Extraction of Vegetation Biophysical Structure from Small-Footprint Full-Waveform Lidar Signals

Paul Romanczyk

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Extraction of Vegetation Biophysical Structure from Small-Footprint Full-Waveform Lidar Signals

by

Paul Romanczyk

B.S. Rochester Institute of Technology, 2009

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Chester F. Carlson Center for Imaging Science College of Science Rochester Institute of Technology

July 27, 2015

Signature of the Author

Accepted by

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The Ph.D. Degree Dissertation of Paul Romanczyk has been examined and approved by the dissertation committee as satisfactory for the dissertation required for the Ph.D. degree in Imaging Science.

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Dr. Scott Brown Date
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Paul Romanczyk

Submitted to the Chester F. Carlson Center for Imaging Science in partial fulfillment of the requirements for the Doctor of Philosophy Degree at the Rochester Institute of Technology

Abstract

The National Ecological Observatory Network (NEON) is a continental scale environmental monitoring initiative tasked with characterizing and understanding ecological phenomenology over a 30-year time frame. To support this mission, NEON collects ground truth measurements, such as organism counts and characterization, carbon flux measurements, etc. To spatially upscale these plot-based measurements, NEON developed an airborne observation platform (AOP), with a high-resolution visible camera, next-generation AVIRIS imaging spectrometer, and a discrete and waveform digitizing light detection and ranging (lidar) system. While visible imaging, imaging spectroscopy, and discrete lidar are relatively mature technologies, our understanding of and associated algorithm development for small-footprint full-waveform lidar are still in early stages of development. This work has as its primary aim to extend small-footprint full-waveform lidar capabilities to assess vegetation biophysical structure.

In order to fully exploit waveform lidar capabilities, high fidelity geometric and radiometric truth data are needed. Forests are structurally and spectrally complex, which makes collecting the necessary truth challenging, if not impossible. We utilize the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model, which provides an environment for radiometric simulations, in order to simulate waveform lidar signals. The first step of this research was to build a virtual forest stand based on Harvard Forest inventory data. This scene was used to assess the level of geometric fidelity necessary for small-footprint waveform lidar simulation in broadleaf forests. It was found that leaves have the largest influence on the backscattered signal and that there is little contribution to the signal from the leaf stems and twigs. From this knowledge, a number of additional realistic and abstract virtual “forest” scenes were created to aid studies assessing the ability of waveform lidar systems to extract biophysical phenomenology. We developed an additive model, based on these scenes, for correcting the attenuation in backscattered signal caused by the canopy. The attenuation-corrected waveform, when coupled with estimates of the leaf-level reflectance, provides a measure of the complex within-canopy forest structure. This work has implications for our improved understanding of complex waveform lidar signals in
forest environments and, very importantly, takes the research community a significant step closer to assessing fine-scale horizontally- and vertically-explicit leaf area, a holy grail of forest ecology.
Acknowledgements

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# Contents

**Foreword** i
- Declaration .................................................. i
- Approval ....................................................... ii
- Abstract ....................................................... iv
- Acknowledgements .......................................... vi
- Table of Contents ........................................... ix
- List of Figures ............................................... xi
- List of Tables ................................................ xii
- Glossaries ..................................................... xii
- List of Acronyms ............................................. xii
- List of Institutions .......................................... xv
- List of OnyxTREE components ................................ xvi
- List of Species ............................................... xvii
- List of Roman Symbols ....................................... xviii
- List of Greek Symbols ........................................ xxi

## 1 Introduction
1.1 Motivation .................................................. 1
1.2 Objectives ................................................... 5
1.3 Layout ....................................................... 6
1.4 Associated Publications and Presentations .................. 6

## 2 Background
2.1 Forest Inventory ............................................ 8
- 2.1.1 Basic Forest Inventory .................................. 8
- 2.1.2 Leaf Area Index ....................................... 9
- 2.1.3 Plant Area Index ...................................... 11
2.2 Lidar ......................................................... 11
- 2.2.1 Lidar Mathematics ..................................... 16
- 2.2.2 Discrete Lidar ......................................... 24
- 2.2.3 Waveform Lidar ....................................... 25
- 2.2.4 Photon Counting Lidar ................................. 28
2.3 DIRSIG ....................................................... 29
- 2.3.1 DIRSIG simulations .................................... 30
- 2.3.2 DIRSIG lidar ........................................... 32

## 3 Literature Review
3.1 Extraction of biophysical structure from lidar ............... 36
3.2 Lidar Simulations ............................................ 37
## CONTENTS

6.3.1 The effect of GPS errors  ......................................................... 109
6.3.2 The Effect of INS Errors  ...................................................... 109
6.3.3 Spatial evolution of errors  ..................................................... 112
6.4 Discussion  ................................................................................. 112
6.5 Conclusions  .............................................................................. 114

7 Attenuation Correction  ................................................................. 116
7.1 Introduction  ................................................................................ 116
    7.1.1 In-canopy attenuation correction  .......................................... 121
    7.1.2 Layout  .................................................................................. 123
    7.1.3 Associated Publications and Presentations  ............................. 124
7.2 Methods  ...................................................................................... 124
    7.2.1 Data  ..................................................................................... 124
    7.2.2 Preprocessing  ....................................................................... 129
7.3 Results  ......................................................................................... 130
    7.3.1 Simple geometry  ................................................................... 130
    7.3.2 A single simulated tree  ......................................................... 132
    7.3.3 A simulated forest  ................................................................. 135
7.4 Discussion  ................................................................................... 137
7.5 Conclusions  ................................................................................ 138

8 Final Conclusions and Future Work .................................................. 140
8.1 Conclusions  ............................................................................... 140
8.2 Future Work  ............................................................................... 143
    8.2.1 Forest scene generation  ......................................................... 143
    8.2.2 Additional Attenuation Analysis  ............................................ 143
    8.2.3 DIRSIG Validation  ................................................................. 145
    8.2.4 Vegetation Biophysical Structure  .......................................... 146

A Additional Scenes  ........................................................................ 148
    A.1 HighPark1  ................................................................................ 148
    A.2 SanJoaquin116  ....................................................................... 151

B Code, Data, and DIRSIG Scenes .................................................... 157
    B.1 DIRSIG-related code  ................................................................. 157
    B.2 Dissertation-related code and DIRSIG simulations  .................... 158
        B.2.1 Code  ................................................................................. 158
        B.2.2 DIRSIG simulations  ......................................................... 158

Bibliography  .................................................................................... 159
## List of Figures

1.1 NEON site map ........................................... 3
2.1 Tree inventory parameters ................................ 9
2.2 LAI Schematic ........................................... 10
2.3 Comparison among discrete, waveform, and photon counting lidar 13
2.4 Lidar scan patterns ....................................... 14
2.5 Schematic of the lidar geolocation process ................. 19
2.6 Lidar footprint calculations ............................... 20
2.7 DIRSIG lidar schematic .................................. 33
3.1 Sun and Ranson (2000) scene example ........................ 40
3.2 Sample trees from Morsdorf et al. (2009) ................ 43
3.3 Tree modeling process from Goodwin et al. (2007) .... 44
3.4 Sample scene from North et al. (2010) ................... 46
4.1 RAMI-IV abstract scenes .................................. 52
4.2 RAMI-IV actual scenes .................................... 53
4.3 Scene construction workflow .............................. 56
4.4 OnyxTREE Broadleaf GUI ................................ 57
4.5 OnyxTREE broadleaf components ......................... 59
4.6 Zoomed OnyxTREE broadleaf components ............... 60
4.7 Sampling methods ....................................... 62
4.8 Sample terrain glist file ................................. 63
4.9 Sample static instance showing drop placement ........ 64
4.10 Sample PROSPECT spectra ............................. 66
4.11 PROSPECT workflow .................................... 67
4.12 Positioning of trees in HarvardForest1 .................. 69
4.13 DIRSIG RGB rendering of HarvardForest1 ............. 69
5.1 Waveform Overlap Schematic ............................ 78
5.2 Sample waveform overlap computation .................... 79
5.3 Comparison between waveform overlap and other metrics 80
5.4 Effect of α on waveform overlap .......................... 81
5.5 HarvardForest1 Sampling ................................ 84
5.6 Sample waveform signals at different geometry levels .... 89
5.7 Waveform overlap comparisons for 4 [ns] and nadir .... 91
5.8 Waveform overlap t-tests for 4 [ns] and nadir .......... 92
5.9 Waveform overlap comparisons for 4 [ns] and nadir .... 94
5.10 Waveform overlap t-tests for 4 [ns] and nadir .......... 95
5.11 Waveform overlap comparison at different scan angles .... 96
5.12 Waveform overlap comparison at different outgoing pulse widths 97
5.13 Effect of scan angle on backscattered signal ........... 99
5.14 Effect of pulse width on backscattered signal .......... 101
6.1 Waveforms with positional jitter ................................................. 110
6.2 Positional jitter box plots ....................................................... 110
6.3 Waveforms with angular jitter .................................................. 111
6.4 Angular jitter box plots ......................................................... 111
6.5 Short Caption ........................................................................ 113
6.6 Correlation in high overlap lidar signals ................................. 113

7.1 Example of within-canopy attenuation ..................................... 118
7.2 Schematic of parallel plate experiment ................................... 119
7.3 Default OnyxTREE Acer rubrum .............................................. 127
7.4 Attenuation for plate experiments ........................................... 131
7.5 Attenuation for red maple experiments ..................................... 133
7.6 Attenuation as a function of scan angle for Forest Scene ............. 136
7.7 Slope of the attenuation correction .......................................... 137

8.1 Sample TLS-derived virtual scene ............................................. 144
8.2 Sample TLS-derived virtual scene (zoom) .............................. 144

