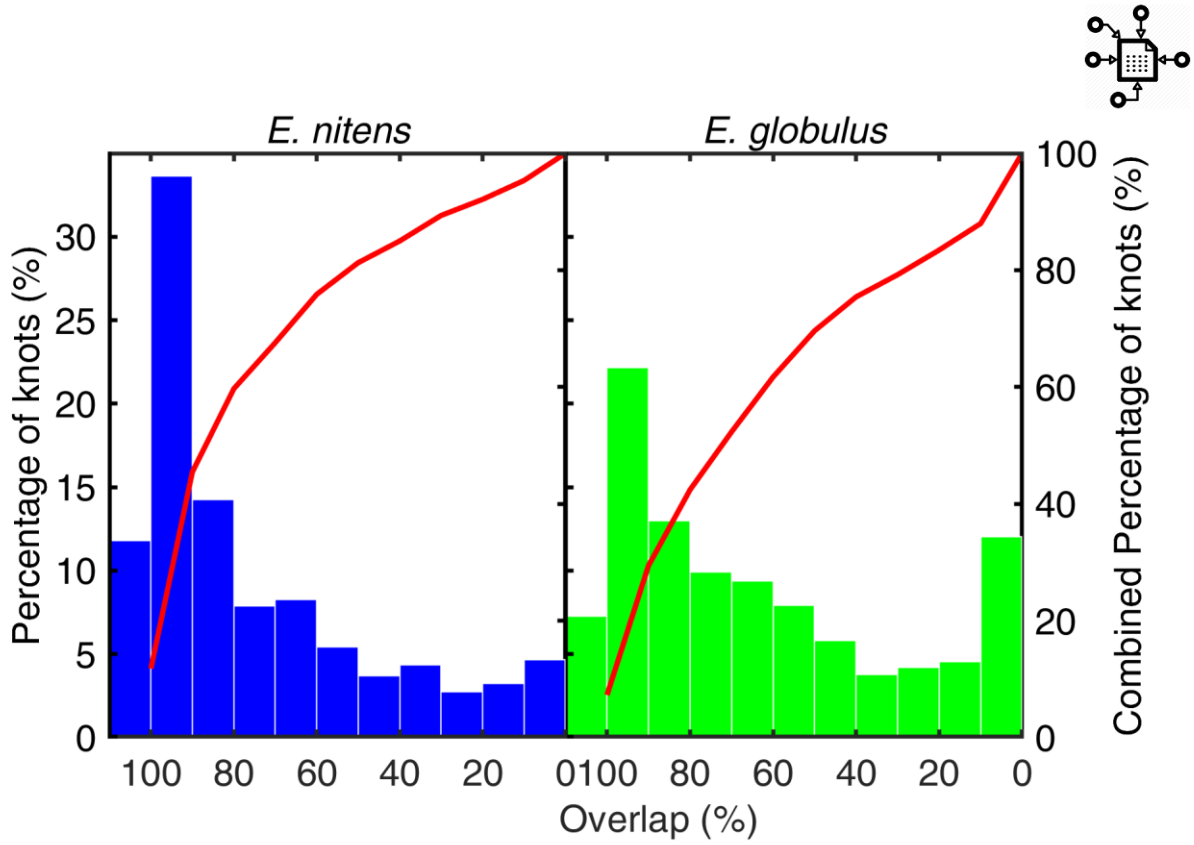


Figure 3-41. The distribution of the percentage of overlap in the area between corresponding knots. The bin size is 10 percent. The right y-axis indicates the combined percentage of differences from 100 to 0. Note: values above 100 percent overlap are the observations that are 100 percent overlapped.

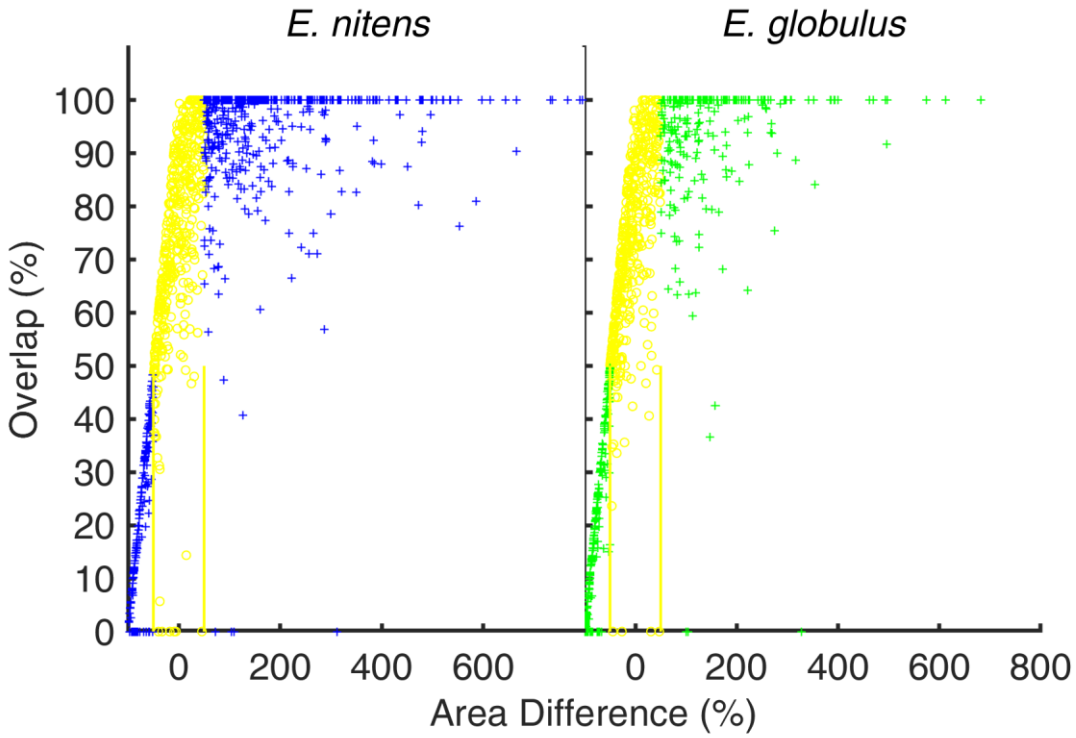


Figure 3-42. The percentage of overlap of bounding boxes between the detected and the corresponding validated knots. Data in yellow indicate values between -50 and 50 percent. Note: the maximum x-axis value for E. nitens is 800.

Using all knots in both datasets, the distribution of frequency differences in board segment lengths was calculated. The distribution of lengths of board segments (distances between knots) varied slightly between the species (Figure 3-43). In general, the frequency of segments in length classes less than 2000 mm was overestimated more in *E. nitens* than for *E. globulus*; however, the segments less than about 1000 mm was underestimated more than for *E. globulus*. The highest rate (-0.82 percent) of overestimation occurred for size class 700-800 mm for *E. nitens*, yet the highest overestimation occurred for the shortest classes in *E. globulus*.

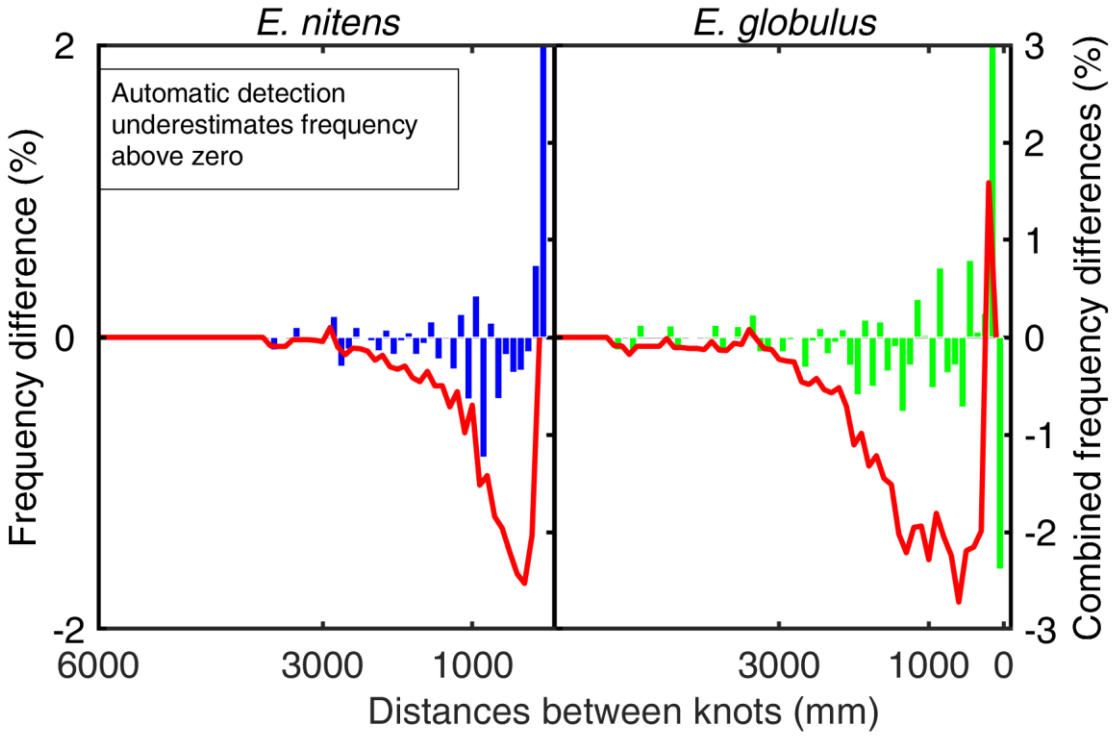


Figure 3-43. Differences in the frequency of board segments free of knots. The bin size is 100 mm. The right y-axis indicates the combined frequency differences from 6000 mm to zero. Note: the maximum x-axis value for E. globulus is 6000 mm.

The final performance of the characterization model was determined by comparing the classification rates of both size and color classes of knots. The size class was predicted well for the small and ex2large classes of knots found in *E. globulus* (Figure 3-44). Knots found in the three other classes were classified as both smaller and larger than validated sizes. The performance of color classification (rule-based) was much better (Figure 3-45). Prediction of the color class was above 67 percent and as high as 92 percent for light knots. Performance for size classification for *E. nitens* was poor for all groups except for the ex2large class (Figure 3-46). However, the knot classifier based on color performed well for both light and dark knots (Figure 3-47).

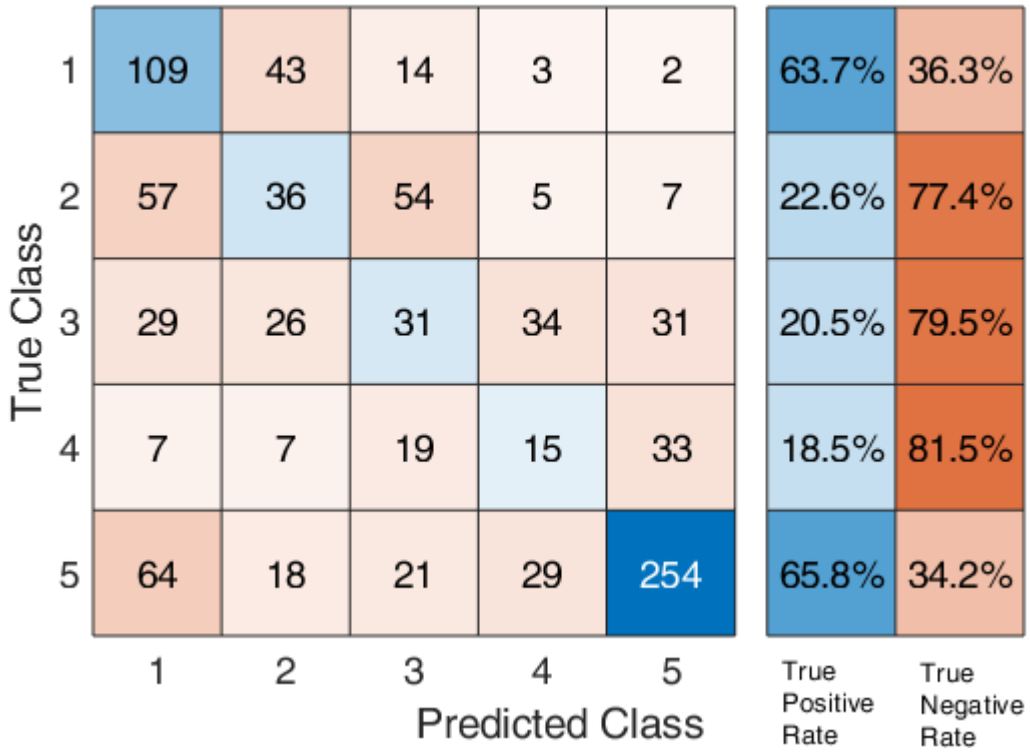


Figure 3-44. Confusion matrix indicating the prediction performance of size classes of bounding boxes of correctly identified knots for E. globulus. See Table 3-3 for categories.

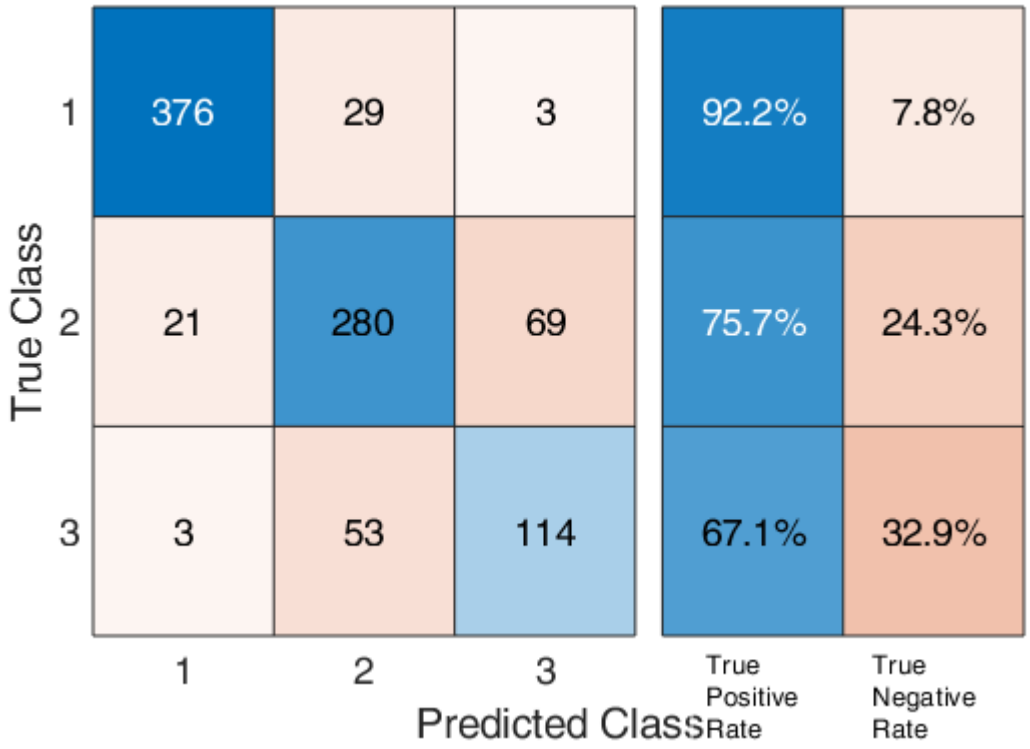


Figure 3-45. Confusion matrix indicating the prediction performance of color classes of correctly identified knots for E. globulus. See Table 3-4 for categories.

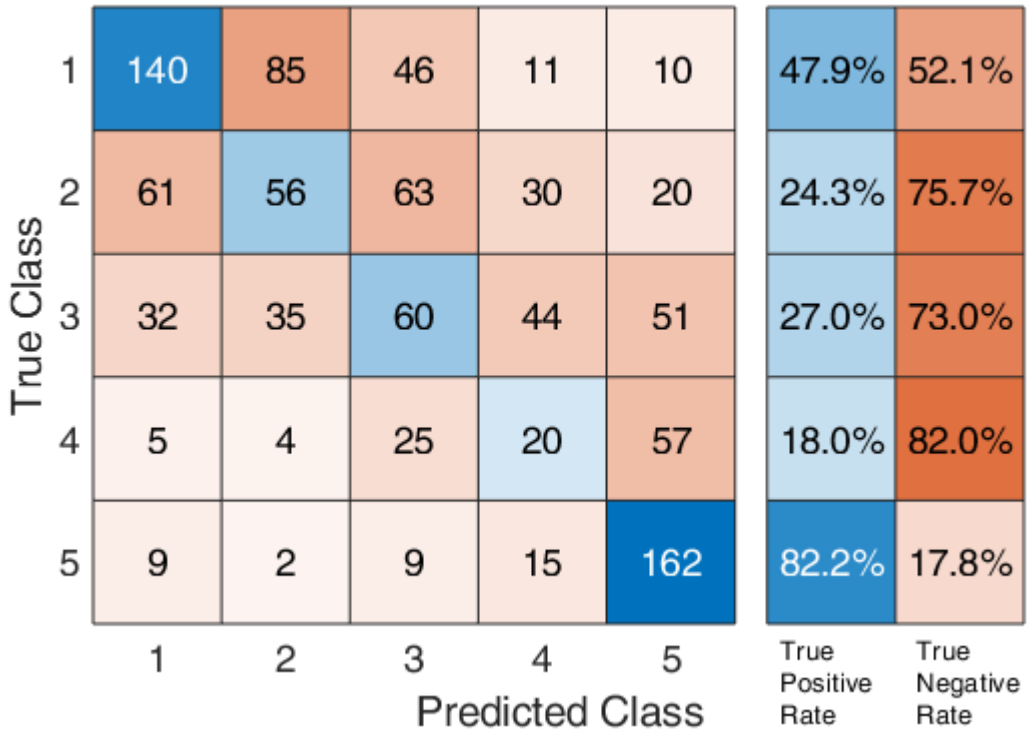


Figure 3-46. Confusion matrix indicating the prediction performance of size classes of bounding boxes of correctly identified knots for E. nitens. See Table 3-3 for categories.

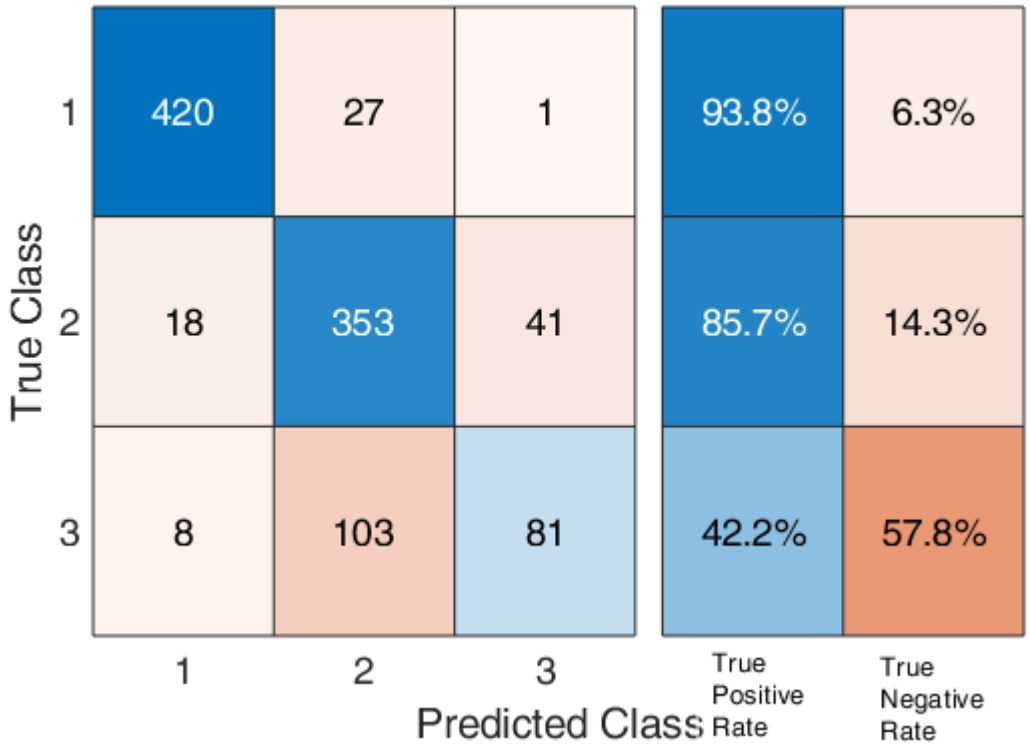


Figure 3-47. Confusion matrix indicating the prediction performance of color classes of correctly identified knots for E. nitens. See Table 3-4 for categories.

3.7.5 Characteristics of False negative Detections

The false negative rate was 11 percent for *E. globulus* and 8.92 percent for *E. nitens*. This means that between 9 percent and 11 percent of the knots were not detected with the method. The bounding box area of missed knots was right-skewed (Figure 3-48). For *E. nitens*, 62 percent were smaller than 400 mm^2, while 51 percent were smaller than 400 mm^2 for *E. globulus*. Over 75 percent were classified as light in both species, which probably accounts for why the methods were unable to detect them (Figure 3-49). However, the distribution of the red ratio was like the validated knots (Figure 3-50).

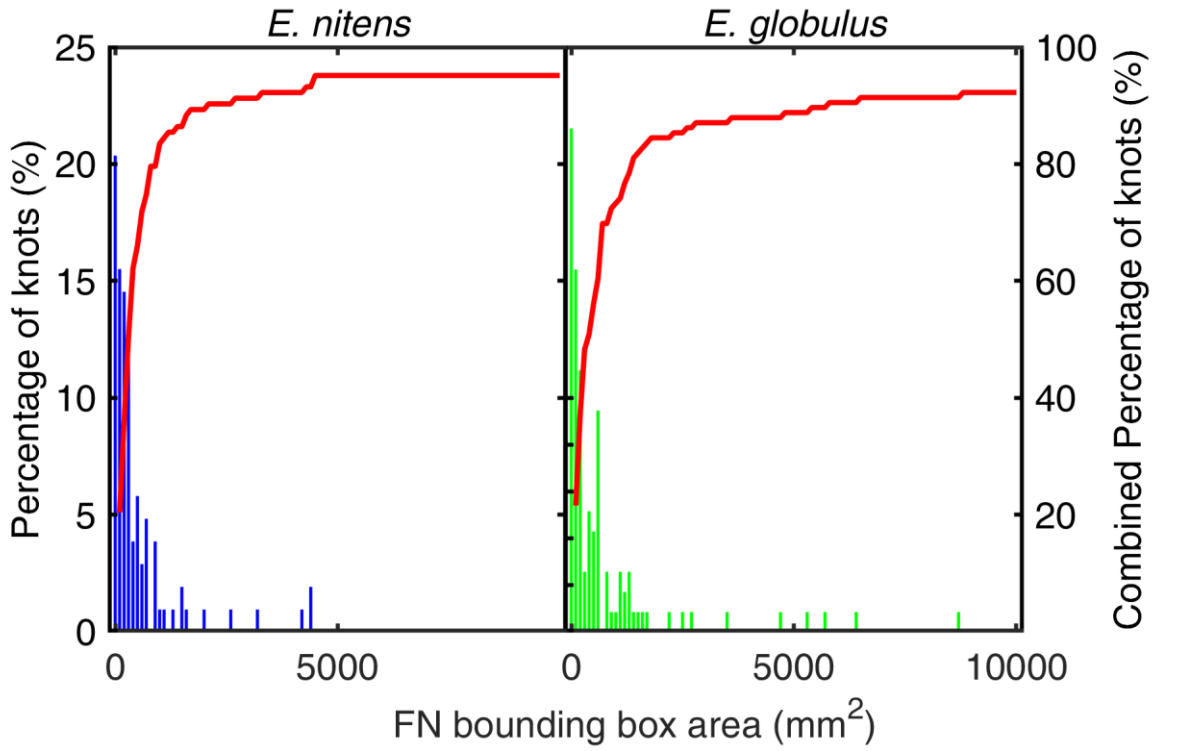


Figure 3-48. Distribution of size classes of false negative (FN) knots for the two species. Note: the maximum x-axis value for E. nitens is 10000.

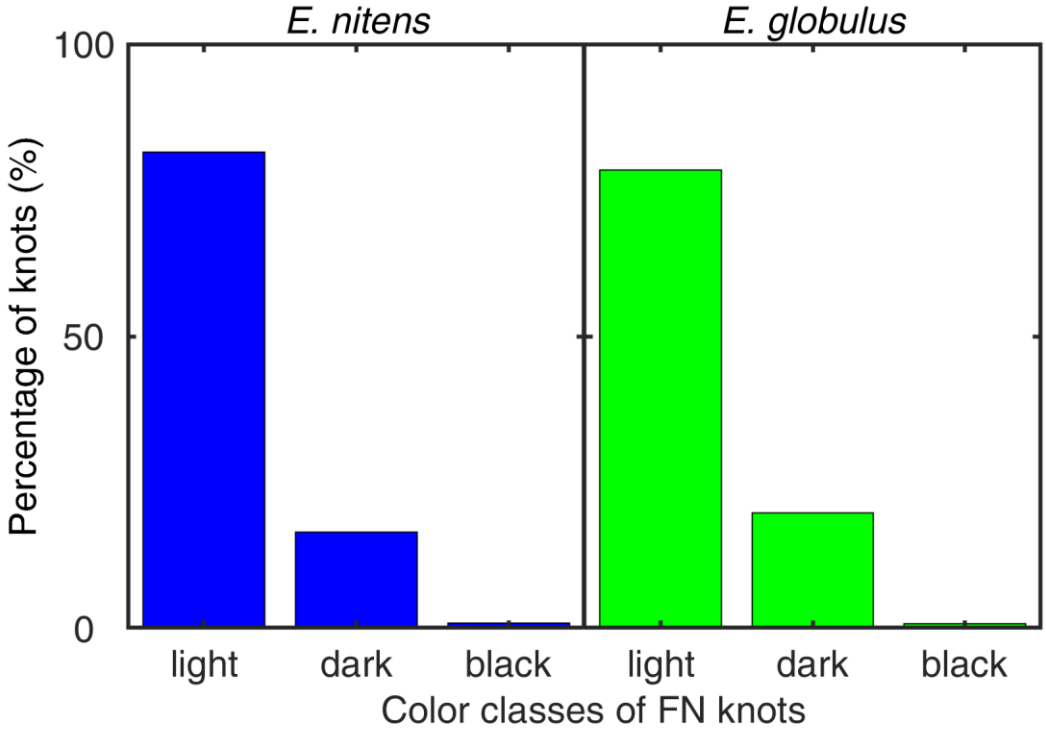


Figure 3-49. Distribution of size classes in the false negative (FN) knots from the two species.

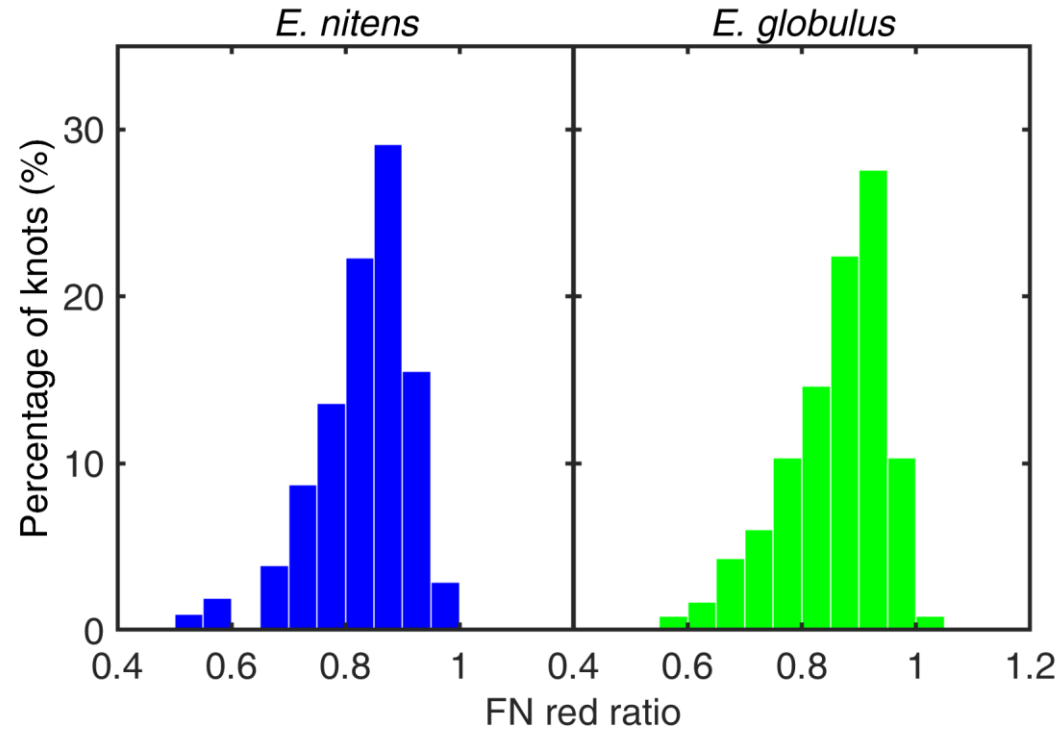


Figure 3-50. Distribution of the red ratio values of the false negative knots from the two species. Note: the maximum x-axis value for E. nitens is 1.2.

3.8 Discussion

The objective of this chapter was to develop a machine vision system to digitally characterize and describe knots from images of board surfaces. This would provide information at the knot-scale—that is this system provides descriptive information about knots but provides little information about how the knots are arranged within individual boards. This objective was addressed by developing an algorithm that automatically detects, classifies, and describes the geometry, orientation, and appearance of knots. The following was developed:

- a means to automatically detect and characterize knots from digital images;
- a means to validate the automatically collected data, and;
- a method to transform knot data into meaningful information describing geometric and appearance attributes of knots.

3.8.1 Characteristics of Validated Knots

The methods used on the validated images indicate that *E. nitens* has a higher proportion of smaller knots than *E. globulus*. However, there were approximately equal proportions of

knots in different color classes between the two species. The color classes may not have captured all the true color range differences because the red ratio in *E. nitens* indicated a higher proportion of darker knots when compared to the surrounding area. However, the pattern was reversed for tone. Overall, for both species, most knots were at least somewhat elliptical; very few were round. In general, most round-shaped (eccentricity less than 0.6) knots were below 1000 mm^2 for both species. At least half of all knots were oriented along the major axis of the board. Most knots occurred within less than 1000 mm of each other. The distribution indicates that ample boards contained a high occurrence of knots. It should be assumed that lumber produced from other short-rotation plantation resources will also contain a similar knot distribution. Based on this assumption, it will be a difficult proposition to integrate lumber from plantation resources into a hardwood supply chain developed during a time when larger, older trees that contain far fewer knots provided most of the resources.

The methods used to characterize knots in the validation images indicate that both species produce frequent knots that vary considerably in size, appearance, shape, and orientation. The way that color was assigned to a knot influenced the color classification, red ratio, and tone results. As there are no published standards that define knot color classes, these parameters were proposed to standardize knot color classes taken from RGB images. Common terms, such as ‘live knot’ and ‘dark knot’ do not carry enough resolution for a detailed selection of different types and appearances of knots. The approach set forth here could be adapted to provide a means to describe the range in knots found in lumber. The approach could also be used to describe other characteristics, which would increase the detail at which the variation in these characteristics can be described.

The approach used to determine the color classification, red ratio, and tone was largely based on the R channel of the image. This was chosen because it appeared that this channel contained enough data to indicate the ‘darkness’ or ‘lightness’ of a knot. For the knots in this study, the relationship between the mean values of the R, G, and B channels was approximately linear (Not shown). It was thought that the R channel would provide enough information for this study. However, the way color of knots is described and defined could be improved by using data from the other channels of the image. Consistent imaging processes

will also improve the way knots can be described relative to the surrounding areas. This may be especially important for other species that produce knots with greater color variation.

Although not attempted in this study, the methods could be expanded to other characteristics, such as gum vein, mineral streaking, grain, figure, or even spalt lines. This would require developing specific methods to describe the shape and appearance of these characteristics. Elliptical fitting would probably not be a good choice for gum vein. Grain (flatsawn vs. quartersawn) would require developing a system of pattern descriptors.

The lumber used in this study did not show a lot of diversity in overall knot color. This is probably because of the management practices of the resource. In a plantation, lower branches that are shaded out from high-density planting schemes will die, fall off and the knot can eventually begin to rot. Rot gives rise to black and dark knots. Typically, live branches higher in the canopy produce lighter knots. Therefore, the knots found along the log vary considerably. This process occurs differently for different types of timber stands and species. For example, the knots found in open-grown hardwood trees may occur less frequently and maybe larger, due to less branch death. Considering that heavily managed stands are supplying a large proportion of hardwood to markets, methods that describe the variation in knots and other growth characteristics could serve to improve how these characteristics can be integrated into design and manufacturing processes.

The selection of individual characteristics, such as knot size and appearance, would solve part of the problem. However, the other half of the problem is about understanding how the knots are arranged within individual boards. The actual placement and density of knots may influence the physical and mechanical properties of a board. For example, a board with a large knot near the middle will likely be weaker than a board with the same sized knot near the end. Also, consider the visual difference between grouped and equally dispersed knots of roughly the same size. Board-scale information is important to describe these arrangements.

3.8.2 Classification Model Performance

Approximately 50 percent of the detected objects were determined to be true knots. The classification models developed to determine if a detected object was a knot or a non-knot

performed with an accuracy of 79 percent for *E. globulus* and 83.8 percent for *E. nitens*. These models used 59 variables that described aspects of color, orientation, and texture of the object. The results demonstrated the feasibility of utilizing the technique to label detections into classes. Such techniques have been used in other studies; however, few have used as many attributes as this study. This is the first known study to apply these techniques to *E. nitens* or *E. globulus* lumber. The image analysis process produced a high percentage of false detections, which could be attributed to many characteristics other than knots. However, based on experience, many false detections occurred on areas of dark grain as shown in Figure 3-51. Detection methods based on thresholding will always prove difficult for material with high contrast between latewood and earlywood (grain). Despite these problems, the classification models performed well using this set of variables.

Figure 3-51. An example of dark grain in an E. globulus board.

The models showed a higher true positive rate for non-knots than for true knots for both species; conversely, the models showed a higher false negative rate for non-knots than for true knots. This indicates that it is harder for the models to predict a non-knot as a non-knot than to predict a true knot as a true knot. This probably occurs because the variables from the automatically detected objects are calculated from potentially a different set of pixels, as would be the case if the detected object were a different size than the validated one. This is the direct result of errors in thresholding operations (discussed below).

In this study, the classification models were limited to determining if a detected object was a knot or a non-knot. In practice, other domains, such as cracks and pith should be included in the classification models. As noted above, this would require additional pixel scale data to describe the characteristics and the development of additional models to classify the other characteristics.

3.8.3 Characterization Model Performance

The characterization model comprises the entire process, from image processing to classification. In this study, the characterization model performed on a par with other studies (see 3.4.1.1). These measures only indicate if a detected object is in the same location as a validated object. The model performed slightly better for *E. nitens*, a pattern that was also reflected in the classification performance. This species contained a slighter higher percentage of darker knots, which could lead to better thresholding accuracy and, hence, better overall performance. Some studies have reported higher rates of true positive detections, but the rates reported here meet the detection objectives of this study.

3.8.4 Comparison Between the Validation and CI Datasets

The characterization model performance is based on how well a detection is classified as a knot or non-knot. A second way to examine the performance of the characterization model is to compare the correctly identified (CI) knots between the two datasets. In this study, this was done by comparing the centroid locations, overlapping area, and the difference in area between an automatically detected knot and a corresponding validated knot. These comparisons are a direct function of which pixels are classified as foreground and background during the thresholding operation.

The comparisons presented above demonstrate the performance of the characterization model developed for this study. The results are conflicting; for example, true positive and false negative rates are high and low, respectively, a large proportion of centroids are close, but large differences in area and overlapping area exist for a significant proportion of knots. Interestingly, little difference in the frequency of most board segment lengths is reported. Despite good agreement in a high proportion of the datasets, classification of knots into size and color classes was poor; many knots were either smaller or large or lighter or darker than the corresponding validated knots. Due to the inherent and unavoidable differences in the way knot edges are defined both visually and by image analysis techniques, these classifications may not be well suited to the size distributions. That is, a slight proportional increase could change a classification of a knot from small to medium, or a different class.

Also, consider the lengths of a side of a box with twice the area of a smaller one is only 1.4 as long, which could significantly influence the size classification results.

The method classified light and dark knots well, but the performance was poor for black knots. The method met the criteria outlined in the objectives for light and dark knots, but not for black knots. This is most likely due to the size differences between the ellipse of the corresponding knots. Even a small size difference could result in a different class label. For example, if a detected knot was smaller than its validated knot but contained the same number of black pixels (in many cases, the center of a knot contains the highest density of dark pixels—possibility due to checking, splitting, or bark inclusions), it could be classified in a darker category. Although no attempt was made to find knots where this precise situation occurred, 27 of the 448 light *E. nitens* knots and 32 of the 408 light *E. globulus* knots were misclassified as dark. The opposite situation could result in automatically detected knots classified in lighter categories. Another possible explanation is that the set of pixels used to calculate the color class could be different enough to influence the calculation. This could occur for knots with low overlapping areas.

There are several reasons why the quality of detection was poor in this study. First, the image acquisition set-up did not provide a way to consistently illuminate the board surfaces, both along the length of the board and from one imaging session to another. This led to a difference in intensity levels on board surfaces, which required extensive image processing to attempt to either remove or correct. It also required the development of a complicated means to transform images (adaptive thresholding) based on a variation on the board color due to inconsistencies in illumination. Second, because the boards were milled from young trees with live branches, the color of many knots were not significantly darker than the surrounding material (in some cases, knots were even lighter than surrounding areas). Because the detection method used here requires objects to be darker than the surrounding background, these types of knots were extremely difficult or impossible to detect. This effect can be seen from the characteristics of the false negative knots, many of which were very light.

This explanation is further supported by examining the size classification results. The method met the performance criteria for small and ex2large knots on *E. globulus* boards and ex2large

knots for *E. nitens*. Patterns show that size classes shifted into both higher and low classes for a high proportion of knots. This pattern points to a significant challenge in knot detection problems. The challenge is how to define the edge of a knot—both during thresholding and image analysis and physically on the board.

Detection could be improved with different image transformation procedures, thresholding settings, and image quality. This study used the segmentation method; however, edge detection, non-segmentation, and discontinuity approaches have been used in other studies with good results (8.1.1). Improved size characterization and classification could be achieved by developing combinations of other image analysis approaches and sensors. Also, most commercial systems use different image capturing sensors and combinations of RGB line scan cameras and laser images to improve image quality (a commercial system was not available for this work). Considering the simplistic image capture set-up, the results presented here are acceptable.

Although many automatically detected knots were considerably larger and smaller than the corresponding validated ones, the misrepresentation can be explained by examining the ways that the comparisons are made. As discussed in 8.1.2 and elsewhere, knots present in a range of shapes and sizes and it is sometimes difficult to define the exact edge of the knot from the surrounding material—it is often a subjective judgment of the expert user. However, this judgment can vary with experience with a material and the intended use. Therefore, manual marking by one person may not agree with marking from another person, and knots can either be overestimated or underestimated, depending on the judgment of the person marking. In this study, efforts were taken to minimize these errors, but undoubtedly some validated knots were not accurately represented. Other errors can occur from calculating areas based on a fit ellipse and the bounding box.

Here, it was assumed that comparing corresponding bounding box areas would provide the least differences between knots. For example, if a knot were oriented differently, had different lengths of major and minor axes, or contained a significantly different set of pixels, a smaller error will be introduced into the calculation of the bounding box size than would be expressed using ellipse area. This is highlighted in the first example given in Figure 3-2. There

would be a significant difference between the marked-up area of the knot and what was automatically detected, however, the difference in bounding box areas would be minimized.

Another source of error occurs during the comparison between the two datasets when comparisons assume that two knots correspond if they are within 75 mm in the long direction and 30 mm in the short direction. In some cases, these distances led to multiple knots in the automatic dataset that corresponds to a single knot in the validation dataset. These duplications may be larger or smaller than the corresponding knot, and therefore, result in extreme differences in overlap and area differences. Color classes are also influenced by size. Slight changes in the set of pixels considered may cause the knot to fall into a different class. Moving forward, improved size and color classification approaches could refine the agreement between validation and automatic detection.

3.8.5 Characteristics of False negative Detections

The false negative detection rate was approximately 10 percent. Most of these knots were small and light. Given the limitations of the thresholding approach, such objects would be difficult to detect. Other pixel classification approaches may improve the false negative rate. Deep learning and semantic segmentation, which clusters parts of images that belong to the same object class (Liu et al., 2019, Thoma, 2016), approaches are likely to result in better characterization, higher characterization accuracy, and lower false negative detection rates. Such systems are used in self-driving cars and other applications. The approach is also under development by companies such as Lucidyne Technologies, Inc (Patrick Freeman, pers com, 2019).

4 Chapter Four - A Method to Improve the Selection and Specification for Size and Appearance of Knots in Wood Panels

4.1 Purpose

This chapter presents a digital method to select and specify knots that can occur in panels. This is done by producing digital artifacts in the form of high-resolution images of wood panels that contain different knot sizes and appearance types. This procedure is performed with both board segments and cutting areas.

4.2 Objectives

As introduced at the beginning of this thesis, the selection and specification of timber are problematic compared to other building materials. The problem occurs because the systems used to select and specify timber products do a poor job accommodating the enormous variability of properties found in the material. The classification (grading) and selection of different wood materials can be based on many factors such as straightness, stability, absence of defects, and overall appearance (Nicholls and Roos, 2006). However, unlike other products, there is insufficient information available for the user to choose between different combinations of visual characteristics. Additionally, there is no method to specify a grade of lumber that would be best suited for different cutting bill requirements.

Although detailed information can be effectively exchanged within digital design and fabrication environments, specification of timber by designers and end-users is limited to restrictive grade standards. Increased agility and information exchange can be achieved by stronger linkages between members of supply chains (Stiess, 2010, Um, 2017). Enhanced specification methods for timber, as suggested by Nolan (1998) would enable specification and supply of differentiated products that could respond to market and aesthetic demands.

The objective of this chapter is to develop a means to select and specify different sizes and types of knots in appearance panels. This objective requires the development of methods to:

- select sizes and types of knots available from a supplied resource;
- locate areas of boards that contain the desired characteristics;

- visualize products assembled from those areas; and
- specify a material that contains the desired characteristics.

4.3 Background

4.3.1 Abstraction

The concept of abstraction was introduced in 2.5. Recall, that abstraction takes place in the digital environment and is used to represent and communicate the geometric shapes of design elements. Every object in the built environment is constructed from materials that originated from a geometric abstraction (Bruot, 2013). These abstractions simplify the complexity of the design concept to geometric forms. This has the advantage in that it allows an understanding of the design's characteristics and spatial relationships to other elements. However, it requires that the designer understand the elements that have been removed for simplification. This results in a situation where the user must understand the "materiality" of the material specific to their designs (Bruot, 2013). Here, materiality refers to the visual characteristics, such as knots, present in wood products. Material properties and characteristics are minimized, while design geometry is emphasized. Although the cutting bill requirements are a direct output of the product design procedure, because of the widespread segmentation of technical specialization and knowledge within the wood products industry (Booth and Nolan, 2016), it follows that it would be unusual for designers to consider specific visual characteristics or material optimization during the design phase, although there may be feedback and feedforward mechanisms between designers and manufacturers that would eventually lead to an optimized material solution, based on availability, costs, and other factors.

An example of a digital abstraction could be an interior wall which is often represented as a rectangular form. This form is helpful to evaluate spatial relationships among other elements. However, due to the primitive level of abstraction (the individual elements have not been indicated), there is little ability to guarantee that the wall will perform the required mechanical requirements or that the required performance is achievable within a limited supply of materials. In the case of interior wood products, such as wall and flooring panels, the abstraction cannot carry specific visual information in enough detail to assess subtle differences within the overall design context.

This situation occurs mainly because these systems are designed to accommodate materials with low or very little variability in physical and mechanical properties. These systems operate under the central assumption that material characteristics are homogeneous. During the design process, a material can be selected and specified with a level of assurance that it will satisfy the performance requirements of the application. Color and other information can be assigned to abstractions to better visualize design outcomes within the digital environment.

The variation present in hardwood lumber is largely ignored. To achieve visual uniformity, parts are removed from clear cutting areas almost exclusively. This practice results in some assurance that products constructed from the same or similar species will have similar visual attributes once manufactured. A design could be conceived that would incorporate certain aspects of color, grain, and other visual characteristics such as knots, however, there is little information available to select or specify for such detail. Also, there is very little digital information that could be assigned to abstractions within the design software to better predict visual outcomes before specification for a certain range of characteristics is made.

As introduced in 2.5, secondary wood products are manufactured from raw materials, such as lumber or sheet goods (e.g. plywood). The products are the result of the design process. In a modern design and architectural practice, the final stages of design are translated into the digital environment using digital design software programs, which can enable simulation of both the design and manufacturing processes. The digital environment provides the capability of exporting digitally created dimensions and geometry for the elements or parts of the product. Here, this list of parts is referred to as the cutting bill. The specifications of each part in the cutting bill include other callouts, which could include required physical and mechanical properties of certain species, finish, or type of material (i.e., plywood, mdf, solid wood, etc). Parts can also be specified to contain certain sizes and types of characteristics.

4.3.2 Selection

Even with a greater understanding of optimized solutions, the ability to choose different combinations of appearance properties remains limited for wood products. Information that describes the actual appearance properties could be integrated into the design workflow. To some degree, this already takes place for other materials. Implementation of new technology

allows a visual display of actual stone slabs within the digital design environment. This allows customers to visually review, rearrange, and select different surfaces and patterns before the digital file is sent for fabrication (Northwood Designs, 2018). Paint is precisely defined within a chosen color space (i.e. RGB), which provides a very accurate and consistent way to represent color in the digital environment.

As powerful as the CAD/CAM environment is, historically it has not been particularly flexible to changes in design parameters. The elements were not linked to each other in any functional way. Over time, parametric design software and techniques were developed that allowed experimentation with design variables and material constraints (Booth and Nolan, 2016). For example, a part manufactured from a standard sheet good does not change its thickness when other dimensions are adjusted. Parametric design software also links elements in such a way that when an adjoining (and linked) part changes, the other linked elements also change to accommodate the changes in the part. Parametric processes are governed by information using a system that allows the selection of a value over some defined range that relates to the available properties of the material in question.

One common tool used to select different characteristics and values of products and services is the slider. A slider is a control element that uses a knob or lever to control a continuous or discrete variable. The volume on the radio is an example of a continuous variable, while categories such as small, medium, and large are an example of a discrete variable. The range of the slider is limited to values available and allowable to the variable or process. Two sliders allow the user to choose a minimum and maximum range of a variable, such as a star rating of hotels and the price. This is one way to define the acceptable limits of a variable. Although the slider is a common way for an end-user to choose from a menu of available options, such tools are very seldom used to choose from different combinations of characteristics available from wood. The slider concept provides a useful context in which to develop a system that would allow the user to engage with and choose between different visual outcomes that result from allowing different levels of specific characteristics to occur in finished products.

The output values from the slider are typically passed to design software. Parametric modeling software uses parameters to define the dimensions of a model. These parameters

originated from a linked decision-making process, which could be a slider interface. For example, a set of sliders could be used to directly control the dimensions or color of a product. This approach is commercially relevant and has been used by manufacturers to stream-line mass-customization efforts. An example is shown in Figure 4-1 from the company tylko.com. The user can choose the size of the overall unit, and then choose the width and height of partitions, within predefined limits. Other aspects such as color, door, and drawer configuration can also be selected. These variables are then used to calculate the price of the unit.

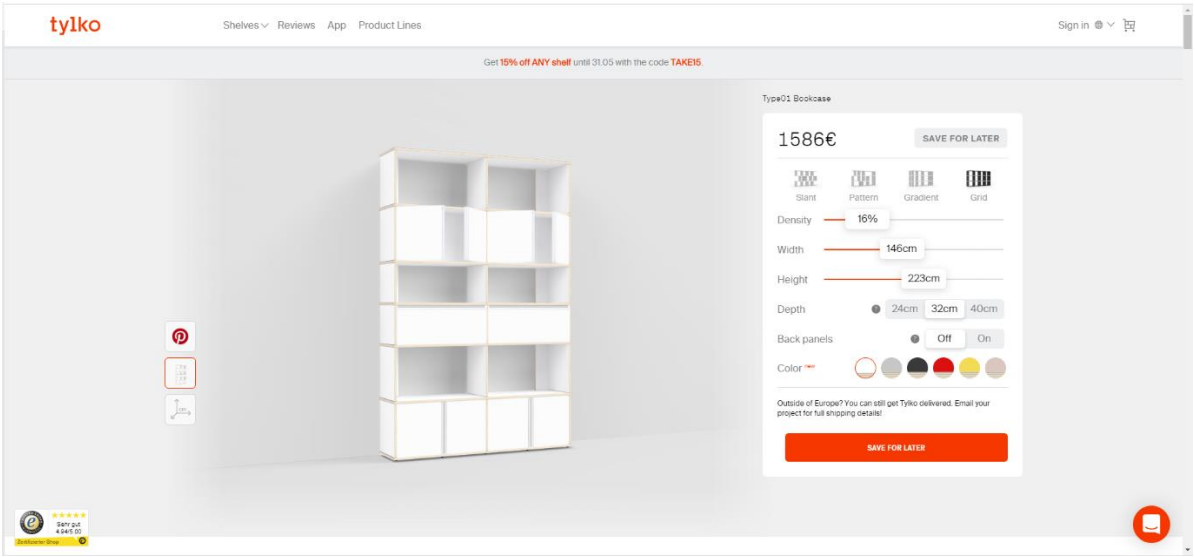


Figure 4-1. A screenshot of the slider interface available to customize shelving units.

In the above example, a user selects aspects of the desired unit and the manufacturer can visualize the design outcome and the price based on the selections. Unbeknownst to the user, the selections were passed to software that rendered the visualizations and calculated the expense of materials and labor required to produce the unit. All these processes are based on standard-sized sheet goods, available color, and hardware. For example, when the user chooses a 'natural' surface, it is represented with a generic picture of wood grain that does not scale when the dimensions of an element change. Such systems are not designed to handle material that is supplied in various sizes and contain random arrangements of characteristics that may or may not be acceptable. To the author's knowledge, there is no known commercial-scale system that integrates the variability of physical and mechanical properties of hardwood lumber into the design and manufacturing processes.

4.3.3 Specification

Lumber is selected by secondary manufacturers based on several attributes. Different market opportunities and consumer acceptance are based on these attributes (Nicholls and Roos, 2006). Due to the large diversification of materials, material price, manufacturing operations, and products, different attributes are important to different manufacturers (Nicholls and Roos, 2006). Nicholls and Roos (2006) found that despite regional differences across North America, appearance-related attributes, such as color and grain patterns, and dimensional stability were among the most important attributes when selecting lumber. In that study, no attempt was made to evaluate the importance of lumber grade, other than to note that lumber containing no knots was a relatively unimportant selection criteria, which could suggest that knots would be tolerated for applications where these visual attributes were important.

Specification is the means to communicate the grade and species of lumber desired by users. It relies on a grading standard that provides the grade name for different batches of materials. The grade name is used to indicate the grade of the material.

The process is limited by the level of detail, or resolution, of information, that both describes the material and the resolution that the grading standard separates different classes of material. Universally, timber gradings standards do not contain the resolution required for specifying a grade that would be best suited to manufacture products that contain different levels of acceptable characteristics. Also, current grading standards provide insufficient information to select and define the desired visual attributes.

4.3.4 Engaging with Visual Attributes

Users have developed several means to overcome the limitations of specifying the best-suited lumber for character-marked products. One common method is for a consumer to describe the desired characteristics with terms like ‘large live knots’ or ‘lots of small knots’. Little information is available to accurately predict the visual outcome using such vague terminology. Another common method involves a physical collection of sample pieces (cuttings) that contain the desired visual attributes. Different sample pieces containing various sizes and types of characteristics are passed between producers and users to arrive

at the acceptable range of characteristics. Although this experience does increase materiality knowledge and allows the user to move beyond commonly used combinations, it is laborious and time-consuming. The method is best employed for projects that require large volumes of lumber containing a certain blend of characteristics. Both methods present the challenge of specifying the best-suited lumber to meet the consumer's expectations.

A third method involves providing standardized products with different visual attributes to consumers. Consumers would choose from a range of available options in much the same way they choose other products, such as paint, carpet, and manufactured flooring. Products containing different visual attributes would carry a name, which would be used to specify the product (in much the same way as lumber grade names are used). This system is restricted by what the industry determines to be desired within the market; it allows very little flexibility for the user to customize the combination of visual attributes. Because it would take some time for the industry to determine the market appeal of different combinations and to detect changes in market trends, it would not contribute to supply chain agility.

As introduced in 2.4, the use of character-marked cuttings to manufacture products both increases the utilization of hardwood lumber and, because it expands the visual outcomes available, manufacturers can use them to remain competitive in a fashion-driven industry (Bumgardner et al., 2001b, Leslie and Reimer, 2003). Fashions reflect the tastes and lifestyle of society; the industry needs to quickly translate new fashion concepts to products (Čiarniene and Vienazindiene, 2014). Consumers choose products to represent a way of life, attitudes, values, a look, or an idea; often changes in furniture styles are correlated with changes in clothing (Leslie and Reimer, 2003). Both require complex supply chains that must respond to changing designs and consumer desires for distinctive and unique products, which has led to the ability for consumers to customize products (Tian et al., 2001). Materials are one source where consumers can express differentness from others (Tian et al., 2001). Also, touch perceptions of raw and finished wood surfaces may provide a major competitive advantage for wood over other materials (Bhatta et al., 2017). These concepts are reflected by preferences for different species, surface textures, and character-marked products.

Hardwood lumber could be used to manufacture products with unique visual outcomes. This would require some method to judge a consumer's preference for certain combinations of characteristics. By necessity, this would require a means to engage with the various possible visual outcomes. In an ideal situation, the consumer would be able to touch and see different combinations of visual attributes. However, the digital environment limits the ability for tactile engagement but provides the capacity to render designs in high-resolution color models. As noted above, the exact color of many materials can be imported directly into this workflow process. However, there are limitations for the user to directly engage with the visual attributes provide by hardwood lumber.

The variation and random distribution of different characteristics (as discussed in Chapter 3) found in solid-wood products represent both opportunities and challenges. Opportunities including the ability to engage with the different characteristics for unique design and visual outcomes (Kotlarewski et al., 2018). However, these outcomes depend on the development of innovative design and manufacturing workflows; workflows that are not part of most design processes. Given the potential to use high-resolution board-scale information during the selection and specification phases, there appears to be an opportunity to expand the role of the designer, perhaps creating a new position within the industry. In this role, the expert user would manipulate the high-resolution board-scale information to inform both the sorting of lumber and the processing of lumber.

There are a few examples that demonstrate the integration of material characteristics and wood and digital design and fabrication. Kotlarewski et al. (2018) integrated knot location into a parametric digital fabrication workflow to fabricate acoustic panels with unique appearances, increased manufacturing efficiency, and differing performances from plantation grown Tasmanian hardwood. The study demonstrated a digital fabrication strategy that considers a set of constraints while also considering and adapting to the characteristics of the material. The resulting product is a direct outcome of the design parameters and material characteristics.

Kotlarewski et al. (2018) highlighted a process that is uncommon in the production of wood products. A more typical approach is to specify the wood type and grade with the general

knowledge of appearance, cost, and yield from the material. Situations that call for certain characteristics, such as knots, are often subjectively described with terms such as “lots of big knots”, or “lots of small black knots”. This results in a situation where producers try to provide materials that they think will yield what the consumer desires and manufacturers try to fabricate products from these materials. Often, this results in consumer dissatisfaction with the resulting appearance.

This chapter presents a means to use the high-resolution information that both describes the geometric relationship of knots found on boards and the appearance properties to predict the visual qualities of wood panels. Two methods are investigated. First, panels are virtually constructed using board segments that contain various sizes and types of knots. Second, panels are virtually constructed using cutting areas that contain various sizes and types of knots. The panel was chosen as a commercially viable product that could be used to capture the visual outcomes available at scale. Panel images produced from the processes developed here can be imported into design software such that the visual outcomes are accurately represented relative to other design elements.

4.4 Methods

4.4.1 Datasets and Terms

Chapter 3 produced and utilized two datasets: validated and automatic datasets. In this chapter, only the validated dataset is used. The focus of this chapter is to demonstrate how the visual characteristics can be captured within a product (solid wood product) from a given resource. It is thought these objectives would be best addressed by using the validated dataset because it most accurately represents the knot distribution, size, and appearance. In practice, the research presented here would use information directly from commercial scanning equipment.

Two ways to process boards are explored. The first and simplest method involves chopping boards into segments (docking)—referred to here as the segmenting method[27]. This method is appropriate in the Australian context given that boards are produced and supplied in

[27] As noted in the introduction, the segmenting method is an extension of the cutting area approach. Conceptually, board segments are cutting areas that are the full width of the board.

standard widths and lengths. This method is commonly known as “docking” to produce panels of clear stock panels. Here, however, the concept is applied to panels that contain specific types of knots. The other method is more common in North America where parts are removed from boards by a combination of ripping and chopping operations. This process produces cuttings from cutting areas of boards that only contain allowable characteristics—typically clear (free of most characteristics), but in some situations, other characteristics are allowed.

4.4.2 Board-scale information

The knot-scale information from Chapter 3 was transformed into board-scale information for every board in the sample set. This was accomplished by attaching the board ID number and location coordinate data to each knot in the dataset. This information was then used to indicate knot locations on boards in real-world units and map knot coordinates to images.

4.4.3 Unsorted Panels

To visualize the variability of knots and other characteristics on the lumber, panels were assembled from random board segments. These panels used segments from different width boards to ensure that the maximum variability would be captured.

4.4.4 Board Segments

4.4.4.1 Locating Segments

In the previous discussions, the term segmenting was used to describe the process of image division (3.6.2.1). For the rest of this thesis, segmenting refers to the process of chopping boards into sections. A module was developed to locate segments of boards that contained a defined size and type of knots. Programmatically, the workflow is presented in Figure 4-2. To explore the appearance of panels assembled from different types of segments, two sets of segmenting definitions were created. The parameters of the two sets of definitions are shown in Table 4-1 and Table 4-2. These definitions were used to classify each knot from the validation data set presented in the previous chapter. Segments were assigned a classification of clear, type 1, type 2, type 3, type 4. As an example, from definition 1, a clear segment contained no knots, while segment types 1-4 contained knots of increasing size and appearance type. A minimum length requirement of 1000 mm was assigned to clear segments using definition 1 and 2000 mm for definition 2. A minimum length requirement of 500 mm

was assigned to the other segment types. The algorithm was designed to prioritize segment length for segments containing smaller knots and progressed from left to right considering each knot along within the board. For example, a type 1 segment extended to the edge of knots classified as type 2, type 2 segments extended to the edge of type 3 knots, and so forth. This approach implies that longer lengths of segments containing smaller knots would be produced preferentially over segment lengths containing larger knots classes. An example of a segmented board is shown in Figure 4-3. Logically the algorithm operates as:

If

distance between knots is greater than the minimum required by the definition

then

stop the previous segment at the back edge of the knot class (x_i-1) and

start segment at the back edge of the knot class (x_i-1) and

stop segment at the front edge of the knot class (x_i)

else if

knot class (x_i+1) is larger than knot class (x_i)

then

stop segment at the front edge of back (x_i+1)

else if

knot class (x_i+1) is equal to knot class (x_i)

then

continue segment to the front edge of knot class (x_i+1)

else if

knot class (x_i+1) is less than knot class (x_i)

then

stop segment to the front edge of the knot (x_i)

end

where (x_i) is the current knot under consideration, and (x_i+1) is the next knot.

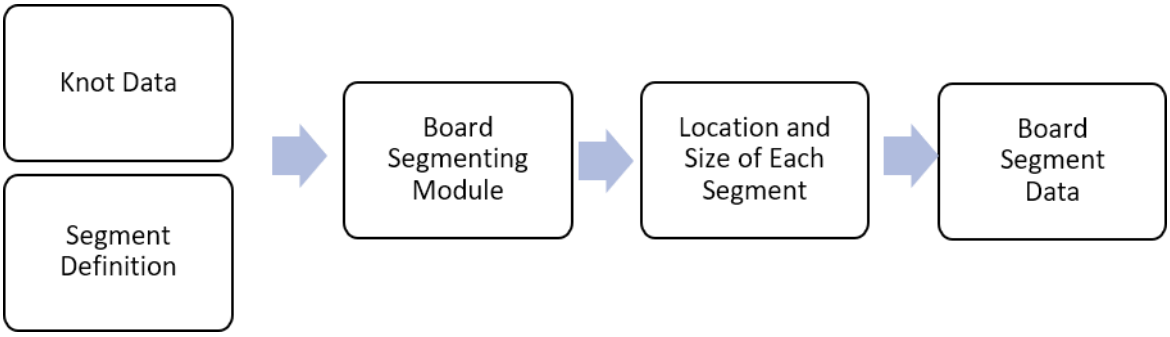


Figure 4-2. Flow chart of the process used to determine board segments.

Table 4-1. Board segmenting definition 1.

Segment type	Knot size (mm^2)	Knot appearance type
Clear (> 1000 mm)	N/A	N/A
	N/A	N/A
	N/A	N/A
Type 1 (>500 mm)	>0; <322.6	Light
	>0; <322.6	Dark
	>0; <322.6	Black
Type 2 (>500 mm)	>322.6; <645	Light
	>322.6; <645	Dark
	>322.6; <645	Black
Type 3 (>500 mm)	>645; <1290	Light
	>645; <1290	Dark
	>645; <1290	Black
Type 4 (>500mm)	>1290	Light
	>1290	Dark
	>1290	Black

Table 4-2. Board segmenting definition 2.

Segment type	Knot size (mm2)	Knot appearance type
Clear (>2000 mm)	N/A	N/A
	N/A	N/A
	N/A	N/A
Type 1 (>500 mm)	<645	Light
	<645	Dark
	N/A	Black
Type 2 (>500 mm)	>645; <1290	Light
	>645; <1290	Dark
	>0; <1290	Black
Type 3 (>500 mm)	>1290; <1600	Light
	>1290; <1600	Dark
	>1290; <1600	Black
Type 4 (>500 mm)	>1600	Light
	>1600	Dark
	>1600	Black

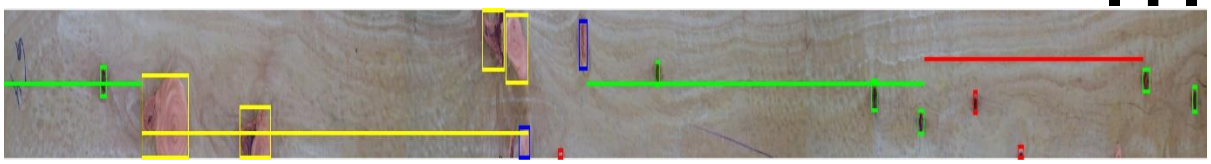


Figure 4-3. An example of a segmented board. The colored lines indicate the location of each of the different segment types. Note: a segment must be at least 500 mm to be identified. The image has also been distorted longitudinally to better illustrate the segment locations.

This process produced board segment data, which described the length and location of each segment for each board. It was performed on each species separately.

4.4.4.2 Panel Assembly

Virtual panels were produced from board segments within the same segment type derived in 4.4.4.1. The flow of information from board segment data and images to the final panel is presented in Figure 4-4. The segmenting process could result in a knot at the end, which would potentially result in problems in the further machining process in a real-world situation. To increase the realistic nature of the simulation, the ends of the segments were either extended or shortened by 50 mm. The process would depend on the next segment type. For example, if there was a knot at the very end of a segment, then the segment was lengthened, otherwise, it was shorted. Each segment was virtually joined to the next and the resulting strip was cut into 2 m lengths which were then edge joined to form panels. In theory, this mimics a finger-jointing panel production operation (Chiang, 1964). The widest boards were arranged at the top of the panels, while the narrowest boards were attached to the bottom of the panels.

This process was repeated for both board sorting definitions presented earlier. Because allowable size and type of knots were defined by each definition, the content, and therefore the appearance of each panel varied greatly. The process resulted in high-resolution images of a variety of knot content and provides an example of a simulation that could be performed by an expert user of such data.

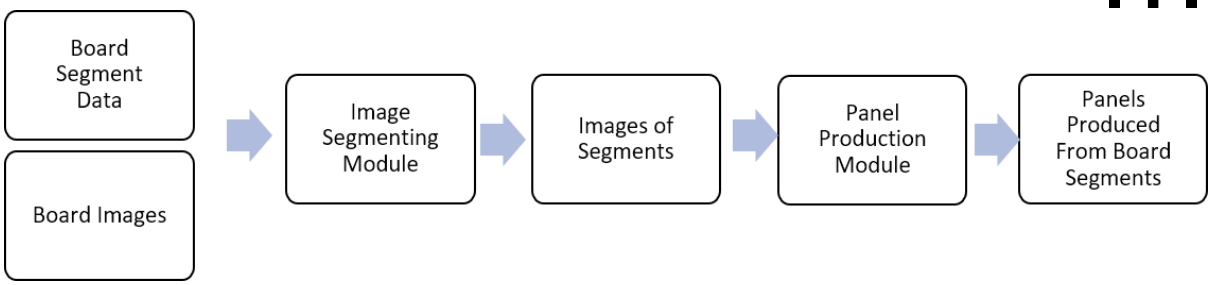


Figure 4-4. Flow chart of the process used to create virtual images of panels constructed from board segments.

4.4.5 Cutting Area

4.4.5.1 Locating Cutting Areas

A second way to produce panels from the material consisted of a standard panel construction process using cuttings from boards. The process used cutting bills, board data files, and board images to create images of the panels. Although like the segmenting approach above, this approach was explored to investigate the visual attributes available using a completely different method of processing. Unlike the panels produced from random length board segments, the panels produced from cutting areas were assembled from random width pieces. The process consisted of multiple operations outlined in Figure 4-5. Briefly, a lumber processing optimization software known as ROMI 4.0 (see 6.3.4 for an in-depth of this software) used a panel cutting bill and the board-scale knot distribution information to simulate the location of the cuttings that would be assembled into the panels. For cuttings to contain different sizes and types of knots, knots within a certain range were removed from board-scale data during the simulations. This allowed ROMI 4.0 to process cuttings from what appear to be clear cutting areas. Simulations used 4 different definitions of allowable knot size and appearance type. The range and type of each knot allowed under the different definitions are shown in Table 4-3. The assembly and visualization were performed with a purpose-designed MATLAB panel production module. It used cutting locations, board images, and produced high-resolution images of panels. Two types of panels were produced: one that contained a mix (referred to as a mixed panel) of both knotty and knot-free cuttings and one that contained only knotty cuttings (referred to as a knotty panel). The knot density (knots/m^2) was calculated for both types of panels and the ratio between the area of knotty panels and the area of mixed panels was also determined. The yield of cuttings was also determined (see 6.3.4 Simulation of Yield for a detailed discussion of yield).

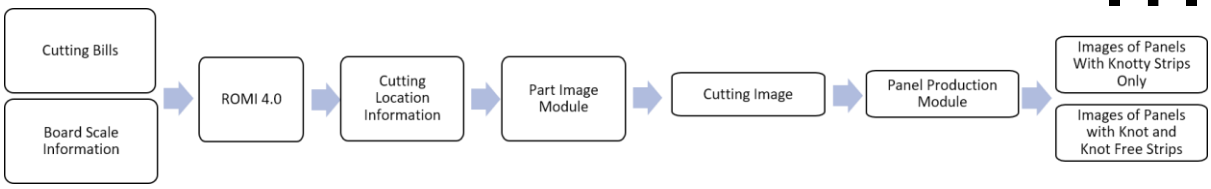


Figure 4-5. Flow chart of the process used to produce panels from cuttings.

Table 4-3. Definitions for knot size and type allowed within cutting areas.

Definition	Knot size (mm^2)	Knot type
Definition 1	N/A	N/A
Definition 2	<300	Light
	<300	Dark
	N/A	Black
Definition 3	<650	Light
	<650	Dark
	<650	Black
Definition 4	>650; <2580	Light
	>650; <2580	Dark
	>650; <2580	Black

The cutting bill consisted of the panel requirements listed in Table 4-4.

Table 4-4. The general panel cutting bill used to produce random strip width panels from boards.

Width (mm)	Length (mm)	Quantity
609.6	304.8	20
609.6	609.6	20
609.6	914.4	20
609.6	1219.2	20
609.6	1828.8	20

ROMI 4.0 used the following settings during the simulations.

- A 22.5 inch Fixed-Blade Best Feed Arbor with 9 blades and spacings set to 3.5, 3.5, 3.5, 1.5, 2.5, 1.5, 1.5, and 1.5 inches.
- Random strip widths allowed

- No salvage parts allowed (by setting the minimum width and length higher than could be processed from the lumber).
- *Complex Dynamic Exponent part prioritization
- No random width or random length parts
- No end or side trim

*Complex Dynamic Exponent is an option available in ROMI that updates part priority continually as parts are cut and the required quantity decreases (Thomas et al., 2015).

This process produced a library of high-resolution images that could be imported into the digital environment to enable enhanced selection for specific sizes and types of knots within the design context.

4.4.6 Digital Modeling

Images were imported into a Google SketchUp model to simulate the appearance of floor and wall surfaces assembled from panels containing different sizes and types of knots. Surfaces were simulated using panels produced from both the segmenting and cuttings methods described above. The model was intended to represent a room complete with furniture. This was done to illustrate a way to utilize the images during the design process to enhance the selection of specific characteristics.

4.5 Results

4.5.1 Board Segments Panel Production

4.5.1.1 Unsorted Panel

Images of panels produced from random board segments are shown in Figure 4-6 and Figure 4-7. These panels show considerable variation in knot size, appearance, and orientation.

Figure 4-6. A panel made from random E. globulus segments. The red line indicates 1 m.

Figure 4-7. A panel made of random E. nitens segments. The red line indicates 1 m.

4.5.1.2 Definition One

Segmenting definition 1 indicated that a range of different board segments was available from the lumber sample set. The lengths of different segment types varied across species and segment type (Figure 4-8). This figure has 2 y-axes. The left one indicates the proportion of segments in each segment bin size (x-axis) compared to all the segments of the same type. The right one is a running combined proportion of the total segment lengths for each type. For example, the proportion of clear segments to the total of all segments is about 30 percent for *E. nitens* and about 45 percent for *E. globulus*. Consequently, *E. nitens* produced more knotty type segments. Most segments were shorter than 1500 mm. As indicated by the combined proportion of segments, the proportion of clear segments was higher than most

other segment types. Overall, *E. nitens* produced a smaller proportion of longer knotty segments than did *E. globulus*. Excluding clear segment types, both species contained about equal combined proportions of the other segment types.

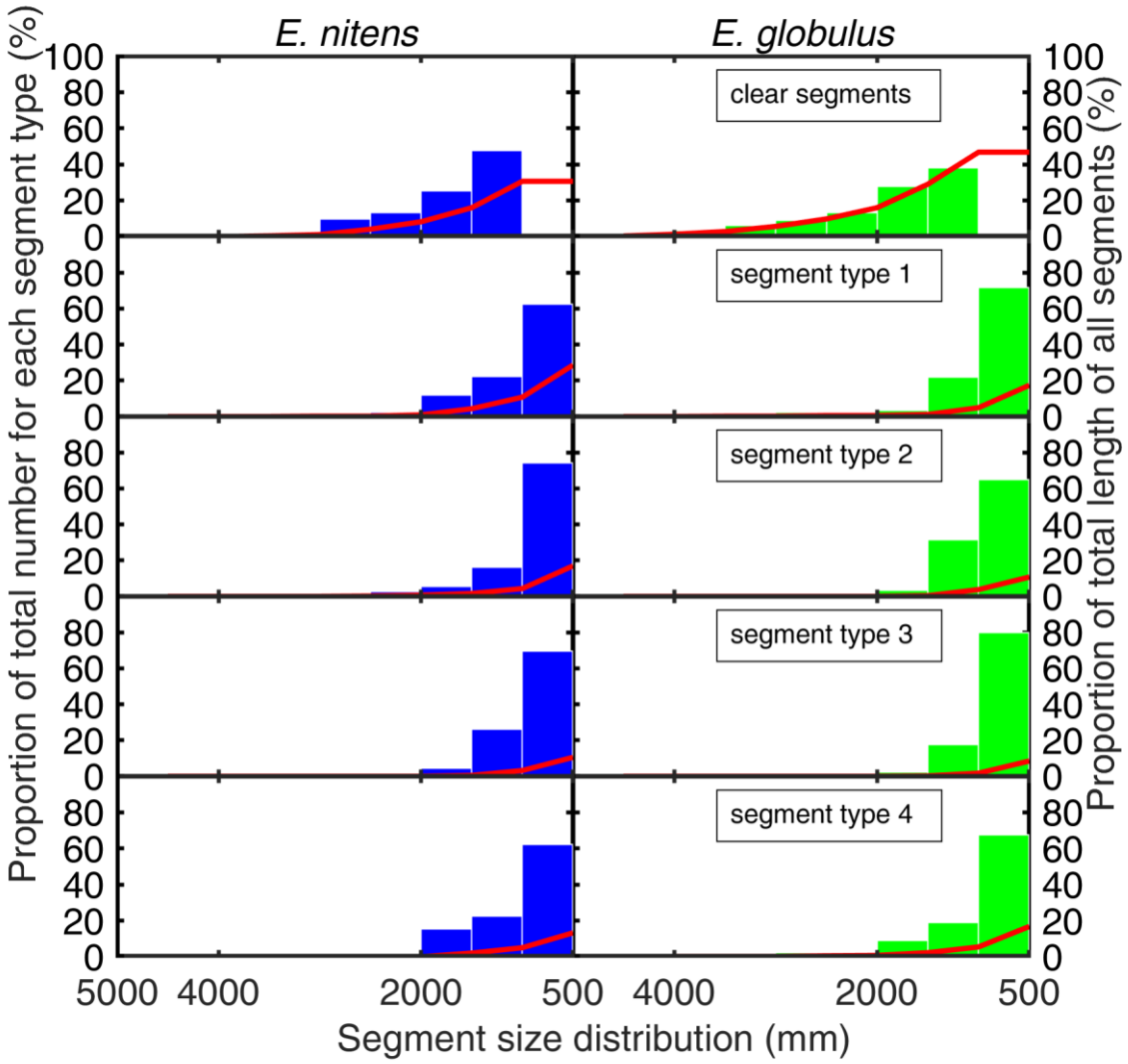


Figure 4-8. Length distribution of different segment types produced under definition 1.

The mean proportion of each segment type at the board scale is given in Table 4-5. Overall, there was a much higher proportion of clear segments than any of the other types for both species. The mean proportion of clear segments was approximately 20 percent higher for *E. globulus* than for *E. nitens*. However, *E. nitens* produced approximately 10 percent more type 1 segments and approximately 4 percent more type 2 segments.

Table 4-5. Mean proportion of boards in each segment type. The minimum and maximum values are shown in parentheses. Note: total may not equal 100 because segments shorter than the minimum allowed by the definition are not included.

Segment type	Mean proportion of board in each type (%)	
	E. globulus	*E. nitens*
Clear	57 (0-100)	38 (0-100)
Type 1	11 (0-92)	20 (0-83)
Type 2	6 (0-49)	10 (0-77)
Type 3	5 (0-47)	7 (0-85)
Type 4	11 (0-76)	10 (0-76)

A parallel coordinates plot for the proportion of segment types for each board is shown in Figure 4-9. Segment types are plotted along the x-axis and the normalized proportion of board in each of the segment types is plotted on the y-axis. Each line represents each board in the datasets. The datasets were ordered according to the proportion of clear segments. Overall, the figure indicates that boards containing high proportions of clear segments (purple) produced a relatively low proportion of other segment types. It also shows that boards that produced low proportions of clear segments (red) often contained high proportions of other segment types. Boards with moderate levels of clear segments (yellow, green, light blue) often produced moderate levels of other segment types. The distinct V-shaped lines indicate boards that produced a high proportion of a segment type. Conversely, lines with a relatively flat shape indicate boards that produced several segment types in roughly equal proportions.

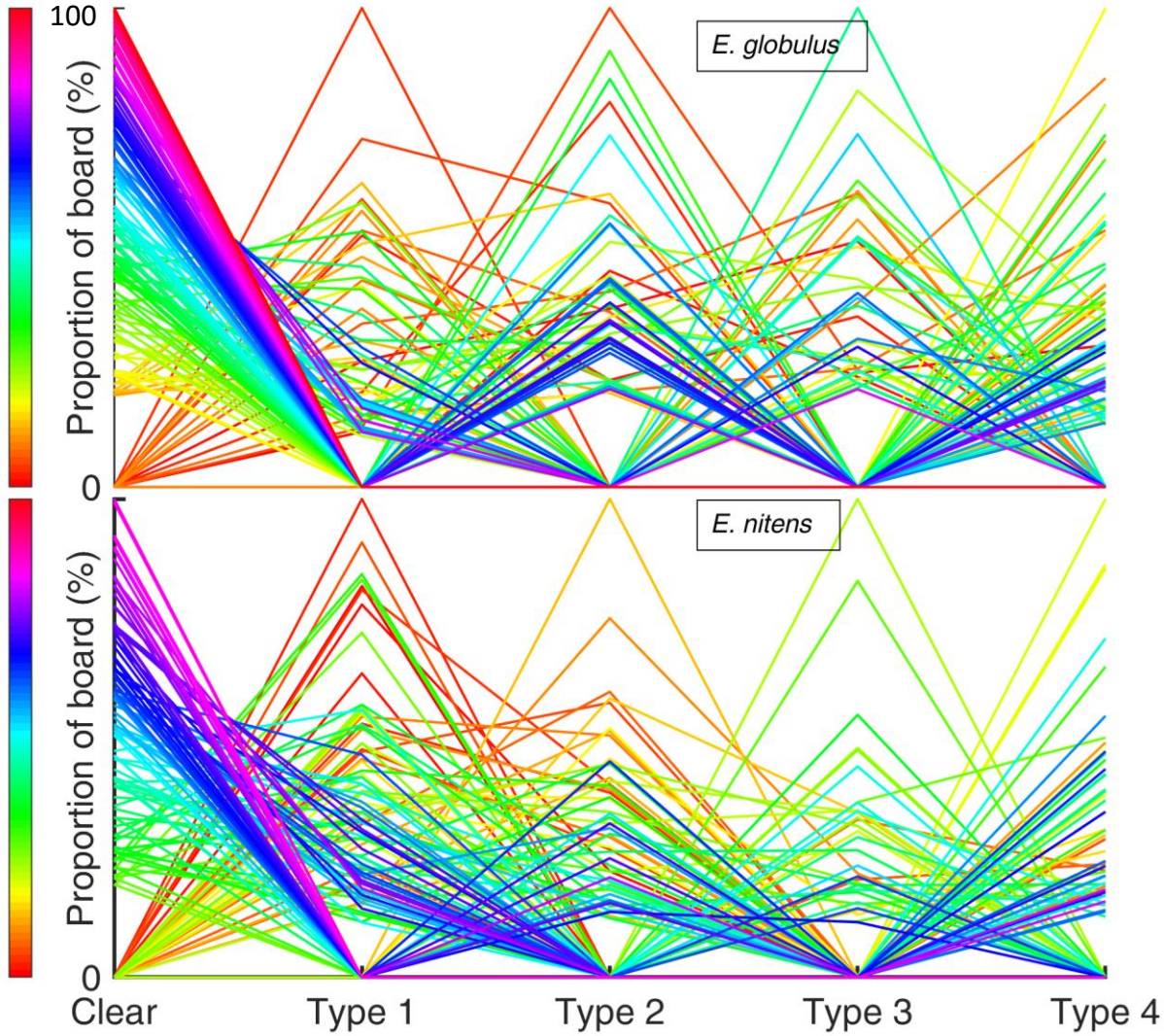


Figure 4-9. The parallel plot of the proportion of different segment types ranked by the proportion of clear segments for each board.

Images of panels assembled from different types of segments are shown in Figure 4-10 through Figure 4-14 for *E. globulus* using definition 1. The same types of images for *E. nitens* are shown in Figure 4-15 through Figure 4-19. These images show "typical" results from the panel production process. As can be observed, the visual attributes differ considerably by segment type. Even infrequent and small knots (type 1 segments) contribute to the appearance qualities of the panels. The method demonstrates the capability to model the appearance of panels produced from the sample lumber.

4.5.1.3 E. globulus Images

Figure 4-10. A panel assembled from E. globulus clear segments using definition 1. The red line indicates 1 m.

Figure 4-11. A panel assembled from E. globulus type 1 segments using definition 1. The red line indicates 1 m.

Figure 4-12. A panel assembled from E. globulus type 2 segments using definition 1. The red line indicates 1 m.

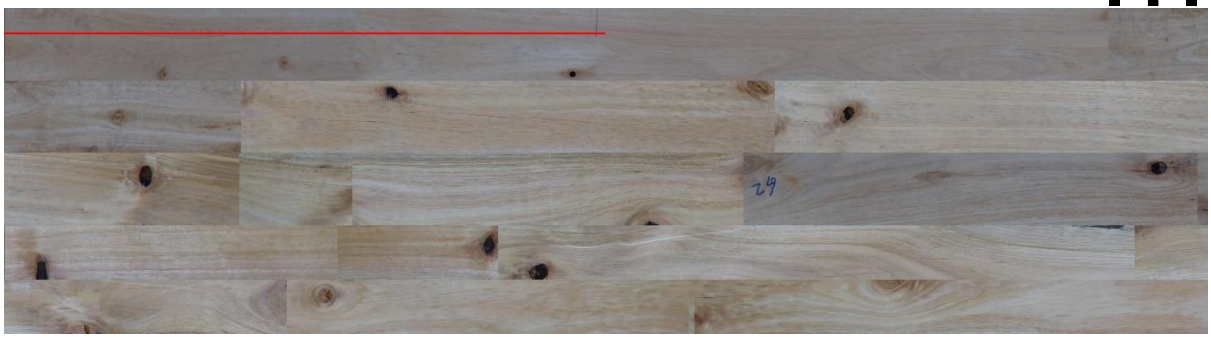


Figure 4-13. A panel assembled from E. globulus type 3 using definition 1. The red line indicates 1 m.

Figure 4-14. A panel assembled from E. globulus type 4 segments using definition 1. The red line indicates 1 m.

4.5.1.4 E. nitens Images

Figure 4-15. A panel assembled from E. nitens clear segments using definition 1. The red line indicates 1 m.

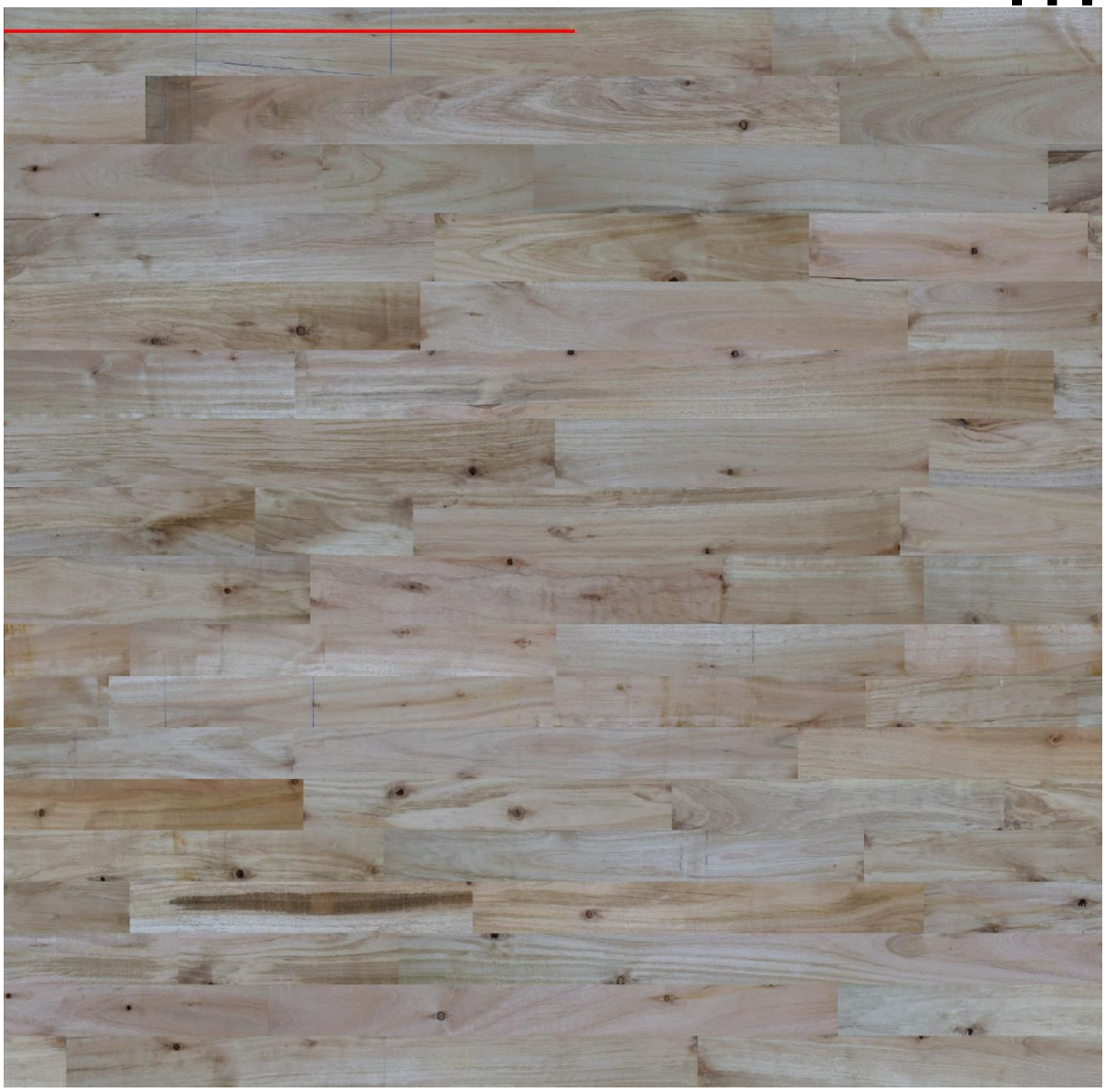


Figure 4-16. A panel assembled from E. nitens type 1 segments using definition 1. The red line indicates 1 m.

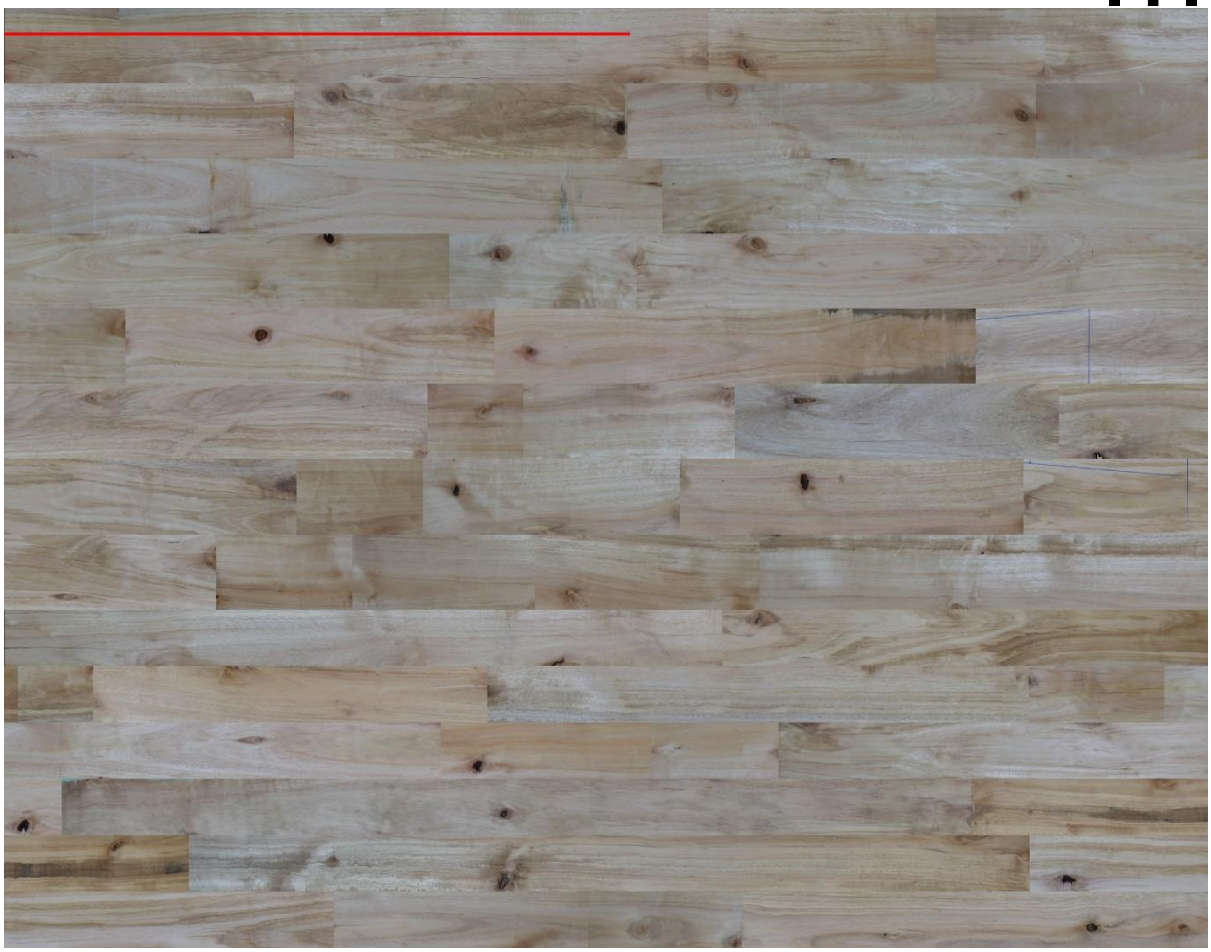


Figure 4-17. A panel assembled from E. nitens type 2 segments using definition 1. The red line indicates 1 m.

Figure 4-18. A panel assembled from E. nitens type 3 segments using definition 1. The red line indicates 1 m.

Figure 4-19. A panel assembled from E. nitens type 4 segments using definition 1. The red line indicates 1 m.

4.5.1.5 Definition Two

Segmenting definition 2 also produced a range of segment types (Figure 4-20). As before, *E. globulus* produced a higher proportion of clear segments than did *E. nitens*. *E. globulus* also

produced slightly longer segments. Excluding clear segments, both species produced about equal proportions of the other segment types. Very little type 3 segments were available from either species.