A.1 HighPark1 side view ............................................................... 149
A.2 HighPark1 nadir view ............................................................ 150
A.3 Probability of product of normally-distributed varaibles ............... 152
A.4 Top view of visible DIRSIG rendering of SJ116 ...................... 156
A.5 Side view of visible DIRSIG rendering of SJ116 ..................... 156
### List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Description of variables in equation 2.6</td>
</tr>
<tr>
<td>2.2</td>
<td>Specifications of lidar systems (Part I)</td>
</tr>
<tr>
<td>2.3</td>
<td>Specification of lidar systems (Part II)</td>
</tr>
<tr>
<td>3.1</td>
<td>Summary of lidar simulations (Part I)</td>
</tr>
<tr>
<td>3.2</td>
<td>Summary of lidar simulations (Part II)</td>
</tr>
<tr>
<td>4.1</td>
<td>OnyxTREE output geometries</td>
</tr>
<tr>
<td>4.2</td>
<td>PROSPECT parameter ranges</td>
</tr>
<tr>
<td>4.3</td>
<td>HarvardForest1 tree parameters</td>
</tr>
<tr>
<td>4.4</td>
<td>HarvardForest1 scene statistics</td>
</tr>
<tr>
<td>4.5</td>
<td>HarvardForest1 optical properties</td>
</tr>
<tr>
<td>5.1</td>
<td>Geometry subsets</td>
</tr>
<tr>
<td>5.2</td>
<td>Lidar transmitter settings</td>
</tr>
<tr>
<td>5.3</td>
<td>Lidar receiver settings</td>
</tr>
<tr>
<td>5.4</td>
<td>Lidar range gate settings</td>
</tr>
<tr>
<td>5.5</td>
<td>RAM usage for leaf-on incremental subset</td>
</tr>
<tr>
<td>5.6</td>
<td>Values of $C(\alpha)$ for the Kolmogorov-Smirnov test</td>
</tr>
<tr>
<td>6.1</td>
<td>Applanix GPS/ins accuracy specifications</td>
</tr>
<tr>
<td>7.1</td>
<td>Parameters used in the simple geometry experiment</td>
</tr>
<tr>
<td>7.2</td>
<td>Slopes of attenuation corrections</td>
</tr>
<tr>
<td>A.1</td>
<td>HighPark1 tree parameters</td>
</tr>
<tr>
<td>A.2</td>
<td>SanJoaquin116 Tree Instancing</td>
</tr>
</tbody>
</table>
# List of Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALS</td>
<td>airborne laser scanning. 3, 12, 15, 21, 26, 27, 37, 98</td>
</tr>
<tr>
<td>AOP</td>
<td>airborne observation platform. 3</td>
</tr>
<tr>
<td>AVIRIS</td>
<td>Airborne Visible / Infrared Imaging Spectrometer. 3</td>
</tr>
<tr>
<td>BOREAS</td>
<td>Boreal Ecosystem-Atmosphere Study. 39, 47, 146</td>
</tr>
<tr>
<td>BRDF</td>
<td>bi-directional reflectance distribution function. 145, 146</td>
</tr>
<tr>
<td>BRF</td>
<td>bi-directional reflectance factor. 38</td>
</tr>
<tr>
<td>BTDF</td>
<td>bi-directional transmission distribution function. 145, 146</td>
</tr>
<tr>
<td>CDF</td>
<td>cumulative density function. 87</td>
</tr>
<tr>
<td>CFD</td>
<td>constant fraction discriminator: a method for producing discrete lidar points. 35</td>
</tr>
<tr>
<td>corr</td>
<td>correlation. 77, 80</td>
</tr>
<tr>
<td>CPU</td>
<td>central processing unit. 86</td>
</tr>
<tr>
<td>CVM</td>
<td>canopy volume method. 37</td>
</tr>
<tr>
<td>CW</td>
<td>continuous wave. 13, 14</td>
</tr>
<tr>
<td>DBH</td>
<td>diameter-at-breast-height. 8, 9, 54, 56, 58, 68, 70, 128, 135, 143</td>
</tr>
<tr>
<td>DEM</td>
<td>digital elevation model. 15, 25, 26, 41, 43, 47, 54–56, 62, 63, 71, 116, 117, 139, 141, 149–151</td>
</tr>
<tr>
<td>DHM</td>
<td>digital height model. 25</td>
</tr>
<tr>
<td>DIAL</td>
<td>differential absorption lidar. 41, 48</td>
</tr>
<tr>
<td>DSM</td>
<td>digital surface model. 25</td>
</tr>
<tr>
<td>DTM</td>
<td>digital terrain model. 25</td>
</tr>
<tr>
<td>DWEL</td>
<td>dual wavelength Echidna® lidar. 26–28</td>
</tr>
<tr>
<td>ENU</td>
<td>east-north-up: a relative coordinate system. 30, 64, 155</td>
</tr>
<tr>
<td>FLIGHT</td>
<td>a Monte Carlo ray tracer. 45–47, 49</td>
</tr>
<tr>
<td>fPAR</td>
<td>fraction of photosynthetic active radiation. 11</td>
</tr>
<tr>
<td>FWHM</td>
<td>full width half max. 96</td>
</tr>
<tr>
<td>gdb</td>
<td>geometry database: a DIRSIG file containing faceted geometry. 30</td>
</tr>
<tr>
<td>GLAS</td>
<td>geoscience laser altimeter system: a lidar system: a large-footprint waveform lidar system on ICESat. 26–28, 39, 41, 45</td>
</tr>
<tr>
<td>GORT</td>
<td>geometric optical and radiative transfer. 38, 39, 49</td>
</tr>
<tr>
<td>GPS</td>
<td>global positioning system. 8, 9, 17–19, 24, 31, 105–107, 115</td>
</tr>
<tr>
<td>GSD</td>
<td>ground sample distance. 114</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>-------------</td>
</tr>
<tr>
<td>HSI</td>
<td>hyper-spectral imagery. 34</td>
</tr>
<tr>
<td>HyspIRI</td>
<td>Hyperspectral Infrared Imager--A proposed spaceborne hyperspectral imager. 54, 148, 154</td>
</tr>
<tr>
<td>ICESat</td>
<td>ice, cloud and land elevation satellite: a NASA satellite mission. 26</td>
</tr>
<tr>
<td>ICESat-2</td>
<td>ice, cloud and land elevation satellite 2: a planned NASA satellite mission. 29, 114</td>
</tr>
<tr>
<td>IFOV</td>
<td>instantaneous field of view. 45</td>
</tr>
<tr>
<td>IMU</td>
<td>inertial measurement unit. 17, 24, 31</td>
</tr>
<tr>
<td>INS</td>
<td>inertial navigation system. 17–19, 105–107, 115</td>
</tr>
<tr>
<td>LAD</td>
<td>leaf angle distribution. 42, 47</td>
</tr>
<tr>
<td>LAI</td>
<td>leaf area index. 3, 8–11, 16, 37, 42, 47, 58, 121, 123, 139, 142, 145–147</td>
</tr>
<tr>
<td>LIBERTY</td>
<td>leaf incorporating biochemistry exhibiting reflectance and transmittance yields. 64, 66, 68, 73</td>
</tr>
<tr>
<td>librat</td>
<td>an extension of the DRAT and ARARAT ray tracers. 38, 45, 46, 48, 50</td>
</tr>
<tr>
<td>LITE</td>
<td>lidar interception and tree environment: a lidar simulator for trees. 38, 42, 48</td>
</tr>
<tr>
<td>LVIS</td>
<td>land, vegetation, and ice sensor: a lidar system. 26–28, 37, 39</td>
</tr>
<tr>
<td>MABEL</td>
<td>multiple altimeter beam experimental lidar: a airborne photon counting lidar system. 29</td>
</tr>
<tr>
<td>MBLA</td>
<td>multi-beam laser altimeter: a lidar system. 26–28</td>
</tr>
<tr>
<td>MODTRAN</td>
<td>moderate resolution atmospheric transmission. 31, 149</td>
</tr>
<tr>
<td>NDVI</td>
<td>normalized difference vegetation index. 4, 42</td>
</tr>
<tr>
<td>NIR</td>
<td>near-infrared. 13</td>
</tr>
<tr>
<td>odb</td>
<td>object database: a DIRSIG file containing instances of geometry objects. 30</td>
</tr>
<tr>
<td>OPW</td>
<td>outgoing pulse width. 81</td>
</tr>
<tr>
<td>PAI</td>
<td>plant area index. 8, 11, 45</td>
</tr>
<tr>
<td>PAR</td>
<td>photosynthetic active radiation. 10</td>
</tr>
<tr>
<td>PCH</td>
<td>proportion of canopy heights. 41</td>
</tr>
<tr>
<td>PD</td>
<td>percent difference. 77, 80</td>
</tr>
<tr>
<td>PDF</td>
<td>probability density function. 151, 152</td>
</tr>
<tr>
<td>POVRAY</td>
<td>persistence of vision ray tracer. 42, 49, 50</td>
</tr>
<tr>
<td>PRF</td>
<td>pulse repetition frequency. 21</td>
</tr>
<tr>
<td>PROSPECT</td>
<td>leaf optical properties spectra: a package for modeling leaf optical properties. 42, 64–67, 71, 73, 151</td>
</tr>
<tr>
<td>RAM</td>
<td>random access memory. 73, 86, 87</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
<tr>
<td>---------</td>
<td>------------</td>
</tr>
<tr>
<td>RAMI</td>
<td>Radiation transfer Model Intercomparison. 52, 53, 143, 146</td>
</tr>
<tr>
<td>RAYTRAN</td>
<td>A Monte Carlo ray tracer. 38, 48, 50</td>
</tr>
<tr>
<td>RMSD</td>
<td>root mean square difference. 65, 79, 80</td>
</tr>
<tr>
<td>RMSE</td>
<td>root mean square error. 37, 117</td>
</tr>
<tr>
<td>RT</td>
<td>radiative transfer. 4, 52, 143, 146</td>
</tr>
<tr>
<td>SAM</td>
<td>spectral angle mapper: a measure of vector difference. 79, 80</td>
</tr>
<tr>
<td>SAR</td>
<td>synthetic aperture radar. 2, 29, 31</td>
</tr>
<tr>
<td>SLA-02</td>
<td>shuttle laser altimeter II: a lidar system. 26–28</td>
</tr>
<tr>
<td>SLICER</td>
<td>scanning lidar imager of canopies by echo recovery: a lidar system: a lidar system. 25–28, 37, 39, 41, 47, 146</td>
</tr>
<tr>
<td>SLS</td>
<td>satellite laser scanning. 12, 27</td>
</tr>
<tr>
<td>SNR</td>
<td>signal to noise ratio. 15</td>
</tr>
<tr>
<td>TLS</td>
<td>terrestrial laser scanning. 12, 26, 27, 49, 71, 143, 144, 146</td>
</tr>
<tr>
<td>TOF</td>
<td>time-of-flight. 13, 14</td>
</tr>
<tr>
<td>TRAC</td>
<td>tracing radiation and architecture of canopies: an instrument for measuring LAI. 10</td>
</tr>
<tr>
<td>UTM</td>
<td>Universal Transverse Mercator: a conformal projection map coordinate system. 17, 30</td>
</tr>
<tr>
<td>VCL</td>
<td>vegetation canopy lidar: a proposed space-based lidar mission. 26, 39</td>
</tr>
<tr>
<td>WCS</td>
<td>world coordinate system. 17–19</td>
</tr>
<tr>
<td>WGS84</td>
<td>World Geodetic System 1984. 17, 18</td>
</tr>
<tr>
<td>XML</td>
<td>extensible markup language. 63</td>
</tr>
</tbody>
</table>
## List of Institutions