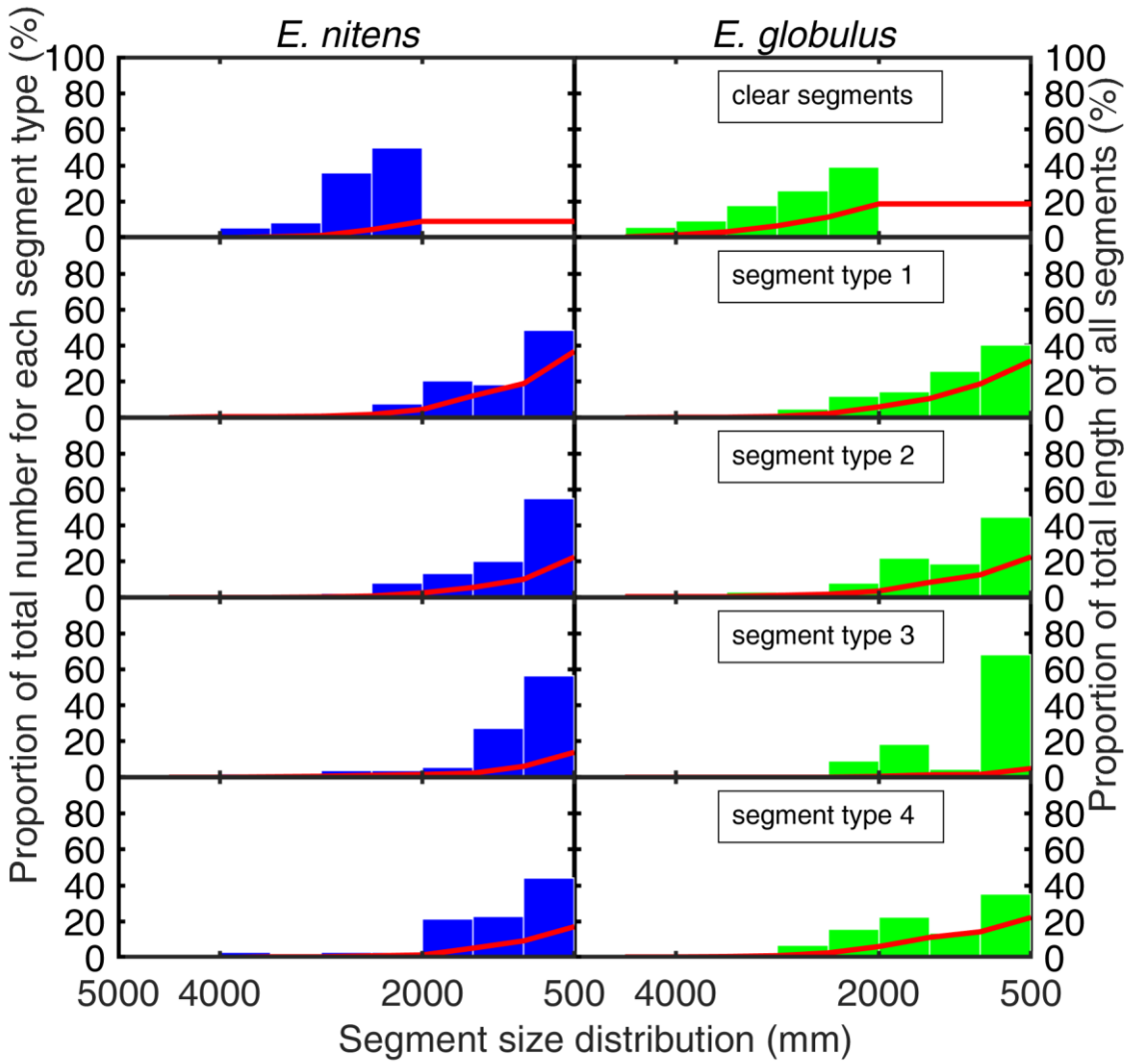


Figure 4-20. Length distribution of different segments produced under definition 2.

The mean proportion of each segment type available from the sample set is given in Table 4-6. Recall that definition 2 requires 2 m long clear segments. Consequently, *E. globulus* produced nearly 30 percent fewer clear segments, and *E. nitens* produced about 24 percent less clear stock than what was produced from definition 1. Under definition 2, *E. nitens* produced about half as much clear stock, about 7 percent more type 1 and type 3, an equal amount of type 2, and about 4 percent less type 4 segments than *E. globulus*.

Table 4-6. Mean proportion of boards in each segment type. The minimum and maximum values are shown in parentheses. Note: total may not equal 100 because segments shorter than the minimum allowed by the definition are not included.

Segment type	Mean proportion of boards in each segment type (%)	
	E. globulus	*E. nitens*
Clear	29 (0-100)	15 (0-100)
Type 1	24 (0-99)	30 (0-100)
Type 2	16 (0-98)	17 (0-85)
Type 3	3 (0-44)	10 (0-91)
Type 4	20 (0-100)	16 (0-100)

A parallel coordinates plot for the proportion of segment types for each board is shown in Figure 4-21. As above, segment types are plotted along the x-axis and the normalized proportion of board in each of the segment types is plotted on the y-axis. Each line represents each board in the datasets. The datasets were ordered according to the proportion of clear segments. Overall, the patterns are like those produced by definition 1. One interesting pattern is the bimodal distribution of the proportion of boards in clear segments. For *E. globulus*, boards either produced a moderate to a high proportion of clear segments or very little. This pattern is similar for *E. nitens*, however, there appear to be far fewer boards that produce a high proportion of clear segments. The V-shaped and relatively flat shaped lines also appear for definition 2.

Under both definitions, the parallel plots indicate groups of boards that produce a high proportion of one or more segment types. This indicates that grouping boards according to the proportion of different segment types may be mathematically possible.

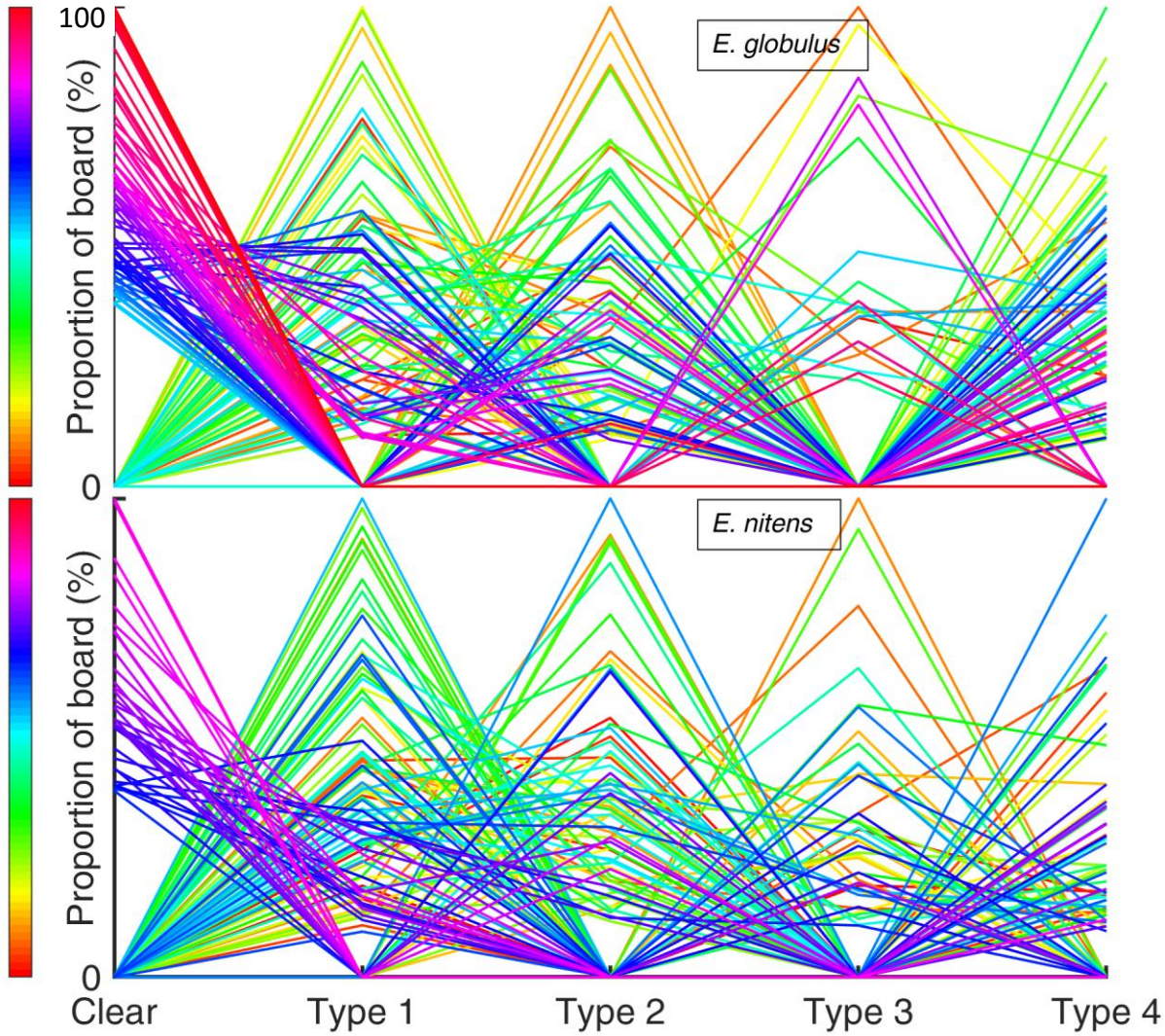


Figure 4-21. The parallel plot of the proportion of different segment types ranked by the proportion of clear segments for each board.

Images of panels assembled from different types of segments are shown in Figure 4-22 through Figure 4-26 for *E. globulus* using definition 2. The same types of images for *E. nitens* are shown in Figure 4-27 through Figure 4-31. These images show "typical" results from the panel production process. As for definition 1, definition 2 also produced a series of panels with different appearance qualities. The concept that a range of knot sizes and appearance types can be selected for and then modeled is demonstrated within this section of the work.

4.5.1.6 E. globulus Images

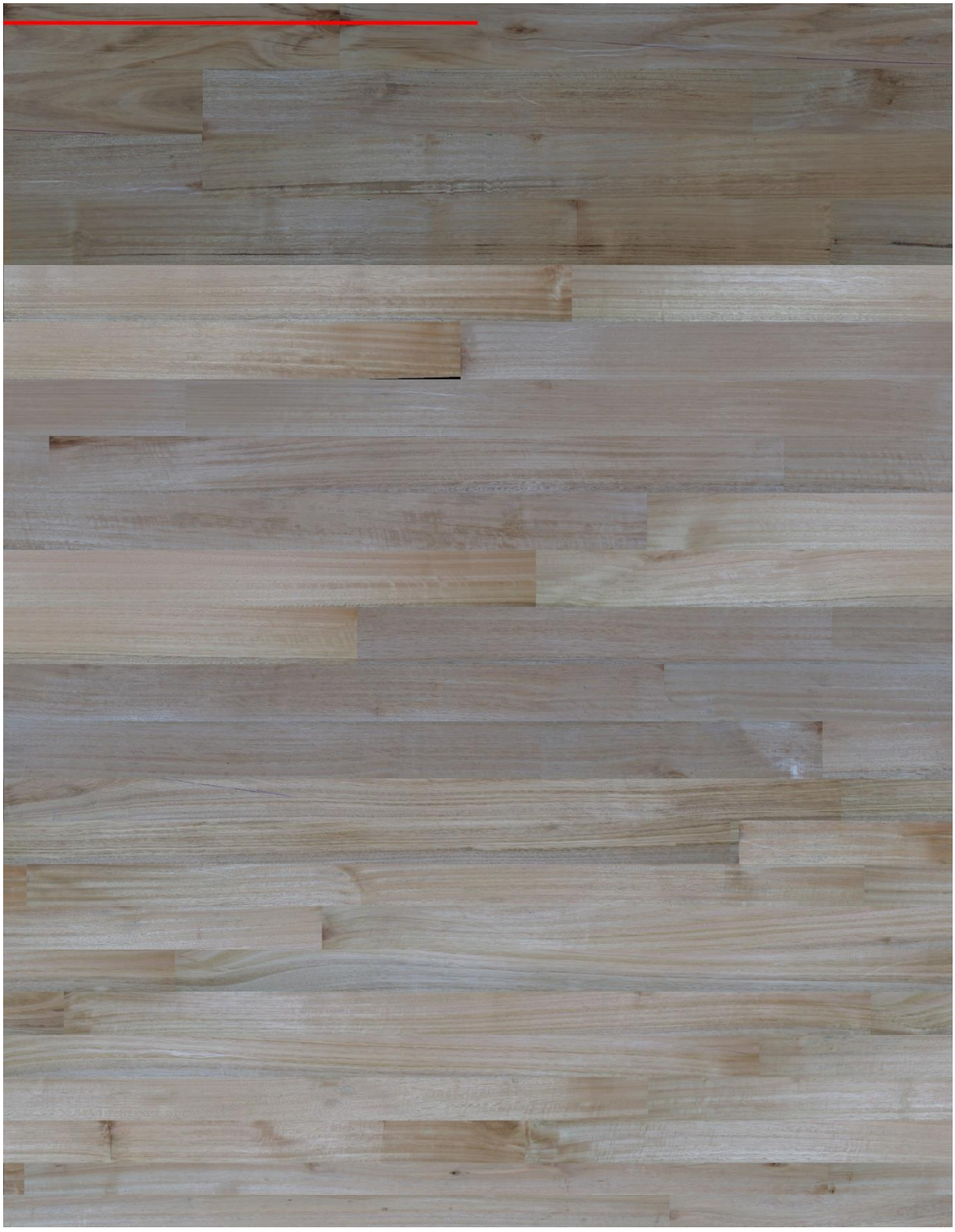


Figure 4-22. A panel assembled from E. globulus clear segments using definition 2. The red line indicates 1 m.

Figure 4-23. A panel assembled from E. globulus type 1 segments using definition 2. The red line indicates 1 m.

Figure 4-24. A panel assembled from E. globulus type 2 segments using definition 2. The red line indicates 1 m.

Figure 4-25. A panel assembled from E. globulus type 3 segments using definition 2. The red line indicates 1 m.

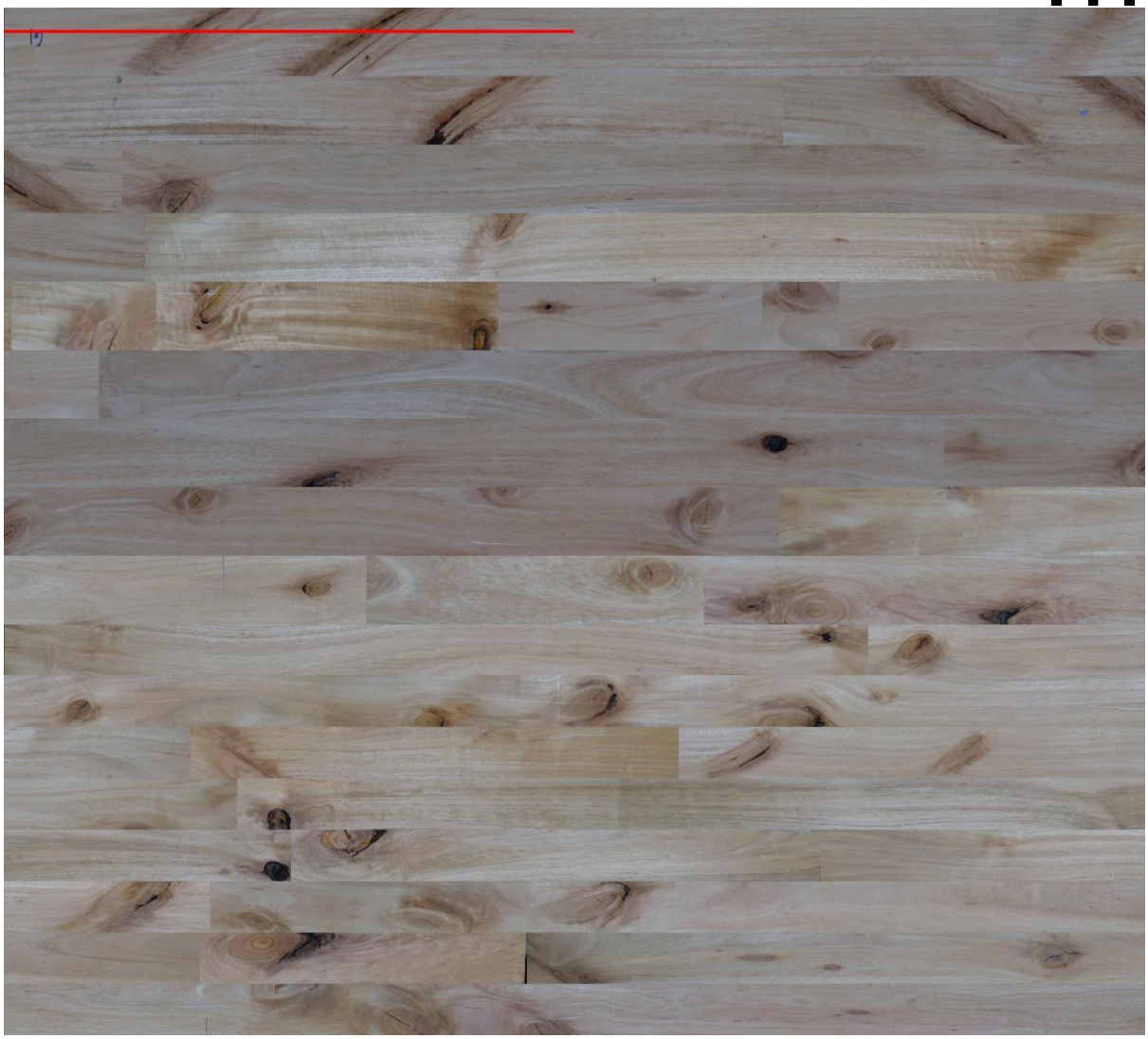


Figure 4-26. A panel assembled from E. globulus type 4 segments using definition 2. The red line indicates 1 m.

4.5.1.7 E. nitens Images

Figure 4-27. A panel assembled from E. nitens clear segments using definition 2. The red line indicates 1 m.

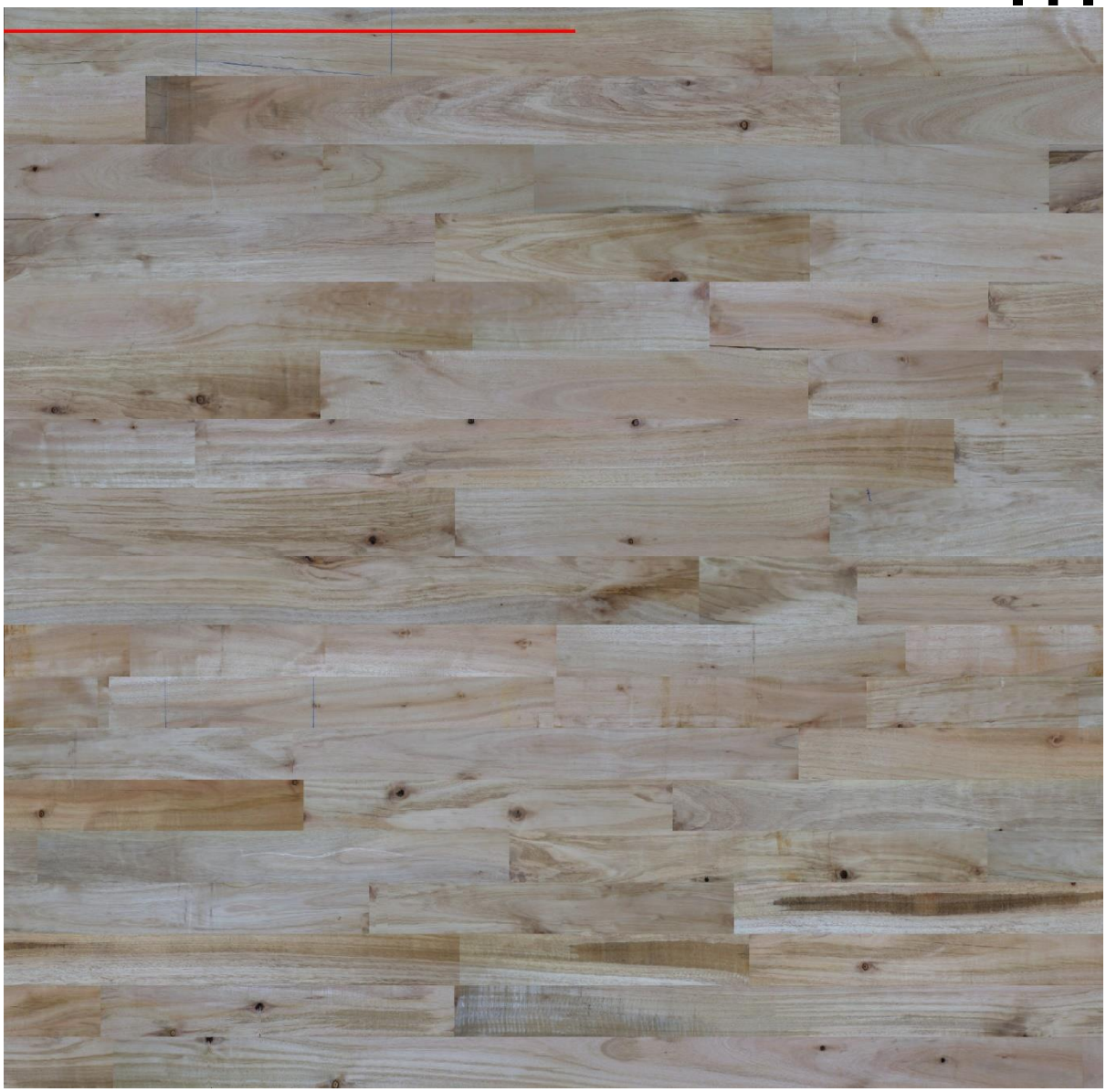


Figure 4-28. A panel assembled from E. nitens type 1 segments using definition 2. The red line indicates 1 m.

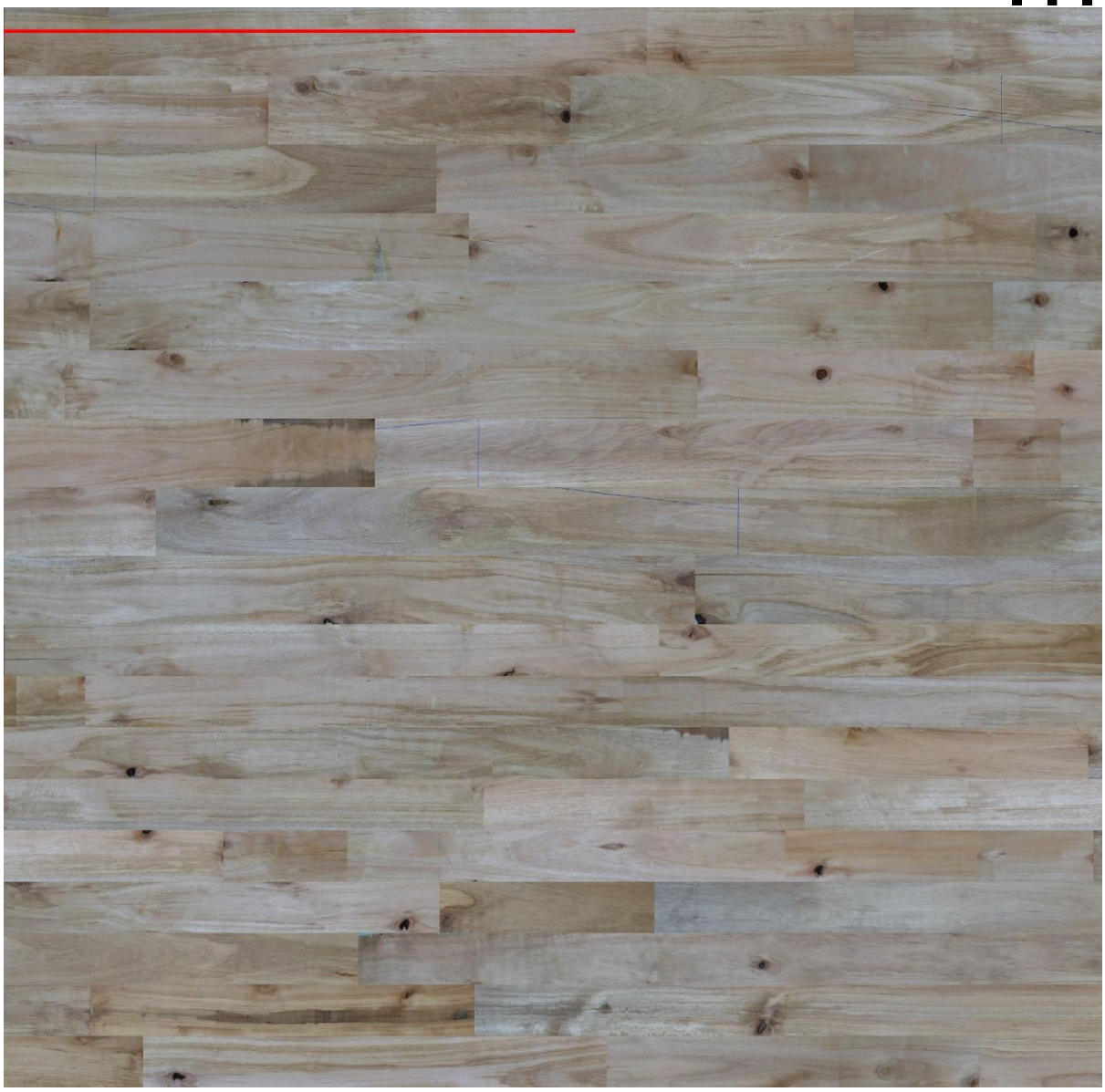


Figure 4-29. A panel assembled from E. nitens type 2 segments using definition 2. The red line indicates 1 m.

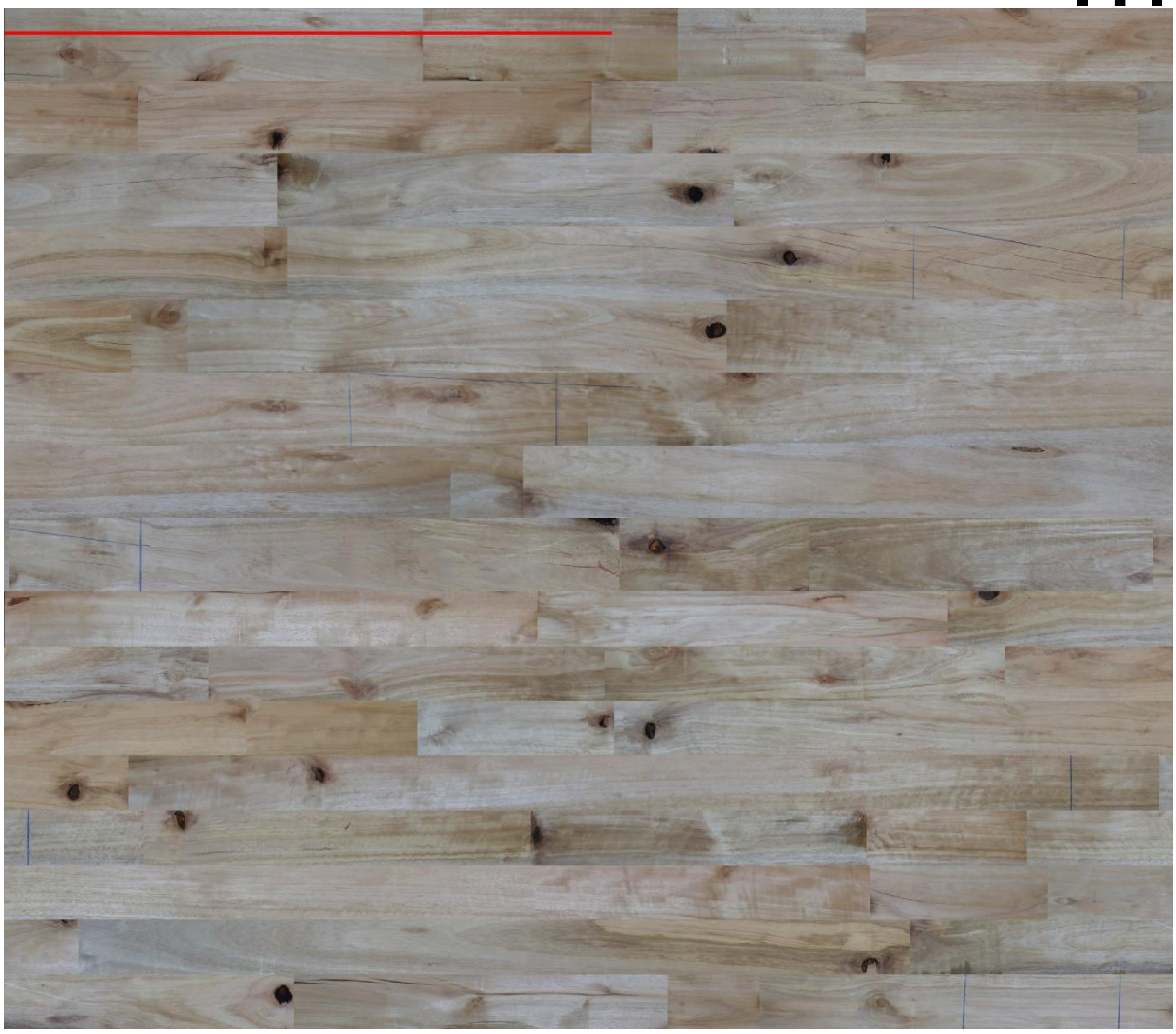


Figure 4-30. A panel assembled from E. nitens type 3 segments using definition 2. The red line indicates 1 m.

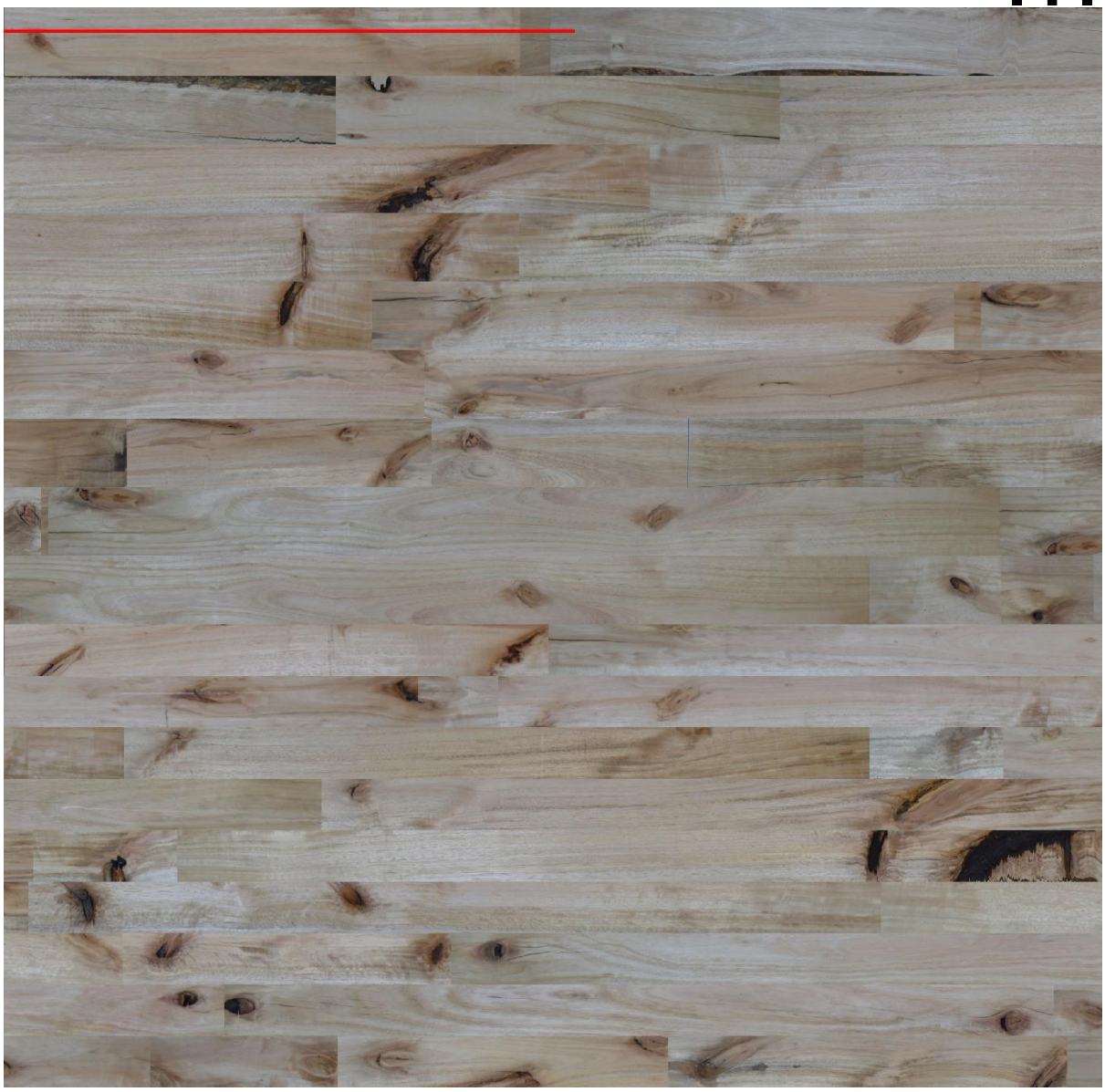


Figure 4-31. A panel assembled from E. nitens type 4 segments using definition 2. The red line indicates 1 m.

4.5.2 Cutting Area Panel Production

4.5.2.1 Definition One

Examples of images of *E. globulus* panels assembled from cutting areas defined by definition 1 are shown in Figure 4-32 and Figure 4-33.

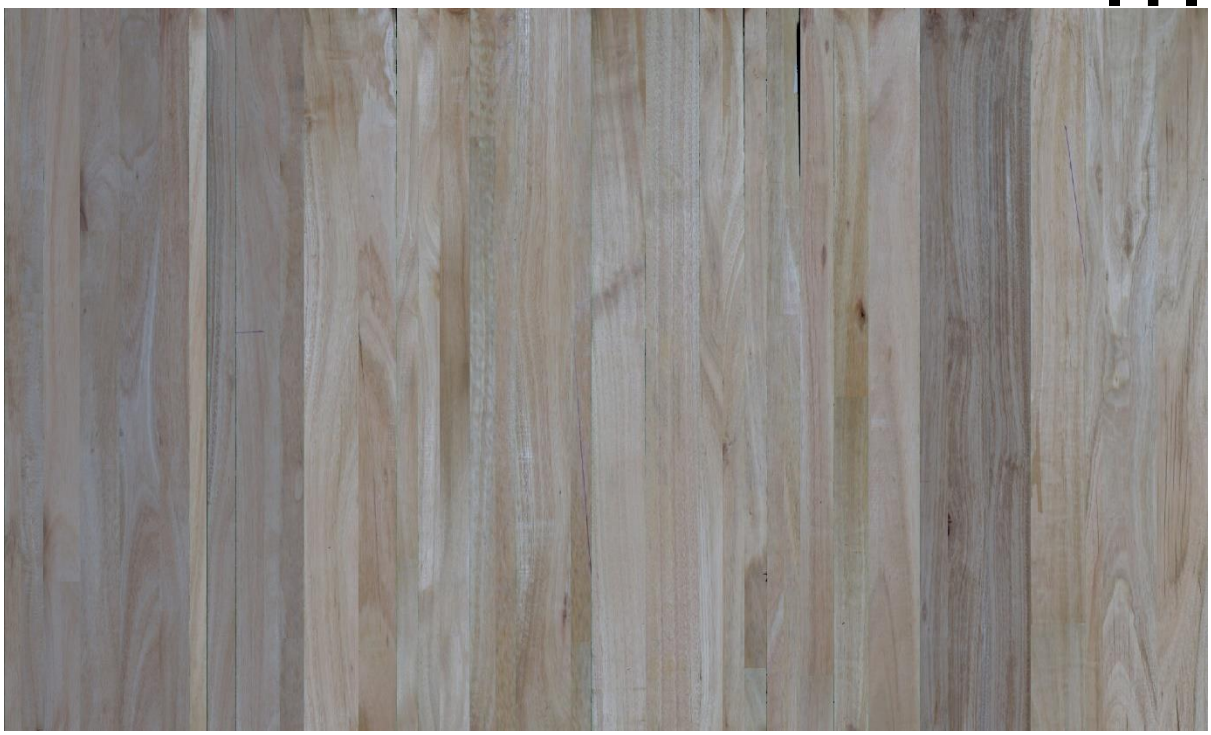


Figure 4-32. An example of a 2 m by 916 mm E. globulus panel assembled from cuttings produced from definition 1.

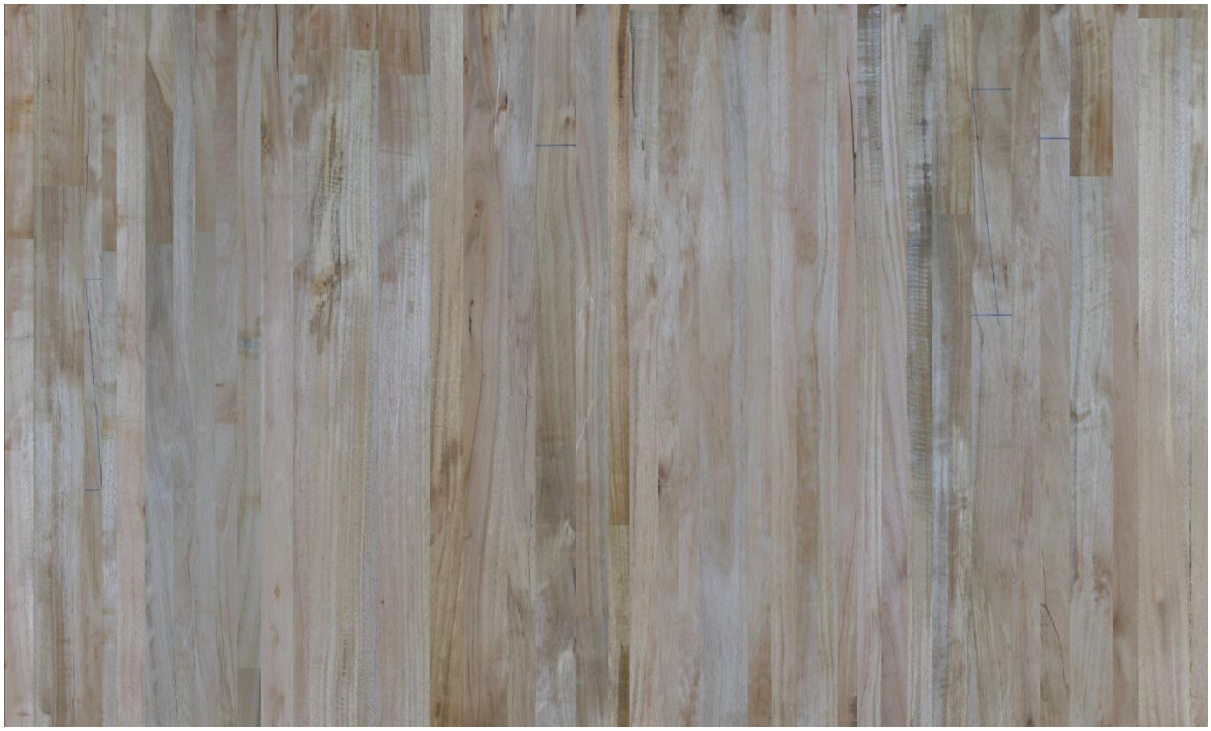


Figure 4-33. An example of a 2 m by 916 mm E. nitens panel assembled from cuttings produced from definition 1.

4.5.2.2 Definition Two

Examples of panels produced from mixed and knotty cuttings of both species are shown in Figure 4-34 through Figure 4-45 using definitions 2, 3, and 4. Each definition allows progressively larger knots to occur in cuttings and this creates dramatic visual differences among the panels.

Figure 4-34. An example of a 2 m by 1829 mm E. globulus mixed panel from cuttings produced from definition 2.

Figure 4-35. An example of a 2 m by 1829 mm E. globulus knotty panel from cuttings produced from definition 2.

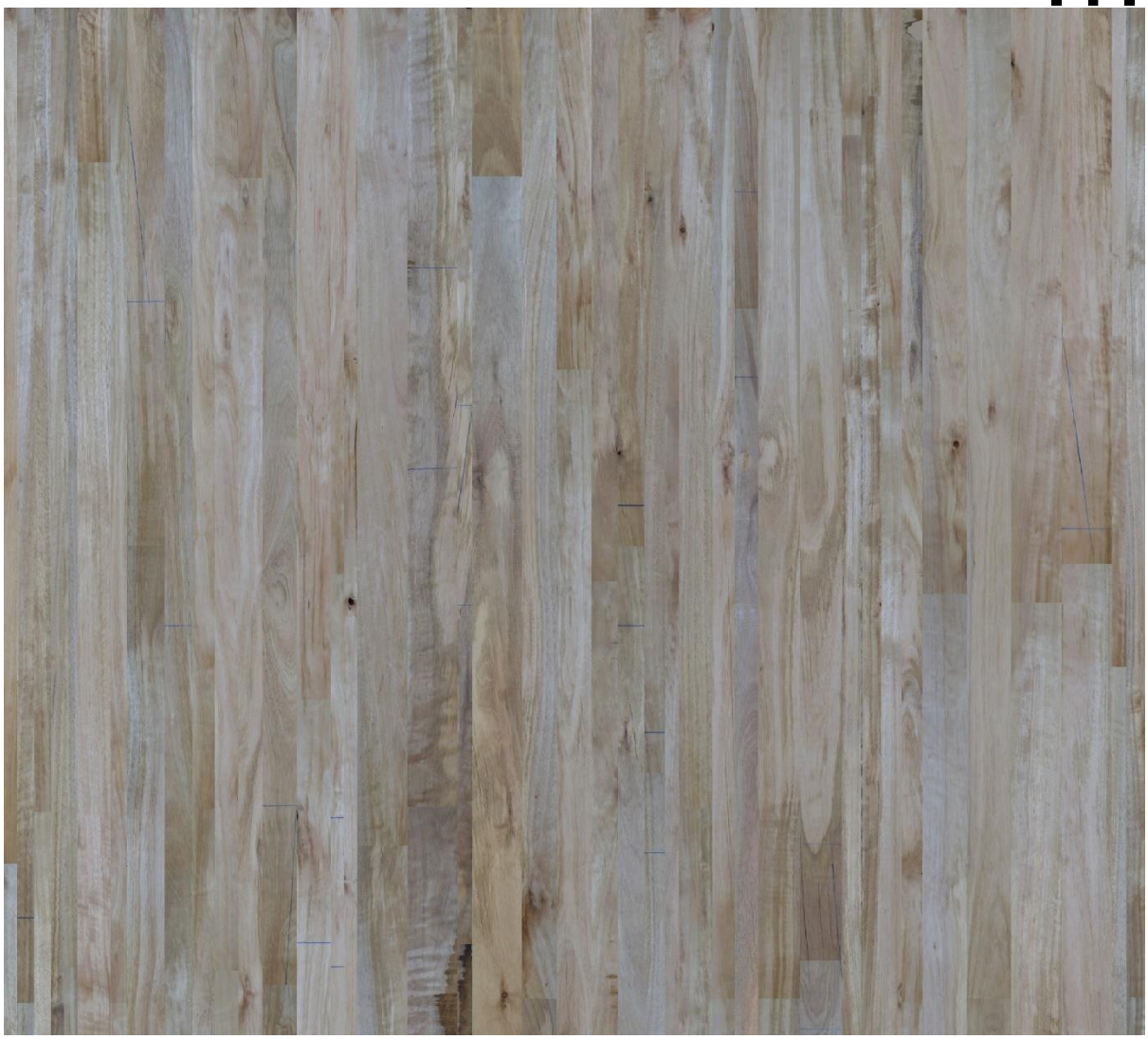


Figure 4-36. An example of a 2 m by 1829 mm E. nitens mixed panel from cuttings produced from definition 2.

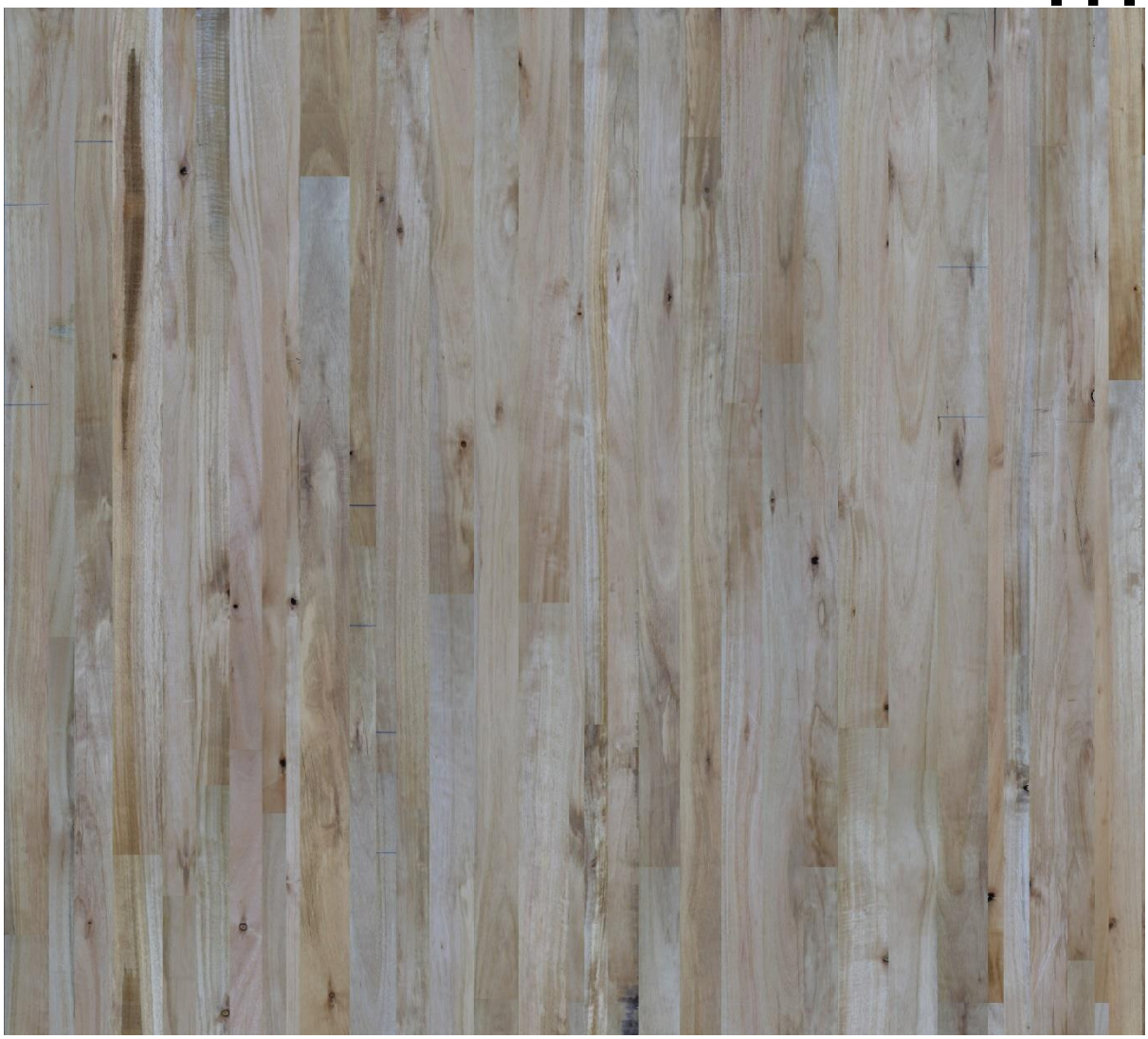


Figure 4-37. An example of a 2 m by 1829 mm E. globulus knotty panel from cuttings produced from definition 2.

4.5.2.3 Definition Three

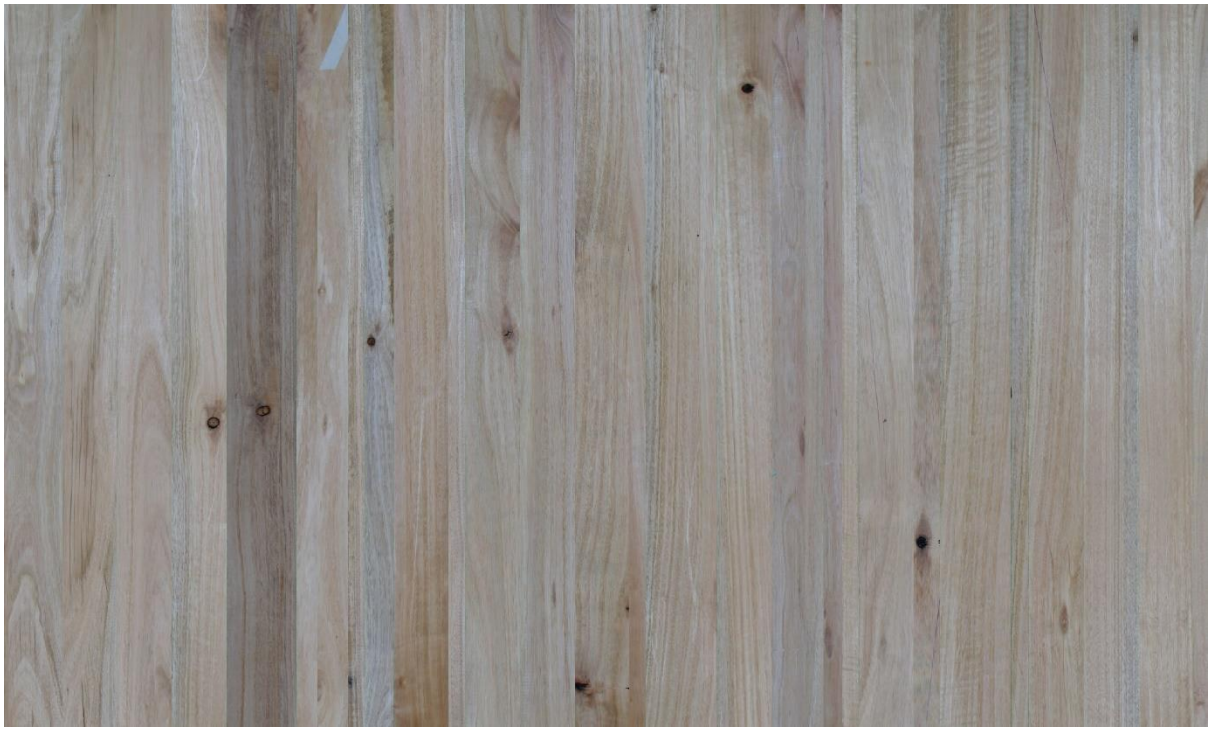


Figure 4-38. An example of a 2 m by 914 mm E. globulus mixed panel from cuttings produced from definition 3.

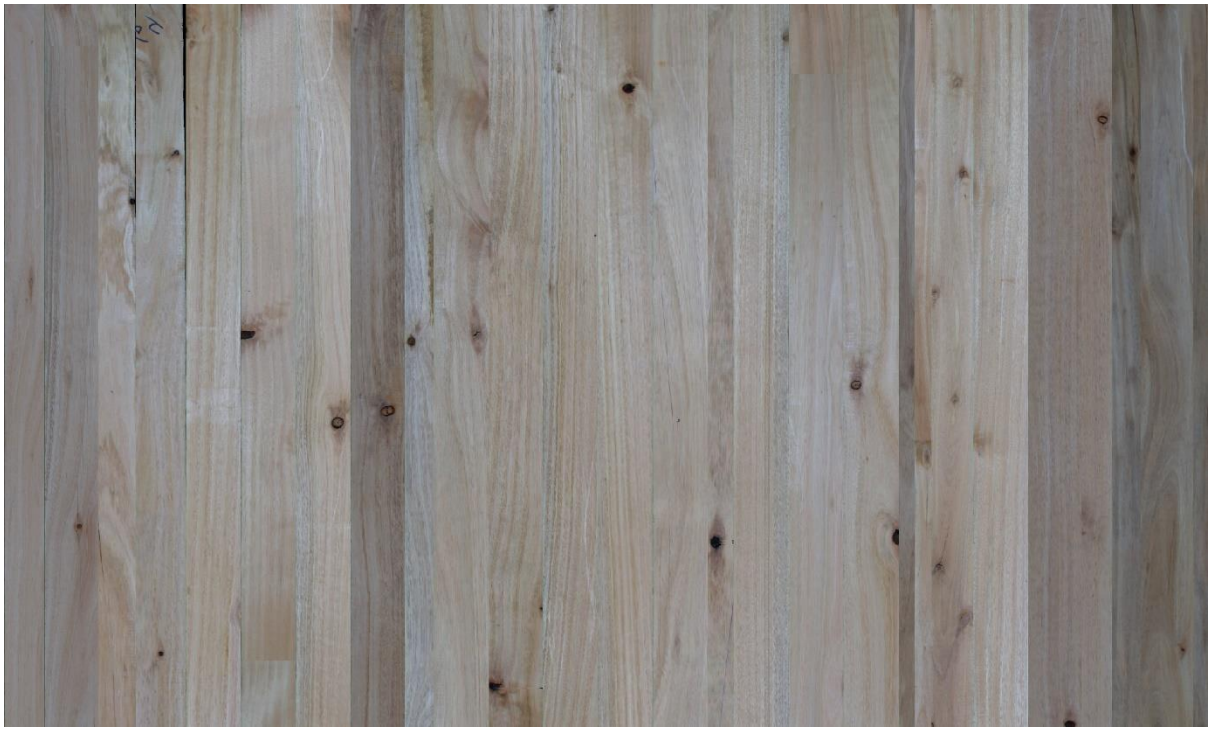


Figure 4-39. An example of a 2 m by 914 mm E. globulus knotty panel from cuttings produced from definition 3.

.

Figure 4-40. An example of a 2 m by 914 mm E. nitens mixed panel from cuttings produced from definition 3.

Figure 4-41. An example of a 2 m by 914 mm E. nitens knotty panel from cuttings produced from definition 3.

4.5.2.4 Definition Four

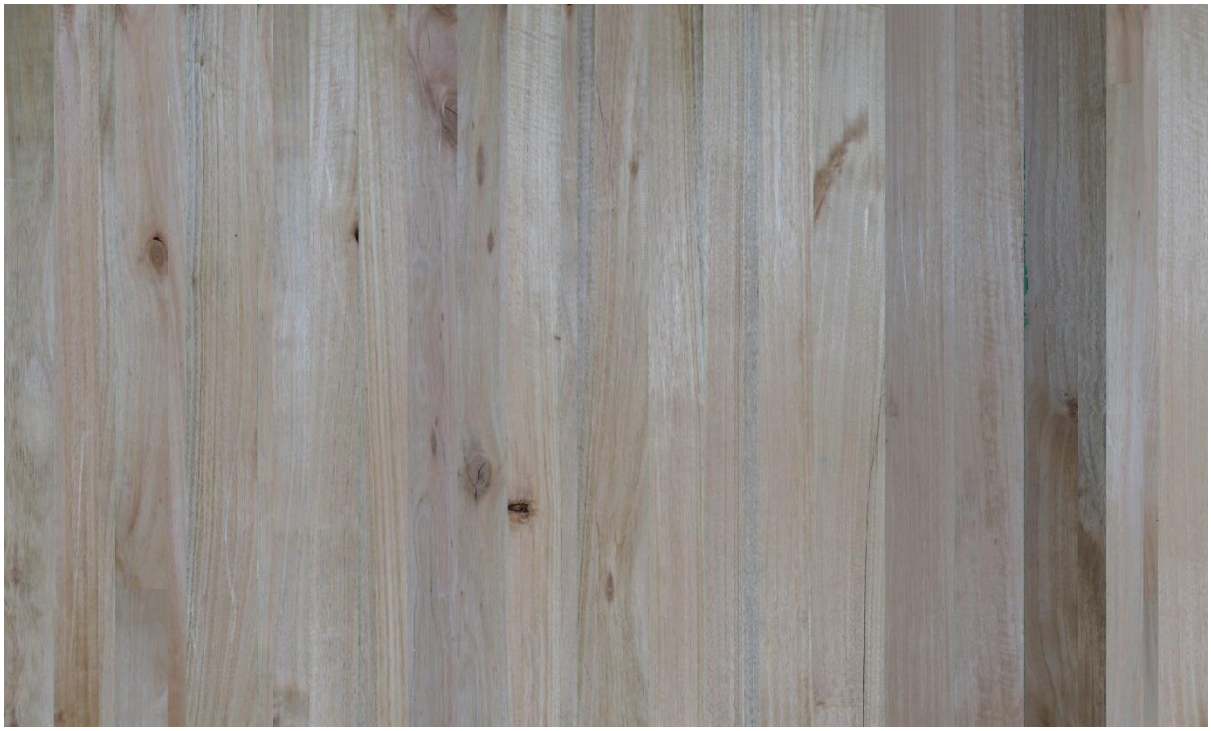


Figure 4-42. An example of a 2 m by 914 mm E. globulus mixed panel from cuttings produced from definition 4.

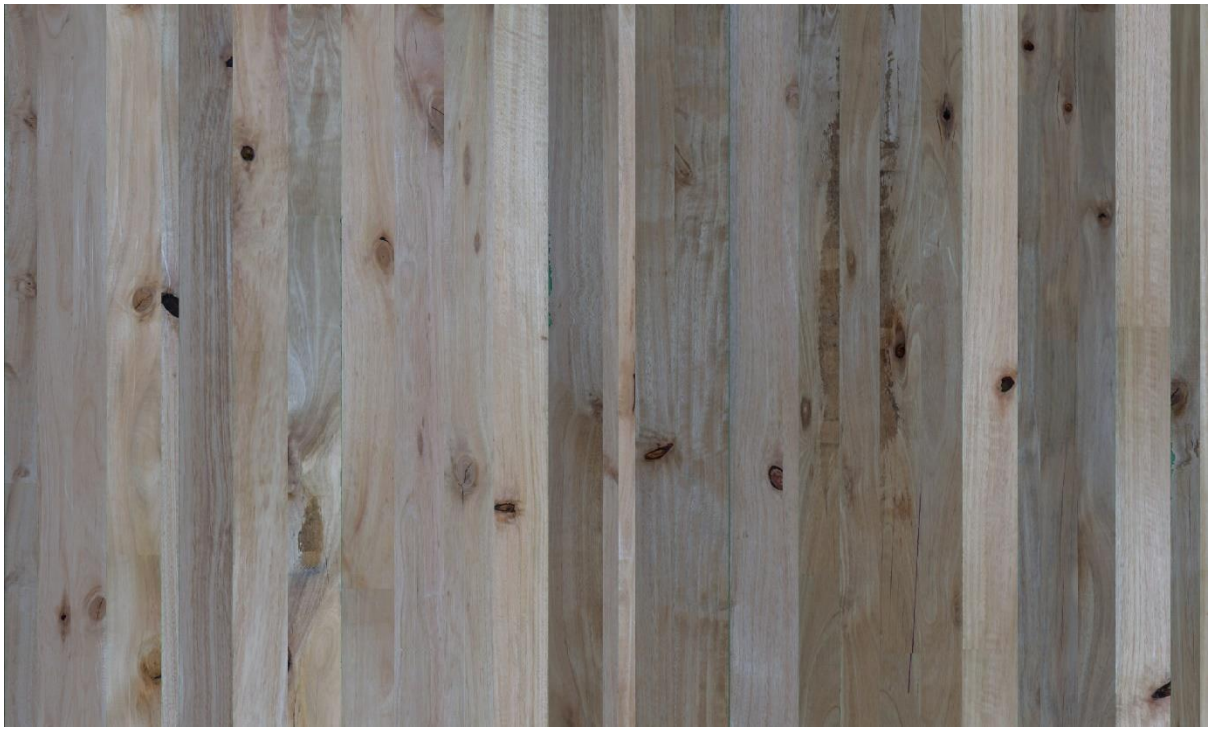


Figure 4-43. An example of a 2 m by 914 mm E. globulus knotty panel from cuttings produced from definition 4.

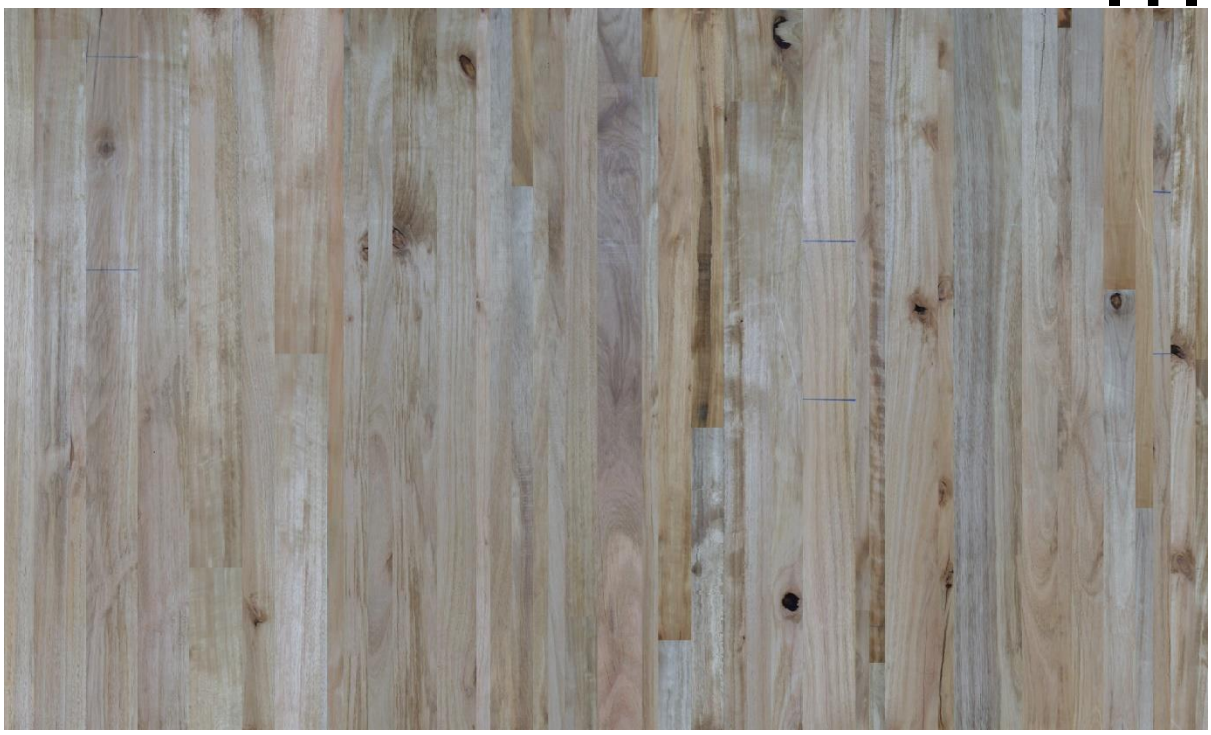


Figure 4-44. An example of a 2 m by 914 mm E. nitens mixed panel from cuttings produced from definition 4.

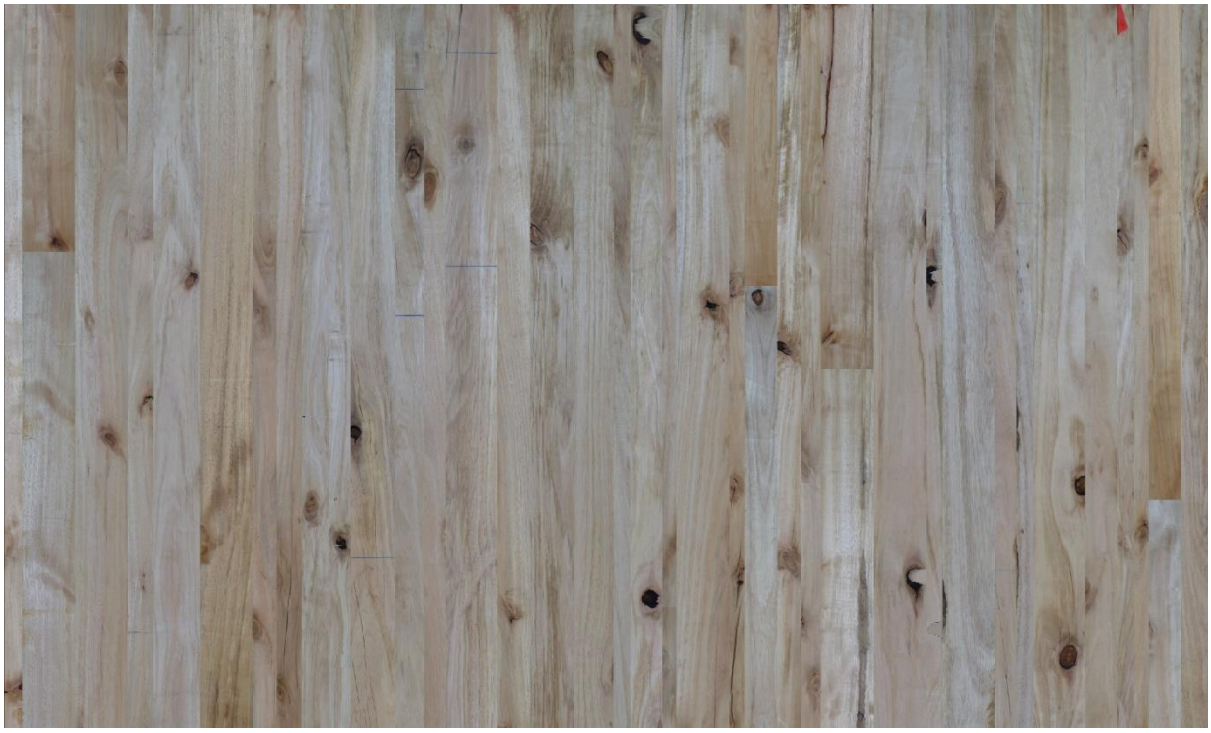


Figure 4-45. An example of a 2 m by 914 mm E. nitens knotty panel from cuttings produced from definition 4.

4.5.2.5 Yield and Knot Density

The yield of cuttings from the sample boards is shown in Table 4-7. In all cases, the yield was higher for *E. globulus* than for *E. nitens*. Yield increased by approximately 3 percent by allowing the first category of knots to occur in cuttings and about 4 percent for definition 3. However, very little increase in yields was found for definition 4. The yield was highest using definition 3 for both species, which allowed knots up to 650 mm^2. A parallel plot of yield from each board is shown in Figure 4-46. This plot shows the yield of cuttings from each board in the sample set for each definition. Overall, boards with the highest yield for definition 1 produce high yield under other definitions. This is because the other definitions allow clear cuttings to be produced in the same manner as definition 1. Boards with slightly lower yield often show an increase in yield under definition 3. Additionally, boards with low yield often show a dramatic increase in yield for definitions 3 and 4. Very few boards produce lower yield by allowing larger knots. These patterns imply natural groups of boards in the sample set. They also indicate that the utility (and value) of certain boards can be improved by allowing a defined range of knot size and type to occur in cuttings. This appears to occur most dramatically for boards with a low yield of clear cuttings.

Table 4-7. Yield of cuttings from sample boards using the cutting bill.

Definition Type	Yield (%)	
	E. globulus	*E. nitens*
Definition 1	77	74*
Definition 2	80	77*
Definition 3	84	83*
Definition 4	83	82*

**Indicates that the cutting bill could not be completely satisfied by the number of boards in the sample set (N=159 for* E. globulus*, N=137 for* E. nitens*).*

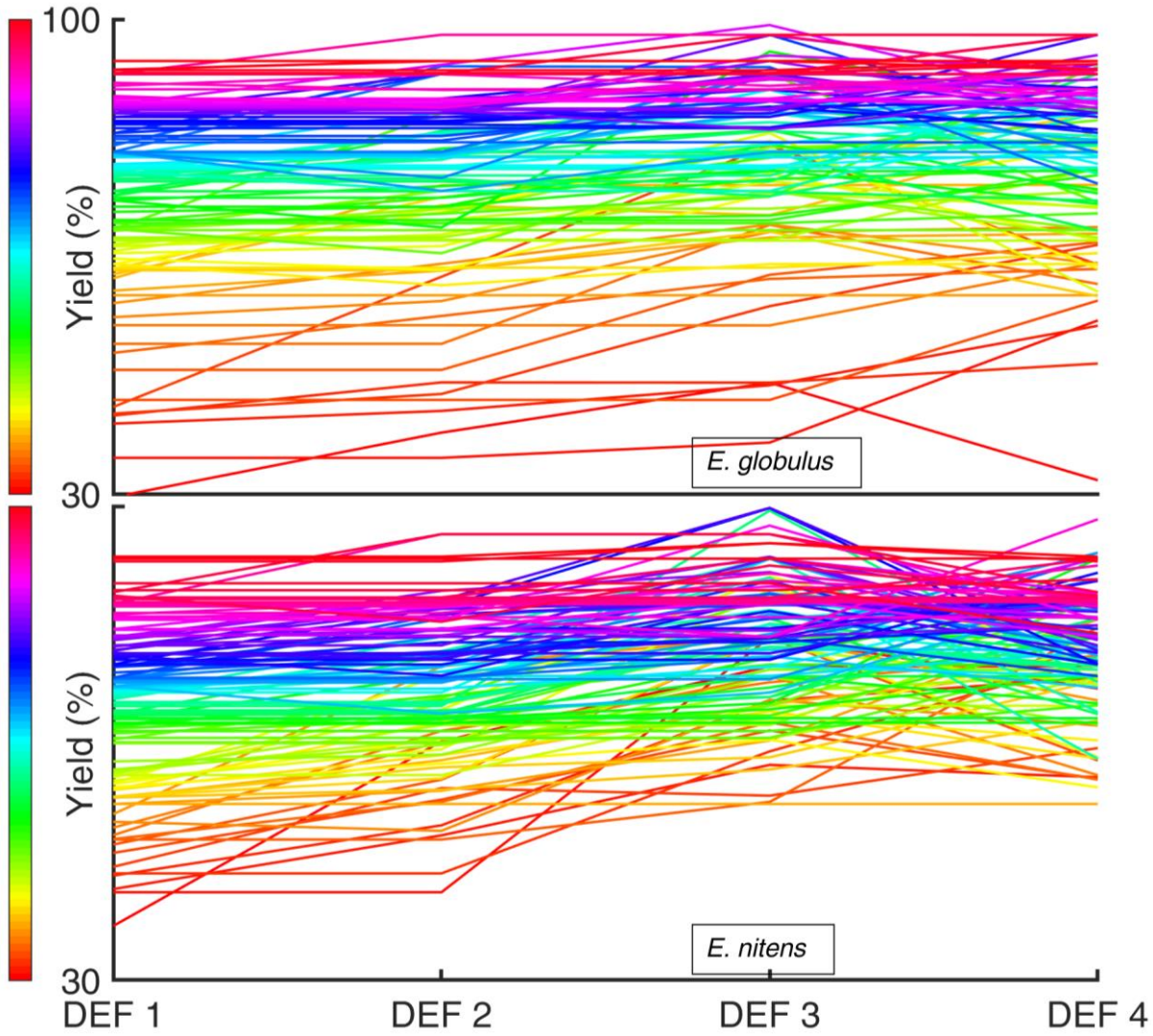


Figure 4-46. A parallel plot of yield for each of the definitions used to produce panels from cuttings.

The knot density and ratio between mixed and knotty panels produced by cuttings using definitions 2, 3, and 4 are shown in Table 4-8. Overall, the knot density was higher for *E. nitens* in both types of panels than for panels produced by *E. globulus* cuttings. The knot density increased as larger knots could occur in cuttings for *E. globulus*; however, this pattern did not occur for *E. nitens* panels. The largest knot density in mixed panels for this species occurred using definition 3. In general, the ratio between mixed and knotty panel area decreased as knot size increased in cuttings. For all three definitions, the ratio was about twice as high for *E. globulus* than for *E. nitens*. Although not determined directly in this study, it can be inferred that only producing knotty panels would decrease yield dramatically. For example, if only knotty *E. globulus* panels were desired, the yield would be about 28 percent under definition

3. These results indicate the range in knot density that could be expected to occur in panels in the dimensions specified by the cutting bill used here.

Table 4-8. Knot density for mixed and knotty panels and the ratio between mixed panel area and knotty panel area for each definition allowing knots to occur in cuttings.

	E. globulus			*E. nitens*		
	Knot density (knots/m^2)		Ratio	Knot density (knots/m^2)		Ratio
	Mixed	Knotty		Mixed	Knotty	
Definition 2	2.4	19.6	8.1	5.4	20.7	3.8
Definition 3	6.1	18.3	3.0	14.4	20.0	1.4
Definition 4	4.5	13.5	3.0	9.6	16.8	1.7

4.5.3 Digital Modelling

Examples of simulated wood panels are shown in Figure 4-47 and Figure 4-48. In Figure 4-47, the floor is modelled using type 4 *E. globulus* segments produced from using definition 1 and wainscoting assembled from clear cuttings of *E. globulus*. Board segment panels are limited to 2 m, however, in practice, the entire floor would be constructed as a single panel. This would eliminate the appearance of segments between sections of the floor. The wainscoting is 1 m tall. In Figure 4-48, the flooring is assembled from *E. nitens* clear segments produced from using definition 2. The wainscoting is produced from 1.2 m *E. nitens* knotty panels produced from definition 3.

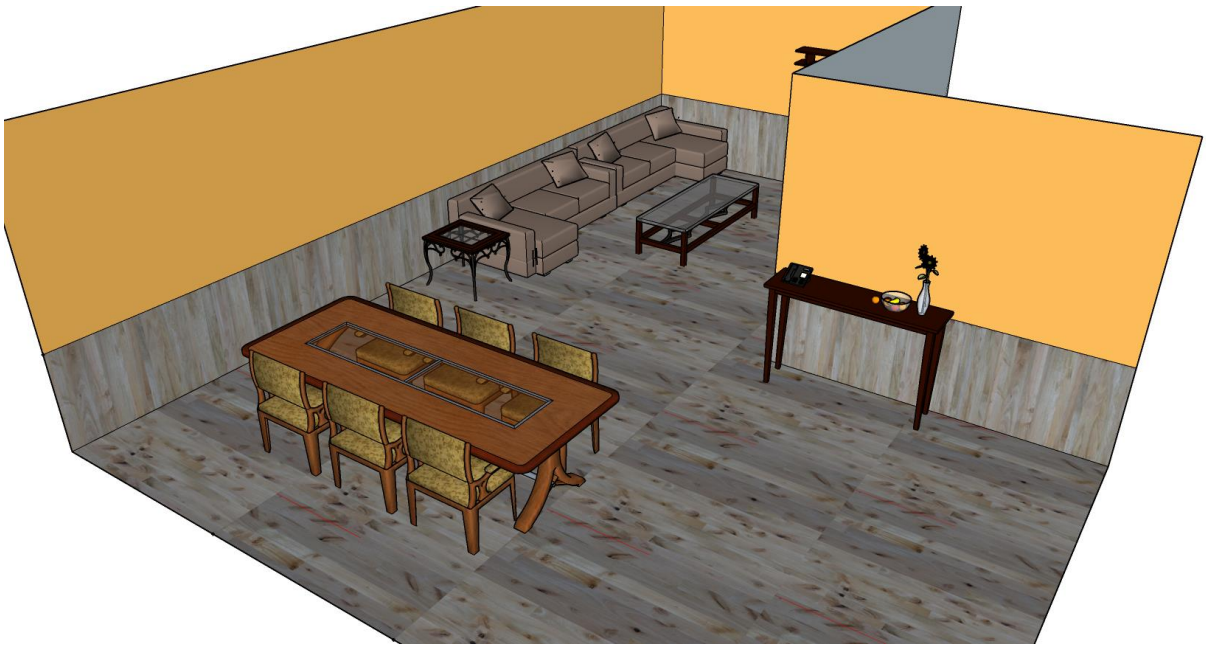


Figure 4-47. An example of wood flooring and wainscoting produced from E. globulus board knotty segments and clear cuttings.

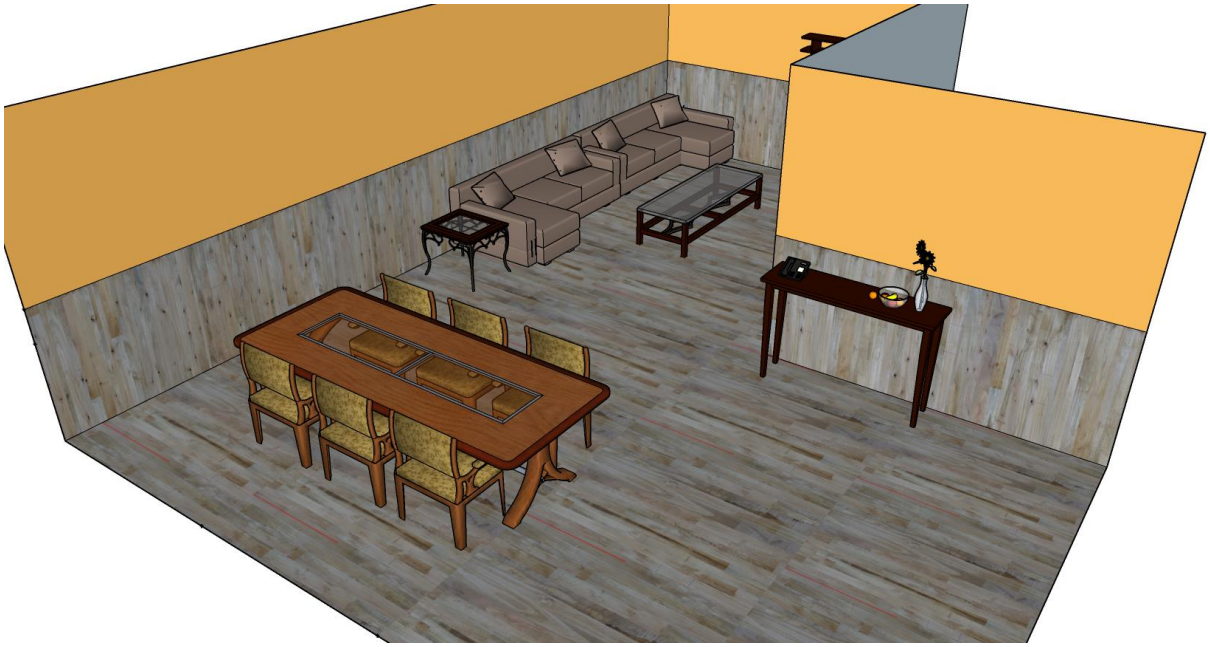


Figure 4-48. An example of wood flooring and wainscoting produced from E. nitens clear segments and knotty panels.

4.6 Discussion

The objective of this chapter was to develop a means to select and specify different sizes and types of knots in appearance panels. This objective was addressed by defining a lower and upper knot size limit of three appearance types (light, dark, black). These limits controlled the

knots that were required to occur within board segments or could occur in cutting areas. The segments were used to create a digital image artifact of a wood panel. The panels provide a means to visually judge, select, and specify a particular knot size and type. For this to be accomplished, the following was developed:

- two definition sets that defined the limits of knot size and type for five types of board segments and four definitions of cutting areas;
- a method to locate and remove areas to assemble panels from segments and cuttings;
- a method to describe the level of knottiness and visualize the attributes that could be achieved in panels, and;
- a method to specify a material that contains the desired characteristics.

The framework presented here provides the foundation to create a system that allows the selection and visualization of wood panels. The selection is based on the upper and lower limits of three appearance types of knots. Like the systems discussed in 4.3.2, the selected values are passed to processing modules that create a digital rendering based on the actual material properties. These renderings can then be used within a 3-D modeling environment. This decreases the level of abstraction associated with digital modeling and simulation of wood elements. The system provides a new and novel method of working with highly variable materials. The system allows the user to engage with the physical properties, such as the visual attributes of knots, in much the same way as other materials. The procedure also provides a means to specify the desired characteristics.

However, unlike the systems discussed in 4.3.2, the framework presented here does not offer a means to estimate manufacturing costs or a means to obtain the best-suited boards for the different selections. These requirements are handled in the systems mentioned earlier by using standard materials of which the only variable is the required parts. The parallel plots indicate that some boards are better-suited than others; ideally, only the best-suited ones would be used to obtain the desired results.

Two methods to select different knot sizes and types are presented. The first method *requires* that board segments contain knots of a specific size and type as defined by the users. This method produces board segments with at least one knot, sometimes more. Segment length

is the result of the distribution of knots along boards. Boards with a narrow range of knot sizes are likely to produce longer segments than a board with a wide range of knot sizes. In this study, most segments were relatively short (Figure 4-8). This is to be expected given that both lumber sample sets are from unthinned and unpruned plantation-grown resources. Other studies have shown that these resources contain an abundance of knots and other characteristics (Derikvand et al., 2016, Derikvand et al., 2018b, Derikvand et al., 2018a, Derikvand et al., 2019, Jiao et al., 2019).

The second method *allows* knots to occur in cuttings produced from boards. This is a more complex operation because cuttings are produced from cutting areas—areas that do not contain characteristics that are not allowed to occur in cuttings. As mentioned in 2.5, this is an example of the irregular multiple stock-size cut-up problem. Panels produced from cuttings in this manner display a range of knot density, which can be modified by including different amounts of knotty cuttings. As mentioned above, the appearance of cuttings will vary according to knot distribution within boards. Undoubtedly, the distribution of knots will vary with different resources. On the board-scale, there was considerable variation in knot size and type (see 5.6.1.1). Results would be different from boards with a narrower range of sizes and appearances of knots.

4.6.1 Board Segment Panels

The images of panels constructed from board segments of *E. globulus* lumber show considerable visual variation attributed to the occurrence of different sizes and types of knots (Figure 4-10, Figure 4-11, Figure 4-12, Figure 4-13, and Figure 4-14). Images of similar panels produced from *E. nitens* lumber are presented in Figure 4-22, Figure 4-23, Figure 4-24, Figure 4-24, and Figure 4-26. Unlike panels randomly assembled from boards, these panels contain variation within the limits set out by the definitions used to segment the boards. The panels also display variation in the length of segments produced by the sample set of boards. These images give a true-life visualization of panels produced from the different segments—they communicate the visual attributes of panels made from these resources. The images also demonstrate the differences between the species. For example, panels from *E. nitens* lumber tend to show more flat sawn grain patterns. This is probably a result of using smaller diameter logs to produce these boards.

At a primary level, these images provide evidence that this material has enormous potential as a feedstock for architectural panel production containing various levels and appearances of knots. The images provide a means to predict a visual outcome. Panels could be viably produced from almost any of the segments, however, each would require the development of a specific processing regime. For example, because the knots are large and some contain voids, segment type 4 panels would probably require some level of void filling, while panels made from clear segments require far less handling. Although not commercially utilized in Australia, the sample boards from *E. nitens* and *E. globulus* used in this study could undoubtedly provide a unique palette for the adventuresome designer or consumer.

The parallel plots indicate differences in the proportion of boards belonging to each segment type. Overall, boards that produce high proportions of clear segments contain very low levels of the other segments. However, another group of boards that produce low levels of clear segments contains a variety of other segment types. One striking pattern is the distinctive V-shape that occurs for a significant proportion of the boards. This indicates the presence of natural groups of boards—groups that could be matched to a desired visual outcome to increase the utilization of a higher proportion of the resource. As different characteristics are selected, the proportion of each segment type would change, and this change would determine the best use of individual boards.

4.6.2 Cutting Area Panels

Images of panels constructed from cuttings areas are shown in Figure 4-32 through Figure 4-45. The images show a range of visual attributes attributed to knots of different sizes and types. Again, the artifacts (images) provide evidence of the potential for these resources to be used as a feedstock to produce appearance panels. This method is different in that it allows, but does not require, knots to occur in cuttings. As with panels constructed from board segments, the production of cuttings is the direct consequence of the distribution and arrangement of knots across the board surface. Cuttings must be taken from cutting areas that do not contain knots that are not allowed by the definitions. It follows, then that the visual attributes of the panels are specific to the available supply of timber.

The yield of cuttings varied according to both the definition used and the species (Table 4-7). Overall, the yield compared well to lumber graded as #1C (73 percent), but lower than FAS lumber (86 percent). See 5.4.1.2 for further explanation of NHLA grades. As expected, yield increased as the allowable knot size increased. The cutting bill used in these simulations required a considerable range in the length of cuttings. The arbor settings used in ROMI 4.0 were also quite narrow. Both parameters probably led to the relatively high yield for the lumber. Other settings and cutting requirements would affect the results.

Figure 4-46 indicates the yield response for individual boards as the allowable knot size and type change. The overall pattern indicates that yield for knotty cuttings in *E. nitens* boards is higher than for *E. globulus* boards. This could be caused by the differences in the distribution of knot sizes and types. Differences in the two species were indicated in 3.7.1, *E. nitens* contains a higher proportion of smaller knots than does *E. globulus*. There appear to be at least two other patterns. The yield for some boards changes very little with changes in allowable knot size, while the response is more dramatic for other boards. This response appears to occur for both moderately clear yielding and low clear yielding boards, but the increase is most apparent for low clear yielding boards. Again, these responses are a direct consequence of knot arrangement patterns; the response would play out differently for other resources. These responses also point out the potential to sort boards such that the low clear cuttings yielding boards are used for cuttings that allow an optimized knot size and type. For example, the utility of most of the red boards in Figure 4-46 would improve if they were used to manufacture cuttings under definition 3. This concept indicates that there may be naturally occurring groups of boards within the sample set. This concept is explored in detail in the next chapter.

Knot density (the number of knots/surface area) varied considerably across the definitions and species. As expected, it was the highest for *E. nitens* panels assembled from cuttings produced with definition 3. This is supported by the shapes of the board traces in the parallel plots. Also, the knot density was considerably higher for knotty panels than for mixed ones. The size and type, as well as the knot density influence the visual attributes of the panels—knot density, becomes an additional parameter that can be selected to achieve the desired

appearance. Here, only the two extremes are shown, panels can be assembled from different proportions of knotty cuttings to further customize visual attributes.

4.6.3 Considerations of the Method

The panels produced by random board segments show considerable variation in knot size as compared to the panels made from segments with defined limits in knot size. The unsorted panels are the result of using the boards as a whole. The other panels are the result of defining a limit to a particular characteristic and assembling panels from those segments. Broman (2000) found that preferences for knotty surfaces related to a blend of characteristics and that it was important to avoid a state of 'disharmony'. This concept would be particularity important for panels where so-called divergent texture, grain, color, or a wide range of knot sizes could be present. It follows that preference for particular levels of knottiness is related to the ability to control divergent characteristics during the manufacturing process. Donovan and Nicholls (2003) found that respondents preferred either clear panels or high levels of characteristics, but less preference for intermediate levels. The ability to customize the outcome leads to a situation where the producers and users are directly connected. As Bumgardner et al. (2000) suggest, the ability to customize the level of specific characteristics may provide a way forward for "character-marked" furniture.

The procedures presented here provide a means to overcome the limitations of the current practice to select for a desired level and type of certain characteristics for appearance purposes found in wood. The board segmenting procedures presented in this chapter establish a means to define different sizes and appearances of knots that must occur on board segments. These segments were examined to determine the resulting visual differences of panels constructed from them. Conceptually, a set of sliders could be used to specify minimum and maximum limits for the different types of appearance classes of knots. Here, knot size is determined by the minimum bounding box, and appearance classes determined by the ratio of pixels in the red channel below pixel value 60 (see Table 3-3). These differences indicate that despite the low frequency of knots (in this study, the total knot area was less than 2 percent of the total board area) the size and type can significantly affect the aesthetic of panels.

Knots can be described using other geometric and appearance attributes as presented in the previous chapter. For example, selection could be based on tone (see Figure 3-28), eccentricity (see Figure 3-29), or orientation (see Figure 3-31). The knots produced for both species studied here present a range of values for these attributes. It is conceivable that other characteristics could be included in the definitions to create other unique visual attributes. Segments could also be sorted based on the color profile of the segment, resulting in the ability to create panels with color range limits. Nicholls et al. (2013) found preferences for stain over knots in birch panels. The authors suggest that a preference for stain in birch was because it looks like hickory, a more expensive species. This suggests that substituting a less expensive species that contain characteristics like more expensive ones may provide a means of valuing lesser-known species.

4.6.4 Specification

As defined in 1.1, the act of defining the required characteristics of a material is referred to as specification. The specification is limited to the resolution at which the material properties are documented or understood by the user. Specification of homogenous man-made materials is relatively straight-forward. This is because the physical and mechanical properties are well understood and documented and can be adjusted to satisfy the application requirements. However, the specification for biological materials is more complicated and limited because often detailed information that describes the properties is not available or the user does not have in-depth material-specific knowledge. The specification of timber for appearance applications requires considerable personal experience and knowledge—knowledge that was held among craftsmen and builders (Hubbe and Buehlmann, 2010) but is now in a strong decline due to the industrial revolution and standardization of products (Shanks et al., 2014).

The procedures proposed here increase the detail at which wood surfaces can be selected. Selection is based on the range of properties available from a given material. Once selected, these surfaces can then be specified—that is the characteristics can be defined in a way that communicates the desired outcome to both producers of lumber and the manufacturers of high-value products. Standard practice is to specify a species and grade based on various

factors concerning color, price, workability, consistency, and form (Nicholls and Roos, 2006). This approach does not allow for a detailed description of specific visual qualities.

The procedures presented here provide a way to include additional detail describing subtle differences in visual qualities into the specification process. The method uses the selection process to define the desired characteristics for the product. As the method does not use a grading standard, it is flexible—the user defines the desired characteristics. An example specification for flooring using the board segmenting method presented above could take the form of:

Flooring Specification	
Area (m^2)	1000
Species	*E. globulus*
Characteristics	
Knot size (mm^2) and appearance	322.6-645 Light 322.6-645 Dark 322.6-645 Black
Color	Full range of available color
Grain	Plainsawn
Width (mm)	120 mm
Length (mm)	Random Lengths greater than 500 mm
Finish	Water-based Polyurethane
Grade	This refers to a document that defines other attributes, such as moisture content and form.

This specification would produce flooring like that shown in Figure 4-12. After the specification has been issued, the products can be manufactured from lumber that is appropriate to the application.