<table>
<thead>
<tr>
<th>Institution</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASPRS</td>
<td>American Society for Photogrammetry and Remote Sensing. 14</td>
</tr>
<tr>
<td>BU</td>
<td>Boston University. 26–28</td>
</tr>
<tr>
<td>CAO</td>
<td>Carnegie Airborne Observatory. 45</td>
</tr>
<tr>
<td>CSIRO</td>
<td>Commonwealth Scientific and Industrial Research Organization. 26–28</td>
</tr>
<tr>
<td>CSU</td>
<td>Colorado State University. 148</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration. 15, 25–29, 54, 141, 148, 154</td>
</tr>
<tr>
<td>NEON</td>
<td>National Ecological Observatory Network. 2, 3, 66, 104, 138, 145, 148, 149, 151, 156</td>
</tr>
<tr>
<td>NGA</td>
<td>National Geospatial Intelligence Agency. 18</td>
</tr>
<tr>
<td>RIT</td>
<td>Rochester Institute of Technology. 29</td>
</tr>
<tr>
<td>SJER</td>
<td>San Joaquin Experimental Range. 66, 151</td>
</tr>
<tr>
<td>TERN</td>
<td>Terrestrial Ecosystem Research Network. 2</td>
</tr>
<tr>
<td>UMD</td>
<td>University of Maryland. 26–28</td>
</tr>
<tr>
<td>USGS</td>
<td>United States Geological Survey. 126</td>
</tr>
</tbody>
</table>
List of OnyxTREE components

t trunks. 58–61, 74, 79, 81–83, 86–98, 100, 102, 106, 149, 153, 154
b boughs. 58–61, 74, 79, 81–83, 86–98, 100, 102, 106, 149, 153, 154
1 branch-level-1. 58–61, 79, 81–83, 86–98, 100, 102, 106, 149, 153, 154
3 branch-level-3. 56, 58–61, 79, 81–83, 86–98, 100, 102, 106
w twigs. 56, 58–61, 79, 81–83, 86–92, 94–98, 102, 141
s leaf stems. 56, 58–61, 81–83, 86–92, 96–98, 102, 141
l leaves. 56, 58–61, 74, 81–83, 86–93, 96–98, 100, 102, 106, 141
p leaf plates. 56, 58
e envelope. 58, 61
n needles. 58
List of Species

*Acer rubrum*  
red maple. 68–71, 126–128, 132–135

*Betula spp.*  
birch. 40, 46

*Betula pubescens*  
downy birch. 45

*Corymbia maculata*  
spotted gum. 43

*Eucalyptus grandis*  
flooded gum. 43

*Eucalyptus microcorys*  
tallowood. 43

*Eucalyptus pilularis*  
blackbutt. 43

*Helianthus annuus*  
sunflower. 42

*Liriodendron tulipifera*  
tulip poplar. 41

*Nyssa sylvatica*  
black tupelo. 45

*Picea spp.*  
spruce. 40

*Picea abies*  
Norway spruce. 40, 42

*Picea mariana*  
black spruce. 41

*Picea sitchensis*  
sitka spruce. 46

*Pinus spp.*  
pine. 40

*Pinus banksiana*  
jack pine. 39, 41

*Pinus contorta*  
lodgepole pine. 148

*Pinus ponderosa*  
ponderosa pine. 148

*Pinus radiata*  
Monterey pine. 42

*Pinus sylvestris*  
scots pine. 40, 42, 43, 45

*Populus deltoides*  
eastern cottonwood. 45

*Populus tremuloides*  
quaking aspen. 45

*Pseudotsuga menziesii*  
Douglas fir. 37, 45

*Quercus spp.*  
oak. 45

*Quercus douglasii*  
blue oak. 151

*Quercus rubra*  
red oak. 68–71, 125, 128, 129, 135

*Quercus wislizeni*  
interior live oak. 151

*Sassafras albidum*  
white sassafras. 45

*Tsuga heterophylla*  
western hemlock. 37

*Zea mays*  
maize/corn. 42
List of Roman Symbols

\( A \) area covered during a collect \([\text{km}^2]\). 10, 11, 21, 22
\( A_{\text{eff}} \) effective area of the target \([\text{m}^2]\). 23
\( A_i \) area of a target \([\text{m}^2]\). 10, 11
\( A_{\text{L}} \) footprint diameter \([\text{m}]\). 18–20
\( A_r \) area of the receive optics \([\text{m}]\). 23
\( A_{\text{tar}} \) area of the target \([\text{m}^2]\). 23

\( B \) power received from the background \([\text{W}]\) \( (i.e., \) the passive term). 23, 35
\( B_{ij} \) area under the \( j \)-th Gaussian of the \( i \)-th waveform. 122, 130
\( B_{\text{ref}} \) area under a reference Gaussian. 122, 123
\( b \) a vector of time bins. 129
\( |b| \) number of time bins. 35, 79, 129
\( b \) a time bin of a waveform. 76–79

\( c \) speed of light in vacuum: \( \approx 3 \cdot 10^8 \text{ [m/s]} \). 16, 17
\( C(\alpha) \) Kolmogorov-Smirnov multiplier. 87, 88
\( C_{\text{ab}} \) PROSPECT parameter: chlorophyll a+b content \([\mu \text{g} \cdot \text{cm}^{-2}]\). 65–67
\( C_{\text{brown}} \) PROSPECT parameter: brown pigments content \([\text{arbitrary units}]\). 65–67
\( c_{ij} \) correction term for the \( j \)-th Gaussian of the \( i \)-th waveform signal. 123, 130
\( C_{\text{ar}} \) PROSPECT parameter: carotenoids content \([\mu \text{g} \cdot \text{cm}^{-2}]\). 65–67
\( C_{\text{m}} \) PROSPECT parameter: dry matter content \([\text{g} \cdot \text{cm}^{-2}]\). 65–67
\( C_{\text{w}} \) PROSPECT parameter: equivalent water thickness \([\text{cm}]\). 65–67

\( D \) point density for a collect \([\text{points/m}^2]\). 22
\( D \) pulse density for a collect \([\text{pulses/m}^2]\). 22
\( d \) range \([\text{m}]\). 16–19, 22–24
\( d_{\text{min}} \) minimum resolvable range separation \([\text{m}]\). 17
\( D_{n,n'} \) Kolmogorov-Smirnov statistic. 87
\( D_r \) diameter of the receive optics \([\text{m}]\). 22–24
\( D_{\text{tar}} \) diameter of the target \([\text{m}]\). 22, 23
\( dx_{\text{across}} \) across track point spacing \([\text{m}]\). 21
\( dx_{\text{along}} \) along track point spacing \([\text{m}]\). 21

\( e \) energy per laser pulse \([\text{J}]\). 22

\( F \) pulse repetition frequency \([\text{kHz}]\). 21, 22
\( F \) Discrete cumulative density function. 87
\( f_s \) scan line frequency \([\text{Hz}]\). 21

\( h \) height of the lidar system above the terrain \([\text{m}]\). 18–21, 23
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I$</td>
<td>intensity $[W \cdot sr^{-1}]$. 119, 120</td>
</tr>
<tr>
<td>$i$</td>
<td>an index variable. 10, 11, 23, 24, 76, 122, 123, 129, 130, 149</td>
</tr>
<tr>
<td>$j$</td>
<td>an index variable. 76, 122, 123, 129, 130</td>
</tr>
<tr>
<td>$k$</td>
<td>an index variable. 130</td>
</tr>
<tr>
<td>$K^i$</td>
<td>number of Gaussians in the $i$-th waveform. 129</td>
</tr>
<tr>
<td>$l$</td>
<td>the length of a flightline $[km]$. 21, 22</td>
</tr>
<tr>
<td>$m$</td>
<td>number of targets interacting with a lidar pulse. 23, 24</td>
</tr>
<tr>
<td>$N$</td>
<td>number of points per scan line. 21</td>
</tr>
<tr>
<td>$N$</td>
<td>PROSPECT parameter: number of compact layers specifying the average number of air/cell walls interfaces within the mesophyll. 65–67</td>
</tr>
<tr>
<td>$N$</td>
<td>a normal distribution. 107, 108, 149, 151</td>
</tr>
<tr>
<td>$n$</td>
<td>index of refraction. 16, 17</td>
</tr>
<tr>
<td>$n$</td>
<td>the number of flight lines in a lidar collect. 21, 22</td>
</tr>
<tr>
<td>$n$</td>
<td>number of lidar returns. 13, 22</td>
</tr>
<tr>
<td>$n$</td>
<td>sample size. 87</td>
</tr>
<tr>
<td>$O$</td>
<td>waveform overlap metric. 76–78, 80, 81, 86–88, 90–92, 94–97, 100, 108–111</td>
</tr>
<tr>
<td>$p^i$</td>
<td>proportion of the reflected signal between two lidar returns. 122</td>
</tr>
<tr>
<td>$p$</td>
<td>probability of the Poisson distribution. 76–78</td>
</tr>
<tr>
<td>$P_{\text{peak}}$</td>
<td>peak power per laser pulse $[W]$. 22</td>
</tr>
<tr>
<td>$P_R$</td>
<td>received power $[W]$. 22–24</td>
</tr>
<tr>
<td>$P_{R,i}$</td>
<td>received power from the $i$-th target $[W]$. 23, 24</td>
</tr>
<tr>
<td>$P_T$</td>
<td>transmitted power $[W]$. 22–24</td>
</tr>
<tr>
<td>$q$</td>
<td>overlap between lidar strips $[%]$. 21, 22</td>
</tr>
<tr>
<td>$R^2$</td>
<td>correlation coefficient. 37</td>
</tr>
<tr>
<td>$R_{\text{gps}}$</td>
<td>rotation matrix from the GPS’ coordinate system to the world coordinate system, e.g., WGS84. 17–19</td>
</tr>
<tr>
<td>$R_{\text{ins}}$</td>
<td>rotation matrix from the INS’ coordinate system to the coordinate system of the GPS. 17–19</td>
</tr>
<tr>
<td>$R_{\text{sys}}$</td>
<td>rotation matrix from the lidar’s coordinate system to the coordinate system of the INS. 17–19</td>
</tr>
<tr>
<td>$R_{\text{scan}}$</td>
<td>rotation matrix form the pulse coordinate system to the lidar coordinate system as caused by the scan mirror angle. 17–19</td>
</tr>
<tr>
<td>$S$</td>
<td>a variable in the signal space of a waveform $[\text{photons}]$. 78</td>
</tr>
</tbody>
</table>
$S_b$ a variable in the signal space of a waveform for a given time bin $b$ [photons]. 76–78

$SW$ swath width [m]. 21, 22

t time of flight to the target and back [ns]. 16, 23, 24

t$_{gps}$ translation from the GPS’ coordinate system to the world coordinate system, e.g., WGS84. 17–19

t$_{ins}$ translation from the INS’ coordinate system to the coordinate system of the GPS. 17–19

t$_{min}$ minimum time between two received echoes needed to separate them. 17

t$_p$ time width of the outgoing laser pulse [s]. 17, 22

t$_{rise}$ rise time of a laser pulse: the time for the optical output to increase from 10% to 90% of the peak power. 17

t$_{sys}$ translation from the lidars’ coordinate system to the coordinate system of the INS. 17–19

$U$ A uniform distribution. 151

$v$ flying speed [m/s]. 21, 22

$v_s$ group velocity of the laser pulse [m/s]. 23, 24

$w$ a waveform. 35

$\tilde{w}$ estimate of the $i$-th waveform. 129

$w'_b$ $\tau$-th time bin of the $i$-th waveform. 76, 77, 79

$w'_i$ $i$-th waveform. 76–79, 129

$\overline{w}$ mean of the $i$-th waveform. 77, 79

$w'_j$ $b$-th time bin of the $j$-th waveform. 77, 79

$w'_j$ $j$-th waveform. 76–79

$\overline{w}$ mean of the $j$-th waveform. 77

$X$ a point in a world coordinate system e.g., WGS84. 17–19

$x$ first component of a Cartesian point. 4, 17, 24, 25, 30, 62, 63, 70, 82, 107–111, 114, 141, 149, 155

$x$ A variable. 87

$y$ second component of a Cartesian point. 4, 17, 24, 25, 30, 62, 63, 70, 82, 107–111, 114, 141, 149, 155

$z$ third component of a Cartesian point. 4, 17, 24, 25, 30, 61, 63, 107–109, 111, 114, 115, 141
List of Greek Symbols

\( \alpha \) critical \( t \) value. 76–78, 81, 87, 88
\( \alpha_j \) amplitude of the \( j \)-th Gaussian of the \( i \)-th waveform. 129
\( \alpha_k \) amplitude of the \( k \)-th Gaussian of the \( i \)-th waveform. 130
\( \beta \) extinction [km\(^{-1}\)]. 119, 120
\( \gamma \) divergence angle of the laser [mrad]. 18–20, 22, 23
\( \delta \) “thickness” of a plate [cm]. 119, 120
\( \Delta d \) range resolution [cm]. 16, 24
\( \Delta t \) resolution of time measurement [ns]. 16, 35
\( \eta \) number of plates. 119, 120
\( \eta \) A random variable. 107, 108, 149
\( \theta \) an angle [rad]. 11, 19
\( \theta_{\text{inc}} \) inclination angle of the local terrain [rad]. 20
\( \theta_{\text{inst}} \) instantaneous scan angle [rad]. 19, 20
\( \theta_{\text{max}} \) maximum scan angle [rad]. 21
\( \kappa \) yaw angle. 17, 108
\( \lambda \) wavelength [nm]. 23, 24
\( \lambda \) parameter and mean of a Poisson distribution. 76, 78
\( \mu_j \) position (mean) of the \( j \)-th Gaussian of the \( i \)-th waveform. 129
\( \nu \) percentile of the Poisson distribution. 76
\( \rho \) reflectance factor. 22, 23, 64, 131
\( \rho \) correlation between two random variables. 151
\( \rho_d \) downward reflectance factor. 119, 120
\( \rho_{\text{eff}} \) effective reflectance factor. 120
\( \rho_u \) upward reflectance factor. 119, 120
\( \Sigma \) variance-covariance matrix. 151
\( \sigma \) apparent effective cross-section. 23, 24
\( \sigma \) standard deviation. 107, 108
\( \sigma^2 \) population variance. 151
\( \sigma_j \) width (standard deviation) of the \( j \)-th Gaussian of the \( i \)-th waveform. 129
\( \sigma_k \) width (standard deviation) of the \( k \)-th Gaussian of the \( i \)-th waveform. 130
\( \sigma'_i \) apparent effective cross-section within the \( i-th \) range interval. 24, 25
\( \tau \) transmittance factor. 64, 119
\( \tau_{atm} \) atmospheric transmission. 22–24
\( \tau_{sys} \) effective transmission through the system. 22–24
\( \phi \) pitch angle. 17, 108
\( \psi \) central area of the Poisson distribution. 76–78
\( \Omega \) solid angle [sr]. 23
\( \omega \) roll angle. 17, 108
Chapter 1

Introduction

1.1 Motivation

Ecological challenges such as climate change, invasive species migration, and forest health are morphing into issues that policy makers and the general public are becoming concerned about. In order to help decision makers develop informed policies, there needs to be the ability to derive definitive metrics to assess these changes, to predict what will happen in the future, and to be able to assess the impact of any mitigation techniques on the ecological health of the planet. Continental-scale ecological measurements are required to be able to use these models.

Forests are a key ecological region for monitoring the health of our planet. They are capable of carbon sequestration (the capture and long term storage of carbon) and preventing that same carbon from being permanently released into our atmosphere. Carbon sequestration is one of the key processes which reduces our carbon footprint. In addition, forests provide raw materials, food, and shelter for both human and animal life. Climate models and reports, such as Solomon et al. (2007) and Stocker et al. (2013), hydrological models, and ecological models such as (Hurtt et al., 2004) need to have good estimates of forest biomass, forest health, and forest composition.
1.1. MOTIVATION

for understanding water and energy balances.

It is challenging for scientists and foresters to measure forests at the continental and global scales by exclusively using field-based data collects. Instead, many scientists must collaborate by taking measurements across a range of forests as well as other natural land types. Continental-scale and global-scale ecology are most efficiently performed from spaceborne measurements, where it is easy to cover large areas of Earth. There is, however, the gap of linking the space-based measurements with fine scale site- or plot-based field measurements. To help speed this process the scientific community must turn to air- and spaceborne methods of measuring forest parameters. Passive remote sensing techniques, such as hyper- and multi-spectral imaging, are useful for optically-based measurements of these parameters, e.g., leaf chemistry. However, these systems are lacking as far as deriving structural measurements. It is here where active remote sensing techniques, e.g., light detection and ranging (lidar) and synthetic aperture radar (SAR), can make their mark. To help address this need for data, landscape-, regional-, and continental-scale observatories, such as National Ecological Observatory Network (NEON) (Kampe et al., 2010) and Terrestrial Ecosystem Research Network (TERN) (Likens and Lindenmayer, 2011), are being constructed, which help to bridge the spatial and temporal scales.

NEON’s mission is to enable understanding and forecasting of the impacts of climate change, land use change, and invasive species on continental-scale ecology. They aim to do this by providing infrastructure and consistent methodologies to support research and education in these areas. As part of this effort, NEON has divided the United States into twenty eco-climatic zones, each of which contains a core site and two relocatable sites for a total of sixty terrestrial sites (see Figure 1.1). The core site will remain constant over the planned thirty-year lifetime of the observatory, while the relocatable sites have the potential to change location every five to ten years, depending on the science needs at the time. In addition to the terrestrial sites, there are an additional forty-six aquatic sites distributed across the United States.
At each site, NEON aims to produce a standardized set of measurements to allow scientists to develop ecosystem models and comparisons across the spatial and temporal extent of the observatory. Some of the data products NEON will collect are plant and animal species information (how many bugs are in a square meter, size and distribution of trees), soil characteristics (nutrient concentrations, water content), water analysis, and the atmospheric characteristics (flux tower measurements, radiance measurements. To help scale the plot-based field measurements up to site-based measurements, NEON will operate three airborne observation platforms (AOPs). Each AOP will contain a next-generation Airborne Visible / Infrared Imaging Spectrometer (AVIRIS) imaging spectrometer, a high-resolution RGB camera, and a airborne laser scanning (ALS) system capable of both full-waveform and discrete digitization. NEON AOP-derived data products include: land cover and land use; vegetation cover and dominant vegetation type; vegetation structure (height, canopy extent, and leaf area index (LAI)); vegetation condition, vegetation biochemistry, and heterogeneity; canopy chemistry (nitrogen index); topography (elevation, slope, and
aspect); and vegetation greenness and health (normalized difference vegetation index (NDVI)).

The inclusion of an imaging spectrometer provides the ability to measure or infer the vegetation chemistry properties, the discrete lidar system is included to measure structure, e.g., canopy height and terrain properties, and the high resolution RGB system provides context. These modalities are relatively mature in their usage for ecological modeling. Waveform light detection and ranging (wlidar) provides an opportunity to directly measure the complex forest structure as a function of range, however this specific modality represents a relatively novel form of lidar.

Small-footprint wlidar is a relatively new remote sensing modality, which offers the potential of being able to extract structural information from forested regions. Wlidar, as opposed to the more traditional discrete lidar, digitizes the entire backscattered signal, instead of just returning $x, y, z$ locations of interactions. This time-varying signal, offers the potential to develop a deeper understanding of the underlying tree structure, as well as the forest understory. Small-footprint systems typically have a footprint extent of less than one meter, allowing for a fine-scale measurement of structure.

Due to the complex nature of forest environments, it is often infeasible, if not impossible, to collect the necessary ground truth to develop models relating the underlying forest structure to the received lidar signal. As a result, radiative transfer (RT) simulations are used for this work, since the “truth” down to the location, orientation, size, and optical properties of every leaf in the scene is known. These simulations require bio-physically representative forest models to be able to approximate a forest environment. From these virtual scenes, it now becomes possible to simulate the complex wlidar–forest interactions and begin to develop models relating the two.

This dissertation outlines the work towards extracting biophysical structure from full-waveform small-footprint lidar signals. As part of this work, virtual digital image and remote sensing image generation (DIRSIG) forest scenes needed to be created and validated, and error analysis was per-
1.2. OBJECTIVES

formed in an attempt to better understand the implications and impacts of this work in real-world lidar systems.

1.2 Objectives

This dissertation addresses the big-picture objective of assessing the feasibility of extracting fine-scale biophysical structure parameters from full-waveform small-footprint lidar signals. While working towards this long-term objective, the specific objectives and sub-objectives of this dissertation are:

1. To assess the ability of DIRSIG to simulate full-waveform small-footprint lidar signals in forested environments, i.e., determine the ability to construct representative virtual forest scenes.

2. To assess the necessary geometric complexity of virtual forest scenes to produce consistent small-footprint lidar signals.
   2.1. To determine the most important geometric component to the backscattered signal.
   2.2. To determine the smallest component contribution that a lidar system has a chance of detecting.

3. To assess the ability of small-footprint lidar to consistently measure structure due to variability in platform positioning.