5 Chapter Five- A Method to Group Boards by User Specification

5.1 Purpose

The purpose of this chapter is to present procedures to group boards based on a user-supplied specification that describes the desired areas that contain the knot size and appearance type. The results of the procedures are illustrated in two ways. The first way is focused on grouping boards according to the proportion of defined board segments. The second way is focused on cutting areas that may or may not contain knots within a defined range. The results indicate that the procedures produce groups of boards with varying proportions of the defined segment and cutting types. The outcome is a method to describe lumber at the batch scale.

5.2 Objectives

As established in 2.3, grading of timber is contextual—that is, it varies according to local and regional customs, processes, capacity, and material supply. In Australia, boards are produced at specific thicknesses, widths, and lengths which suit industry needs. The industry is accustomed to processing lengths of boards that suit product requirements-that is, mostly chopping and little ripping. Therefore, it is important to describe the distribution (frequency and length) of segments of boards containing defined properties (size and type of knots). In the North American context, the suitability of lumber for different applications is assessed based on the size and number of cutting areas a board contains. Therefore, in much the same way, it becomes necessary to fully describe what sizes of cutting areas are available to select the best-suited board or group of boards for an application. To make such a selection, boards must be grouped accordingly. The objective of this chapter is to develop and demonstrate a novel lumber classification system based on the distribution of areas within boards that contain a defined range of knot size and type. This requires a method to determine:

- a set of variables that describe the distribution of defined areas at the board-scale;
- a procedure that clusters boards with similar distributions of defined areas (unsupervised);
- a classification method that sorts boards according to the cluster solution (supervised), and;

- a means to describe the segment or cutting area distribution within each group.

5.3 Background

During the production of lumber, the growth characteristics of each board are characterized and classified according to size, shape, and frequency. Common classes of characteristics are knots, splits, bark pockets, bird pecks, checks, decay, wane, want, wormholes, pith, gum veins, and holes. The domain is defined as all the possible classes of characteristics. The size, shape, appearance, and distribution of these characteristics is used to assign a grade to each board. As introduced in 2.3, lumber grading is accomplished using human vision, machine vision, and machine assessment, or a combination of human and machine vision and machine assessment. A grade is a name for any group of material, and a grade definition lists the acceptable limits of form and properties admissible in the grade. In timber grading, form describes the size, shape, straightness, and other physical dimensions, while properties describe the type, level, and frequency of natural growth characteristics-knots, splits, decay-typically referred to and considered defects in most grade definitions because these characteristics reduce the quality and suitability of the pieces. A grade standard is a document to be used to define the properties of a material. Its development brings together all interested parties of the material. It should standardize and streamline a process and reduce transaction costs. A standard contains the definitions for each of the different grades and, therefore provides a mechanism to specify a group of materials.

Inherent to grading theory is the quest to determine and communicate wood quality and value within the supply chain: buyers must be able to obtain the quality (desired characteristics) required and sellers must receive the highest possible price (Kretschamann and Hernandez, 2006). However, quality and value are not necessarily the same concept; the terms have a different meaning for different segments of the supply chain and may change over time (Luppold and Bumgardner, 2003).

As introduced in 2.3, quality is generally a physical concept determined by an agreed-upon grading or assessment system of the properties of the material. Judgments of quality include both subjective and objective performance requirements. Value is driven by supply and demand within the market (Luppold and Bumgardner, 2003). Supply is a function of a long-

term biological process, while the value is a comparison to other products (Luppold and Bumgardner, 2003). Value can increase by developing new processes and products that more effectively utilize the material in higher-value products, such as furniture, or with changes in consumer preferences and material availability. As mentioned in 2.3, value is loosely associated with these standards under the assumption that grades reflect some level of production efficiency and product suitability (Luppold and Bumgardner, 2003). As applied, these assumptions systematically disadvantage a large proportion of the current hardwood supply and limit the range of quality attributes available to end-users.

There exists three main approaches to appearance grading (Figure 5-1). Under a defect system, the whole board is assessed against grading rules that specify maximum allowable sizes and levels of each type of characteristic. This is known as the board as a whole system. A cutting area approach is based on the amount or proportion of each board free of defects, or with allowable features, contained within defined areas of cuttings. Grades are based on minimum board sizes, the number of cutting areas within the board, and the proportion of each board that falls within the cutting areas. Fit-for-purpose grading describes characteristics that affect the performance of the piece in demanding and special applications, such as tool handles.

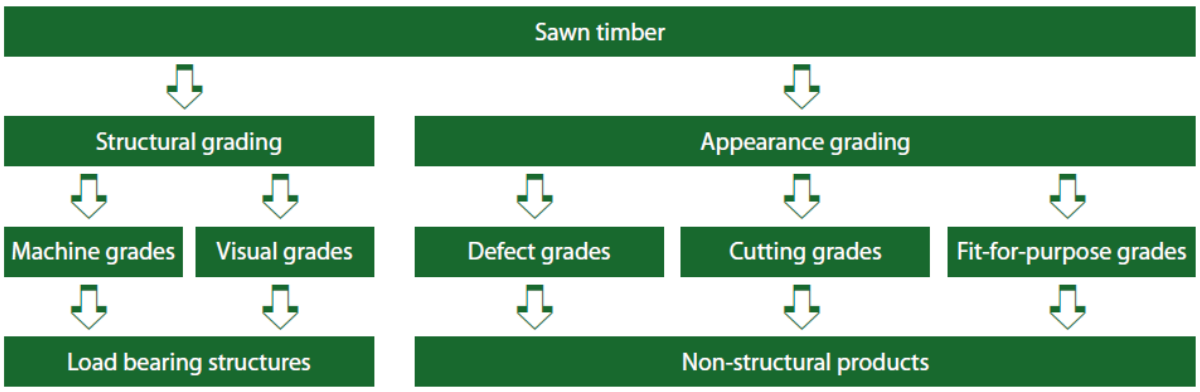


Figure 5-1. Summary of the different types of sawn timber grading (Davies and Watt, 2005).

The type of assessment of sawn wood products depends greatly on the intended end use (Figure 5-1). Grading for non-structural or appearance purposes is based on the appearance of the surface characteristics and board dimensions (the form of the piece). As stated above, boards are graded either by considering the characteristics present on the board as a whole

(defects system) or as a proportion of the board contained within clear areas[28]. While the entire board approach is appropriate in situations where very little additional processing is expected, the clear area cutting approach assumes that boards will undergo major processing to recover what has been determined to be useable areas.

It is important in this work to recognize the difference between grading and sorting. Here, sorting is defined as the process that produces groups of boards (sometimes referred to as board classes) with similar levels of useable areas. In this context, properties include a reference to the useable areas of boards. Grading, on the other hand, is the procedure that considers the suitability of an individual board or group of boards for specific processes and applications based on other aspects, such as warping, twisting, avoidable mechanical damage, dimensional stability, density, and mechanical characteristics.

5.4 Hardwood Grading

5.4.1.1 Board as a Whole

Under the Australian hardwood timber grading standard AS 2796, boards are excluded from grade classes that contain characteristics, such as knots, outside permissible limits (size and number) for each class, that is, the grade description describes what is not allowed in boards of different grades (Figure 5-1). This is known as a negative description model (Lycken, 2006a). This standard was developed for lumber milled from mature, slow grown large trees of the *Eucalyptus* family. A similar approach is taken for the grading of Oak in Europe (APECF, 2009) and hardwood grown in the UK (Table 4.2) (Davies and Watt, 2005). These standards select against characteristics; the higher the number and size of characteristics found on boards, the less aesthetically pleasing, and the lower the quality it is presumed to be (Nolan, 1998). This results in lower grades, or quality classes, containing material with a greater size range and frequency of natural growth characteristics, greater variability in board dimensions, and other avoidable features. Examples of Select, Standard, and High-Feature boards are shown in Figure 5-2. Material that falls below High-Feature grade contains a random assortment of unavoidable and avoidable characteristics, such as variation in target width and thickness outside limits specified by the standard (Kotlarewski et al., 2017). Lower-grades of timber

[28] NHLA grading does contain character-marked grade definitions for a limited number of species.

could contain many potentially useful and desirable combinations of characteristics or short sections of feature free material, but little consideration has been given to a means to describe or batch it for various end-uses.

Table 5-1. Limits of permissible characteristics in AS 2796 hardwood grades (Australia Standards, 2006).

SUMMARY AS 2796 Permitted limits	SELECT GRADE	MEDIUM FEATURE - STANDARD GRADE	HIGH FEATURE GRADE
TIGHT GUM VEINS Quartersawn	< 2mm wide, < 250mm long, < 1/2 length in total	< 5mm wide & any length	< 5mm wide & any length
Backsawn	X	< 60 mm wide & 1m long & 2mm deep	Any width & any length & 2mm deep
LOOSE GUM VEINS Confined to one surface	X	< 3mm wide & in total < 1/5 board length	< 3mm wide & in total < 1/5 board length
BORER HOLES For boards 60 mm or wider	width < 2mm, length < 15mm	width < 3mm, length < 1/3 board width up to 40mm	width < 3mm, length < 3/8 board width up to 50mm
In a board length of	*100mm* *900mm*	*100mm* *900mm*	*100mm* *900mm*
Number permitted in a board width 50 to 100mm	5 10	16 24	16 24
Number permitted in a board width > 100mm	8 16	24 36	24 36
Larger holes	X	X	width 3mm <10mm - Up to 3 per meter
HOBNAIL Darker coloured portion	<15mm wide	<40mm wide	✓
NATURAL DISCOLOURATION	Slight	✓	✓
TIGHT KNOTS For boards 60 mm or wider	<15mm wide	1/3 the width up to a maximum of 40mm	3/8 the width up to a maximum of 50mm
KNOT CHECKS	X	< 2mm wide	<3mm wide
CHECKS	<1mm wide & 250mm long	<2mm wide & 250mm long	< 2mm wide & any length
GUM POCKETS & OVERGROWTH Confined	X	<10mm wide & 50mm long	<15mm wide & 75mm long
to one surface	X	Backsawn < 2mm deep	Backsawn < 2mm deep

KEY < - permitted up to, X - not permitted, ✓ - permitted without restriction, Slight - having little effect on the overall appearance

Table 5-2. Permissible characteristics for the main grades of hardwood grown in the UK (Davies and Watt, 2005).

Features	The main grades		
	1	2	3
Fully and partly inter-grown knots [3]	One ≤20mm diameter or several smaller up to a combined diameter of 20mm	Three ≤40mm diameter or several smaller up to a combined diameter of 120mm [4] [5]	No restrictions providing the appearance and mechanical properties are suitable for its intended use. More detailed criteria may be set in the supply agreement [10]
Non inter-grown knots and rotten knots [3]	Occasional if measured-out	Occasional	
Checks	Occasional surface [6]	Limits may be set [6] [7]	
Shake	No	Occasional if measured-out	
Colour	Limits may be set [7] [9]	No restrictions	
Grain	Straight or nearly straight [8]	Course grain and minor sloping grain permitted [8]	
Bark	One surface pocket if measured-out	One surface pocket if measured-out	
Rot and insect attack	No	One small area if measured-out	
Warp	Limits may be set [7]	Limits may be set [7]	
Wane (square-edged pieces only)	Limits may be set [7]	Limits may be set [7]	
Sapwood (oak and sweet chestnut only)	Limits may be set [7]	Limits may be set [7]	

Figure 5-2. Examples of Select (top), Standard (middle), and High-Feature (bottom) Tasmanian Oak boards graded under AS 2796.

5.4.1.2 Cutting Area

In contrast to hardwood grading in Australia, the grading standard issued by the National Hardwood Lumber Association (NHLA), seeks to account for the proportion of a board's surface that is free of the natural characteristics of tree growth (such as knots, splits, decay) on one or both sides. The standard is structured around the assumption that the board will be cut into smaller pieces, or parts, during processing (Bowyer et al., 2007, NHLA, 2014). This is referred to as the cutting area approach. The grading standard is presented in Table 5-3. Examples of graded boards are presented in Figure 5-3. Examples of characteristics allowed to occur withing cutting areas are shown in Figure 5-4.

Table 5-3. Minimum requirements set out by NLHA grading rules (NHLA, 2014).

	FAS	F1F	SELECT	#1 COM	#2A & 2B
Minimum Size Board	6″ x 8′	Same as FAS for species being graded	4″ x 6′	3″ x 4′	3″ x 4′
Minimum Size Cutting	4″ x 5′ 3″ x 7′	Better Face to Grade FAS Poor Face to Grade #1 Common		4″ x 2′ 3″ x 3′	3″ x 2′
Basic Yield	SM x 10 83-1/3%			SM x 8 66-2/3%	SM x 6 50%
Formula to Determine Number of Cuts	$\frac{SM}{4}$ (4 max)			$\frac{SM + 1}{3}$ (5 max)	$\frac{SM}{2}$ (7 max)
SM Needed to Take Extra Cutting	6-15′ SM			3-10′ SM	2-7′ SM
Extra Yield Needed for Extra Cutting	SM x 11 91-2/3%			SM x 9 75%	SM x 8 66-2/3%
Special Yields	97% Rule - 2 cuts full widths any length; Pcs. 6″ & wider with 6-12′ SM SM x 11.64 for Yield	97% Rule - On Better Face	97% Rule - On Better Face; 2′ x 3′ SM to be 100% clear or SM x 11 in one cutting	1′ SM - SM x 12 or 100% clear 2′ SM - SM x 9	1′ SM - SM x 8 #2A Com - Clear Cuttings #2B Com - Sound Cuttings

Table 5.3 continued

#3A COM	#3B COM	FAS Limits	
3″ x 4′	3″ x 4′	Pith = SM in inches Wane = 1/2 Length Knot = 1/3 SM Warp = Entire board must be flat enough to S2S to S.S.T. Splits: Not to exceed 2 x SM or 12″ whichever is greater Splits shall not diverge 1″ in 12″ First Lineal Rule: Applies to both ends of Board to contain not less than 50% clear wood, 25% sound wood.	**Wane in FAS 1 FACE** FAS limitation applies to Better Face #1 Common side: 1/3 W or 1/2 L Widest wane added together; Length can be on both edges
3″ x 2′	Not less than 1-1/2″ wide containing 36 sq. inches		**Wane in Selects** <u>Pcs. 6″ & Wider</u> FAS limitation applies to Better Face. #1 Common side: 1/3 W or 1/2 L Widest wane added together. Length can be on both edges. <u>Pcs. 4″ & 5″ Wide</u> 1/3 W or 1/2 L applies to both faces. Add widest wane together. Add total length of wane from both edges.
SM x 4 33-1/3%	SM x 3 25%		
Unlimited	Unlimited Sound Cuttings		
#2A Com on Better Face and reverse side of cuttings sound; will also qualify for 3A Com			NOTE: This chart summarizes the main requirements for the standard grades. For complete imformation, consult the appropriate section of the NHLA Rule Book.

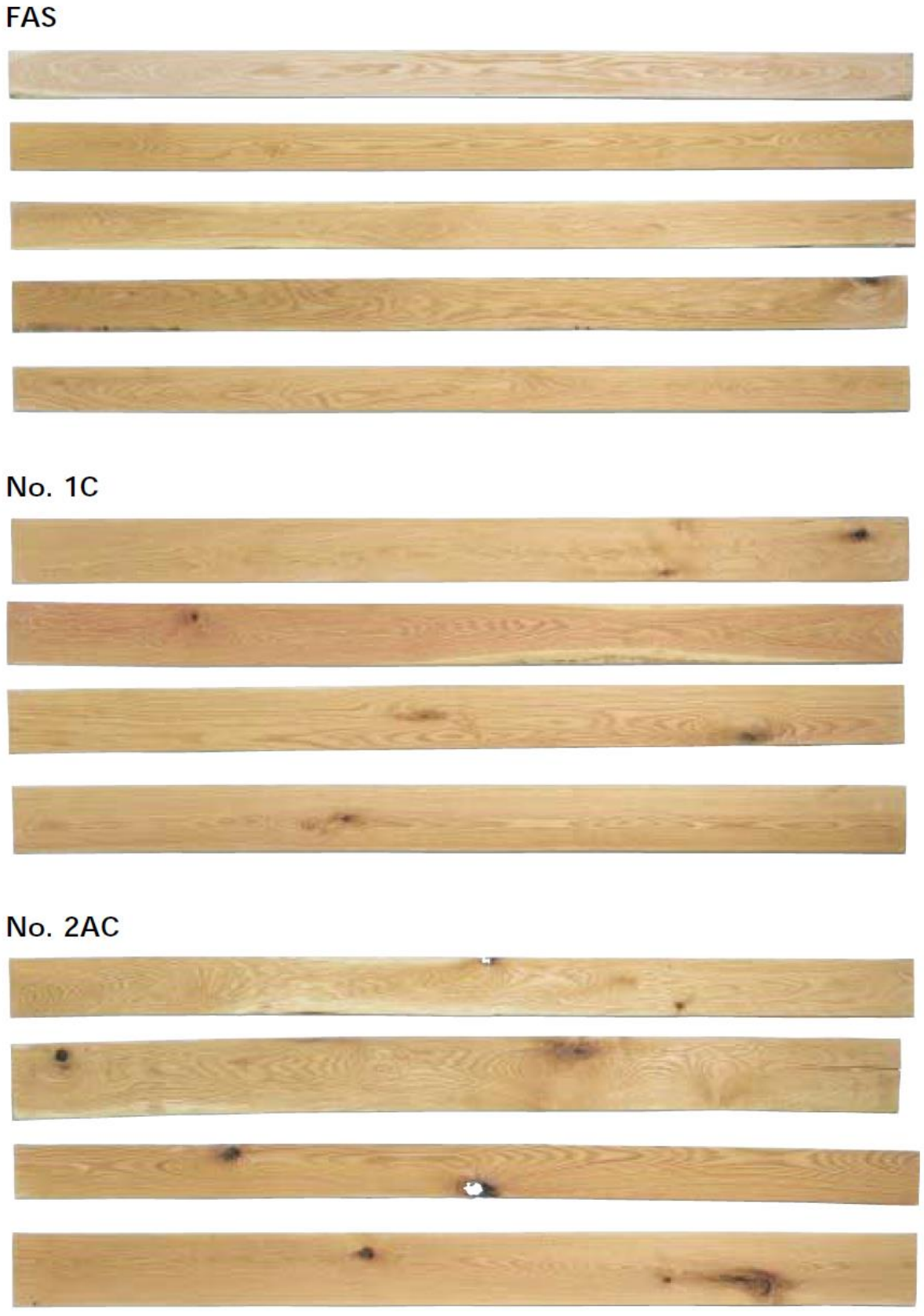


Figure 5-3. Examples of FAS, #1C, and #2AC, American red oak graded under the National Hardwood Lumber Association grading standards (American Hardwood Export Council, 2008).

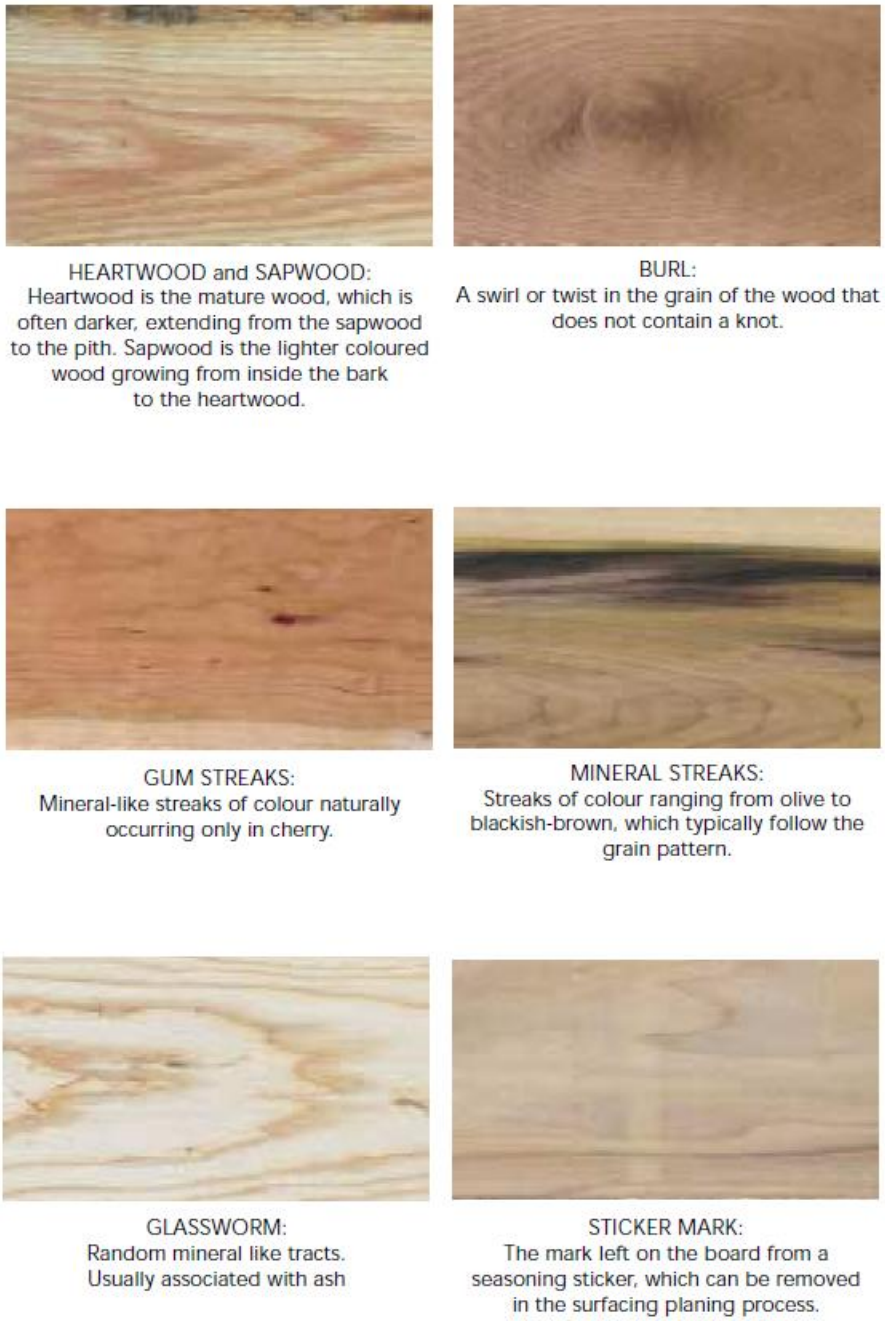


Figure 5-4. Characteristics allowed in clear area cuttings under NHLA grading rules (American Hardwood Council, 2008)

Although the standard is primarily focused on the clear cutting approach, it does provide amendments for different tree species and product requirements. For example, the character-marked grade allows "any kind, number, or distribution of…heartwood, sapwood, knots, burls, swirls, bird pecks, holes and grooves up to ½ in. in diameter and not extending through the piece".

This standard is considered a positive one-sided limited model (Lycken, 2006c). The grade standards state the minimum requirements of potential yield and the minimum size of cutting area that the board can contain. The association that issues the standard dates from 1897 and "since that time has revised or enlarged (the standard) to reflect the industry's needs with the advice of a standing committee representing the various species and producing areas" (NHLA, 2014). From 1898 to 1932, the standard considered the number and size of features for the whole piece, a defect system, like the current Australian standard. In 1932 (Forest Products Laboratory, 2010), the concept of clear cuttings was introduced, presumably at the request of a changing industry or a declining supply of hardwood resources compatible with the defect system. In 2018, NHLA rules were used to grade approximately 3.9 billion BF of hardwood lumber (Spessert, 2017). This standard sets forth 7 clear face grades and 3 sound grades (NHLA, 2014). In 2017, there were approximately 4.5 million m^3 of hardwood lumber exported from North America (Wheiler, 2019). Of this volume, China has historically been the largest importer, however, other countries in Asia have also imported significant volumes of hardwood (Wheiler, 2019).

The NHLA grade is largely determined by the minimum potential yield, minimum board size (width), and the presence of at least one clear cutting area meeting the minimum size requirement of the grade. Provisions are laid out for each grade for the maximum number of cutting areas; grades with smaller required cutting areas allow more cutting areas within each board. As stated elsewhere, the standard does not provide any information describing the size and distribution of the other cuttings present on the board. This system can result in batches of lumber that contain a large range of different sized cutting areas. Using this method over 50 percent of the lumber is relegated to lower quality grades, such as #1C and #2C (Gatchell, 1987). For example, the highest grade of hardwood lumber, FAS (firsts and seconds), must yield at least 83.3 percent clear cutting areas and contain at least one cutting area 4 in. by 5 ft. or 3 in. by 7 ft.

The percentage of cutting areas on boards is determined using the cutting unit method (NHLA, 2014). A cutting unit is 1 in. by 1 ft. Cutting units are determined for each clear area on the poorest face of the board, except for a few of the grades. Total cutting units of a board are given by multiplying the width in inches by the length in feet. The surface measure (SM) of a

board is given by multiplying the width by the length and dividing by 12. The percentage of yield of cuttings is determined as:

$$Yield = 100 \times \frac{\sum cutting\ units}{Surface\ measure \times 12}$$

Equation 5-1. Yield determined using a cutting unit method.

Suppose a 9 ft. 3/8 in. wide board 16 ft. long contains the following clear face cutting areas (2014 NHLA rule book):

8-1/2 in. x 6 ft.	51 cutting units
3 in. x 9-1/2 ft.	28 ½ cutting units
4 in. x 2-3/4 ft.	11 cutting units
3 in. x 3-1/3 ft.	10 cutting units
Total	100 ½ cutting units

The surface measure is calculated as:

$$\frac{9/16}{12} = 12$$

And yield would be calculated as:

$$\frac{100.5}{12 \times 12} \times 100 = 69.8\%$$

This board would grade as a #1C because it contains more than the minimum yield for the grade, but less than the next higher grade. The grading rules provide no information as to the size of the remaining cutting areas available on the board. Examples of clear cutting areas marked out on the highest grade of boards (FAS) and a lower grade (#2AC) are illustrated in Figure 5-5. Boards with a higher proportion of wide and long clear cutting sections are considered higher-quality and, consequently, higher-grade and higher-value (Table 5-4) (Gatchell, 1987, Luppold and Bumgardner, 2003), while those with shorter and narrower clear cutting areas are assigned to lower-grades.

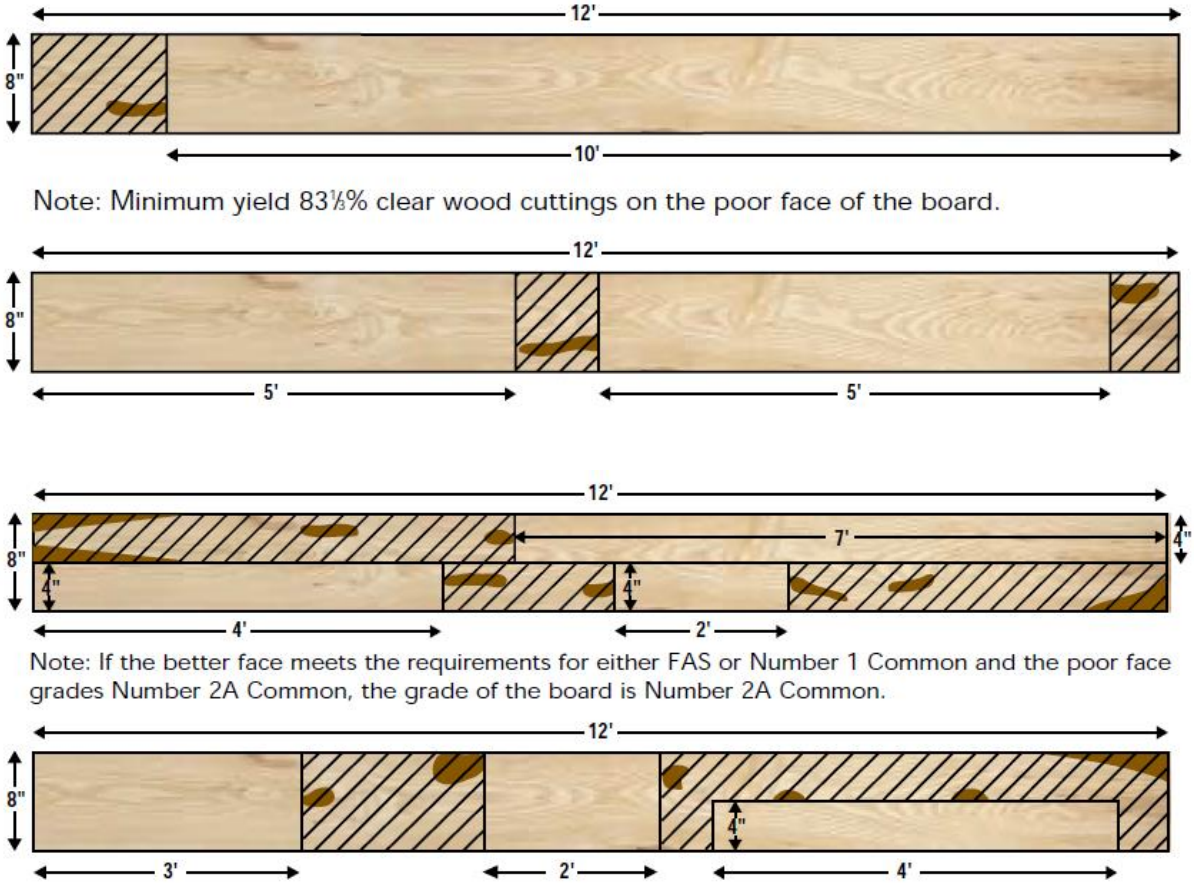


Figure 5-5. Examples of clear cuttings marked out on FAS (top) and #2AC boards (bottom) using NHLA grading rules (NHLA, 2014).

Table 5-4. Examples of 4/4 southern hardwood lumber grade values in USD per MBF for December 28, 2018, from the Hardwood Market Report (December 28, 2018).

	NHLA Lumber Grade			
Species	FAS	#1C	#2AC	#2A/#3A
Red Oak	930	675	605	540
White Oak	1680	930	600	545
Poplar	860	510		360

Although these standards form a complex set of grading rules, they have developed over time to establish relative values between groups of boards and to provide users a standard by which different grades can be purchased for different end uses. For example, products that require only short and narrow clear or sound pieces can be matched to a grade of lumber that supposedly contains shorter and narrower cuttings (at a reduced yield), while grades can be purchased that contain long or wide sections for the manufacture of items that require such cutting sizes. Sometimes, but not always, the decrease in yield is compensated for by the lower cost (Buehlmann, 2008).

Although NHLA grading rules stipulate a minimum cutting area size, the grades are not necessarily formulated according to a particular set of cutting requirements. Yield could be about the same for boards containing many short cutting areas as for a board with long cutting areas for a cutting bill calling for mostly short cuttings. Despite the attempt to match grades of lumber to actual uses, Gatchell (1989) stated that at least 25 percent of clear furniture parts are 533 mm (21 in.) or shorter and that at least 55 percent of the interior (sound) parts are shorter than 457 mm (18 in.). From this example, most parts are shorter than the minimum 609 mm (24 in.) clear cutting area specified for #2AC lumber.

The cutting area method may not accurately represent the useable areas on boards. This occurs when cutting areas are determined using different rules that either prioritize the length or width of the cutting. For example, a cutting nested between knots could either be long and narrow or wide and short. The implications of different rules could affect the utilization of the cutting area. Also, because cutting areas can occur in any arrangement, board breakdown processes may not be able to effectively remove parts from all the possible cutting areas.

While the Australian approach limits the size, type, and frequency of characteristics within boards overall, the North American standard considers the number and size of clear areas that can be obtained from boards—which may or may not correspond to required parts sizes. Neither approach describes or defines the actual distribution of size and frequencies of the characteristics found on the board. Neither system provides detailed information about the distribution of cutting area sizes or information about the characteristics found within character-marked cuttings. Although certain types of characteristics, such as splits, deep cracks, or decay will render sections unusable for most higher-value products and will be considered defects during grading and processing, other features have the potential to provide visually engaging attributes. Also, no commercial standard exists to specify and define character-marked cutting sizes.

5.4.1.2.1 Character-Marked Cuttings

As introduced in 2.4, there appears to be a strong interest in character-marked wood in consumer products. However, the production of character-marked furniture has been met

with challenges (Nicholls and Bumgardner, 2015). One particularly vexing problem is strategically batching and suppling lumber best suited to viably produce products that contain the characteristics desired by consumers (Nicholls and Bumgardner, 2015). Although a defecting-system may provide a method to group boards with similar-sized features for applications that utilize the complete board as a part, such as exterior cladding or flooring, the method may not provide a satisfactory method to segregate of boards that contain a variety of characteristics that vary in size. To date, there has been little research that examines the potential of sorting boards based on the size, frequency, and distribution of sections or cutting areas that contain a defined range of certain characteristics. Character-marked cutting areas taken collectively at the board scale would provide a means of creating a board-scale feature profile, perhaps providing useful parameters for alternate sorting models.

Under current grading standards that select against most features and standard lumber processing procedures, it is difficult to manufacture consistent character-marked products from available resources, especially considering the risk-averse nature of the furniture industry (Bumgardner et al., 2000). Given the parallels between furniture and other fashion products (Leslie and Reimer, 2003), improvements in material sourcing, sorting, and product design may reduce risk and increase competitiveness for firms that wish to expand product offerings.

Recent additions to both the North American and Australian hardwood grading standards are aimed at providing ways to market lumber with excessive character-marks and to provide a means to grade lumber from species that are currently undervalued and underutilized because they contain a high occurrence of growth characteristics. New names such as ‘knotty Alder’ and ‘high-feature’ are among the additions (Nicholls et al., 2004b, Nolan, 1998). At best, these additions provide a rudimentary means to describe the actual characteristics likely to be found within the grade and are not particularly useful for specification of alternative aesthetic appearances (Nolan, 1998) or further processing requirements, but have been shown to improve market value. For example, Nicholls et al. (2004b) suggest that the market value of Alaska birch, a species that contains numerous small knots, could potentially increase by USD 154.37/MBF by not considering characteristics up to 0.5 in. (12.5 mm) to be grade (and value) reducing features.

Despite the increased market value, the alternate rules are based on the NHLA grading structure that only considers the minimum cutting area size and proportion of board that falls in cutting areas. It does not distinguish between character-marketed and clear cuttings that could be present within the material. There is no information describing the proportion of cuttings that may or may not contain a knot.

Differentiating material based on the features and defined cutting area sizes would require using a positive description (Lycken, 2006a), and could provide a means to sort lower grades into industry-relevant groups. Breinig et al. (2015) sorted knotty Scots pine lumber into 15 appearance classes based on knot size and type, pith, and grain orientation to produce groups with greater visual similarity among boards within classes. The authors propose, as have Donovan and Nicholls (2003) and Nicholls and Barber (2010), that this approach to sorting could increase the overall value of the resource by providing greater flexibility to specifying and selecting the appearance of timber surfaces. As demonstrated by the above studies, this approach may be viable for those resources that produce boards with relatively consistent appearances, such as conifers with consistent knot sizes. However, for resources that produce a range of knot sizes and other characteristics within the board, this approach would not be appropriate.

5.4.2 Machine Grading

Recent developments in computer vision have demonstrated that surface and geometric characteristics can reliably be detected and classified using a range of sensors, image types, and processing approaches. These high-resolution digitized board maps can then be used to grade lumber, either to existing standards or by creating a classification model based on a desirable set of properties (Conners et al., 1997b, Conners et al., 1997a, Hashima et al., 2015, Kline et al., 1997, Lu et al., 1997, Olofsson et al., 2019, Xiao, 1998). Automatic grading systems have reduced the need for grading rules that are easy to understand and implement.

Machine grading of hardwood can be done according to established grading standards, or differences between boards can be determined using statistical procedures, which can be ‘fine-tuned’ for unique customer orders and available resources (Olofsson et al., 2019). Combined with feature detection and optimization software, other systems could be

designed that can sort according to a different set of priorities and models. For example, under a conditional model, the limits or requirements for certain attributes would be conditional depending on the presence of other features. In a dynamic model, grading rules could change depending on available resources, market cycles, and customer requirements. Any number of rules can be designed around different models expanding the way wood products are described and distributed. However, regardless of which system is agreed upon, accuracy in measuring and classification is of fundamental importance.

Most work on the subject has been rule-based; that is, computer programs have been designed to grade lumber according to the rules set out in grading standards, such as those of the NHLA. As early as 1970 (Hallock and Bugrin, 1970, Hallock and Galiger, 1971), programs were developed to determine lumber grade based on the distribution of 22 growth characteristics. The system was accurate and fast but limited to a single face or side of boards. Later in 1994 (Klinkachorn et al., 1994) developed a method to examine boards for the best possible cutting area combinations, which was an attempt to optimize lumber grade. Kline et al. (2003) used multiple-sensor scanner system to achieve 63 percent on-grade accuracy on a board-by-board basis. These results were at least 31 percent more accurate than human line graders. Gazo et al. (2018) used a commercially available Microtec Goldeneye 300 Multi-Sensor Quality Scanner to obtain an average of 92.2 percent on-grade accuracy for 9 species of hardwood.

In 1998 the Ultimate Grading and Remanufacturing System (UGRS) was developed and released (Moody, 1998a). At the time, it was the most advanced computer-based approach to both grading and remanufacturing (process low-value boards into higher-value components) to increase value (Moody, 1998a). The Ultimate Grading and Remanufacturing System (UGRS) grades hardwood lumber to NHLA rules. It can be used as a training and research tool. It uses digital maps of 10 characteristics on both sides of the board to determine cutting areas and the corresponding NHLA grade (Moody, 1998a, Moody, 1998b). UGRS operates by determining the maximum amount of surface measure (SM) in the maximum allowable cutting areas that meet the highest possible grade requirements (highest value grade). Using the largest cutting area, UGRS tests against the requirements for the highest grade (Moody, 1998a). If the requirements are not met, it then considers the next lower

grade. The requirements for each grade can be customized to determine cutting areas sizes required for different grades. It is widely believed that UGRS grades lumber with 100 percent accuracy (Thomas, 2017).

Because of their simplicity and flexibility, statistics-based models have been explored to automatically grade hardwood lumber. Although such models may be less accurate, simpler models are often faster and are capable of greater flexibility for special grades, character-marked lumber, and short lumber (Boden et al., 2005). Boden et al. (2005) developed a discriminate model using 8 variables of knot distribution and one describing knot size that achieved an overall accuracy of 73.4 percent by comparison to the true NHLA grade.

Other pattern recognition, classification, and machine learning techniques have also been used to automatically grade lumber. For example, Thomas (2017) achieved an overall on-grade accuracy of 80.2 percent using an artificial neural network (ANN) machine learning model. This model used knot, decay, holes, and split distribution variables, part yield, and part size to create the ANN grading model. The part yield and average part size were determined by matching clear areas to a list of different sized parts. This measure proved to be one of the most important indicators of NHLA grade in this model, as would be expected given that the grade standard is developed around this concept. Despite this seemingly low grading accuracy, the overall market value of the sample boards was less than 1 percent below that of the certified graded lumber. The objectives of that study was to develop classification models with greater simplicity, flexibility, and speed to grade lumber using digitized board data according to NHLA standard rules (i.e. clear cuttings).

Although these models produce acceptable results, they do not provide the ability to supply greater descriptive detail concerning the actual distribution of the cutting sizes or cuttings that contain a specific combination of characteristics.

There have been other attempts to use multivariate models to sort and predict board classes using machine learning techniques. Breinig et al. (2015), first used unsupervised explorative clustering analysis (Hierarchical-agglomerative clustering) to reveal naturally occurring classes of Norway spruce boards with consistent visual appearance based on knot variables such as number of knots, number of different types of knots, minimum and maximum knot

size, and relative area of different types of knots. Secondly, the authors performed a discriminant analysis to determine which variables most effectively discriminated the groups from one another. The resulting appearance clusters were compared to the results of manual sorting. It was found that the clustering procedure produced groups with a good approximation of visual similarity. However, the variables found from the discriminant analysis provided low accuracy to predict visual classes consistent with human sorting.

A study by Olofsson et al. (2019) used a partial least squares (PLS) regression to sort boards into quality classes. Unlike the previous study, boards were divided into 3 sections and each section was manually assigned a quality class, therefore, increasing the resolution at which the characteristics of a board could be described. The PLS analysis used 22 variables describing 6 defect types on 3 sides for 9 zones (board sections), for a total of 3564 combinations. Grading in this system is based on a single PLS outcome of a probability that a plank belongs to a class of boards. The threshold at which the system operates becomes a decision between the sawmill and the customer. The PLS models from this study (using a threshold of 0.56) obtained an 83 percent overall correct grading accuracy, which compares well to other studies that have used PLS models (Berglund et al., 2014, Lycken and Oja, 2006).

The above examples highlight research in applying rule-based automatic grading systems to hardwood lumber (Berglund et al., 2014). These systems are efficient and more accurate than manual grading. The rule-based approach sets discrete levels of allowed characteristics; when any rule is violated, the board is downgraded to a lower grade (presumably lower values are assigned to these boards). This results in downgraded and undervalued boards that customers might accept given that they contain most of what the customer subjectively desires (Berglund et al., 2014). In many cases, the customer desires some level of subjectivity and is willing to accept a few boards with defects larger than the grade allows if there are also a few boards of a higher grade in the order (Berglund et al., 2014). Manual grading does accomplish this because grading standards are “subjectively” applied by human graders (Berglund et al., 2014). It also results in the customer receiving unwanted boards that happen to meet the grade requirements (Berglund et al., 2014).

When customers desire a special sort or combination of characteristics, due to the complexity of the rules, re-configuring rule-based automatic grading (RBAG) systems take time and investment (Berglund et al., 2014). The holistic-subjective automatic grading (HSAG) approach is an attempt to combine the advantages of both manual and rule-based automatic grading (Berglund et al., 2014). Such an approach would take into account many variables (multivariate) of the board to predict the grade. Berglund et al. (2014) proposed a system where HSAG replaced RBAG at the end of lumber production to determine board grade based on the size and frequency of 3 types of knots. The model used a partial least squares (PLS) approach against lumber that had been graded according to a set of customer preferences. In this study, the preferences, or custom graded lumber is used to calibrate the model. It is a time-consuming endeavor to create each custom grade for different customer requirements. Therefore, the objective of that study was to develop a method to replace the calibration procedure and to investigate if such an approach would be used to increase profitability at the sawmill and satisfaction for the customer. The result was a model with 76-87 percent accuracy as compared to the manual grading procedure, however, the in-place rule-based system graded boards 64 percent accurately.

These studies point out the capacity to computerize the grading of lumber by packaging high-resolution digitized board-scale knot (and other characteristics) information into existing low-resolution lumber grading standards or perceived visually consistent groups of boards. Description of the actual properties at the board-scale within the group of lumber is lost within the overall grade or sort description. Aside from the Thomas (2017) study, the actual properties, such as the areas or segments of boards that match design requirements, are not used during the cluster or sorting procedures.

The classification models used by Breinig et al. (2015) are based on board-scale statistical distribution parameters, such as the mean, median, minimum, and maximum knot size. This approach is appropriate for use on resources that produce boards with consistently sized knots from different positions in the log and tree. Indeed, the classification scheme in that study treated boards separately according to the “log-sector classes”. This approach may not apply to short-rotation hardwoods, which are likely to produce boards containing a greater diversity of knot size and type within individual boards.

Another shortfall of the above examples is the lack of flexibility. As pointed out by the researchers mentioned, validation of the cluster and sorting solution must be performed manually, either by the customer or by a grading expert to ensure that it meets the grade standard or the expectation of the consumer. This can be a time-consuming task given that most machine learning techniques require large training datasets. Secondly, each new grade of lumber requires both sawmill and customer involvement to calibrate the combination of different desirable characteristics. A possible solution would be to develop customer-adapted grading by developing classification models directly from customer judgment of images (Olofsson et al., 2019). This would reduce the investment involved in developing the classification models but would not necessarily improve the resolution at which the actual material properties, in terms of the proportion of a board or the distribution and frequency of different sizes of pieces that meet particular requirements.

It follows then, a way to sort lumber that is flexible and provides the end-user with greater detail concerning the distribution of areas of boards desired by the customer may increase the use of a higher proportion of the hardwood resource. In this thesis, the area of interest in boards is defined as either a segment (sections of boards) or a cutting area. Ideally, such a system would group the boards that contain the highest proportion of pieces required for different applications, providing a means of delivering the best-suited lumber to different requirements. Such a sorting approach would need to be able to adapt to defined parameters that describe the allowable set of characteristics contained with the desired pieces of material. As in the previous chapter, a set of limits that define the size and appearance of acceptable characteristics would be created. These limits would then be used to define areas within a board that contains the characteristics. From this, sorting would then group boards with similar levels or sizes of the different types of areas recoverable from boards. As this method is based on the actual recoverable pieces, the end-user could more accurately predict utilization and producers could more accurately describe the distribution of the different types of material available from the groups.

5.5 Materials and Methods

5.5.1 Datasets and Terms

This chapter uses two datasets developed from Chapter 3. The first dataset is from 295 manually validated boards. It represents the "ground truth", or best estimate of knot distribution, size, and appearance. As discussed, this dataset may not perfectly represent the knot size, but it should be considered the best estimate of the knot parameters available. It is referred to as the validated dataset or validated boards. The second is the automatic dataset. It is the result of using the automatic detection routine developed in Chapter 3 on the same set of boards.

As in other chapters, two ways to process boards are explored. The first and simplest method involves chopping boards into segments—referred to here as the segmenting method, which produces board segments[29]. This method is appropriate in the Australian context given that boards are produced and supplied in standard widths and lengths. The other method is more common in North America where parts or pieces are removed from boards by a combination of ripping and chopping operations from areas of boards that do not contain unallowable characteristics. This process is focused on cutting areas.

5.5.2 Board-scale Knot Distribution Patterns

The knot distribution patterns were calculated using the validated dataset produced in 3. Briefly, this dataset contained 1040 knots for *E. globulus* and 1198 knots for *E. nitens* from 159 and 136 board surfaces, respectively. The knots were classified by size and appearance type as defined in Table 3-3 and Table 3-4. The number of knots per board was determined and the Simpson Index (D) for both size and color classes was calculated using Equation 5-2. The Simpson Index is a measure of diversity that takes into account the number of species (in this case, knot size and appearance classes) and the relative abundance of knots in each class (Simpson, 1949). A value of 1 indicates high diversity and a high probability that any two knots selected will belong to different knot classes. It is used here to describe the variation in knot sizes and appearance types found within boards. It was determined that this analysis would

[29] Recall that segments are an extension of the cutting area concept where the segment is the same width as the board.

not be meaningful on the automatic dataset because of the low rate of correct size and appearance type classification. The calculation is:

$$D = 1 - \left(\frac{\sum n(n-1)}{N(N-1)}\right)$$

Equation 5-2. The Simpson Index

where

n is the total number of knots in each class within a board, and

N is the total number of knots in all classes within a board.

The range of the minimum bounding box area for each knot on each board was also examined by plotting the mean box size along with the areas of each knot for each board. This illustrated how the knot distribution varied across individual boards within the sample set.

5.5.3 Board Classification

5.5.3.1 Board Segments

One of the main objectives of this chapter was to develop a method to meaningfully cluster boards based on the proportion of a board containing a defined limit of knot sizes and appearance types and to create a classifier that groups boards according to the cluster solution. This concept is explored using both board segments and cutting areas. The workflow is shown in Figure 5-6.

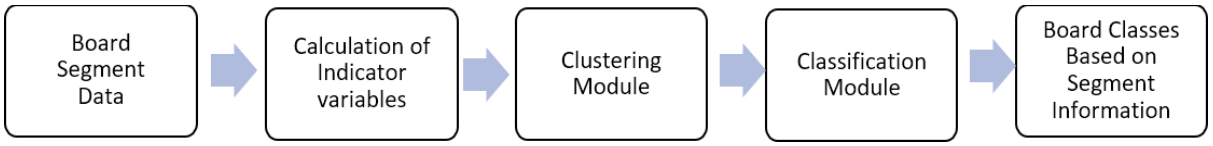


Figure 5-6. Flow chart of the process used to classify boards using the segmenting method.

The proportion of each board belonging to a segment class was calculated for each of the width classes of boards using methods presented in 4.4.4.1 using the segmenting definitions presented in Table 4-1 and Table 4-2. In this chapter, the proportion of each board in the different segments was compared between the validated dataset and the automatic dataset on a board-by-board basis. This was performed to determine the sensitivity of the segmenting

approach to both the false negative and the classification of the knot size and the appearance of the automatic detection routine.

Broad-scale information was used to create a feature vector for each board based on the calculated indicator variables. This required testing many possible combinations of variables. The best results used the indicator variables calculated according to Table 5-5. These are referred to as indicator variables because they indicate information about the distribution of segment types across board surfaces. These variables were used in an exploratory agglomerative hierarchical clustering analysis to map each board to a class (see 0) using the `pdist and linkage` functions in MATLAB. A dendrogram was produced to visually assess the results of the cluster solution. The resulting cluster solution used a Ward algorithm to compute the distances between clusters. The goal was to find a clustering solution that faithfully represented the dissimilarities in the boards. Dissimilarity (c) was calculated using the cophenetic correlation coefficient function `cophenet` in MATLAB. Because the indicator variables are continuous and correlated, values of c were never higher than 0.5. The best cluster solution from the validation dataset used 5 clusters for both species.

Table 5-5. Indicator variables used for the cluster analysis in the board segmenting study.

Variable	Description
Number of knots per meter	Number of knots normalized by length
Mean segment length	The mean length of board segments in all types over the minium-1000 mm or 2000 mm for clear segments; 500 mm for all others
Number of segments	This is the number of total pieces per board over the minimum length
Number of clear segments	The number of clear segments over 1000 mm or 2000 mm per board
Number of type 1 segments	The number of type 1 segments per board over 500 mm
Number of type 2 segments	The number of type 2 segments per board over 500 mm
Number of type 3 segments	The number of type 3 segments per board over 500 mm
Number of type 4 segments	The number of type 4 segments per board over 500 mm
Percent of the clear segment	The percentage of the board that is in clear segments over 1000 mm
Percent type 1 segment	The percentage of the board that is in type 1 segments
Percent type 2 segment	The percentage of the board that is in type 2 segments
Percent type 3 segment	The percentage of the board that is in type 3 segments
Percent type 4 segment	The percentage of the board that is in type 4 segments
Percent above minimum	The percentage of the board in any segment type over the minimum

Once the clusters were determined, a classification model was developed using the classification app in MATLAB. This app can be used to explore various supervised machine learning models, such as Decision trees, Support Vector Machines (SVM), and Nearest Neighborhood classifiers. The goal was to determine the model with the highest accuracy of classifying boards according to the cluster solution. For both species, an SVM model was selected that provided 97.5 percent and 94.1 percent accuracy for *E. globulus* and *E. nitens*, respectively. The classification model was then used to re-classify each board into board classes. Using the resulting classification of each board, the profile of each class in terms of

knot frequency and proportion of different segment types was calculated and compared against one another.

In other classification studies (Thomas, 2017), samples would be divided; one set used to develop the classification model, and the other used to validate the model results. This is common practice for most classification problems. However, because of the limited sample set, the same boards were used to train and test the classification models presented here.

5.5.3.2 Cutting Area

Cutting areas were determined for each board in the datasets for each species. The software application Ultimate Grading and Remanufacturing System developed by the United States Department of Agriculture (Moody, 1998b) was used to locate the cutting areas. The process used knot data, cutting area definitions, and UGRS rules to describe the cutting area distribution at the board-scale. The workflow is shown in Figure 5-7. This was done by first formatting knot distribution data (validated and automatic datasets) to be read into UGRS. The grading rules concerning the size and number of cuttings were modified according to Table 9-1. UGRS output was then reformatted into a spreadsheet containing the location and size of each cutting area found for each board.

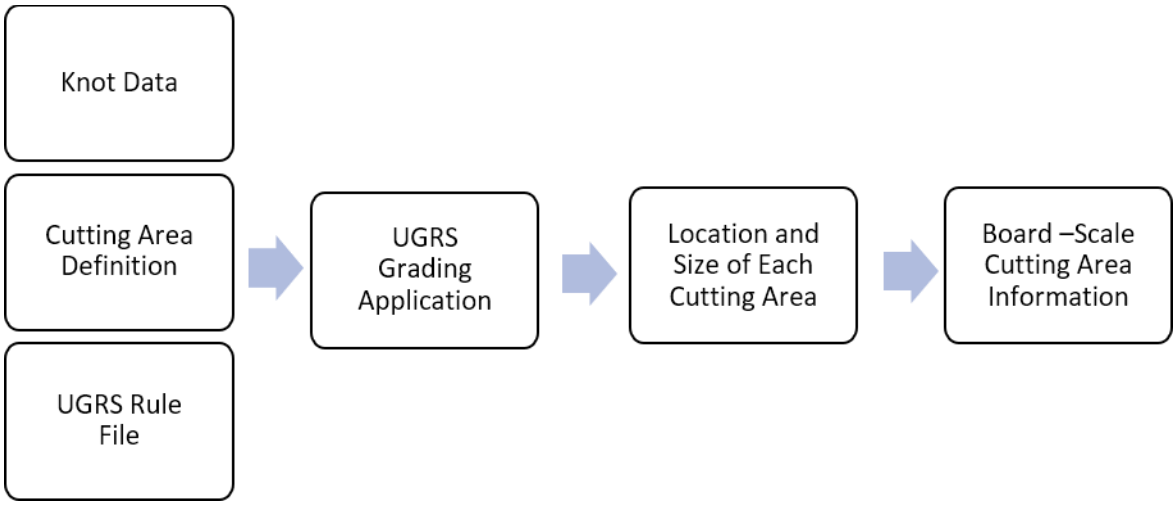


Figure 5-7. Flow chart of the process used to find cutting areas in boards.

The above process was repeated to determine the size and distribution of cutting areas that could contain knots of specific sizes and types using definitions presented in Table 4-3. The influence of knot size and type on cutting areas was tested in three ways. The first method

examined cutting areas from clear wood only; the second method allowed small light and dark knots; and the third method allowed larger light, dark, and black knots in cuttings. The fourth method tested the influence of both lower and upper limits on the knot size. As suggested in 4.3.2, this simulates the selection of different knot sizes and types like the way a user would operate a slider interface to select different characteristics.

Cutting areas were also determined for #1C and #3AC NHLA graded lumber using UGRS with the same system rules used to produce clear cuttings areas above. This was accomplished by using boards of this grade from the red oak database (Gatchell et al., 1997). Because boards in this database contain information about all the characteristics for both sides of boards, cutting areas were determined using the full suite of characteristics. To be comparable to the boards in this study, cuttings wider than 140 mm (the widest board in this study) were removed from the following analysis.

The second method of grouping boards was based on the concept of cutting areas. There are at least two methods that could be used for this approach. One method could use knot distribution data directly (i.e. statistical information describing the distribution and dispersion of knots and other characteristics) as used in other studies (Boden et al., 2005). The other method would be similar to the segmenting approach where board-scale indicator variables based on the distribution of cutting area sizes within boards are calculated and used to find clusters and to develop classification models. In this case, the variables would describe the cuttings areas available from boards. As above, board clusters were derived using the feature vector information, and a model was trained to classify the boards into the cluster solution obtained. The samples were not divided into training and validation sets because of the limited number of boards available for the study.

The process that used board-scale cutting area information to determine board classes is shown in Figure 5-8. Based on the cluster solution (see above), a classification model was developed that classified boards into pre-determined clusters. This was an exploratory process; the best results used the indicator variables listed in Table 5-6. The best results were obtained using 4 clusters for both species. For definition 1, a k-nearest neighbor (k-NN)[30]

[30] The k was set to 4 in the k-NN classification modele used in this work.

classification model with 100 percent accuracy was the best model for *E. globulus* and a k-NN classification model with 99 percent accuracy was used for *E. nitens*. These models were then used to re-classify each board into one of 4 board classes.

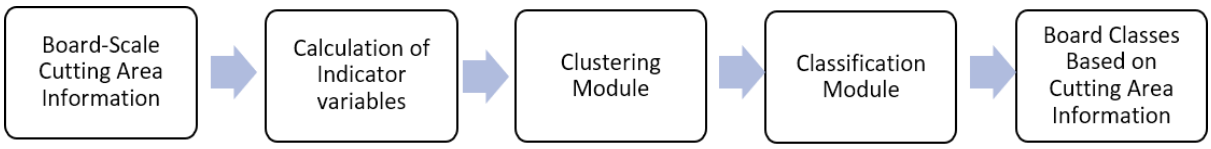


Figure 5-8. Flow chart used to determine board classes using cutting area information.

Table 5-6. Indicator variables used for the cluster analysis in the cutting area study.

Variable	Description
Board Area	The total area of the board
Cutting area	The total area of all cuttings longer than 250 mm
Number of cuttings	Total number of cuttings longer than 250 mm
Max size	The area of the largest cutting
Min size	The area of the smallest cutting
Mean size	The mean size of all cuttings longer than 250 mm
The proportion of board in cutting areas	The total area of the board divided by the total area of cutting areas
Cutting density	Total board area divided by the number of cuttings longer than 250 mm

Cutting areas were classed into bins in 15 mm width and 250 mm length intervals. The distribution of cutting area sizes was explored using heatmaps. Heatmaps are like histograms in that the frequency of 2-dimensional information can be displayed and understood. In this case, one dimension is the length of the cutting area interval and the other is the width interval. A color bar is used to indicate the relative abundance of cutting areas in each bin size class.

The proportion of cutting areas produced by each bin was calculated for each board class. The proportion of cutting areas in each bin was calculated as the contribution of the average cutting area for each bin to the overall total cutting area. For example, given a total cutting

area 1,000,000 mm^2 and given that 10 cuttings in the bin class of 35 mm to 50 mm by 1000 mm to 1250 mm, the cutting area would be calculated as:

$$Cutting\ area\ percent = \frac{number\ of\ cuttings * (mean\ cutting\ width) * (mean\ cutting\ length)}{total\ area} * 100$$

where:

$$Cutting\ area\ percent\ = \frac{10 * ((35 + 50)/2) * ((1000 + 1250)/2)}{1000000} * 100$$

=47.8%

It was observed that the distribution of this variable was highly non-normal, therefore no statistical tests were performed to determine differences in mean or median values between species or board classes.

5.5.4 NHLA Grades

UGRS assigned an NHLA grade to each board using the modified rules outlined in Table 9-1. This process was repeated for the same boards from the automatic dataset. A comparison was made for each board to determine how well the results of the NHLA grade from the automatic dataset agreed with the validation set. For each board, the number of cuttings in each class in both datasets were compared to determine missed or extra cuttings found in the automatic dataset. This was done to understand the sensitivity in cutting area production between the automatic detection performance and validation dataset.

Based on the grade and the current value published on August 23, 2019, Hardwood Market Report (HMR, 2019) of two comparable species the approximate value of 1 m^2 was calculated for each species. The comparable species were green (not kiln dried) 5/4 Northern Red Oak and Northern Birch. These species were chosen because they are both commercially available in #3A and are considered general-purpose hardwoods suited to several applications. The current sawmill value is shown in Table 5-7.

Table 5-7. Current sawmill value (USD) of two comparable North American hardwoods (HMR, 2019).

	NHLA Grade			
Species	Select	#1C	#2A	#3A
Red Oak	880	630	545	440
Birch	1175	760	485	335

5.6 Results

5.6.1 Board-scale Knot Distribution Patterns

5.6.1.1 Validated Boards

For the validated boards, the number of knots per board varied greatly for both species (Figure 5-9). However, a significant proportion of boards had fewer than 10 knots (Figure 5-9). The pattern between the species varied slightly; a higher proportion of *E. globulus* boards had fewer than 10 knots than for *E. nitens*. The Simpson index for knot size classes ranged from 0 to 1, with a significant proportion of boards from both species above 0.6 (Figure 5-10). This finding agrees with the appearance of panels presented in Figure 4-6 and Figure 4-7, which indicate a wide range of knot sizes and types in the boards. Few boards had a Simpson index above 0.9. For *E. globulus*, there were 16 boards where the Simpson index could not be calculated because there was only one knot of one type present (one knot in total). Additionally, for the same species, there were 16 boards where the Simpson index was zero, indicating more than one knot of a single type was present (one type in total). Both conditions involved the full range of knot size classes. For *E. nitens*, there were 7 boards with a Simpson index of zero and 4 with an incalculable Simpson index. Overall, the values indicate that a high proportion of boards were both rich and diverse in knot size classes and that there were few boards containing knots in a single knot size class. This pattern was approximately the same for the Simpson index of knot color class (Figure 5-11), indicating few boards contained a single type of knot. However, there were fewer values above 0.8. Because the knot types were developed to represent the industry parlance of live and dead knots, it can be concluded that few boards contained only live or only dead knots.

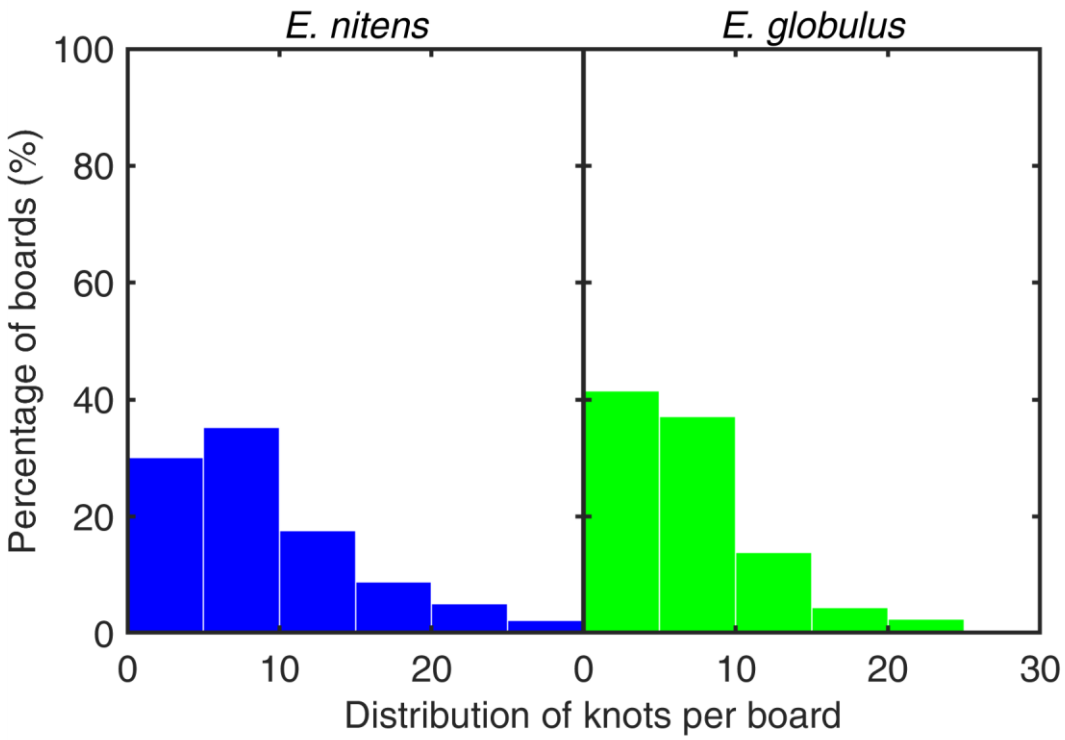


Figure 5-9. The number of knots per board for both species for the validation dataset. Note: the maximum x-axis value is 30 for E. nitens.

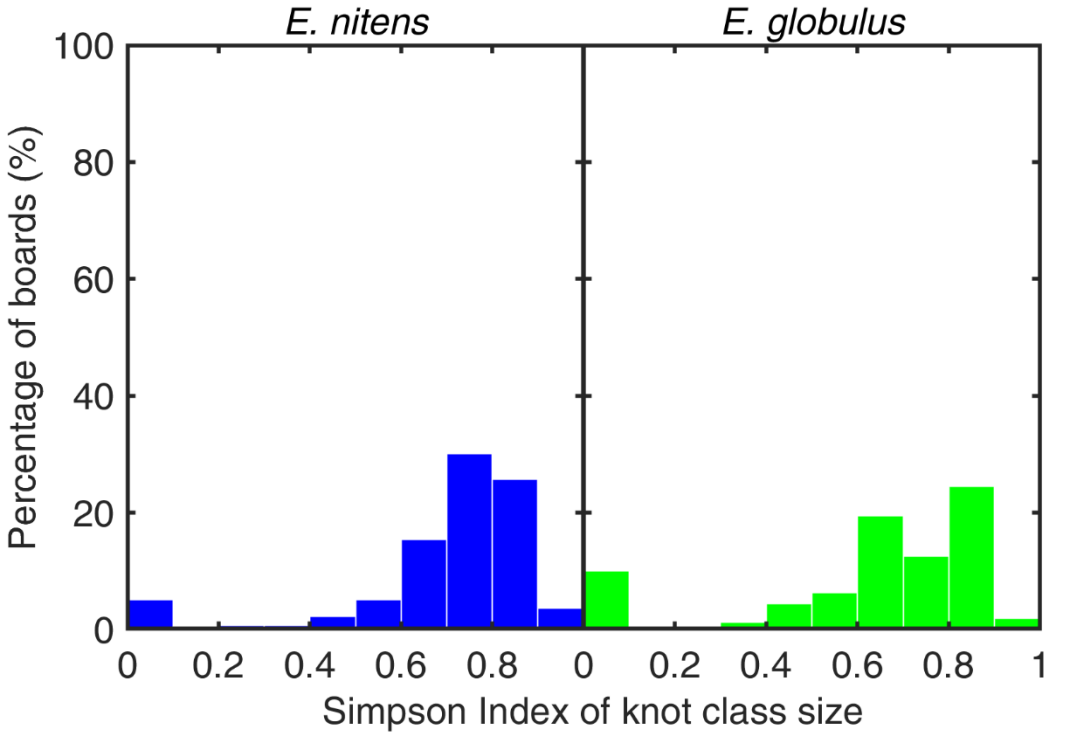


Figure 5-10. Simpson Index for knot size classes for both species for the validation dataset. Note: the maximum x-axis value is 1 for E. nitens.

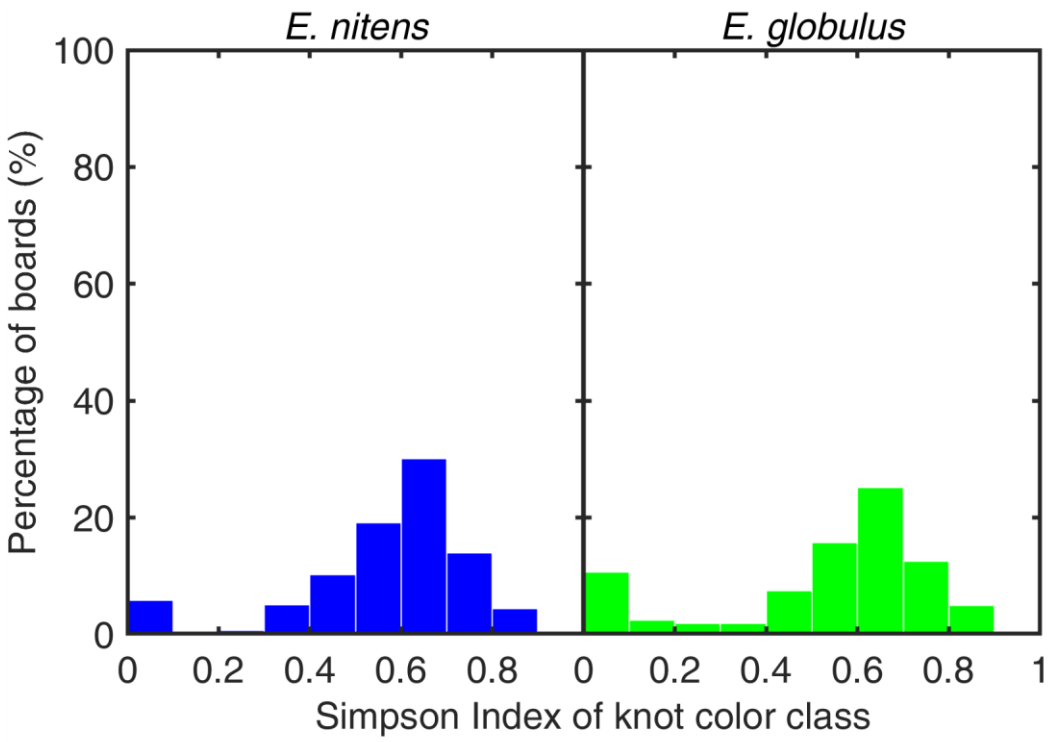


Figure 5-11. Simpson index for knot color class for both species for the validation dataset. Note: the maximum x-axis value is 1 for E. nitens.

The knot size range varied by the average knot size at the board-scale for both species (Figure 5-12 and Figure 5-13). In general, the lower the average knot area, the lower the range of knot sizes found on any individual board. The plots also indicate that most boards contained a wide range of knots.

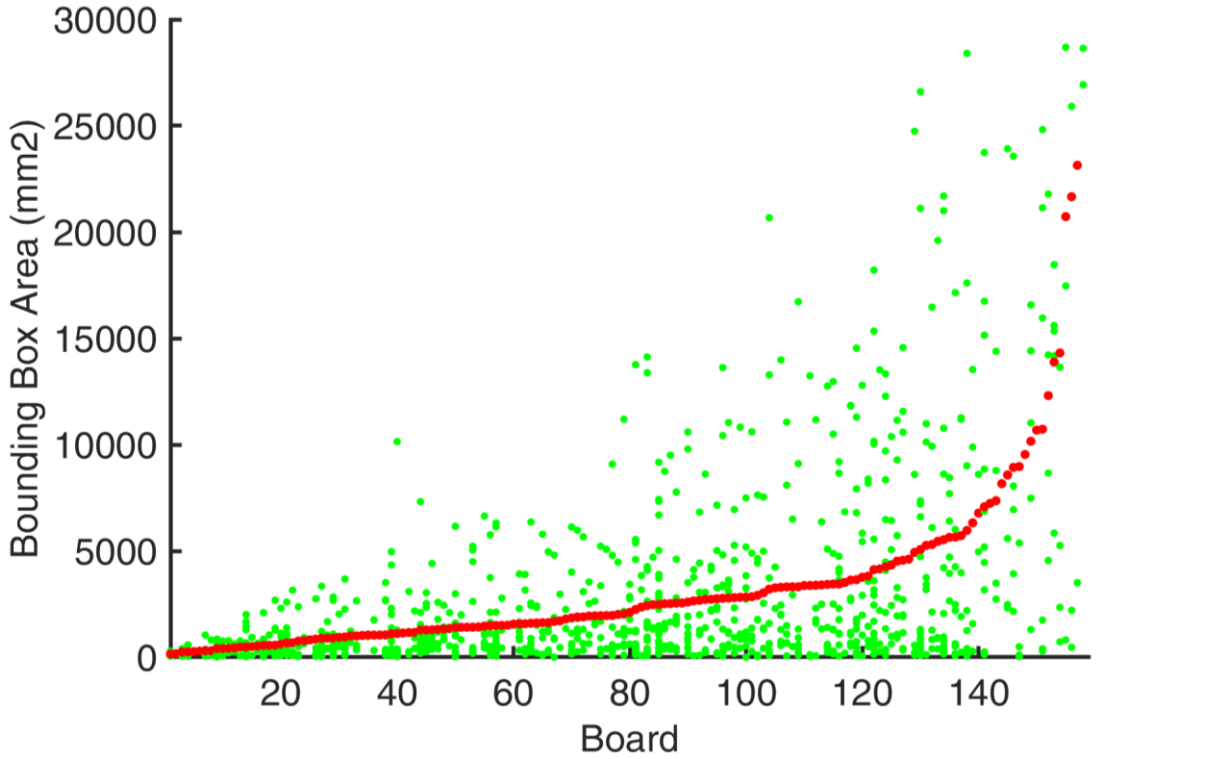


Figure 5-12. Scatter plot of minimum bounding box area for each knot for each E. globulus board in green. Red indicates the mean knot size for each board. Note: there were 9 knots above 30,000 mm².

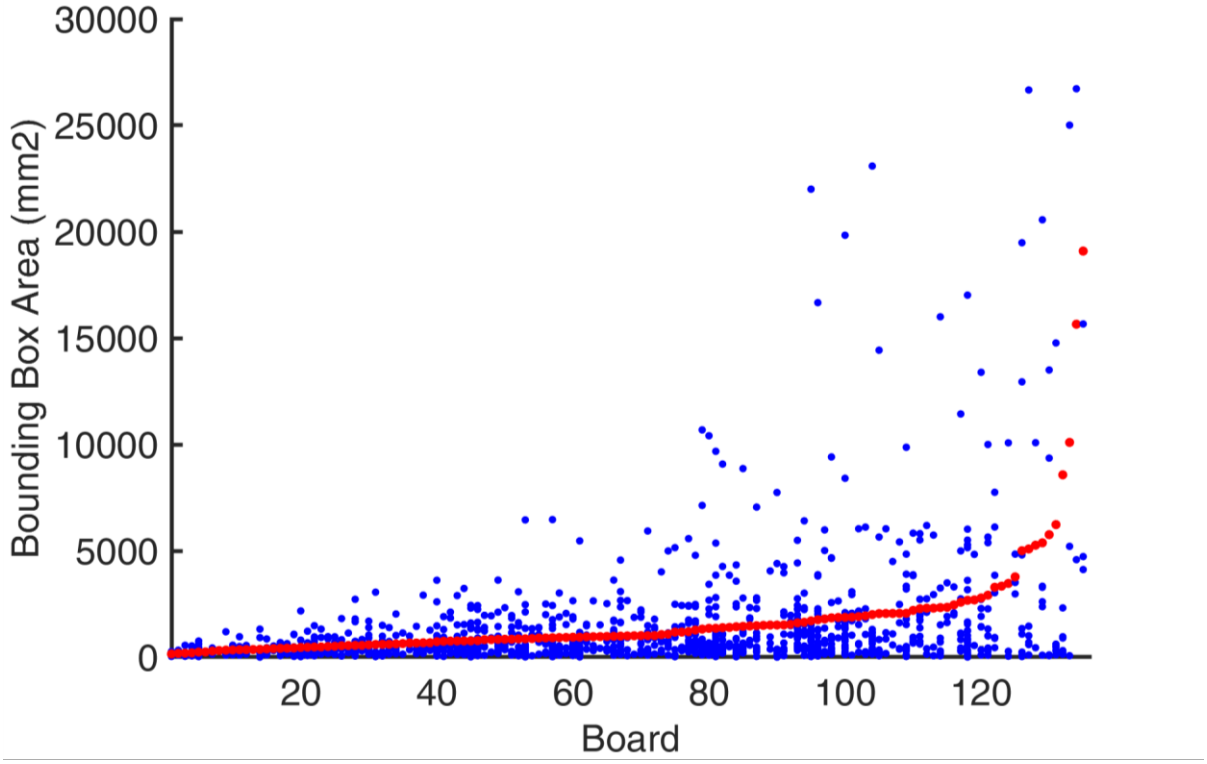


Figure 5-13. Scatter plot of minimum bounding box area for each knot for each E. nitens board in blue. Red indicates the mean knot size for each board. Note: there were 3 knots above 30,000 mm².

5.6.2 Board Segments

5.6.2.1.1 Validated Boards

This section presents the results of the first set of definitions for board segment types. It is intended to show how segments are distributed across boards and vary between the two species examined. For brevity, the segment figures for the second set of definitions are not presented. Figure 5-14 shows the distribution of the proportion of boards containing a clear segment over 1000 mm. In this figure, there are two y-axes. The left y-axis indicates the percentage of boards in each of the bins indicated by the x-axis. The right y-axis indicates the running combined proportion of boards in each of the bins. For example, there is about 5 percent of the boards with more than 90 percent in clear segments for *E. nitens*. The overall pattern indicated that there was a higher proportion of *E. globulus* board surfaces with more clear segments than for *E. nitens*. Approximately 20 percent of the *E. globulus* boards contained over 90 percent clear segments, while only about 8 percent of *E. nitens* boards contained this level of clear segments. Also, approximately 60 percent of the *E. globulus* boards contained at least 50 percent clear segments, while this pattern held for only about 42 percent of the *E. nitens* boards. This pattern agrees with the conclusion from Chapter 3 that knot frequency is higher for *E. nitens*.

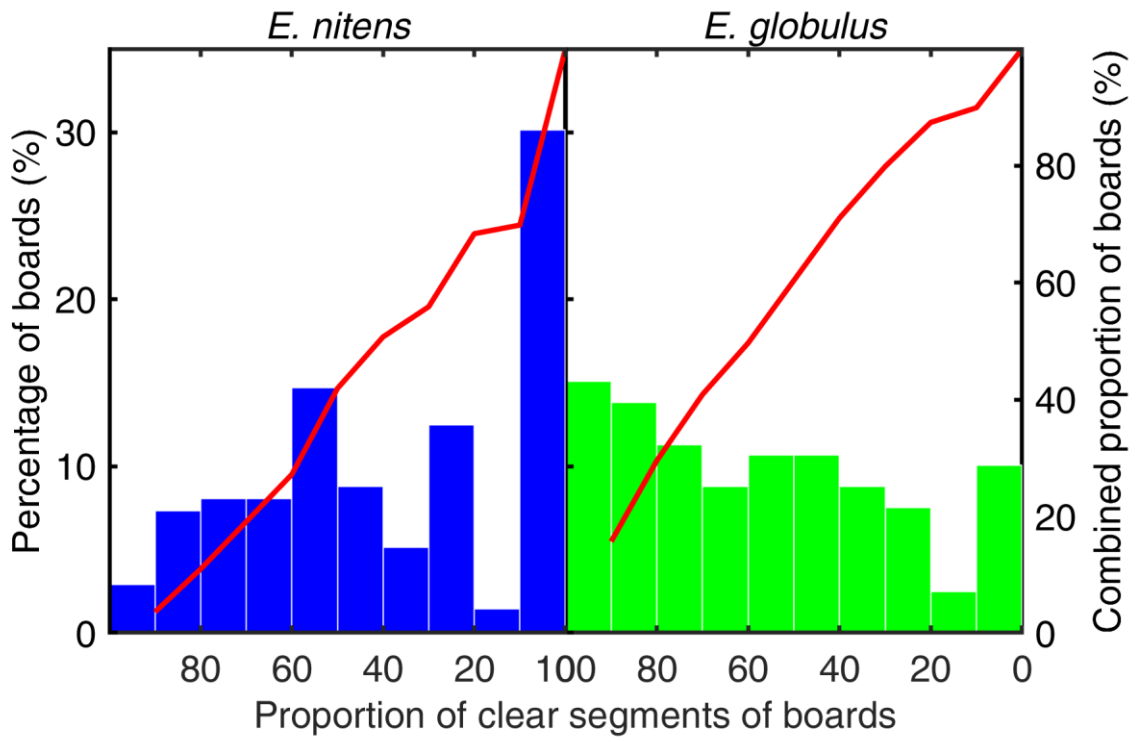


Figure 5-14. Distribution of the proportion of boards with clear segments greater than 1000 mm for both species.

The overall distribution of segment types is given in Figure 4-8. The distribution of different segments is explored according to board width classes here. As indicated by the distribution of clear segments across the board width classes, the highest proportion and longest clear segments occurred in the 90 mm width class (Figure 5-15). The shortest segments and the lowest proportion occurred in the 140 mm width class. Overall, *E. nitens* showed the lowest proportion of clear segments, however, the species showed slightly higher combined proportions of the other segment types (Figure 5-16, Figure 5-17, Figure 5-18, Figure 5-19). In general, there was a higher proportion of type 4 segments longer than 1000 mm than the other knotty segment types. Figure 5-20 shows examples of how the distribution of segment types varies across boards. Some boards have very long segments, while others have more, but shorter segments. Colored lines are used to indicate the section types within the board's surface. Black indicates clear segments, red indicates a type 1 segment, green indicates a type 2 segment, blue indicates a type 3 segment and yellow indicates a type 4 segment. Knots are boxed with the same color codes.

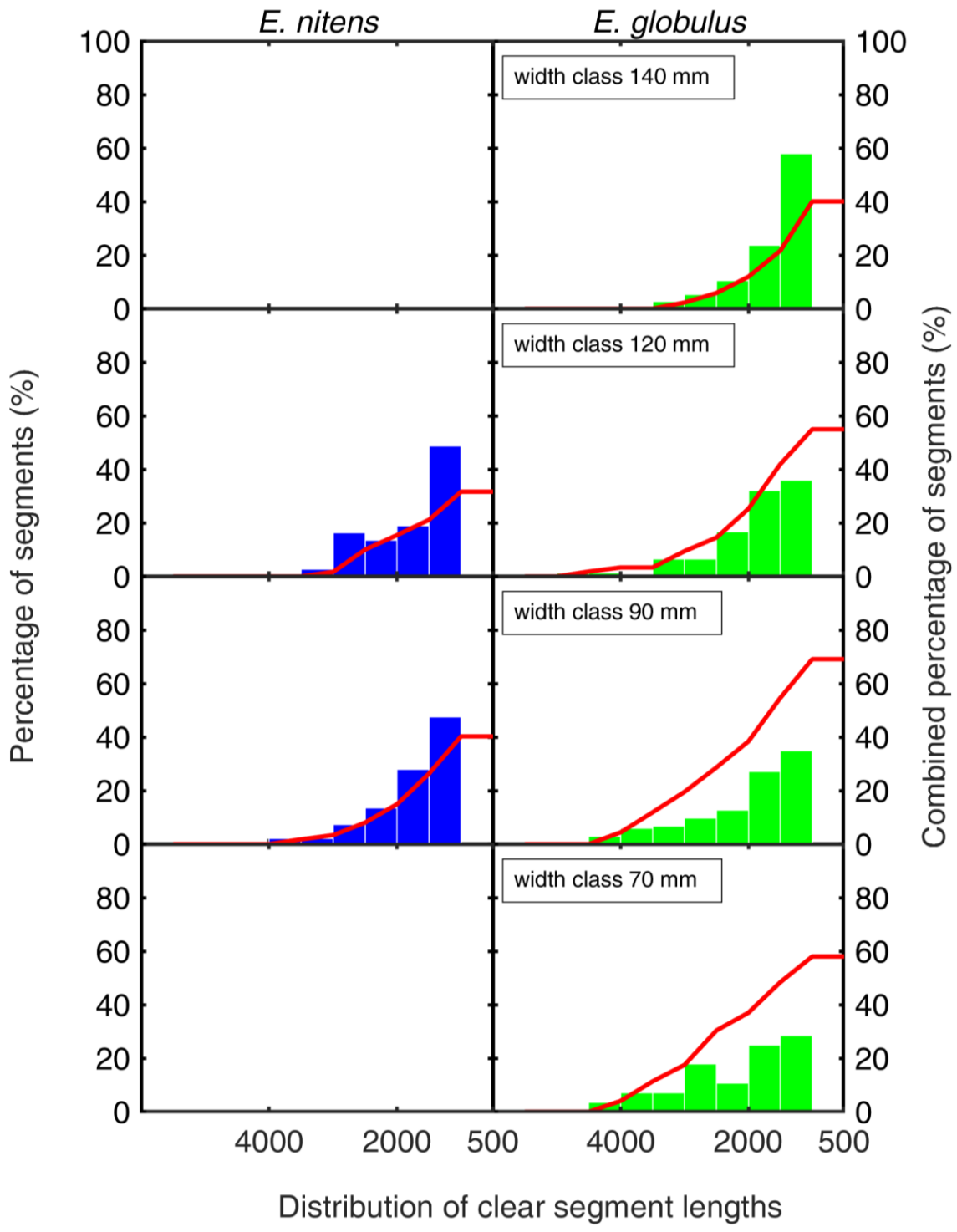


Figure 5-15. Distribution of clear segments across the width classes of boards. Note: the maximum x-axis value is 6000 mm for both species.

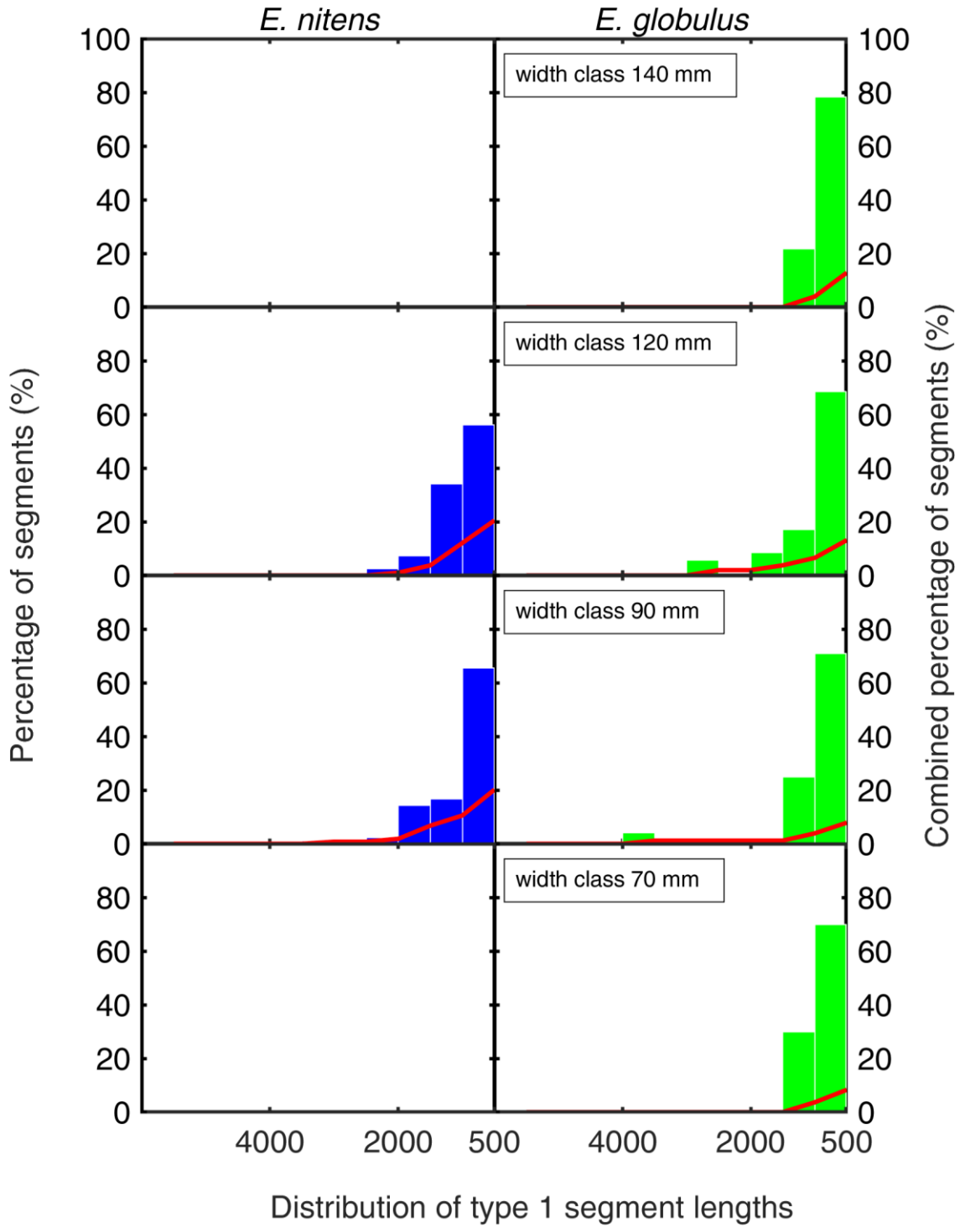


Figure 5-16. Distribution of type 1 segments across the width classes of boards. Segment lengths are in mm.

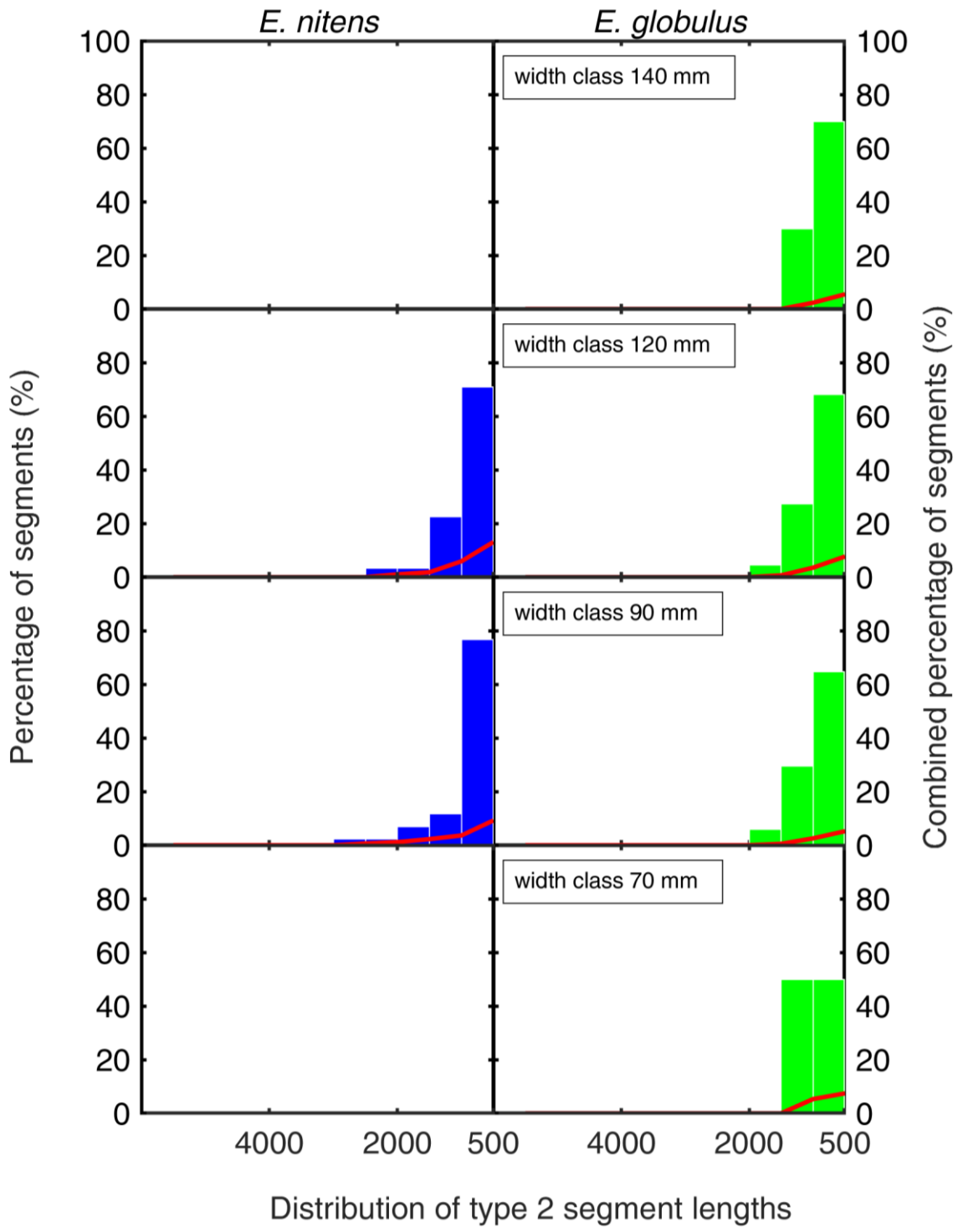


Figure 5-17. Distribution of type 2 segments across the width classes of boards. Segment lengths are in mm.