4. To determine the feasibility of correcting for within canopy attenuation of the lidar signal, i.e., to quantify the impact that leaf optical properties have on the propagation of a lidar pulse through the canopy.
1.3 Layout

The rest of this dissertation is divided up into eight chapters. Chapter 2 provides the relevant background to forest inventory and lidar remote sensing theory. Chapter 3 contains a literature review of other lidar simulation methods and biophysical parameter extraction from lidar. Chapter 4 describes the methods for creating the virtual forest scenes that were used in this dissertation in accordance with Objective 1. Chapter 5 contains the methods and results of a study to determine what level of geometric fidelity is needed for consistent wLidar simulations as part of Objective 2. Chapter 6 shows the effect positional and orientation uncertainty have on wLidar signals of forested scenes in accordance with Objective 3. Objective 4. is addressed in Chapter 7, which describes a within-canopy attenuation correction algorithm. Finally, Chapter 8 summarizes the conclusions, implications, and outlook from this dissertation.

1.4 Associated Publications and Presentations


Chapter 2

Background

2.1 Forest Inventory

In order to assess forest health and productivity levels, the forest needs to be measured. This Section contains three parts: basic forest inventory (Section 2.1.1), leaf area index (LAI) (Section 2.1.2), plant area index (PAI) (Section 2.1.3).

2.1.1 Basic Forest Inventory

Traditional forest inventory methods involve sending a trained forester into the field to manually measure the trees. As part of the inventory, simple measurements, e.g., species, stem location (range and bearing from a reference location), diameter-at-breast-height (DBH), where breast height is defined as 1.3 [m] above the ground, tree height, height to living crown, and canopy extent typically are collected. In addition to the tree parameters, information about the scene, including global positioning system (GPS) measurements of reference locations, are also collected. See Figure 2.1 for an illustration of these parameters.

These parameters are measured by foresters manually. For example, measuring a tree location
involves taking a GPS measurement of a reference location, using either a range finder or tape measure to get the range to the stem, and a compass to find the azimuth angle to the stem. All of these parameters have some level of uncertainty, which may lead to displacement of tree stems of up to a meter or two from its true location in a map. Height is a particularly challenging parameter to measure from the ground, as it requires being able to see both the top and bottom of the same tree from within a potentially dense forest.

### 2.1.2 Leaf Area Index

In addition to the basic forest parameters, more advanced forest parameters may be collected, for example leaf area index (LAI). Although it has many definitions, for the purposes of this dissertation, LAI (Chen and Black, 1992; Chen, 1996; Chen et al., 1997; Zheng and Moskal, 2009) shall be defined as the sum of the one-sided green leaf area per unit ground surface area.
Mathematically, this may be written as

\[ LAI = \frac{\sum_i A_i}{A}, \]  

(2.1)

where \( A_i \) is the one-sided area of the \( i \)-th leaf and \( A \) is the area of the ground over which the LAI is being calculated. LAI is a way to try to measure the efficiency of a plant in converting photosynthetic active radiation (PAR) into carbohydrates—the more leaves a tree has the more light it can capture. Figure 2.2 shows a schematic of LAI.

Figure 2.2: Schematic showing the projections of leaf areas on the ground to create a LAI measurement: (a) has a higher leaf density and higher LAI than (b); (c) is the key showing the continuous LAI values from parts (a) and (b). Forest-, stand-, and plot-level LAI are aggregated over a larger area, e.g., the total projected leaf area divided by the total area (grey base).

The precise way of measuring LAI is to remove the leaves from a tree(s) and run them through a scanner to compute their area. There are techniques/devices, such as hemispherical photography, the LI-COR LAI-2000, line ceptometers (e.g., AccuPAR LP-80), and tracing radiation and architecture of canopies (TRAC), which can approximate the LAI measurements from the ground. With the exception of TRAC, all of the other field-based LAI measurements are point measurements and do not provide information on leaf distributions. These measurements make possible
2.2. LIDAR estimates of the fraction of photosynthetic active radiation (fPAR): the ratio of below-canopy to above canopy light in the visible range (400–700 [nm]) to derive an estimate of the LAI. All of the field-based LAI measurement techniques are time consuming, and sensitive to variables such as time of day and instrument location. As a result of these issues, we seek a remote-sensing based solution for estimating spatially-varying LAI values.

2.1.3 Plant Area Index

Although LAI is often the desired metric to observe, it is challenging to separate the leaves from the remainder of a tree. As a result, a related parameter, plant area index (PAI), can be computed. PAI refers to all sun-blocking parts of the canopy including leaves, branches, and twigs, and not just the leaf area. PAI is the one-sided projected area of all sun-blocking geometry onto the ground divided by the area of the intersection of that projected area (Chen et al., 1991). PAI is often what many field-based measurements of LAI that use illumination conditions (hemispherical photography, ratios of fPAR) are able to measure. PAI can be computed by:

\[
P_{\text{AI}} = \frac{\sum A_i \cos (\theta_i)}{A},
\]

where \(A_i\) is the area of the \(i\)-th upward facing, opaque sun-blocking tree component, \(\theta_i\) is the angle between that component and vertical, and \(A\) is the area of the ground over which the PAI is being calculated. Only the upward facing components are used to avoid double counting the area of the top and bottom surface.

2.2 Lidar

In order to remotely measure the forest structure, we will make use of a light detection and ranging (lidar) system. Lidar sometimes stylized LiDAR, is an active remote sensing technique used to
compute ranges to objects. The underlying premise of lidar systems is to send out a pulse of light, and let it propagate until it interacts with an object. Some of this light will backscatter towards the detector. By measuring the roundtrip time this takes, a range to a target can be computed.

There are many different ways that a lidar system may be characterized:

i. wavelength(s)

ii. footprint size:
   - large (tens of meters)
   - small (<1 [m])
   - medium (in the middle)

iii. platform location:
   - terrestrial laser scanning (TLS)
   - airborne laser scanning (ALS)
   - satellite laser scanning (SLS)

iv. digitization (see Figure 2.3):
   - discrete
   - waveform
   - photon counting

v. scan patterns (see Figure 2.4):
   - conic
   - oscillation
   - line
   - fiber
2.2. LIDAR

vi. laser type

- continuous wave (CW)
- pulsed

vii. range detection type:

- time-of-flight (TOF)
- phase shifted

The research in this dissertation focuses on airborne, near-infrared, pulsed/TOF, small-footprint waveform light detection and ranging (wlidar) systems.

Figure 2.3: Comparison among (a) discrete, (b) waveform, and (c) photon counting lidar systems. The discrete system records n ranges and intensities (not shown). The wlidar system digitizes the backscattered signal at a given rate and is able to capture range, intensity, and interaction width information from each return. The photon counting system records when every photon is received, but is sensitive to noise, which is helps in cases of low outgoing pulse power, but is more sensitive to atmospheric and system noise.

While any laser may be used as part of a lidar system, typically near-infrared (NIR) wavelengths are used, e.g., 1064 [nm]. One reason for this is the ability to use more powerful lasers than in the visible, while still meeting eye-safety requirements. Another reason for the use of NIR
wavelengths for the sensing of vegetation is the high reflectance and transmittance of leaves in this spectral region. There are two primary ways from which a range can be computed from a lidar system: TOF or phase shifted. TOF systems send out a pulse of light and record the round trip time for the pulse to bounce off a target and return to the sensor. Phase shifted systems use CW lasers and compare the phase difference between the transmitted and reference signals (Wehr and Lohr, 1999).

The three digitization methods for a lidar system are discrete, waveform, and photon counting. The most common digitization of a lidar signal is discrete (see Figure 2.3a). Here, the signal from the sensor is a small set of gelocations, ranges, and intensities that form a point cloud. The system computes the ranges to the target(s) in hardware and stores geolocation metadata for post-processing into a point cloud. The point data from a discrete system are often stored in the American Society for Photogrammetry and Remote Sensing (ASPRS)'s las format (ASPRS, 2015). The las file form (up to version 1.3) allows for up to 7 returns per outgoing pulse to be stored. A more detailed description of discrete lidar can be found in Section 2.2.2. A generalization of the discrete digitization is full-waveform (or just waveform) lidar (see Figure 2.3b). Rather than compute the ranges in hardware, a full-lidar system records the time varying backscattered signal with some temporal sampling (typically 1 [ns]). This allows for many more ranges to be recorded. In addition, information about the temporal distribution from the returns is also returned. A more
detailed description of lidar can be found in Section 2.2.3. Finally, a photon counting system (see Figure 2.3c) is closest to the underlying physics governing all three discretization types. A record of time and intensity for every received photon is recorded. A photon counting system is useful in cases where there is a low signal to noise ratio (SNR), e.g., National Aeronautics and Space Administration (NASA)’s proposed ICESat-2 mission (Abdalati et al., 2010). A low SNR will occur when the transmitting power of the laser is low, e.g., for eye safety or system power requirements. Photon counting systems, especially those with low SNRs, will suffer from having a noisy signal, due to also recording detections of photons that are not from the laser, e.g., solar photons, upwelling photons, etc. A drawback of using photon counting lidar systems with strong outgoing pulse powers is that there is large file size compared to the waveform data. The returns from a photon counting system might be binned together to for a waveform signal to reduce data size and the effects of noise. A more detailed description of photon counting lidar can be found in Section 2.2.4.

Early lidar systems were profiling, i.e., they used a single, fixed laser position to build up a transect as they flew. This produced a 2D representation of the structure (height and along-track position). In order to cover a larger 3D space, the laser needs to be scanned across the across track direction. Figure 2.4 shows common scan patterns. Using a set of fiber optics, the laser scanner can be split into a number of tracks (see Figure 2.4a). By using a oscillating mirror perpendicular to the direction of flight, a sinusoidal scan pattern can be produced (see Figure 2.4b). A regular prism-shaped mirror, rotating in one direction, produces a series of parallel lines in approximately the across track direction (see Figure 2.4c). The difference in these lines from the across track direction is caused by the platform’s speed and the relative angle of the scanning mirror. Finally, using a two-axis scan mirror can produce a conical scan pattern (see Figure 2.4d).

One of the most common uses of ALS data is to produce topographic digital elevation model (DEM) models (Asner et al., 2005; Naesset, 1997; Naesset, 2002; Nilsson, 1996). Laser remote sensing (lidar) has been used to directly measure forest canopy structure including tree height (Duncanson et al., 2010; Lefsky et al., 1999a; Naesset, 1997; Næsset, 2002; Nilsson, 1996; Rosette
et al., 2008), stand volume (Nilsson, 1996), tree delineation (Chen et al., 2006; Persson et al., 2002; Koch et al., 2006; Popescu et al., 2003; Reitberger et al., 2009), broadleaf vs. conifer classification (Reitberger et al., 2006; Reitberger et al., 2008), biomass (Drake et al., 2002; Hyde et al., 2005; Popescu, 2007; Popescu et al., 2004; Zhao et al., 2009), and LAI (Farid et al., 2008; Martens et al., 1993; Morsdorf et al., 2006; Tang et al., 2012).

2.2.1 Lidar Mathematics

This section provides a brief mathematical background for pulsed lidar systems. This is a partial summary of Baltsavias (1999), Measures (1984), Shan and Toth (2008), and Wyman (1969). This section is broken up into five parts, providing a mathematical background in lidar ranging (Section 2.2.1.1), geolocation (Section 2.2.1.2), footprint size (Section 2.2.1.3), system coverage (Section 2.2.1.4), and radiometry (Section 2.2.1.5).

2.2.1.1 Lidar Ranging

Using simple physics relating distance to time and velocity, the range \(d\) from a lidar system to a target can be computed using

\[
d = \frac{c \cdot t}{2 \cdot n}
\]

(2.3)

where \(c\) is the speed of light (299,792,458 [m/s]), \(n\) is the index of refraction, and \(t\) is the round-trip time of flight to the target and back. The two in the denominator is to take into account that a laser pulse will need to propagate to the target and then back to the sensor and the index of refraction accounts for the deviation in velocity from \(c\) that occurs in the atmosphere. The range resolution (\(\Delta d\)) is given by

\[
\Delta d = \frac{c \cdot \Delta t}{2 \cdot n}
\]

(2.4)

where \(\Delta t\) is the resolution of the time measurement. A common interpretation of equation 2.4 in most atmospheric conditions is 1 [ns] corresponds to roughly 15 [cm] of range. Equation 2.4 leads
to a range resolution \( (d_{\text{min}}) \):

\[
d_{\text{min}} = \frac{c \cdot t_{\text{min}}}{2 \cdot n}
\] (2.5)

where \( t_{\text{min}} \) is the minimum amount of time needed to resolve two echoes. Depending on the application, \( t_{\text{min}} \) can be defined as the outgoing pulse width \( (t_p) \), \( t_p/2 \), or \( t_p + t_{\text{rise}} \), where \( t_{\text{rise}} \) is the rise time of the pulse. The rise time is the amount of time for the optical output to increase from 10% to 90% of the peak power.

### 2.2.1.2 Lidar Geolocation

Once a range \( (d) \) has been calculated, is is possible to geolocate it in a world coordinate system (WCS), e.g., Universal Transverse Mercator (UTM) from a reference datum, e.g., World Geodetic System 1984 (WGS 84). To do this, knowledge of scan mirror location, the system position as measured by a GPS, and system orientation as measured by an inertial navigation system (INS) are required. The system orientation is often defined by the Euler angles of roll \( (\omega) \), pitch \( (\phi) \), and yaw or heading \( (\kappa) \). An INS is sometimes referred to as an inertial measurement unit (IMU).

In addition to the GPS and INS measurements, knowledge of the positions of these instruments relative to the lidar system are needed to perform the geolocation. The conversion from range \( (d) \), position, and orientation information to a geo-referenced point \( (X = [x, y, z]^T) \) is given by:

\[
X = R_{\text{gps}} R_{\text{ins}} \left( R_{\text{sys}} R_{\text{scan}} \begin{bmatrix} 0 & 0 & d \end{bmatrix}^T + t_{\text{sys}} + t_{\text{ins}} \right) + t_{\text{gps}}.
\] (2.6)

The variables in this equation are described in Table 2.1 and shown in Figure 2.5. Equation 2.6 can be interpreted as a series of levers that transform the range from one coordinate space to the next, finally winding up in a geo-referenced WCS. The difference between the system, INS, and GPS coordinate systems are that they are physically separate from each other and mounted to different portions of the aircraft, e.g., the GPS antennas are often mounted to the top of the aircraft, while the lidar system looks out a port in the bottom of the aircraft (Wolf et al., 2014). A more thorough
2.2. LIDAR

An explanation of the lidar geolocation process can be found in the National Geospatial Intelligence Agency (NGA) Standardization Document NGA Standardization Document (2011).

Table 2.1: Description of variables in equation 2.6. See Figure 2.5 for a schematic showing the relationship between these variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>The range from sensor to target.</td>
</tr>
<tr>
<td>$R_{\text{scan}}$</td>
<td>The rotation matrix from the pulse coordinate system to the lidar coordinate system as caused by the scan mirror angle.</td>
</tr>
<tr>
<td>$R_{\text{sys}}$</td>
<td>The rotation matrix from the lidar’s coordinate system to the coordinate system of the INS.</td>
</tr>
<tr>
<td>$R_{\text{ins}}$</td>
<td>The rotation matrix from the INS’ coordinate system to the coordinate system of the GPS.</td>
</tr>
<tr>
<td>$R_{\text{gps}}$</td>
<td>The rotation matrix from the GPS’ coordinate system to a WCS, e.g., WGS84.</td>
</tr>
<tr>
<td>$t_{\text{sys}}$</td>
<td>The translation from the lidar’s coordinate system to the coordinate system of the INS.</td>
</tr>
<tr>
<td>$t_{\text{ins}}$</td>
<td>The translation from the INS’ coordinate system to the coordinate system of the GPS.</td>
</tr>
<tr>
<td>$t_{\text{gps}}$</td>
<td>The translation from the GPS’ coordinate system to a WCS, e.g., WGS84.</td>
</tr>
<tr>
<td>$X$</td>
<td>The geolocated point in a world coordinate system, e.g., WGS84.</td>
</tr>
</tbody>
</table>

2.2.1.3 Lidar Footprint Size

A laser beam does not just intersect an object at a single point, but diverges into an area. The laser footprint diameter ($A_L$) at nadir on ground whose normal is in the direction of the sensor is given by

$$A_L = 2 \cdot h \cdot \tan\left(\frac{\gamma}{2}\right)$$

(2.7)

where $h$ is the height of the sensor above the ground and $\gamma$ is the divergence of the laser beam. For systems where $\gamma$ is small, equation 2.7 can be approximated by

$$A_L \approx h \cdot \gamma.$$  

(2.8)
2.2. LIDAR

Figure 2.5: Schematic of the lidar geolocation process. The range \((d)\) is converted to a WCS via the scan, system, INS, and GPS coordinate systems. \(\hat{x}, \hat{y}, \) and \(\hat{z}\) are the basis vectors in each of the coordinate systems. The differences in the system, INS, and GPS coordinate systems are due to the physical separation of these instruments from each other on the aircraft platform. The grey fan on the right represents the area into which the scan-mirror could project a laser pulse. A description of the variables may be found in Table 2.1.

This is illustrated in Figure 2.6a. The error of this approximation can be found by looking at the omitted terms of the series expansion of the tangent function

\[
\tan(\theta) = \theta + \frac{1}{3} \theta^3 + \frac{2}{15} \theta^5 + \frac{17}{315} \theta^7 + \cdots
\]

(2.9)

In cases where the terrain is not orthogonal to the height vector, equation 2.7 generalizes to

\[
A_L = h \cdot \left[ \tan \left( \frac{\theta_{\text{inst}} + \gamma}{2} \right) - \tan \left( \frac{\theta_{\text{inst}} - \gamma}{2} \right) \right]
\]

(2.10)

which is mathematically equivalent to

\[
A_L = \frac{h \cdot \gamma}{\cos^2(\theta_{\text{inst}})}
\]

(2.11)
for a system with scan angle $\theta_{\text{inst}}$. See Figure 2.6b for an illustration of the flat-ground off-nadir case.

Finally, these equations can be further generalized by taking into account the ground slope

$$A_L = \frac{\cos(\theta_{\text{inst}} + \theta_{\text{inc}}) + \sin(\theta_{\text{inst}} + \theta_{\text{inc}}) \cdot \tan(\theta_{\text{inst}} + \theta_{\text{inc}} + \frac{\gamma}{2})}{\sin(\frac{\gamma}{2})} \cdot \left[ 2 \cdot h \cdot \sin\left(\frac{\gamma}{2}\right) \right],$$

(2.12)

where $\theta_{\text{inst}}$ is the instantaneous scan angle and $\theta_{\text{inc}}$ is the inclination angle of the ground relative to zenith. An illustration of the general case is given in Figure 2.6c and d. For the purposes of reporting system characteristics, the reported footprint size is that at nadir on flat terrain, i.e., equation 2.7.

Figure 2.6: Illustration of the effect of scan angle ($\theta_{\text{inst}}$) and terrain slope ($\theta_{\text{inc}}$) on footprint size ($A_L$). All four sub-figures have the same flying height ($h$) and laser divergence angle ($\gamma$). (a) shows a nadir shot with a flat (orthogonal) ground, (b) shows an off-nadir shot with the ground orthogonal to the nadir vector, (c) and (d) show an off-nadir shot with sloped ground. Sub-figures (b-d) all have the same scan angle. The magnitude of the ground-tilt in (c) and (d) is the same. The footprint size ($A_L$) increases with the difference between the scan angle ($\theta_{\text{inc}}$) and normal to the terrain increases.
2.2.1.4 Lidar System Coverage

The coverage of a ALS system affects the flight planning required for a collect. Trade-offs will need to be made between the area covered by the lidar survey, the point density, and the amount of time (cost) required for the collection. The swath width ($SW$) or the distance covered by the across-track direction of the scanner covered by the lidar system, is given by

$$SW = 2 \cdot h \cdot \tan\left(\frac{\theta_{\text{max}}}{2}\right),$$

where $\theta_{\text{max}}$ is the maximum scan angle. The number of pulses per scan line ($N$) is

$$N = \frac{F}{f_s},$$

where $F$ is the pulse repetition frequency (PRF), i.e., the number of times the laser fires each second, and $f_s$ is the scan line frequency. For a system traveling at $v$ [m/s], the across track pulse spacing ($dx_{\text{across}}$) is

$$dx_{\text{across}} = \frac{SW}{N},$$

and the along track pulse spacing ($dx_{\text{along}}$) is

$$dx_{\text{along}} = \frac{v}{f_s}.$$

For a collect, the total area covered during a rectangular collect ($A$) is

$$A = SW \cdot l \cdot \left[ (n - 1) \cdot \left(1 - \frac{q}{100}\right) + 1 \right]$$

where $l$ is the length of the flight lines, $n$ is the number of flight lines, and $q$ is the overlap percentage.
The pulse density (\(D\)) for the collect is

\[
D = \frac{F \cdot n \cdot SW \cdot l}{A \cdot v}
\]

(2.18)

\[
D = \frac{F \cdot n}{v \cdot [(n - 1) \cdot (1 - \frac{q}{100}) + 1]}
\]

(2.19)

The common lidar collect metric of point density, e.g., [points/m²], is scene dependent. In places where there is only a single return per pulse, point and pulse density will be the same. However, in cases where there are partial hits within the footprint, or transmissive targets, the point density will exceed the pulse density, i.e., when there are multiple returns per pulse. The point density for a collect is the average number of returns per unit area of the collect:

\[
D = \frac{n}{A},
\]

(2.20)

where \(n\) is the number of returns collected over the collection area \(A\).