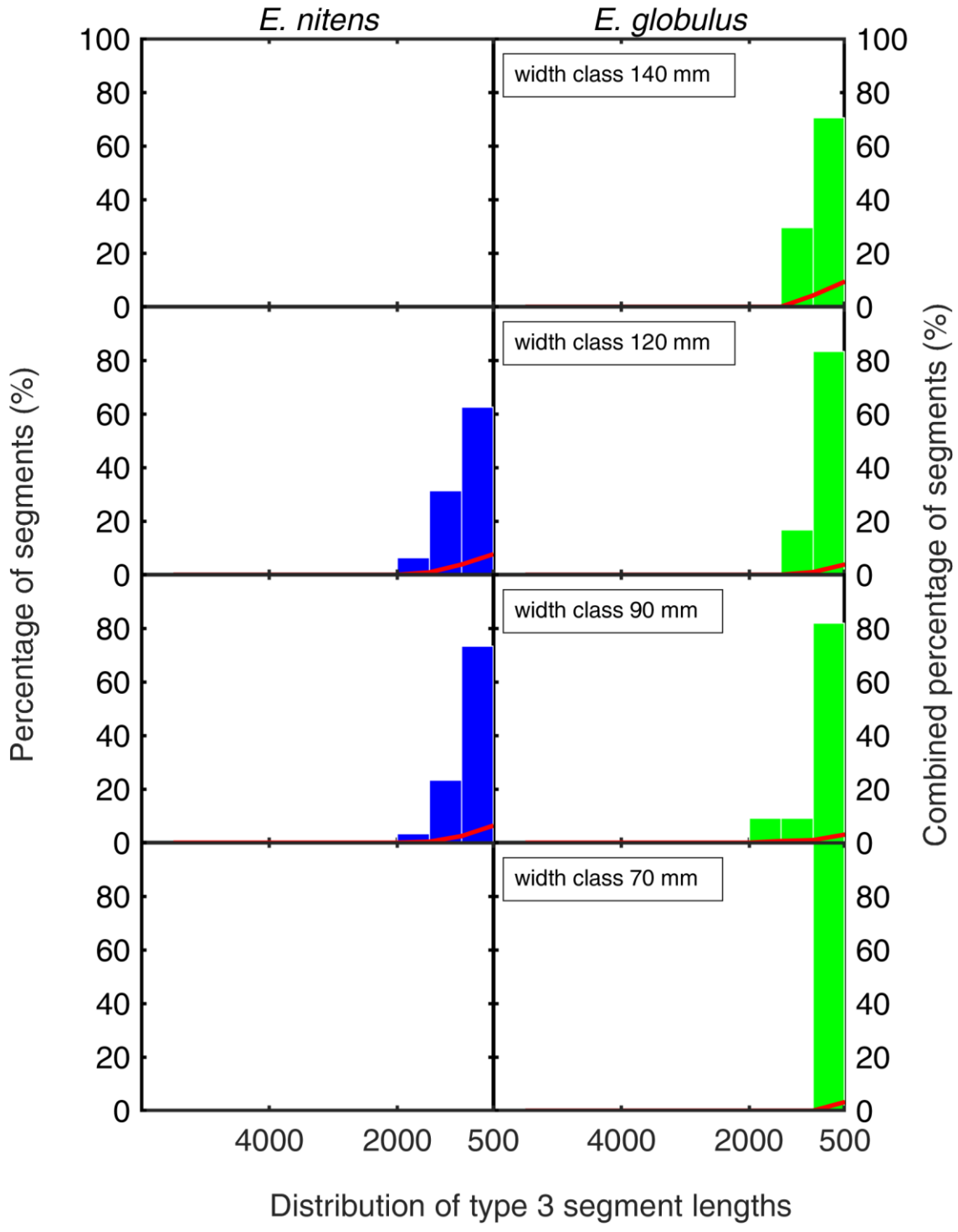


Figure 5-18. Distribution of type 3 segments across the width classes of boards Segment lengths are in mm.

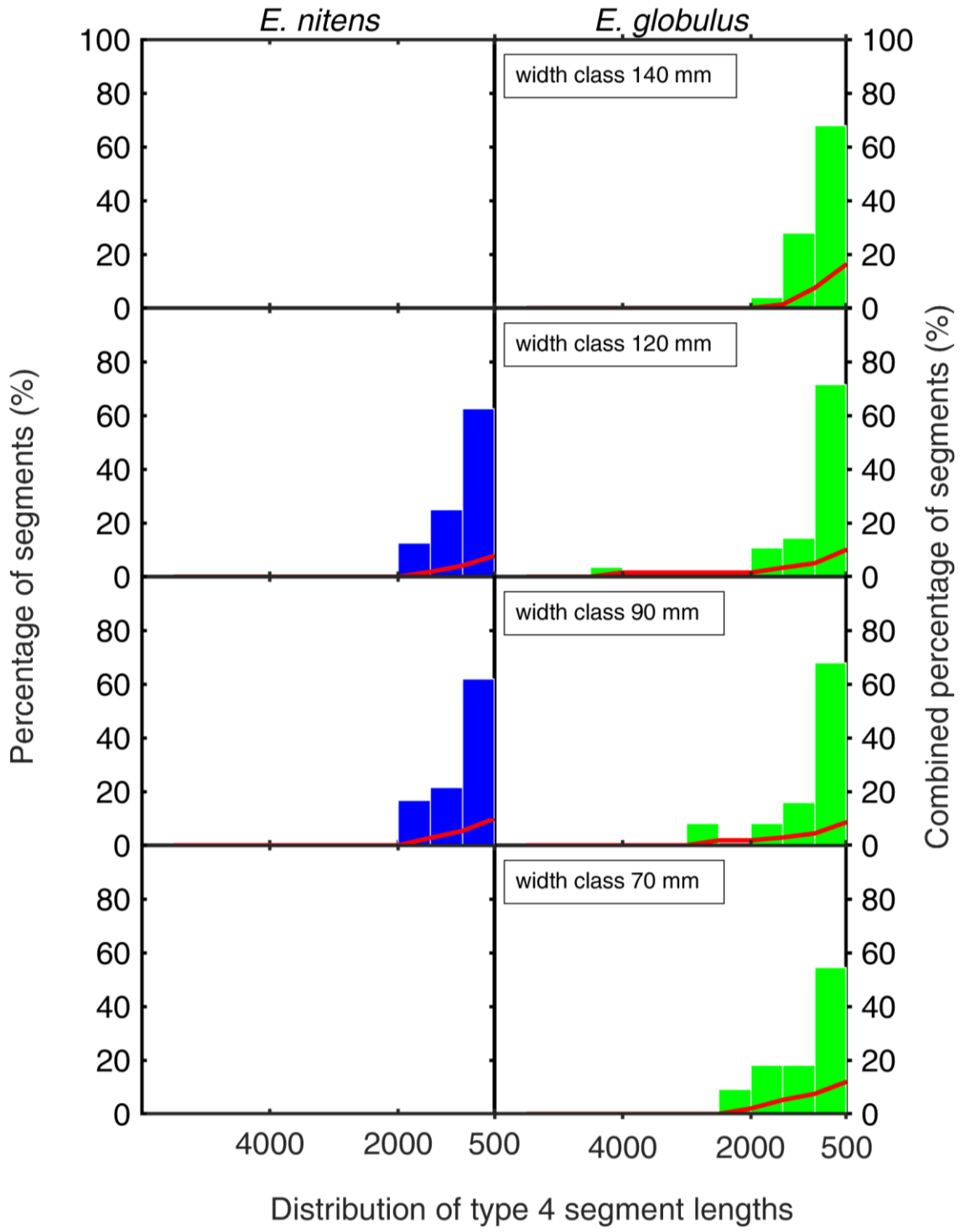


Figure 5-19. Distribution of type 4 segments across the width classes of boards. Segment lengths are in mm.

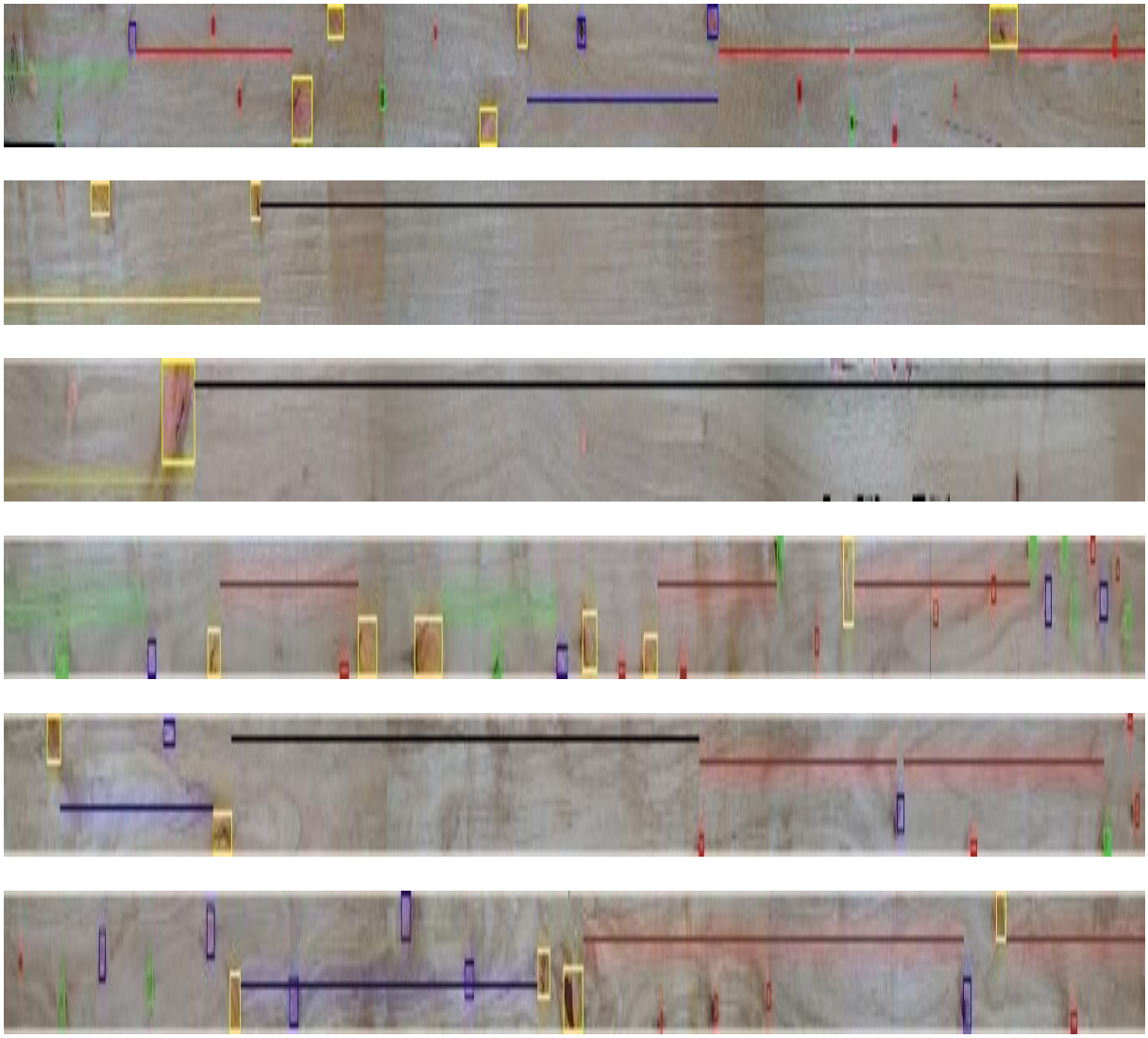


Figure 5-20. Examples of different segment types across boards are coded by different colors. Segments that contain smaller knots are indicated by lines closer to the top of the boards. The top three are E. globulus; the bottom 3 are E. nitens.

5.6.2.1.2 Comparison Between the Validated and Automatic Detection Boards

This section compares the segments defined for the validated boards to the automatic detection of the same set of boards. For approximately 90 percent of the boards in each species, the difference in the number of clear segments was zero between the two datasets (Figure 5-21). However, the rate was much lower for the other segment types. For example, about 50 percent of *E. nitens* and 40 percent of the *E. globulus* boards had 1 or 2 fewer or 1 or 2 more type 1 and type 2 segments. However, there were fewer additional or missing type 3 and type 4 segments. Approximately 80 percent of the boards contained a difference of less than 10 percent of the proportion of the boards in clear segments (Figure 5-22). For *E. nitens*, between approximately 50 percent and 65 percent, the proportion of each segment type was

estimated to a difference of less than 10 percent. This rate was higher for *E. globulus*, ranging between 65 percent and 70 percent. In general, the automatic detection dataset underestimated the proportion of each segment type more frequently than the opposite.

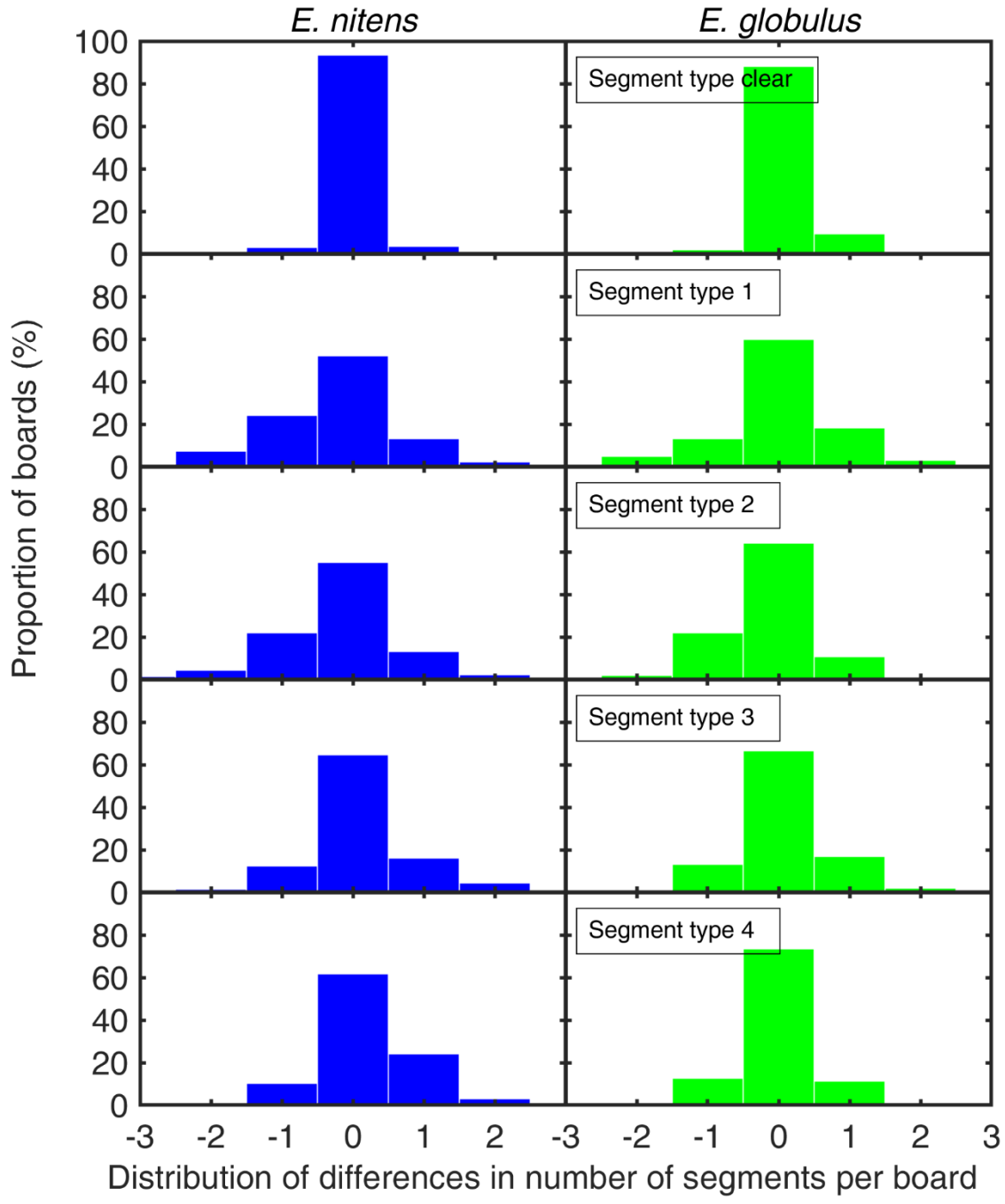


Figure 5-21. Distribution of the differences in segment types for each board in the validation and automatic detection sets. Negative values indicate that the automatic detection routine underestimates the number of segments.

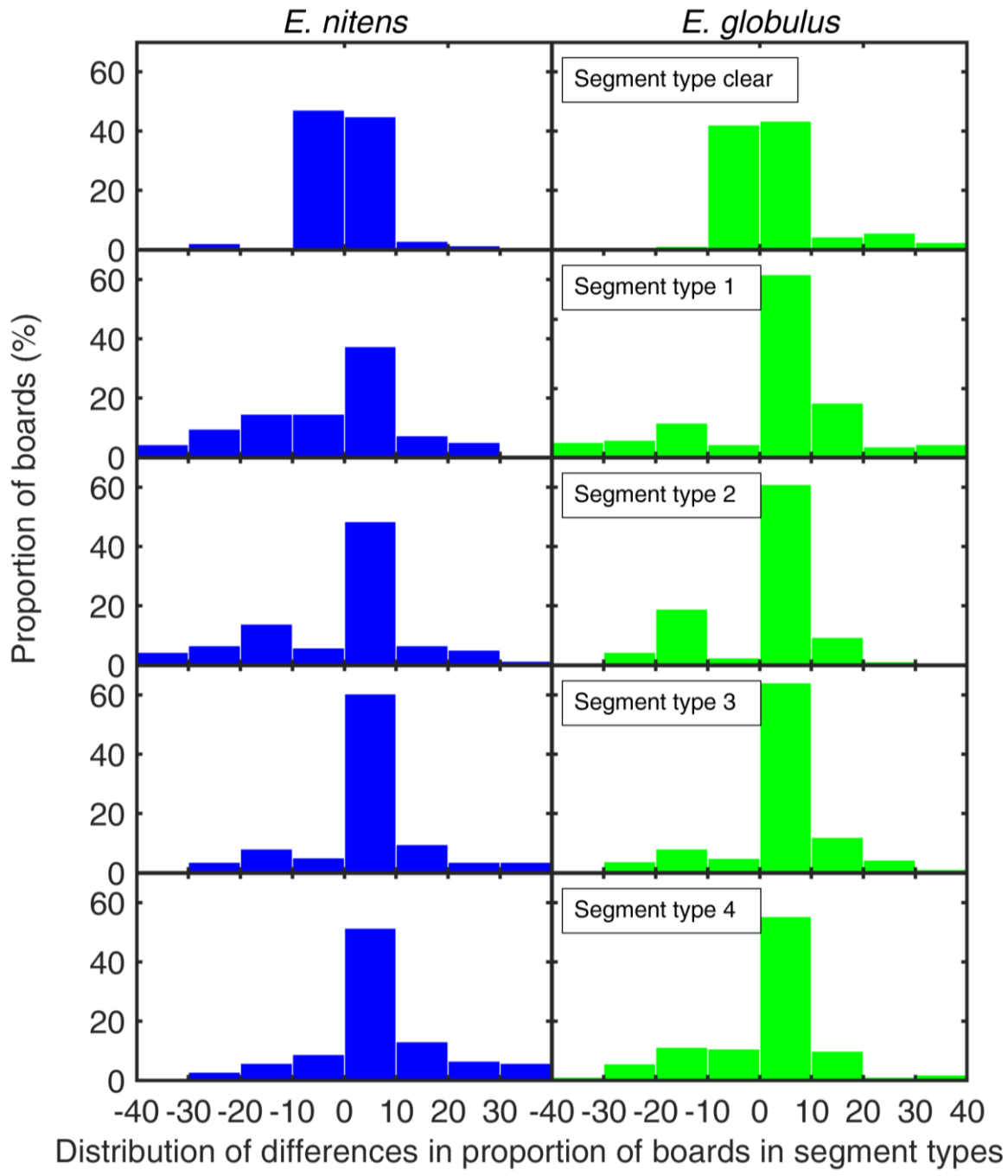


Figure 5-22. Distribution of the differences in the proportion of boards between the validation and automatic datasets. Negative values indicate that the automatic detection routine underestimates the proportion of the board in each segment type.

5.6.3 Board Classification

5.6.3.1 Segmenting Method

5.6.3.1.1 Segment Definition 1

The boards in the validation set were clustered based on the indicator variables from

Table 4-1. The best analysis indicated 5 clusters for both species. The number of boards in each cluster is shown in Table 5-8. The cluster solution and classification model for *E. globulus* are shown in Figure 5-23 and Figure 5-24, respectively. The final cluster solution for *E. nitens* is shown in Figure 5-25 and the final classification model is shown in Figure 5-26.

Table 5-8. The number and proportion of boards in each board class for both species using segmenting definition 1. The proportion of board in each board class compared to the total is shown in parentheses ().

Board Class	*E. nitens*	*E. globulus*
1	16 (12)	29 (18)
2	30 (12)	43 (27)
3	39 (28)	25 (16)
4	22 (16)	37 (23)
5	29 (21)	25 (16)

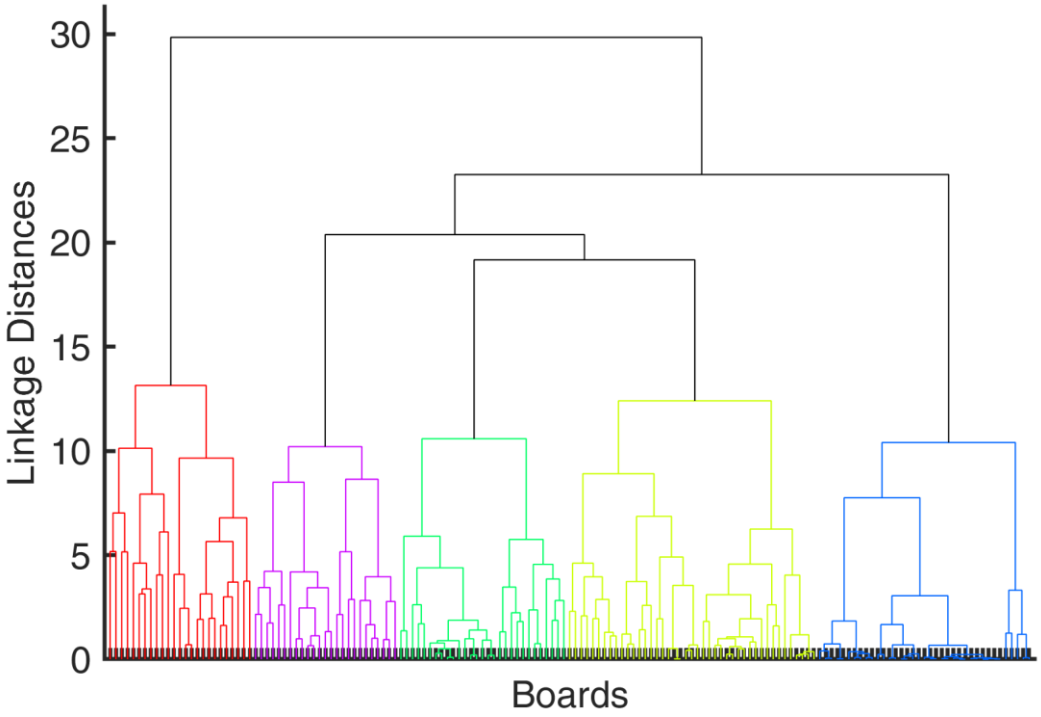


Figure 5-23. Final cluster solution for E. globulus using segmenting definition 1.

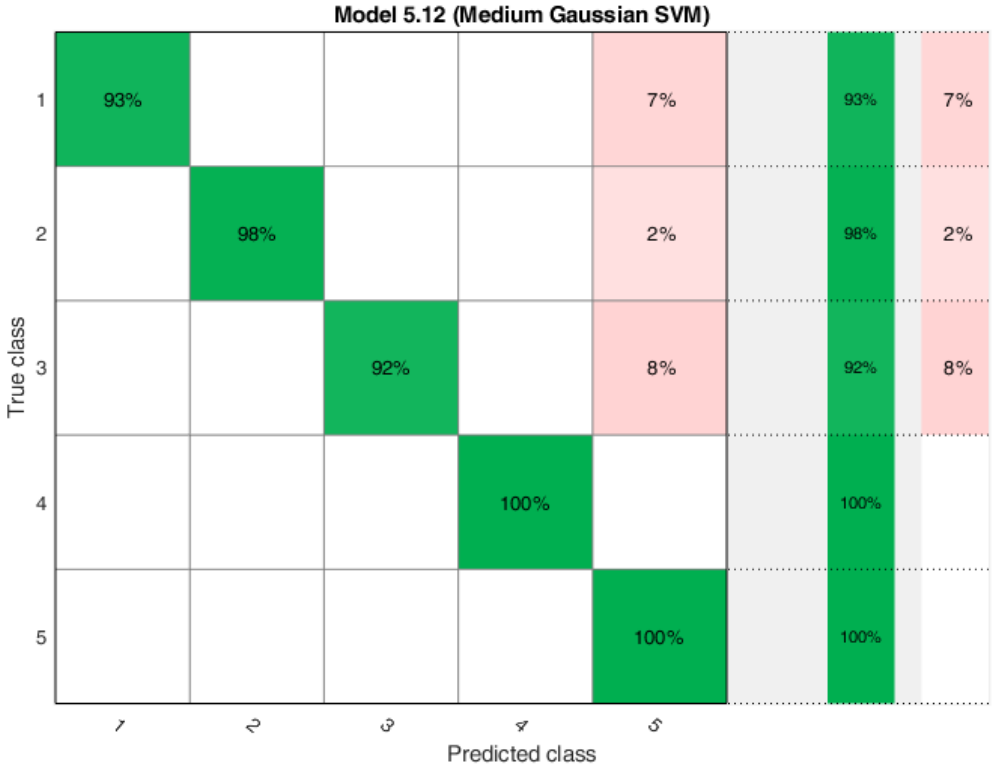


Figure 5-24. Final confusion matrix for the E. globulus classification model using segmenting definition 1.

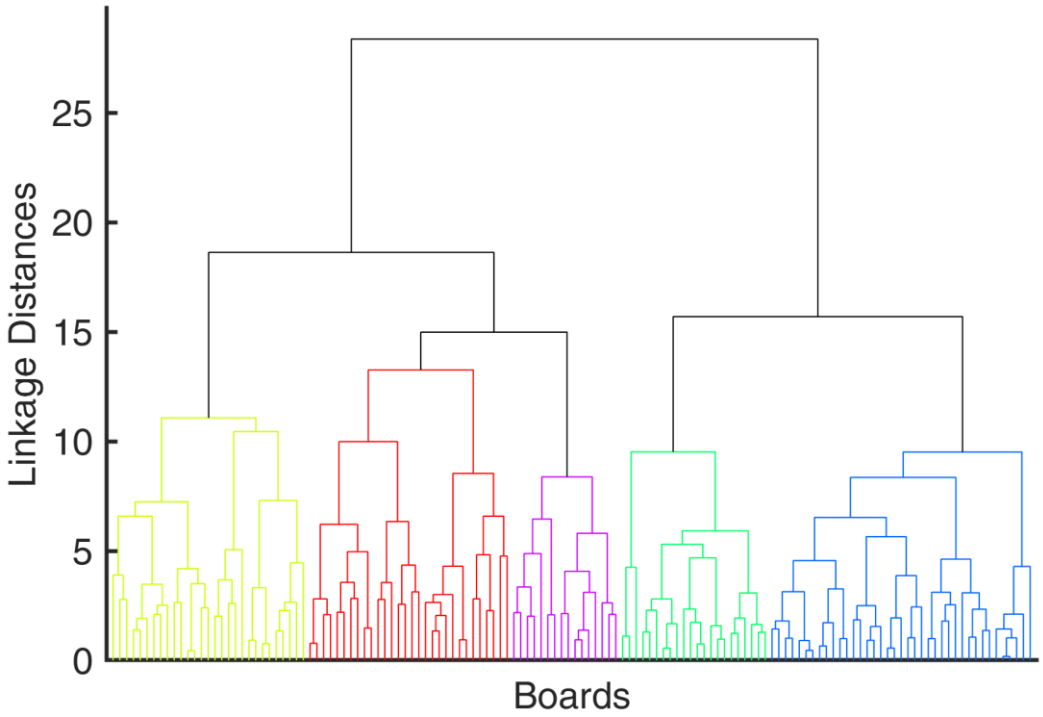


Figure 5-25. Final cluster solution for E. nitens for segmenting definition 1.

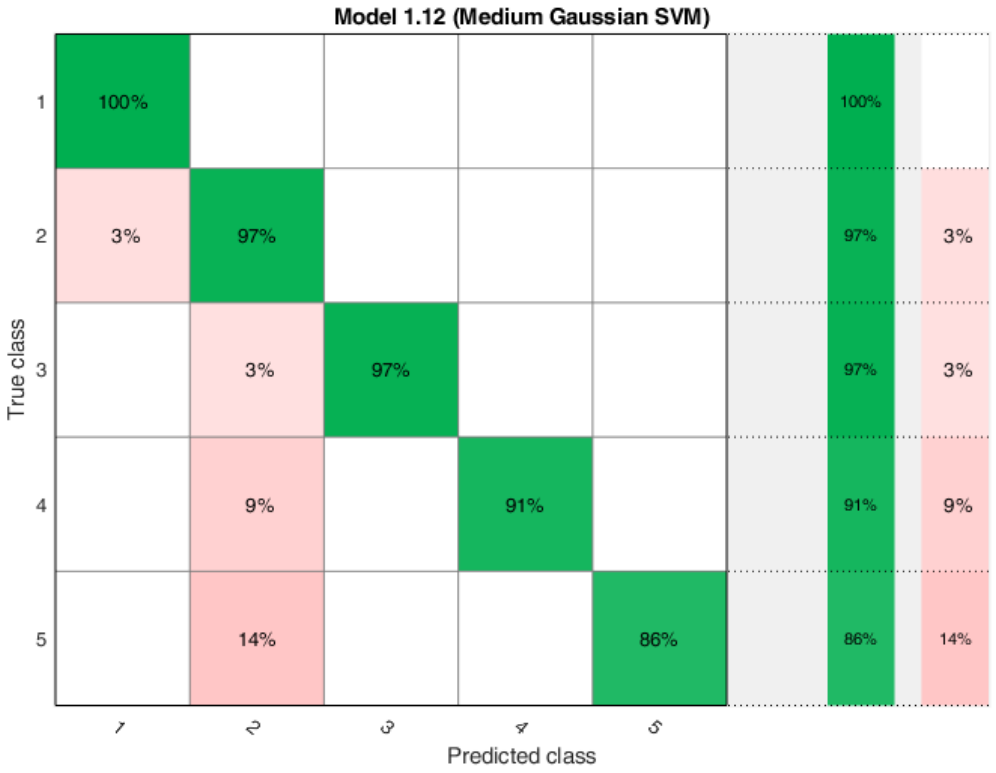


Figure 5-26. Final confusion matrix for the E. nitens classification model using segmenting definition 1.

Overall, the classification sorted boards into groups that contained different levels and frequency of knots and the proportion of board in different segment types (Figure 5-27, Table 5-9, and Table 5-10). For *E. nitens*, board classes 1, 3, and 4 contained a distribution of boards with approximately the same level of knots per meter of surface, while board classes 2 and 5 contained boards that had a slightly higher frequency of knots (Figure 5-27). In *E. globulus*, this pattern was repeated for board classes 1, 2, and 4, and 3 and 5 respectively (Figure 5-27). The proportion of boards in the minimum allowable segment lengths was, in general, lower for *E. nitens* that for *E. globulus* (Figure 5-28). In board classes 1 through 4, over 60 percent of the boards contained over 90 percent in segments for *E. globulus*, however only 3 classes of *E. nitens* boards contained over 40 percent of the boards with this level of segment content (Figure 5-28). In *E. nitens*, board class 2 contained the lowest proportion of boards containing segments, while board class 3 and 5 contained boards with less proportion of segments that the other classes for *E. globulus*.

Table 5-9. Mean proportion of E. globulus boards in the segment types for the different board classes segmenting definition 1. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with second-highest proportion.

	Segment type				
Board class	Clear	Type 1	Type 2	Type 3	Type 4
1	58	8	20	0	4
2	59	11	1	1	23
3	48	4	5	21	8
4	93	0	0	0	0
5	9	35	11	7	17
Mean	57	11	6	45	11

Table 5-10. Mean proportion of E. nitens boards in the segment types for the different board classes segmenting definition 1. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion.

	Segment type				
Board class	Clear	Type 1	Type 2	Type 3	Type 4
1	13	57	13	0	3
2	11	20	24	5	16
3	71	11	6	0	0.0
4	49	10	0	0	31
5	28	19	8	27	4
Mean	38	20	10	7	10

The proportion of different segment types differed between the board classes and species. In general, board classes 1, 2, and 5 contained very few clear segments for *E. nitens*; however, this pattern only occurred for board class 1 in *E. globulus* (Figure 5-29). For this species, board class 4 contained boards with a high proportion of clear segments. The distribution of boards was similar for board classes 3 and 4 for *E. nitens* and 1, 2, and 3 for *E. globulus*. A significant proportion (above 40 percent) of segment type 1 occurred in board class 1 for *E. nitens* and board class 5 for *E. globulus* (Figure 5-30). This pattern was also observed for segment type 2 in board class 1 for *E. nitens* and board classes 1 and 5 for *E. globulus* (Figure 5-31). Significant type 3 segments occurred in board class 3 for *E. globulus* only (Figure 5-32). However, significant amounts of segment type 4 occurred in board class 4 for *E. nitens* and board classes 2 and 5 for *E. globulus* (Figure 5-33).

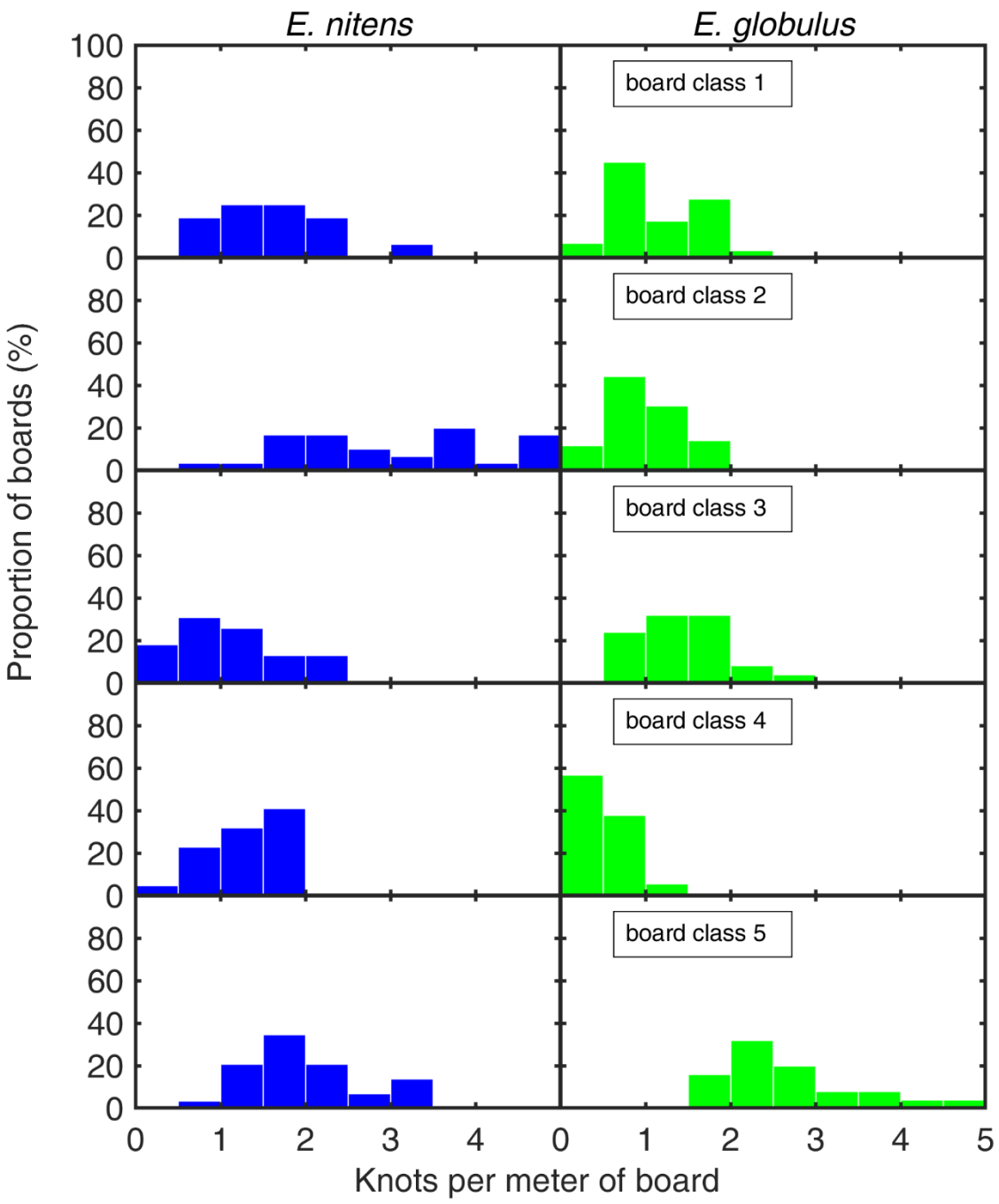


Figure 5-27. Distribution of knots per meter of the board for the different board classes determined by the classification model using segmenting definition 1.

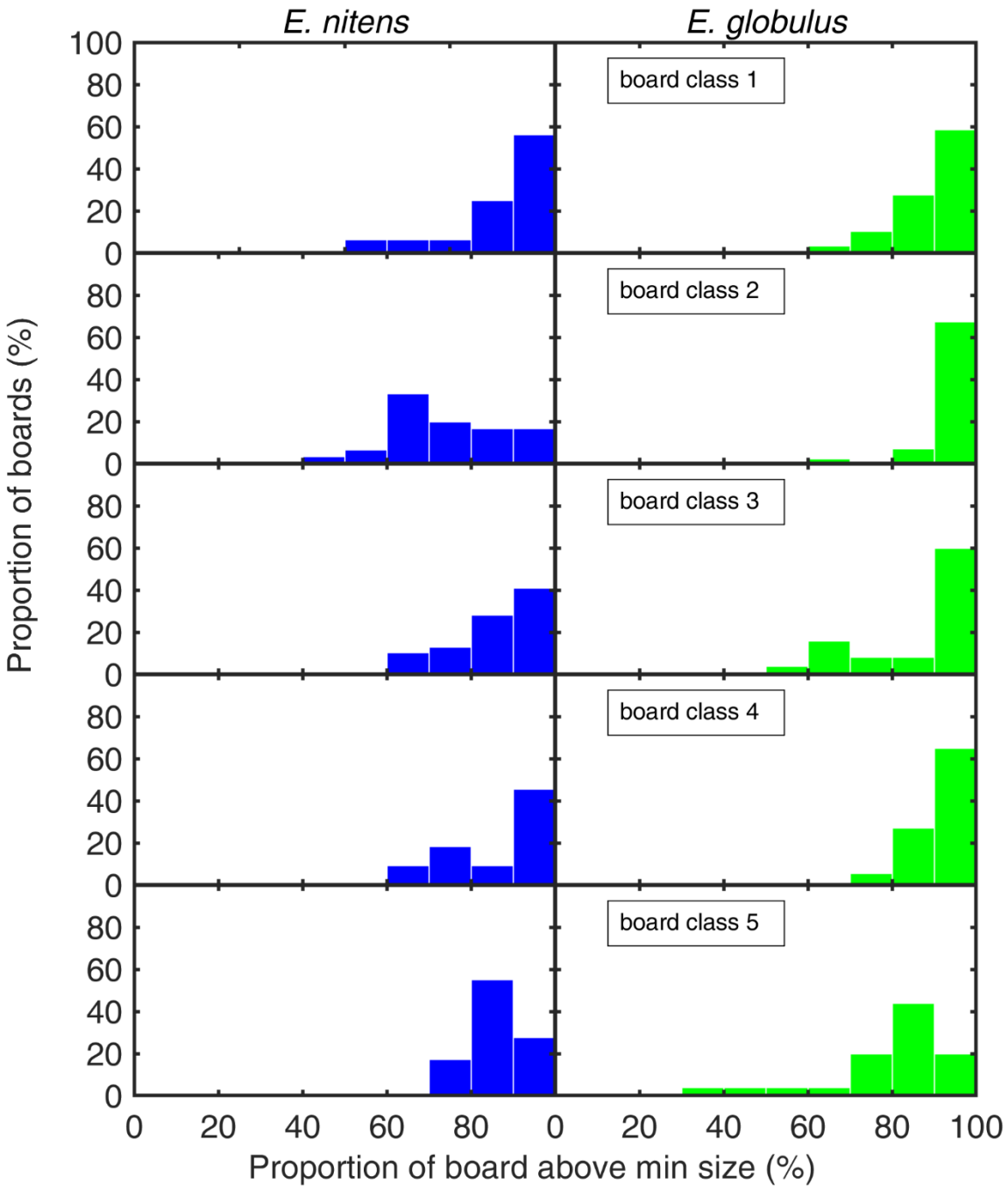


Figure 5-28. Distribution of the proportion of board containing <u>all</u> segment types above the minimum lengths for the different board classes using segmenting definition 1. The minimum lengths for knotty types are 500 mm and 1000 mm for clear type.

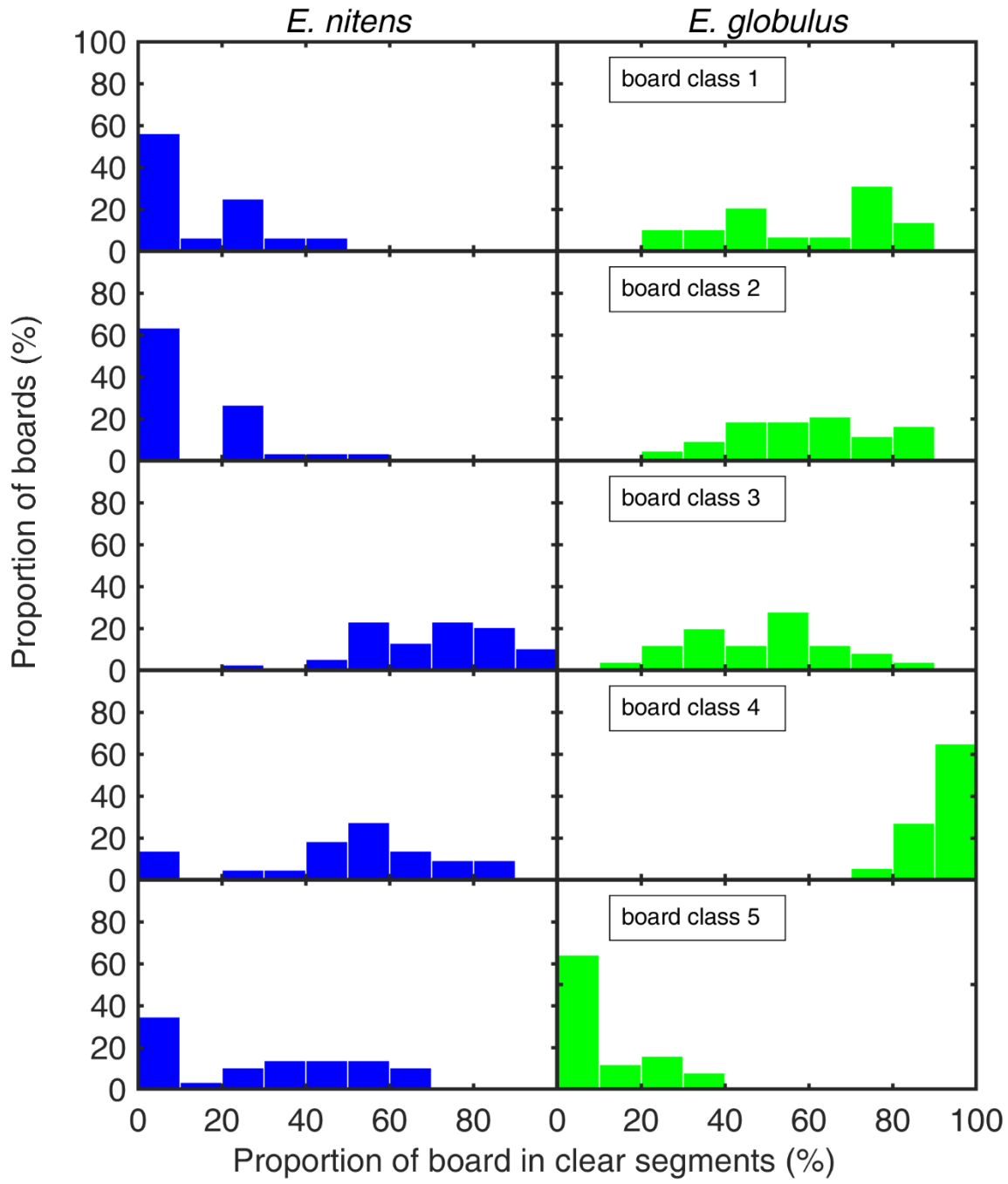


Figure 5-29. Distribution of the proportion of board in clear segments for the different board classes using segmenting definition 1.

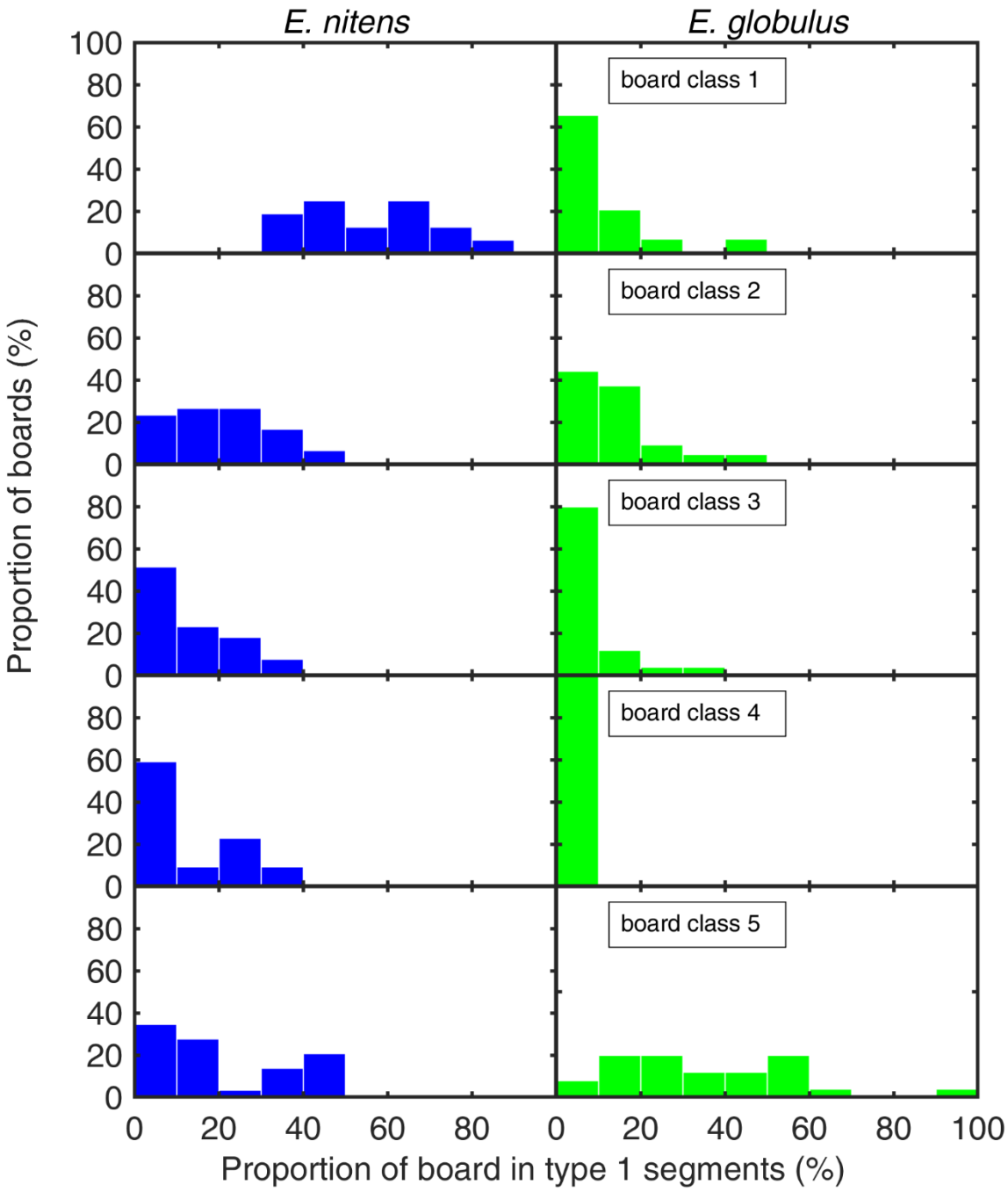


Figure 5-30. Distribution of the proportion of board in type 1 segments for the different board classes using segmenting definition 1.

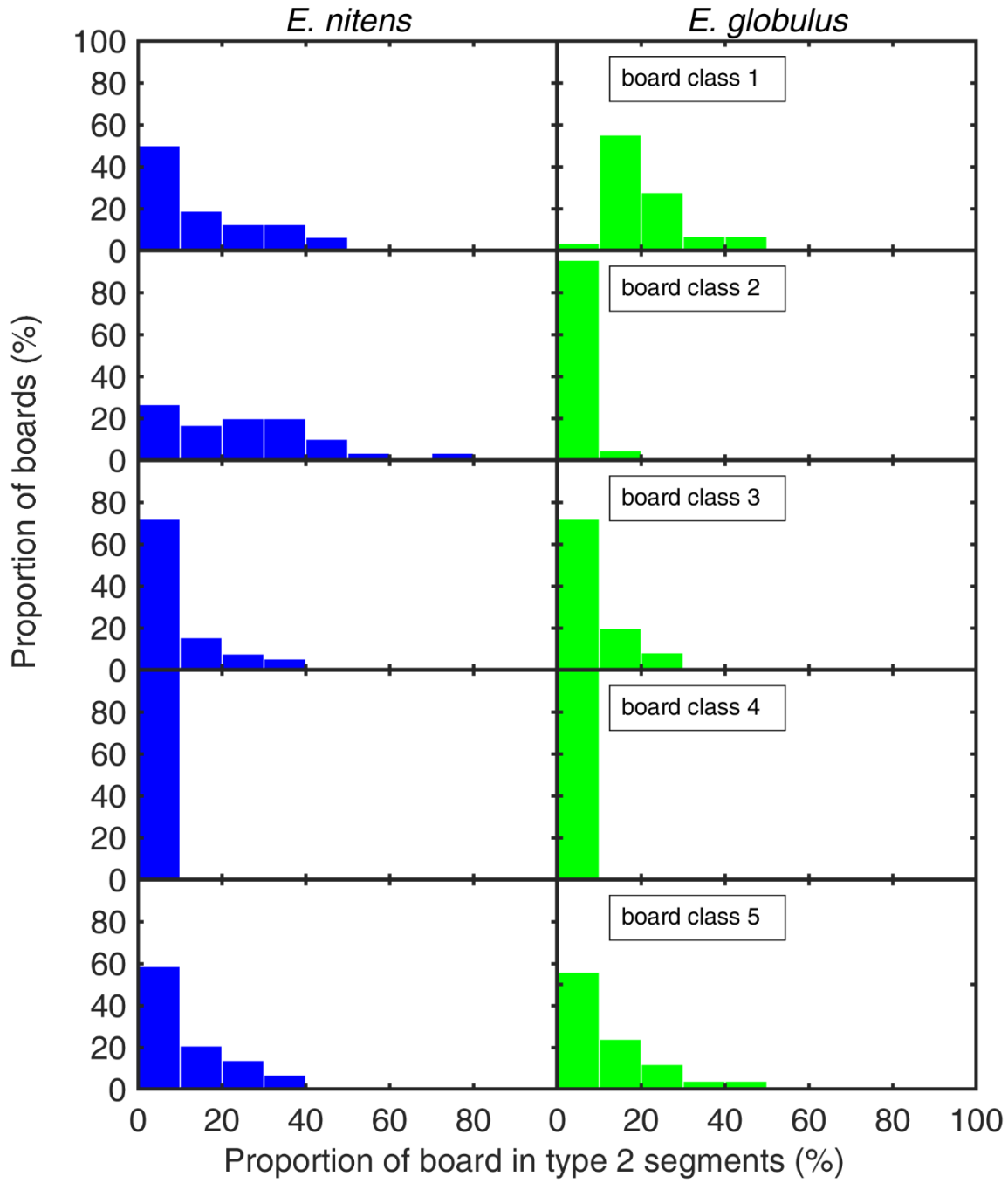


Figure 5-31. Distribution of the proportion of board in type 2 segments for the different board classes using segmenting definition 1.

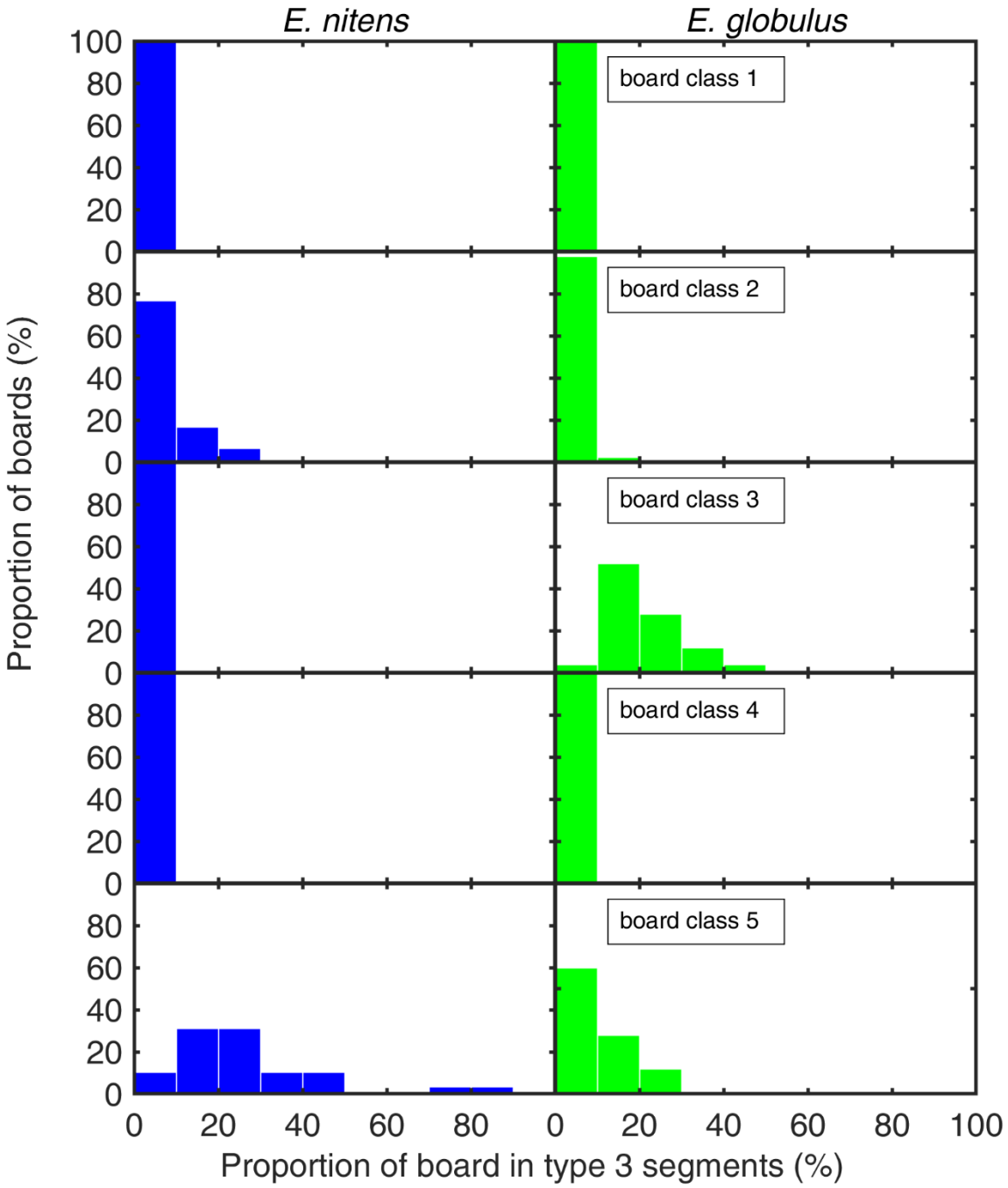


Figure 5-32. Distribution of the proportion of board in type 3 segments for the different board classes using segmenting definition 1.

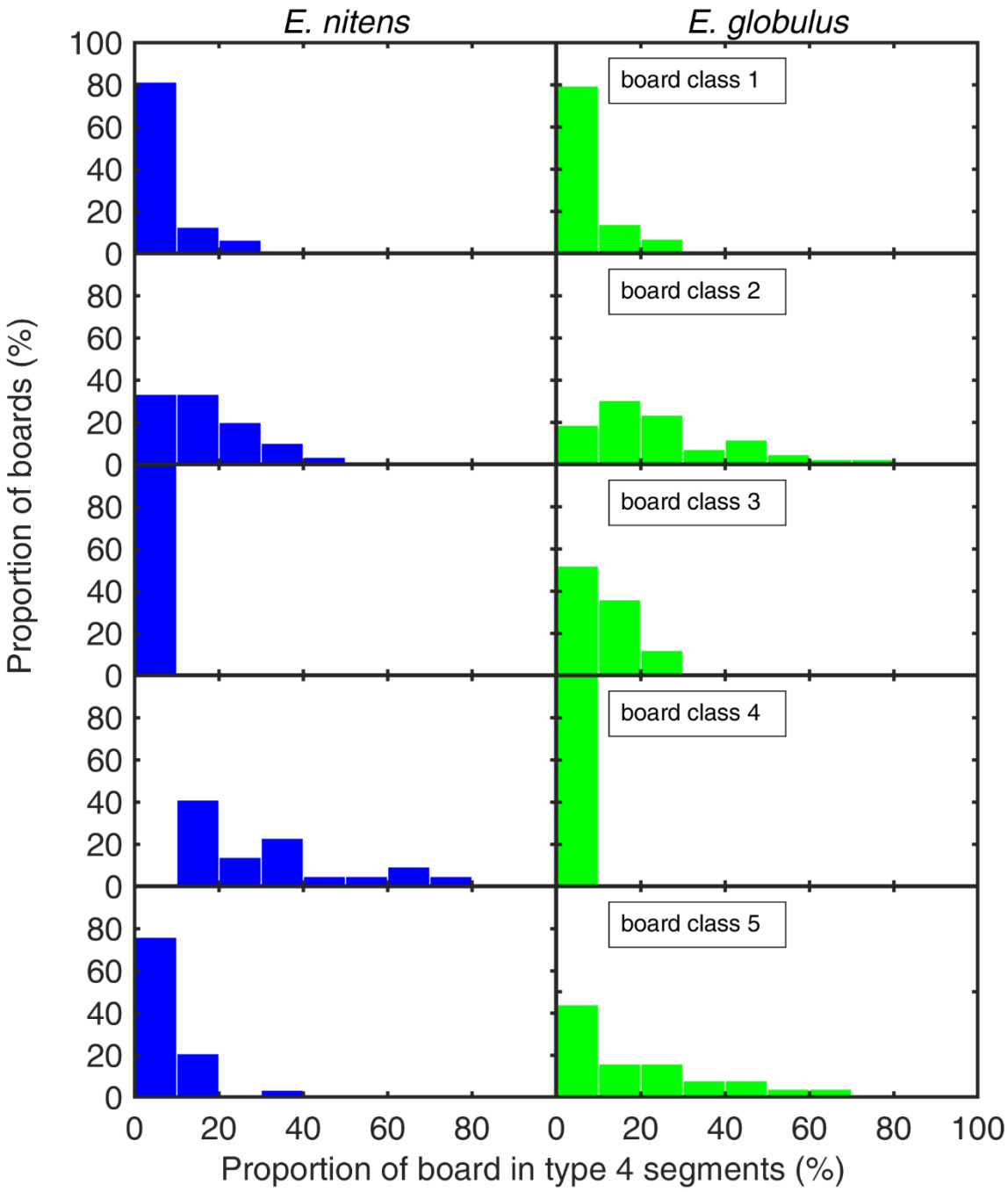


Figure 5-33. Distribution of the proportion of board in type 4 segments for the different board classes using segmenting definition 1.

The sorting procedure produced groups of boards containing combinations of significantly different proportions of segment types (Table 5-9). For example, the proportion of board in clear segments was 58 percent and 20 percent in type 2 segments for board class 1. Other similar patterns can be observed for the other board classes. For *E. globulus*, board classes 1, 2, 3, and 4 contained significantly higher proportions of clear segments that the other segment types (Table 5-9). Board class 1 contained 93 percent clear segments, while the

others ranged between 48 percent and 59 percent, and they also contained between 20 percent and 23 percent some other segment types. Board class 5 contained a relatively low proportion of all segment types. The distribution of clear segment lengths ranged from 1000 mm to over 4000 mm for board classes 1, 2, 3, and 4 (Figure 5-34). However, most segments were between 1000 mm and 2000 mm. Board class 4 had the highest proportion of segments over 2000 mm. The lengths of other segment types ranged from 500 mm to about 1500 mm; few segments were over 1500 mm for either species.

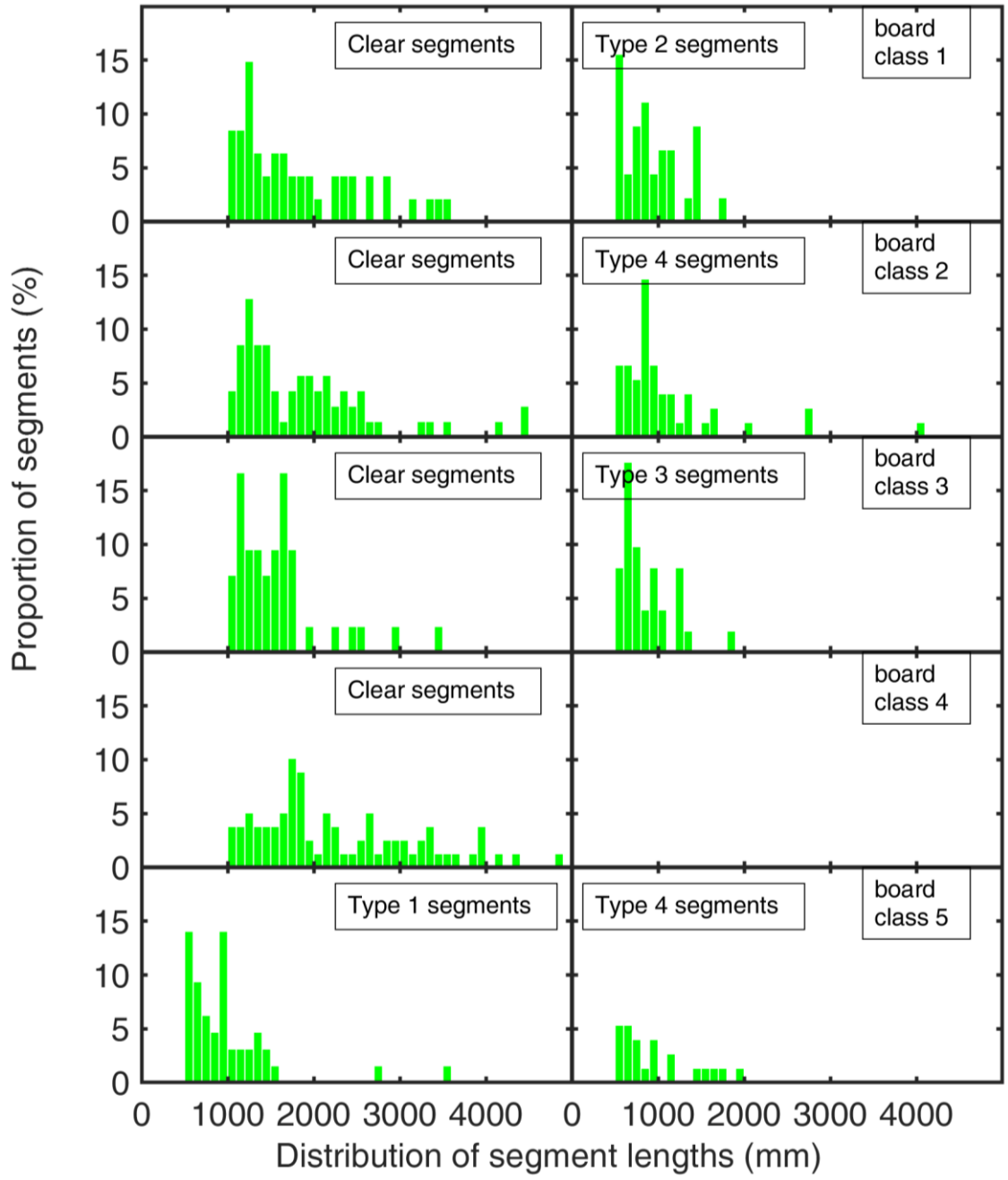


Figure 5-34. Distribution of segment lengths for the board classes determined for E. globulus using segmenting definition 1. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm.

The classification procedure produced similar patterns for *E. nitens*; different board classes contained unique combinations of a significant proportion of different segment types (Table 4.9). Board class 2 contained a significantly higher proportion of clear segments than other types. Board classes 4 and 5 contained relatively similar levels between clear and type 4 and

type 3, respectively. Board class 1 contained significantly more type 1 than type 2, and board class 2 contained about equal amounts of type 2 and type 1 segments. For board classes 3 and 4, the lengths of most clear sections were between 1000 mm and 2000 mm; however, board class 3 contained many clear segments over this range (Figure 5-35). The length of most of the other segment types ranged between 500 mm and 1500 mm.

In general, *E. globulus* contained a higher proportion of clear segments than did E. nitens (Table 5-9 and Table 5-10). Approximately 23 percent of the *E. globulus* boards contained a mean of 93 percent clear segments, while 28 percent of the *E. nitens* boards contained a mean of 71 percent clear segments. *E. nitens* contained almost twice the proportion of type 1 segments than did *E. globulus*. The content of other segment types was similar. There was also a higher proportion of clear segments over 2000 mm found for *E. globulus*.

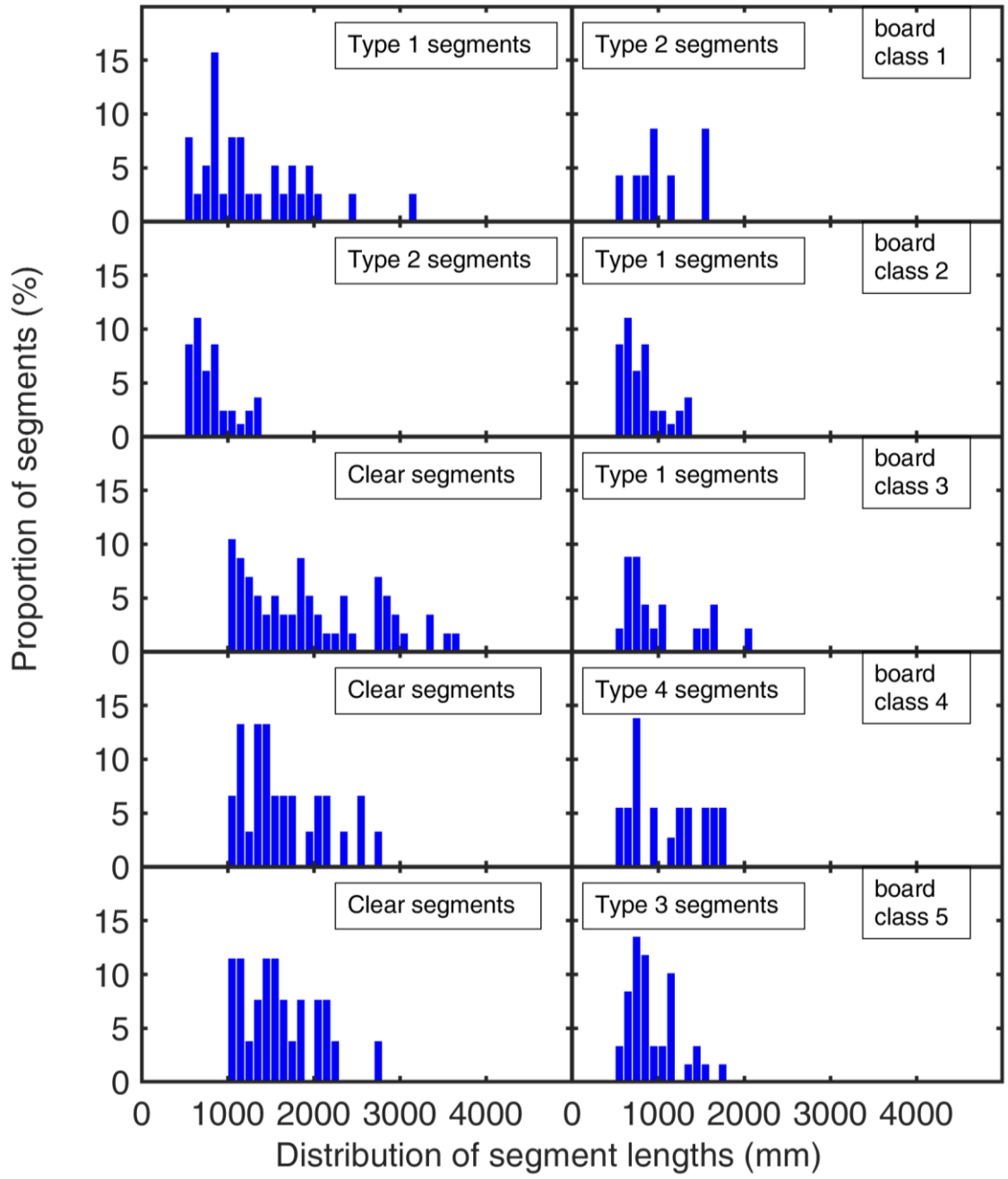


Figure 5-35. Distribution of segment lengths for the board classes determined for E. nitens using segmenting definition 1. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm.

5.6.3.1.2 Segment Definition 2

For brevity, cluster and model results are not presented in this section, but the procedure produced similar dendrograms and accuracy in the models. The proportion of boards containing a certain amount of each segment type is not presented either. The number of

boards varied between the board classes and species for using the second segment definitions (Table 5-11). Both species had one board class with significantly more boards than the other classes (class 4 for *E. nitens* and class 5 for *E. globulus*). Overall, a lower proportion of clear segments was discovered within the samples. However, classification based on definition 2 contained different combinations of a significant proportion of segment types (Table 5-12 and Table 5-13). No clear segments were found in board classes 1, 2, and 3 for *E. globulus*, however, these classes contained significant proportions of knotty types. Board class 5 contained a high proportion of clear segment and a smaller proportion of type 1, while board class 4 contained roughly equal proportions of clear, type 1, type 3 and type 4 segments. The pattern was approximately the same for board classes 1, 2, and 3 in *E. nitens*. Board class 4 produced approximately equal proportions of type 1 and type 2. Board class 5 was the only class with a significant proportion of a clear segment.

The clear segment length for board classes 4 and 5 for *E. globulus* ranged between 2000 mm and greater than 4000 mm (Figure 5-36). This method of defining segments resulted in approximately 45 percent of the *E. globulus* boards containing a mean of 57 percent clear segment, but only 20 percent of the *E. nitens* boards contained a mean proportion of 61.4 percent clear segment. The range in size of type 2 segment for board class 1 and type 4 segment for board class 2 ranged from 500 mm to over 3500 mm. for *E. globulus*. Also, for *E. globulus* the proportion of the second-highest type was below 20 percent (except for type 3 for board class 4), which does not warrant discussion here. For *E. nitens*, the distribution of type 1 segment lengths for board class 1 departs from the general patterns mentioned above (Figure 5-37). Here, the proportion of longer lengths is higher than for shorter lengths, yet for board class 4 the lengths of type 1 segments are skewed towards short pieces.

Table 5-11. The number and proportion of boards in each board class for both species using segmenting definition 2.

Board Class	*E. nitens*	*E. globulus*
1	9 (6)	20 (12)
2	16 (12)	25 (16)
3	29 (21)	23 (15)
4	54 (39)	19 (12)
5	28 (20)	72 (45)

Table 5-12. Mean proportion of E. globulus boards in the segment types for the different board classes using segmenting definition 2. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion.

	Segment type				
Board class	Clear	Type 1	Type 2	Type 3	Type 4
1	0	16	63	2	13
2	0	19	12	0	58
3	0	58	16	0	11
4	26	19	8	22	20
5	57	18	7	0	13
Mean	29	24	16	3	21

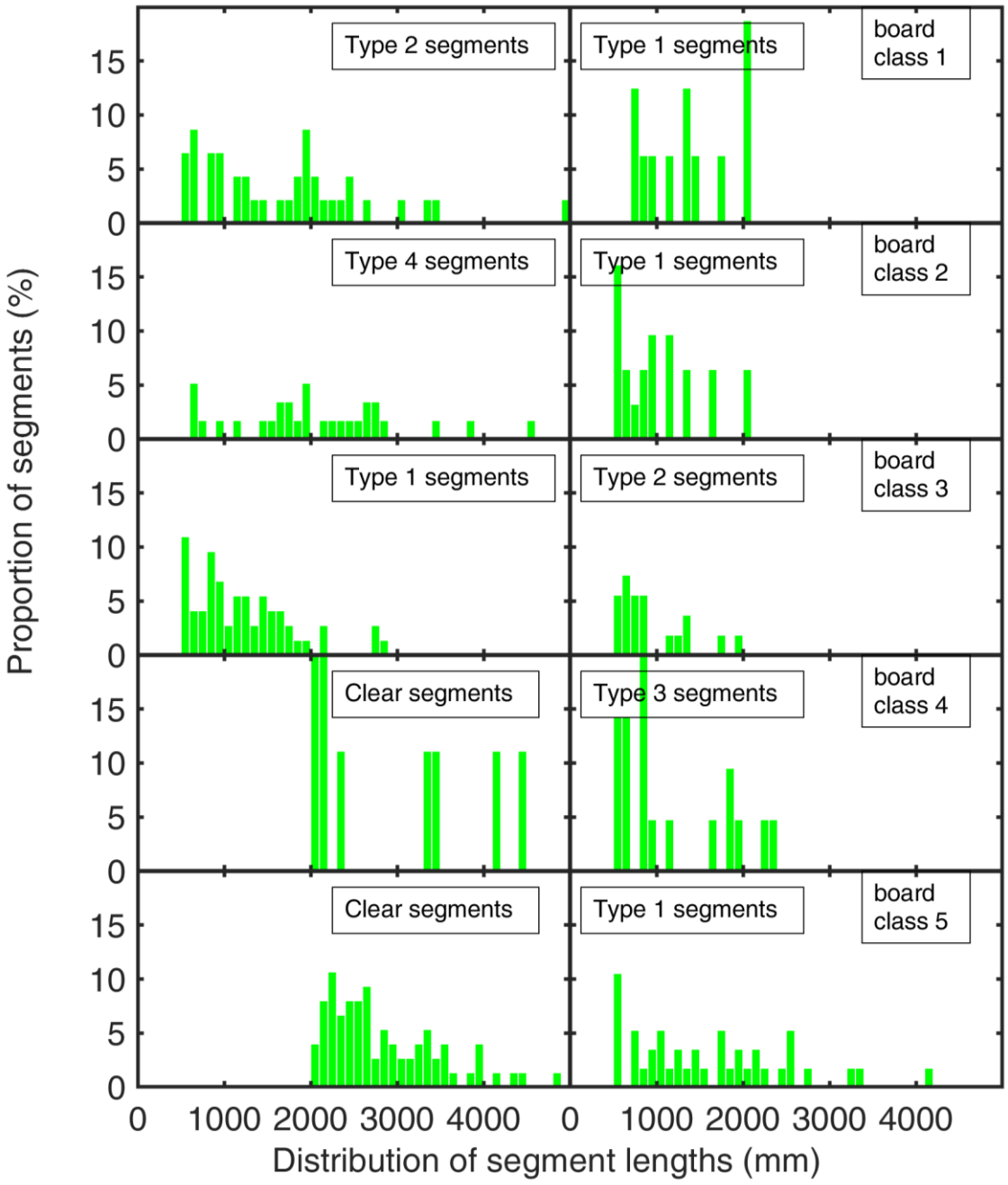


Figure 5-36. Distribution of segment lengths for the board classes determined for E. globulus using segmenting definition 2. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm.

Table 5-13. Mean proportion of E. nitens boards in the segment types for the different board classes using segmenting definition 2. Cells in yellow indicate the segment type with the highest proportion and green indicates the segment type with the second-highest proportion.

	Segment type				
Board class	Clear	Type 1	Type 2	Type 3	Type 4
1	0.0	92	0.0	0.0	0.0
2	0.0	23	1	0.0	67
3	10	27	8	37	8
4	0.0	33	33	5	11
5	61	11	8	0.0	11
Mean	15	30	17	10	16

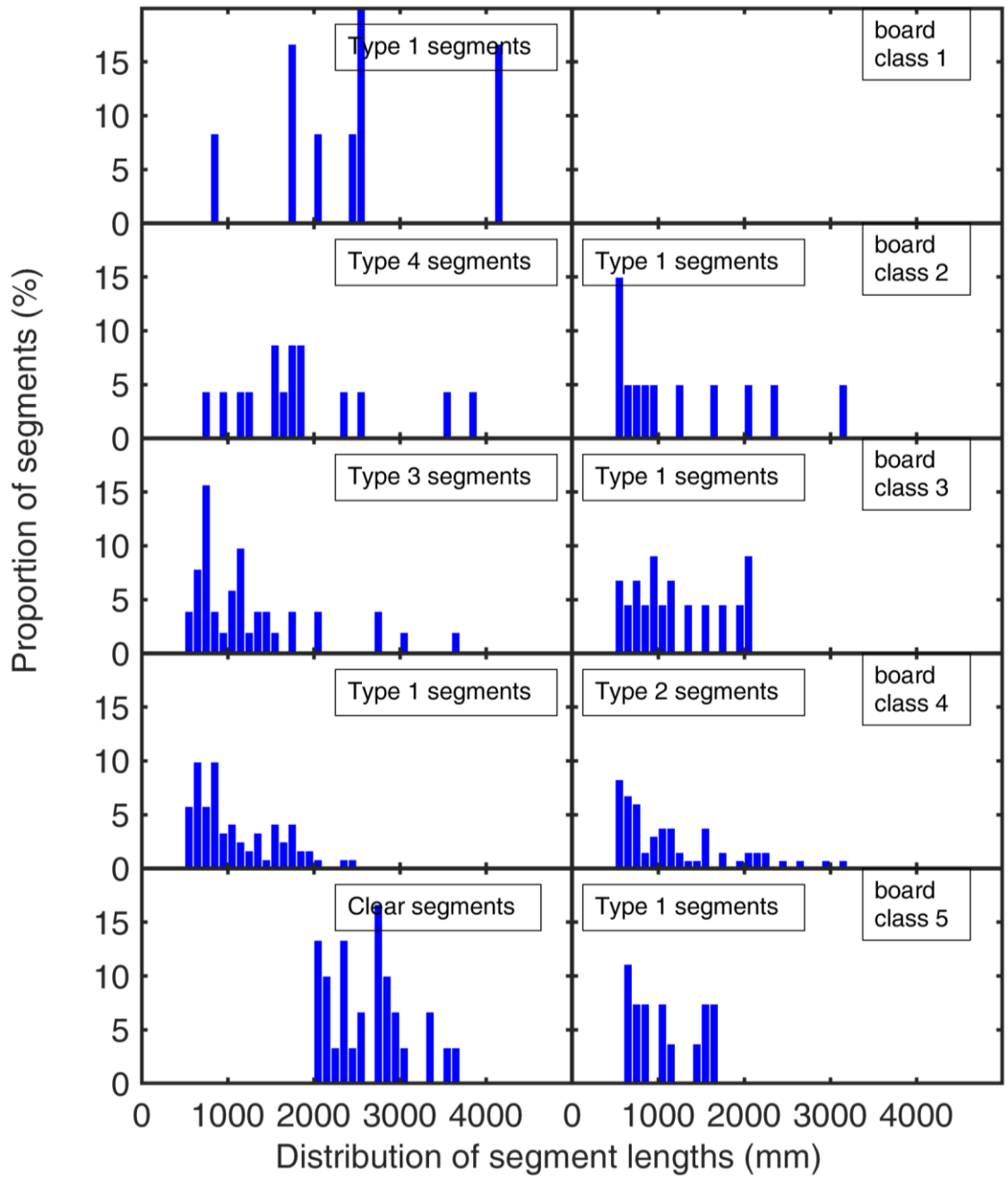


Figure 5-37. Distribution of segment lengths for the board classes determined for E. nitens using segmenting definition 2. The segment type with the highest proportion is shown on the left side and the segment type with the second-highest proportion is shown on the right. The proportion of segments is calculated using the number of the same segment type for the class. The bin size is 100 mm.

5.6.3.2 Cutting Area Method

5.6.3.2.1 Cutting Area Definition 1

The cluster solutions developed to sort boards based on cutting area distribution are shown for *E. nitens* and *E. globulus* in Figure 5-38 and Figure 5-40, respectively. The confusion matrix

from the model results for each species is shown in Figure 5-39 and Figure 5-41. The distribution of boards in each board class is given in Table 5-14. The proportion of cuttings found from each board class and the mean proportion of cutting area for each board class is shown in Table 5-15. Overall, the number of boards in each class differed, both within and between species. The total number of cuttings greater than 250 mm in length found for *E. nitens* was 564 and 604 for *E. globulus*. The overall mean proportion of boards in cutting areas was 76 percent for *E. nitens* and 83 percent for *E. globulus*. The minimum for *E. nitens* was 73 percent and the maximum was 86 percent, while the minimum for *E. globulus* was 73 percent and the maximum was 90 percent. Board class 1 contained six percent of the overall number of cuttings for *E. nitens* and board class 4 contained 5 percent of the cuttings for *E. globulus*. Other classes contained a much higher proportion of the cuttings.

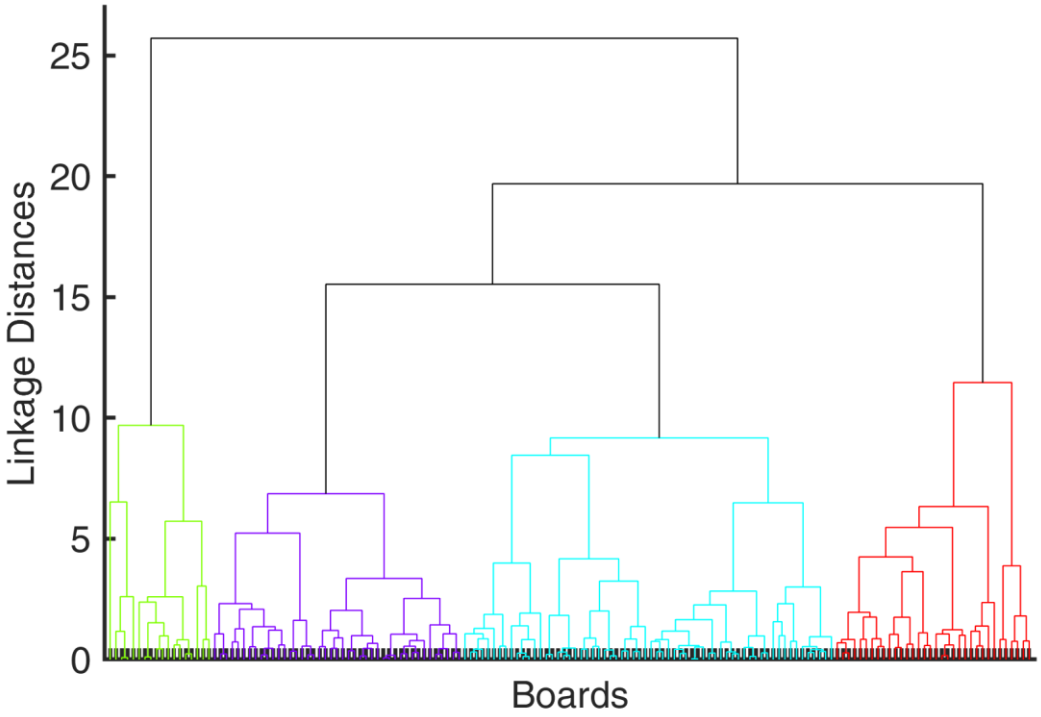


Figure 5-38. Cluster solution for E. globulus based on cutting area distribution using cutting area definition 1.

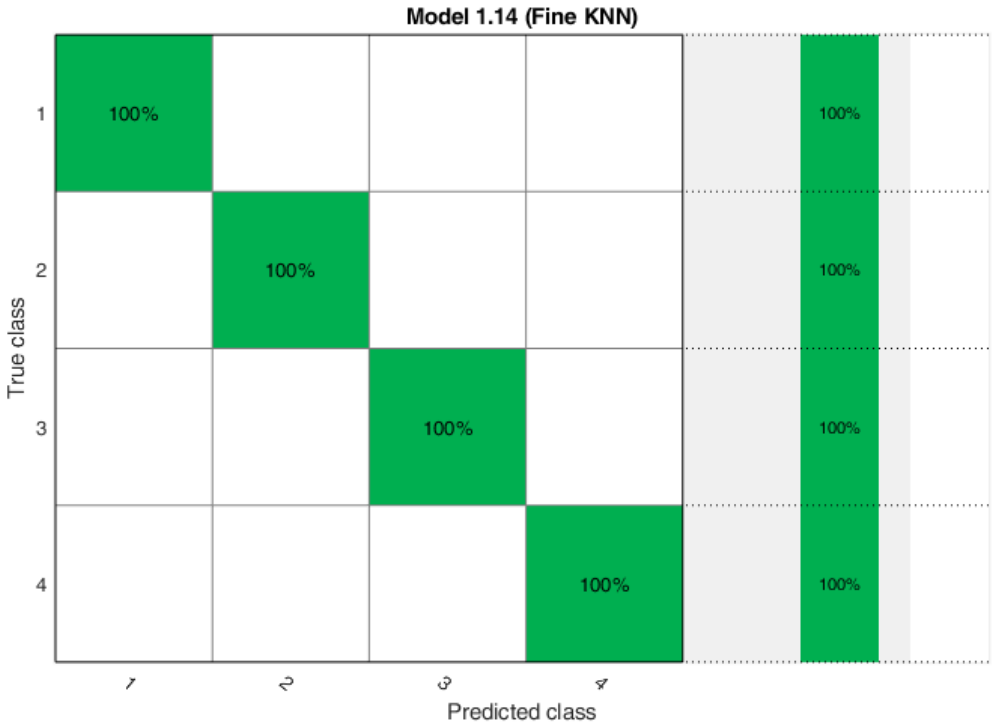


Figure 5-39. Confusion matrix for E. globulus classification model based using cutting area definition 1.

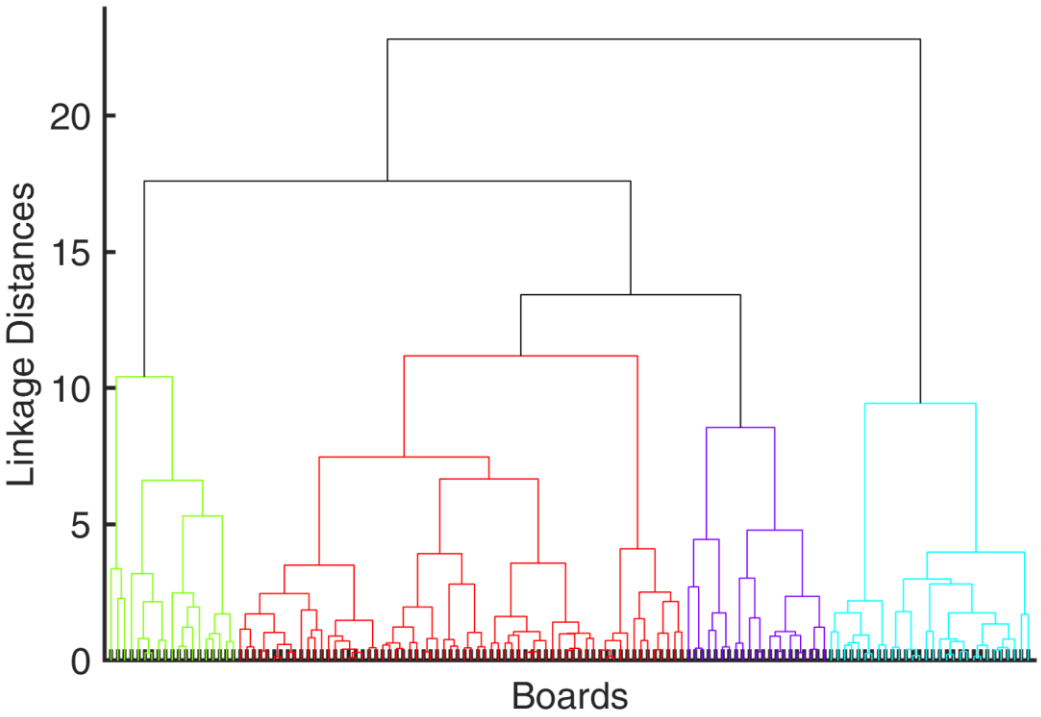


Figure 5-40. Cluster solution for E. nitens based using cutting area definition 1.

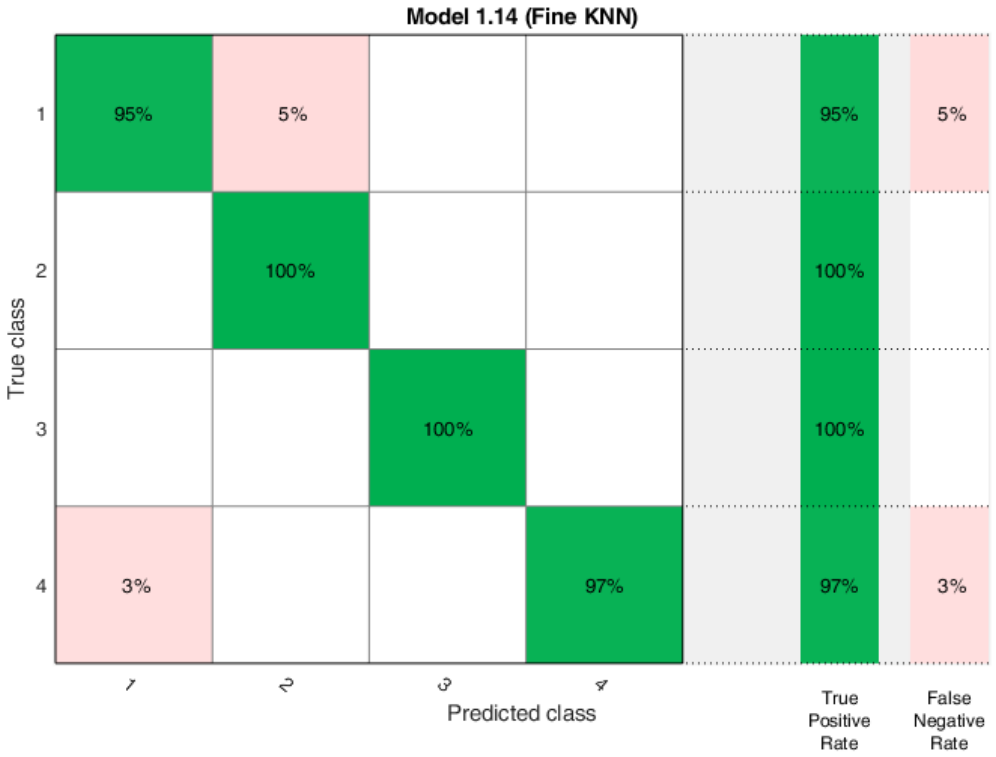


Figure 5-41. Confusion matrix for E. nitens classification model using cutting area definition 1.

Table 5-14. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 1.

Board class	*E. nitens*	*E. globulus*
1	21 (15)	43 (27)
2	66 (49)	64 (40)
3	19 (14)	34 (21)
4	30 (22)	18 (11)

Table 5-15. The proportion of cuttings found in each board class and the mean proportion of boards in cutting areas using cutting area definition 1.

	E. nitens		*E. globulus*	
Board class	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of cuttings (%)	Proportion of boards in cuttings (%)
1	6	75	30	73
2	45	73	30	90
3	8	86	35	76
4	41	79	5	84
Overall mean		76		82

The distribution of cutting sizes and cutting area is shown in Figure 5-42 for *E. globulus*. Considering all the boards (left top panel), cutting areas ranged between 35 mm to 140 mm wide and from 250 mm to 3250 mm long. The highest proportion of cuttings occurred for cutting sizes between 65 mm to 110 mm wide and from 250 mm to 1000 mm long. In terms of the proportion of cutting area (see 5.5.3), cutting areas in size classes between 80 mm and 125 mm wide and between 750 mm and 2000 mm made up the highest proportion of the area.

The distribution of cutting areas and the proportion of area differed significantly for each board class for *E. globulus* (Figure 5-42). There was a high occurrence of wide, but relatively short cuttings in board class 1; board class 2 contained significant proportions of moderately narrow, but relatively long cuttings; board class 3 was characterized by a high proportion of narrow and short cuttings, and board class 4 contained the proportion of wide and long cuttings. This pattern was similar for the distribution of cutting area. However, in a few instances, the contribution of a bin to the total area was larger than the proportion of the same size class of cuttings. For example, this occurred for the 110 mm by 4750 mm bin in board class 4. That size class made up 4 percent of the cuttings, but 8 percent of the area.

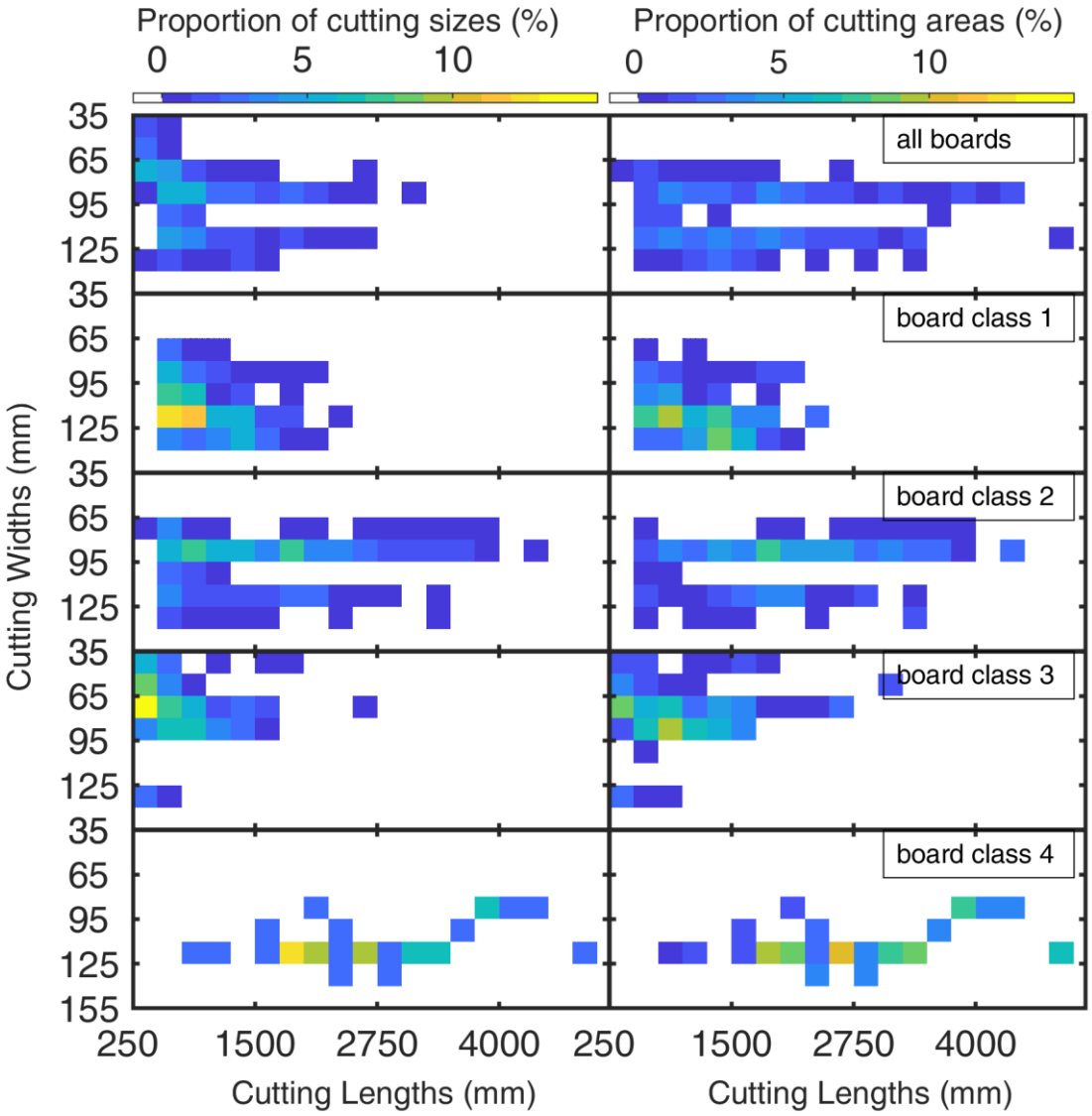


Figure 5-42. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 1 (clear). Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures.

The distributions of cutting area bins and proportion of area are shown for all boards and the board classes for *E. nitens* in Figure 5-43. Overall, the width of cutting areas ranged from 35 mm to 125 mm and the length ranged from 250 mm to 3000 mm. Overall, most cutting areas were relatively narrow and short, typically less than 1250 mm. A significant proportion of the cuttings were in widths between 35 mm and 95 mm and lengths between 250 mm and 1500 mm. The occurrence of cutting area sizes and the proportion of the area differed between the board classes. Cutting area sizes were mostly limited to 80 mm width classes and most cuttings were between 500 mm and 1750 mm long for board class 1. In contrast, board class

2 was characterized by a wider range of width classes, but shorter cuttings. Board class 3 contained wider cuttings and contained a significant proportion of longer cuttings. Board class 4 contained significant proportions of moderate to very narrow and short cuttings. This pattern was, by and large, repeated in the distribution to the proportion of area occupied by each size class.

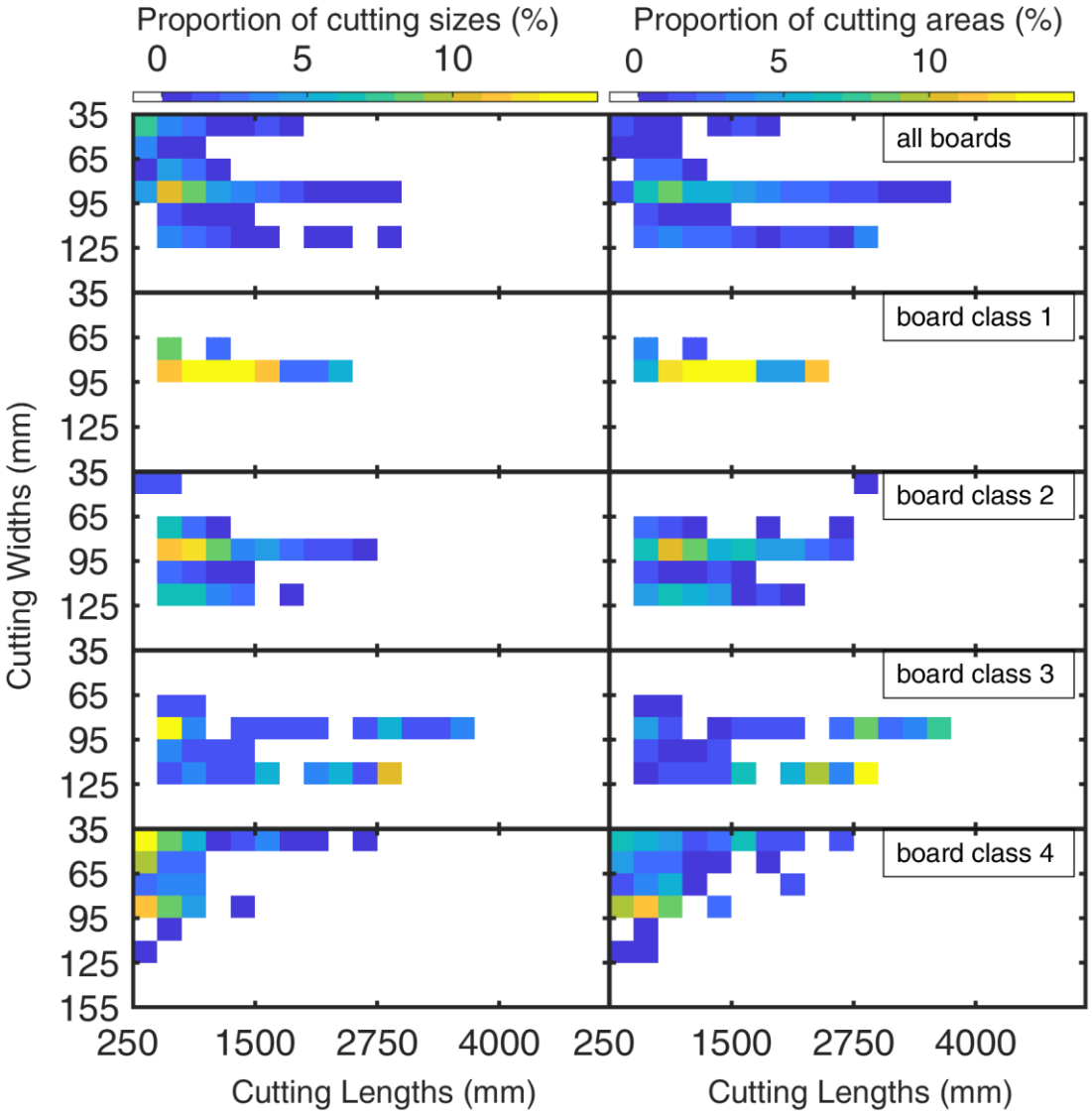


Figure 5-43. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 1 (clear). Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear indicated on area proportion figure.

5.6.3.2.2 Comparison of the Two Species

As expected, given that *E. nitens* is marked by a higher frequency of knots (see 5.6.1), a higher proportion of clear cuttings found for this species were narrow and short as compared to *E. globulus*. The most frequent size class for *E. nitens* was between 80 mm and 95 mm and 500 mm and 750 mm in length. There were also a few other sizes that occurred in higher proportions than most of the other classes (i.e. cuttings 35 mm to 50 mm wide and 250 mm to 500 mm long). However, there was a relatively even distribution of sizes across the range for *E. globulus*. Despite the differences in distribution patterns observed between the species, the patterns of cutting size distribution were similar between individual board classes for the two species. For example, the pattern for board class 3 in *E. globulus* and board class 4 in *E. nitens* indicates the boards in those classes contain a relatively high proportion of narrow and short cuttings. Another similarity exists in the occurrence of cuttings between board class 4 of *E. globulus* and board class 1 of *E. nitens*. These classes contained cuttings restricted in width but showed a wide range in length.

5.6.3.2.3 Cutting Area Definition 2

The same method was used to determine board classes using definition 2 as was used for definition 1. The cluster tree and classification model are not shown here, but results were similar to test 1. The number and proportion of boards from each board class for test 2 are shown in Table 5-16. For *E. nitens* the proportion of boards ranged from 14 percent to 50 percent across the classes, however, for *E. globulus* the range was between 10.7 percent and 43 percent. The method used for test 2 produced 520 cutting areas for *E. nitens* and 561 cuttings for *E. globulus*. The overall mean of boards contained in cutting areas was 79 percent for *E. nitens* and 83.0 percent for *E. globulus* (Table 5-17). This was an increase of 1 percent for *E. globulus* and 3 percent for *E. nitens* from test 1. The proportion of boards contained within cutting areas ranged from 70 percent to 89 percent for *E. nitens*, but from 76 percent to 91 percent for *E. globulus*. The proportion of cutting areas contained within board classes 1 and 4 was low (6 percent and 7 percent) for *E. nitens*, but only one board class for *E. globulus* was near this range (6 percent for board class 4). Interestingly, the same number of boards from each species (22 boards were classified into class 4 for each species) produced slightly

different proportions of cuttings. This was probably because cuttings were larger for *E. globulus* than for *E. nitens* and occupied a larger proportion of the boards.

Table 5-16. The number and proportion of boards in each board class for both species using cutting area definition 2.

Board class	*E. nitens*	*E. globulus*
1	19 (14)	52 (33)
2	68 (50)	68 (43)
3	27 (20)	17 (11)
4	22 (16)	22 (14)

Table 5-17. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 2.

Board class	*E. nitens*			*E. globulus*		
	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)
1	6	70	5	26	91	24
2	49	77	56	45	76	47
3	37	84	31	23	76	19
4	7	89	9	6	89	10
Overall mean		79			83	

The distribution to knotty cutting areas varied across the board classes. Board class 2 for *E. globulus* contained 47 percent of the cutting areas (Table 5-17). This group also contained approximately 45 percent of all cutting areas, which was produced from 43 percent of the boards for the species, with a comparatively low mean proportion of boards in cutting areas. Judging from the knotty cutting areas size distributions, board class 1 would contain a wide range of width classes, but a relatively short range of length classes. In contrast, 56 percent of the knotty cutting areas were found in 50 percent of the boards, which produced 49 percent of the cutting areas with a mean of 77 percent of the boards in cuttings (Table 5-17). Board class 2 would be expected to contain a narrow range of width and length classes of knotty cutting areas.

Overall, the distribution of cutting areas ranged from 35 mm to 140 mm wide by 250 mm to 4500 mm in length for all boards (Figure 5-44) for *E. globulus*. The higher occurrence occurred between 65 mm to 125 mm wide and between 250 mm to 1500 mm long. The highest occurrence of cutting area proportion occurred for the 80 mm to 95 mm wide by 1250 mm to 2750 mm long and 110 mm to 125 mm by 2000 mm to 2500 mm size classes. There were significant differences in cutting area size and area patterns for the board classes. Board class 1 contained an abundance of 80 mm to 95 mm by 500 mm to 2750 mm long cuttings. Board class 2 was characterized by mid to very wide by mid-length cutting areas. Board class 1 contained mostly very narrow and short cuttings. Board class 4 contained the widest and the longest cutting areas. These patterns were similar in the *E. globulus* cutting areas.

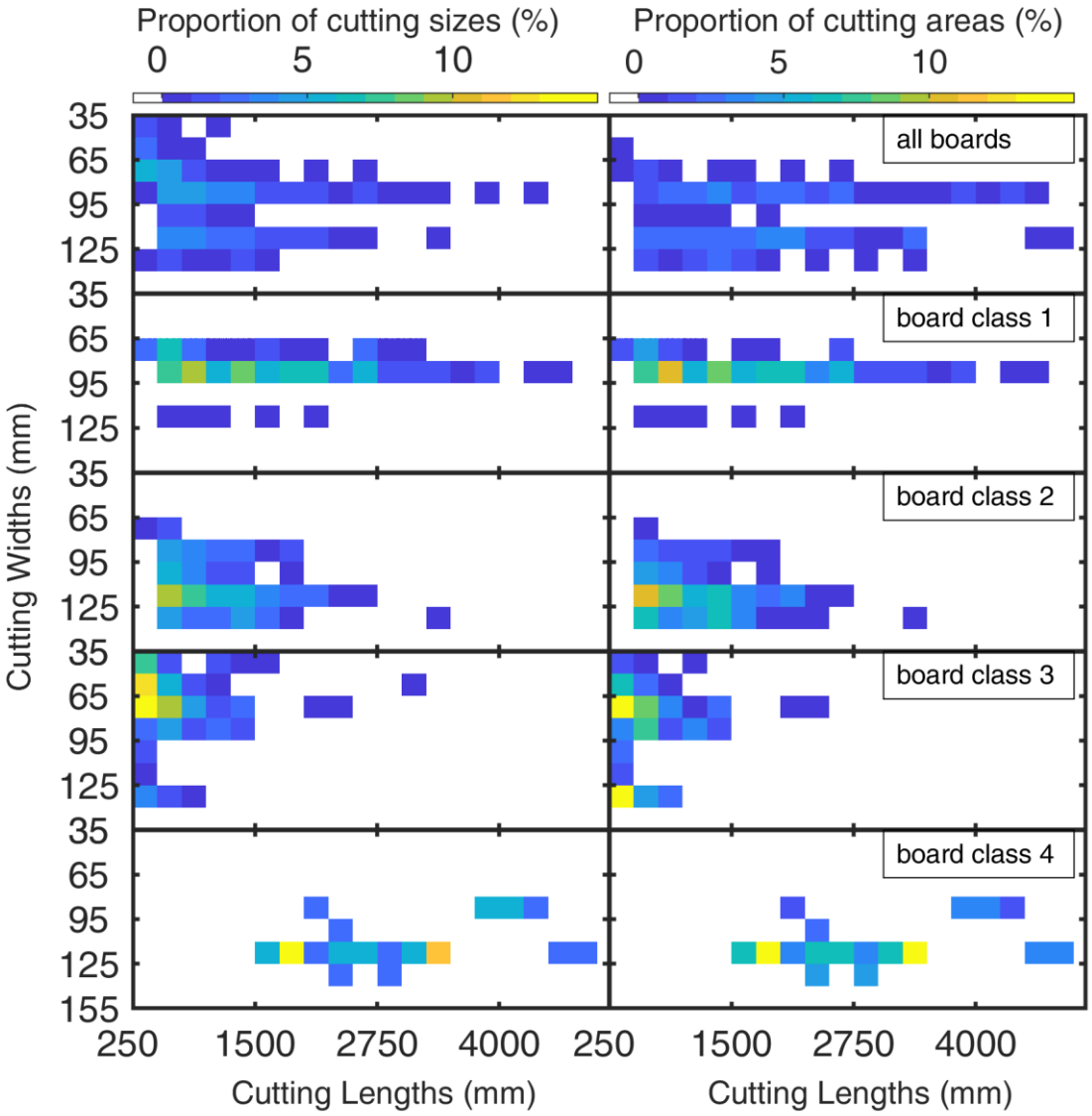


Figure 5-44. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 2. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on the area proportion figure.

Overall, a high proportion of cuttings belonged to relatively narrow and short bin classes for *E. nitens* (Figure 5-45), although there were significant differences between the patterns of cutting area sizes within the board classes. Notable examples are the patterns between board classes 1 and 4. Board class 1 is characterized by a relatively small range in width and length of cutting areas, while board class 4 has a similar range in width, but a much greater range in length of cutting areas. Board classes 2 and 3 also show differences. Board class 2, in general, contains many wider and longer cutting areas than did board class 3.

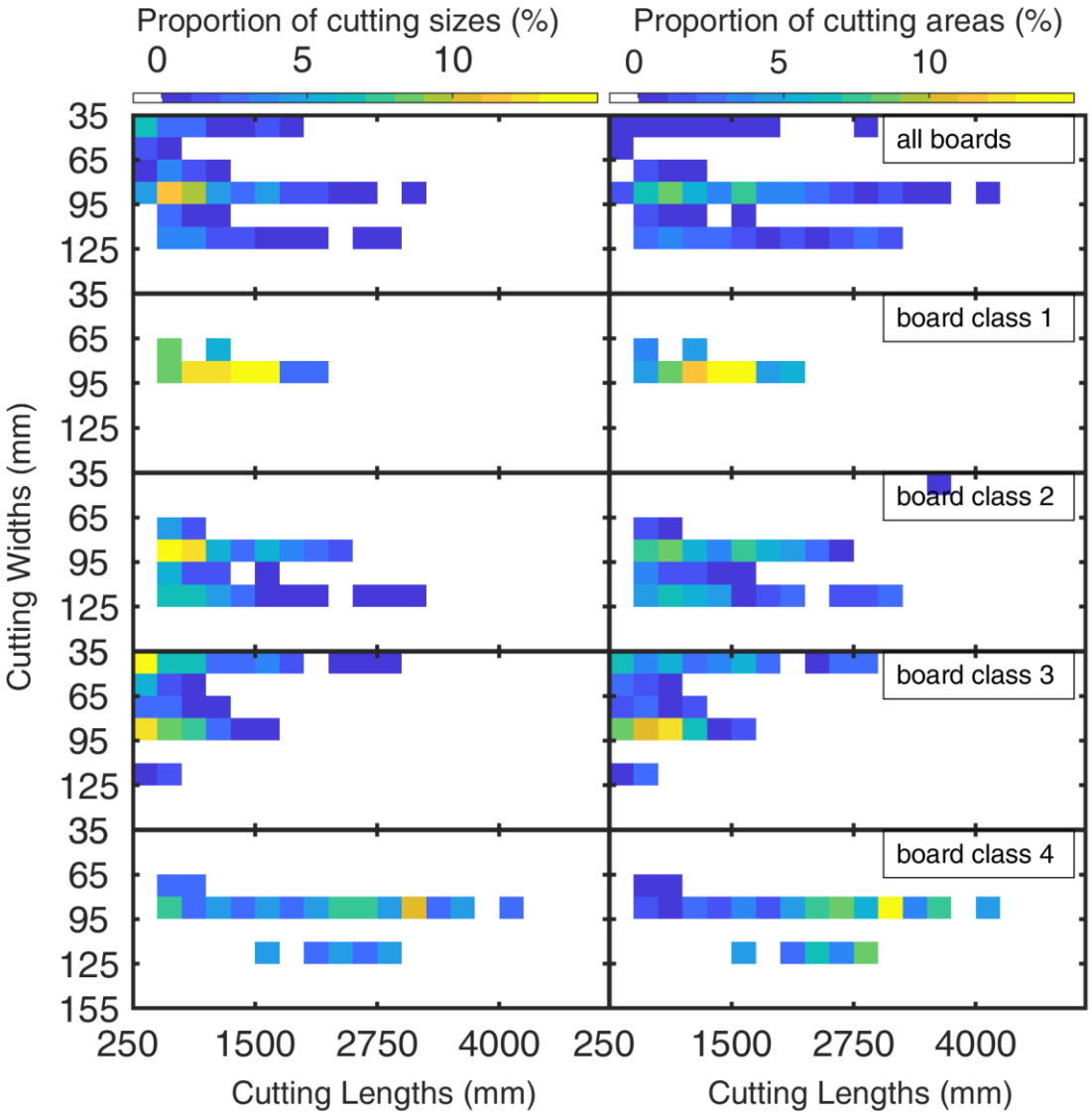


Figure 5-45. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 2. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might occur on the area proportion figure.

Of the 520 cutting areas produced by definition 2 for *E. nitens*, there were 150 that contained at least one knot. The minimum number of knots was 1 and the maximum was 7. Of the 150 cutting areas, 105 contained only 1 knot, 27 contained 2 knots, 9 contained 3 knots, and the rest contained between 4 and 7 knots. The highest proportion occurred in the width class between 85 mm and 95 mm and length classes between 500 mm and 1750 mm (Figure 5-46). For *E. globulus*, only 98 of the 561 cutting areas contained at least one knot; 64 contained 1 knot, 22 contained 2 knots, and the rest contained between 3 and 5 knots. The highest

proportion of knotty cuttings occurred for width classes between 65 mm and 125 mm and length classes between 500 mm and 1250 mm (Figure 5-46).

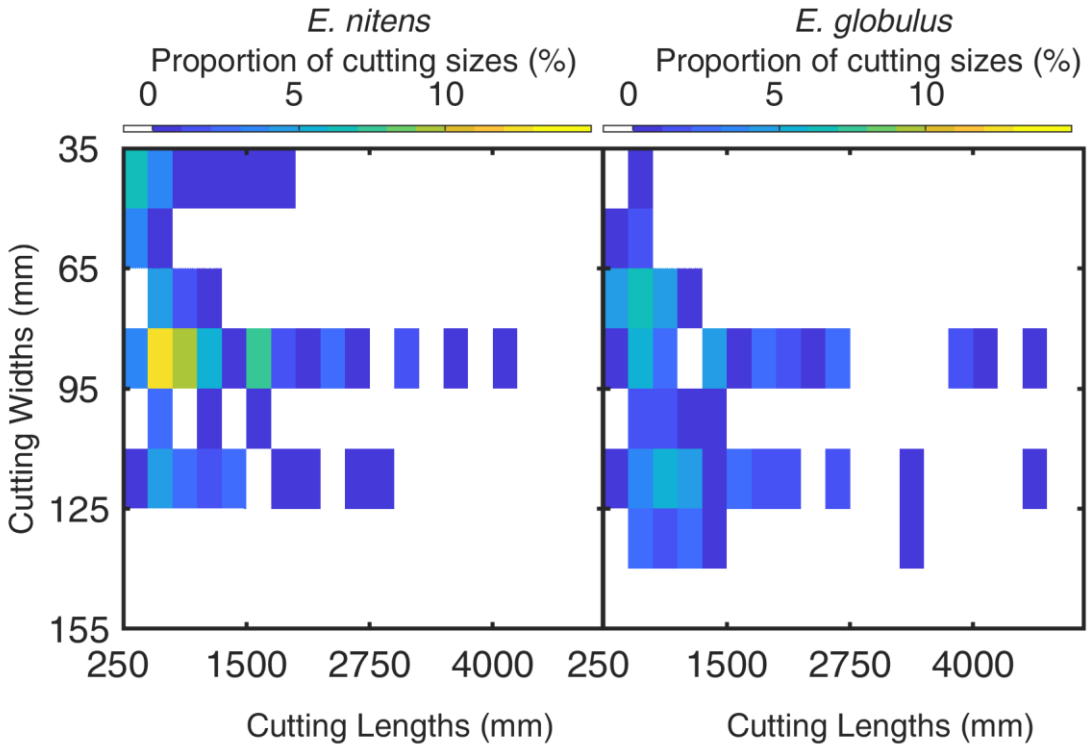


Figure 5-46. Distribution of cutting areas containing at least 1-knot using cutting area definition 2.

5.6.3.2.4 Cutting Area Definition 3

The same method was used for definition 3 as was used for definition 1. The cluster tree and classification model are not shown here, but results were similar to those from definition 1. The definition produced 461 cutting areas for *E. globulus* and 390 for *E. nitens*. The number and proportion of boards from each board class for test 3 are shown in Table 5-18. For *E. nitens* the proportion of boards ranged from 6 percent to 48 percent across the classes, however, for *E. globulus* the range was between 7 percent and 33 percent. The overall mean of boards contained in cutting areas was 84 percent for *E. nitens* and 86 percent for *E. globulus* (Table 5-19). Two classes of boards contained less than 10 percent of the cutting for *E. nitens*, while this occurred for only one class for *E. globulus*. 42 *E. nitens* boards from board class 3 produced 23 percent of the cuttings, while 43 *E. globulus* boards from class 1 produced 30 percent of the cuttings. Using this cutting area definition allows the overall mean of the

proportion of cuttings to increase 8 percent over definition 1 for *E. nitens*; however, the increase was only 4 percent for *E. globulus*.

Table 5-18. The number and proportion of boards in each board class for both species using cutting area definition 3.

Board class	*E. nitens*	*E. globulus*
1	8 (6)	43 (27)
2	21 (15)	52 (33)
3	42 (31)	53 (33)
4	65 (48)	11 (7)

Table 5-19. The proportion of cuttings and proportion of board in cuttings in each board class for each species using definition 3.

Board class	*E. nitens*			*E. globulus*		
	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)
1	2	94	3	30	82	27
2	9	93	12	46	79	41
3	23	86	20	21	93	27
4	66	79	64	2	92	6
Overall mean		84			86	

Cuttings sizes for *E. globulus* occupied all the bin width classes and ranged in length from 250 mm to over 4000 mm (Figure 5-47). The highest occurrence of cutting areas was in the 500 mm to 1500 mm length bins. Board class 1 contained mostly narrow cutting areas that ranged in length between 250 and 3000 mm, with a higher occurrence between 250 mm and 1500 mm. Board class 2 contained mostly mid to very wide cutting areas that ranged between 500 mm and 1500 mm. Board class 3 contained the highest occurrence of long cutting areas in bin width classes of 80 mm to 95 mm and 110 mm to 125 mm. Board class 4 very contained few cuttings but these were the widest and longest cuttings found during this test.

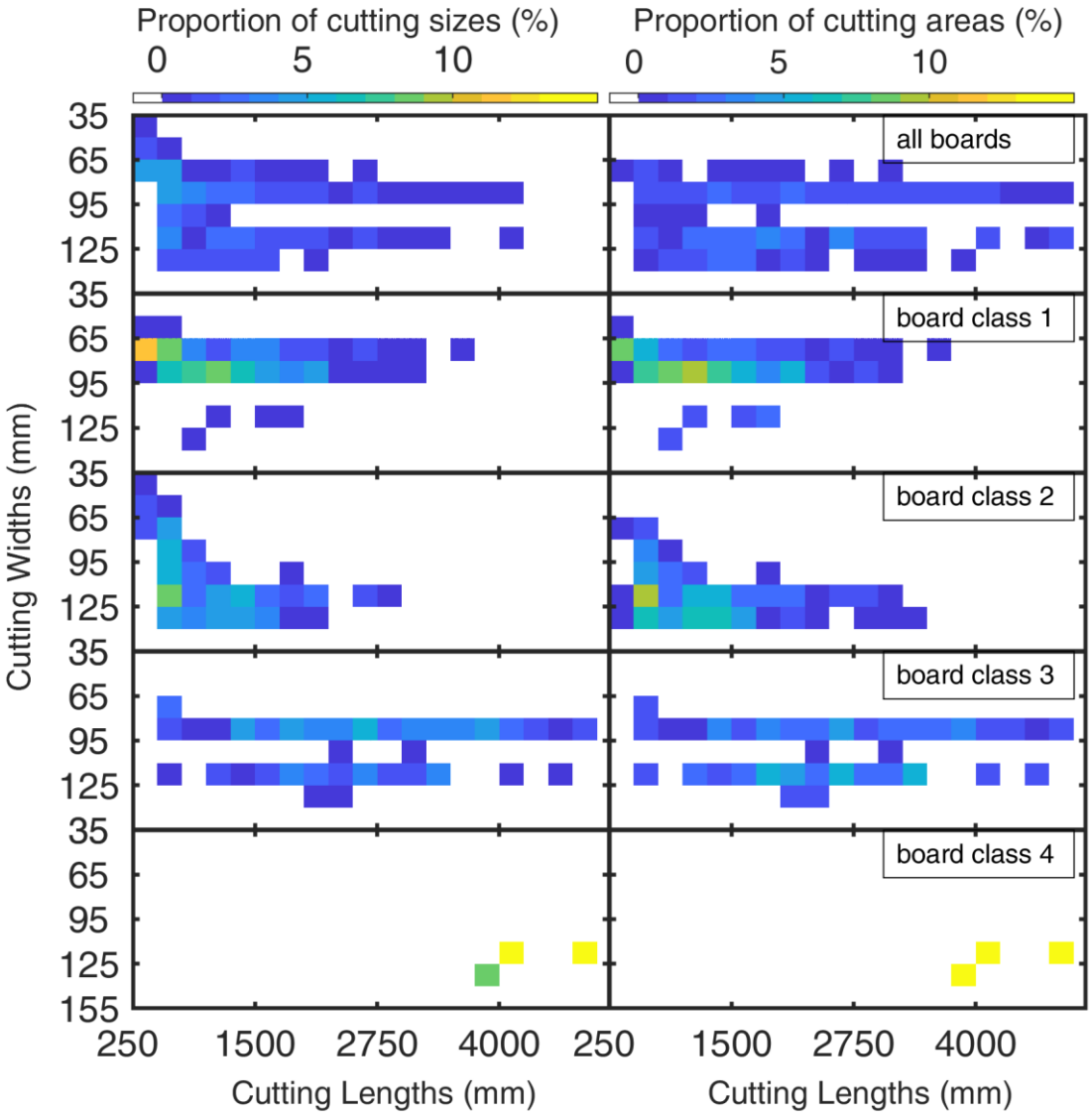


Figure 5-47. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 3. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on the area proportion figure.

Overall, cutting areas mostly occurred in the 80 mm to 95 mm and 110 mm to 125 mm bin width classes for *E. nitens* (Figure 5-48). Board class 1 contained mostly wide and very long cutting areas, while board class 2 contained a range of lengths in the 80 mm to 95 mm bin width class. Because of wide and long cutting areas, more than 60 percent of the area proportion was made up of very long cuttings in these two classes. Board class 3 also contained cuttings in this bin width class but had a higher occurrence in the shorter size classes. Board class 4 had the highest occurrence in mid to very wide bin classes and from 500 mm to 1500 mm bin length classes.

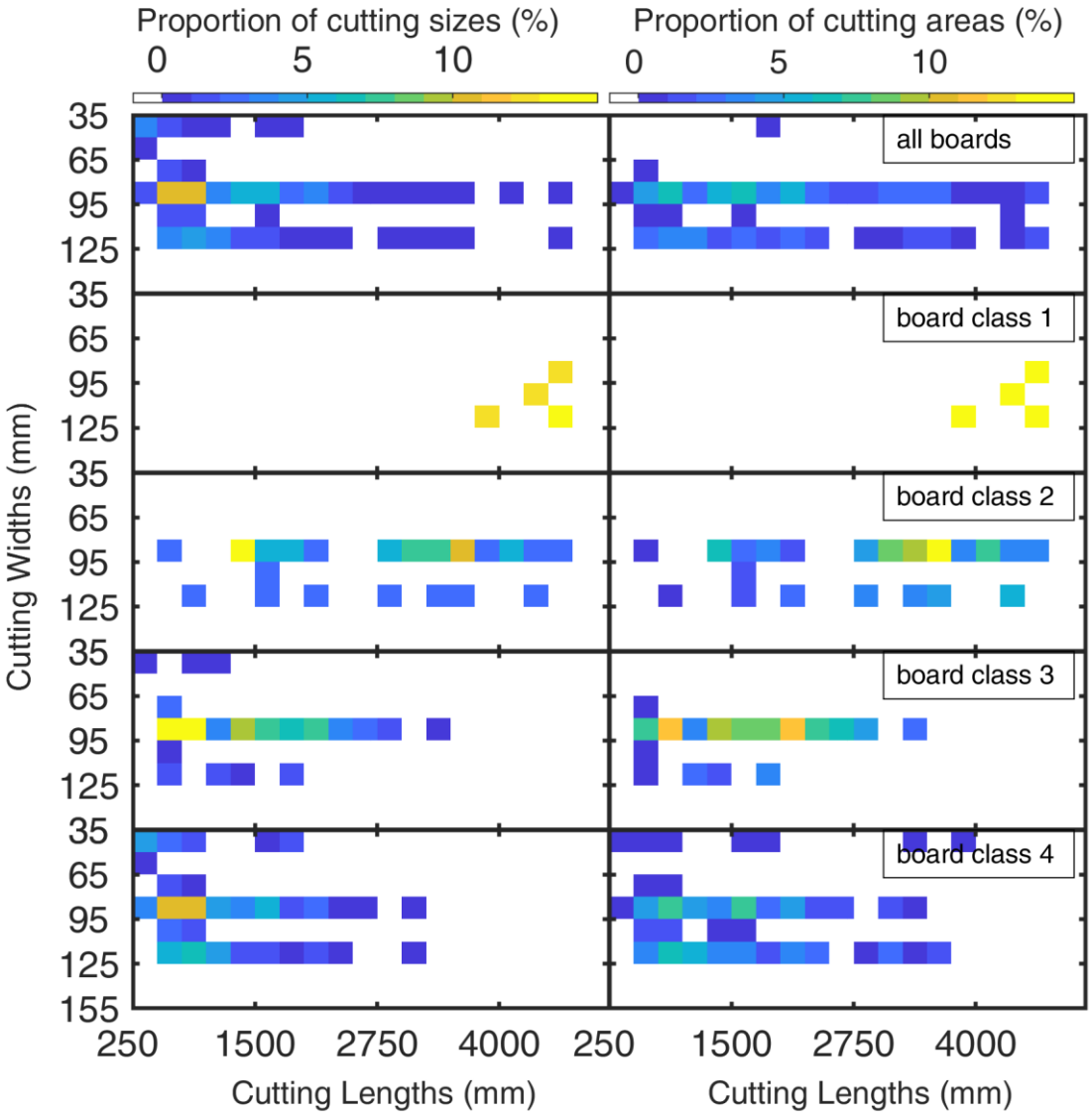


Figure 5-48. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 3. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might be indicated on area proportion figures.

Of the 390 cuttings produced with the definition for *E. nitens*, 234 contained at least 1 knot; 126 contained 1 knot, 75 contained 2 knots, 50 contained 3 knots, and the rest contained between 4 and 10 knots. Of the 461 cutting areas found for *E. globulus*, 178 contained at least 1 knot. The number of knots ranged from 1 to 9 and 82 contained 1 knot, 42 contained 2 knots, 27 contained 3 knots, and the rest contained between 4 and 9 knots.

The distribution of knotty cuttings varied considerably among the board classes for both species, however, the range was much greater for *E. nitens* (Table 5-19). Board class 2 for *E.*

globulus contained 40.5 percent of the knotty cutting areas, while board classes 1 and 2 both contained 26.9 percent of the cutting areas. As before, the board class (1) with the highest proportion of knotty cuttings also contained the highest proportion of cuttings overall and was produced with the lowest mean proportion of board in cutting areas. For *E. nitens*, board class 4 contained 64 percent of the knotty cuttings, 66 percent of the cuttings overall, the highest proportion of boards, and the lowest proportion of boards in cuttings. Interestingly, the converse of the above patterns can also be observed in the cutting area patterns.

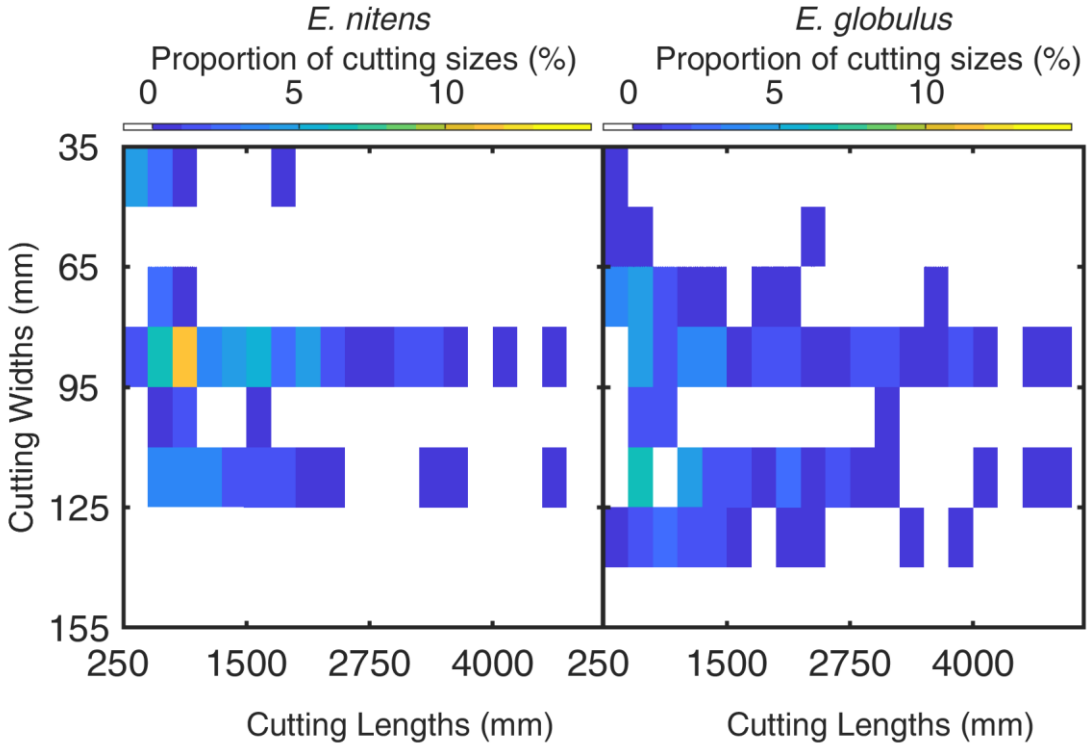


Figure 5-49. Distribution of cutting areas that contain at least one-knot using cutting area definition 3.

5.6.3.2.5 Cutting Area Definition 4

The same method was used to determine board classes using definition 4 as was used with definition 1. However, unlike the previous tests, this test defined allowable knots sizes from 650 mm^2 to 2580 mm^2. This test explored the effects of upper and lower limits on knot size. The cluster tree and classification model are not shown here, but results were similar to test 1. The definition produced 496 cutting areas for *E. globulus* and 414 for *E. nitens*. The number and proportion of boards from each board class for test 4 are shown in Table 5-20. For *E. nitens* the proportion of boards ranged from 5 percent to 63 percent across the classes,

however, for *E. globulus* the range was between 8 percent and 38 percent. The overall mean of boards contained in cuttings was 83 percent for *E. nitens* and 86 percent for *E. globulus* (Table 5-21). Three classes of boards contained less than 11 percent of the cuttings for *E. nitens*, while this occurred for only one class for *E. globulus*. 86 *E. nitens* boards from board class 2 produced 78 percent of the cuttings, while 54 *E. globulus* boards from class 2 produced 49 percent of the cuttings. Using this cutting area definition allows the overall mean of the proportion of cuttings to increase 6 percent over definition 1 for *E. nitens*; however, the increase was only 4 percent for *E. globulus*.

Table 5-20. Number and proportion of boards in each board class using cutting area definition 4.

Board class	*E. nitens*	*E. globulus*
1	24 (18)	61 (38)
2	86(63)	54(34)
3	19 (14)	12 (8)
4	7 (5)	32 (20)

Table 5-21. The proportion of cuttings and proportion of board in cuttings in each board class for each species using cutting area definition 4.

Board class	*E. nitens*			*E. globulus*		
	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)	Proportion of cuttings (%)	Proportion of boards in cuttings (%)	Proportion of knotty cuttings (%)
1	10	81	9	38	89	29
2	78	82	79	49	79	47
3	10	89	10	3	99	20
4	2	89	1	10	88	4
Overall mean		83			86	

Overall, the distribution of cutting area sizes ranged in bin width classes between 65 mm to 140 mm and bin length classes of 500 mm to over 5300 mm for *E. globulus* (Figure 5-50). The highest occurrence of cutting areas was in bin width classes between 65 mm to 125 mm and bin length classes of 500 mm to 2250 mm. Board class 1 contained mostly narrow cutting areas that ranged in length between 250 and 4000 mm, with a higher occurrence between

250 mm and 2000 mm. Board class 2 contained mostly mid to very wide cutting areas that ranged between 500 mm and 2000 mm. Board class 3 contained the highest occurrence of long cutting areas in bin width classes of 110 mm to 140 mm and bin lengths greater than 4750 mm (note that 10 cuttings exceed axis range). Board class 4 very contained wide cutting areas ranging in length from 1500 to 5000 mm.

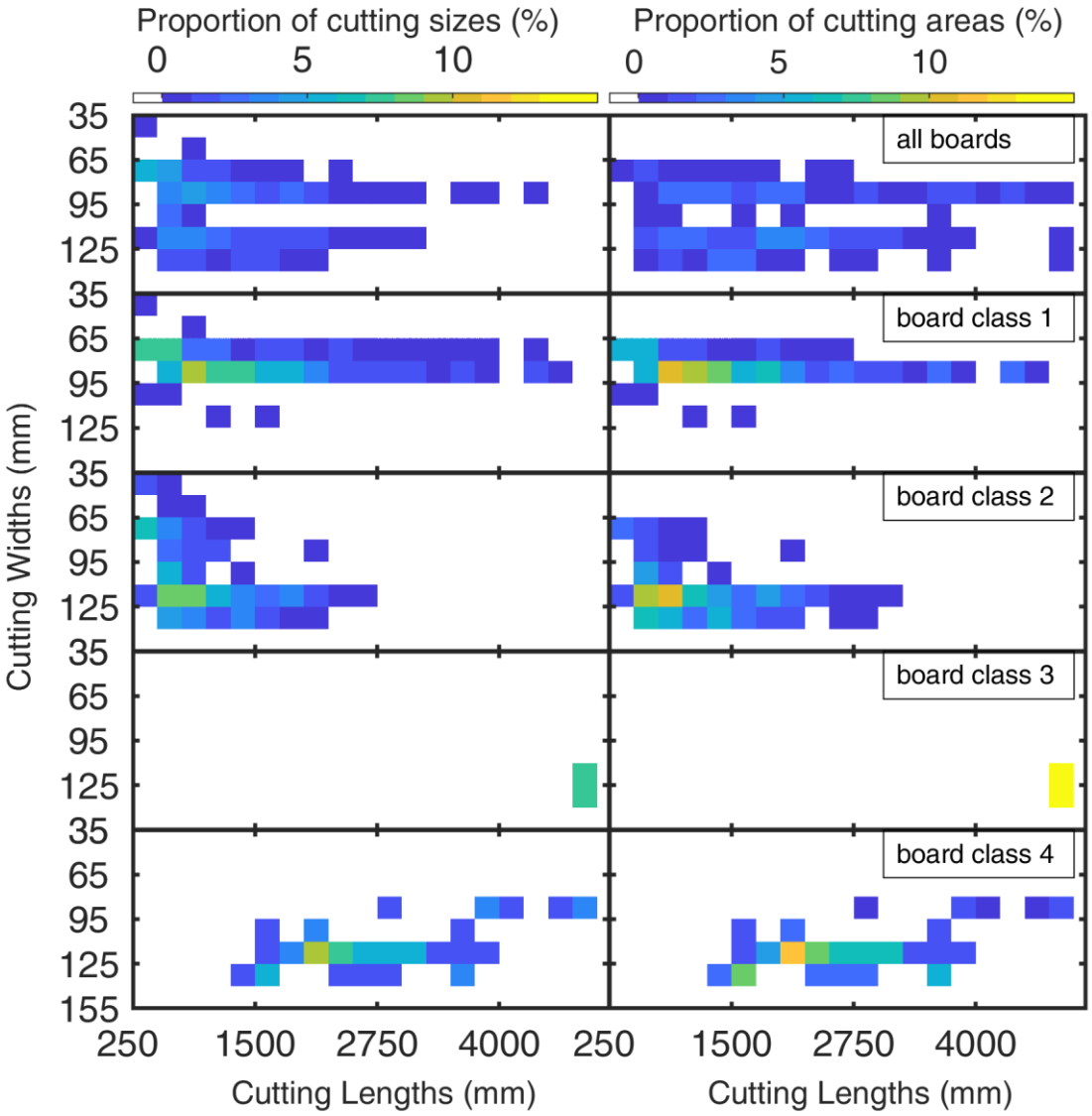


Figure 5-50. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. globulus using cutting area definitions 4. For board class 2, 10 cuttings exceeded the axis range. They were greater than 5300 mm in length. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures.

Overall, the distribution of cutting area sizes ranged in bin width classes between 65 mm to 125 mm and bin length classes of 250 mm to over 5000 mm for *E. nitens* (Figure 5-51). The highest occurrence of cutting areas was in bin width classes between 35 mm to 125 mm and bin length classes of 250 mm to 1750 mm. Board class 1 contained cutting areas mostly in the 80 mm to 95 mm bin width class and ranged in length from 500 to 2750, with a higher occurrence between 500 mm and 1750 mm. Board class 2 contained mostly narrow to wide cutting areas that ranged in length between 250 mm and 1500 mm. Board class 3 contained mid to wide cutting areas that ranged in length from 500 to over 4000 mm. Board class 4 very contained wide and long cuttings (note that 1 cutting exceeds the axis range).

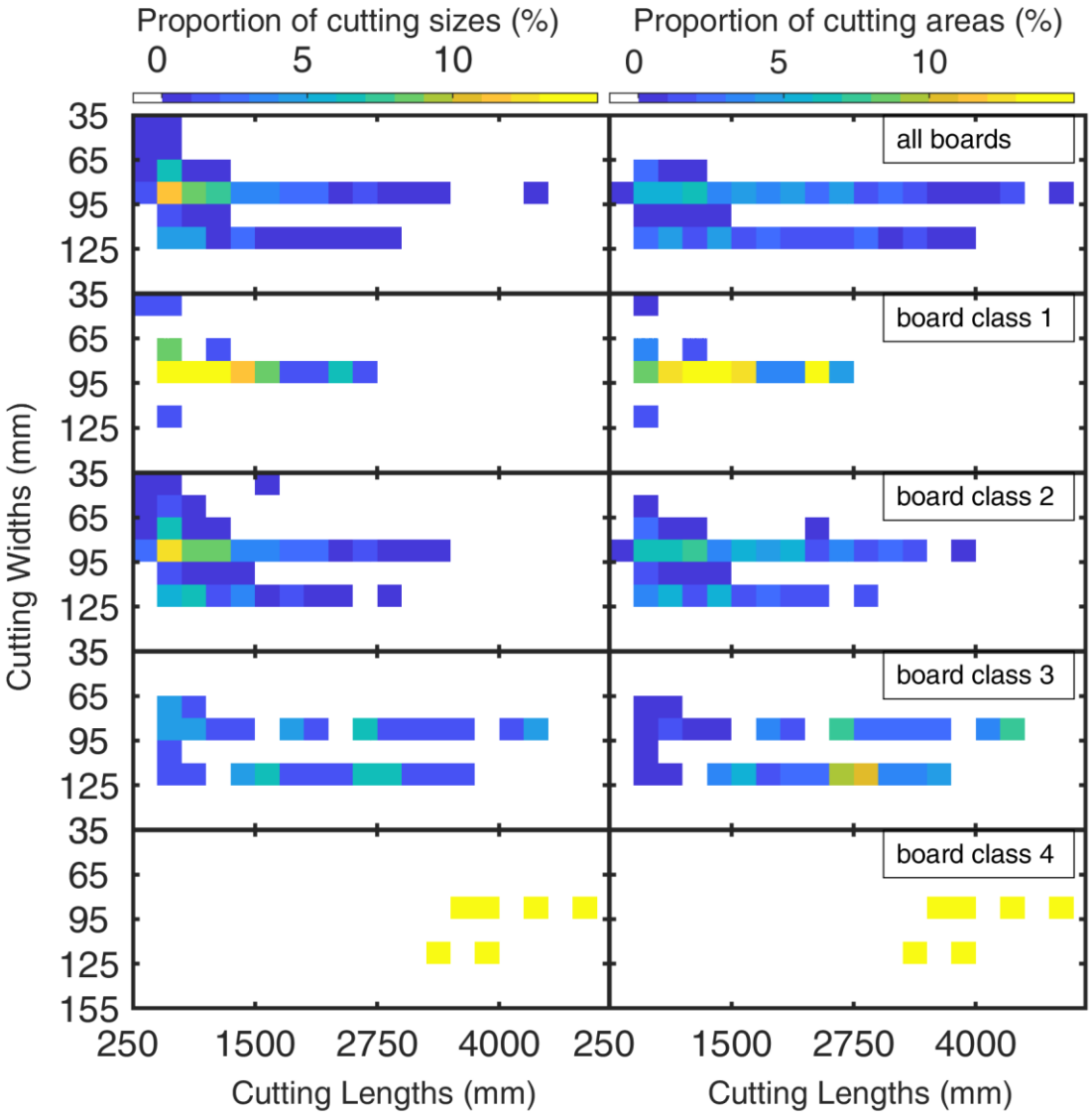


Figure 5-51. Distribution of cutting sizes and areas for all boards and the 4 board classes derived from the classification model for E. nitens using cutting area definitions 4. For board class 4, there was 1 cutting that exceeded the axis range. It was 5276 mm in length. Note that due to rounding errors, low occurrences may not be indicated on cutting size figures but might appear on area proportion figures.

Of the 414 cutting areas produced with the definition for *E. nitens*, 232 contained at least 1 knot; 133 contained 1 knot, 56 contained 2 knots, 24 contained 3 knots, and the rest contained between 4 and 7 knots. The number of knots ranged from 1 to 7. Of the 496 cutting areas found for *E. globulus*, 199 contained at least 1 knot; 130 contained 1 knot, 36 contained 2 knots, 22 contained 3 knots, and the rest contained between 4 and 6 knots. The number of knots ranged from 1 to 6.

As before, the lowest mean proportion of boards in cutting areas was correlated to the highest proportion of cutting areas overall and the highest proportion of knotty cutting areas in board class 2 for *E. globulus*; however, these results occurred for only about one-third of the boards for the species (Table 5-21). In contrast, the range of the proportion of knotty cutting areas and the proportion of cutting areas overall was much greater for *E. nitens*. For example, board class 2 produced 79 percent of the knotty cutting areas from 63 percent of the boards but with a relatively low proportion of boards in cutting areas overall (Table 5-21). Most of the knotty cutting areas for *E. nitens* will be moderately wide, but relatively short, in a range between 500 mm and 1500 mm (Figure 5-52).

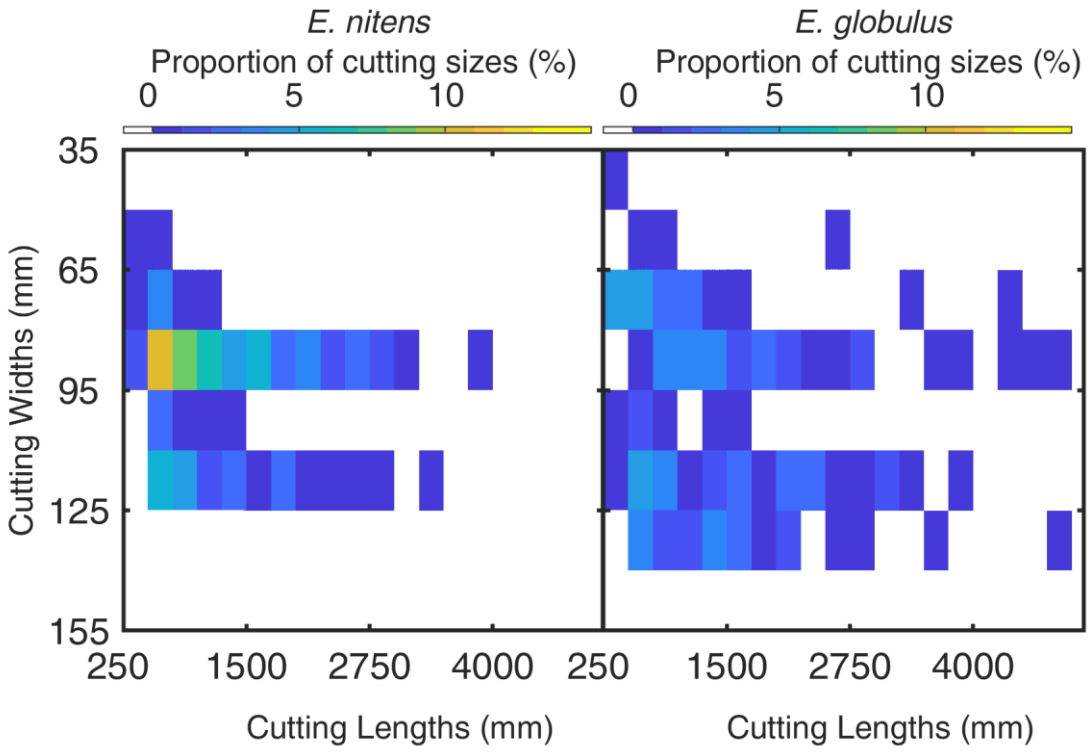


Figure 5-52. Distribution of cutting areas that contain at least one-knot using cutting area definition 4.

5.6.3.2.6 Comparison to NHLA Graded Lumber

The distribution of cutting areas for lumber graded to NHLA grades is shown in Figure 5-53. The 1038 #1C boards produced 3510 cutting areas, of which 2668 were longer than 250 mm and narrower than 140 mm. This grade of lumber is characterized by cutting areas ranging in width from 65 mm to 140 mm (cuttings above 140 mm were removed) and from 500 mm to 1750 mm. The absence of cutting areas widths below 65 mm is expected because the

minimum cutting width allowed in #1C lumber is 76.2 mm. The 239 #3AC boards produced 1491 cutting areas, of which 1436 were longer than 250 mm and narrower than 140 mm. The highest proportion occurs between 65 mm and 140 mm wide by 500 mm to 100 mm long. This grade of lumber is characterized by much narrower and shorter cutting areas than #1C; most cutting areas were in bin widths between 35 and 95 mm and bin lengths between 250 and 750 mm. The high proportion cutting areas in small bin size classes for #3AC is a direct function of the slight modification in the system rules for that grade which allowed very narrow and short cuttings to be found (Table 9-1). Under normal NHLA rules, the minimum width would be 76.2 mm wide by 609 mm in length.

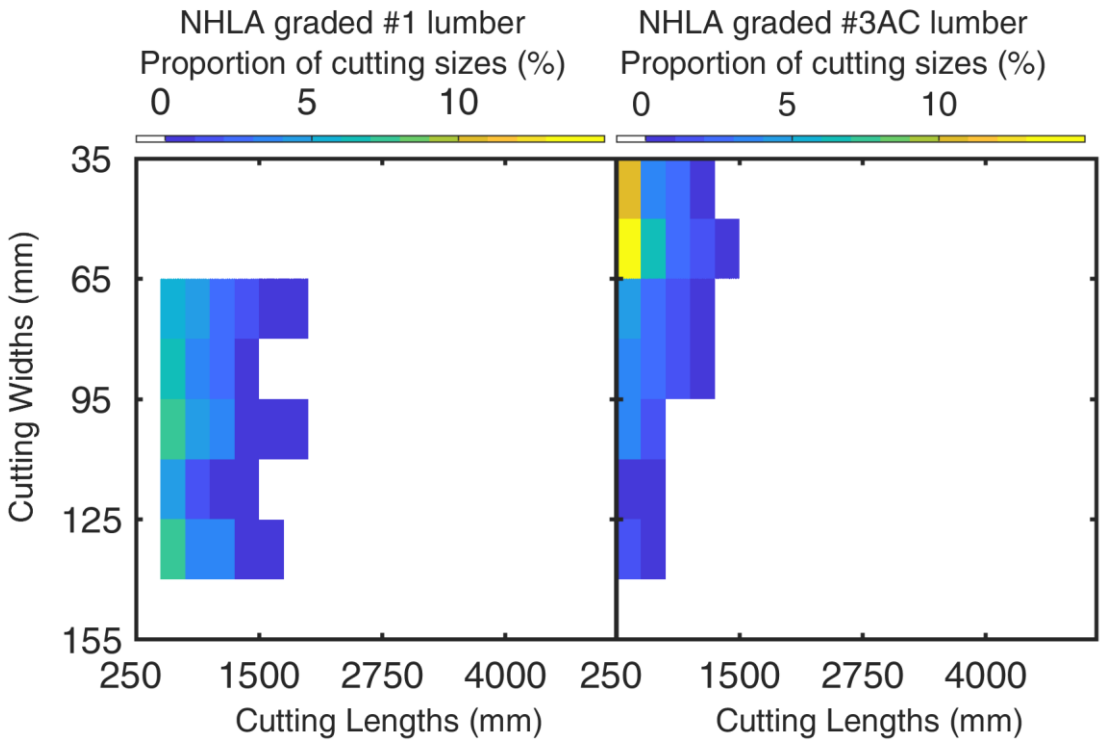


Figure 5-53. Cutting area distribution for NHLA #1C and #3AC graded lumber from the red oak database. The #1 lumber included 1038 boards and the #3AC lumber included 239 boards. All characteristics in the database were used to determine the cutting areas.

5.6.3.2.7 Comparison Between Validated and Automatic Datasets

The distribution of missed and extra clear cutting areas is shown in Figure 5-54. Missed cutting areas are defined as cutting areas in a class that is not found using the automatic detection method but are present on boards in the validation set. Extra cutting areas classes are those that are found on boards using the automatic detection method but are not found using the

validation dataset. They are both determined at the individual board scale—that is, each board was evaluated independently, and the misses and extras were summed. Additionally, missed and extra cuttings are a direct function of both knot detection and knot size. Because NHLA grading is based on the minimum cutting areas found on the board, missed and extra cuttings may or may not affect the overall grade of the board. For *E. nitens*, there were a total of 226 extra cutting areas in classes not found in the validated data and 223 missed cutting areas in classes that were present in the validated dataset. For *E. globulus*, there were 184 extra cutting areas and 223 missed cutting areas. Overall, missed and extra cutting areas were narrower and shorter for *E. nitens* than for *E. globulus*. This could result in not having samples of 140 mm wide boards in the *E. nitens* samples. However, the distribution of missed and extra cuttings was more evenly distributed for *E. globulus* than for *E. nitens*.

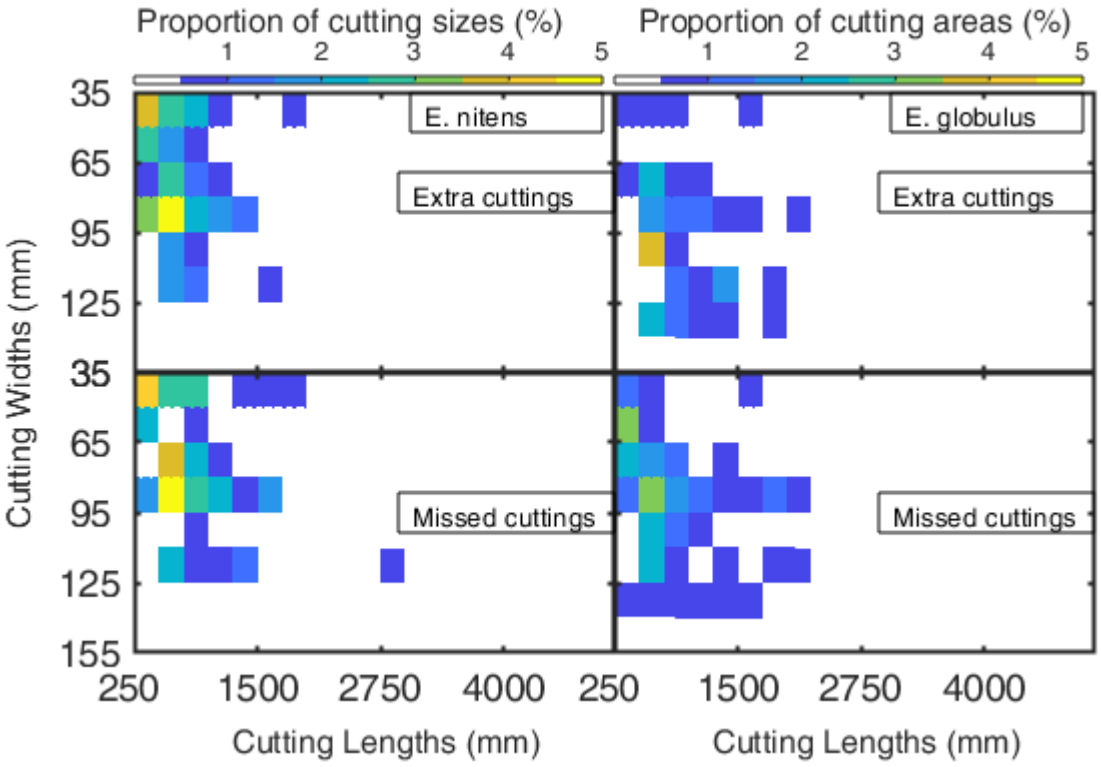


Figure 5-54. Distribution of missed and extra cuttings found between the validation and automatic detection datasets.

5.6.4 NHLA Grades

5.6.4.1.1 Validated Boards

The distribution of boards assigned to 1994 NHLA grades is shown in Table 5-22. The distribution was highly skewed towards #1C; 61 percent of the *E. nitens* boards and 80.5

percent of the *E. globulus* boards were determined to be this grade. The lowest number of boards in both species was graded as Selects for both species; however, *E. globulus* contained a low proportion of #2AC and #3AC boards. A moderate proportion of *E. nitens* boards graded as #2AC and #3AC. From the red oak database of 3473 boards (Gatchell et al., 1997), 8 percent were graded as Select, 30 percent were graded as #1C, 27 percent were graded as #2AC, and 7 percent were graded as #3AC. Other information about the NHLA grading results from the automatic dataset can be found in 9.2 NHLA Grades for Automatic Dataset.

Table 5-22. The number and proportion (percent) of boards in each NHLA grade for both species from the validated dataset.

NHLA Grade	*E. nitens*	*E. globulus*
Selects	2 (2)	9 (6)
#1C	83 (61)	128 (81)
#2AC	19 (14)	7 (4)
#3A	32 (24)	15 (10)

Based on the current sawmill value of green Red Oak and Birch (HMR, 2019), *E. nitens* has a value of approximately AUD 361/m^3 and AUD 392/m^3 respectively, and *E. globulus* would have a value of AUD 389/m^3 and AUD 457/m^3, respectively.

5.7 Discussion

The objective of this chapter was to develop and demonstrate a novel lumber classification system based on the distribution of areas within boards that contain a defined range of knot size and type. The objective was approached using two different board break-down processes. The first lumber classification system was based on defining a board segment that must contain a knot of a defined size and type. The second system was based on the cutting areas that may contain a knot of a defined size and type.

For this to be accomplished, the following was developed:

- a set of variables was identified that described the frequency and proportion of board segments and cutting areas at the board-scale;
- a clustering procedure that indicated four or five meaningful board clusters existed for both the segmenting and cutting area methods;

- classification methods (SVM for segment method, KNN for cutting area method) were developed that faithfully replicated the clustering solutions, and;
- the cutting area geometry and distribution of the different board classes were described at the batch scale with heatmaps.

The procedures presented above used the board-scale information from Chapter 3 to sort lumber into different classes. The available segments and cutting areas of each class of lumber were then described at the batch scale.

5.7.1 Board-scale Knot Distribution Patterns

The boards used in this study were milled from 15-year-old *E. nitens* and 26-year-old *E. globulus* unthinned and unpruned plantation-grown hardwood logs from northwestern Tasmania (Jiao et al., 2019). The diameter of these logs ranged from 345 mm to 403 mm respectively and recovery into lumber was between 25.8 percent and 31.8 percent, respectively (Jiao et al., 2019). The boards produced from these resources contain a range of wane, limb trace, and knots. The number of knots per board ranged from 30 to 1, but most boards (~ 70 percent for *E. nitens* and ~80 percent for *E. globulus*) contained less than 10 knots (Figure 5-9). There was a higher proportion of the *E. globulus* boards with fewer knots than *E. nitens* and there were more *E. nitens* boards with more than 10 knots than for *E. globulus* boards. This could be related to the age of the trees at harvest, the branching habit of each species, or the position of the log that the board was milled from within the tree.

The Simpson index was used as a measure of both frequency and diversity of different knot sizes and types. For example, a board containing 2 knots from 4 size classes and one from the remaining class would have an index of 0.9. It indicated that few boards contained knots in a single size or appearance class (Figure 5-10 and Figure 5-11), indicating the random distribution of knots within individual boards. The Simpson index indicated greater knot diversity for *E. nitens* in a higher proportion of boards than for *E. globulus*. This implies that a sorting system with upper or lower limits (or both) on knot size, such as the current AS 2796, would not be able to segregate boards into groups containing different knots within a specific size range effectively or produce sorts with similar visual characteristics such as suggested by Breinig et al. (2015). This concept is reinforced given the large range of knot areas found on

most of the boards (Figure 5-12 and Figure 5-13). This implies a sorting approach that is based on defining the allowable size and type of characteristics in segments or areas of boards that may provide a more appropriate means to sort boards by the amount of useable areas that contain a defined range of specific characteristics.

5.7.2 Board Segments

5.7.2.1 Validated Dataset

The two unsorted resources produced boards with a relatively high amount of one-sided clear sections greater than 1000 mm in length (Figure 5-14). Approximately 60 percent of the *E. globulus* and about 42 percent of the *E. nitens* boards contained greater than 50 percent clear segments (Figure 5-14). The lengths of clear segments varied between 1000 mm and 4000 mm for *E. globulus* and 3000 mm for *E. nitens*; however, the vast proportion was below 2000 mm for both species (Figure 5-15). In total, clear segments over 1000 mm account for approximately 30 percent for *E. nitens* and 45 percent for *E. globulus* of the total board lengths. The clear segment length distribution pattern varied by the width class of boards as well (Figure 5-15). This pattern was also found by Derikvand et al. (2018b). In that study, the average length of clear segments ranged from 1151 mm to 987 mm for the different width classes of *E. globulus* boards used in this study. That study also found that approximately 50 percent of the boards were in clear segments greater than 500 mm. However, another study by Derikvand et al. (2018a) found the 70 mm wide *E. nitens* boards contained 61 percent clear segments, while the other width classes contained much less clear wood. This study found significantly more clear wood for width classes 90 mm and 120 mm than the previously mentioned one; this could be due to the exclusion of other characteristics (such as unrecoverable collapse, insect trace, wane, and mechanical damage), the examination of a single side of the board, and the low number of samples used in the other studies (that study used 13 and 14 boards in width classes 90 mm and 120 mm, this study used 95 boards in the 90 mm and 41 boards in the 120 mm width classes).

These findings indicate that despite the current sentiment that these resources produce boards with low utility and value, under a short-section operation, the recovery of useable material from boards could be acceptable for some types of products, such as solid-panels that contain different types and sizes of knots. Finger-jointing is a common way of extending

short stock, salvaging waste, upgrading lumber, and has been used commercially since the mid-1960s (Chiang, 1964). Finger-jointing is the process for joining random length stock to produce longer lengths suitable for a wide range of both structural and appearance products. Because the resulting finger-jointed stock contains no or very few strength reducing characteristics, such as knots, the stock has bending and compression strength and dimensional stability equal to or higher than the solid stock of the same dimensions (Chiang, 1964).

The feasibility of finger-jointed stock depends on the characteristics of the raw material (available boards) the value of the final finger-jointed stock, and the difference between the material input value and the output value (Chiang, 1964). Finger-jointing operations are particularly suited to regions with decreasing volumes of high-grade lumber (Chiang, 1964). Further study is needed to fully understand the economics of finger-jointing operations located in Tasmania, however, this technique is used elsewhere to profitably produce a wide range of high-quality products from what is commonly considered low-quality materials. Finger-jointed material has the potential to increase the value of the plantation grown hardwood above the current value of pulp produced for the pulp and paper industry.

The boards also contain ample amounts of segments containing knots of various sizes and types in a range of lengths (Figure 5-16, Figure 5-17, Figure 5-18, and Figure 5-19). Extending the concept of finger-jointing, operations, and products utilizing segments that contain both clear and knotty type 1 segments could recover approximately 20 percent and 30 percent more *E. globulus* and *E. nitens* board. Such operations could either combine the two segment types to produce differentiated products; one containing clear material, the other containing knots allowed under definition 1 (Table 4-1), or any other definition that specifies desirable characteristics. Another use for such material would be to use the knotty segments as core in laminated products, such as engineered wood flooring (EWF). EWF is made by laminating a "wear" layer to a substrate or core of less desirable material.

Random length tongue-and-groove end-matched overlay flooring is another product that would also make good use of such resources. This product has been a long-term staple in North America and is produced from a range of species, including softwoods with densities around 422 kg/m^3. Although random length flooring does not appear common in the

Australian context, it is a product that consumes large quantities of low-grade, low-value hardwood elsewhere. It is also a product that requires little knowledge about the "back-side" of the board. The appearance qualities depend only on the "good" side—the side containing the specific types and sizes of characteristics desired by the end-users. Given the current trends toward using a wider range of knots in appearance products, a strategy that segregates clear and knotty segments could be used to fill the end-users' desire for specific sizes and types of knots. Because the current Australian industry produces boards in finished widths and thicknesses, the product only requires the development of digital characterization, processing, drying, and market research to be realized from the current resource.

The above discussion describes the frequency and geometry of board segments as they occur in unsorted lumber. Although there may be potential to use unsorted lumber as feedstock to finger-jointing or flooring operations, it may be possible to obtain better efficiency by sorting the lumber so that the best-suited boards are used to achieve specific visual outcomes. The rest of this chapter focuses on that endeavor.

5.7.2.2 Comparison Between the Validation and Automatic Detection Datasets

As outlined in Chapter 3, the automatic detection method used in this research achieves a false negative rate of approximately 10 percent—that is about 10 percent of the knots are missed by the method. The missed knots are mostly very small and light in color (Figure 3-48). The method also resulted in a very low false negative rate. Not surprisingly, there was little difference in the estimate of the number of clear segments (Figure 5-21) or the proportion of boards in clear segments (Figure 5-22) between the validated and automatic datasets. However, because the performance of the knot size classification of the automatic method was low (Figure 3-44 and Figure 3-45), estimates of knotty type segments were relatively low for both species. Interestingly, despite the better performance of size classification of knots for *E. nitens*, the estimates of the number of segments and proportion of boards in each segment type were worse for *E. nitens* than for *E. globulus*. These findings point out the importance of accurate characterization of knots by vision systems designed to characterize characteristics of boards to locate segments or areas that contain characteristics of specific sizes and types.

5.7.3 Board Classification

5.7.3.1 Segmenting Method

This work presents a method that uses the distribution of size and frequency of segment types to find naturally existing groups of boards. It was hoped that these groups would contain boards with a proportion of different segments more like each other than to boards in other groups. A clustering procedure is performed to map each board to a class. A classification model is then developed using these classes. This classification model can then be used to sort new boards into the groups. This method should not be thought of as grading; rather, this method sorts boards into groups containing similar levels of segments containing various sizes and types of knots.

One objective of this work was to develop a flexible sorting procedure to group boards with similar levels of segment types. Such a system needs to be able to respond to changes in the way segment types are defined. Under such a system, the rules would change depending on not only demand for certain segment types, but also the available resources, market cycles, and customer and product requirements. A dynamic sorting model best describes such a system (Lycken, 2006b). Unlike current hardwood grading procedures, such a system would not necessarily be easy to implement using manual visual procedures or to understand the specific limits of allowable characteristics or combinations of characteristics, or the complex interplay between various rules. This approach would require digitized board scale information and a classification model that could sort boards into meaningful groups. Although other research has found this approach to produce acceptable results (Boden et al., 2005, Olofsson et al., 2019, Thomas, 2017). In most cases, the goal was to grade lumber according to existing standards, such as the NHLA grades. The methods presented here suggests a new approach that allows flexibility not offered by most other grading procedures.

Suppose someone selected the visual attributes produced by clear segments of *E. globulus* as shown in Figure 4-10, board class 4 would be a good choice given that it contains many long segments and potential recovery of 93 percent. Given the differences between the two species in this study, an equivalent is not available in *E. nitens*. However, board class 3 could potentially provide approximately 71 percent recovery and a small proportion of segment type 1 flooring if *E. nitens* was desired. Now suppose a panel with the visual attributes

produced by type 2 *E. globulus* segments as shown in Figure 4-12. Now suppose a manufacturer desired to produce products that were clear and contained knots specified in type 2 segments under definition 1. Board class 1 for *E. globulus* would make a good choice. These examples highlight the hypothetical use of both communication and description to obtain the best-suited batch of lumber to achieve desired visual outcomes.

The segmenting method developed in this research successfully sorted boards that contain different proportions of segments containing specific sizes and types of knots. This approach differs significantly from most current timber grading procedures. First, it is based on defining the allowable knots within segment types, second, it treats the segment types independently and without priority. That is, knotty segments are treated in the same way as clear segments. The method does not operate from the rule-based procedure, therefore a violation of a single rule does not necessarily result in the downgrading of the entire board. The approach produces results similar to the holistic-subjective grading as proposed by Olofsson et al. (2019) in that customers can receive groups of boards that contain most of what they desire. Holistic-subjective grading is based on manual visual assessment and sorting to determine the subjective grouping of boards that meet a customer's expectations. Then a model is devised and validated. The process needs to be repeated for every special situation and arrangement between producer and manufacturer, a process that quickly becomes cumbersome and time-consuming.

The sorting approach proposed here does not rely on such laborious procedures; rather, it only requires defining what characteristics and segment lengths a consumer or combination of consumers is willing to accept. Using these definitions, a classification model can be created and "loaded" into the production stream to achieve the desired results. In theory, any number of models could be loaded over a shift to produce any number of different special sorts of lumber for different customers.

5.7.3.2 Cutting Area Method

A second approach was also explored during this project. This approach is based on the cutting area method of grading common to hardwood in North America. As discussed in 5.4.1.2, this method is based on the size of areas within boards that can be used to

manufacture high-value products. The two primary factors that determine a grade are the size of the minimum cutting and the proportion of a board that falls within the cutting areas. A critical concept is that cutting areas must be located between the randomly distributed unallowed defects found on the board. Therefore, knot frequency and arrangement determine the size of the cutting areas available. The standard does not provide a means to convey the size and number of the other cutting areas contained within a batch of lumber.

This method also employed the concept of user-specified definitions of knot size allowance. To demonstrate the method, 4 definition sets, 3 allowing knots of various sizes classes and one that did not allow knots, were tested. These definitions were used to locate cutting areas from boards, which were then used to calculate indicator variables used in the cluster and classification operations. The definitions were designed to test the relationship between allowable knot size and cutting size distribution. They did this in three ways. First, the distribution of clear cutting areas was examined, then the effects of an upper size limit were tested, and finally, the concept of upper and lower limits was studied.

The distribution of cutting areas available from the two species differed. *E. nitens*, in general, contained narrower and shorter cuttings that did *E. globulus*. Given that knot frequency is higher for the *E. nitens* boards in the validation sample set in this study, this is not unexpected. Also, the mean proportion of boards in cuttings was slightly lower (albeit no statistical test was performed) in *E. nitens* than for *E. globulus*. Again, this was probably related to the higher occurrence of knots for the species. The wide range of cutting widths and lengths from these findings suggest that knot distribution is highly randomized within individual boards and the sample set. This is the result of the natural growth habit of trees, log position in the stem, and board position within the log. Understanding the relationship between cutting area distribution and milling, harvesting, and growth habit would help to explain and expand the usefulness of this approach in matching the material to manufacturing requirements, thus potentially increasing utilization.

The sorting method successfully sorted boards containing different distributions of cutting sizes and proportion of board surface in cuttings for all 4 definitions. Using definition 1, which was designed to understand the distribution of clear cutting areas, it was revealed that for *E.*

globulus boards in class 1 contained a high proportion of cuttings less than 1500 mm long, board class 2 contained much longer cutting areas, board class 3 contained narrow and short cutting areas, and board class 4 contained mostly wide and long cutting areas (Figure 5-42). This pattern was repeated for *E. nitens* (Figure 5-43), even though a separate model was developed for each species. The mean proportion of boards in cuttings differed among the board classes for both species by as much as 17percent.

Definition 2 was developed to understand the effects of allowing small knots to occur in cutting areas. It produced similar results, but with slight increases in the proportion of board surface area in cutting areas. Although it has been suggested in many studies, this study did not observe a dramatic increase in the proportion of board surface area in cutting areas or significant changes in the distribution of cutting area sizes that allowed light and dark knots up to 300 mm^2. Under definition 3, the overall mean proportion of boards in cutting areas increased dramatically for *E. nitens*, but not much for *E. globulus*. Cutting areas produced under definition 3 increased the mean proportion of boards in cutting areas by 8 percent for *E. nitens*, but only 4 percent for *E. globulus*. Interestingly, this value decreased under definition 4 for *E. nitens* but not for *E. globulus*. This behavior supports the concept that knots are randomly distributed across the board surface.

These findings suggest that a higher proportion of the area of boards can be recoverable (under these cutting area rules) by allowing knots of certain sizes and types to occur within cutting areas. However, based on these results, the increase is not linearly related to knot size—that is, increases in cutting area proportions do not scale with increases in allowable knot size. This is demonstrated by a doubling of the allowed knot size does not increase the proportion of cutting area in any predictable way. It was also noted that increases in cutting areas were not the same between species for the different allowable sizes of knots.

Although changes in the yield of “character-marked” parts have been studied extensively, (Buehlmann et al., 1998), few if any researchers have investigated the relationship between changes in cutting areas and increasing allowable knot sizes. Although little increases were seen in this study, the distribution of cutting areas sizes changed as allowable knot size increased—that is, in general, cuttings became wider and longer, and the number of cutting

areas decreased from definition 1 to definition 3. This suggests that longer and wider cutting areas can be obtained by increasing the size of allowable knots, but the number decreases. This pattern was also observed for definition 4.

Because of the random distribution and wide range of knot sizes found on boards, not all cuttings produced by definitions 2-4 contained knots. Under definition 2, only 29 percent and 18 percent of the cutting areas contained at least 1 knot for *E. nitens* and *E. globulus,* respectively. Under definition 3, the knotty cutting area rate increased to 60 percent for *E. nitens* and 39 percent for *E. globulus*. Under definition 4, the rate for *E. nitens* decreased to 56 percent but only increased slightly to 40 percent for *E. globulus*. Most knotty cutting areas were relatively wide and long, compared to those produced as clear cuttings. A significantly high proportion of knotty cutting areas belonged to one or, in a few cases, two of the board classes. This co-occurred with those board classes containing the highest proportion of cutting areas overall. This behavior indicates the differences in knot production for different species and differences that may occur under different management strategies. Understanding these differences could lead to advanced utilization of different resources to obtain the greatest yield from the available lumber. In this work, definition 3 resulted in the highest knotty cutting area rate for E. nitens, while definition 4 resulted in the greatest knotty cutting area rate. This advanced understanding of potential knotty cutting area rates may allow the user to specify different resources to obtain a desired visual outcome based on the expected knotty cutting area rate of different species. This approach would greatly expand the potential to work with the actual variation of the distribution of different growth characteristics produced by natural materials.

It also suggests a method by which a user can select a particular board class that both contains cutting areas meeting the requirements and contains a certain proportion of those cutting areas with knots. Again, suppose that the appearance of the panels shown in Figure 4-38 or Figure 4-39 using definition 3 is desired. Depending on the distribution lengths of the required parts and the desired level of knottiness (knot density) a manufacturer may choose to use bone board class over another.

For example, board class 2 produced under definition 3 in *E. globulus* would contain most cuttings from 35 mm to 140 mm wide and 500 mm to 1500 mm long and about 41 percent of those cuttings would contain at least one knot. The same board class, which, in general, contained wider and longer cutting areas in *E. nitens* would have about 13 percent of the cutting areas with at least one knot. However, increased knottiness was desired for *E. nitens*, board class 4, which was marked with a cutting area distribution similar to board class 2 in *E. globulus*.

The relationship between allowable knot size and cutting area distribution appears to be species and management specific—that is, because different management practices and species produce differences in the distribution of knot size and appearance, a detailed understanding of these distributions is needed to optimize the characterization of cutting areas. Here, as noted in 3.7.1, the distribution of knot sizes indicated a higher proportion of larger size classes of knots for *E. globulus* than for *E. nitens*. A particular set of definitions may not be well suited for all available materials. For example, smaller and darker knots may be found with higher frequency in boards from lower in the log than from boards higher in the log.

Also, the sorting structure proposed in this study may lend itself to product diversification. For example, board class 2 in *E. globulus* produced under definition 3 contains approximately 45 percent of the cuttings overall and approximately 47 percent of those contain at least one knot. The board class contains a good mix of widths and lengths, and the knotty cuttings size distribution overlaps this range well. This class of lumber would be suited to products that call for parts that could be manufactured from these cutting areas; however, the manufacturer would be able to produce two versions, one containing knots and the other made from clear areas. The system gives a measure of flexibility to both the producer and the manufacturer, which is not currently available in ether AS 2796 or the NHLA grading standard.

5.7.4 NHLA Grades

The *E. nitens* and *E. globulus* board surfaces in this study produced a significant proportion of cuttings longer than NHLA graded lumber. There are several reasons for this. First, cuttings were determined from the NHLA graded lumber using a full suite of characteristics on the

front and back of the boards. They include stain, checks, knots, wane, splits, pith, holes, decay, voids, and bark pockets. Although these characteristics could affect the size of available cuttings from the boards in this study, these features (excluding copious drying induced surface checking) were not commonly observed on the sample lumber. Derikvand et al. (2018a) and Derikvand et al. (2018b), found a loss of volume from mechanical damage and the unrecoverable collapse of approximately 10 percent for *E. nitens* and 4 percent, 3 percent, 11 percent, and 22 percent for *E. globulus* boards in the width classes used in this study.

Therefore, it can be concluded the distribution of cuttings areas was well represented by using the knots only. Second, the boards in the validation dataset used in the study were, on average, much longer than those in the red oak database. Approximately 50 percent of the #1C red oak boards were longer than 3 m, and only 8 percent of the boards were longer than 4.8 m. The distribution of board lengths was approximately the same for the #3AC lumber in the database. Very few *E. nitens* boards in the validation set were shorter than 3 m, and almost all *E. globulus* boards were longer than 4.8 m (Figure 3-6). It follows that longer boards would statistically produce longer cuttings given the interplay between knot distribution patterns and board length. Interestingly, #3AC lumber contained a higher proportion of narrow cuttings than did the species in the sample set.

The boards in this study were limited to 140 mm wide, whereas the board for both #1C and #3AC was as wide as 330 mm. Only 55 cuttings from #3AC were above 140 mm; theoretically, boards this wide should produce a higher proportion of wide cuttings. If other characteristics would minimally affect cutting area distribution for the species in this study, it can be concluded that these resources would produce boards comparable to #1C and #3AC lumber graded to NHLA standards. If the proportion of each grade of lumber in the red oak database represents the mill production of each grade, there was a far higher proportion of #1C and far lower proportion of #2AC from the boards in this study than would be typical for red oak.

5.7.5 Further work

The lumber sample size was small for both species in this study. The material had been produced for other projects (Derikvand et al., 2019, Jiao et al., 2019, Kotlarewski et al., 2019), before this research started. The findings presented above would undoubtedly change slightly

with larger sample sizes, especially in the 70 mm and 140 mm width class for *E. nitens*. It also requires a much larger sample size to fully explore the range of knots and other characteristics found on in the resources. A study by Breinig et al. (2015) sorted 810 boards into 15 visual classes and (Buehlmann et al., 1998) stated that a lumber sample size of 150 boards is necessary to eliminate error in the calculation of part yield. Therefore, to produce the 5-board segment-based board classes or the 4 board cutting area classes, at least 650 boards of each species would be necessary. Also, a study that tracked board location in logs would contribute knowledge about how the distribution of characteristics varies in the tree.

6 Chapter Six - A Method to Match Board Classes to Product Requirements

6.1 Purpose

This chapter presents procedures that were developed to understand the relationship between yield, manufacturing costs, and the achievable visual attributes for the board classes and various product cutting bill requirements. These procedures form the final module of the overall system developed in this thesis and are used to estimate the production expenses for wood panels that contain different sizes of knots. This is done in three ways. First, lumber value and manufacturing costs are calculated for a series of cutting bills calling for clear dimension parts. Second, various levels of the visual attributes of different-sized knots are explored for wood panels. Third, a suite of manufacturing and appearance properties are combined to form a system that determines the most suitable class of lumber for six different panel cutting bills.

6.2 Objectives

As discussed in 1.1, established low-resolution grading standards present a major barrier to increasing the utilization of lumber containing high amounts of growth characteristics. In general, these standards do not provide the resolution necessary to communicate the full range of useable properties, such as frequency and size of cutting areas or other desired visual attributes. To use a broader range of characteristics, a careful consideration of market response, product design, and a clear and logical way to sort it, process it, and communicate the properties along the supply chain are needed (Breinig et al., 2015, Broman, 2001, Nicholls et al., 2004b, Ozanne and Smith, 1996).

In the previous chapter, a means of grouping boards based on the proportion of the board with cutting areas that contained a defined range of knot size and type was developed. The objective of this chapter is to understand the relationship between the cutting bill (cutting requirements), manufacturing costs and desirable appearance attributes to determine the most suitable group of lumber. This requires the development of:

- a means to determine yield and estimate manufacturing costs to calculate overall costs to produce dimension parts from the different board groups, and;
- a means to determine the most suitable group while considering a suite of visual and manufacturing properties indices related to increasing efficiency.