### 2.2.1.5 Lidar Radiometry

Transitioning from the geometry of a lidar system to the radiometry, the energy in each laser pulse \((e)\) is

\[
e \propto t_p \cdot P_{\text{peak}},
\]

(2.21)

where \(P_{\text{peak}}\) is the peak power for a laser pulse. For a Lambertian disk (target) with diameter \(D_{\text{tar}}\), reflectance \(\rho\), located \(d\) [m] away from the sensor, and oriented orthogonal to the direction of beam propagation, the received power \(P_R\) is given by

\[
P_R = \frac{\rho \cdot \tau_{\text{atm}}^2 \cdot D_{\text{tar}}^2 \cdot D_r^2 \cdot \tau_{\text{sys}} \cdot P_T}{4 \cdot d^4 \cdot \gamma^2}
\]

(2.22)

where \(\tau_{\text{atm}}\) is the atmospheric transmission, \(D_r\) is the diameter of the receiver optics, \(\gamma\) is the laser beam divergence, \(\tau_{\text{sys}}\) is the transmission through the optics, and \(P_T\) is the transmit power. In
cases where the target fills the field of view of the optics, equation 2.22 can be simplified to:

\[ P_R = \rho \cdot \tau_{atm} \cdot A_r \cdot \tau_{sys} \cdot \frac{\pi}{d^2} \cdot P_T, \quad (2.23) \]

where

\[ A_r = \frac{\pi \cdot D_r^2}{4} \quad (2.24) \]

is the area of the target. This is due to

\[ A_{tar} = \frac{\pi \cdot D_{tar}^2}{4} = \frac{\pi \cdot (\gamma \cdot d)^2}{4} \quad (2.25) \]

Both equations 2.22 and 2.23 do not take into account the passive terms (B) or noise terms and have the assumption that the plane of the target is orthogonal to the direction of laser beam propagation. The product of target terms, \( \rho \cdot A_{tar} \), is inherently linked and different combinations of each may lead to the same expressed lidar signal. Using Wagner et al. (2006)’s notation, the observed signal can be observed as the integral

\[ P_R(t) = \frac{D_r^2}{4 \cdot \pi \cdot \lambda^2} \int_0^h \frac{\tau_{atm} \cdot \tau_{sys}}{d^4} \cdot P_T\left(t - \frac{2 \cdot d}{v_g}\right) \sigma(d) \, dd \quad (2.26) \]

where \( v_g \) is the group velocity of the laser pulse and \( \sigma \) is the apparent effective cross section.

\[ \sigma = \frac{4 \cdot \pi}{\Omega} \cdot \rho \cdot A_{eff} \quad (2.27) \]

where \( \Omega \) is the solid angle into which the target scatters and \( A_{eff} \) is the effective cross-sectional area of the target. In the case where there are multiple signals, the total observed signal can be written as

\[ P_R(t) = \sum_{i=1}^{m} P_{R,i}(t) \ast \tau_{atm}^2(t) \ast \tau_{sys}(t) \quad (2.28) \]
where \( P_{R,i}(t) \) is the echo of the \( i \)-th object:

\[
P_{R,i}(t) = \frac{D_r^2}{4 \cdot \pi \cdot \lambda^2} \int_{d_i - \Delta d}^{d_i + \Delta d} \frac{1}{d_i} \cdot P_T \left( t - \frac{2 \cdot d_i}{v_g} \right) \sigma_i(d) \, dd
\]  

(2.29)

and * is the convolution operator. In cases where \( \Delta d \ll d \):

\[
P_{R,i}(t) \approx \frac{D_r^2}{4 \cdot \pi \cdot \lambda^2 \cdot d^4} P_T(t) * \sigma'_i(t)
\]  

(2.30)

where \( \sigma'_i \) is the apparent cross-section of \( i \)-th object within the range interval. Plugging equation 2.30 into 2.28 yields

\[
P_R(t) = \sum_{i=1}^{m} \frac{D_r^2}{4 \cdot \pi \cdot \lambda^2 \cdot d^4} P_T(t) * \tau_{sys}(t) * \underbrace{\tau_{atm}^2(t) * \sigma'_i(t)}_{\text{environment contribution}}
\]  

(2.31)

The system contribution is the time-varying system-dependent parameters that impact received power and the environmental contribution is the scene-dependent factors that influence the received power.

### 2.2.2 Discrete Lidar

Discrete return lidar is the most common type of lidar system. For each outgoing pulse, the discrete ranges of each interaction are recorded. The range information, along with platform geolocation from GPS and IMU instruments, and system information (e.g., scan mirror angle) are combined to calculate an \( x, y, z \) location for each return. Typically, a discrete lidar system returns only a small number of returns per pulse, e.g., the Leica ALS60 records the first, second, third, and last returns. This allows for the best chance for returns from the canopy and ground to both be recorded in forested environments. More modern discrete systems may return up to six returns per outgoing pulse. In discrete return lidar, the shape of the response is lost. In the example schematic of Figure 2.3a, there are four returns in the lidar system: one at the top of the canopy,
two in the middle of the canopy, and one at the ground. The information that the third return is broader than the other three (see Figure 2.3b) is not captured by a discrete return system. The intensities at these locations is proportional to the product of the amplitude and width of the return. The collection of all of the \(x, y, z\) returns make up a “point cloud”.

Once a point cloud has been collected, it is typically interrogated to produce useful products. The lower, ground-classified points are interpolated to find a digital elevation model (DEM) and is a digital representation of the height of the terrain. A DEM is also referred to as a digital terrain model (DTM). The upper points are also interpolated to find a digital surface model (DSM). The difference in the DSM and DEM produces a digital height model (DHM).

\[
DHM = DSM - DEM. \tag{2.32}
\]

The DHM, which is in the same units as the DEM/DHM and is expressed as the height above ground, can be used to make structural inferences about the trees, buildings, etc., that are in the lidar scan.

### 2.2.3 Waveform Lidar

Full-waveform lidar (often just called waveform light detection and ranging (wlidar)), digitizes the entire backscattered laser signal (Mallet and Bretar, 2009). This digitization occurs at high sample rates (typically 1 [ns]) and allows for the capture of return distributions that discrete lidar misses. This digitization allows for an arbitrary (up to Nyquist sampling limit) number of returns captured. In addition, the return intensity and width are decoupled, allowing for deconvolution methods (e.g., Wu et al. (2011)) to extract structure at finer scales than outgoing pulse width, i.e., to extract the effective cross section terms \(\sigma'\) from equation 2.31.

Over the years, NASA has used a number of wlidar systems for assessing land cover. The scanning lidar imager of canopies by echo recovery (SLICER) is a medium footprint lidar sys-
tem that was used to characterize vertical canopy structure, specifically relating to tree ages and species (Lefsky et al., 1999b). The shuttle laser altimeter II (SLA-02) sensor was mounted aboard the space shuttle and used to verify the accuracy of a global 1 [km] DEM (Harding et al., 1999). The land, vegetation, and ice sensor (LVIS) is an improved version of SLICER. It was used to provide data to evaluate the performance of the future (and later canceled) vegetation canopy lidar (VCL) mission and develop algorithms pre-launch. Blair et al. (1999) showed the potential of lidar to measure below-canopy topography. The multi-beam laser altimeter (MBLA) is part of the abandoned VCL mission. MBLA, as designed by NASA and University of Maryland (UMD), consisted of five beams with 25 [m] contiguous along-track resolution. The geoscience laser altimeter system (GLAS) is the lidar sensor on the ice, cloud, and land elevation satellite (ICESat) satellite mission (Cohen et al., 1987; Schutz et al., 2005). GLAS had both 1064 [nm] and 532 [nm] lasers. The ICESat mission was designed to study the roughness and thickness of land and sea ice in the polar regions, as well as the vertical structure of clouds and aerosols (Brenner et al., 2003).

From the TLS perspective, the dual wavelength Echidna® lidar (DWEL) lidar system was developed as a collaboration between Boston University (BU) and Australia’s Commonwealth Scientific and Industrial Research Organization (CSIRO) (Douglas et al., 2012). The DWEL uses two wavelengths, 1064 and 1548 [nm], to help separate green vegetation from tree bark and the ground. The system covers most of the sphere by sweeping out 360 [°] in azimuth and 119 [°] in elevation in approximately 40 [min].

In addition to the experimental lidar systems, there are many commercially available waveform systems. These commercial systems tend to be small-footprint ALS systems. Producers of commercial lidar systems include Leica (Switzerland/Germany), Optech (Canada), Riegl (Austria), TopEye (Sweden), and TopoSys (Germany). To help maintain a competitive advantage, many of the sensor properties for commercial systems are not published, which poses a challenge when trying to produce a simulation using a commercial lidar system.
Tables 2.2 and 2.3 show technical specifications for several commercial and scientific lidar systems. All of the commercial systems listed in these Tables (as well as the DWEL) capture small-footprint lidar signals when flown at around 1000 [m]. Lidar systems typically use near-infrared illumination, with 1064 and 1550 [nm] being the two most common wavelengths.

Table 2.2: Specifications of lidar systems (Part I). Adapted from Douglas et al. (2012), Hollaus et al. (2014), Kukko and Hyvönen (2009), Mallet and Bretar (2009), and Wulder et al. (2012), and manufacturer websites: http://www.leica-geosystems.us/, http://www.optech.com/, and http://www.riegl.com/. The scan mode “Osc.” is an abbreviation for oscillating. Continued in Table 2.3.