6.3 Background

6.3.1 Introduction

As primary producers are concerned with characterizing, or grading, boards, to obtain the highest value for the lumber produced, secondary manufacturers seek to utilize the maximum amount of each board at the rough mill. The goal is to produce the least amount of waste and the highest quantity of parts that contain the specified visual attributes[31]. In modern manufacturing, the cutting bill is generated directly from the digital design environment. The cutting bill specifies the required geometric parameters, material type, grade, and the quantities of all individual components based on product design specifications. The cutting quality, or part-grade, specifies allowable levels of visual characteristics, such as grain patterns, knots, or other features located on one or both sides of the part.

6.3.2 Rough Mill Operations

The production of most higher-value products consists of a series of wood machining processes; initial lumber breakdown takes place at the rough mill (Prak and Myers, 1981). See 2.2 for a discussion of the rough mill concept at different scales. The complexity of these processes is associated with the product design and requirements, and the characteristics of the incoming resource (Motsenbocker, 2005). Poor decisions made at the rough mill can translate into lower yield due to rejection and reprocessing of parts and wasted lumber. The primary objective of the rough mill is to produce the highest quantity and quality of parts using the lowest volume of lumber (Buehlmann et al., 2011b).

The design of wood processing equipment found in the rough mill is capable of two basic operations: ripping and chopping. The rip-first strategy cuts lumber into strips of certain widths along the grain. These strips are then cut across the grain to produce parts. The chop-

[31] Here, the term visual attributes refer to the visual characteristics of wood surfaces, such as the frequency of different types of knots or the absence of knots for “clear” parts.

first strategy cuts lumber across the grain first, then creates strips by ripping. Yield can vary dramatically between the two strategies.

As introduced in 2.2, the yield of parts is influenced by the cutting bill requirements, the properties of the incoming lumber, machinery limitations, and production systems (Prasetyo, 2018). The relationship between the cutting bill and the yield is complex because of the wide range of part sizes, quantity requirements, the type and size of characteristics allowed in the part, and the arrangement of the characteristics that need to be accommodated (Buehlmann et al., 1998, Buehlmann et al., 2011a).

Because raw materials can account for up to 70 percent of total manufacturing costs and up to 50 percent of the total cost of a piece of furniture, the efficiency of the rough mill is important (Buehlmann et al., 1998, Buehlmann et al., 2011a, West and Hansen, 1996). An industry rule-of-thumb states that a one percent increase in yield will reduce production costs by two percent (Wengert and Lamb, 1994). Kline et al. (1998a), estimated that just a one percent increase in the yield of rough parts could save the average North American furniture company USD 150,000 per annum. Another example points out that an improvement of one percent at the rough mill for a company processing 12 MBF of lumber per day at a market value of USD 900/MBF would result in an approximate savings of USD 58,000 annually (Mitchell et al., 2003). Hence, improving the understanding of the relationship between cutting bill requirements and yield from lumber of different grades and cost is critical, particularly considering the decreasing supply of high-quality forest resources.

Decisions about how to cut boards are typically made by human operators. The operators, or markers, must rapidly decide which characteristics are acceptable or unacceptable, a difficult task to perform consistently (Buehlmann and Thomas, 2002). The outcome of the process is largely dependent on the experience and skill of operators. Markers are susceptible to error (Huber et al., 1985) in much the same way as lumber graders are inconsistent (see 5.3). Error in marking can account for as much as a 16 percent reduction in the yield of parts from lumber (Buehlmann and Thomas, 2002).

Under some situations, the value of 1 BF of lumber could double by the time it leaves the rough mill (Figure 6-1). Industrial rough mills process lumber using multi-blade gang-ripsaws

of various configurations to produce strips from lumber (Figure 6-2). Blades can be all fixed, all movable, or some combination to control strip width. The spacing between blades is optimized to cutting bill requirements for part widths (Thomas et al., 2015). The operations involved are shown in Figure 6-3.

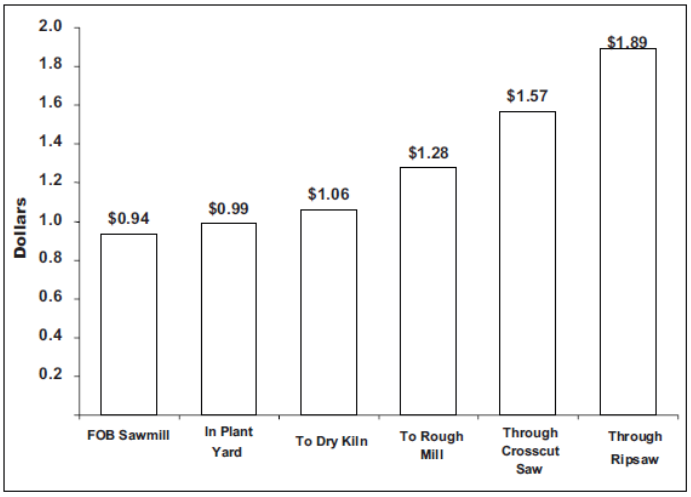


Figure 6-1. Approximate value of an increase of 1 BF of lumber as it is processed by the rough mill (Mitchell et al., 2003)

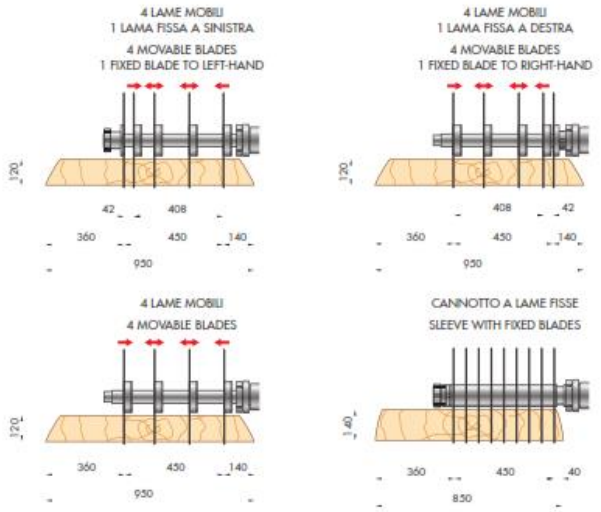


Figure 6-2. Various types of multi-blade arbor rip saw types (www.primultini.com).

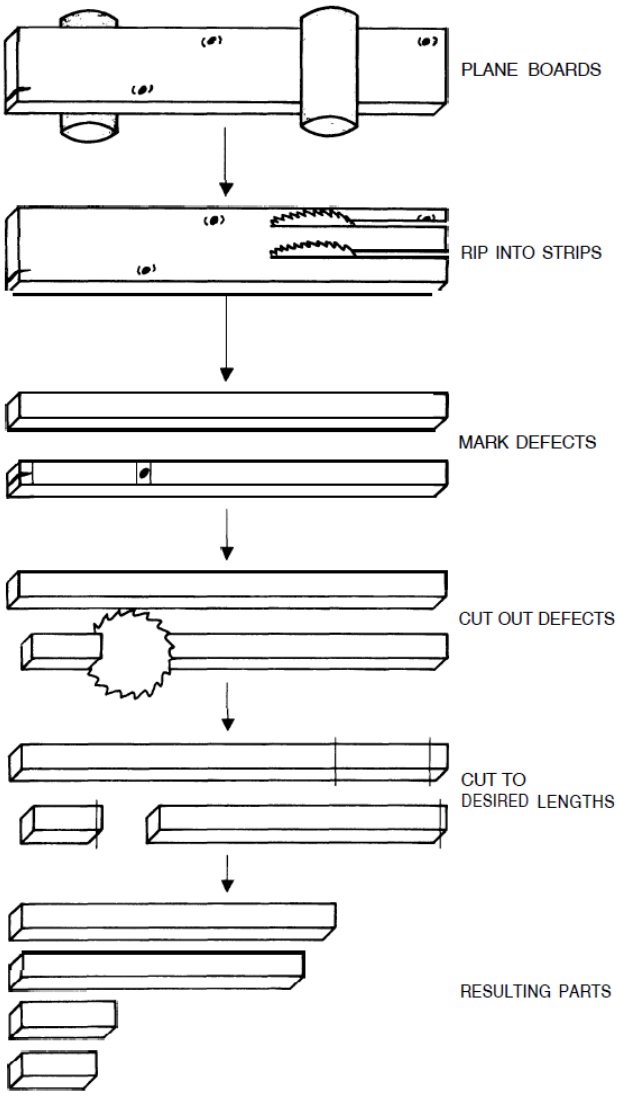


Figure 6-3. The sequence of operations used in a rip-first rough mill to produce parts from lumber (Araman, 1977).

Yield can vary depending on lumber grade and cutting bill requirements (Buehlmann et al., 1998, Buehlmann et al., 2011a, Wengert and Lamb, 1994), but rip-first operations are widely thought to produce higher yields over crosscut-first operations (Gatchell, 1987, Mitchell et al., 2003). Mitchell et al. (2003) presented the average yield of 12 cutting bills for FAS under rip or crosscut-first operations and yield for seven cutting bills for #1C and #2AC lumber (Table 6-1). This study demonstrates the significant differences between rip-first and crosscut-first operations and lumber grade. Dual-line operations are set up to either rip- or crosscut-first to further optimize yield. In general, as the lumber quality decreases, dual-line systems outperform rip-first or crosscut-first processing (Thomas and Weiss, 2006).

Table 6-1. Generalized part yield benchmarks for rip and crosscut-first mills and different grades (Mitchell et al., 2003). [a] indicates simulations based on 12 cutting bills from Wiedenbeck and Thomas (1995). [b] indicates simulated yield from 7 cutting bills under rip-first and crosscut-first configurations (Buehlmann et al., 1998, Buehlmann et al., 1999).

Rough mill type	Rip-first					Crosscut-first			
Lumber grade	FAS[a]	1C[b]	2C[b]	1C[b]	2C[b]	1C[b]	2C[b]	1C[b]	2C[b]
Cutting quality	C2F	C2F	C2F	C1F	C1F	C2F	C2F	C1F	C1F
Yield (%)	74	65	51	75	66	64	53	70	64

Modern ripsaw optimization procedures have been found to under-utilize boards during the production of strips (Thomas and Buehlmann, 2002, Thomas and Buehlmann, 2003). This occurs largely because most ripsaw systems optimize strip area and strip length for individual boards. Often this approach does not fully take into account the useable areas or the cutting bill requirements (Thomas and Buehlmann, 2003). A higher yield can be achieved by optimizing at the "global" level which considers ripping and crosscutting operations together for all possible board cut-up solutions (Thomas and Buehlmann, 2003). This is not a common approach due to the expense associated with high-resolution board scale information.

The yield of desirable pieces is typically between 40 percent and 75 percent but can vary significantly depending on lumber grade and cutting bill requirements (Buehlmann, 1998, Gatchell, 1985, Thomas and Buehlmann, 2016). The NHLA grade has been used as a surrogate to predict the yield of clear parts (Buehlmann et al., 1998, Gatchell, 1985, Gatchell and Thomas, 1997, Wengert and Lamb, 1994) and mill productivity (Pepke, 1980, Perera, 1994). Yield varies considerably for different cutting bill requirements for the same grade of lumber (Figure 6-4). Most research has focused on efforts to optimize yield for each board, which is a standard cut-up problem encountered in other industries (Buehlmann et al., 2010, Buehlmann et al., 2011b, Dyckhoff, 1990).

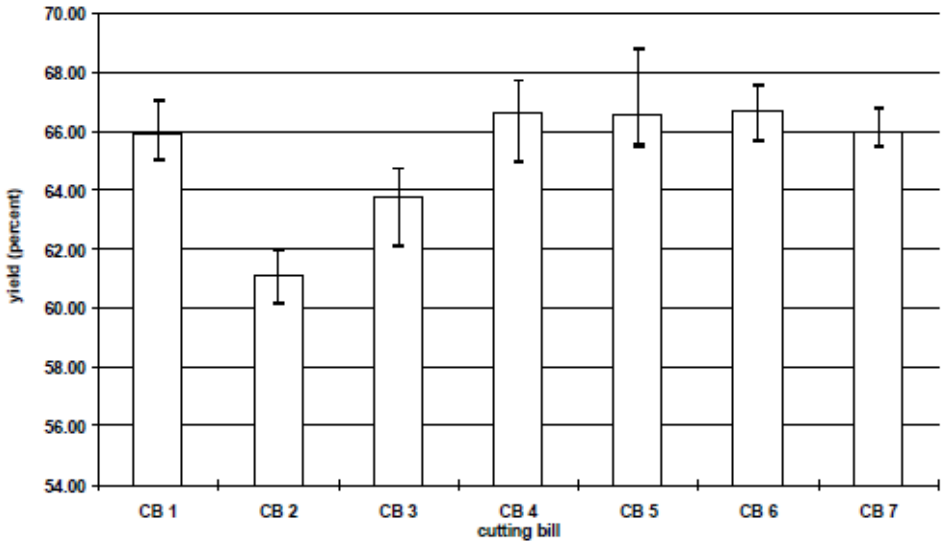


Figure 6-4. Influence of cutting bill requirements on yield for #1C lumber in a rip-first configuration (Buehlmann et al., 1998, Buehlmann, 1998).

Yield is the result of complicated interactions between the number of parts of different sizes and distribution of part widths and lengths, part grades, and the arrangement of growth characteristics on the board (Buehlmann et al., 2003), and the mode of lumber processing (rip/chop operations). Buehlmann et al. (2003) present an in-depth analysis of these interactions using digitized #1C red oak boards graded under NHLA rules. Yield is also influenced by avoidable[32] lumber manufacturing characteristics. Clément et al. (2006) showed that on average yield decreased by 10 percent from these characteristics on NHLA graded lumber. Also, drying checks are attributed to about 5 percent of the reduction in yield.

The grading of hardwood lumber under NHLA rules is primarily concerned with the number and size of clear cuttings, available within boards. However, cutting bills specify a vast array of part sizes, which often don't correspond directly to the cutting areas stipulated by grading rules (Gatchell, 1989). The geometric requirements are a major factor that determines the maximum achievable yield of desired parts from input material (Buehlmann, 1998, Wengert and Lamb, 1994). Cutting bills that contain a wide range of lengths and widths and emphasize short lengths and narrow widths are considered "easy to meet". Difficult or "hard" to meet cutting bills contain a high proportion of wide and long parts. Table 6-2 demonstrates that in

[32] Avoidable characteristics are commonly known as manufacturing defects and are caused by rough handling, processing, and drying operations.

general, yield increases when cutting bills contain many short and narrow parts and decreases when the cutting bills call for a high proportion of long and wide parts (Buehlmann, 1998, Thomas, 1996). Buehlmann et al. (2003) demonstrated that yield is primarily controlled by the shortest lengths in the cutting bill. This is because short pieces can be cut from remaining areas of a board not used in longer parts. In general, changes in width do not have as much impact on yield as changes in length (maximum change of less than 2.5 percent for width as compared to 7.3 percent for length) (Buehlmann et al., 2003).

Table 6-2. Descriptions of cutting bills ranked from "easy" to "difficult" (hard) (Thomas, 1996).

Cutting Bill	# of Widths Range (in)	# of Lengths Range (in)	Comments
(Easiest)	4	9	Mostly short and narrow
1	1.5 to 2.75	12 to 48	
2	7 1.75 to 5.25	14 10 to 31.5	Most parts are narrow. Wider parts are narrow
3	3 2 to 2.75	5 16 to 32	Most parts are in wider widths
4	4 2 to 4.75	7 11 to 53	Long wide and short narrow parts with good distribution in between
5	7 1.5 to 4.25	12 19.5 to 87.75	Wide cuttings are short. Good Distribution of lengths and widths
6	12 2 to 3.25	6 15 to 72	Mostly short (41 in. and under) and narrow parts
7	2 1.5 to 3	8 18 to 72	A large gap between short and long lengths; 3-in width requires twice as many parts in longest lengths as a single short length
8	4 2 to 4.5	10 15 to 72	Most parts are long and wide with few short and wide parts
9	5 2 to 4.5	5 16 to 84	The widest parts are short. Equal numbers of short and long parts
10 (Hardest)	5 4 to 6	3 29 to 84	Only one short and two very long lengths. More long, wide parts than short

As suggested by Buehlmann (1998), a greater understanding of the relationship between the cutting bill requirements and the distribution of potential cutting areas could lead to higher yield. This could be achieved by actively designing cutting bills better suited to the actual cutting areas. As stated elsewhere, current grading standards do not provide the detailed information necessary for this to occur. Also, there are no commercially established means to pass such information or mechanisms to use such information by the manufacturer.

6.3.3 Cutting Efficiency

Although lumber accounts for a significant proportion of the manufacturing cost of parts, the expense of labor to produce the parts must also be considered. Therefore, increasing rough mill efficiency (number of required cuts) or cutting efficiency favor higher grades of lumber because fewer cuts are required to produce the same number of parts. Steele (1999) found the ratio between lumber grade and the number of cuts required (crosscut and rip cuts) differed significantly (Table 6-3). For an easy cutting bill, approximately 2.5 more cuts are needed to produce the same number of parts from #3AC lumber than from FAS lumber. However, the number of cuts increases by a factor of 5.3 between #3AC and FAS under difficult cutting bills. Although the number of cuts does not appear to differ significantly between cutting bills within grades, this study did not consider the combined effect of yield and cutting efficiency, which would become a factor under 'real-world' considerations.

Table 6-3. The Mean number of total (rip and crosscut) required cuts (10 repetitions) from different lumber grades and cutting bills (Steele, 1999). Means with the same capital letter are not significantly different.

	Cutting bill		
Lumber grade	Easy	Moderate	Difficult
FAS	23,031 A	17,567 A	18,175 A
FIF	25,797 B	21,580 B	21,439 B
IC	31,259 C	28,348 C	30,948 C
2AC	40,292 D	48,463 D	62,956 D
3AC	56,453 E	92,393 E	96,602 E
LSD	483.7	1,688.0	2,107.6
p-value, grade	0.0001	0.0001	0.0001
p-value, run	0.7408	0.1757	0.3794

Another way to look at cutting efficiency is the ratio between the number of cuts to a given area of parts. In this way, the cutting efficiency depends on the cutting bill requirements. In theory, cutting bills with long and wide parts will have a higher efficiency than bills with short and narrow parts. Wiedenbeck et al. (2004), showed that despite a similar yield between two cutting bills (rip-first, 38.4 percent, and 37.2 percent), the cutting efficiency differed from 5.0 to 3.6 cuts/BF of parts produced. This difference contributes to the overall cost of producing dimension parts and can be used to inform the choice of lumber grade.

Although the number of cuts required to satisfy a cutting bill can be taken as a surrogate for production cost and time (Steele, 1999), the yield of parts from different grades combined with the cutting efficiency provides a means to determine the relative value of boards. Considering both the reduction in yield and the increased labor costs to produce the same number of parts from #2AC and #3AC, Wiedenbeck et al. (2004) suggested that a price difference of USD 217 would need to exist between the lower and higher grades of lumber to make #3AC a viable alternative. Considered as a percentage, the market value of #3AC would need to be approximately 60 percent or less that of #2AC in 2004 dollars to make the use of the lower grade a viable proposition.

The above values assume that it costs between USD 0.37/BF and USD 0.67/BF (USD 3.7/m^2 and USD 6.7/m^2) to produce parts from #2AC lumber. Based on differences in cutting efficiency between #2AC and #3AC lumber, an estimate of cutting costs of between USD 0.44/BF and USD 0.8/BF was calculated for #3AC lumber. Another estimate by Buehlmann et al. (2011b) suggests a cost of approximately USD 200/MBF of lumber processed to produce parts. The method put forth by Wiedenbeck et al. (2004) applies an “inflation” factor based on the ratio between the best efficiency possible given the lumber grade and the cutting bill requirements and the other grades. These types of studies are limited as they require high-resolution information about the location of characteristics. All known studies have been performed using NHLA graded lumber and most have utilized the same dataset of red oak boards created in 1998 (Gatchell et al., 1997).

Although the Wiedenbeck et al. (2004) study compared the yield and cutting efficiency of 2 cutting bills on 3-grade mixes, this study did not consider optimizing cutting bill requirements specific to #3AC lumber. For instance, because #3AC lumber likely has a greater range and frequency of knot sizes and appearance types, the yield of parts for cutting bills calling for character-marked parts may favor this grade over others. That is, a lower grade of lumber might be more suited to producing these types of products than a so-called higher grade. Also, cutting bills requiring a high proportion of shorter and narrower pieces, such as those used to produce small panels, would favor lower grades.

6.3.4 Simulation of Yield

The yield of parts can be simulated with lumber cut-up simulation tools (Buehlmann and Thomas, 2001, Thomas and Buehlmann, 2002, Thomas and Buehlmann, 2003). Perhaps the most widely used and most advanced lumber processing simulation software available is ROMI 4.0: Rough Mill Simulator (Grueneberg et al., 2012). This fully functional simulator includes advanced features that allow the user to specify mixed grades, different parts grades for different parts within cutting bills, as well as the ability to simulate under different cutting modes (rip-first or chop-first) (Grueneberg et al., 2012, Thomas et al., 2015). ROMI 4.0 simulates the optimal yield of parts from a cutting bill for a batch of lumber based on user-specified breakdown strategies and part grades (Thomas and Buehlmann, 2002). ROMI 4.0 produces two categories of parts. Primary parts are parts that require two cuts to produce (rip-first and crosscut or vice versa). (Thomas et al., 2015). Salvage parts require at least one additional cutting operation and are therefore considered more expensive to produce and less desirable (Thomas et al., 2015). Users can simulate the production of different cutting bills on different grades of lumber to understand differences in cutting efficiency for different combinations.

An earlier version, ROMI-RIP, was validated to simulate an increase of 7 percent yield above that of a “real world” rough mill not using a rip optimizer to determine cut-up solutions (Buehlmann and Thomas, 2001). ROMI 4.0 uses a database of 3487 kiln-dried digitized red oak boards in 6 NLHA grades (Gatchell et al., 1997), which gives the user the ability to test a wide range of cutting bills with different grades of lumber and to compare theoretical yield to actual yield from a rough mill cutting trial.

6.3.5 Character-Marked Parts

Most work on the utilization of so-called low-grade lumber has focused on primary processing strategies (deriving clear cutting areas), industrial products, such as railroad ties, and the production of higher-value products relatively free of character-marks (Luppold and Bumgardner, 2003, Nicholls and Bumgardner, 2015). There is vast potential for improving the utilization of what is currently considered low-grade timber to produce higher-value products. Instead of optimizing the production of clear parts from boards, another approach is to allow a specified level and type of feature in certain parts. As noted in 5.4.1.2.1, this topic has been

investigated extensively and requires careful consideration of consumer response, product design, retailer and wholesaler perceptions, and a clear and logical way to differentiate and communicate material characteristics for various end products (Brinberg et al., 2007, Broman, 1995b, Donovan and Nicholls, 2003, Nicholls et al., 2004c, Nicholls et al., 2004a, Ozanne and Smith, 1996, Wilhelm, 1994).

Given the vast array of high-pressure laminate flooring products one can observe featuring character-marks, there appears to be a strong market desire for these aesthetic options. In North America, the inclusion of character-marks in solid wood products has mostly been restricted to rustic styles (i.e., Early American, Western, and Shaker), however, observing trends from popular design magazines (e.g., dwell.com) and other home decorating idea sources, it appears that the use of character-marks is becoming an option in the contemporary design palette. The use of character-marked and upcycled lumber is becoming popular in many major retail and convenience spaces and becoming a major contributor of the higher-value products segment (Pitti et al., 2020).

Aspects of character-marked products undoubtedly respond to changes in other fashion products as suggested in 2.4 and these changes can be accommodated during the manufacturing process of these products. During manufacturing a decorative layer is bonded to a high-density fiberboard substrate. The decorative layer is printed from a high-resolution photo-reproduction of real wood surfaces. The wood surfaces are selected based on a combination of visual attributes that have been determined to be marketable. This process can produce a range of “standard” uniform products. However, after installation, because the planks are reproduced from a few actual samples, repetition in the grain patterns and knots can easily be observed.

Yield studies have shown dramatic increases in yield for products containing character-marks and optimizing the geometry between cutting bill requirements and different grades of lumber (Buehlmann et al., 1998, Buehlmann, 1998). The production of character-marked products has been suggested as a way to utilize increasing supplies of so-called lower grades of hardwood lumber (Nicholls and Bumgardner, 2015). Buehlmann et al. (1998), estimated that yield would increase by 14 percent by allowing knots up to two inches in diameter for

certain rough parts from #2A boards and a modest increase of four percent by allowing one-inch character-marks on one face of parts. However, yield response is also dependent on lumber grade. For example, Buehlmann et al. (1998) showed that yield estimates increased more for mid-grade (#2C) lumber than for other grades by allowing knots up to 2 inches (5 cm) to occur in cutting areas.

There is a significant opportunity to increase the yield of character-marked cuttings from lumber containing frequent characteristics not typically allowed to occur in cuttings, and hence, reduce waste of lumber. However, in industrial situations, human operators can't be expected to be able to manage the complex task of detecting and deciding which features to include in strips during ripping operations, as mentioned 6.3.2 (Huber et al., 1985). This is because the identification and classification of allowable characteristics are error prone. First, an operator determines if a feature is acceptable within the part and then marks it for further processing. Then, either by human judgment or a mark-sensing chopsaw, the strips are cut to produce the required parts. During this process, characteristics may not be accurately marked, may be missed, or parts may not be accurately chopped, resulting in decreased yield and increased part rejection at the rough mill (Thomas and Buehlmann, 2002). Computer-aided processing coupled with machine vision systems that accurately and consistently define specific characteristics would improve both the speed and accuracy at which parts could be produced. These systems linked to automatic ripping and crosscutting machinery, could potentially reduce judgment errors and enable the complex decisions necessary to produce parts containing specific characteristics sets (Buehlmann et al., 1999).

6.3.6 Suitability Index

Grouping boards using a pre-defined set of criteria based on the distribution and frequency of the characteristics produced by the resource solves half of the problem. The specification requires information that defines available material attributes at a level useful to producers and end-users. The other half of the problem is providing high-resolution material descriptions that could be used to quantitatively judge the suitability of different grades to achieve the desired outcome.

Suitability is a measure of the various quality aspects and properties of a material as they are judged for an application. Taken together, they indicate how suitable a particular board or batch of lumber is to a particular application—a suitability index. The suitability index is a numerical (0 to 1) index that represents the capacity of a given material to perform at a certain level. A suitability index of 0 describes a material not suited for a particular application, while an index of 1 denotes the best available material for an application. The index can be built around any set of characteristics or properties that relate to manufacturing, performance, or performance.

Sandak (2017) developed a series of quality indices to determine the suitability of logs for different product streams. The concept of the suitability index has also been used for the valuation of hardwood logs in North America based on the species, log diameter, lumber yield by grade, and current market prices of lumber by grade (McConnell, 2016). In this thesis, the suitability index is determined by combining the yield, the manufacturing (cutting) efficiency of lumber, the relative value of different groups of boards, and two visual attributes about the use of knots in panels.

6.4 Material and Methods

6.4.1 Datasets and Terms

This chapter utilizes the validated dataset produced in Chapter 3. Because the focus of this chapter is to determine yield and estimate manufacturing costs to produce dimension parts and a means to select the most suitable group to satisfy a suite of manufacturing considerations, it was thought that the validated dataset would produce the most accurate results.

The chapter is focused on the board classes derived from the cutting area method.

6.4.2 Dimension Parts

The workflow that uses cutting bills and board-scale information to estimate the total cost of parts is shown in Figure 6-5. The goal was to demonstrate that the boards produced by plantation resources from Australia could be suitable for such operations and that simulation could be used to determine the relative value of different board classes developed in Chapter

4. The yield of dimension parts and cross-cutting[33] efficiency was determined for the boards grouped by cutting area definition 1 (clear parts). Six standard cutting bills were used to simulate yield from *E. globulus* only and the descriptions are given in Table 6-4. Through experimentation, it was determined that because the *E. nitens* sample set lacked wider boards most simulations of the board class/cutting bills combination could not be completed and thus would not provide realistic comparisons.

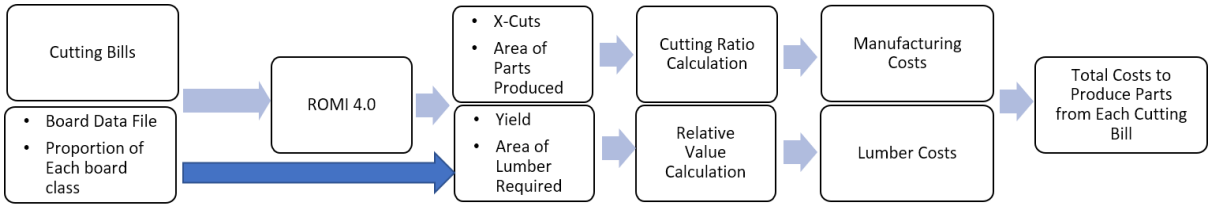


Figure 6-5. Flow chart of the processing steps to determine the total cost of producing dimension parts from E. globulus board classes.

The Buehlmann (B) cutting bill is a hypothetical cutting bill developed by Buehlmann (1998) to test for the maximum yield possible under various configurations and lumber grade mixes (Thomas and Buehlmann, 2016). The other five are variations of cutting bills that have been used in other research on lumber yield (Thomas and Buehlmann, 2016). The ranking of the six cutting bills was determined by the average yield across the *E. globulus* board classes. The ranking may vary from other publications using the same cutting bills. This is probably because those rankings are based on lumber graded using NHLA standards. The lumber used in this study was not sorted by those standards and therefore would not produce yields comparable to NHLA graded lumber.

[33] The term cross-cut is sometimes abbrivated as X-cut in table and figure captions.

Table 6-4. Descriptions of the cutting bills used and rank from easiest to the most difficult as determined in this study.

Cutting bill (Rank)	Widths	Lengths	Mean yield (%)	Comments
1	7	11	65.5	Bedroom dresser and chest of drawers
2	2	7	60.6	A moderately difficult bill
3	6	9	58.3	An easy bill
4	5	14	53.7	A kitchen cabinet parts bill
5 (B)	4	5	53.6	The Buehlmann bill, moderately difficult in most studies
6	3	9	41.4	A contrived bill designed to be difficult

To compare the lumber used in this study to NHLA graded lumber, yield and cutting efficiency were determined using these cutting bills and FAS, #1C, and #2AC lumber from the red oak database (Gatchell et al., 1997). The cost of lumber was estimated by using current values for Northern Area kiln-dried red oak (August 23, 2019, Hardwood Market Report). FAS red oak listed at USD 1235/MBF, #1C was listed at USD 870, and #2AC was listed at USD 750. By comparison, FAS Soft maple was listed at USD 1665, #1C was listed at USD 1120, and #2AC was listed at USD 830.

6.4.2.1 Board Data Files

ROMI 4.0 requires board data that describes the width and length of each board and the location, size, and type of different characteristics. This data was the result of Chapter 3. Because the number of boards was limited in this research, board data files were developed from the boards in each class by replicating the boards in each class to generate a board file that would likely be able to satisfy the cutting requirements of the panel cutting bills. Each board file contained approximately 128.8 m^2 (SD=0.13) of lumber.

6.4.2.2 ROMI Settings

Simulated lumber processing was accomplished using ROMI 4.0 with the following settings.

- A Fixed-Blade Best Feed Arbor optimized by board class of the lumber or by NHLA grade
- Rip first
- No salvage cut to primary length and width for *E. globulus* lumber
- Salvage uses primary widths and lengths for NHLA graded lumber
- Total yield (includes primary and salvage to calculate yield)
- *Complex Dynamic Exponent part prioritization
- No random width or random length parts
- Continuous update of part counts
- No end or side trim

*Complex Dynamic Exponent is an option available in ROMI that updates part priority continually as parts are cut and the required quantity decreases (Thomas et al., 2015).

6.4.2.3 Board Value

As introduced in 6.3.3, lumber can be valued in terms of the yield of required parts, the cost of producing the parts, and the availability of different grades. As described elsewhere, boards that are expected to produce a high yield with low processing costs carry a higher market value than those that produce lower yield with higher processing costs. However, boards in higher grades are typically less available than boards in grades that are expected to produce lower yield and higher part production costs. The availability potentially contributes to market value.

The cutting ratio (C_r) was calculated as the ratio between the cutting efficiency of each board class for each simulation to the lowest value obtained across different cutting bills within each board class. Calculated in this way, C_r is de-coupled from high yielding board classes. Under these simulation settings, only the number of chop cuts were included because the number of rip cuts depends on the board and cutting widths (Wiedenbeck et al., 2004). The cutting efficiency is calculated as the number of cross-cuts per BF or m^2 of parts produced.

$$Cr = \frac{Cutting\ Efficiency}{Minimum\ Cutting\ Efficiency\ observed\ for\ each\ cutting\ bill}$$

The manufacturing cost (M_c) of parts was calculated as the cost multiplied by cutting ratio multiplied by the area of obtained parts. In this study, the cost of USD 0.71/unit area of parts was used. A value of between USD 0.37 and USD 0.67 is given by Wiedenbeck et al. (2004) for #2AC lumber and value of between USD 0.44 and USD 0.80 for #3AC lumber. There are few other published estimates about the cost of producing rough parts, therefore, the mean of the values given for #2AC lumber was used as the reference in this study. Because most boards in this study graded as #1C, this assumption probably over-estimates the manufacturing cost. The value used in this study (USD 0.71) is the mean of those values in 2020 USD.

$$Mc = cutting\ cost * Cr * Area\ of\ obtained\ parts$$

The final cost of manufacturing rough parts is the sum of the lumber value and the cost to produce the parts.

The relative value of each board class was normalized by dividing the mean yield of the class with the highest mean yield. A value of 1 (USD 423/m^3 for 25 mm thick lumber) was assigned to the highest yielding class; the other classes were assigned a value by:

$$V_{BCi} = \frac{mean\ BCi\ yield}{mean \max yield / \max value}$$

where

BCi is the mean of the board classes.

The values were further normalized by the proportion of area for each board class:

$$V_{BCVi} = \frac{V_{BCi}}{\frac{BCi\ area}{Total\ board\ area} + (1 - Max\left(\frac{BC\ area}{Total\ board\ area}\right)}$$

where

V_{BCVi} is the value normalized by the area of the boards in the board class *I*, and

$BC\ area$ is the area of lumber in each board class.

The proportion of the area of each board class, the normalized lumber value, and the value normalized by area (proportion) are given in Table 6-5. The proportion term attempts to adjust the value of different classes of lumber based on the proportion of each class that the resource produces. Here, it is used in combination with the yield and cutting efficiency to estimate the relative cost to produce rough parts. It penalizes classes that contain a high proportion of the resource, while rewards those that do not. This can be seen in Table 6-5. For example, board class four is given a value of 1 based on yield, but this value is increased to 1.33 given that the class is produced in low supply.

Table 6-5. The calculated relative lumber values for E. globulus.

	BC 1	BC 2	BC 3	BC 4
Proportion of BC (%)	34	37	17	12
V_{BCi}	0.85	0.87	0.52	1
V_{BCVi}	0.88	0.87	0.65	1.33

The value of lumber (Vli) consumed by each board class for each simulation was:

$$Vli = V_{BCVi}(obtained_area/yield)$$

The cost of lumber needed to produce the required parts from NHLA lumber was determined by the yield and the market value of USD 1235/MBF for FAS, USD 870 for #1C, and USD 750 for #2AC (August 23, 2019, Hardwood Market Report (HMR, 2019)). The cutting costs were estimated using USD 0.71/BF of parts as a reference value to the highest cutting efficiency found across the 3 grades for each cutting bill. The other cutting costs were calculated as the reference multiplied by the cutting efficiency of each grade/cutting bill combination. The total manufacturing costs (T_c) were calculated as the sum of the lumber costs and the cutting costs.

To directly compare the costs of parts from *E. globulus* lumber and the listed prices of red oak and soft maple lumber, an arbitrary overall value of AUD 930/m^3 was assigned to the *E. globulus* boards. This was achieved by adjusting the value of board class 4 to 1.65. This change coupled with the other parameters produced a relative value of AUD 930/m^3 for the unsorted

sample lumber. Based on conversations with industry personnel, it is thought that this approximates the costs of production for non-kiln dried lumber in the Australian context.

6.4.3 Panel Production

This section is focused on matching panel cutting bills that require different distribution of cutting lengths to board classes that contain a different distribution of cutting area sizes as determined by the cutting definitions set out in Table 4-3. The purpose is to better understand the potential to capture knots within cuttings to be assembled into panels. This concept was discussed briefly in 4.5.2.5, however, in this section, the ratio between all the available knots that fall within cutting areas and the utilized ones are examined. This ratio is termed knot utilization. As shown in Figure 4-34 through Figure 4-45, the knot density (knots/m^2) has a significant impact on the visual attributes on panels. Therefore, the selection of different board classes could benefit by understanding how cutting bill requirements influence both the number of cuttings that contain knots and knot utilization. The proposed procedures also examine the changes in yield and cross-cutting efficiency with changes in both cutting requirements and board classes. The workflow is shown in Figure 6-6.

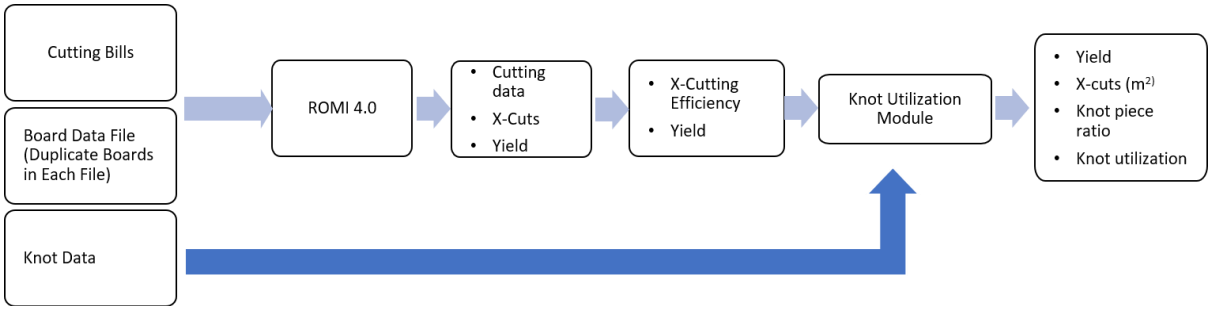


Figure 6-6. Flow chart of the process used to produce panels from the standard and special panel cutting bills to determine knot utilization.

6.4.3.1 Panel Cutting Bills

In Chapter 4, a panel bill with 5 different sizes of panels was used to create high-resolution images of wood panels from cutting areas that may or may not contain knots according to a defined knot size and appearance. The yield of the panel area was determined from the entire sample set of ungrouped lumber. In this section, four special panel cutting bills were designed to investigate the yield and cross-cutting efficiency of all the board classes based on the classification models developed in the previous chapter. These panels are produced from

random width cuttings, ranging between 38 mm and 89 mm. and panel lengths between 305 mm and 1829 mm (Table 6-6). The yield and cross-cutting efficiency of the standard panel cutting bill (Table 4-4) used in Chapter 3 were also examined for boards grouped by definition 1. Panel bill A contains mostly short panels, which would require short pieces. Panel bill B also contains short panels, but also a significant proportion of long panels. Panel bill C contains mostly long panels and panel bill D is similar to panel bill B but contains far fewer long panels. Taken together, these panel bills represent a wide range of real-life situations that could be encountered during the manufacturing of panels.

Table 6-6. The specialized panel cutting bills used to produce random strip width panels from boards grouped by definitions 2-4.

		Panel bill A	Panel bill B	Panel bill C	Panel bill D
Width (mm)	Length (mm)	Quantity	Quantity	Quantity	Quantity
609.6	304.8	35	50	10	50
609.6	609.6	25	30	10	25
609.6	914.4	20	25	25	25
609.6	1219.2	5	20	30	10
609.6	1828.8	5	20	30	10

It was thought that each specialized cutting bill could be matched to each board class to obtain the highest yield of strips and therefore panel surface area. Therefore, panel cutting bills calling for short pieces were matched to those board classes that contained a high proportion of relatively short cutting areas according to the heatmaps presented in Chapter 5 (see Figure 5-42, Figure 5-44, Figure 5-47, and Figure 5-50). The combinations of each panel cutting bill and board classes are shown in Table 6-7.

Table 6-7. The panel cutting bills used to examine processing parameters on the 4 groups of boards. D1-D4 indicates the definition used to group boards (refer to 5.5.3.2). A-D indicates which panel bill was used for the simulation.

	E. nitens				*E. globulus*			
Board Class	D 1	D 2	D 3	D 4	D 1	D 2	D 3	D 4
1	A	A	C	C	B	A	C	C
2	B	B	C	B	C	B	C	B
3	C	D	D	C	D	D	D	C
4	D	C	B	B	A	C	B	D

6.4.3.2 Simulation

ROMI 4.0 was used to simulate the production of each of the board class/panel bills outlined above.

- A 22.5 inch Fixed-Blade Best Feed Arbor with 9 blades and spacings set to 3.5, 3.5, 3.5, 1.5, 2.5, 1.5, 1.5, and 1.5 inches. The blade spacing optimization engine built into ROMI was used to determine these spacings.
- Random strip widths allowed
- No salvage parts allowed (by setting the minimum width and length higher than could be processed from the lumber).
- *Complex Dynamic Exponent part prioritization
- No random width or random length parts
- No end or side trim

*Complex Dynamic Exponent is an option available in ROMI that updates part priority continually as parts are cut and the required quantity decrease (Thomas et al., 2015).

Yield, rip, and cross-cut counts were taken directly from the ROMI 4.0 output. The other variables were calculated using a purpose-built module that automatically processed a full simulation run directly from the ROMI 4.0 output. The MATLAB application consisted of a part image, knot utilization, and panel production modules (Figure 6-6). Based on the board data, the knot utilization module calculated information about knot utilization. The application recorded the number of knotty and knot-free pieces produced as well as the number of knots

occurring in the cutting areas and the number of utilized knots occurring in panel strips. This data was used to calculate the ratio of knotty pieces and the ratio of knot utilization for all board class/panel bill combinations.

6.4.4 Suitability Index

In this work, 9 categories of properties were identified and combined to produce a suitability index to potentially provide a means to better match each group of boards to a set of desired manufacturing and visual outcomes. The process that used the cutting bills and board data files to calculate the suitability index is shown in Figure 6-7. It consisted of the ROMI 4.0 simulator and several processing modules built into a MATLAB application.

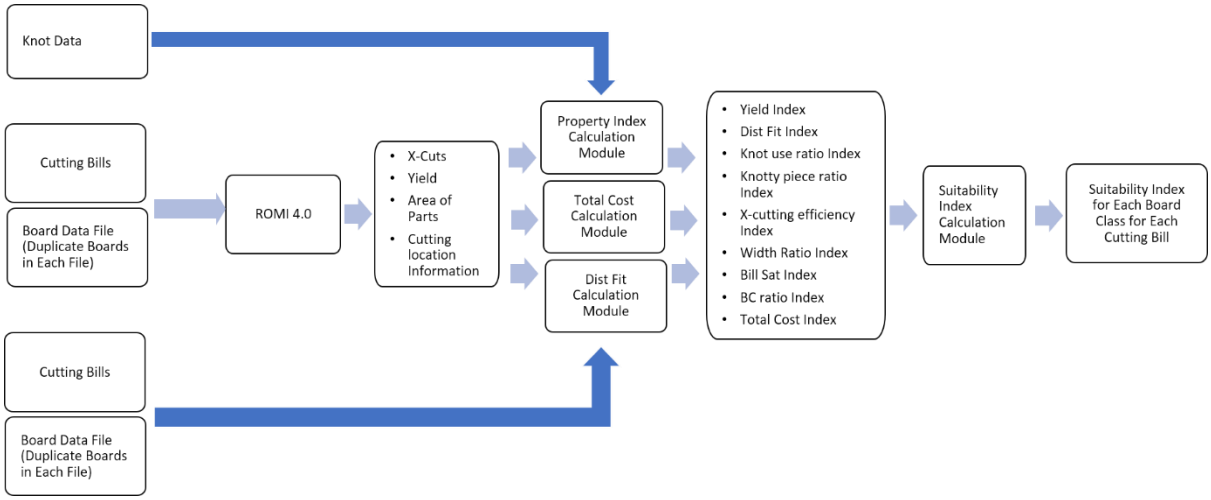


Figure 6-7. Flow chart of the process used to calculate the Suitability index.

It was intended that such a suitability index would increase the ability to select a board class that would be best suited to the desired outcome. A linear combination of individual property indices allows for customization of importance level for a quality selection scenario. In such an arrangement, different weights can be assigned to properties resulting in a different overall suitability index. The mathematical relationship is given as:

$$Si = \frac{\sum(Wi * Sp)}{\sum Wi}$$

Equation 6-1. Suitability Index

where

Wi is the weight assigned to a property index, and

Sp is the value of the individual property indices.

Also, further criteria can be used to define a lower minimum threshold that a particular board class must exceed to be considered a viable solution. This can be represented as such:

$$\forall\, Si > threshold(W_i)$$

where

$threshold(W_i)$ is the minimum allowed value of Si for some specific application.

In this thesis, the application is the manufacturing of high-value products from hardwood lumber. A minimum allowable value of W_i was assigned 0.5. Thereby, a board class with an Si value below 0.5 would not be considered a viable material for the cutting and design requirements at hand. Although this was an arbitrary value, it was illustrative of the concept. In practice, this value would depend on a set of manufacturing and cost limitations.

6.4.4.1 Property indices

The major considerations have always been the yield/price ratio and the number of cuts required to produce a given surface area of parts (cross-cutting efficiency). Here, additional properties are introduced. These properties are focused on how well a given class of lumber can satisfy different cutting bills and the efficiency at which knots of a particular size and type can be utilized. The individual properties are:

Yield:

Yield is the ratio between the surface area of parts produced and the surface area of the lumber processed.

Dist Fit:

Dist Fit is defined as a measure of how well the length distribution of cuttings in the lumber matches the length distribution of the parts required by the cutting bill. Short parts can be

produced from lumber containing either long cuttings or short cuttings with slight decreases in yield. However, long parts can never be produced from cuttings shorter than the parts. This leads to a situation where lumber with long parts is in demand for both the production of short and long parts. The goal is to use the best suited, but no better, boards for each cutting bill. The Dist Fit property is meant to provide information about how well the distribution of available cutting areas represents those that need to be produced. Here it is calculated on length alone. It is also calculated post-hoc—that is, it is calculated from the ROMI output after simulating the cut-up solutions. The parts and cutting areas are binned by length and normalized. This results in a matrix of similar lengths for which a simple root-mean-squared error calculation can be used to indicate the degree of difference between distributions. The root-mean-squared error calculation is typically used to judge the fit between a model prediction and the observed values. Here it is used to judge the similarity between the proportion of cuttings and parts occurring in particular bin sizes. Low values indicate a better match between the cutting areas and the required part sizes. The formula is given by:

$$Dist\ Fit = \sqrt{mean(parts - cuttings)^2}$$

where:

$parts$ is the normalized vector of part lengths, and

$cuttings$ is the normalized vector of cuttings lengths.

Knot use:

This property is the ratio between the number of available knots of specific sizes and types in the lumber to those that occur in the parts after the simulation. It indicates how well a cutting bill can incorporate knots within the selected range from the cutting areas.

Knot Pieces:

This property is the ratio between the knotty and knot-free parts produced during the simulations. It indicates a visual level of “knottiness” in a panel. The greater the ratio, the more strips in the panel will contain at least one knot.

Cross-Cut:

This property indicates the cross-cutting efficiency of the production of the strips during the simulation. A low value is more desirable than a higher value. It is calculated as the number of cross-cuts required to produce 1 m^2 of the finished panel.

Width Ratio:

This property indicates the ratio between the number of wider strips and narrower strips in the panel. Here, the ratio was calculated as the number of strips above or equal to 63.5 mm wide divided by the number of strips less than 63.5 mm wide. This width was selected because it was the mean width of arbor spacing found during simulation using ROMI. The ratio also contributes to the visual properties of a panel. The Width Ratio and Cross-Cut indicate processing efficiency because a low Width Ratio would necessitate a high Cross-Cut to produce a given panel area. The Width Ratio property also provides an estimate of further manufacturing costs associated with assembling the panels from the strips. Here, no attempt was made to estimate this cost.

Bill Sat:

This property is a measure of how well a given amount of lumber from a particular group can satisfy the cutting bill. This property is different than yield in that yield only considers the ratio between parts produced and lumber processed. This property indicates the ratio of the required part surface area to be produced from a given surface area of lumber. Given a rough mill production rate, this property indicates the relative production rate of the cutting bill. Indirectly, this is also a measure of the match between the cutting bill requirements and the lumber being cut.

BC Ratio:

This indicates the relative ratio between the proportions of different board classes within the population. Here it is based on the sample set of boards in the validation set only. It contributes to the selection of a particular group because of supply and demand. For example, a board class with ideal properties which contains few boards in proportion to what a given

resource produces would have a high market value, under the current supply and demand structure of the industry.

Tot Cost:

This property represents the total cost of manufacturing parts for the panel cutting bills. As presented in 6.4.2, the total cost module shown in Figure 6-5 was used in the suitability calculation.

All properties were normalized across all board classes and panel bills for both species. The axes were reversed for Dist Fit and Cross-Cut, and Tot Cost which means lower values are more desirable than higher values, similar to the other properties.

6.4.4.2 Panel cutting bill development

The procedure described here used another set of 6 contrived cutting bills for edge joined panels. The size and quantity of the panels are given in Table 6-8.

Table 6-8. The Panel cutting bills used to develop the suitability index. The quantities are listed under each panel bill.

		Panel cutting bill					
Width (mm)	Length (mm)	A	B	C	D	E	F
609.6	304.8	80	80	75	10	170	10
609.6	609.6	40	70	31	10	70	8
609.6	914.4	26	40	25	25	35	8
609.6	1219.2	20	10	20	30	10	8
609.6	1828.8	14	15	31	30	5	23
609.6	2438.4	10	2	1	10	0	33

These cutting bills were designed such that each one contained approximately 90.05 m^2 (SD=3.0) of the required panel surface area. However, the distribution of the area varied across the panel width classes for the panel cutting bills. The proportion of each panel width class in each cutting bill is given in Figure 6-8. These bills were designed to test the effectiveness of the above property indices to distinguish one board class from another in terms of how well different classes may be suited to the production of each cutting bill.

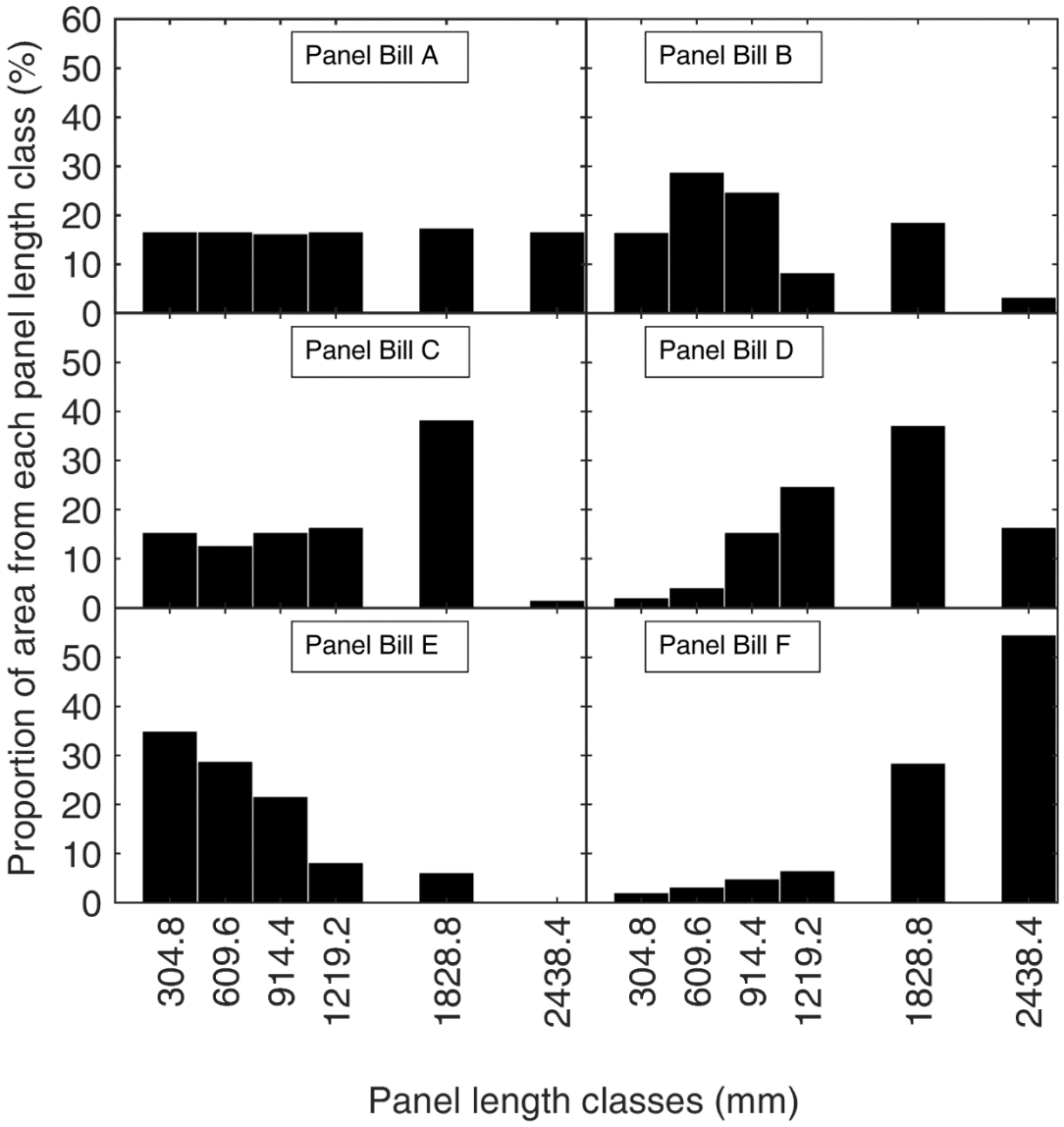


Figure 6-8. The distribution of the proportion of area for each panel with class in each cutting bill.

6.4.4.3 Board Data Files

The board data files used were the same as discussed in 6.4.2.1 Board Data Files. Because the goal was to test certain aspects of lumber utilization, an optimistic yield of 70 percent was used to create the total area of each of the cutting bills. Each board file contained approximately 128.8 m^2 (SD=0.13) of lumber, however, there were many more boards in each board file for *E. nitens* than for *E. globulus*.

6.4.4.4 Simulation

As before, ROMI 4.0 was used to simulate board cut solutions for each board class/panel bill pair using the following settings.

- Fixed-blade-best feed arbor with 11 blades set to 3.5, 3.5, 3.5, 1.5, 2.5, 2.5, 1.5, 1.5, 1.5, 4.5 inch spacing.
- Rip first
- Salvage not allowed (primary parts only)
- Random width strips allowed; minimum of 1.5 in, maximum of 4.5 in.
- *Complex Dynamic Exponent part priority
- No end or side trim

*Complex Dynamic Exponent is an option available in ROMI that updates part priority continually as parts are cut and the required quantity decrease (Thomas et al., 2015).

For each ROMI simulation, the number of cross-cuts was recorded. However, the other properties were determined with custom-built modules in MATLAB. In some cases, the yield differed few percentage points between the two approaches. It is thought that is probably due to the rounding error and the unit conversion processes (ROMI 4.0 board files are in 1/16 inch (1.5mm) in increments where the MATLAB application is capable of 0.4 mm increments).

6.5 Results

6.5.1 Dimension Parts

The parts yield and cross-cutting efficiency for board classes of *E. globulus* lumber grouped by definition 1 are shown in Table 6-9. As expected, the results indicate that yield varies by both cutting bills and cutting size distribution (see Figure 5-42), providing validation of the method. The yield was typically higher for easy cutting bills and lower for difficult ones. Board class 4 (widest and longest cuttings) of *E. globulus* lumber produced the higher yield, and board class 3 (narrowest and shortest cuttings) of that species produced the lowest yield. In some cases, parts production was not completed. This was due to either a lack of wide cutting areas or a lack of cutting areas that would satisfy the cutting bills. In many cases, high cross-cutting efficiency (low values) was not associated with high yield. For example, cutting bill 3

produced a yield of 67.3 percent with a cross-cutting efficiency of 43.4 cuts/m^2 using board class 2, but a yield of 72 percent and a cross-cutting efficiency of 47.3 cuts/m^2 for board class 4. This is a case where yield went up, but cross-cutting efficiency went down from one board class to another.

Table 6-9. Yield and cross-cutting efficiency for E. globulus lumber grouped by definition 1.

	BC 1		BC 2		BC 3		BC 4	
Cutting Bill	Yield (%)	X-cuts (m^{-2})	Yield (%)	X-cuts (m^{-2})	Yield (%)	X-cuts (m^{-2})	Yield (%)	X-cuts (m^{-2})
1	65.5*	41.1	75.1	25.4	47.6*	52.6	73.7	25.1
2	58.5	37.8	67.7	28.7	42.8*	49.8	73.4	28.3
3	60.4	52.5	67.3	43.4	33.5	57.9	72.0	47.3
4	55.3	94.3	55.9	85.3	44.5*	95.6	58.8	87.8
5 (B)	63.6	39.9	53.5	38.0	26.5*	112.5	71.4	28.4
6	47.5	29.8	38.6	22.0	17.8*	46.5	61.7	20.2
Mean	58.5		59.7		35.45		68.5	

* Indicates that parts production was incomplete.

The estimated lumber costs, manufacturing costs, and total costs to manufacture the parts from the cutting bills are given in Table 6-10. As expected, the total cost to manufacture the parts varied by board class for all cutting bills. Board class 1 indicated the lowest cost to produce parts from the two hardest cutting bills (as determined from this study), while cost was lowest for cutting bills 1, 2, and 4 for board class 3 lumber. Board classes 1 and 2 indicated nearly identical costs for producing cutting bill 5 and board classes 1 and 4 indicated similar costs for cutting bill 6.

Using the estimated normalized values and relative proportions of each board class, the overall value of the sample boards was 89 percent of the initial value of 1 unit assigned to the highest yielding board class. Accordingly, board class 1 would carry a value of 0.88, board class 2 would be valued at 0.87, board class 3 would be valued at 0.64, and board class 4 would be valued at 1.33 per BF. This would translate to 376 value units/m^3 of lumber produced.

The ranking presented in Table 6-10 appears to be stable with regards to lumber value and cross-cutting costs. Within the set of assumptions laid out here, approximately 88 percent of the lumber provides a viable feedstock to manufacture the products represented by these cutting bills. Simulations indicated that a doubling of cutting costs did not change the rank of

total costs of production. Likewise, a 4-fold increase in the value of the highest yielding board class did not change the ranking of total cost either.

Table 6-10. Cutting ratio, lumber value, manufacturing costs, and the total cost to manufacture parts from the E. globulus board classes based on an arbitrary value of 1 for board class 4. The proportion of each board class is shown in (). See 6.4.2.3 for an explanation of variables.

		BC 1	BC 2	BC 3	BC 4
Cutting Bill	Values	(34 %)	(37 %)	(17 %)	(12 %)
1	C_r	1.6	1.0	2.1	1
	Vli	1848	2093	1322	3164
	M_c	1601	1297	1450	1241
	T_c	3450*	3391	2773*	4406
2	C_r	1.33	1.0	1.75	1
	Vli	2305	2232	1682	3036
	M_c	1451	1249	1388	1186
	T_c	3757*	3482	3070*	4223
3	C_r	1.2	1.0	1.3	1.0
	Vli	1226	1097	1586	1522
	M_c	723	601	779	637
	T_c	1949	1699	2366	2159
4	C_r	1.1	1.0	1.1	1.0
	Vli	1439	1414	1144	2077
	M_c	710	644	620	650
	T_c	2150	2059	1765*	2728
5 (B)	C_r	1.4	1.3	3.9	1
	Vli	655	578	704	862
	M_c	448	426	1027	459
	T_c	1103	1004	1731*	1321
6	C_r	1.5	1.1	2.3	1
	Vli	1259	1546	1461	1497
	M_c	711	530	655	492
	T_c	1970	2076	2117*	1989

* Indicates that parts production was incomplete.

The part yields and cutting efficiency for FAS, #1C, and #2AC NHLA graded lumber are shown in Table 6-11. As would be expected, the mean yield was highest for FAS, moderate for #1C, and low for #2AC. While yield varied on lumber grade for most cutting bills, cutting efficiency was relatively consistent across grades. Difficult bills (2, 5, and 6) showed a high yield in FAS lumber but showed low yield in #2AC. The total costs to manufacture parts from the cutting bills is given in Table 6-12. In most cases, the lowest costs could be achieved by using #2AC, however, as indicated, using that grade often resulted in incomplete production. In the cases when #2AC provided the lowest costs but incomplete production, the next lowest cost

resulted in using #1C lumber. For 5 of the 6 cutting bills, the lowest costs would be achieved using #1C. The results indicate that using FAS lumber never provides the lowest cost to achieve parts. These results appear stable regarding cutting cost increases and lumber grade prices. For example, only one change was noted by increasing cutting costs to USD 1.5/BF and no changes were noted using the more expensive soft maple during the simulations.

Table 6-11. Yield and cross-cutting efficiency for NHLA graded lumber.

	FAS		#1C		#2AC	
Cutting Bill	Yield (%)	X-cuts (m^{-2})	Yield (%)	X-cuts (m^{-2})	Yield (%)	X-cuts (m^{-2})
1	68.1	13.4	55.1	13.5	49.5	13.8
2	76.0	18.2	61.4	17.8	50.3	18.3
3	56.3	16.8	40.2	16.7	50.3	23.4
4	80.0	33.6	61.3	29.0	59.5	29.8
5 (B)	72.8	17.8	68.5	19.7	46.9	18.6
6	75.1	14.3	60.0	13.7	43.6	12.8
Mean	71.4		57.8		50.0	

Table 6-12. Cutting ratio, lumber value, manufacturing costs, and the total cost to manufacture parts from NHLA graded lumber. See 6.4.2.3 for an explanation of variables.

		FAS	#1C	#2AC
Cutting Bill	Values			
1	C_r	1.0	1.0	1.03
	Vli	4730	3501	2596
	M_c	1149	1168	1170
	T_c	5879	4669	3640*
2	C_r	1.01	1.0	1.02
	Vli	2844	2634	2596
	M_c	1250	1230	1170
	T_c	4094	3864	3767*
3	C_r	1.01	1.0	1.4
	Vli	5021	3782	1359
	M_c	576	570	753
	T_c	5597	4353	2112*
4	C_r	1.15	1.0	1.02
	Vli	2009	1514	1356
	M_c	731	550	664
	T_c	2741	2065*	2020
5 (B)	C_r	1.0	1.10	1.03
	Vli	858	613	1059
	M_c	306	350	336
	T_c	1164	963	1396
6	C_r	1.12	1.07	1.0
	Vli	1153	1082	1419
	M_c	462	504	470
	T_c	1615*	1587	1889

The minimum comparable costs to produce each of the cutting bills from *E. globulus*, red oak, and soft maple lumber is shown in Table 6-13. Each value shown is the cost to produce the entire cutting bill and may not necessarily reflect the lowest costs indicated in Table 6-10 and Table 6-12. The lumber costs for *E. globulus* were assigned an overall value of AUD 930/m^3, which resulted in the values of AUD 917/m^3 for board class 1, AUD 909/m^3 for board class 2, AUD 675/m^3 for board class 3, and AUD 1391/m^3 for board class 4 using the calculations outlined in the methods section. Cutting bill 3 could be produced for the lowest cost using *E. globulus*, however, the others were produced with the lowest costs using red oak. Cutting bill 1 was produced by *E. globulus* at a lower cost than when using soft maple but slightly more expensive than using red oak.

Table 6-13. Comparative costs to manufacture each cutting bill using E. globulus boards and two NHLA graded lumber.

		Minimum cost (USD)*		
Cutting Bill	Level of Difficulty	*E. globulus*	Red oak	Soft Maple
1	Moderate	4856	4669	5676
2	Difficult	5045	3864	4621
3	Easy	2467	4353	5440
4	Moderate	3049	2020	2165
5 (B)	M. Difficult	1410	963	1139
6	Difficult	2852	1587	1897

** Results are based on the published values of the red oak and soft maple (August 23, 2019, Hardwood Market Report) and an adjusted overall value of AUD 930/m³ for* E. globulus *lumber. Cutting bills are listed from easiest to most difficult as determined from lumber used in this study. The level of difficulty indicates the ranking of cutting bills from other studies (see Table 6-4). See the text for further details.*

6.5.2 Panel Production

6.5.2.1 Definition 1

The results of the general cutting bill for boards grouped by definition 1 are presented in Table 6-14 and Table 6-15. The obtained parts are shown in 10.2. As expected, the highest yield and cross-cut efficiency were observed for groups of *E. globulus* boards with a significant proportion of long cutting areas (see Figure 5-42) and the lowest yield and highest cross-cutting efficiency were observed for the board class with the narrowest and shortest cutting areas. This pattern was also observed for *E. nitens* (see Figure 5-43). However, in general yield and x-cut efficiency were lower and cross-cut efficiency was higher across the board classes for *E. nitens* than for *E. globulus*.

Table 6-14. Processing parameters for E. globulus using the general cutting bill for boards grouped by definition 1.

E. globulus					
Board Class	Board count	Yield (%)	Rip-cut count	X-cut count	X-cuts (m^2)
1	119	73.6	156	1827	30.6
2	141	86.2	54	1264	21.1
3	170	58.9	181	2093	46.8
4	118	86.3	97	1298	21.8

Table 6-15. Processing parameters for E. nitens using the general panel bill for boards grouped by definition 1.

E. nitens					
Board Class	Board count	Yield (%)	Rip-cut count	X-cut count	X-cuts (m^2)
1	168	78.4	113	916	30.7
2	161	71.4	181	1274	21.4
3	136	83.8	82	1319	22.1
4	150	57.0	164	1801	50.8

The simulation results obtained from using the special cutting bills is shown in Table 6-16 and Table 6-17. The obtained parts are shown in 10.2. For *E. globulus*, the highest yield was obtained by the board class 3/panel bill D combination. The lowest was obtained from the board class 1/panel bill B combination. However, the lowest cross-cut efficiency was obtained from the board class 2/panel bill C combination, which interestingly produced a low yield. Panel bill B produced the lowest yield and the highest cross-cut efficiency. In *E. nitens*, the highest yield was obtained from the board class 3/panel bill C combination, which also produced the lowest cross-cut efficiency. The lowest yield was produced the board class 4/panel bill D combination, which also produced the highest cross-cut efficiency.

All tested combinations, except for the board class 4/panel bill D, produced impressive yields. The yield was higher for *E. globulus* than for *E. nitens* for panel bills A, B, and D. Cross-cuts/m^2 were lower in all cases for *E. globulus*.

Table 6-16. Processing results obtained from the special cutting bills for E. globulus lumber grouped using definition 1.

		E. globulus				
Board class	Panel bill	Board count	Yield (%)	Rip-cut count	X-cut count	X-cuts (m^{-2})
1	B	137	77.7	164	2533	37.6
2	C	187	80.7	101	1444	20.5
3	D	101	86.7	87	1470	30.3
4	A	74	85.8	62	1105	32.2

Table 6-17. Processing results obtained from the special cutting bills for E. nitens lumber grouped using definition 1.

		E. nitens				
Board class	Panel bill	Board count	Yield (%)	Rip-cut count	X-cut count	X-cuts (m^{-2})
1	A	168	77.6	92	947	35.3
2	B	182	77.0	188	3016	44.7
3	C	152	81.7	98	1230	20.3
4	D	150	66.9	156	2649	66.9

6.5.2.2 Definition 2

The simulation results of the board class/panel bill combinations for *E. globulus* and *E. nitens* boards grouped using definition 2 are shown in Table 6-18 and Table 6-19. The yield was higher for *E. globulus* for panel bills A, B, and C. In general, the knotty piece ratio was higher for *E. nitens* than for *E. globulus*. However, the knot use ratio was higher for *E. globulus* than for *E. nitens*. This results in a higher proportion of pieces containing at least one knot for *E. nitens*. However, there also appears to be some lost opportunity to fully capture the available knots using these board class/panel bill combinations as compared to *E. globulus*. Cross-cut efficiency showed approximately the same range for both species. However, it was lowest for panel bills D and C using board classes 3 and 4 for *E. nitens* and highest for the other combinations of panel bills/board classes. As expected, the panel bill with the longest pieces (Bill C) showed the lowest values, while panel bill D showed the highest (least desirable).

Table 6-18. Simulation results from the special panel bills for E. globulus lumber grouped by definition 2.

E. globulus								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	A	24.5	678	47	6.9	65	63	96.9
2	B	32.0	1505	99	6.6	150	123	82.0
3	D	64.8	1561	182	11.7	360	295	81.9
4	C	16.3	961	85	8.8	147	112	76.2

Table 6-19. Simulation results from the special panel bills for E. nitens lumber grouped by definition 2.

E. nitens								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	A	37.8	771	84	10.9	198	143	72.2
2	B	36.6	1606	236	14.7	396	298	75.3
3	D	56.7	1514	233	15.4	457	330	72.2
4	C	15.7	622	85	13.7	181	123	68.0

6.5.2.3 Definition 3

The simulation results for *E. globulus* and *E. nitens* lumber grouped by definition 3 are shown in Table 6-20 and Table 6-21. The yield was higher for panel bill C using *E. nitens* than for *E. globulus*. For the panel bills examined here, *E. nitens* showed a higher ratio of pieces that contained at least 1 knot than did *E. globulus*. For panel bill C, the knotty piece ratio varied between 21.9 percent and 43.5 percent for the different board classes and species. The knot use ratio was higher for panel bill D and B for *E. globulus* and higher for panel bill C for *E. nitens*. The ratio varied between 70.8 percent and 92.2 percent for panel bill C. The highest knot use ratio was 96.8 percent for the board class 4/panel B combination in *E. globulus* and it was 92.2 percent for the board class 1/Panel bill C combination. Recall that panel B has the highest proportion of short pieces while panel bill C calls for a high proportion of long pieces.

Table 6-20. Simulation results from the special panel bills for E. globulus lumber grouped by definition 3.

E. globulus								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	C	24.9	772	186	24.1	460	345	75.0
2	C	22.7	1092	239	21.9	480	340	70.8
3	D	23.1	1019	156	15.3	235	212	90.2
4	B	20.4	1345	284	21.1	435	421	96.8

Table 6-21. Simulation results from the special panel bills for E. nitens lumber grouped by definition 3.

E. nitens								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	C	13.0	865	314	36.3	665	613	92.2
2	C	13.9	796	346	43.5	744	601	80.8
3	D	22.3	643	216	33.6	400	337	84.3
4	B	33.5	1522	541	35.5	1072	846	78.9

6.5.2.4 Definition 4

The simulation results for E. globulus and E. nitens lumber grouped by definition 4 are shown in Table 6-22 and Table 6-23. The yield was higher for *E. globulus* for panel bill C, but about the same between the two species for panel bill D and B. In general, the knotty piece ratio was high in both species but lower than for *E. nitens* grouped by definition 3. In three cases it was approximately 80 percent, but in one combination, it was 100 percent, indicating that all the available knots were captured in cuttings. The knot use ratio was also high and on par with the other groups. The highest knotty piece ratio was observed using panel bill C in both species. For the replicated panel bill (C), the knotty piece ratio varied between 18.6 percent and 31.6 percent. The knotty piece ratio also differed according to the board class of lumber used for *E. nitens* (it varied slightly for *E. globulus*).

Table 6-22. Simulation results from the special panel bills for E. globulus lumber grouped by definition 4.

E. globulus								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	C	18.6	753	185	24.6	291	229	78.7
2	B	33.5	1552	261	16.8	364	324	89.0
3	C	12.3	897	209	23.3	245	245	100.0
4	D	25.0	1112	137	12.3	170	150	88.2

Table 6-23. Simulation results from the special panel bills for E. nitens lumber grouped by definition 4.

E. nitens								
Board class	Panel bill	Cross-cuts (m^{-2})	Piece count	Knotty pieces	Knotty piece ratio	Available knots	Utilized knots	Knot use (%)
1	C	23.2	462	86	18.6	168	135	80.4
2	D	36.7	1251	329	26.3	510	431	84.5
3	C	16.9	909	287	31.6	472	374	79.2
4	B	16.3	872	254	29.1	308	286	92.9

6.5.3 Suitability Index

The simulation results of the 6 contrived panel cutting bills on the board classes of *E. globulus* lumber grouped by definition 2 varied greatly. The individual property values (non-normalized) are shown in Table 6-24. The total value of the lumber sample was estimated at 105 percent of the value of the highest yielding board class. The calculated value of board class 1 was 1.24, board class 2 was 0.84, board class 3 was 0.87, and board class 4 was 1.6 of the arbitrary value of 1 assigned to the highest yielding class. This would convert to 444 value units/m^2 for 25 mm thick lumber.

These results indicate that the board classes/panel bill combinations capture a high proportion of the knots within the defined limits. For all but board class 3, this rate was above 75 percent (except for panel bill F). Despite this high rate of knot use, the ratio of knotty pieces was low; it ranged between 0 and 13.2 percent. This is a direct result of the arrangement of the allowed range of knots on the sample boards. This ratio would probably be different for the *E. nitens* lumber given that the species produced a higher proportion of smaller knots (see

Chapter 3). It also depends on the defined range of knot size; a larger range may result in a higher ratio of knotty pieces.

The width ratio varied between 22.4 percent and over 1000 percent. A 100 percent value would indicate an equal number of strips wider than 63.5 mm and narrower than 63.5 mm. A value of 1000 percent indicates that there are 10 times more wide strips than narrow ones. In general, board class 1 produced the highest yield, knot use ratio, highest cross-cut efficiency (low values), and highest width ratio (the ratio between wide and narrow strips). Except for a few cases, board class 3 produced the lowest yield, best Dist Fit (lowest values), lowest knot ratio, the highest rate of knotty pieces, lowest cross-cut efficiency, and lowest width ratio. As a trend, as the proportion of panel strip length increased (panel bill D and F had a greater proportion of long panels than did the others), the cross-cut efficiency increased, and the width ratio decreased.

Parts were consistently produced most cost-effectively using board class 3. However, this class showed very low yield and Bill Sat indicating poor performance. The lowest Tot Cost for parts production would be better estimated for board class 2 for all but panel bill F. As presented here, more than one measure is required to decide the best match between different board groups and cutting bills.

Table 6-24. Simulation results for the 9 property values developed in this study for E. globulus.

Panel Bill	Board Class	Yield (%)	Dist Fit	Knot use (%)	Knot pieces (%)	Cross-Cut (m^{-2})	Width Ratio (%)	Bill Sat (%)	BC Ratio (%)	Tot Cost
A	BC1	85.8	9.0	93.3	8.9	21.5	1213.3	98.8	26.9	2347
A	BC2	77.6	10.5	84.3	6.6	32.6	69.9	97.5	50.1	2096
A	BC3	52.1	3.9	56.4	10.2	56.3	32.6	74.8	9.2	1995
A	BC4	86.7	12.5	77.5	5.8	24.7	117.5	98.5	13.8	2943
B	BC1	85.8	8.7	93.3	8.3	23.5	1292.0	99.2	26.9	2470
B	BC2	76.9	9.1	79.4	6.0	35.3	80.9	98.5	50.1	2234
B	BC3	51.3	4.7	57.9	10.7	55.6	39.9	73.0	9.2	1973
B	BC4	86.3	13.1	77.5	5.4	27.3	124.0	98.4	13.8	3103
C	BC1	85.9	9.1	93.3	9.4	20.9	1033.9	98.9	26.9	2345
C	BC2	77.4	11.0	80.4	6.7	31.9	64.6	98.5	50.1	2112
C	BC3	49.1	4.0	50.5	9.6	54.8	32.9	69.9	9.2	1929
C	BC4	86.7	12.4	77.5	6.1	23.6	133.0	98.9	13.8	2923
D	BC1	78.0	7.0	85.5	12.0	16.2	255.1	98.2	26.9	2249
D	BC2	66.9	8.9	65.6	9.2	22.7	57.6	95.9	50.1	1910
D	BC3	36.0	12.3	37.9	12.1	36.7	19.4	51.3	9.2	1563
D	BC4	83.7	10.6	75.0	9.2	16.0	121.8	98.8	13.8	2597
E	BC1	85.4	12.5	93.3	6.5	29.3	1659.3	98.6	26.9	2718
E	BC2	76.7	13.9	80.9	5.0	42.7	97.0	98.4	50.1	2478
E	BC3	55.8	3.0	67.2	11.0	59.5	59.6	79.5	9.2	2098
E	BC4	86.1	15.5	77.0	4.2	35.0	141.9	98.4	13.8	3484
F	BC1	68.6	8.0	76.1	12.3	15.0	90.8	97.1	26.9	2369
F	BC2	53.2	10.6	44.8	9.2	20.1	38.3	76.4	50.1	1688
F	BC3	20.9	9.2	23.4	13.2	37.6	22.4	29.8	9.2	1419
F	BC4	83.4	14.0	0.0	0.0	13.6	105.8	97.8	9.2	2451

The relationships between the normalized property indices indicate differences among the board classes for *E. globulus* lumber (Figure 6-9). This figure is a series of radar plots. The radar plot can be used to show the relative differences in variables between different groups. The variable axes are represented as spokes radiating from the center of the plot. Value is usually normalized and plotted along each axis. The radar plot makes it easy to compare how values differ among groups. Three property indices (Dist Fit, Cross-Cut, and Tot cost) are plotted on a reverse axis so that desirable values are towards the outside of the plot axes. The suitability index (Si) was calculated using Equation 6-1 with all properties weighted equally. The Si for board classes 1 and 2, which made up the highest proportions of the sample set (over 75 percent combined), was consistently higher or similar to the other board classes. For all panel bills, board class 1 showed the highest Si. However, for all but panel bill

F, board class 3 showed the best Dist Fit values and either higher or equivalent levels of knotty piece ratio. In most cases, Si was below W_i for board class 3. Given that board class 3 does not meet the minimum threshold, it can be assumed that approximately 71 percent of the *E. globulus* lumber would provide viable material to manufacture these panels. This is based on the assumption that any board class with a $W_i < 0.5$ would not provide reasonable material. Here, this is only an example of a potential application; it is not based on any real-world evidence.

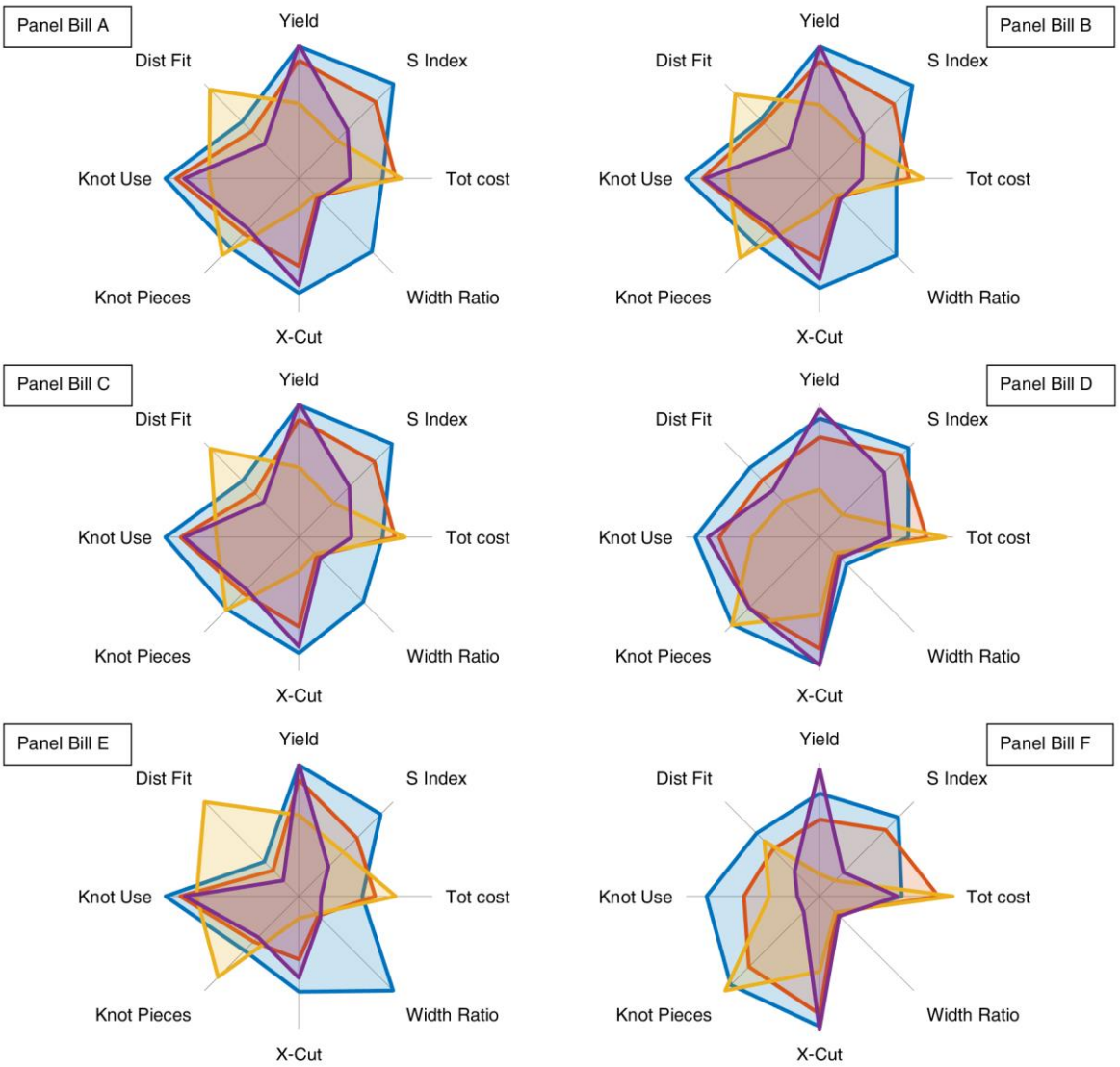


Figure 6-9. Radar plots of the indices and the calculate Si for E. globulus. Blue indicates board class 1; red indicates board class 2; yellow indicates board class 3; purple indicates board class 4. Note: X-Cut is used in the figure instead of Cross-Cut, which is used in the text.

The simulation results of the 6 contrived panel bills on the board classes of *E. nitens* lumber grouped by definition 2 varied greatly. The individual property values (non-normalized) are shown in Table 6-25. The value of board class 1 was 1.5, board class 2 was 0.8, board class 3 was 1.1, and board class 4 was 1.8 of that of the initial value of 1 assigned to the highest yielding class. The overall value of the lumber was calculated as 106 percent of the value of the highest yielding board class. This would translate to 451 value units/m^3 if the initial value was assigned 1.

These results indicate that the board classes/panel bill combinations do not capture as high of a proportion of the knots within the defined limits as for *E. globulus* lumber. In most cases, the knot use ratio was below 77 percent and, in some cases, it was below 50 percent. However, the ratio of knotty pieces was, in general, higher than for *E. globulus* lumber. In most cases, it was above 10 percent and in some cases above 18 percent (panel bill D/board classes 2 and 3). In most cases, board class 4 showed the highest knot use efficiency, highest cross-cut efficiency (low values), and highest width ratios, but it made up the second-lowest proportion of the sample set. It was also the least likely to satisfy the cutting bills (low Bill Sat values). Trends between increasing proportions of long strips and the ratio of wide to narrow strips were not apparent, but as expected, were lower for cross-cut efficiency. Parts were consistently produced the cheapest using board class 2, despite less than optimal yield or lowest cross-cutting efficiency in some cases.

Table 6-25. Simulation results for the 9 property values developed in this study for E. nitens.

Panel Bill	Board Class	Yield (%)	Dist Fit	Knot use (%)	Knot pieces (%)	Cross-Cut (m^{-2})	Width Ratio (%)	Bill Sat (%)	BC Ratio (%)	Tot cost
A	BC1	64.7	11.4	60.6	9.8	38.8	30.4	92.0	8.3	3234
A	BC2	75.5	11.7	78.7	15.5	36.0	62.9	98.6	59.2	2096
A	BC3	58.5	2.6	49.6	14.2	57.9	3.1	83.1	17.8	2411
A	BC4	86.6	11.3	73.4	10.0	22.1	213.7	98.7	14.8	3102
B	BC1	72.7	10.4	65.8	10.9	40.0	39.3	97.4	8.3	3244
B	BC2	75.2	9.7	78.6	14.7	37.9	84.9	98.2	59.2	2166
B	BC3	63.7	4.1	54.3	14.0	57.4	8.7	89.8	17.8	2488
B	BC4	86.2	11.2	74.7	9.9	24.0	260.8	98.6	14.8	3234
C	BC1	68.2	11.4	62.2	10.9	36.5	29.3	96.2	8.3	3226
C	BC2	75.6	12.0	79.1	15.8	36.5	53.5	97.9	59.2	2111
C	BC3	54.3	2.9	46.0	14.3	57.8	2.7	76.5	17.8	2343
C	BC4	86.8	11.4	73.9	10.4	21.6	183.1	98.8	14.8	3104
D	BC1	60.9	8.3	48.5	11.1	24.7	32.8	86.0	8.3	2780
D	BC2	62.0	10.9	49.8	18.1	26.1	31.7	88.6	59.2	1831
D	BC3	44.9	11.3	31.1	18.0	38.3	0.9	63.5	17.8	1947
D	BC4	81.5	8.9	63.3	14.7	15.1	162.6	98.1	14.8	2872
E	BC1	72.4	14.5	67.9	9.1	48.2	44.1	97.4	8.3	3500
E	BC2	74.4	14.3	76.8	11.6	44.4	105.7	98.3	59.2	2366
E	BC3	67.3	2.4	63.0	12.9	64.7	21.8	95.0	17.8	2682
E	BC4	86.0	14.6	75.3	7.8	31.4	231.1	98.6	14.8	3609
F	BC1	39.9	10.0	23.0	12.4	21.6	52.2	56.5	8.3	2491
F	BC2	47.9	11.7	37.8	20.0	22.8	25.1	68.6	59.2	1604
F	BC3	26.4	8.5	13.1	14.1	34.9	2.3	37.4	17.8	1724
F	BC4	75.7	13.3	0.0	0.0	13.3	119.5	98.1	17.8	2933

The relationships between the normalized property indices indicate differences among the board classes for *E. nitens* lumber (Figure 6-10). The suitability index (Si) was calculated using Equation 6-1 and normalized. The Si for board class 2, which made up the highest proportions of the sample set, was consistently higher compared to the other board classes, except for panel bill D. Board classes 2 and 3 consistently showed the highest knotty piece ratio, and board class 2 frequency showed the highest knot use ratio. Board class 4 consistently showed the highest width ratio and highest cross-cut efficiency. The results indicate that in most situations, board class 2 or board class 4 would be the most suitable lumber for the production of these panel bills. These two board classes make up approximately 75 percent of the *E. nitens* lumber samples, therefore indicating that at least that proportion could be useful to manufacture panels. The other board classes offer an opportunity to customize the level of knot used or the level of knotty pieces produced.

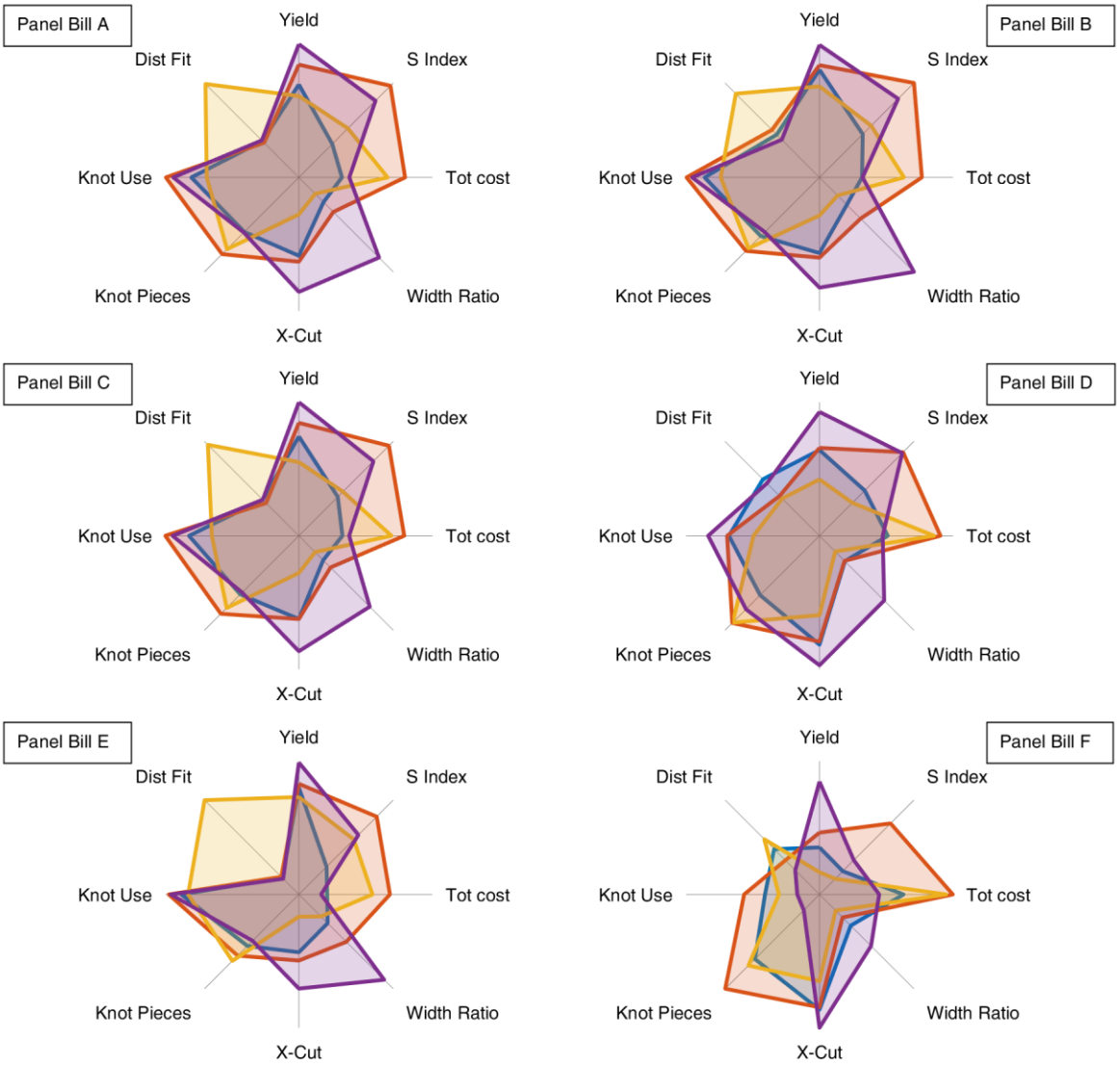


Figure 6-10. Radar plots of the indices and the calculate Si for E. nitens. Blue indicates board class 1; red indicates board class 2; yellow indicates board class 3; purple indicates board class 4. Note: X-Cut is used in the figure instead of Cross-Cut, which is used in the text.

6.6 Discussion

Currently, there is a poor understanding of the stock cut-up problem when applied to hardwood lumber. Although many studies have examined this problem using NHLA graded lumber, there has been almost no research focused on understanding the dynamic

relationship between yield, manufacturing costs, and the production of character-marked parts.

The objective of this chapter was to establish a means to understand the relationship between the cutting bill requirements, manufacturing costs, and the desired appearance attributes of hardwood lumber. This is a challenge in the industry because the information necessary to simulate yield and to estimate the visual outcome from different groups of lumber is not commonly available to the rough mill. This information makes it possible to better understand the manufacturing implications of specifying a defined range of allowable knot sizes in cutting areas.

Understanding these relationships makes it possible to estimate material and labor expenses associated with manufacturing products that contain a defined size and type of growth characteristics. It also makes it possible to match the best-suited boards to different cutting bill requirements. These procedures are a series of algorithms that estimate the manufacturing costs from the best-suited boards for a series of panel cutting bills. They form the last module of the system proposed in this research.

To address the objective, the following was developed:

- a means to determine yield and estimate manufacturing costs to calculate overall costs to produce dimension parts from the different board groups, and;
- a means to determine the most suitable group while considering a suite of visual and manufacturing properties indices related to increasing efficiency.

This objective was approached in two ways. First, a means to determine the yield and manufacturing costs from boards grouped by the size distribution of clear cuttings from the previous chapter was developed and used to demonstrate the overall costs of production varied among the different board groups and cutting bill requirements (dimension parts). The methods were then used to estimate the yield, cross-cutting efficiency, and the rate of utilization of knots for a special panel cutting bill. Second, a method to determine the best-suited group of lumber was developed that considered material and labor expenses, the rate

of knot utilization, and distribution of strip widths. This system makes it possible to compare the likely cost and visual attributes of panels produced from different board groups.

6.6.1 Dimension Parts

Although it appears that the lumber used in this study can produce dimension parts at reasonable yields and cross-cutting efficiency, which provides a way to value the resources, the other objective was to develop a framework that would incorporate the material characteristics into the manufacturing process. This section sets out the steps that could be used to determine which board class should be used for any cutting bill. It does this by ultimately providing an estimate of the cost to produce dimension parts. Therefore, providing a method to select the best-suited boards to produce different cutting bills. Although there have been many yield studies on hardwood lumber, almost all of them use the red oak database of NHLA graded lumber from 1997 (Gatchell et al., 1997), which may not represent hardwood lumber produced today. The work presented here is the first known study that examines yield and cross-cutting efficiency for boards from Australian plantation-grown hardwood. The findings indicate lumber produced from these resources may serve as a viable feedstock for the manufacture of many secondary products calling for parts within the size range used in this work.

The cutting area system is a second common method used to transform hardwood lumber into a useable form for high-value products. As discussed extensively, the National Hardwood Lumber Association grading system has been based on this concept for almost 100 years. It assumes that boards will be both ripped into strips and cross-cut producing slightly over-sized parts for different types of products. This process is applied at a wide range of scales from bespoke one-of-a-kind to commercial operations. At the bespoke level, a craftsman makes deliberate decisions about where to rip or chop individual boards to achieve the best possible pieces for the projects. At the commercial level, boards are usually ripped using a multi-blade arbor rip saw at the rough mill. Operators position boards based on experience in hopes of achieving the best yield of strips that are then cross-cut to length to produce the required parts. The process presented here is designed to represent a commercial rough-mill operation.

As introduced in 5.4.1.2, the cutting area method may not necessarily represent the maximum yield. In part, this occurs because of the way the cutting areas are defined. In this thesis, UGRS was used to find the cutting areas and board sorting was based on those cuttings. However, a simple simulation using all the cutting areas as master sheets and the cutting bills found that yield was 2-3 percent below what was found using ROMI on whole boards. This indicates that cuttings were being partially removed from areas outside the cutting areas isolated by UGRS. This finding (although not investigated in-depth here) indicates a clear mismatch between the cutting area method and lumber breakdown operations. Better optimization may be obtained using other types of cutting machines, such as CNC machines.

The production costs of parts from the 6 different cutting bills were estimated based on yield, lumber value, and cross-cutting efficiency as presented in 6.5.1. The results indicate a method to calculate the costs of manufacturing parts from different board classes of lumber based on yield, supply, and cross-cutting efficiency—three important considerations during the conversion of hardwood lumber to high-value products. Using these estimates, it could be possible to assign a real-world market value to the different classes of boards and then use these values to estimate real-world manufacturing costs. Washusen et al. (2004) suggested a market value of approximately AUD 1000/m^3 for boards produced from a similar resource (kiln-dried). Under the assumption that manufacturing costs will equal market value, increasing the arbitrary value by 1.7 results in an overall market value AUD 930/m^3 of unsorted lumber. The lumber costs increase for each cutting list, however, because manufacturing costs did not change the overall rankings and the real-world manufacturing costs can be estimated.

The costs to produce rough parts from the cutting lists used in this study indicate that at an overall value of AUD 930/m^3, *E. globulus* boards can produce so-called easy cutting bills at a lower cost than red oak or soft maple (at the current market value). This is probably due to the large proportion of very narrow and short parts required from this cutting bill. Other cutting bills such as 2, 5, and 6 could not be produced at costs on par with other species. For *E. globulus* to produce these at low cost, the material would need to be supplied to the market at about AUD 760/m^3.

The information presented above provides validation for the procedures developed and presented in this thesis. This information is ordinarily gained through experience as it is not a common practice to simulate yield at the rough mill for different quality classes of lumber and cutting bills. Using this information, it is possible to predict the total cost to produce different cutting bills and to compare the costs for different species of lumber.

The total costs of rough part production indicate that the use of different board classes can be optimized to different cutting bills (Table 6-10). Here 3 of the 4 classes provided the lowest cost for at least 1 of the cutting bills, although in a few cases the difference in costs from one board class as compared to another would probably be irrelevant in the real world. Interestingly, board class 4, which comprised the lowest proportion of the sample set, did not provide good value as compared to the other classes for the cutting bills tested. The method appears to be robust to changes in both lumber value and manufacturing cost. Simulations using a doubling of manufacturing costs and a 4-fold increase in lumber value revealed that the rankings remained similar to those presented. The procedures demonstrate a method to match the best-suited boards to different cutting bills. This ability addresses a key gap in current industry practice.

Also, there are patterns among the board classes. For example, board class 1 appears to provide an optimal cost solution for so-called hard cutting bills (cutting bills 5 and 6), whereas board class 3 appears better suited to easy cutting bills (cutting bills 1 and 2). This is probably due to the different distributions in the cutting area widths available in the two classes. Board class 1 contains a much higher proportion of wide cutting as compared to board class 3, despite a roughly equal distribution of cutting lengths (Figure 5-42). Although yield simulations need to be performed on a wider range of cutting bills, given cutting bill descriptions, these patterns could be used as a rough estimate when choosing one class of lumber over another.

Currently, there exists a low capacity to estimate the production costs of different types of products from lumber that contains a high occurrence of growth characteristics. These costs are highly dependent on the arrangement of knots and other characteristics, the cutting requirements, and the ability to optimize rip and chopping. The matter is further complicated

if a certain size and type of characteristics are required to occur on parts. Current grading methods offer little assurance that products can be viably manufactured from the material; therefore, market value is typically low, or as is the situation in Australia, market value is based on lumber production costs (~AUD 1000/m^3)

The approach developed here provides a means to estimate the manufacturing costs and thus provide a means to assign a market value to the resource, which, may be higher than the cost of lumber production. An arbitrary value of 1 was assigned to the highest yielding class; the value of other classes was adjusted according to the average yield and proportion of material in each class. This resulted in the arbitrary market value of about 376 value units/m^2. Here, a value of 0.71 was used as an estimate of the cost of producing 1 BF of parts. Buehlmann et al. (2011b) suggest a processing cost of USD 290/MBF (USD 200 in 2001) of lumber. Assuming a 50 percent yield of rough parts, a cost of USD 0.58/BF would result. This cost will undoubtedly change with cutting bill requirements (sizes of required parts), manufacturing operations, and regions. Despite differences, the rankings appear stable within a range of costs and lumber values that are likely to be encountered. A simulation (not shown here) using a 3-fold increase in the value of lumber and cutting cost showed only 1 change in the rankings, as did a simulation using a value of 0.4 as the cost of parts production. The results presented here demonstrate that the approach could be used to optimize the match between different board classes and cutting bills to determine the lowest cost combination within dynamic lumber markets.

From a yield perspective, plantation-grown hardwood from Australia may provide a reasonable export product to China or other Asian countries and to supplement the declining supplies of other hardwood resources within Australia. However, given that the secondary manufacturing industry has developed utilizing slow-grown hardwood in Australia, such a substitution would require the development of new products that utilize the material differently and new methods of board breakdown.

The above discussion has focused on providing a feedstock at the lowest possible price. Often, price is not the only factor influencing a consumer's decision about which wood species to purchase, and different species become more or less desired over time (Luppold and

Bumgardner, 2007). Often supply influences price as well (Luppold and Bumgardner, 2007). Sometimes factors other than grade influence selection. For example, factors such as dimensional stability, appearance, ease of machining, and the ability to accept a finish are more important than a stable supply or low price (Nicholls and Roos, 2006). The selection of timber is usually based on known attributes, such as price and workability; different species and grades are seldom selected based on the overall cost of producing parts or the potential visual outcomes available from a particular species. The results presented here provide a means to estimate these costs. The results show plantation-grown material can provide the feedstock to produce dimension parts. Future research should be focused on reducing processing and drying defects during the production of lumber. For example, Dawson et al. (2020) present the potential to use a supercritical CO_2 lab-scale pre-treatment that was shown to reduced collapse by 75 percent and washboard depression by 71 percent for *E. nitens* lumber. Reducing these drying defects could significantly increase the recovery of lumber from plantation grown logs.

Based on the limited board widths available for *E. nitens*, the cutting bills were not tested on this species in this study. However, based on other work in this thesis, it is assumed that values would not be as high for this material for these applications and manufacturing methods.

Although not investigated here, there also exists the potential to create the least-cost board class mixes that reduce the overall cost further. For example, a certain proportion of a mix could be used to supplement board class 4 and obtain lower production costs. This would require only minor modifications to the MATLAB application that produces these results. As discussed by Buehlmann et al. (2011b), this approach takes advantage of the market price differential that exists between high-grade (high yield) and low-grade (low yield) lumber. Lumber valued under the proposed approach also shows a differential that could be taken advantage of to further reduce the cost of parts production. This approach could also reduce the problem where cutting bills could not be completely produced using a specific board class. A more in-depth analysis is required to fully understand which specific combinations of board classes would satisfy the cutting requirements. A cost analysis could then be performed to understand the supply side.

6.6.1.1 Limitations to the Method

Although the results suggest that the classification procedure developed in Chapter 4 and the methods to estimate manufacturing costs presented in this chapter can effectively provide an estimate of manufacturing costs for this material, several assumptions and limitations need to be discussed. First, the methods proposed here were developed from a small sample set of boards. Board class 4 was composed of only 18 boards. The board data file contained 221 boards, which means that each board was replicated more than 12 times. If the individual boards did not represent the full variation that could occur in the class, this would restrict the number of cutting solutions and potentially result in poor estimates of yield for the class. This could also affect the ranking of mean board class yield.

A second limitation concerns the use of front-side only board descriptions. As compared to panel production where the appearance of the backside may not be a concern, for dimension parts this is often a consideration and may significantly reduce yield. As the analysis presented in this chapter uses clear cuttings and produces clear parts only, it is likely that yield would be reduced by including back-side characteristics into the analysis.

A third limitation would focus on the inability of board class 3 to produce all the parts required for the cutting bills. During the simulations, care was taken to modify the number of parts in each cutting bill so that most parts could be produced, it was not always possible given that board class 3 contains very few cuttings above 3 inches (80 mm)—a size called for by most of the cutting bills used here. Given that the goal was to differentiate boards into classes with the different distribution of cutting sizes, it was assumed that this would be characteristic of the class using any number of boards. Therefore, this class will almost certainly produce low yields and incomplete production for cutting bills calling for wide parts. This class is better utilized for cutting bills that allow for random width parts, such as those used in panel construction. A fourth assumption involves the limited number of board classes. Based on Figure 5-40 and Figure 5-42, it appears that the sample set could be separated into more board classes that would provide better delimitation among board classes. For example, board class 2 could be divided into 2 classes, one containing narrow cutting areas and one containing wider ones. This could lead to different manufacturing cost estimates.

Most other processing studies use several simulations on different batches of boards that provide a means to statistically determine differences between outcomes (Buehlmann et al., 2011b, Smith, 2004, Wiedenbeck et al., 2004). In this study, the number of boards were limited and had been produced for other projects (Derikvand et al., 2018b, Derikvand et al., 2018a, Derikvand et al., 2019, Jiao et al., 2019). Therefore, simulation results were based on one run for each of the different combinations of board classes/cutting bills. No statistical testing was possible; however, the results indicate the methodology developed here could be expanded to include more samples and cutting bills to truly understand the relationship between processing and different groups of boards.

The cost comparison analysis made several assumptions that may or may not hold up under real-world conditions. The method assumes that knots are the only characteristics found on the boards that need to be considered during cutting decisions. This study focused on knots as they likely have the most influence on the visual attributes of products. Most character-marked grading standards and most wood surface perception studies focus on knot size and appearance. The boards in this study contained numerous end splits, and surface checks, some of which could be eliminated with better harvesting, processing, and drying techniques. However, even with improvements, it is likely that the lumber would retain some level of processing and drying defect, reducing the yield and increasing the total cost to manufacture parts. Also, the cost comparisons were made using lumber found in the red oak database. As mentioned before, these boards may not represent current lumber of the same grade, which could potentially influence lumber cost comparisons.

6.6.2 Panel Production

The purpose of this section was to examine the relationship between yield, cross-cutting efficiency, and board classes under different cutting requirements. This was done in two ways. First, a general cutting bill was tested on all board classes. Second, a series of special cutting bills were visually matched to different board classes. This was done by matching the cutting areas distribution to the cutting requirements of each bill. The results provide a means to communicate an estimate of yield, cross-cutting efficiency, and the ability of the cutting bill/board class combinations to capture the knots that have been selected for. In this section of the work, lumber value was not addressed. Using the procedures outlined in the other

sections, manufacturing costs and therefore a real-market value could have been calculated for the material.

This exercise is focused on understanding the complex 2-D stock cut-up problem for lumber. This is a common manufacturing problem that seeks to “nest” the required parts onto standard-sized sheets of material. The problem is more complicated for lumber given that nesting must consider areas of boards that cannot be included in parts. It is an attempt to exploit the geometric relationship between the cutting areas available within a group of boards and the size of the required parts. This problem is encountered in other industries, such as the initial cut-up of leather. Baldacci et al. (2014), proposed a heuristic algorithm and an automated system that would reduce waste and improve product quality. However, because the processing of lumber is different than leather, the approach presented here is specific to the production of dimension parts from lumber. This approach is also unique in that it makes it possible to compare the potential visual outcomes (i.e., knottiness of a panel) from different resources.

The simulations presented here were based on the constraints found in current rough mill operations. Further work should include investing the potential for “punch” cutting lumber. This could result in higher yield because it avoids the rip first/chop first procedure. This would require developing different algorithms, similar to those presented by Baldacci et al. (2014) for the nesting and processing of leather.

6.6.2.1 Definition 1

As noted elsewhere in this thesis, much work has focused on understanding yield from lumber, however, despite some research about preferences of “character-marked” furniture and the appearance of solid wood panels, little effort has examined the distribution of knots or the level of knottiness that results from utilizing knots of certain sizes and types. Also, little work has examined how the visual attributes differ between wood species. Peoples' preferences for panels that contain different levels and sizes of natural characteristics have been studied with mixed results. As discussed in 2.4, it appears that ‘disharmony’ among different characteristics should be avoided during manufacturing. However, few studies have clearly defined limits of preferred combinations and sizes of characteristics. The framework

proposed in Chapter 4 gives the expert user the ability to place limits on the size and type of knots and visualize panel production. This increases the resolution at which consumers can judge a particular combination of characteristics in panels. This chapter is focused on determining which board class should be used to obtain the desired results.

In the first cutting bill, the general bill, there was an apparent relationship between yield and cross-cutting efficiency for parts that did not contain knots as grouped by definition 1 (Table 6-14 and Table 6-15). Although no direct comparison could be found in the literature as most researchers use cutting bills of dimension parts (this study looked at panel production), the yield from the general cutting bill was relatively high for all but board class 3 for *E. globulus* and board class 4 for *E. nitens*. This pattern held up under the special cutting bill as well (Table 6-16 and Table 6-17). The cross-cutting efficiency varied considerably but compared well to other studies. Wiedenbeck et al. (2004) found a cross-cutting efficiency of between 36 and 57 cuts/m^2 for cabinet and moulding cutting bills, respectively. In a few cases, the cross-cutting efficiencies found in this study are significantly lower than those found in the previously mentioned study. However, most board classes produced a higher yield than those reported by Buehlmann (1998) and Wiedenbeck et al. (2004). These findings suggest that overall, *E. nitens* and *E. globulus* boards produced from these resources are comparable in terms of yield to lumber graded under NHLA rules. These results are also supported by the findings in 6.5.1.

The true value of understanding the relationship between the available cutting areas and the cutting bill requirements allows the two to be matched to produce the highest yield possible from the different groups of lumber. In this study, the four special cutting bills contained a different proportion of long and short panels, which were matched to cutting area maps that were believed to have the potential to result in high yield. Although somewhat subjective, it provides a means to select lumber best suited to a cutting bill. Given that the NHLA standard does not provide detail about the cutting area distribution, the current practice is to purchase the grade that is “believed” to produce the best yield. Because the potential cutting areas are described by the methods in Chapter 4, it is possible to make an informed choice as to which board class is most likely to produce an acceptable yield.

The goal was to assign cutting bills to board classes so that cutting bills that call for short parts are matched to lumber that contains cuttings of roughly the same length. In this way, lumber that matches the requirements, but does not exceed them is used. This results in a situation where the best-suited[34] lumber is used for different cutting bill requirements. This logic was used when choosing the particular board class/cutting bill combinations for testing. The results indicate that for the cutting bills tested and the lumber sample set, the approach was successful. For *E. globulus* lumber grouped by definition 1, every board class/cutting bill combination produced over 77.7 percent using the special cutting bills (Table 6-16). This exceeds most, if not all, published values of the yield of parts from hardwood lumber (Buehlmann et al., 1999, Smith, 2004, Wiedenbeck and Buehlmann, 1995, Wiedenbeck et al., 2004). Although not examined in depth it should be noted that the panel bills used in this work produced yield between 78.8 percent and 81.5 percent for F1F (FAS, but one clear face only) lumber NHLA graded lumber, further supporting the concept that this lumber compares well to other hardwood resources.

Within the current context of the Australian hardwood lumber market, boards produced from plantation grown resources have a low market value (Nolan et al., 2005, Washusen et al., 2004). This is the result of perceptions within the industry that these boards will not satisfy the expectations of users. These expectations are probably based on the properties and characteristics of historically available resources, which were mostly knot free. As noted in 2.1, the availability of the timber resource has and continues to change (Washusen and Waugh, 1999). Given the transformation taking place within the Australian forest industry, expectations are likely to shift once lumber from plantation resources is widely available and marketed alongside other premium-priced materials. The results presented here indicate that lumber produced from plantation resources would likely produce yields of clear dimension parts as well as hardwood lumber graded using NHLA standards for at least the products tested here. The results also suggest lumber produced from these resources would likely result in significant yields of character-marked products. The concepts developed in this thesis could be extended to determine the range of products suited to this new material,

[34] As defined in 1.1.

consequently substituting the declining native resource, and reducing pressure to harvest those resources.

The outcome was slightly confounding for *E. nitens*. Despite good yield and cross-cutting efficiency for board class/panel combinations, 1/A, 2/B, and 3/C, board class 4/panel bill D showed comparatively low yield and high cross-cut efficiency (Table 6-17). Panel bill D is made up of a high proportion of short panel (and strips) and board class 4 contains a high proportion of short cuttings, much like board class 3 in *E. globulus*, which produced much higher yield and lower cross-cutting efficiency values (better efficiency) for the same panel bill. It was hypothesized that a more complex geometry exists for this combination resulting in narrower strips that require more cross-cutting operations to obtain the desired parts within the random arrangement of other knot sizes.

6.6.2.2 Remaining Definitions

As introduced in Chapter 3, the use of the slider concept provides a way to imagine the selection of knot size and type process. Once a particular size and type have been selected, the geometric arrangement of the desired characteristics and the cutting bill requirements determine the rate that the selected knots will be captured during the manufacturing process. Here, 3 sizes and types of knots were selected and the rate at which the different sizes were utilized was studied. The processing results are shown in Table 6-18 through Table 6-25. As expected not every strip within a panel contained a knot. Only *E. nitens* lumber grouped under definition 3 resulted in a knotty piece ratio greater than 30 percent (Table 6-21). Surprisingly, the knot use ratio did not increase much for *E. globulus* as allowable knot size increased from definition 2 to definition 3. However, it did increase for *E. nitens*. Both the increase in knot use ratio and the knotty piece ratio was evident in the sample panels produced in Chapter 3.

Definition 4 was designed to further understand the potential to capture knots with a lower and upper size limit. Knotty piece ratios were on a par, if not a bit lower, than for the other definitions. Despite a moderate knotty piece ratio, the larger size class of knots contributes a dramatically different appearance to these panels (see Chapter 3).

The utilization of characteristics will vary with knot arrangement within single boards. For example, two boards might contain the same size distribution of knots, but one board might

contain 3 or 4 adjacent knots within the size class, which would produce a long cutting capturing all those knots. A different board might contain 1 knot in the size class followed by a larger or smaller knot, which could produce several short cuttings, some of which may contain a knot. Different resources will undoubtedly provide different ranges and types of patterns. The only way to truly understand the visual outcome is to work with the actual board-scale information from a representative sample set of the available materials.

Although beyond the scope of this study, these results indicate a complex geometric problem exists between the distribution pattern of knots, potential cutting areas, and the cutting bill requirements. Understanding this problem for different species, management strategies, and sources of material could direct the production of future resources.

Due to the settings used during the simulations, strips vary in width—an attribute that could be adjusted by using different arbor spacing. Given the high yields achieved, the choice of arbor spacing appears to result in high utilization at the cost of producing some proportion of narrow strips. Further tests are required to understand the relationship between the distribution in strip widths and yield, cross-cut efficiency, knotty piece ratio, and the knot use ratio and how these variables translate into visual differences. The methods developed in this research were designed to be customizable in these ways. As suggested in 2.5, such modeling would require specialized expertise; perhaps creating the opportunity for new design professionals.

6.6.3 Suitability Index

The set of property indices as described above is an attempt to objectively characterize the diverse processing, visual, and material availability variables considered during the conversion of hardwood lumber to high-value products. The suitability index presented here is composed of nine (9) properties. The processing properties include yield and cross-cut efficiency. The visual properties are the knot use ratio, knotty piece ratio, and width ratio of strips produced from the lumber. The availability properties were the Dist Fit, Bill Sat, BC Ratio, and BC Use terms. Six cutting bills were contrived to test the extremes of the board classes grouped by definition 2. The simulation results for *E. globulus* and *E. nitens* are shown in Table 6-24 and Table 6-25. The normalized values and the Si are presented in Figure 6-9 and Figure 6-10.

From a manufacturing point of view, *E. globulus* board class 2 provides the lowest cost parts for all board class/panel bill combinations. However, when the other properties are taken into consideration using the suitability index developed here, board class 1 or board class 2 provides the optimal material for the panel bills tested here. This translates into approximately 77 percent of the lumber produced by this species is appropriate for panel production. In comparison, about 75 percent of the *E. nitens* lumber provides a good solution for this mix of panel bills.

The suitability index indicates the relative ranking of each board class for each cutting bill. In most cases, Si was above 0.5 for *E. globulus* board classes 1, 2, and 4, demonstrating that either of these would provide overall viable material for the panel bills. However, board class 3 and, in many cases, board class 1 had values below 0.5, rendering those classes as poor choices for the panel bill requirements. These values assumed that the importance of each property is equal. The approach can be customized by assigning different weights to specific properties that may be important according to the expert user. For example, by increasing the importance of the knotty piece ratio and the Tot cost by 3, board class 3 becomes a viable choice for *E. nitens* for most panel bill requirements (not shown). Because property values are plotted relative to each other, it is also possible to select a board class based on one or two individual property indices. For example, even though *E. globulus* board class 3 would overall be considered a poor choice compared to other classes, it might be a good choice if a high ratio of knotty pieces or low manufacturing costs were desired above other considerations. This would allow the expert user to choose to some degree the level of knottiness required. Another example is the width ratio property. In four cases of the six, board class 1 provides the highest width ratio (a high ratio of wide to narrow strips, considered a desirable characteristic in this work); however, if more consistent strip widths were desired, a weight could be assigned to this property or board classes with low width ratios could be selected.

In this work, the development of the suitability index was performed using one definition of allowable knot size and type. Although this definition was used to illustrate the procedures of the suitability index, the same procedures could be used for any definition of allowable knot size and type. Because boards are sorted differently using other definitions, the results of the suitability index would undoubtedly be different as well. It is conceivable and likely based on

results presented elsewhere, that producing panels that allowed large knots would influence the knot use ratio, knotty piece ratio, width ratio, and cross-cutting efficiency. These influences may result in greater utilization and lower manufacturing expense and would certainly impact the visual attributes of the panels. The same would also be true for different panel cutting bills.

Although important from both the consumer and manufacturer perspective, given the large variation in manufacturing processes and material characteristics the outcomes are nearly impossible to predict within the current hardwood lumber supply chain. As argued during this work, the information exchange between the producers and users that describes the characteristics of hardwood lumber does provide the high-resolution data to allow simulation of the potential visual attributes attainable from different resources or the expense associated with the production of different type of panels. The system developed here overcomes these problems by demonstrating how the potential exchange and use of digital information could be used to refine the ways that natural materials are defined and described within the supply chain.

7 Chapter Seven – Thesis Discussion

The research presented in this thesis addresses the problem of manufacturing high-value products with varying levels of visual attributes obtained by allowing knots of different size and appearance to occur within cuttings. The aim was to present a systematic approach that uses high-resolution information describing the distribution of knots to be passed and used along the hardwood lumber supply chain to enable lower-value lumber to be moved into high-value applications, increasing the market value of such resources. Fundamentally, it involves using the best-suited boards to achieve the highest possible yield of parts that contain an accepted range of certain growth characteristics, which reduces the costs of lumber consumed. This becomes a complex sorting (grading) and cutting stock problem. Currently sorting is accomplished with industry grading standards, which provide little assurance that any given batch of lumber will contain the best boards. Yield has been the subject of much research, both academic and industry-driven. However, it has been mostly focused on understanding the relationship between cutting bills and lumber graded to NHLA standards. Little research has focused on alternate sorting procedures and the relationship between different sorts of lumber and resulting yield for various cutting bills.

The problem addressed in this thesis is fundamentally one of information flow between members of the appearance hardwood supply chain; specifically, between the producers and manufacturers of lumber and high-value products. Currently, the information between these two segments of industry describing the characteristics of lumber is rudimentary. Variation in the size, appearance, distribution, and frequency of naturally occurring growth characteristics is packaged into low-resolution paper-based lumber grading standards. The research gap identified during the project was the lack of research and development of systems to overcome this problem.

The research question was about how high-resolution information can be used to increase the utilization efficiency of lumber that contains an elevated frequency of natural growth characteristics, such as knots. To address this question, a system was developed that allowed the user to first visualize, and then specify accepted types of knots. This information was then used to sort for the boards that result in the highest yield of parts. The system provided the

end user with the ability to predict not only the resulting visual attributes, but also the anticipated processing costs from different combinations of cutting bills and sorts of lumber.

The goal of this research was to develop and establish procedures to collect, format, and use high-resolution board-scale information to improve the utilization of a wider range of the natural growth characteristics found in lumber. This goal was divided into four objectives. Each objective was accomplished by creating computer algorithms that perform the necessary tasks. The four objectives were:

1. to develop a module to digitally characterize and describe the knot population of lumber produced from these resources, and to use this data to develop a means to describe the size, appearance, and orientation that is currently available, as described in Chapter 3;
2. to develop a module to select and specify different sizes and types of knots in appearance panels, as described in Chapter 4;
3. to develop and demonstrate a module for a novel lumber classification based on the distribution of areas within boards that contain a defined range of characteristics, as described in Chapter 5; and
4. to develop a module to understand the relationship between the cutting requirements, manufacturing costs, and desired outcomes to determine the best-suited board groups for different product requirements, as described in Chapter 6.

Taken together, the modules make up a conceptual lumber processing system that uses data from images of lumber surfaces to enable the selection and estimate the expense of manufacturing panels that contain a defined size and type of knot. The modules could be assembled to create an all-in-one system like the example given in Chapter 4. The system was tested on two short-rotation plantation-grown resources from Tasmania, Australia.

The modules are made up of the following tools and techniques:

- the techniques and tools to assess the characteristics of boards;
- the procedures to refine selection and specification procedures based on the available resources;

- the interfaces for flexible sorting processes;
- the methods to sort boards into batches with a similar distribution of visually desirable areas, and;
- the procedures to optimize the processing of boards into products.

The thesis demonstrates a concept for a system that allows producers and users to communicate the characteristics of hardwood lumber more effectively and efficiently along the supply chain. This improves the ability for the producer to supply lumber batched according to user-supplied definitions and increases the utilization of the resources. Because the system provides a means of passing high-resolution digital information, the framework provides a means to recognize and utilize the variability of the physical properties produced by a biological resource.

The system works by supplying high-resolution information describing the knot size, shape, appearance, and distribution in a representative sample of boards to an expert user. This information enables the user to define a range of acceptable knots that can occur within usable areas of boards. Because the information is digitized, it allows for an almost infinite range and type of knot to be specified. This allows the specification of knots like the methods used for manufactured materials (see 1.1 for a detailed discussion of the differences between manufactured and natural materials.). Also, because the information includes aspects of color and grain texture, the expert user can visualize not just the knot patterns, but also the overall visual attributes of products within the digital design environment. This assists with choosing a certain range and type of knot over a different one, therefore, reducing, the guesswork associated with character-marked products. The information enables true customization and consistency of product outcomes.

The specification is then used to create a classification model that can sort boards such that the best-suited batch for different applications can be supplied to the manufacturer. In this thesis, the best-suited boards are those that result in the best yield of cutting from cutting areas that contain an accepted range of certain characteristics. Also, because this system envisions a situation where every board carries high-resolution information, digitally optimized cutting solutions for each board can be passed to automatic rough mill operations.

Cutting solutions could also be passed to CNC routers in cases where better yield could be achieved with a punch cutting approach.

The approach could theoretically be used to overcome the lag of technological development that would increase the agility of the hardwood supply chain. Increased agility would allow the industry to rapidly respond to changing consumer desires and produce customized products with unique visual attributes. In this work, this concept was demonstrated using appearance wood panels. This ability allows the user to choose from standard offerings or specify what visual attributes are desired, like specification procedures used for manufactured materials. The system enables the utilization and conversion of both physical material and digital information along the supply chain to increase the use of lumber. It is particularly applicable to lumber that contains a high frequency of growth characteristics, which can be used to produce unique visual attributes in products. This allows accurate prediction of visual outcomes and an estimate of the manufacturing costs.

As the forest industry transitions to an innovative “market-driven, precision manufacturing” sector, the incorporation of accurate material descriptions will ultimately be necessary to maximize the utilization of new resources that are unlike historical ones. The industry is under transition as industry 4.0 technologies are developed and adapted to suit the needs of the industry (Müller et al., 2019). The research provides a framework for advanced analytics of sorting lumber that improves the match between harvested (available) timber resources and customer requirements, which assists the transition from a push market to a pull market supply (Müller et al., 2019). As future developments will involve the capture, supply, and allocation of data, it will be the future of research to demonstrate how this data can become useful information to be used to connect and integrate parts of the supply chain (Müller et al., 2019). To be successful and competitive in a fashion-driven industry, the appearance hardwood supply chain must offer the customer the ability to customize the visual attributes of products. This can only be achieved with high-resolution information and interfaces that allow customers to define the customizable parameters of the product and the development of tools and techniques that allow manufacturers to be able to produce custom products and accurately predict the manufacturing costs of doing so. These tools included ways to batch

lumber for different applications, match the best-suited batches to different application requirements, and accurately predict manufacturing costs.

7.1 Contribution to Knowledge

7.1.1 Industry

The system developed in this thesis was tested on two species of plantation grown hardwood from Tasmania, Australia. These resources are not managed to produce lumber for solid-wood applications and are currently used to produce fiber for the pulp and paper industry. Lumber produced from these resources contains a higher proportion of knots and natural characteristics compared to boards produced by the slow-growing native forests. It is because of these properties, lumber from these resources are well suited to validate the approach developed here.

The grading standards used in Australia do not provide the detail to effectively communicate the visual attributes available from the resources. The North American approach provides a limited description of the size of clear cuttings available within each grade of lumber. Both systems systematically attempt to ignore the naturally occurring characteristics that occur within the material.

This thesis makes significant contributions to knowledge in two general areas. The first contribution is the demonstration that from a yield perspective lumber from plantation resources may be suitable for the production high-value secondary products. This contribution assumes that more research is needed to reduce drying induced checking and other techniques to reduce the twisting, cupping, warping and other defects related to harvesting, drying, processing, and management strategies. This finding should encourage the Australian timber industry to invest in the production of lumber from these resources. As demonstrated the system was primarily tested by simulating the production of solid appearance panels manufactured from lumber produced from plantation resources. The results indicate that such products could be produced and may provide a significant increase in the value of these resources. Standard sized appearance panels may also serve as an export commodity as an intermediary product to be manufactured into other higher-value products.

This work only considered the relative expense of producing the strips for such panels from the lumber in the sample set.

The work also showed that the lumber compared well to hardwood lumber from North America, suggesting that it could be exported to countries currently importing a significant volume of lumber from North America. This would result in the diversification of products produced from the plantation resource and potentially increase the value of the timber. Also, the system developed in this work could be used to add value to the supply of undervalued and underutilized hardwood resources in North America. Examples include alder, birch, and other species that produce a high occurrence of growth characteristics, and lumber that is currently considered “low grade”.

As the characteristics of the hardwood lumber supply continue to change, it will become increasingly important to utilize new resources produced from small, younger trees by the secondary products industry. Traditional grading systems will not apply to these resources. The system developed here sorts lumber by a system of inclusion; that is, cutting areas are defined by what can occur within the cutting area. Although this requires information about the variation of the material, it provides a method to understand the distribution of useable areas within the boards. The system uses this distribution of cutting area sizes to group similar boards. This is a novel and unique approach to lumber grading and results in the ability to choose the best-suited group of lumber for different cutting bill requirements. It also allows the breakdown of lumber at the rough mill to be optimized and the manufacturing costs estimated. This is a key component for the “furniture enterprises of the future” (Azouzi et al., 2009) because it allows for an increased level of customization, a key component of competitiveness (Nicholls and Bumgardner, 2018).

The second significant contribution is the use of high-resolution information to define, visualize, and select potential visual outcomes from hardwood lumber. This is significant because the process is ordinarily performed with uniform materials, such as paint. Accurately modeling the actual visual attributes of wood surfaces within the digital environment increases the users' ability to engage with the characteristics of different species and resources, improving specification detail. This contribution provides an accurate and rapid

means of specifying unique visual combinations of different characteristics, a process that is currently lacking detail and is time-consuming and laborious. This ability should expand the use of hardwood lumber and the variation of the visual attributes available from it. It should also result in reduced product development timelines and decrease the risk of new product offerings.

These two general contributions are industry-specific. That is, the knowledge should be promoted to industry personnel as a means of improving the distribution and use of hardwood lumber. Although the system demonstrated here is limited, the industry should begin to consider ways that the concepts developed in the thesis could be implemented at a small-scale to begin to understand potential benefits and challenges that will need to be overcome.

7.1.2 Academic

In this work, four research academic areas were investigated. These are considered academic because of the technical developments required that would typically be performed in a research setting, such as a university or a technology provider. The results from each area provided information to the next, which illustrated how the framework could achieve results unavailable in current industry practice.

7.1.2.1 Characterization of Knots

The first area focuses on the characterization of knots on the surface of the boards. To address this problem, advanced image processing and analysis protocols were developed and validated. These consist of a series of image transformations, contrast adjustments, a novel dynamic thresholding procedure, object segmentation, and object classification. This forms a series of processes that automatically use pixel-level data to create knot-scale information. The 'lab-scale' module demonstrates a proof of concept that could be expanded and improved. The algorithms could also be adapted for other research projects that involve image analysis of lumber surfaces. Commercial systems are available that can perform these tasks at high speed in commercial settings. However, these systems are expensive (USD 100,000 – USD 800,000 (Buehlmann et al., 2007a)) and are seldom available to the researcher. Therefore, the characterization model developed here provides the basis for a system that

could be integrated into other 'lab-scale' equipment designed to assist with image acquisition processes.

Although there have been many machine vision studies focused on the characteristics of wood, few have used the range of properties employed in the model proposed here. Because the material contained a wide range of color, methods based on thresholding will never be able to reach the performance level stated in other studies. As mentioned in 3.8, other methods will probably be needed to improve the detection and classification of characteristics from this material.

The methods developed here achieved reasonable detections rates (see Table 3-5), but the quality of the detections could be improved (see 3.7.4). As discussed 3.5, the detection of checks, wane, and cracks were attempted, however, it was realized that detection of these characteristics would require higher-resolution images and better control of illumination during the imaging process. Owing to the difficulty to detect those characteristics, the analysis did not include them. Improvements in detection will come by improving the imaging process, refined image transformation, thresholding procedures, segmentation, and classification of pixels as either background or foreground. These scripts make up an application that could be modified in future research settings for images of other board samples. The detection script was modified and tested on Alder, a hardwood species that produces numerous knots (Davis, 2019). It could also be modified to classify a larger domain of characteristics, such as checks, splits, and wane, and to integrate other sides of boards.

There have been few attempts to digitally characterize *E. globulus* and *E. nitens* boards (Booth et al., 2017, Kotlarewski et al., 2018). The work presented in these studies was limited in scope, did not propose a validation procedure, and was not designed to become part of a 'lab-scale' system. The content of this phase of the research makes a unique contribution to the field of image processing and analysis of lumber surface characteristics.

The characterization module, which includes a validation procedure, demonstrated that lumber from these resources contains a wide variety of size, frequency, and appearance of knots found in boards. The method indicated that *E. nitens* produced a higher proportion of

smaller knots than did *E. globulus*. The module also showed that knots occur frequently; most occurring within 1000 mm of each other.

The framework put forth here demonstrates one way of packaging this information. The manufacturer could use this information to drive processing machines, influence design decisions, and increase utilization efficiency. However, this would require moving information in parallel with the physical material. One scenario involves providing a "guaranteed analysis", or an assay of the boards received in the form of a digitized file containing data formatted for users.

7.1.2.2 Selection and Specification

The second area examined by this research was a method that enables the selection of defined sizes and types of knots in wood panels. This was conceptually based on other commercially systems that allow the user to specify certain variables. The values of these variables are used to visualize the product and calculate the material expense, and price of the object. These systems are limited to uniform materials supplied in standard form. As stated elsewhere, these systems are not particularly useful for wood.

The second module enabled the user to select a defined range of knot size and type to estimate the visual attributes of panels produced using this definition. It was done with both board segments and cutting areas. The module indicated that the material used in this study was able to produce panels with a range of visual attributes. Owing to the variation in knot size and type, dramatic differences could be observed between the panels. The panels provide a library of images that could be used to inform design decisions. This approach provides a way for the user to communicate a defined knot size and type to producers They could also be imported into digital modeling programs to make judgments about different combinations of materials in-situ. The panels offer the designer the ability to specify the use of knots in far greater detail than is currently available—a significant contribution to the design field.

7.1.2.3 Classification of Boards

As presented in 2.3, grading is the process by which boards are classified according to a grading standard. The classifier has a structure and a means of interpreting information about

what is being grouped. Current timber grading standards for appearance and non-structural lumber group boards according to a perceived level of suitability for end users. The current standards package the complex arrangement of the results of tree growth and processing damage into a low-resolution grade name. Most are rule-based—that is, if one rule is violated, then the piece is downgraded to the next lowest grade. The grade standard contains a grade definition that lists the acceptable limits of form and properties for each grade treated by the standard.

The current grading approach does not communicate detailed batch scale information along the supply chain. There is little assurance that particular visual attributes or products can be viably produced from a given grade of lumber. The standard is not flexible; due to the human inspection process, changes are difficult to implement.

The third area that this research explored was the feasibility of sorting lumber based on the distribution of areas that contain characteristics of a certain size and frequency. This phase of the research proposes a new way of grouping boards that contain similar levels of specific types of areas. This is not a method commonly employed to sort timber resources. The method consists of a series of procedures that first take in board-scale knot data and a user-supplied definition that specifies the level and type of characteristics that can be included in what will become a useable area. The method then identifies the areas meeting the definitions. The distribution of these areas is used to cluster boards into groups containing similar levels of the different types of areas. A classifier is then created from the cluster solution.

These procedures were demonstrated using 6 different definitions. In all cases, a reasonable classifier could be found for each of the clustering solutions and clear differences in the proportion of different areas were evident between the board classes. Two definitions involved a simple segmenting operation of boards, which has merit and context in the Australian industry where boards are produced and supplied in standard widths that could be processed to produce a wide variety of different panel products. The remaining four definitions have focused on the concept of cutting areas, which is common in North American hardwood processing operations. During this analysis, a second application (UGRS) was used

to find the cutting areas used for the clustering and classification operations. The clustering and classification procedures are customizable within the MATLAB application, providing flexibility in the number of clusters and board classes achievable from the sample sets. This area of the project presents a complete procedure that takes in board-scale data and outputs board-classes of lumber. This is a significant contribution to the sorting of timber resources.

The classification module indicated that knots were mostly randomly dispersed within boards, demonstrating the need for more advanced sorting systems. Overall, knots were more common on *E. nitens* than in *E. globulus* boards. This could be due to the different ages of the trees at harvest, or it might be due to different growth habits of the species. The knot distribution leads to a wide variation in segment lengths for both species. However, *E. nitens* produced fewer clear segments than *E. globulus*, but *E. nitens* provided more type 1 and 2 (clear segments and segments that contain knots less than 650 mm^2) segments than *E. globulus*. This finding indicates that *E. nitens* could potentially provide better-suited stock for applications where some level of knottiness is desired. Overall, *E. nitens* contained narrower and shorter cutting areas than did *E. globulus*, a finding that is borne out by the knot distribution patterns. Findings indicated that *E. globulus* produced a far higher proportion of #1C boards than did *E. nitens* when graded according to NHLA standards (one-sided).

7.1.2.4 Matching Lumber to Applications

The final aspect of this research was to develop the means to match board classes to different cutting bill requirements and estimate the manufacturing costs. Conceptually, this is similar to the above-mentioned approach, however, here it is more complicated because variation in the master stock needs to be taken into account. The system proposed here calculates yield using board-scale information and predicts manufacturing costs to indicate the best-suited board class for various cutting bill requirements. The system estimates the cost to produce panels according to a user-supplied definition of what either must be in the panel or what may be included (depending on the segmenting or cutting area methods). The system was expanded to include several other variables associated with visual attributes to create the basis for a suitability index calculation.

There exists no other platform that can perform these tasks within the digital environment. The tools developed here could be directly embedded into existing approaches to enable the variation in the distribution, frequency, and appearance of growth characteristics to be digitally communicated and used to achieve customized visual outcomes and increase utilization of lumber that contains an elevated occurrence of characteristics.

The module indicated that the yield of parts to produce panels was on a par with yield from other hardwood lumber, suggesting that approximately 88 percent of the material may be suitable for such applications. The yield of dimension parts was also acceptable from *E. globulus* boards. Based on this and other manufacturing considerations, it appears that if processing and drying defects could be reduced and if the material could be supplied to the market at about 760AUD/m^3 it could be a competitive export against the current price of North American red oak. At a market value of AUD 1000/m^3 the material may also provide a substitute for higher value hardwoods, such as maple. This phase of the work also examined the possibility to create a suitability index that would assist the expert user in choosing the best-suited class of lumber for a particular cutting bill. For the cutting bills tested, it appeared that 71 percent of the *E. globulus* lumber would provide viable feedstock for these products. The proportion of *E. nitens* boards were lower, indicating yet another difference between the species.

7.2 Implementation

The framework developed and tested in this thesis currently resides in numerous MATLAB files and functions. Some of the scripts are linked, while others require user input to operate, but they perform the complete set of operations proposed in this thesis. The system also requires input from 2 other processing applications (UGRS and ROMI 4.0). The processing modules from these applications need to be reverse-engineered and programmed into the MATLAB workflow. For the concepts to be implemented at a commercial scale, the processing logic would need to be translated to another programming language and a stand-alone software package would need to be developed. The software package would integrate with a commercially available machine vision system, perhaps a Microtec Goldeneye 3000 used by Gazo et al. (2018) to scan hardwood lumber. As suggested, the package would be intended for the expert user—a user that has extensive knowledge about the software and hardwood

processing. It is envisioned that the expert user would occupy a position that does not currently exist within the hardwood lumber supply chain. The expert user would provide physical material and communicate digital information between producers and manufacturers using the system developed here. The system would need to perform all of the functions developed in this thesis, and it would also need to integrate market prices and output cutting instructions for automatic cutting machines, such as computer-controlled lumber cutting optimization systems seen in some rough mills (Thomas and Buehlmann, 2016).

As proposed in Figure 1-2, the real-world use of such a system could take many forms and different levels of use. One potential way it could be used is a 4-step procedure involving producers and users. In the beginning, the expert user would need high-resolution information that truly represents the materials that producers can supply to the market. This would provide a reference database from which the expert user could engage with using the software package. Ideally, the database would include information on several species. The expert user would then run a series of scenarios about the potential visual attributes, yield, and cost of different classes of boards for specific applications and design requirements. Once a decision is reached, a classifier would be sent back to the producer. The producer would load the classifier to sort boards during production. During the scanning process, boards would be assigned a unique identification number so that board-scale information could be linked directly to each piece. Different users would probably require a select number of classes of lumber; the producer would need to supply diverse markets to recover the maximum value for the available resource. As users develop experience with different board classes, a certain number of the most frequently used combinations would be established and supplied as a matter of routine.

After the user receives the material and the digital information describing each board, the expert users would perform the 4th-step, which is the second phase of the optimization process. In this phase, the expert user runs a second set of simulations on the material on hand to create cutting instructions for the automatic lumber breakdown equipment.

This represents a high level of involvement by the expert user which would require the development of a complete system in stages. Other less involved applications of the framework are also possible. Some users may only want the visual components, while others may only be interested in exploring yield and cutting efficiency studies. Whatever the level of engagement, the conversion, and transmission of high-resolution board-scale information between producers and the manufacturing sector is the basic requirement and the intention of this research project.

7.3 Future Research Areas

Although this research project presents a 'lab-scale' version of a system that can address the variation found in timber products, there are several areas of future research. First, the approach should be tested using more and higher quality knot-scale data. Such data could be obtained from companies such as Lucidyne Technologies Inc. or other researchers that have access to commercial-scale systems. This would allow more characteristics to be integrated into the characterization model. Also, it would allow both sides of the boards to examined concurrently. This would result in more accurate yield estimates and allow a wider range of characteristics to be selected. More data would also facilitate testing and developing better board classification models.

Second, the scripts should be compiled into a stand-alone application. This undoubtedly requires the expertise of a computer scientist and outside investment. Third, this approach should be presented to the industry, including the design professionals.

In addition to developing industry-specific systems of information transfer material handling and sorting techniques and a complete software system, a study should assess the commercial potential of the production of solid wood appearance panels in the State of Tasmania. That study should address current and future demand and markets for solid wood panels at a national and international level, generate a business plan, and estimate the necessary capital investment and perceived financial benefits of such an endeavor. Such a study would incorporate the manufacturing techniques and considerations presented in this thesis work to diversify product range, type, and sizes. The aims of the study should be to

determine the feasibility of operating a large scale in-state manufacturing facility capable of producing a range of appearance solid wood panels.

8 Appendix 1

8.1 Image Acquisition and Processing

Successful object detection depends on image acquisition, image processing, and image analysis methods. Image acquisition consists of adequate illumination and appropriate sensor and camera type for the inspection purpose and object(s), a mechanical means to position either the sample, the sensor, and the camera, and a way to capture and store the digital image information. A digital image is made up of picture elements, or pixels. In general, pixels can be classified as belonging to the background or foreground of the image. In the fields of image processing and analysis, background pixels are darker than those of the foreground. Objects of interest to the researcher are composed of foreground pixels and appear lighter in the image. This is not the case for images of wood surfaces, where the objects of interest are usually darker than the surrounding areas. For these situations, it is necessary to calculate the complement of that image; light pixels become dark. This procedure can be performed anytime during the image processing workflow.

Cameras capture the visual image of objects as a function of the quality of the illumination, therefore consistent, constant, and reproducible illumination ensures quality visual inspection of objects. Indeed, illumination is considered one of the most critical aspects of successful image analysis. Illumination is defined as “the luminous flux per unit area on an intercepting surface” according to the Merriam Webster dictionary. When the luminous flux of light is uneven across the surface during image acquisition, the resulting image is said to have nonuniform background illumination. Similar background objects do not appear uniform in such an image. An example of this is shown in Figure 8-1. Here, the background appears lighter in the upper left-hand corner than the lower right-hand corner.

Figure 8-1. An example of an image with a nonuniform background.

A second consideration of the amount of illumination is the type of illumination. The color temperature of an illumination source is defined as the temperature of an ideal black body radiator that emits light of a color comparable to that of the source. Color temperatures above 5000k are referred to as “cool”, while those below are known as “warm”. This is because of the varying proportion of blue and yellow in the spectrum of emitted light. In digital photography, different color temperatures of light render certain colors different than that of human perceptions. The human eye adjusts such that the appearance of objects appears the same under different types of illumination; an apple always appears the same under different light sources. This ability is known as chromatic adaptation. However, digital cameras require acquired data to be corrected so that colors displayed appear to have the same appearance as the color in the original scene. Because many light sources do not emit light that corresponds to that of a black-body radiator, the color temperature is corrected using correlated color temperature to that of a black-body radiator of that temperature. This adjustment is called white balance and results in a color-balanced image. Many techniques have been developed for different situations; however, the main purpose is to transform the image components such that objects appear in images as they were perceived by the human eye.

Digital images may be defined as a two-dimensional function $f(x, y)$, where x and y are the coordinates and f is the intensity value of the image at that point or pixel (Gonzalez et al., 2010). Images are values in matrix form; the origin is the upper left corner where x=1 and y=1. The integer value, f, of the elements in an 8-bit image range from 0 to 255 or from 0 to 65535 for a 16-bit image. The total possible intensity levels are given as G. An intensity value of 0

represents pure black, while an intensity value of 255 represents pure white. Most image processing transforms this scale to a range of 0 and 1. A common notation is [0, 1], which would denote the range from 0 to 255 for an 8-bit image. For monochrome images (grayscale), the term gray level is used to refer to the intensity of the image. Intensity values represent shades of gray and the distribution of the intensity values can be graphically displayed with *a* histogram where values on the x-axis represent intensity values on the y-axis represent the frequency of intensity levels across the entire image (Figure 8-2). The y-axis can be discrete values, as in the example below or it can be made of bins that contain data within a certain range, for example, intensity values between 0 and 10. The histogram is fundamental to many further image transformation concepts and image analysis procedures.

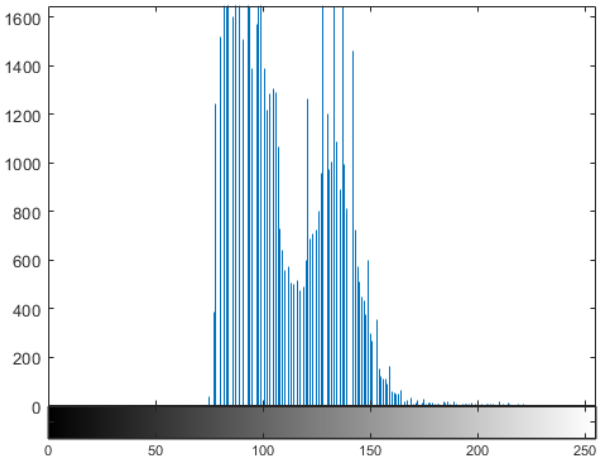


Figure 8-2. Histogram of intensity values over the entire image (https://www.mathworks.com/help/images/ref/imhist.html).

The histogram is defined as the discrete function given by:

$$h(r_k) = n_k$$

where:

r_k is the kth intensity level in the interval [0, G], and

n_k is the number of pixels whose level is r_k.

Many procedures in image analysis require normalized histograms. Normalized histograms have the unique property in that the frequency of all intensity values sum to 1, and therefore, any given probability of any intensity value is given by:

$$p(r_k) = \frac{h(r_k)}{n}$$

$$= \frac{n_k}{n}$$

Where the probability of any given intensity value, r_k, is given by $p(r_k)$. A normalized histogram is shown in Figure 8-3.

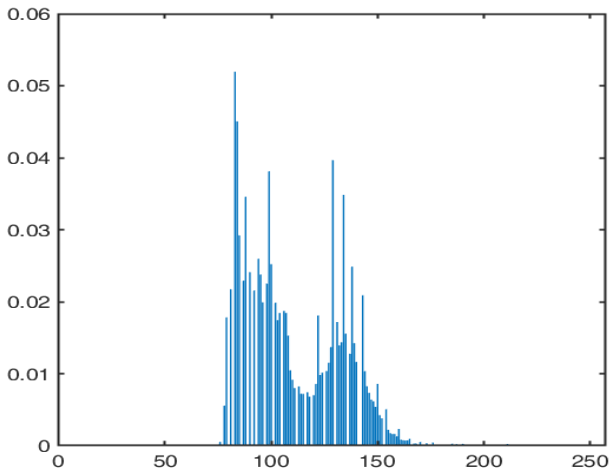


Figure 8-3. The normalized histogram from Figure 8-2.

The contrast of an image is the range between the lowest and highest values of intensity within the image-it is the difference between light and dark tones. Mathematically, contrast is defined as the maximum intensity subtracted from the minimum intensity value. An image is said to have good contrast where there is a sharp and a well-defined difference between black and white objects and will have a wide range of intensity values (Figure 8-4). A binary image is a degenerate case of a monochrome where 0 and 255 are the only intensity values in the image. This type of image is typically called a black-and-white and is sometimes referred to as a logical image containing only the values of 0 and 1.

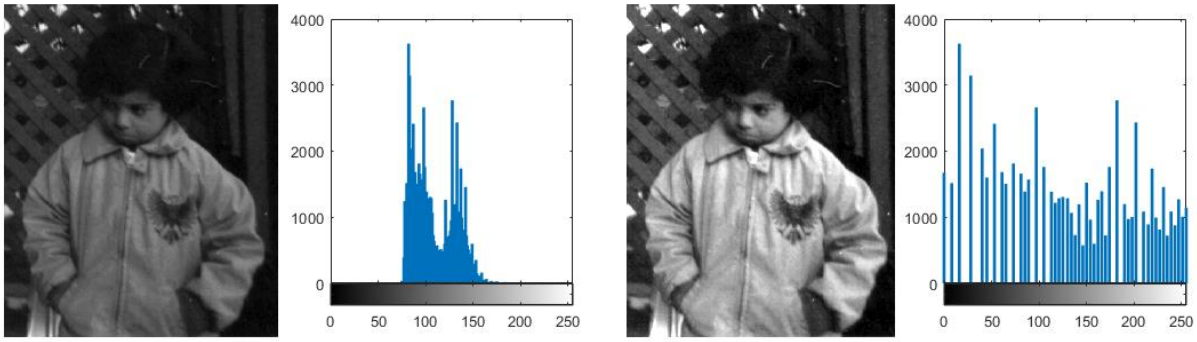


Figure 8-4. Two images and histograms that show poor (left) and good (right) contrast (https://www.mathworks.com/help/images/contrast-adjustment.html).

A color image is formed by combining individual two-dimensional images. For example, an RGB image is composed of red (R), green (G), and Blue (B) monochrome images. Such an image made up of 8-bit monochrome images is termed a 24-bit image. For this reason, many image processing techniques developed for monochrome images can be performed on color images. Each color pixel contains values from the red, green, and blue components, or channels, of an RGB image. The number of possible colors is a function of the bit depth of each channel. It follows then, the maximum number of colors for an 8-bit RGB image is 16,777,216. The brightness of an image refers to the notion of intensity. Hue represents the dominant color as perceived by the observer. Saturation describes the level of purity of a hue. It refers to the amount of white light mixed with a hue. Because color images contain more information about the subject, color images can improve inspection accuracy for items that have color properties. However, color is more affected by inconsistencies in illumination, and processing color images can be computationally intense.

All possible values of the *RGB* color space can be shown graphically as a cube (Figure 8-5). The values of each pixel can be used directly or converted to other color spaces that may be more useful for inspection purposes. The HSV (hue, saturation, value) is a color space considerably closer than the RGB system to the way people perceive color. It can be directly formulated from the RGB color cube by mapping the colors around the diagonal gray axis. This results in a hexagonally shaped color palette (Figure 8-6). In HSV color space, the hue is expressed as an angle around this color palette. The value component represents shades of gray between 0 and 1 along the vertical axis of a cone with a point value of 0. Saturation is a measure of the purity of the color and is the distance between 0 and 1 from the V axis.

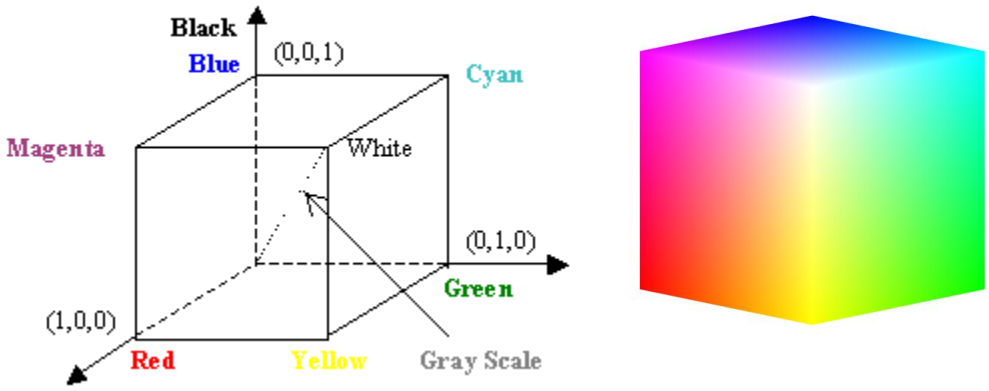


Figure 8-5. Schematic (left) of the RGB color cube showing the primary and secondary colors at the vertices. The RGB color cube (right).

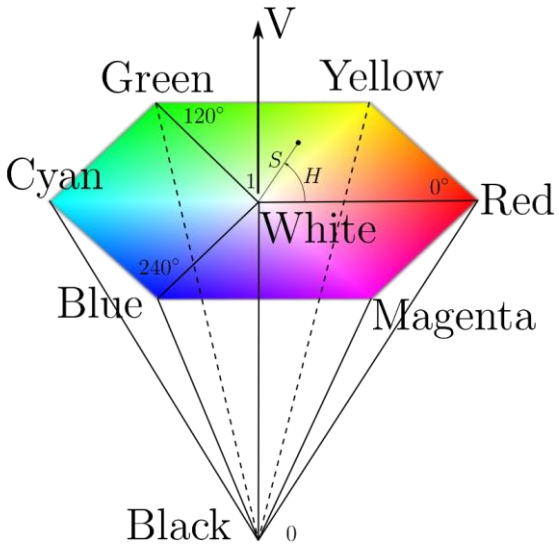


Figure 8-6. The HSV color hexagon and HSV color hexagon cone. (http://argos.vu/devnotes-9-16-16-ui-work-initialization-serialization/)

The statistical distribution of pixel values for image components can be calculated for an entire image or parts of an image. Standard histogram-based calculations include the mean, variance, skewness, and points of global (entire image) or local (part of an image) minima and maxima of pixel values. The measure of spatial organization, or texture, of pixel values, can also be useful for inspection and classification purposes.

Once images are acquired and pre-processed into the desired format, most images require some form of image processing methods. The input and output of these methods are images. Basic image processing includes cropping, intensity transformation, filtering, sharpening, and the morphological operations of dilation and erosion. These techniques operate directly on the pixel of the image. The general form of a transformation function can be expressed as:

$$g(x,y) = T[f(x,y)]$$

Where $f(x,y)$ represents the input image, $g(x,y)$ is the output image, and T is the operator on f over a specified neighborhood about the point (x,y) (Gonzalez et al., 2010).

Intensity transformations map the intensity value of a pixel to a new value such that the range of intensity values increases or decreases for the new image (Gonzalez et al., 2010). This operation is usually used to increase the contrast of the image to enhance detail occluded in low contrast areas. T can be used to specify which pixel values from the original image are mapped to new values and the shape of the relationship between the old and new values. This is commonly referred to as the gamma parameter and it can be used to weigh mapping procedures toward darker or lighter intensities. Undesirable image noise induced by sensor circuitry can be removed using the median filter. An example of a filtered image using a 7-by-7 pixel neighborhood is shown in Figure 8-7. Image sharpening is used to decrease, or sharpen, the transition between dark and light objects in the image.

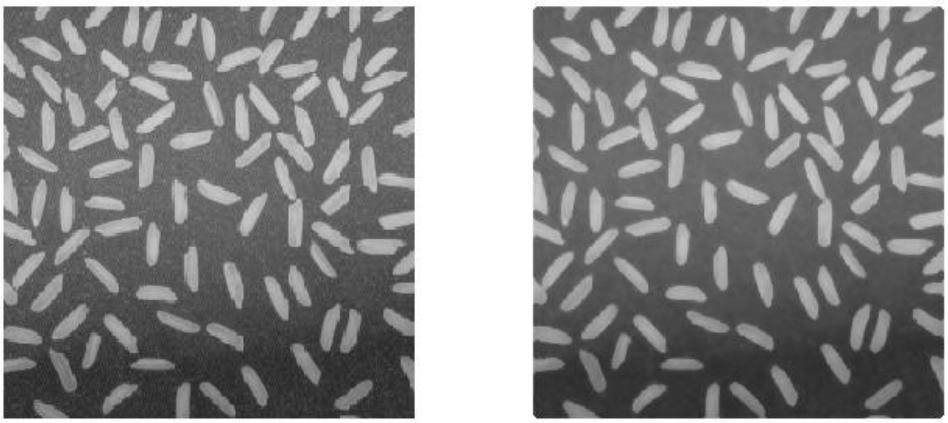


Figure 8-7. An example of a median filter applied to an image that contains "salt and pepper" noise. original image (left), filtered image (right).

Mathematical morphology, used in conjunction with other image analysis techniques, are important tools that help to describe the contents of images (Gonzalez et al., 2010). Morphological operations are useful for special image filtering, thinning, and pruning of objects in binary images. Dilation and erosion are two logical operations useful for binary images. Dilation is used to grow or thicken (make a thin object wider) foreground (value of 1) objects in images; while erosion is used to thin or shrink foreground objects. Both are the result of the union between the image and a structuring element. The shape of the structuring

element controls the extent of dilation or erosion of the objects in the image. The dilation of A by B is denoted by $A \oplus B$ and is defined as:

$$A \oplus B = \left\{ z \middle| \left(\hat{B}\right)_z \cap A \neq \emptyset \right\}$$

where $\emptyset$ is the empty set and B is the structuring element, and $\hat{B}$ is the reflection of a set B.

The dilation of A by B is the set, or binary image, where the origin of B overlaps at least one element in A. Erosion is defined as:

$$A \ominus B = \{ z | (B)_z \cap A^c \neq \emptyset \}$$

In words, erosion of A by B is the set of all structuring element origin locations where no part of B overlaps the background of A.

An example of how erosion can be used to remove image components is shown in Figure 8-8.

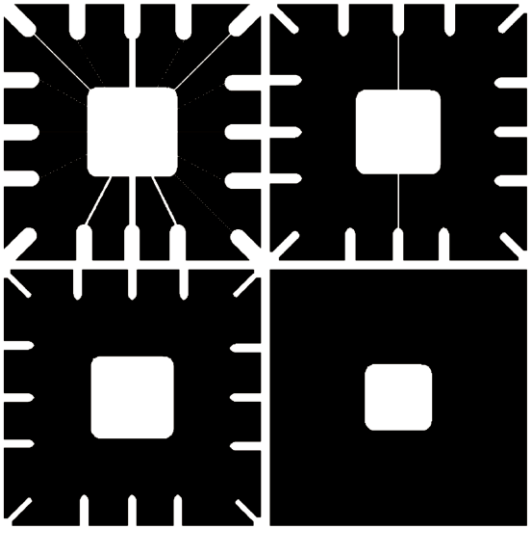


Figure 8-8. An illustration of erosion using a disk structuring element with different radii (Gonzalez et al., 2010). Original image (upper left), radius 10 (upper right), radius 5 (lower left), and radius 20 (lower left).

During image processing, dilation and erosion are often used together, sometimes with differently shaped structuring elements. The opening of an image is the erosion followed by dilation. Furthermore, image closing is dilation followed by opening. An example of the function of opening and closing on an image is shown in Figure 8-9.

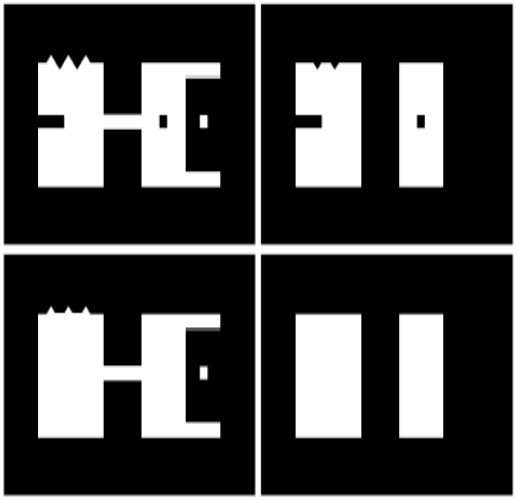


Figure 8-9. Illustration of opening and closing (Gonzalez et al., 2010) original image (upper left), open image (upper right), closed image (lower left), and closing of opened image (lower right).

These concepts can be extended to grayscale images. In general, opening operations on grayscale images removes small bright details while unaffecting the overall gray intensities and large bright features. In contrast, the closing of a gray-scale image suppresses dark details smaller than the structuring element. These operations can be useful to either remove features with certain types of geometry or to capture more pixels belonging to an image object. For example, small checks and cracks on wood surfaces can be removed from further image analysis, leaving only larger attributes, such as knots to characterize.

A special case of the use of pixels relationships and morphological opening exists when an object has been identified that contains background pixels within its boundary. Hole filling operations are used to join these background pixels to foreground object pixels.

8.1.1 Object Detection

The preceding section has presented many of the basic image processing techniques used in this work. The input and output of these techniques are images. This section begins to describe major image analysis methods necessary to extract meaningful information about objects in images. The inputs are images and the outputs are feature vectors-vectors of information describing the objects belonging to the domain of interest in the image. The domain in this chapter is the classes of knot types. Before presenting the image analysis methods in detail, a brief description of different approaches will be presented.

The fundamental aim of any vision inspection system is to detect foreground objects from background objects in images. That is, the process seeks to divide the image into objects of interest belonging to the foreground and background. The accuracy at which this is accomplished determines the success of the inspection procedure. The level of division depends on the aims of the inspection procedure. The division is generally based on discontinuity or similarity image intensity values (Funck et al., 2003). Discontinuity based techniques focus on locating abrupt changes in intensity levels, such as would be found at the edges of objects. Similarity seeks to define regions in the image that are similar according to a set of defined criteria (Gonzalez et al., 2010).

There are at least 3 general approaches to achieve image division: pixelwise classification, non-segmenting, and segmenting (Astrand, 1996, Kauppinen, 1999). The pixelwise approach determines if each pixel belongs to a defined set of objects. The non-segmenting approach has been used for a variety of wood feature detection problems and consists of examining non-overlapping areas to determine if the area needs further analysis (Conners et al., 1983, Koivo and Kim, 1988, Niskanen et al., 2001, Silven et al., 2003, Ziadi et al., 2007b). The third detection approach partitions groups of pixels sharing similar measures or values into segments within the image. This process assigns all pixels a value of 0 or 1. The basic difference between non-segmenting and segmenting is that non-segmenting operations can be performed on sections locally as the material is digitized (Hashima et al., 2015). Both methods result in the segmentation of the image, in the sense that pixels belonging to foreground objects are segmented from background pixels. From here on, segmentation is used to refer to this outcome. The following discussion focuses on a special approach to segmentation known as thresholding. Here, thresholding combined with the concept of similarity is used to define objects in images. Edge detection, or discontinuity, techniques are not used in this work, but such algorithms have been used by others for detecting wood characteristics (Funck et al., 2003).

The region-based approach forms a block of connected pixels that become part of the object of interest. This approach is said to have an advantage over the boundary-based approach because it can increase the accuracy of detection and can tolerate a range of threshold values (Kauppinen, 1999). The region-based segmentation approach has been used successfully to

detect surface features in many timber inspection problems (Cho et al., 1990a, Cho et al., 1990b, Deshmukh and Shinde, 2006, Hu et al., 2003, Hu et al., 2004, Kim and Koivo, 1990, Kline et al., 2003, Pham et al., 2005, Rinnhofer et al., 2005) and produces results sufficient for grading where information about very small features and subtle differences are important for grading proposes (Kauppinen, 1999).

The first image analysis operation is thresholding- a fundamental operation in image segmentation due to its intuitive and simple means of implementation (Gonzalez et al., 2010). Thresholding separates the foreground objects from the background. Suppose a gray-scale image $f(x, y)$ has light objects on a dark background, a histogram would show intensity levels grouped into two modes as is shown in Figure 8-10. Successful thresholding depends on accurately determining the value used to partition the image. Often this value can be obtained from a histogram of values within the channel of interest and is taken as the valley point from the distribution of values. One way to extract the objects from the background would be to manually or automatically select a threshold value, T, that separates the modes. At any point (x, y) at which $f(x, y) > T$, is an object point. In this example, a value around 140 would separate most foreground points from the dark background. The result is a thresholded binary image g such that:

$$g(x, y) = \begin{cases} a \; if \; f(x, y) > T \\ b \; if \; f(x, y) \leq T \end{cases}$$

Pixels labeled 'a' correspond to objects, while those labeled 'b' correspond to the background. An example is shown in Figure 8-11. When a single value of T is across an entire image, the technique is referred to as *global* thresholding. As can be seen in Figure 8-11 and Figure 8-12, a single value may not produce the desired result; some object pixels are labeled as background. The challenge is to select a value for T that optimizes the segmentation between foreground and background pixels. Otsu's method chooses the threshold value T to maximize the between-class variance of foreground and background pixels (Gonzalez et al., 2010). Despite the procedure, global optimization methods usually fail to produce desired results (Figure 8-12) when the background illumination is not uniform, as is the case for the original example images below.

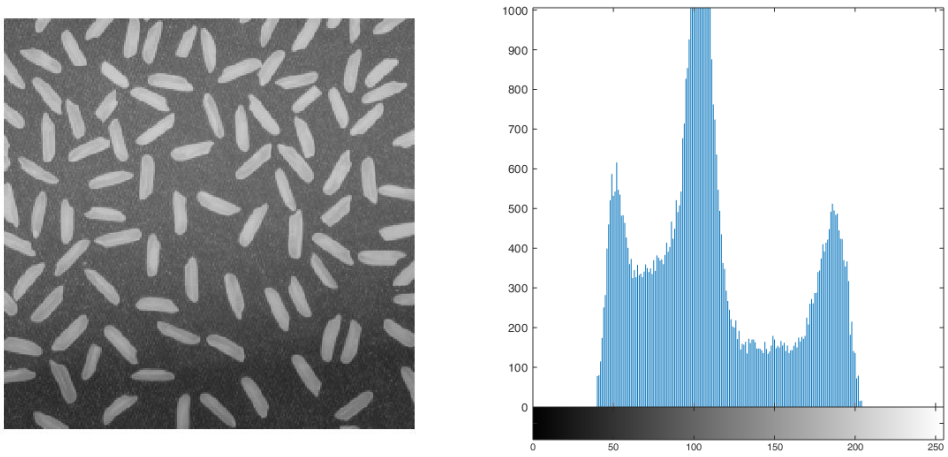


Figure 8-10. A grayscale image containing light objects on a dark background (left) and an accompanying histogram of intensity values(right).

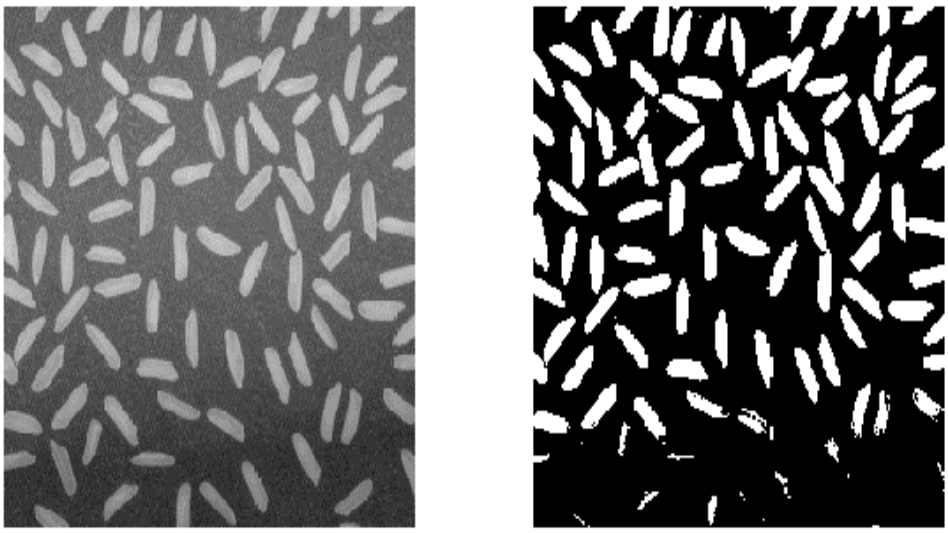


Figure 8-11. An example of a grayscale image thresholded using a global value of T (T=140).

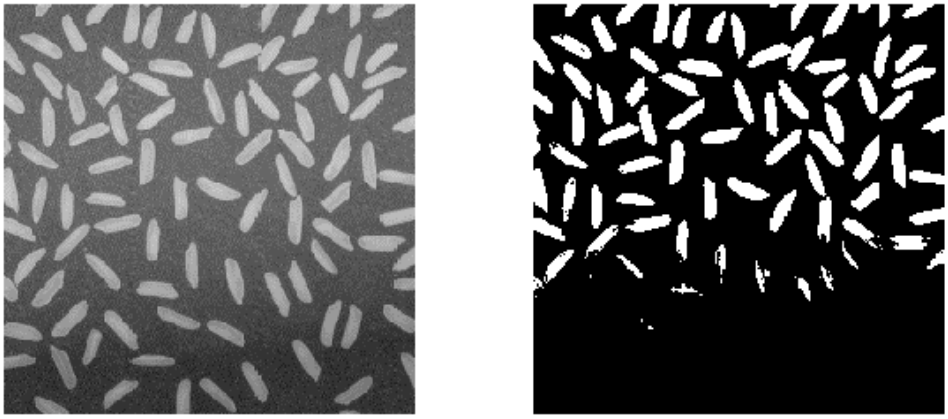


Figure 8-12. An example of using Otsu's method to determine the threshold value.

For images that have nonuniform background intensity values or illumination, a local threshold approach can produce significantly better object detection. Such techniques are referred to as local methods and are generally based on the standard deviation and the mean of pixel values in a specified neighborhood (Gonzalez et al., 2010). This results in a different value of T calculated for each pixel in the image.

The above discussion presents basic techniques to segment foreground objects from background pixels for grayscale images. Because color images are made up of individual arrays that represent red, blue, and green, most of the above techniques can be applied to the separate arrays of the color image. This is known as color region segmentation. Color region segmentation determines the distance in 3-D color space between any given set of pixel values and the mean color set as the desired segmentation value (Gonzalez et al., 2010).

If this distance is less than a specific threshold, T, the pixel is considered a foreground object. The Euclidean distance is calculated by:

$$D(z,m) = \sqrt{(z_R - m_R)^2 + (z_G - m_G)^2 + (z_B - m_B)^2}$$

Where z any pixel value in the image and m denotes the mean color of interest. Segmented points are determined as:

$$D(z,m) \leq T$$

This procedure produces a solid sphere with radius T in 3-D color space; points inside or on the surface of the sphere are foreground objects, while those outside of the sphere is background pixels. In some cases, the covariance of the color of interest is useful to segment the images. This method requires the Mahalanobis distance calculation and results in an ellipsoid instead of a sphere in 3-D space. In either case, the image can be recorded as a binary, segmented image and treated with the same object characterization methods as any other binary image. As in gray-scale thresholding, the intensity values of each color must be pre-determined before segmentation can take place.

As described, thresholding has many advantages over other techniques. Thresholding is fairly easy to implement, gives closed boundaries and regions, and can be modified to be less susceptible to uneven illumination and noise (Funck et al., 2003). The procedure assumes that different classes of objects in the image have different modes that can be identified from histogram-based techniques and are limited to objects that are lighter than the background. This is often not the situation for images of wood and wood characteristics where foreground objects occupy a very small percentage of the overall image (for this study, approximately 2 percent of the image area was occupied by knots). Take for example the image in Figure 8-13 of a piece of veneer containing one large knot and few small ones. Clearly, the histograms did not show an easily identifiable valley by which to assign a threshold value. Also, natural growth characteristics not of interest during segmentation, such as grain (latewood), which contains a significant proportion of dark pixels. The converse also occurs for knots; some areas of knots contain light pixels. Even if a threshold value could be determined that segmented foreground and background pixels at the required level, due to the natural variation between

different pieces, the threshold value would need to be recalculated for each successive sample. Due to variation within and among pieces, the small percentage of foreground objects, and the background complexity of wood images, successful segmentation of classes of characteristics is a challenging task- the researcher is virtually seeking the proverbial needle in a digital haystack.

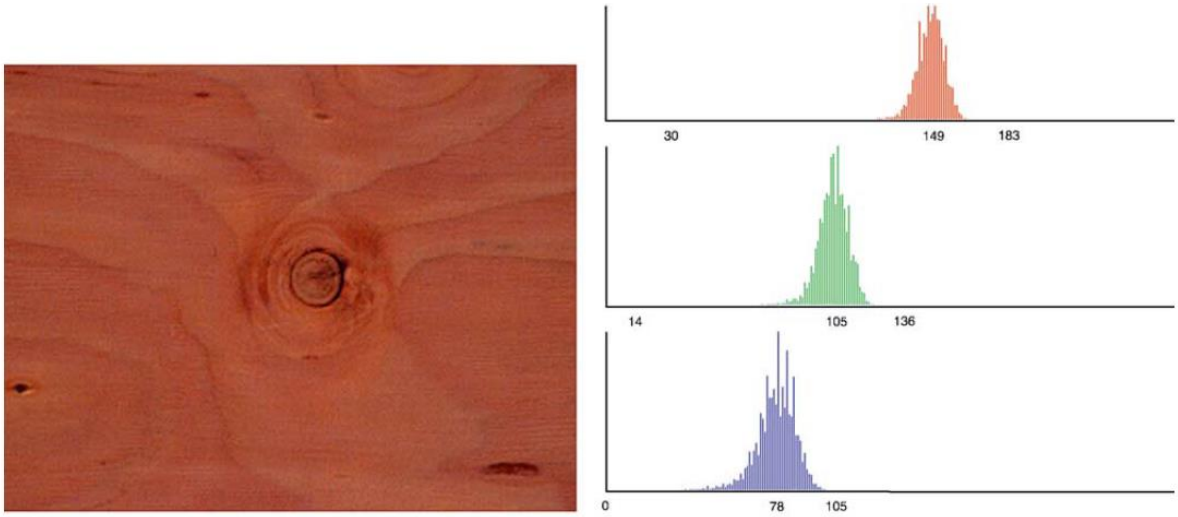


Figure 8-13. Image of a knot on a piece of veneer (left). Corresponding histograms of the red, green, and blue channels of the image (Funck et al., 2003).

Most image processing and analysis workflows include a "cleaning" procedure to remove incorrectly marked spots from binary images. This is usually achieved by setting an acceptable minimum size applicable to the application and requirements of the process (Funck et al., 2003).

The preceding tools and techniques have focused on the individual foreground and background pixels; these tools provide no information as to how individual pixels are related to the complete set of pixels in the image. The concept of connected components can help to group pixels belonging to individual objects within a binary image. The connection path between pixels is defined by either its adjacent or diagonal neighbors. A 4-connect path includes only adjacent pixels; an 8-connected path consists of all adjacent and diagonal pixels. Two foreground pixels are 4-connected if there is a 4-connected pixel path between them. Therefore, a component is the set of all connected pixels under either a 4-connected path or an 8-connected path. The connected component concept allows for pixels to be grouped according to their relationship to other pixels in the image. Because all pixels belonging to

objects may not threshold accurately, blobs within a certain number of pixels are combined to segment the complete object of interest more accurately. The maximum number is a function of the characteristics of the sample and can only be determined by experience by the researcher. These groupings lead to the ability to label blobs or groups of pixels belonging to individual objects, which produces a special numeric array where the pixels that are parts of discrete foreground objects are labeled with unique integers from 1 to the number of objects (background pixels are labeled by a 0). This array in matrix form is called the label matrix; it is the same dimension as the original image. Because some areas of objects may not threshold as foreground pixels (Figure 8-14), labeled groups may not include all the pixels belonging to an object of interest.

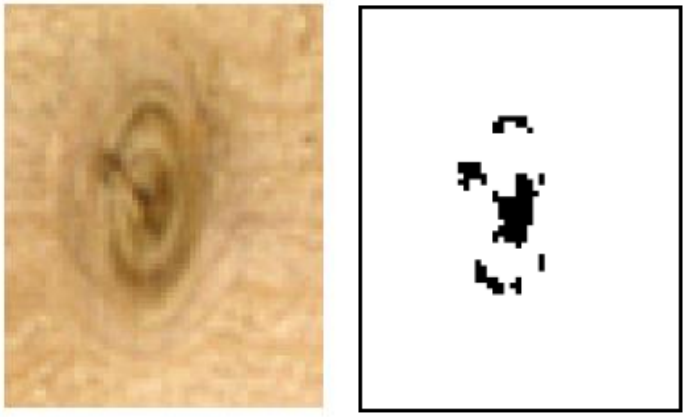


Figure 8-14. An example where not all the pixels belonging to the object have been thresholded, but have been labeled as belonging to the same group (Kauppinen, 1999)

The researcher must develop a way to determine the accuracy of the thresholding, segmentation, and detection for individual objects and overall rates of the approach. When considering the detection accuracy of individual objects, detection types are determined, while the performance of the system overall for many sample images is expressed as a rate of detection type for an entire run over a given set of images.

Segmentation creates a binary image of pixels belonging to the foreground (white) and background (black). Consider this image a mask with openings that indicate the location, shape, and size of objects of interest from the original image-the segmentation mask. Each opening in this mask has a unique identification label provided by the label matrix. Segmentation accuracy is assessed by comparing the location of an opening in this mask to a

mask produced from hand-marked images. Hand-marked reference images are produced by manually coding the visual objects on images within the domain of the study. Hand-marked images can be processed to produce binary masks of actual objects and are used to validate the results of segmentation algorithms. Hand-marked images are referred to as the validation image set or validation dataset. Coding the hand-marked images is a very time consuming and error-prone task; because different people judge the boundaries of objects differently, it should be independently reviewed to provide as accurate as possible "ground truth" information about the objects. Sample images should be selected to contain all possible objects and all combinations of foreground and background pixels arrangements. In classification tasks, the hand-marked images are used to train and test the classifier.

Segmentation or detection accuracy is commonly characterized by calculating the detection type that has occurred (Sokolova and Lapalme, 2009). The detection type is based on whether the segmentation method has detected an object within a specified distance from a validated object indicated by the hand-marked mask. Although straightforward in theory, in practice the validation of automatic object detection algorithms requires a way to define how well individual objects are detected and described as compared to the validation set. For example, there may be several detections for a single object, there may be detections that do not match actual locations and there may be objects that were not detected by the method (Figure 8-15). Each situation is defined differently during the validation of the detection for each object. A true positive detection occurs when there is an agreement between the segmentation mask and the hand-marked mask for an actual object. A false positive detection (false alarms) occurs when the segmentation mask indicates the location of an object where the hand-marked mask does not. A false negative (error escapes) detection occurs when the segmentation mask does not indicate the location of an object where the hand-marked mask does. A true negative detection occurs when the segmentation mask indicates an object, but it is eliminated in later processing. The sum of each detection type can be shown using a confusion matrix (Table 8-1), where each cell indicates the number of each type of detection.

Table 8-1. A confusion matrix indicating detection types.

	Segmented object	
Validated object	Yes	NO
Positive	True positive (TP) Actual object correctly detected	False negative (FN) Actual object not correctly detected
Negative	False positive (FP) Object incorrectly detected	True negative (TN) Object detected and removed

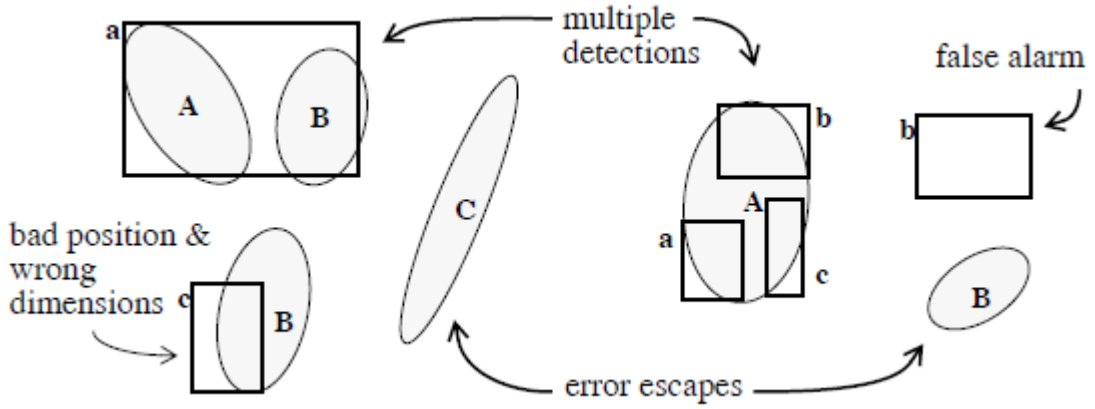


Figure 8-15. Examples of common detection mistakes. Uppercase letters indicate actual objects, lowercase letters indicate objects detected by the automatic method (Kauppinen, 1999).

The overall performance rates of an automatic object detection routine across many samples require the number of true positive detections, the number of false positive detections, and the number of false negative detections. The number of actual objects is the sum of false negative and true positive detections. The rates of detection types are calculated using the equations given in Equation 8-1. As defined by Equation 8-1, the *true positive rate* indicates the proportion of the correctly detected objects from the validation dataset. The *false negative rate* indicates the proportion of missed objects, and the *false positive rate* represents the proportion of detections that do not occur in the validation set.

$$TP\ rate = \frac{number\ of\ True\ Positive\ detections}{(number\ of\ False\ Negative + number\ of\ True\ Positive\ detections)}$$

$$FN\ rate = \frac{number\ of\ False\ Negative\ detections}{(number\ of\ False\ Negative + number\ of\ True\ Positive\ detections)}$$

$$FP\ rate = \frac{number\ of\ False\ Positive\ detections}{(number\ of\ False\ Positive + number\ of\ True\ Negative\ detections)}$$

$$TN\ rate = \frac{number\ of\ Ture\ Negative\ detections}{(number\ of\ True\ Negative + number\ of\ False\ Positive\ detections)}$$

Equation 8-1. Equations to calculate the true positive, false positive, false negative, and true negative rates for an automatic detection method. Adapted from Kohavi and Provost (1998).

The accuracy and precision of a detection method are given by Equation 8-2.

$$Accuracy = \frac{number\ of\ True\ Negative + number\ of\ True\ Positive\ detections}{(number\ of\ True\ Positive + False\ Negative + False\ Positive + True\ Negatvive\ detections)}$$

$$Precision = \frac{number\ of\ True\ Positive\ detections}{(number\ of\ False\ Positive + True\ Positive\ detections)}$$

Equation 8-2. Equation for accuracy and precision of the detection method. Adapted from Kohavi and Provost (1998).

The detection types and rates described above provide little information about the quality of the detection, only that the segmentation method detected an object within a specified distance of a validated object and overall performance measures about the detection method. Measures describing the quality of the detection method would indicate how well detected objects and actual objects overlap, both in terms of the location of the center and area of the object, and differences in the area between the objects (Funck et al., 2003, Kauppinen, 1999). These measures require a method to define the area of the objects. The most common method is to use the area of the smallest possible rectangle that completely encompasses the object. This is known as the *minimum bounding* box. Other methods could define the area by fitting an ellipse to the pixels belonging to an object and considering the area of this ellipse to represent the area of the object. The difference between the centroids of detected and validated objects is given by Funck et al. (2003):

$$C = \sqrt{(x_i - x_i')^2 + (y_i - y_i')^2}$$

Equation 8-3. Centroid location difference

Where x_i and y_i are the centroid coordinates for the *i*th detected object and x_i' and y_i' are the centroid coordinates for the *i*th validated object.

The proportion of overlap area between detected objects and actual objects is given by:

$$O_p = \frac{Overlapped\ area_i}{Actual\ area_i}$$

Equation 8-4. Difference in the overlapping area

Where $Overlapped\ area_i$is the area in common to the *i*th detected object and the *i*th validated object. $Actual\ area_i$ is the area calculated for the *i*th validated object. The final measure is the relationship between the areas of the detected and validated objects. It is given by:

$$A_r = \frac{Area\ detected_i}{Area\ Validated_i}$$

Equation 8-5. Area Difference

Where $Area\ detected_i$ is the area of the *i*th detected object and $Area\ Validated_i$ is the area of the *i*th validated object.

The closer to 1 the values of O_p and A_r are, the better the detection method. Values for these two parameters can be plotted on a 2-dimensional scatter plot to assess the goodness of the detection method.

The performance of the detection method can also be calculated by the mean and standard deviations of the differences in centroid coordinates, overlap area, and area relationship.

8.1.2 Object Description

Detection type and overall performance of a detection algorithm are based on the comparisons between the objects found in the segmentation mask and the hand-marked

mask. The detection phase of image analysis provides little information about the attributes that describe the object of interest. Common descriptions of objects include both geometric and textural attributes (Hashima et al., 2015, Kauppinen, 1999, Xiao, 1998). Scrutiny of objects identified during detection is considered the object description phase of the image analysis procedure-it gives real-world meaning to objects detected in the image. Objects become an instance in the dataset after a feature vector has been determined that describes the object.

Object description requires a method to extract the properties of pixels belonging to objects from the original image. The coordinates of grouped pixels can be mapped back to the original image, which provides a way to extract information about those pixels. However, recall that labeled pixels may not represent the full extent of the object, therefore other methods that better approximate the object need to be used. The minimum bounding box provides one possible solution; however, this approach often includes pixels that do not belong to the object, especially if the shape of the object is elliptical (Figure 8-16). Another approach is to fit an ellipse to the grouped pixels as is shown in Figure 8-14 and Figure 8-16. The ellipse is considered to be a good choice for knots (Kauppinen, 1999) In practice, both methods are used to characterize different attributes.

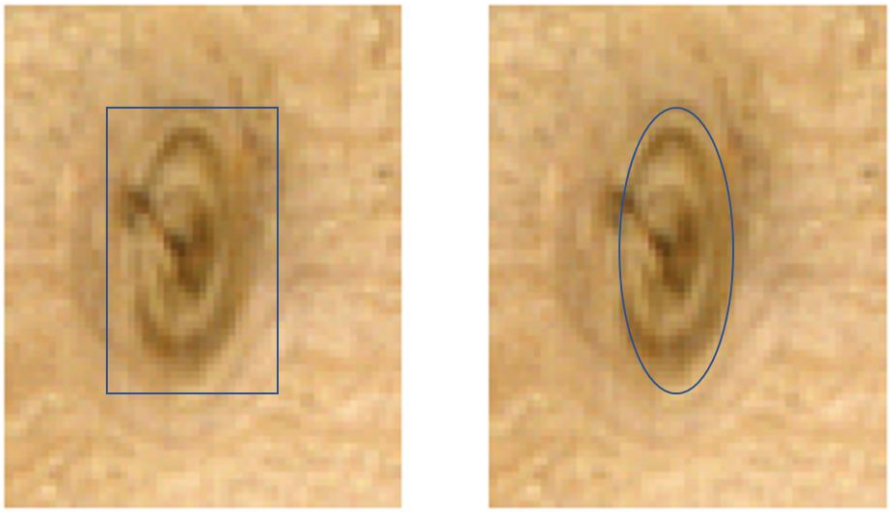


Figure 8-16. The minimum bounding box (left) and elliptical fit (right) to an object (knot).

Certain attributes can be described from the label matrix directly, while other features are extracted from either the pixels belonging to the object or pixels within the bounding box from a gray-scale array of the original image or a transformation of it. The geometric attributes of width, height, area and location of the bounding box and centroid location,

length of the major and minor axis, eccentricity (a measure of roundness), orientation (angle of the major axis to horizontal), and solidity (concavities of object boundary) of an object are all calculated from the label matrix. Because these attributes do not require contiguous pixels to calculate, they are extracted directly from the label matrix. These properties are often referred to as descriptors and carry the unit of the pixel. After these descriptors have been converted to real-world units, they become part of the feature vector of the object.

The calculation of textural attributes requires contiguous, touching pixels. To extract all intensity values of pixels belonging to objects, the third type of mask is mathematically produced from the geometric descriptors. The object mask approximates the shape of the object by either fitting a bounding box or ellipse to pixels belonging to groups from the label matrix. Then the coordinates from each pixel in objects from the object mask are mapped back to the image to extract intensity levels from those pixels. These intensity values are used to statistically quantify the texture of the object (Gonzalez et al., 2010). One method is based on the statistical properties of the intensity histogram. The attributes calculated from intensity histograms include the mean, standard deviation, smoothness, skewness, uniformity, and entropy (Table 8-2).

This class of properties is based on the statistical moments given by the nth moment about the mean given by (Gonzalez et al., 2010):

$$\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i)$$

where m is given by:

$$m = \sum_{i=0}^{L-1} z_i \, p(z_i)$$

z is a random intensity variable, $p(z_i)$ is the histogram of the intensity levels, L is the number of possible intensity levels (Gonzalez et al., 2010). These measures provide a statistically-based way to compare the intensity values of pixels from images or objects. These measures are useful when comparing the texture of a group of pixels. For example, a coarse image with random intensity values would have a higher entropy level than a smooth image with a narrower range of intensity values.

Table 8-2. Descriptions of texture based on intensity histograms (Gonzalez et al., 2010).

Property	Expression	Measure of Texture
Mean	$m = \sum_{i=0}^{L-1} z_i\, p(z_i)$	A measure of average intensity
Standard deviation	$\sigma = \sqrt{\mu}_2 = \sqrt{\sigma^2}$	A measure of average contrast
Smoothness	$R = 1 - \frac{1}{(1+\sigma^2)}$	A measure of the smoothness of the intensity levels
Skewness	$\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$	A measure of the skewness of the histogram of the intensity levels
Uniformity	$U = \sum_{i=0}^{L-1} p^2(z_i)$	A measure of uniformity in the intensity levels
Entropy	$e = \sum_{i=0}^{L-1} p(z_i) log_2 p(z_i)$	A measure of randomness

Although useful to compare intensity values, measures of texture computed from histograms do not provide any information about the relative relationship between adjacent pixels. A second method maps the object mask back to a monochrome image using the minimum bounding box. Information about how intensity values vary with respect to each other can be added to the texture analysis (Gonzalez et al., 2010). Consider the operator, O, that defines the position of two pixels relative to one another in image, $f(x, y)$ with $\mathcal{L}$ levels of possible intensities. An example of O could be 'one pixel immediately to the right'. The matrix, $\mathcal{G}$, contains elements that indicate how often a pair with intensities z_i and z_j occur in the position

specified by O. $\mathcal{G}$ is termed the co-occurrence matrix; its size is the number of possible intensity levels in the image. Because $\mathcal{G}$ depends on O, the presence of textural patterns can be detected by choosing an appropriate O and analyzing the elements in $\mathcal{G}$. The resulting matrix provides a means to calculate information regarding the relative position of pixels with respect to each other (Gonzalez et al., 2010). The total number of pairs that satisfy O is the sum of all elements in O. Then the probability that any given pair of pixels will satisfy O is given by:

$$p_{ij} = \frac{g_{ij}}{n}$$

Where n is the sum of all elements in $\mathcal{G}$, and g_{ij} are the pair.

These probabilities will sum to 1 and are given by:

$$\sum_{i=1}^{K}\sum_{i=1}^{K} p_{ij} = 1$$

Where K is the number of rows or columns in $\mathcal{G}$.

These descriptors include contrast, correlation, energy, homogeneity, and entropy (Table 8-3). The variables used in the calculation of correlation are:

$$m_r = \sum_{i=1}^{K} iP(i)$$

$$m_c = \sum_{i=1}^{K} jP(j)$$

$$\sigma_r^2 = \sum_{i=1}^{K} (i - m_r)^2 P(i)$$

$$\sigma_c^2 = \sum_{i=1}^{K} (j - m_c)^2 P(j)$$

where

$$P(i) = \sum_{i=1}^{K} P_{ij}$$

$$P(j) = \sum_{i=1}^{K} P_{ij}$$

m_r is the mean of $\mathcal{G}$ calculated along the rows,

m_c is the mean calculated along the columns,

σ_r and σ_c are the standard deviations calculated along rows and columns, respectively.

Table 8-3. Properties calculated from the co-occurrence matrix (see Gonzalez et al. (2010) for further explanation), subscripts r and c refer to rows and columns, subscripts I and j refer to the ith and the jth element of the normalized co-occurrence matrix.

Property	Expression	Measure
Contrast	$\sum_{i=1}^{k}\sum_{j=1}^{k}(i-j)^2 p_{ij}$	A measure of the intensity contrast between pixel neighbors
Correlation	$\sum_{i=1}^{k}\sum_{j=1}^{k}\frac{(i-m)(j-m_c)p_{ij}}{\sigma_r\sigma_c}$	A measure of how correlated a pixel value is to its neighbor over the entire range
Energy	$\sum_{i=1}^{k}\sum_{j=1}^{k}p_{ij}^2$	Sum of squared elements
Homogeneity	$\sum_{i=1}^{k}\sum_{j=1}^{k}\frac{p_{ij}}{1+\lvert i-j\rvert}$	A value of the closeness of the distribution of elements in the co-occurrence matrix to the diagonal
Entropy	$\sum_{i=1}^{k}\sum_{j=1}^{k}p_{ij}log_2 p_{ij}$	A measure of randomness of intensity

8.1.3 Object Classification

Object classification is the procedure by which instances are mapped to discrete classes, or labels, using a classifier (Kohavi and Provost, 1998, Nisbet et al., 2018). At a minimum, classifiers have a form (structure) and a procedure to interpret information (Kohavi and Provost, 1998). A classifier is a predictive model to predict unlabeled classes and a descriptive model that distinguishes instances from different classes (Tan et al., 2018). A familiar example is an email spam detection model. This is a binary model as there are only 2 classes of email: spam or not spam. The classes can be defined by rules, class boundaries, or a mathematical function (Nisbet et al., 2009). Many types of classifiers have been developed for different types of classification problems. Common algorithms include the linear regression, support vector machines (SVMs), decision trees, boosted trees, random forest, neural networks, and nearest neighbor (Akinsola, 2017, Kotsiantis, 2007). The classifier uses the information about an object's attributes contained within feature vectors to make decisions as to which label to map to an instance. The information can be quantitative or qualitative. However, the success of the classifier depends on the quality of the data that describes the attributes of the instances. A sample, or instance as used here, s, with n features is presented as n-dimensional vector (feature vector), $s = [s_1, \ldots . s_n]$, $s \in \mathbb{R}^n$ where $\mathbb{R}^n$ is considered the feature space. Machine learning is the study of developing predictive models without explicit instructions. It typically uses a training set and a testing set to determine model performance. Two general types of classifiers exist. A supervised classification operation is based on known class assignments and the features of the instance to be classified (Nisbet et al., 2009). In situations where the classes are not known, then an unsupervised operation is used (Nisbet et al., 2009). Common applications of unsupervised classification are to explore data for naturally occurring undefined classes or clusters of objects. This general class of classification is referred to as clustering or cluster analysis. This thesis uses both types of classification. Supervised classification is presented in Chapter 3 to map instances to pre-determined classes of knots; unsupervised classification is used to explore new classes of boards in Chapter 5.

The supervised learning procedure is when a classifier is trained on a dataset with predetermined classes. Let $L = [l_1, \ldots l_n]$, where L includes all possible labels of the classes. The classifier is trained to predict labels for unseen instances. A quantitative classifier is a

function, f, that transforms any s input instance to an output l. This is typically done by dividing the data into a training set and a test set (Nisbet et al., 2009). The training set is used to decide how the features are weighed and combined to separate the classes-it is used to develop the classifier. During the testing phase, the procedure determined with the training set is applied to the test set to calculate classification error. The error is used to adjust an aspect of the classifier. In classification problems with a low number of labels and features, few iterations will be required to achieve an acceptable model. A third dataset, the validation set, is used to determine the prediction performance. Nisbet et al. (2009), argue the importance of avoiding setting up a tautology between the training and testing set—if possible, the validation data should never be used to test or train a classifier.

Developing a classifier involves many considerations (Nisbet et al., 2009). The purpose of the classification needs to be specified-what are the consequences of inaccurate classification? The required accuracy of the classification needs to be understood; does a classifier with low accuracy demonstrate the principle and justify the investment to develop a better classifier? The required understandability of the classification procedure needs to be stated- how do the predictor variables influence labeling? The required generality and robustness of the procedure need to be explored-will the classifier performs on new data equally well?

Classifier performance can be judged from a confusion matrix, or confusion chart containing rows and columns for each class or type (Figure 8-17). For multi-group classification problems, the rows indicate the true classes or groups, while the columns indicate the predicted classes. True classes are those that have been predetermined by some means of validation. Diagonal and off-diagonal cell values correspond to the correct and incorrect classification of the observations. Row summaries display the percentages (or number) of observations correctly and incorrectly classified for each true class type. These values are known as the true positive rate or recall rate. Column summaries indicate the percentages (or number) of correctly and incorrectly classified observations for each predicted class type. These values are known as positive predictive value or precision rates. For the example shown (Figure 8-17), row summaries indicate the true positive rate of classification as 100 percent for the *setosa* class, 94 percent for the *versicolor* class, and 92 percent for the *virginica* true class. The precision of classification is 100 percent for the *setosa* group, 92.2percent for the *versicolor* group, and

93.9percent for the *virginca* group. As opposed to detection type, object classification assumes that all instances can be labeled into $\mathbb{R}^n$. In some situations, one measure may be more important than another, depending on the question the research is seeking to answer (Funck et al., 2003, Sokolova and Lapalme, 2009).

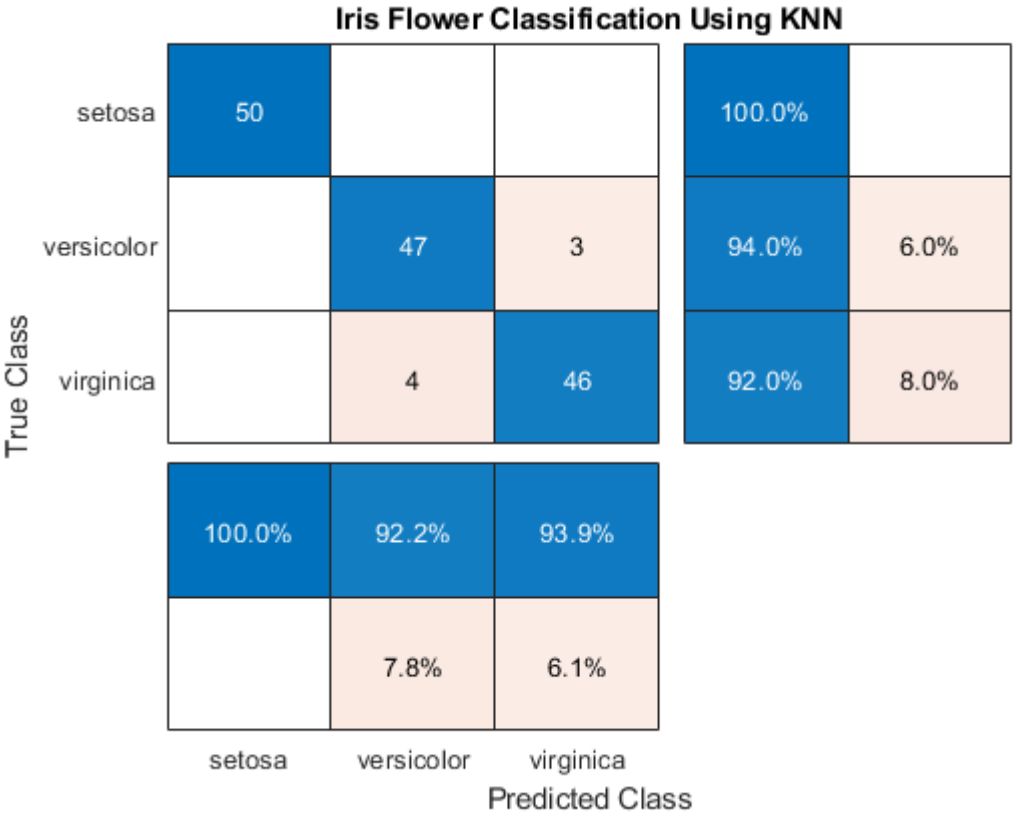


Figure 8-17. A confusion matrix indicating classification performance of a k-nearest neighbor classifier of iris species from petal measurements (mathworks.com/help/stats/confusionchart.html).

The characterization of wood characteristics depends on the classification method and the results of object detection and description- the two processes are inherently connected. Therefore, performance is a function of both the accuracy at which the object was detected and described during the image analysis phase and the accuracy at which the classifier can map a label to an instance. Taken together, the procedures of detection, description, and classification, are considered the characterization model in this work. The performance of different characterizations models can be compared by calculating the parameters defined above. The results of these comparisons lead to improvements in both the image analysis and classification processes. Improvements usually follow an iterative process until the desired performance is reached or limitations of the model are reached. Typically, a model is

developed, and performance parameters are calculated and judged. Based on the performance parameters, some aspect of the model is changed. These changes may include basic image processing procedures, image analysis procedures, feature selection, and classification methods. After making the adjustments, the model is re-run and the results are re-examined. This continues until a model that produces the results necessary for the problem at hand has been developed.

9 Appendix 2

9.1 UGRS System Rules

Table 9-1. System rules for UGRS based on 1994 NHLA rules with slight modifications. Units of inches are used for width, length, and surface measure.

	Grade					
Variable	FAS	F1F	Selects	#1C	#2A	#3A
Minimum board width (in.)	6	6	4	3	3	3
Minimum board length (in.)	96	96	72	48	48	48
Different minimum sized cuttings	2	2	2	2	1	2
Number of size categories	5	5	6	7	8	1
Minimum cutting length (in.)	60 84	60 84	60 84	24 24	24	12 24
Minimum cutting width (in.)	4 3	4 3	4 3	4 3	3	1.75 3
Maximum number of cuttings for each size class	1 1 2 3 4	1 1 2 3 4	1 1 1 2 3 4	9 9 9 9 9 9 9	1 1 2 3 4 5 6 7	20
Minimum surface measure	4 6 8 12 16	4 6 8 12 16	2 4 6 8 12 16	1 2 3 5 8 1 14	1 2 4 6 8 10 12	1

					14	
Maximum surface measure	5 7 11 15 100	5 7 11 15 100	3 5 7 11 15 100	1 2 4 7 10 13 100	1 3 5 7 9 11 13 100	100
Percentage of clear area for each size category	83.33 83.33 83.33 83.33 83.33	83.33 83.33 83.33 83.33 83.33	91.67 83.33 83.33 83.33 83.33 83.33	100 75 66.67 66.67 66.67 66.67 66.67	66.67 50.0 50.0 50.0 50.0 50.0 50.0 50.0	40.0

9.2 NHLA Grades for Automatic Dataset

The NHLA grades of boards were determined using UGRS from the automatic dataset and are shown in Table 9-2. A significant proportion of boards graded to #1C and very few boards graded to Selects. Overall, grades were better predicted for *E. nitens* than for *E. globulus* (Figure 9-1 and Figure 9-2). For both species, the true positive rate was lowest for the #2AC grade and much lower for *E. globulus* than for *E. nitens*. This may be due to the slightly lower false negative detection rate for *E. nitens*. Based on this outcome, the comparable value of *E. nitens* was AUD 358 and AUD 386 and the value for *E. globulus* was between AUD 390 and AUD 460 per cubic meter.

Table 9-2. The number and proportion (percent) of boards in each NHLA grade in both species from the automatic dataset.

NHLA grade	*E. nitens*	*E. globulus*
Select	2 (2)	6 (4)
#1C	80 (59)	134 (84)
#2AC	19 (14)	11 (7)
#3A	35 (26)	8 (5)

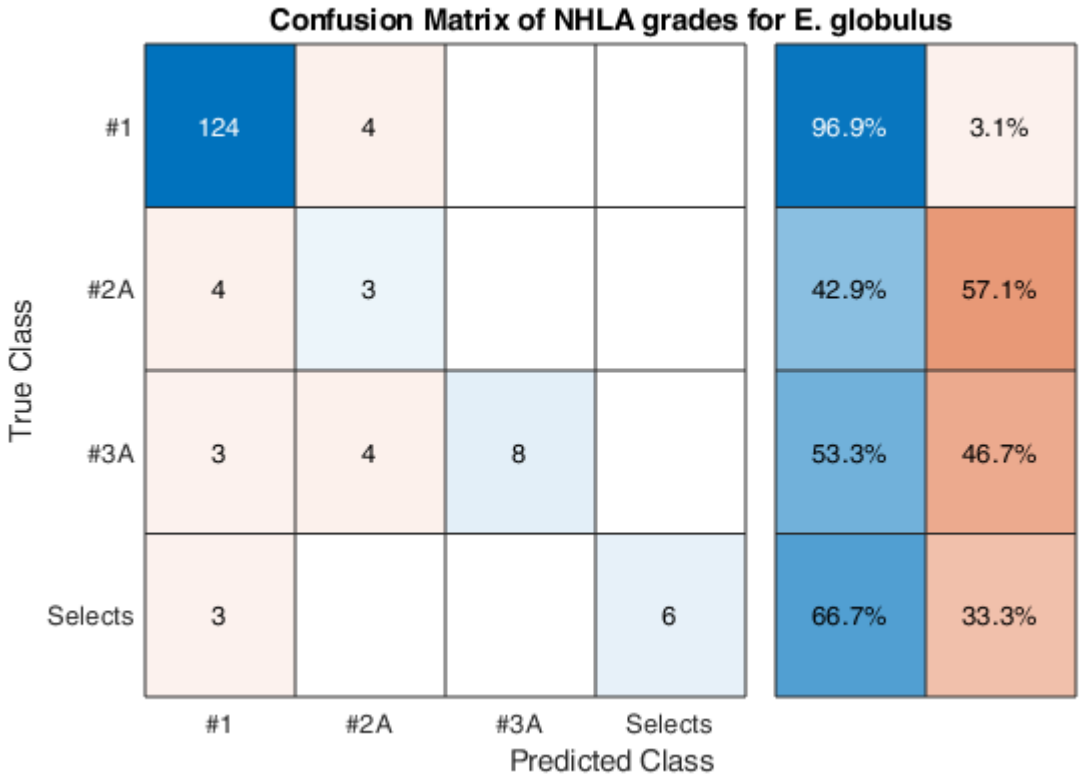


Figure 9-1. Confusion matrix of NHLA grading results from the validation and automatic datasets for E. globulus.

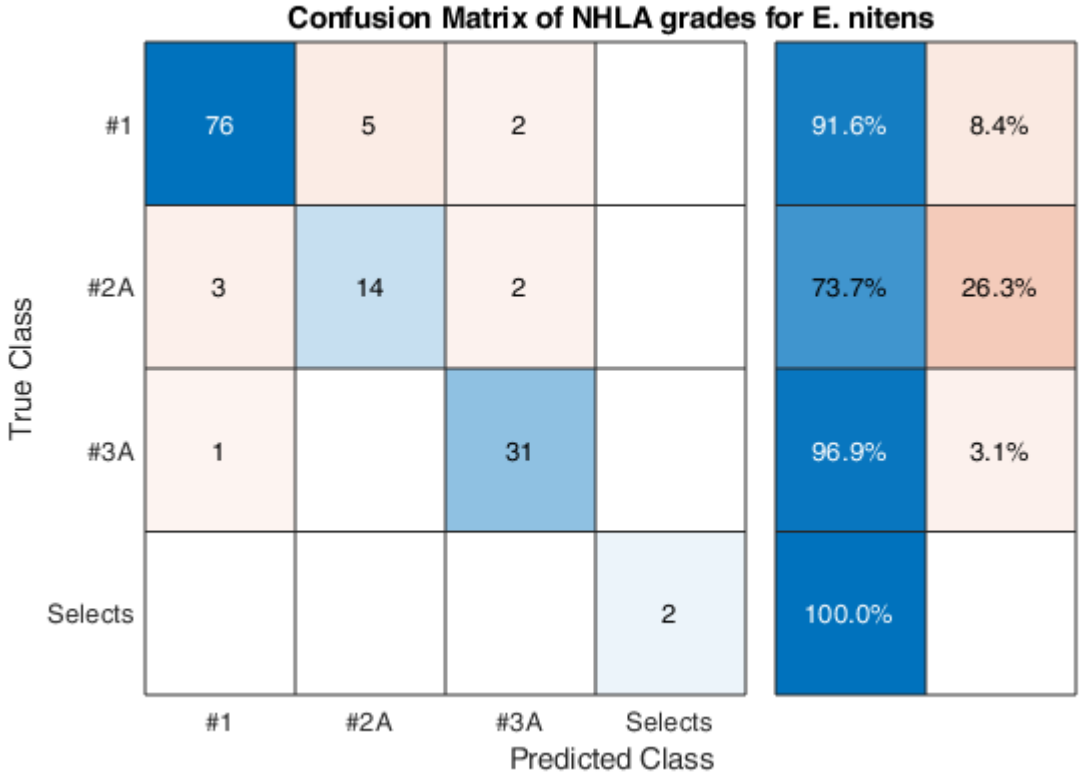


Figure 9-2. Confusion matrix of NHLA grading results from the validation and automatic datasets for E. nitens.

10 Appendix 3

10.1 Cutting Bills Used for Dimension Parts Study

Table 10-1. Description of Cutting bill 1.

Width (in)	Length (in)	Quantity
1.5	30.0	304
1.5	48.25	240
2.25	22.75	50
2.25	30.0	101
2.25	48.25	120
2.25	64.5	33
2.25	80.5	33
2.25	87.75	70
2.75	19.5	75
2.75	30.0	101
2.75	48.25	120
3.0	28.25	21
3.0	30.0	102
3.0	33.25	60
3.25	30.0	202
3.25	48.25	60
3.25	56.0	307
4.0	23.5	307
4.25	21.0	90
4.25	33.25	140

Table 10-2. Description of Cutting bill 2.

Width (in)	Length (in)	Quantity
1.5	18.0	450
1.5	24.0	450
1.5	28.0	450
1.5	44.0	600
1.5	72.0	290
3.0	20.0	450
3.0	36.0	450

Table 10-3. Description of Cutting bill 3.

Width (in)	Length (in)	Quantity
1.5	16.75	1250
1.5625	12.0	250
2.0625	19.875	125
2.0625	48.0	100
2.25	29.25	125
2.875	13.875	250
2.875	28.75	200
2.875	44.0	250
4.9375	27.0	32

Table 10-4. Description of Cutting bill 4.

Width (in)	Length (in)	Quantity
1.75	10.0	33
1.75	12.25	17
1.75	15.0	183
1.75	18.75	133
1.75	20.5	33
1.75	24.75	383
1.75	27.75	167
2.0	15.0	333
2.0	18.75	67
2.0	20.5	17
2.0	24.75	217
2.0	31.5	33
2.25	13.0	67
2.25	14.5	25
2.25	18.75	133
2.25	21.0	150
2.25	22.5	133
2.25	24.75	383
2.25	28.25	233
3.75	13.5	17
3.75	28.25	66
4.5	21.0	50

Table 10-5. Descriptions of the Buehlmann (B) Cutting bill 5.

Width (in)	Length (in)	Quantity
1.5	10.0	34
1.5	17.5	74
1.5	27.5	108
1.5	47.5	61
1.5	72.0	26
2.5	10.0	38
2.5	17.5	75
2.5	27.5	120
2.5	47.5	65
2.5	72.0	25
3.5	10.0	11
3.5	17.5	25
3.5	27.5	37
3.5	47.5	22
3.5	72.0	14
4.25	10.0	12
4.25	17.5	25
4.25	27.5	40
4.25	47.5	21
4.25	72.0	10

Table 10-6. Descriptions of Cutting bill 6.

Width (in)	Length (in)	Quantity
2.0	15.0	90
2.0	18.0	25
2.0	25.0	65
2.0	33.0	75
2.0	50.0	100
2.75	15.0	43
2.75	25.0	65
2.75	45.0	150
2.75	72.0	37
3.5	15.0	65
3.5	38.0	65
3.5	50.0	150
3.5	60.0	25

Table 10-7. Simulation results using NHLA graded red oak lumber and the cutting bills from this study.

Cutting Bill	NHLA Grade	Price ($/MBF)	Yield (%)	Parts Area (BF)	Lumber Area (BF)	Cros-Cuts	Lumber Costs ($)	Cutting Costs ($)	Total Costs ($)
1	FAS	1235	68.08	1619.06	3830	4793	4730.05	1149.533	5879.583
2	FAS	1235	76.05	1730.89	2303	3890	2844.205	1250.098	4094.303
3	FAS	1235	56.31	803.62	4066	6365	5021.51	576.3664	5597.876
4	FAS	1235	80.04	891.18	1627	5081	2009.345	731.8026	2741.148
5	FAS	1235	72.82	432.28	694.8	1154	858.078	306.9188	1164.997
6	FAS	1235	75.1	581.19	933.8	1243	1153.243	462.0888	1615.332
1	#1C	870	55.13	1644.16	4025	5040	3501.75	1168.042	4669.792
2	#1C	870	61.4	1732.77	3028	5028	2634.36	1230.267	3864.627
3	#1C	870	40.21	804.1	4348	6738	3782.76	570.911	4353.671
4	#1C	870	61.3	775.15	1741	4701	1514.67	550.3565	2065.027
5	#1C	870	68.48	447.22	705	1291	613.35	350.0827	963.4327
6	#1C	870	60.04	664.53	1244	1581	1082.28	504.4477	1586.728
1	#2AC	750	49.53	1429.66	3462	4456	2596.5	1044	3640.5
2	#2AC	750	50.4	1611.48	3462	5883	2596.5	1170.889	3767.389
3	#2AC	750	50.26	755.3	1813	3946	1359.75	753.1746	2112.925
4	#2AC	750	59.47	913.17	1809	5004	1356.75	664.1975	2020.948
5	#2AC	750	46.98	456.16	1413	2437	1059.75	336.3124	1396.062
6	#2AC	750	43.56	662.12	1892	2249	1419	470.1052	1889.105
1	FAS	1235	68.08	1619.06	3830	4793	4730.05	1149.533	5879.583

10.2 Simulation Results of Panel Production

Table 10-8. Obtained results from the general cutting bill for E. globulus boards grouped by definition 1.

			E. globulus			
Board Class			1	2	3	4
Width	Length	Quantity				
609.6	304.8	20	20.1	20.1	20.1	20.1
609.6	609.6	20	20.1	20.1	20.0	20.1
609.6	914.4	20	20.1	20.1	15.0	20.0
609.6	1219.2	20	20.1	20.1	17.5	20.0
609.6	1828.8	20	20	20.1	10.9	20.0

Table 10-9. Obtained results from the general cutting bill for E. nitens boards grouped by definition 1.

			E. nitens			
Board Class			1	2	3	4
Width	Length	Quantity				
609.6	304.8	20	16.2	20.0	20.1	20.0
609.6	609.6	20	9.5	20.0	20.1	20.1
609.6	914.4	20	7.0	20.1	20.0	12.8
609.6	1219.2	20	10.3	20.1	20.1	11.5
609.6	1828.8	20	10.5	20.0	20.1	7.7

Table 10-10. Obtained results from the special cutting bill for E. nitens boards grouped by definition 1.

		E. nitens							
Board Class		1		2		3		4	
Cutting Bill		A		B		C		D	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	35	19.8	50	50.1	10	10.1	50	49.6
609.6	609.6	25	15.7	30	30.0	10	10.1	25	24.7
609.6	914.4	20	19.0	25	25.1	25	14.5	25	15.8
609.6	1219.2	5	5	20	20.0	30	26.0	10	9.0
609.6	1828.8	5	5	20	20.0	30	29.1	10	7.2

Table 10-11. Obtained results from the special cutting bill for E. globulus boards grouped by definition 1.

E. globulus									
Board Class		1		2		3		4	
Cutting Bill		B		C		D		A	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	50	50.0	10	10.0	50	50.0	35	35
609.6	609.6	30	30.1	10	10.1	25	25.1	25	25.1
609.6	914.4	25	25.0	25	25.0	25	25.0	20	20.0
609.6	1219.2	20	20.0	30	30.1	10	10.1	5	5.0
609.6	1828.8	20	20.1	30	30.0	10	10.1	5	5.0

Table 10-12. Obtained pieces from E. nitens boards grouped by definition 2.

E. nitens									
Board Class		1		2		3		4	
Cutting Bill		A		B		D		C	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	35	21.6	50	50.0	50	49.7	10	10
609.6	609.6	25	17.8	30	30.0	25	20.7	10	8.0
609.6	914.4	20	19.1	25	25.0	25	22.8	25	9.0
609.6	1219.2	5	5.1	20	20.1	10	10.0	30	19.1
609.6	1828.8	5	5.1	20	20.1	10	8.6	30	27.1

Table 10-13. Simulation variables obtained from E. nitens boards grouped by definition 2.

E. nitens										
Board Class	Panel Bill	Board count	Yield	Rip-cut count	X-cut count	X-cut efficiency	Piece count	Knotty pieces	Available knots	Utilized knots
1	A	152	76.6	87	1165	37.8	771	84	198	143
2	B	170	78.4	148	2620	36.6	1606	236	396	298
3	D	162	72.1	161	2649	56.7	1514	233	457	330
4	C	154	86.2	57	849	15.7	622	85	181	123

Table 10-14. Obtained pieces from E. globulus lumber grouped by definition 2.

E. globulus									
Board Class		1		2		3		4	
Cutting bill		A		B		D		C	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	35	35.0	50	50.0	50	50.0	10	10.1
609.6	609.6	25	25.1	30	30.1	25	25.0	10	7.9
609.6	914.4	20	20.1	25	25.0	25	18.5	25	23.8
609.6	1219.2	5	5.0	20	20.1	10	9.4	30	29.2
609.6	1828.8	5	5.1	20	20.0	10	6.6	30	30.0

Table 10-15. Processing parameters from E. globulus lumber grouped by definition 2.

E. globulus										
Board Class	Panel Bill	Board count	Yield	Rip Count	X-Cut Count	Cutting Efficiency	Piece Count	Knotty Pieces	Available Knots	Utilized Knots
1	A	93	88.2	9	891	24.5	678	47	65	63
2	B	142	79.4	142	2300	32.0	1505	99	150	123
3	D	153	60.1	177	2804	64.8	1561	182	360	295
4	C	154	86.7	99	1196	16.3	961	85	147	112

Table 10-16. Obtained pieces from E. nitens lumber grouped by definition 3.

E. nitens									
Board Class		1		2		3		4	
Cutting bill		C		C		D		B	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	10	10.1	10	10.1	50	18.0	50	50.0
609.6	609.6	10	4.4	10	8.5	25	20.2	30	30.1
609.6	914.4	25	23.7	25	22.0	25	21.0	25	25.1
609.6	1219.2	30	29.6	30	28.3	10	10.1	20	20.1
609.6	1828.8	30	30.0	30	30.1	10	10.1	20	20.1

Table 10-17. Processing parameters from E. nitens lumber grouped by definition 3.

E. nitens										
Board Class	Panel Bill	Board count	Yield	Rip Count	X-Cut Count	Cutting Efficiency	Piece Count	Knotty Pieces	Available Knots	Utilized Knots
1	C	152	92.7	76	941	13.0	865	314	665	613
2	C	168	89.5	54	1006	13.9	796	346	744	601
3	D	168	85.1	44	924	22.3	643	216	400	337
4	B	171	78.5	129	2409	33.5	1522	541	1072	846

Table 10-18. Obtained pieces from E. globulus lumber grouped by definition 3.

E. globulus									
Board Class		1		2		3		4	
Cutting bill		C		C		D		B	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	10	10.1	10	10.1	50	50.1	50	50.1
609.6	609.6	10	10.0	10	10.1	25	25.1	30	30.0
609.6	914.4	25	13.8	25	24.3	25	25.1	25	25.1
609.6	1219.2	30	17.6	30	30.1	10	10.1	20	20.0
609.6	1828.8	30	22.0	30	30.0	10	10.1	20	20.1

Table 10-19. Processing parameters from E. globulus lumber grouped by definition 3.

E. globulus										
Board Class	Panel Bill	Board count	Yield	Rip Count	X-Cut Count	Cutting Efficiency	Piece Count	Knotty Pieces	Available Knots	Utilized Knots
1	C	172	72.5	85	1267	24.9	772	186	460	345
2	C	156	70.2	193	1703	22.7	1092	239	480	340
3	D	110	91.5	40	1190	23.1	1019	156	235	212
4	B	133	95.0	84	1466	20.4	1345	284	435	421

Table 10-20. Obtained pieces from E. nitens lumber grouped by definition 4

E. nitens									
Board Class		1		2		3		4	
Cutting bill		C		D		C		B	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	10	10.1	50	50.0	10	10.0	50	25.0
609.6	609.6	10	10.1	25	25.0	10	10.1	30	22.4
609.6	914.4	25	4.2	25	25.0	25	20.0	25	24.0
609.6	1219.2	30	9.0	10	10.1	30	28.4	20	20.1
609.6	1828.8	30	12.6	10	10.1	30	30.0	20	20.1

Table 10-21. Processing parameters from E. nitens lumber grouped by definition 4.

E. nitens										
Board Class	Panel Bill	Board count	Yield	Rip Count	X-Cut Count	Cutting Efficiency	Piece Count	Knotty Pieces	Available Knots	Utilized Knots
1	C	168	77.6	101	666	23.2	462	86	168	135
2	D	132	79.2	88	1887	36.7	1251	329	510	431
3	C	152	84.6	90	1208	16.9	909	287	472	374
4	B	154	90.9	57	1039	16.3	872	254	308	286

Table 10-22. Obtained pieces from E. globulus lumber grouped by definition 4.

E. globulus									
Board Class		1		2		3		4	
Cutting bill		C		B		C		D	
Width	Length	Required	Obtained	Required	Obtained	Required	Obtained	Required	Obtained
609.6	304.8	10	10.0	50	50.0	10	10.0	50	50.0
609.6	609.6	10	10.0	30	30.1	10	10.0	25	25.0
609.6	914.4	25	12.3	25	25.1	25	25.1	25	25.0
609.6	1219.2	30	23.8	20	20.1	30	30.0	10	10.1
609.6	1828.8	30	28.6	20	20.1	30	30.1	10	10.1

Table 10-23. Processing parameters from E. globulus lumber grouped by definition 4.

E. globulus										
Board Class	Panel Bill	Board count	Yield	Rip Count	X-Cut Count	Cutting Efficiency	Piece Count	Knotty Pieces	Available Knots	Utilized Knots
1	C	183	78.9	58	1153	18.6	753	185	291	229
2	B	140	79.4	150	2403	33.5	1552	261	364	324
3	C	139	94.7	72	924	12.3	897	209	245	245
4	D	100	89.7	75	1284	25.0	1112	137	170	150

11 References

ABARES 2016. Australia's plantation log supply 2015–2059. Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra, December. CC BY 3.0.

ABARES 2019. Australia's forests at a glance 2019: with data to 2017-18. Canberra: Australian Bureau of Agricultural and Resource Economics and Sciences.

ABBOTT, A. L. & KLINE, D. E. 2003. Imaging and analysis of logs and lumber. *Computers and Electronics in Agriculture,* 41**,** 1-6.

AJANI, J. 2008. Australia's Transition from Native Forests to Plantations: The Implications for Woodchips, Pulpmills, Tax Breaks and Climate Change. *Agenda - A Journal of Policy Analysis and Reform,* 15.

AKINSOLA, J. E. T. 2017. Supervised machine learning algorithms: classification and comparison. *International Journal of Computer Trends and Technology (IJCTT),* 48**,** 128-138.

AMERICAN HARDWOOD EXPORT COUNCIL 2008. The Illustrated Guide to American Hardwood Lumber Grades. Memphis, TN (USA): American Hardwood Export Council.

APECF 2009. Grading of Oak Sawn Timber. *European Standard EN 975-1 (2009).* French Timber and Association for the Promotion of French Oak.

ARAMAN, P. 1977. *Use of computer simulation in designing and evaluating a proposed rough mill for furniture interior parts,* Little Upper Darby, PA, Forest Service, U.S. Department of Agriculture, Northeastern Forest Experiment Station.

ASLAM, M., KHAN, T. M., NAQVI, S. S., HOLMES, G. & NAFFA, R. 2019. On the application of automated machine vision for leather defect inspection and grading: a survey. *IEEE Access,* 7**,** 176065-176086.

ASTRAND, E. 1996. *Automatic inspection of sawn wood.* PhD, Linkoping University, Sweden.

AUSTRALIA STANDARDS 2006. Timber—Hardwood—Sawn and milled products Part 2: Grade description, AS 2796-2006. *In:* STANDARDS AUSTRALIA, A. (ed.).

AZOUZI, R., BEAUREGARD, R. & D'AMOURS, S. 2009. Exploratory case studies on manufacturing agility in the furniture industry. *Management Research News,* 32**,** 424-439.

BALDACCI, R., BOSCHETTI, M. A., GANOVELLI, M. & MANIEZZO, V. 2014. Algorithms for nesting with defects. *Discrete Applied Mathematics,* 163**,** 17-33.

BARNETT, J. R. & JERONIMIDIS, G. 2003. *Wood quality and its biological basis,* Oxford : Boca Raton, FL, Blackwell.

BELLEVILLE, B., ASHLEY, P. & OZARSKA, B. 2016. Wood machining properties of Australian plantation-grown Eucalypts. *Maderas. Ciencia y tecnología,* 18**,** 677-688.

BERGLUND, A., BROMAN, O., OJA, J. & GRÖNLUND, A. 2014. Customer adapted grading of Scots pine sawn timber using a multivariate method. *Scandinavian Journal of Forest Research,* 30**,** 87-97.

BHATTA, S. R., TIIPPANA, K., VAHTIKARI, K., HUGHES, M. & KYTTÄ, M. 2017. Sensory and emotional perception of wooden surfaces through fingertip touch. *Frontiers in Psychology,* 8**,** 367-367.

BLACKBURN, D., HAMILTON, M., HARWOOD, C., INNES, T., POTTS, B. & WILLIAMS, D. 2010. Stiffness and checking of Eucalyptus nitens sawn boards: genetic variation and potential for genetic improveement. *Tree genetics and genomes,* 65**,** 757-765.

BLACKBURN, D. P. 2012a. *Improving Eucalyptus nitens for sawn-board, veneer and paper products.* Ph.D., University of Tasmania.

BLACKBURN, D. P. 2012b. *Improving Eucalyptus nitens for sawn-board, veneer and paper products.* PhD, University of Tasmania.

BODEN, C. T., STEELE, P. H. & HARDING, O. V. 2005. Accelerated statistical prediction of lumber grades and part yields. *Forest Products Journal,* 55.

BOND, B., KLINE, D. E. & ARAMAN, P. 1998. Characterization of defects in lumber using color, shape, and density information. *Fusion International Conference.*

BOND, B. H., KLINE, D. E. & ARAMAN, P. A. 2002. Differentiating defects in red oak lumber by discriminant analysis using color, shape, and density. *Wood and Fiber Science,* 34**,** 516-528.

BOOTH, P. & NOLAN, G. Parametric fabrication of engineered timber products in a pedagogical environment. World Conference on Timber Engineering, 2016 Vienna, Austria.

BOOTH, P., MAXWELL, I. & SCHORK, T. Timber 4.0: A computer-vision approach for visual grading low-grade plantation hardwood. *In:* SCHNABEL, M. A., ed. Back to the Future: The next 50 years (51st International Conference of the Architectural Association (ANZAScA)), 2017. Architectural Science Association (ANZAScA).

BOWYER, J., SHMULSKY, R. & HAYGREEN, J. 2007. *Forest Products and Wood Science: An Introduction,* Ames, Iowa, Blackwell Publishing

BREINIG, L., BROMAN, O., BRÜCHERT, F. & BECKER, G. 2014. Optimization potential for perception-oriented appearance classification by simulated sawing of computed tomography-scanned logs of Norway spruce. *Wood Material Science & Engineering,* 10**,** 319-334.

BREINIG, L., LEONHART, R., BROMAN, O., MANUEL, A., BRÜCHERT, F. & BECKER, G. 2015. Classification of wood surfaces according to visual appearance by multivariate analysis of wood feature data. *Journal of Wood Science,* 61**,** 89-112.

BRINBERG, D., BUMGARDNER, M. & DANILOSKI, K. 2007. Understanding perception of wood household furniture: application of a policy capturing approach. *Forest Products Journal,* 57**,** 21-26.

BROMAN, O. 1995a. Attitudes toward Scots pine wood surfaces: A multivariate approach. *Mokuzai Gakkaishi,* 41.

BROMAN, O. 1995b. Visual Impressions of features in Scots pine wood surfaces: A qualitative study. *Forest Products Journal,* 45**,** 6.

BROMAN, O. 1996. Two Methods for measuring people's preferences for Scots pine wood surfaces: A comparative multivariate approach. *Mokuzai Gakkaishi,* 42.

BROMAN, O. 2000. *Means to measure the aesthetic properties of wood.* PhD, Lulea Tekniska Universitet, Skelleftea Campus.

BROMAN, O. 2001. Aesthetic properties in knotty wood surfaces and their connection with people's preferences. *Journal of Wood Science,* 47**,** 192-198.

BRUNNER, C. C., BUTLER, D. A., MARISTANY, A. G. & VANLEEUWEN, D. 1990a. Optimal clear-area sawing patterns for furniture and millwork blanks. *Forest Products Journal,* 40**,** 51-56.

BRUNNER, C. C., SHAW, G., BUTLER, D. A. & FUNCK, J. W. 1990b. Using color in machine vision systems for wood processing. *Wood and Fiber Science,* 22.

BRUNNER, C. C., MARISTANY, A. G., BUTLER, D. A., VANLEEUWEN, D. & FUNCK, J. W. 1992. An evaluation of color spaces for detecting defects in Douglas-fir veneer. *Industrial Metrology,* 2**,** 169-184.

BRUOT, A. 2013. *Material Logic.* Master of science in architecture, University of Washington.

BUEHLMANN, U. 1998. *Understanding the relationship of lumber yield and cutting bill requirements: a statistical approach.* PhD, Virginia Tech.

BUEHLMANN, U., WIEDENBECK, J. & KLINE, D. E. 1998. Character-marked furniture: Potential for lumber yield increase in rip-first rough mills. *Forest Products Journal,* 48**,** 43.

BUEHLMANN, U., WIEDENBECK, J. & KLINE, D. E. 1999. Character-marked furniture: potential for lumber yield increase in crosscut-first rough mills. *Solid Wood Products,* 49.

BUEHLMANN, U. & THOMAS, E. 2001. Lumber yield optimization software validation and performance review. *Robotics and Computer Integrated Manufacturing,* 17**,** 27-32.

BUEHLMANN, U. & THOMAS, D. E. 2002. Impact of human error on lumber yield in rough mills. *Robotics and Computer Integrated Manufacturing,* 18.

BUEHLMANN, U., WIEDENBECK, J. & KLINE, D. E. 2003. Effect of cutting bill requirements on lumber yield in rip-first rough mill. *Wood and Fiber Science,* 35.

BUEHLMANN, U., ZUO, X. & THOMAS, E. 2004. Linear programming and optimizing lumber quality composition in secondary hardwood dimension mills. *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture,* 218.

BUEHLMANN, U., LIHRA, T., RANCOURT, V. & AIT-KADI, D. 2007a. Detection capabilities of automated hardwood lumber defect-detection systems. *Forest Products Journal,* 57**,** 51-57.

BUEHLMANN, U., LIHRA, U., RANCOURT, T. & AIT-KADI, D. 2007b. Detection capabilities of automated hardwood lumber defect-detection systems. *Forest Products Journal,* 57**,** 51-57.

BUEHLMANN, U., KLINE, D. E., WIEDENBECK, J. & NOBLE, R. 2008a. The influence of cutting-bill requirements on lumber yield using a fractional-factorial design Part II. Correlation and number of part sizes. *Wood and Fiber Science,* 40.

BUEHLMANN, U., KLINE, D. E., WIEDENBECK, J. & NOBLE, R. 2008b. Validation of the standardized and simplified cutting bill. *Wood and Fiber Science,* 40**,** 202-213.

BUEHLMANN, U., ZUO, X. & THOMAS, E. 2010. Second-order polynomial model to solve the least-cost lumber grade mix problem. *Forest Products Journal,* 60**,** 69-77.

BUEHLMANN, U., BUCK, R. & THOMAS, R. E. 2011a. Integrated least-cost lumber grade-mix solver. *Proceedings of the 17th Central Hardwood Forest Conference.*

BUEHLMANN, U., THOMAS, R. E. & ZUO, X. 2011b. Cost minimization through optimized raw material quality composition. *Robotics and Computer-Integrated Manufacturing,* 27**,** 746-754.

BUEHLMANN, U. W., JANICE K.; NOBLE, R., JR.; KLINE, D. EARL 2008. Creating a standardized and simplified cutting bill using group technology. *Wood and Fiber Science,* 40.

BUMGARDNER, M., BUSH, R. & WEST, C. 2001a. Product development in large furniture companies: A desriptive model with implicaitons for character-marked products. *Wood and Fiber Science,* 33**,** 302-313.

BUMGARDNER, M., NICHOLLS, D. & BARBER, V. 2009. Character-marked furniture made from red alder harvested in southeast Alaska: product perspectives from consumers and retailers. *Canadian Journal of Forest Research,* 39**,** 2450-2459.

BUMGARDNER, M. S., BUSH, R. J. & WEST, C. D. 2000. Beyond yield improvement: Selected marketing aspects of character-marked furniture. *Forest Products Journal,* 50**,** 51-58.

BUMGARDNER, M. S., BUSH., R. J. & WEST, C. D. 2001b. Knots as an incongruent product feature: A demonstration of the potential for character-marked hardwood furniture. *Journal of the Institute of Wood Science,* 15**,** 327-335.

BURDON, R. D. 2010. Wood properities and genetic improvement of radiata pine. *New Zealand Journal of Forestry,* 55**,** 22-27.

BUTLER, D., BRUNNER, C. C. & FUNCK, J. W. 1989. A dual-threshold image sweep-and-mark algorithm for defect detection in veneer. *Forest Products Journal,* 39.

CHIANG, T. 1964. The feasibility of establishing finger-jointing operations in Georgia. The Georgia Department of Industry and Trade.

CHO, T., COMERS, R. W. & ARAMAN, P. A. 1990a. A computer vision system for analyzing images of rough hardwood lumber *Proceedings. 10th International Conference on Pattern Recognition.* Atlantic City.

CHO, T., CONNERS, R. & ARAMAN, P. A computer vision system for automated grading of rough hardwood lumber using a knowledge-based approach. 1990 IEEE International Conference on Systems, Man, and Cybernetics Conference Proceedings, 4-7 Nov. 1990 1990b. 345-350.

CHO, T., CONNERS, R. W. & ARAMAN, P. A computer vision system for analyzing images of rough hardwood lumber. Proceedings. 10th International Conference on Pattern Recognition, 16-21 June 1990 1990c. 726-728 vol.1.

ČIARNIENE, R. & VIENAZINDIENE, M. 2014. Management of contemporary fashion industry: characteristics and challenges. *Procedia - Social and Behavioral Sciences,* 156.

CLÉMENT, C., LIHRA, T., GAZO, R. & BEAUREGARD, R. 2006. Maximizing lumber use: The effect of manufacturing defects on yield, a case study. *Forest Products Journal,* 56**,** 60-65.

CONNERS, R. W., MCMILLIN, C. W., LIN, K. & VASQUEZ-ESPINOSA, R. 1983. Identifying and locating surface defects in wood: Part of an automated lumber processing system. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 5.

CONNERS, R. W., CHO, T.-H., NG, C. T., DRAYER, T. H., ARAMAN, P. A. & BRISBIN, R. L. 1992. A machine vision system for automatically grading hardwood lumber. *Industrial Metrology,* 2**,** 317-342.

CONNERS, R. W., KLINE, D. E., ARAMAN, P. & DRAYER, T. H. 1997a. Machine vision technology for the forest products industry. *Computer,* 30**,** 43-48.

CONNERS, R. W., KLINE, E. D., ARAMAN, P. & DRAYER, T. H. 1997b. Machine vision technology for the forest products industry. *Computer,* 30**,** 43-48.

DAVIES, I. & WATT, G. 2005. *Making the Grade- A guide to appearance grading in UK grown hardwood timber.,* 8 Campbell's Close, Edinburgh, Scottland, Arcamedia.

DAVIS, K. Optimized utilization of low-grade hardwood. Western Hardwood Association Annual Convention, September, 19-21 2019 Portland, OR.

DAWSON, B. S. W., PEARSON, H., KIMBERLEY, M. O., DAVY, B. & DICKSON, A. R. 2020. Effect of supercritical CO2 treatment and kiln drying on collapse in Eucalyptus nitens wood. *European Journal of Wood and Wood Products,* 78**,** 209-217.

DEAVER, M. 2006. *Economic feasibility of a solid hardwood panel manufacturing enterprise.* Masters of Science, North Carolina State University.

DERIKVAND, M., NOLAN, G., JIAO, H. & KOTLAREWSKI, N. 2016. What to do with structurally low-grade wood from Australia's plantation Eucalyptus; building applicaitons? *BioResources,* 12**,** 4-7.

DERIKVAND, M., KOTLAREWSKI, N., LEE, M., JIAO, H., CHAN, A. & NOLAN, G. 2018a. Visual stress grading of fibre-managed plantation Eucalypt timber for structural building applications. *Construction and Building Materials,* 167**,** 688-699.

DERIKVAND, M., KOTLAREWSKI, N., LEE, M., JIAO, H. & NOLAN, G. 2018b. Flexural and visual characteristics of fibre-managed plantation Eucalyptus globulus timber. *Wood Material Science & Engineering***,** 1-10.

DERIKVAND, M., KOTLAREWSKI, N., LEE, M., JIAO, H. & NOLAN, G. 2019. Characterisation of physical and mechanical properties of unthinned and unpruned plantation-grown *Eucalyptus nitens* H. Deane & Maiden Lumber. *Forests,* 10.

DESHMUKH, A. K. & SHINDE, B. G. 2006. Adaptive color image segmentation using fuzzy min-max clustering. *Engineering Letters,* 13.

DONOVAN, G. H. & NICHOLLS, D. 2003. Consumer preferences and willingness to pay for character-marked cabinets from Alaska birch. *Forest Products Journal,* 53**,** 27-32.

DOWNHAM, R. & GAVRAN, M. 2020. Ausralian plantation statistics 2020 update. ABARES, Canberra, June, CC BY 4.0. DOI.

DYCKHOFF, H. 1990. A typology of cutting and packing problems. *European Journal of Operations Research,* 44**,** 145-159.

ENGLERTH, G. & DUNMIRE, D. 1966. Programming for lumber yield. *Forest Products Journal,* 16.

ENGLERTH, G. & SCHUMANN, D. 1969. Charts for calculating dimension yields from hard maple lumber. Research Paper FPL 118. USDA Forest Service, Forest Products Laboratory, Madison, WI.

ESTEVEZ, P. A., FERNANDEZ, M., ALCOCK, R. J. & PACKIANATHER, M. S. Selection of features for the classification of wood board defects. 1999 Ninth International Conference on Artificial Neural Networks ICANN 99. (Conf. Publ. No. 470), 7-10 Sept. 1999 1999. 347-352 vol.1.

ESTÉVEZ, P. A., PEREZ, C. A. & GOLES, E. 2003. Genetic input selection to a neural classifier for defect classification of radiata pine boards. *Forest Products Journal,* 53.

FELL, D. 2004. Assessing preferences for wood characteristics in visual applications. *Value to Wood Program.* Forintek Canada Corp.

FILIPESCU, C. N., STOEHR, M. U. & PIGOTT, D. R. 2018. Variation of lumber properties in genetically improved full-sib families of Douglas-fir in British Columbia, Canada. *Forestry: An International Journal of Forest Research,* 91**,** 320-326.

FOREST PRODUCTS LABORATORY 2010. *Wood Handbook-Wood as an engineering material. General Technical Report,* Madison, WI: U.S., Department of Agriculture, Forest Service, Forest Products Laboratory.

FREUND, Y. & SCHAPIRE, R. E. 1997. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of Computer and System Sciences,* 55**,** 119-139.

FUNCK, J. W., ZHONG, Y., BUTLER, D. A., BRUNNER, C. C. & FORRER, J. B. 2003. Image segmentation algorithms applied to wood defect detection. *Computers and Electronics in Agriculture,* 41**,** 157-179.

GARUD, H., RAY, A. K., MAHADEVAPPA, M., CHATTERJEE, J. & MANDAL, S. 2014. A fast auto white balance scheme for digital pathology. *International Conference on Biomedical and Health Informatics***,** 153-156.

GATCHELL, C., J.; WIEDENBECK, JANICE K.; WALKER, ELIZABETH S. 1996a. The effects of crosscutting before gang-ripping on dimension part yields from no. 1 and 2A common red oak lumber. *Forest Products Journal,* 46.

GATCHELL, C. J. Impact of rough-mill practices on yields. *In:* WHITE, J. C., ed. Eastern Hardwood: the source, the industry, and the market, 1985 Harrisburg, PA. Forest Products Research Society, 146-156.

GATCHELL, C. J. 1987. Rethinking the design of the furniture rough mill. *Forest Products Journal,* 37.

GATCHELL, C. J. 1989. Recognizing interactions among lumber grading rules, gang-ripping technology, and industry needs could increase the use of No. 2 common lumber. *Forest Products Journal,* 39.

GATCHELL, C. J. 1996b. Designing a fixed-blade gang ripsaw arbor with a pencil. *Wood and Fiber Science,* 46.

GATCHELL, C. J. & THOMAS, E. 1997. Within-grade quality differences for 1 and 2A common lumber affect processing and yields when gang-ripping red oak lumber. *Forest Products Journal,* 47.

GATCHELL, C. J., THOMAS, E. & WALKER, E. 1997. 1998 Data bank for kiln-dried red oak lumber. Northeastern Research Station: United States Department of Agriculture, Forest Service.

GAZO, R., WELLS, L., KRS, V. & BENES, B. 2018. Validation of automated hardwood lumber grading system. *Computers and Electronics in Agriculture,* 155**,** 496-500.

GONZALEZ, R., WOODS, R. & EDDINS, S. L. 2010. *Digital Image Processing Using Matlab, Second Edition,* Upper Saddle River, New Jersey, Pearson Prentice Hall.

GONZALEZ, R. C., WOODS, R. E. & EDDINS, S. L. 2004. *Digital Image Processing Using MATLAB,* Upper Saddle River, New Jersey, Pearson Prentice Hall.

GRUENEBERG, T., THOMAS, E. & BUEHLMANN, U. 2012. ROMI 4.0: Updated rough mill simulator. *Forest Products Journal,* 62**,** 373-377.

GU, I. Y. H., ANDERSSON, H. & VICEN, R. Automatic classification of wood defects using support vector machines. 2009 Berlin, Heidelberg. Springer Berlin Heidelberg, 356-367.

HALLOCK, H. & BUGRIN, E. 1970. Tomorrow: Computer-made sawing decisions? *Forest Products Journal,* 20**,** 52-56.

HALLOCK, H. & GALIGER, L. 1971. Grading hardwood lumber by computer. *Research paper FPL-157.* Madison, WI, US Department of Agriculture, Forest Service: Forest Products Laboratory.

HASHIMA, U. R., HASHIMB, S. Z. & MUDAA, A. K. 2015. Automated inspection of timber surface: a review *Jurnal Teknologi,* 77**,** 127-135.

HITTAWE, M. M., MUDDAMSETTY, S. M., SIDIBÉ, D. & MÉRIAUDEAU, F. Multiple features extraction for timber defects detection and classification using SVM. 2015 IEEE International Conference on Image Processing (ICIP), 27-30 Sept. 2015 2015. 427-431.

HMR 2019. Hardwood Market Report, August 23, 2019. Volume XCVII, No. 34.

HOADLEY, R. B. 2000. *Understanding Wood: A Craftsman's Guide to Wood Technology*, The Taunton Press.

HØIBØ, O. & NYRUD, A. Q. 2010. Consumer perception of wood surfaces: the relationship between stated preferences and visual homogeneity. *Journal of Wood Science,* 56**,** 276-283.

HOWARD, J. & LIANG, S. 2019. United State Forest Products Annual Market Review and Prospects, 2015-2019. Forest Products Laboratory, Madison, Wisconsin, USA.

HU, C., TANAKA, C. & OHTANI, T. 2003. Locating and identifying splits and holes on sugi by the laser displacement sensor. *Journal of Wood Science,* 49.

HU, C., TANAKA, C. & OHTANI, T. 2004. Locating and identifying sound knots and dead knots on sugi by the rule-based color vision system. *Journal of Wood Science,* 50**,** 115-122.

HUBBE, M. A. & BUEHLMANN, U. 2010. A continuing reverence for wood. *BioResources,* 5**,** 1-2.

HUBER, H., MCMILLIN, C. W. & MCKINNEY, J. 1985. Lumber defect detection abilites of furniture rough mill employees. *Forest Products Journal,* 35.

IVKOVIĆ, M., WU, H. X., MCRAE, T. A. & MATHESON, C. A. 2006a. Developing breeding objectives for radiata pine structural wood production. II. Sensitivity analyses. *Canadian Journal of Forest Research,* 36**,** 2932-2942.

IVKOVIĆ, M., WU, H. X., MCRAE, T. A. & POWELL, M. B. 2006b. Developing breeding objectives for radiata pine structural wood production. I. Bioeconomic model and economic weights. *Canadian Journal of Forest Research,* 36**,** 2920-2931.

IWASAKI, S. & SADOH, T. 1991. Measurements of knots in hinoki sugi lumbers by optical scanning method. *Journal of Japan Wood Research Society,* 37.

JABO, S. 2011. *Machine Vision for Wood Defect Detection and Classification.* Masters of Science, Chalmers University of Technology.

JIAO, H., NOLAN, G., LEE, M., KOTLAREWSKI, N. & DERIKVAND, M. 2019. Developing high-mass laminated flooring products from fibre-managed plantation hardwood. Forests and Wood Products Australia (FWPA).

KAUPPINEN, H. 1999. *Development of a color machine vision method for wood surface inspection.* PhD, Oulu University.

KAUPPINEN, H., RAUTIO, H. & SILVEN, O. Non-segmenting defect detection and SOM based classification for surface inspection using color vision. Conference on Polarization and color techniques in industrial inspection, June, 17-18 1999 Munich, Germany.

KELLY, M., TREDINNICK, J., CUTBUSH, G. & MARTIN, G. 2005. *Impediments to investment in long rotation timber plantations* Melbourne, Vic, Forest and Wood Products Research and Development Corporation.

KIM, C.-W. & KOIVO, A. J. 1994. Hierarchical classification of surface defects on dusty wood boards. *Pattern Recognition Letters,* 15**,** 713-721.

KIM, C. & KOIVO, A. 1990. Hierarchical classification of surface defects on dusty wood boards. *Pattern Recognition Letters,* 15**,** 713-721.

KIM, C. W. 1985. *Classification of surface defects on wood boards.* PhD, Purdue University.

KLINE, D. E., CONNERS, R. W. & ARAMAN, P. 1997. Scanning hardwood lumber for processing and grading-what to do now and why. *7th International conference on scanning technology and process optimization for the wood products industry.* Charlotte, North Carolina.

KLINE, D. E., WIDOYOKO, A., WIEDENBECK, J. & ARAMAN, P. 1998a. Performance of color camera-based machine vision system in automated furniture rough mill systems. *Forest Products Journal,* 48**,** 38-45.

KLINE, D. E., WIDOYOKO, A., WIEDENBECK, J. & ARAMAN, P. 1998b. Performance of color camera machine vision in automated furniture rough mill systems. *Forest Products Journal,* 48**,** 38-45.

KLINE, D. E., SURAK, C. & ARAMAN, P. 2003. Automated hardwood lumber grading utilizing a multiple sensor machine vision technology. *Computers and Electronics in Agriculture,* 41**,** 139-155.

KLINKACHORN, P., KOTHARI, R., ANNAVAJJHALA, R. & MCMILLIN, C. 1994. Enhancement of the computer lumber grading program to support polygonal defects. *Forest Products Journal,* 42**,** 41-46.

KOHAVI, R. & PROVOST, F. 1998. Glossary of Terms. Editorial for the special issue on application of machine learning and the knowledge of discovery process. *Machine Learning,* 30.

KOIVO, A. & KIM, C. Parameter estimation of CAR models for classifying wood boards. Proceedings of the 1988 IEEE International Conference on Systems, Man, and Cybernetics, 1988. 1376-1379.

KOIVO, A. J. & KIM, C. W. 1989. Automatic classification of surface defects on red oak boards. *Forest Products Journal,* 39**,** 22-30.

KOJIMA, M., YAMAMOTO, H., YOSHIDA, M., OJIO, Y. & OKUMURA, K. 2009. Maturation property of fast-growing hardwood plantation species: A view of fiber length. *Forest Ecology and Management,* 257**,** 15-22.

KOTLAREWSKI, N., LEE, M. & NOLAN, G. 2017. Grade-reducing features in timber products. *New Zealand Journal of Forestry,* 62**,** 33-35.

KOTLAREWSKI, N., TAYLOR, L. & BOOTH, P. 2018. Embracing natural timber features of plantation hardwood: Material-aware digital workflows in product design and development. *In:* PRIYADARSINI RAJAGOPALAN & ANDAMON, M. M. (eds.) *52nd International Conference of the Architectural Science Association (ANZAScA), Engaging Architectural Science: Meeting the Challenges of Higher Density.* Melbourne, Australia.

KOTLAREWSKI, N., DERIKVAND, M., LEE, M. & WHITEROAD, I. 2019. Machinability study of Australia's dominate plantation timber resources. *Forests,* 10**,** 805.

KOTSIANTIS, S. B. 2007. Supervised Machine Learning: A Review of Classification Techniques. *Proceedings of the 2007 conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Applications in eHealth, HCI, Information Retrieval and Pervasive Technologies.* IOS Press.

KRETSCHAMANN, D. E. & HERNANDEZ, R. 2006. Grading timber and glued structural members *In:* WALKER, J. C. F. (ed.) *Primary Wood Processing.* Springer Netherlands.

LAMB, F. M., WENGERT, E. M., ARAMAN, P. A., AVELLAR, B., KAMKE, F. A., MUENCH, J. & WHITE, M. S. 1990. Industrial Development Opportunities For Wood Products In Virginia.

LESLIE, D. & REIMER, S. 2003. Fashioning furniture: restructuring the furniture commodity chain. *Area,* 35**,** 427-437.

LIHRA, T., BUEHLMANN, U. & BEAUREGARD, R. 2008. Mass customisation of wood furniture as a competitive strategy. *International Journal of Mass Customisation,* 2**,** 200-215.

LIU, X., DENG, Z. & YANG, Y. 2019. Recent progress in semantic image segmentation. *Artificial Intelligence Review,* 52**,** 1089-1106.

LOTT, R. & GOODING, G. Eucalypt plantations for solid-wood products in Southern Australia: A review of research investment needs. Plantation Eucalypts for high-value timber: Embracing investment through research and development, 9-12 October 2007 2007 Moorabin, Victoria.

LU, Q., SRIKANTESWARA, S., KING, W., DRAYER, T., CONNERS, R., KLINE, E. & ARAMAN, P. Machine vision system for color sorting wood edge-glued panel parts. 23rd International Conference on Industrial Electronics, Control, and Instrumentation Volume 3 of 4 Emerging Technologies Factory Automation Robotics, Vision, and Sensors, 1997.

LUO, W. & SUN, L. 2019. An improved binarization algorithm of wood image defect segmentation based on non-uniform background. *Journal of Forestry Research*.

LUPPOLD, W. & BUMGARDNER, M. 2003. What is low-value and/or low-grade hardwood? *Forest Products Journal,* 53(3).

LUPPOLD, W. & BUMGARDNER, M. 2004. An examination of eastern US hardwood roundwood markets. *Forest Products Journal,* 54.

LUPPOLD, W. & BUMGARDNER, M. 2007. Examination of lumber price trends for major hardwood species. *Wood and Fiber Science,* 39.

LUPPOLD, W. & PUGH, S. 2016. Diversity of the eastern hardwood resource and how this diversity influences timber utilization. *Forest Products Journal,* 66**,** 58-65.

LYCKEN, A. 2006a. *Appearance Grading of Sawn Timber.* PhD, Luleå University of Technology Skeria 3, S-931 87 Skellefteå, Sweden.

LYCKEN, A. 2006b. Comparison between automatic and manual quality grading of sawn softwood. *Forest Products Journal,* 56.

LYCKEN, A. 2006c. Comparison between automatic and manual quality grading of sawn softwood. *Forest Products Journal,* 56**,** 13-18.

LYCKEN, A. & OJA, J. 2006. A multivariate approach to automatic grading of Pinus sylvestris sawn timber. *Scandinavian Journal of Forest Research,* 2006 v.21 no.2**,** pp. 167-174.

MACHADO, J. S., LOUZADA, J. L., SANTOS, A. J. A., NUNES, L., ANJOS, O., RODRIGUES, J., SIMÕES, R. M. S. & PEREIRA, H. 2014. Variation of wood density and mechanical properties of blackwood (Acacia melanoxylon R. Br.). *Materials & Design (1980-2015),* 56**,** 975-980.

MANUEL, A., LEONHART, R., BROMAN, O. & BECKER, G. 2015. Consumers' perceptions and preference profiles for wood surfaces tested with pairwise comparison in Germany. *Annals of Forest Science,* 72**,** 741-751.

MANUEL, A., LEONHART, R., BROMAN, O. & BECKER, G. 2016. How do consumers express their appreciation of wood surfaces? Norway spruce floors in Germany as an example. *Annals of Forest Science,* 73**,** 703-712.

MASUDA, M. & NAKAMURA, M. 1987. Influence of knots on psychological images of panels. *Bulletion of Kyoto Univeristy Forests,* 59.

MASUDA, M. 1992. Visual characteristics of wood and the psychological images. *Japanese Journal of Wood Science,* 38**,** 1075-1081.

MCCONNELL, E. 2016. White Oak Quality index, 2016. *Wood Products Notes.* NC State Extension Publications

MCDANIEL, P. 2003. *Opportunities for utilization of non-traditional species in wood-based component manufacturing.* Master Thesis, Virginia Polytechnic institute and State University.

MCGAVIN, R., BAILLERES, H., FEHRMANN, J. & OZARSKA, B. 2015. Stiffness and density analysis of rotary veneer recovered from six species of Australian plantation hardwoods. *BioResources,* 10**,** 6395-6416.

MITCHELL, H. L., WIEDENBECK, J. & AMMERMAN, B. 2003. Rough mill improvement guide for managers and supervisors. Northeastern Research Station United States Department of Agriculture.

MOODY, J. G., CHARLES J.; WALKER, ELIZABETH S.; KLINKHACHORN, POWSIRI 1998a. An introduction to UGRS: the ultimate grading and remanufacturing system. *Forest Products Journal,* 48**,** 45-50.

MOODY, J. G., CHARLES J.; WALKER, ELIZABETH S.; KLINKHACHORN, POWSIRI 1998b. User's guide to UGRS: the Ultimate Grading and Remanufacturing System (version 5.0). *Gen. Tech. Rep. NE-254.* Radnor PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 40 p.

MOREIRA, M. P., LIHRA, T., D´AMOURS, S. & BEAUREGARD, R. 2008. Implementation of mass customization in a furniture manufacturing plant: the case of Shermag Inc. CIRRELT.

MOTSENBOCKER, W. D., P.H. STEELE, S.L. HUNTER, S.H. BULLARD, A. SCHULER 2005. Wood furniture components: Implementation of flow-line technology based on lean manufacturing concepts. Forest and Wildlife Research Center, Bulletin FP333, Mississippi State University, 15p.

MÜLLER, F., JAEGER, D. & HANEWINKEL, M. 2019. Digitization in wood supply – A review on how Industry 4.0 will change the forest value chain. *Computers and Electronics in Agriculture,* 162**,** 206-218.

NAKAMURA, M., MASUDA, M. & HIRAMATSU, Y. 1994. Visual factors influencing psychological images of wood and stones. *Japanese Journal of Wood Science,* 40**,** 364-376.

NAKAMURA, M. & MASUDA, M. 1995. Visual characteristics of shadings in edge-grain patterns. *Japanese Journal of Wood Science,* 41**,** 301-308.

NAKAMURA, M., MASUDA, M. & SHINOHARA, K. 1999. Multiresolutional image analysis of wood and other materials. *Jounal of Wood Science,* 45**,** 10-18.

NHLA 2014. National Hardwood Lumber Association. *Rules for the Measurement and Inspection of Hardwood and Cypress.* Memphis, TN: National Hardwood Lumber Association.

NICHOLLS, D., PARRENT, D. & PAVIA, K. J. 2004a. The potential for developing alternate grading rules for birch lumber in Alaska. *Forest Products Journal,* 54.

NICHOLLS, D., PARRENT, D. & PAVIA, K. J. 2004b. The potential for developing alternate grading rules for birch lumber in Alaska. *Forest Products Journal,* 54**,** 57-60.

NICHOLLS, D. & ROOS, J. 2006. Lumber attributes, characteristics, and species preferences as indicated by secondary wood products firms in the continental United States. *Holz als Roh- und Werkstoff*.

NICHOLLS, D. & BUMGARDNER, M. 2007. Evaluating selected demographic factors related to consumer preferences for furniture from commercial and from underutilized species. *Forest Products Journal,* 57**,** 79-82.

NICHOLLS, D., FUNCK, J. W., BRUNNER, C. & REEB, J. 2009. Influence of edging practices on cutting yield of Alaska birch lumber. *Forest Products Journal,* 59.

NICHOLLS, D., BUMGARDNER, M. & BARBER, V. 2013. Consumer and manufacturer perceptions of hardwood panels made from character-marked lumber. *International Wood Products Journal,* 1**,** 28-34.

NICHOLLS, D. & BUMGARDNER, M. 2015. Low-grade and character-marked hardwoods: A research review and synthesis of solid wood manufacturing and marketing. *The Forestry Chronicle,* 91**,** 548-559.

NICHOLLS, D. & BUMGARDNER, M. 2018. Challenges and opportunities for North American hardwood manufacturers to adopt customization strategies in an era of increased competition. *Forests,* 9**,** 186.

NICHOLLS, D. L., DONOVAN, G. H. & ROOS, J. 2004c. Consumer preferences for kitchen cabinets made from red alder: A comparison to other hardwoods. *Wood and Fiber Science,* 36**,** 432-442.

NICHOLLS, D. L. & BARBER, V. 2010. Character-marked Red Alder lumber from Southeastern Alaska: Profiled panel product preferences by residential consumers. *Forest Products Journal,* 60**,** 315-321.

NISBET, R., ELDER, J. I. V. & MINER, G. 2009. *Handbook of Statistical Analysis and Data Mining Applications,* San Diego, UNITED STATES, Elsevier Science & Technology.

NISBET, R., MINER, G. & YALE, K. 2018. Chapter 9 - Classification. *In:* NISBET, R., MINER, G. & YALE, K. (eds.) *Handbook of Statistical Analysis and Data Mining Applications (Second Edition).* Boston: Academic Press.

NISKANEN, M., SILVEN, O. & KAUPPINEN, H. 2001. Color and texture based wood inspection with non-supervised clustering. Oulu, Finland: University of Oulu.

NOLAN, G. 1998. Specifying natural feature timber. Center for Sustainable Architecture with Wood: University of Tasmania.

NOLAN, G., GREAVES, B., WASHUSEN, R., PARSONS, M. & JENNINGS, S. 2005. Eucalypt plantations for solid wood products in Australia- A review. Forest and Wood Products Research and Development Corporation.

NORDVIK, E. & BROMAN, O. Visualising the Qualities of Wood. Luleå University of Technology Division of Wood Technology 931 81 SKELLEFTEÅ SWEDEN.

NORDVIK, E., SCHUTTE, S. & BROMAN, O. 2009. People's perceptions of the visual appearance of wood flooring: A Kansei engineering approach. *Forest Products Journal,* 59.

NORTHWOOD DESIGNS, I. 2018. *SlabSmith* [Online]. Available: slabsmith.com [Accessed December 3 2018].

OLOFSSON, L., BROMAN, O., SKOG, J., FREDRIKSSON, M. & SANDBERG, D. 2019. Multivariate product adapted grading of Scots pine sawn timber for an industrial customer, part 1: Method development. *Wood Material Science & Engineering***,** 1-9.

OZANNE, L. K. & SMITH, P. M. 1996. Consumer segments for environmentally marketed wooden household furniture *Wood and Fiber Science* 28**,** 461-477.

OZARSKA, B. 1998. A review of current research of native Australian species for value-added opportunities. *Forest Products Journal,* 48.

PEPKE, E. 1980. *Analysis of rough mill practices.* Michigan State Univesity, East Lansing, MI.

PERERA, A. 1994. *The influence of lumber characteristics on productivity of crosscut-first rough mills.* Master's, Mississippi State Universality, Mississippi State, MS.

PHAM, D. T. & ALCOCK, R. J. 1998. Automated grading and defect detection: A review. *Forest Products Journal,* 48**,** 34.

PHAM, D. T., ELDUKHRI, E. E., SOROKA, A. J., RUZA, G. A. & ESTÉVEZA, P. A. 2005. Image segmentation using fuzzy min-max neural networks for wood defect detection. *Intelligent Production Machines and Systems*.

PITTI, A., ESPINOZA, O. & SMITH, R. 2020. The case for urban and reclaimed wood in the circular economy. *Bioresources,* 15.

PRAK, A. & MYERS, T. 1981. *Furniture Manufacturing Processes,* North Carolina State University

PRASETYO, V., BELLEVILLE, B., OZARSKA, B. & MO, J. 2019. A wood recovery assessment method comparison between batch and cellular production systems in the furniture industry. *Journal of ASTM International,* 3**,** 1-17.

PRASETYO, V. E., BELLEVILLE, B., AND OZARSKA, B. 2018. A proposed method and its development for wood recovery assessment in the furniture manufacturing process. *BioResources,* 13**,** 3846-3867.

RAMAGE, M. H., BURRIDGE, H., BUSSE-WICHER, M., FEREDAY, G., REYNOLDS, T., SHAH, D. U., WU, G., YU, L., FLEMING, P., DENSLEY-TINGLEY, D., ALLWOOD, J., DUPREE, P., LINDEN, P. F. & SCHERMAN, O. 2017. The wood from the trees: The use of timber in construction. *Renewable and Sustainable Energy Reviews,* 68**,** 333-359.

REYNOLDS, H. W. G., CHARLES J. 1979. Marketing low-grade hardwoods for furniture- a new approach. *Forest Service Research Paper NE-444.* Forest Service, U.S. Department of Agriculture, .

RIEKKINEN, M., LUKKARINEN, A., LINDSTRÖM, H. & VERKASALO, E. Timber assortments and selected aesthetic wood properties of Nordic Scots pine. Proceedings of Forestry Woodchain Conference, 2004 Edinburgh 28-30 September.

RINNHOFER, A., JAKOB, G., E.DEUTSCHL, BENESOVA, W., ANDREU, J., PARZIALE, G. & NIEL, A. 2005. A multi-sensor system for texture based high-speed hardwood lumber inspection. *Image Processing: Algorithms and Systems IV.* San Jose, California, USA.

SANDAK, J. 2017. Implementation and calibration of prediction models of log/biomass quality classes and report on the validation procedure. SLOPE- Integrated processing and control systems for sustainable production in mountain ares.

SCHUMANN, D. & ENGLERTH, G. 1967. Dimension stock yields of specific width cuttings from 4/4 hard maple lumber. Research Paper FPL 85. USDA Forest Service, Forest Products Laboratory, Madison, WI.

SHANKS, J., BOOTH, P. & NOLAN, G. Re-emerging Designer-maker roles in digital design and construction with timber. *In:* MADEO, F. & SCHNABEL, M. A., eds. Across: Architectural Research through to Practice: 48th International Conference of the Architectural Science Association 2014, 2014. The Architectural Science Association and Geneva University Press, 469-478.

SHUPE, T. & VLOSKY, R. 2010. Why and how to market wood products. Louisiana Forest Products Development Center, School of Renewable Natural Resources.

SILK, J. W. F., ARROYO-RODRÍGUEZ, V., AIBA, S.-I., ALVAREZ-LOAYZA, P., ALVES, L. F., ASHTON, P., BALVANERA, P., BASTIAN, M. L., BELLINGHAM, P. J., VAN DEN BERG, E., BERNACCI, L., DA CONCEIÇÃO BISPO, P., BLANC, L., BÖHNING-GAESE, K., BOECKX, P., BONGERS, F., BOYLE, B., BRADFORD, M., BREARLEY, F. Q., HOCKEMBA, M. B., BUNYAVEJCHEWIN, S., MATOS, D. C. L., CASTILLO-SANTIAGO, M., CATHARINO, E. L. M., CHAI, S.-L., CHEN, Y., COLWELL, R. K., ROBIN, C. L., CLARK, C., CLARK, D. B., CLARK, D. A., CULMSEE, H., DAMAS, K., DATTARAJA, H. S., DAUBY, G., DAVIDAR, P., DEWALT, S. J., DOUCET, J.-L., DUQUE, A., DURIGAR, G., EICHHORN, K. A. O., EISENLOHR, P. V., ELER, E., EWANGO, C., FARWIG, N., FEELEY, K. J., FERREIRA, L., FIELD, R., DE OLIVEIRA FILHO, A. T., FLETCHER, C., FORSHED, O., FRANCO, G., FREDRIKSSON, G., GILLESPIE, T., GILLET, J.-F., AMARNATH, G., GRIFFITH, D. M., GROGAN, J., GUNATILLEKE, N., HARRIS, D., HARRISON, R., HECTOR, A., HOMEIER, J., IMAI, N., ITOH, A., JANSEN, J. A., JOLY, C. A., DE JONG, B. H. J., KARTAWINATA, K., KEARSLEY, E., KELLY, D. L., KENFACK, D., KESSLER, M., KITAYAMA, K., KOOYMAN, R., LARNEY, E., LAUMONIER, Y., LAURANCE, S., LAURANCE, W. F., LAWES, M. J., DO AMARAL, I. L., LETCHER, S. G., LINDSELL, J., LU, X., MANSOR, A., MARJOKORPI, A., MARTIN, E. H., MEILBY, H., MELO, F. P. L., METCALFE, D. J., MEDJIBE, V. P., METZGER, J. P., MILLET, J., MOHANDASS, D., MONTERO, J. C., DE MORISSON VALERIANO, M., MUGERWA, B., NAGAMASU, H., NILUS, R., OCHOA-GAONA, S., et al. 2015. *An estimate of the number of tropical tree species*.

SILVEN, O., NISKANEN, M. & KAUPPINEN, H. 2003. Wood inspection with non-supervised clustering. *Machine Vision and Applications,* 13**,** 275-285.

SIMPSON, E. H. 1949. Measurement of Diversity. *Nature,* 163**,** 688-688.

SMITH, B. P. S. J. W. R. L. 2004. Opportunities for expanded and higher value utilization of No. 3A Common hardwood lumber. *Forest Products Journal,* 54**,** 77-85.

SOBEY, P. J. & SEMPLE, E. C. 1989. Detection and sizing visual features in wood using tonal measures and a classification algorithm. *Pattern Recognition,* 22**,** 367-380.

SOKOLOVA, M. & LAPALME, G. 2009. A systematic analysis of performance measures for classification tasks. *Information Processing & Management,* 45**,** 427-437.

SPESSERT, D. 2017. NHLA 2019 Rules change proposals & current US Hardwood markets.

STEELE, P. H. W., JAN; SHMULSKY, RUBIN; PERERA, ANURA 1999. The influence of lumber grade on machine productivity in the rough mill. *Forest Products Journal,* 49.

STERN, P. & MCDONALD, K. 1978. Computer optimization of cutting yield from multiple-ripped boards. USDA Forest Service, Forest Products Laboratory, Madison, WI.

STIESS, T. 2010. *Information Sharing in the Hardwood Supply Chain.* Ph.D., Virginia Polytechnic Istitute and State University.

SUVEER, A. 2015. PerformAWB. Uppsala University, Sweden.

TAN, P.-N., STEINBACH, M., KARPATNE, A. & KUMAR, V. 2018. *Introduction to Data Mining (2nd Edition)*, Pearson.

TEISCHINGER, A. 2006. Kundenorientierte und ressourceneffiziente Fertigung von Holzprodukten am Beispiel einer Parkettfabrikation. Institut für Holzforschung, BOKU Wien.

TEPPER, C. Site matching and establishing Eucalypt sawlog species in Southern Australia. Plantation Eucalypts for high-value timber: Enhancing investment through research and development, 9-12 Ocotber 2007 Moorabin, Victoria.

THOMA, M. 2016. A Survey of Semantic Segmentation. Available: https://ui.adsabs.harvard.edu/abs/2016arXiv160206541T [Accessed February 01, 2016].

THOMAS, D. E. 2017. An artificial neural network for real-time hardwood lumber grading. *Computers and Electronics in Agriculture,* 132.

THOMAS, E. 1996. Prioritizing parts from cutting bills when gang-ripping first. *Forest Products Journal,* 46.

THOMAS, E. & BUEHLMANN, U. 2002. Validation of the ROMI-RIP rough mill simulator. *Forest Products Journal,* 52**,** 23-29.

THOMAS, E. & BUEHLMANN, U. 2003. Performance review of the ROMI-RIP rough mill simulator. *Forest Products Journal,* 53**,** 80-85.

THOMAS, E. & WEISS, J. 2006. Rough mill simulator version 3.0: analysis tool for refining rough mill operations. *Forest Products Journal,* 56.

THOMAS, E. & BUEHLMANN, U. Using low-grade hardwoods for CLT production: A yield analysis. International Scientific Confernence on Hardwood Processing, 2015.

THOMAS, E., GRUENEBERG, T. & BUEHLMANN, U. 2015. ROMI 4.0: Rough mill simulator 4.0 users manual. Northern Research Station.

THOMAS, E. & BUEHLMANN, U. 2016. Potential for yield improvement in combined rip-first and crosscut-first rough mill processing. *BioResources,* 11**,** 1477-1493.

THOMAS, R. E., ESPINOZA, O. & BUEHLMANN, U. Improving lumber yield using a dual system. Proceedings of the 24th International Conference on Flexible Automation & Intelligent Manufacturing FAIM 2014, 2014 2014 May 20-23; San Antonio. TX. Lancaster, PA: DEStech Publications: 771-776: DEStech Publications, Inc.

TIAN, K., XA, TEPPER, BEARDEN, W., XA, O, HUNTER, G., XA & L 2001. Consumers’ Need for Uniqueness: Scale Development and Validation. *Journal of Consumer Research,* 28**,** 50-66.

TODOROKI, C. L., LOWELL, E. C. & DYKSTRA, D. 2010. Automated knot detection with visual post-processing of Douglas-fir veneer images. *Computers and Electronics in Agriculture,* 70**,** 163-171.

UM, J. 2017. Improving supply chain flexibility and agility through variety management. *International Journal of Logistics Management,* 28**,** 464-487.

VENKATACHALAPATHY, S. M. A. K. 2012. Wood Knot Classification using Bagging. *International Journal of Computer Applications,* 51.

WALKER, J. 2013. Wood Quality: A Perspective from New Zealand. *Forests,* 4**,** 234.

WANG, Q., SHI, G. & CHAN-HALBRENDT, C. 2004. Market potential for fine furniture manufactured from low-grade hardwood: Evidence from a conjoint analysis in the northeastern United States. *Forest Products Journal,* 54**,** 19-25.

WANG, Y., WANG, H. & MO, L. Research on recognition of wood texture based on integrated neural network classifier. 2010 International Conference on Intelligent Control and Information Processing, 13-15 Aug. 2010 2010. 512-515.

WASHUSEN, R. & WAUGH, G. 1999. Timber Processing and Products. *The Farmer's Log*.

WASHUSEN, R., REEVES, K. H., R., DAVIS, S., MENZ, D. & MORROW, A. 2004. Processing pruned and unpruned Eucalyptus globulus managed for sawlog production to produce high value products. *Forest and Wood Products Research and Development Corporation Report PN03.1315.* Melbourne, Australia.

WEIDENHILLER, A. & DENZLER, J. K. 2014. On the suitability of colour and texture analysis for detecting the presence of bark on a log. *Computers and Electronics in Agriculture,* 106**,** 42-48.

WEINFURTER, S. & HANSEN, E. 1999. Softwood lumber quality requirements: examining the supplier/buyer perception gap. *Wood and Fiber Science,* 1.

WENGERT, E. M. & LAMB, F. M. 1994. A handbook for improving quality and efficiency in rough mill operations: practical guidelines, examples, and ideas. R. C. Byrd Hardwood Technology Center, Princeton, WV.

WEST, C. D. & HANSEN, B. G. 1996. Informal yet sleek furniture please. *Asian Furniture* 2**,** 16-21.

WHEILER, K. 2019. Western Hardwood Export Markets & Impact of China's Tariffs. *Western Hardwood Association Annual Convention.* Portland, Or.

WIEDENBECK, J. & BUEHLMANN, U. Character-marked furniture: The yield picture. Proceedings of the twenty-third Annual Hardwood Symposium of the Hardwood Research Council, 1995. 85-90.

WIEDENBECK, J. & THOMAS, E. 1995. Don't gamble your fortunes--focus on rough mill yield. *Wood & Wood Products,* 100**,** 148.

WIEDENBECK, J., P. SHEPLEY, B. & SMITH, R. 2004. Rough-mill yield and cutting deficiency for No. 3A Common lumber compared to other lumber grade mix options. *Forest Products Journal,* 54**,** 132-140.

WILHELM, S. 1994. Operating in a high-cost hardwood lumber environment. *Wood and Wood Products.,* 99**,** 237-238.

XIAO, X. 1998. *A multiple sensor approach to wood defect detection.* PhD, Virginia Polytechnic Institute.

YANG, J., XIAO, J., FU, W., CHEN, J., YAN, L. & WANG, S. 2017. Image processing and identification of lumber surface knots. *Acta Techina,* 62**,** 99-108.

ZIADI, A., NTAWINIGA, F. & MALDAGUE, X. Neural networks for color Image segmentation: application to sapwood assessment. 2007 Canadian Conference on Electrical and Computer Engineering, 22-26 April 2007 2007a. 417-420.

ZIADI, A., NTAWINIGA, F. & MALDAGUE, X. 2007b. Neural networks for color image segmentation: application to sapwood assessment. *Canadian Conference on Electrical and Computer Engineering.*

ZOBEL, B. 1984. The changing quality of the world wood supply. *Wood Science Technology,* 18**,** 1-17.

ZOBEL, B. J. & SPRAGUE, J. R. 2012. *Juvenile Wood in Forest Trees*, Springer Berlin Heidelberg.