<table>
<thead>
<tr>
<th>Company/Institution</th>
<th>Sensor</th>
<th>Type</th>
<th>Scan Mode</th>
<th>Scan Freq. [Hz]</th>
<th>Pulse Freq. [kHz]</th>
<th>Scan Angle [°]</th>
<th>Beam Div. (1/e²) [mrad]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Experimental</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NASA</td>
<td>SLICER</td>
<td>ALS</td>
<td>Osc.</td>
<td>80</td>
<td>0.075</td>
<td>—</td>
<td>2</td>
</tr>
<tr>
<td>NASA</td>
<td>SLA-02</td>
<td>SLS</td>
<td>None</td>
<td>N/A</td>
<td>0.01</td>
<td>N/A</td>
<td>0.3</td>
</tr>
<tr>
<td>NASA</td>
<td>LVIS</td>
<td>ALS</td>
<td>Osc.</td>
<td>500</td>
<td>0.1–0.5</td>
<td>≥7.0</td>
<td>8</td>
</tr>
<tr>
<td>NASA</td>
<td>GLAS</td>
<td>SLS</td>
<td>None</td>
<td>N/A</td>
<td>0.04</td>
<td>0</td>
<td>0.11–0.17</td>
</tr>
<tr>
<td>NASA/UMD</td>
<td>MBLA</td>
<td>SLS</td>
<td>Osc.</td>
<td>—</td>
<td>0.01/0.242</td>
<td>—</td>
<td>0.06</td>
</tr>
<tr>
<td>BU/CSIRO</td>
<td>DWEL</td>
<td>TLS</td>
<td>N/A</td>
<td>N/A</td>
<td>20</td>
<td>360×119</td>
<td>1.25/2.5/5</td>
</tr>
<tr>
<td><strong>Commercial</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leica</td>
<td>ALS50</td>
<td>ALS</td>
<td>Osc.</td>
<td>25–70</td>
<td>83</td>
<td>±37.5</td>
<td>0.33</td>
</tr>
<tr>
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<td>ALS50-II</td>
<td>ALS</td>
<td>Osc.</td>
<td>35–90</td>
<td>150</td>
<td>±37.5</td>
<td>0.22</td>
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<tr>
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<td>ALS60</td>
<td>ALS</td>
<td>Osc.</td>
<td>&lt; 90</td>
<td>≤50</td>
<td>±37.5</td>
<td>0.22</td>
</tr>
<tr>
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Table 2.3: Specifications of lidar systems (Part II). Adapted from Douglas et al. (2012), Hollaus et al. (2014), Kukko and Hyvönen (2009), Mallet and Bretar (2009), and Wulder et al. (2012), and manufacturer websites: http://www.leica-geosystems.us/, http://www.optech.com/, and http://www.riegl.com/. Continued from Table 2.2.

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2.2.4 Photon Counting Lidar

In cases of extremely low signals, e.g., due to using low-powered lasers to address eye-safety concerns or power requirements of a space-based platform, photon counting lidar should be used. Photon counting lidar records the time and intensity of every photon that is received by the sensor.
A trade-off of using a photon counting system is that events will also be recorded for the passively generated photons, e.g., photons from the sun.

A photon counting lidar system is planned for NASA’s planned ice, cloud, and land elevationation satellite (ICESat-2) mission, which is scheduled to be launched around 2017 (Abdalati et al., 2010). In order to process the noisy data, statistical filtering of the data are required to derived ground elevation and tree height profiles (Moussavi et al., 2014). In order to simulate ICESat-2-like data prior to launch, NASA developed the airborne photon counting system multiple altimeter beam experimental lidar (MABEL) (McGill et al., 2013).

2.3 DIRSIG

The digital image and remote sensing image generation (DIRSIG) simulation environment (Schott et al., 1999) has been under development at Rochester Institute of Technology (RIT) since the late 1980’s. DIRSIG is a first principles-based synthetic image generation model intended to be able to produce single-, multi-, and hyperspectral passive imagery (e.g., sunlight, skylight, moonlight, starlight, and in-scene lights) from the visible to the thermal infrared spectral domains. In addition to the passive remote sensing capabilities of DIRSIG, it is also able to simulate lidar and has a growing synthetic aperture radar (SAR) capability. It is possible to simulate polarization with the previous modalities. The DIRSIG environment has gone through a number of validations, which are summarized in Brown and Schott (2010).

In general, DIRSIG measures front of the aperture radiances from virtual scenes. DIRSIG, like other simulation environments allows a user to perform trade studies to assess the impact of various system or scene parameters on an image or to perform experiments which are significantly harder to collect truth for with a real system.

The research described in this dissertation was performed using fourth edition of the DIRSIG
simulation environment. More specifically, the DIRSIG 4.5.x – 4.6.x releases were used. Care was taken to always use the latest stable DIRSIG build for the simulations.

2.3.1 DIRSIG simulations

A DIRSIG simulation has five major components: (i) the scene (Section 2.3.1.1), (ii) the atmosphere (Section 2.3.1.2), (iii) the platform (Section 2.3.1.3), (iv) the platform motion (Section 2.3.1.4), and (v) the tasks (Section 2.3.1.5). These components, along with an optional options file (Section 2.3.1.6), constitute a DIRSIG simulation file (Section 2.3.1.7).

2.3.1.1 DIRSIG scenes

The scene file tells DIRSIG what geometry and materials to use. The geometry (as defined by a combination of geometry files: wavefront obj, geometry database (gdb), and DIRSIG primitives; and instance files: object database (odb) and glist files) locations are generally listed in an east-north-up (ENU) coordinate system. ENU is a coordinate system relative to the scene origin with axes of east, north, and up representing the $x$, $y$, and $z$ coordinates. DIRSIG also has the ability to use absolute coordinate systems, such as UTM, to position objects within the scene. The geometry for DIRSIG must be explicitly defined (i.e., the geometry is either triangular facets or primitives). The material file will in turn point to sets of reflectances/emissivities, transmissions/extinctions, and/or sources which contain the optical properties of the geometries that are used within a scene. The scene file also sets the location of the scene center in a real-world coordinate system (latitude/longitude/altitude).

2.3.1.2 DIRSIG atmospheres

The DIRSIG atmosphere file allows the user to set the optical properties of the simulation. Basic simulations assume an ideal atmosphere (perfect transmission and no atmospheric scattering). It
is possible to use the moderate resolution atmospheric transmission (MODTRAN) model (Berk et al., 1987; Berk et al., 2005) with DIRSIG to produce participating atmospheres (i.e., atmospheres with transmission and scattering abilities).

2.3.1.3 DIRSIG platforms

A DIRSIG platform describes the sensor(s) and its properties. Sensor types include single-, multi-, or hyperspectral passive, lidar, and SAR. The properties include aspects like scan type e.g., framing camera, line scanner, whisk broom, pixel size, and timing. In addition, the platform file allows for the generation of truth images, which may contain things such as the material of first interaction, path radiance, path length, first intersection location, and last interaction location. A platform may also contain data loggers, such as a GPS and IMU. The platform allows for multiple instruments on the same platform, each with a potential offset from the reference location of that platform.

2.3.1.4 DIRSIG platform motions

The DIRSIG platform motion file describes where the imaging platform is located and orientated within a scene at different times. This file allows for the construction of flight lines or remaining stationary in the same position for an entire collect.

2.3.1.5 DIRSIG tasks

The DIRSIG tasks file controls when the sensor(s) is on. The file allows for an instantaneous capture, or for captures over an extended period. The task file can be thought of as when to turn the instrument(s) on and off during a multiple flight line collect.

2.3.1.6 DIRSIG options

The DIRSIG options file allows for setting the properties of photon bundles (described in Section 2.3.2). These properties are the maximum number of photon bundles cast into the scene, the
maximum number of interactions per photon bundle, and the maximum number of events in the photon map per pulse.

2.3.1.7 DIRSIG sims

The DIRSIG simulation file combines the aforementioned files (scene—Section 2.3.1.1, atmospheres—Section 2.3.1.2, platforms—Section 2.3.1.3, platform motion—Section 2.3.1.4), tasks—Section 2.3.1.5, and options—Section 2.3.1.6) into a simulation.

2.3.2 DIRSIG lidar

The DIRSIG lidar simulations (Burton et al., 2002; Burton, 2002; Brown et al., 2005; DIRSIG, 2015) are produced numerically using a direct+photon mapping approach. The direct (single) bounce returns are calculated by solving the laser radar equation (eqn. 2.31). The multiple scattering contributions are calculated by using a two-pass hybrid forward-backward Monte Carlo method (Metropolis and Ulam, 1949) called photon mapping (Jensen, 2001). The method for producing a w lidar signal in DIRSIG is as follows (see Figure 2.7 for a schematic of this process):

1. Compute the direct (single-bounce) contribution by solving the laser radar equation (eqn. 2.31). See Figure 2.7a.

2. Compute the multi-bounce contribution by photon mapping:

   (a) Forward pass (see Figure 2.7a):

   i. A ray (photon bundle) is randomly cast into the scene from the transmitter. The spatial and spectral distributions of photons are based on the settings from the platform file (Section 2.3.1.3).

   ii. The photon bundle will undergo a random walk through the scene based on the optical properties (transmission, reflection, absorption, scattering, and polarization) of the geometry it encounters.
Figure 2.7: Schematic illustrating the forward (a) and backward (b) photon-mapping process DIRSIG uses to compute the multiple scattering within a lidar signal. (a) Use the laser radar equation to solve for the direct term. Photon mapping is then used to computed the multiple scattering component of the signal. To do this, a photon bundle (red arrows) is cast out into the scene. At each interaction with the geometry (green and brown triangles), an event (○’s and ×’s) is stored in the photon map. The photon bundle propagates based on the optical properties it encounters until it is either absorbed (×’s) or a maximum number of interactions is reached. The first interaction with a photon bundle and geometry are computed by the radiometry engine associated with the geometry, while the secondary interactions are computed by the photon mapping process. (b) In the backward pass, all of the interactions (and not the geometry from the forward pass) within the frustum from each pixel or sub-pixel are recorded. These interactions are shown in blue. (c) At each intersection with an event in the map, the temporal and radiometric information (cyan curves) are added together along with the passive term ("pixels" on left side) to get an output signal (teal curve).
2.3. DIRSIG

iii. At each interaction, an event is created in a map containing the location in the scene, number of photons at that location, and time of interaction. The temporal distribution of photons is based on the settings from the platform file (Section 2.3.1.3).

iv. The random walk will continue until a maximum number of interactions have occurred or the photon bundle is absorbed. The exception to this maximum number of interactions are the direct rays (those that are transmitted directly through a leaf plate), which are propagated until absorbed, or reflected out of the direct path.

v. Forward pass steps i–iv are repeated until either a maximum number of photon bundles is cast into the scene, the maximum number of events in the photon map is reached, or a convergence of the signal base been reached. The maximum number of photon bundles and maximum events in the map are set in the options file (Section 2.3.1.6).

(b) Backward pass (see Figure 2.7a):

i. From the center of each detector (or sub-detector), a ray is backward-projected from each detector element into the scene (photon map). Note that adaptive sampling—probabilistically sending out rays from the detector until either a convergence is reached or a maximum number of back-projected rays are cast from the pixel—may be used either in place of or in addition to regularly sub-sampling the detector.

ii. At each interaction with the back-projected ray and the photon map, the number and distribution of photons at that interaction are added to the signal.

iii. Backward pass steps i–ii are repeated for all pixels/sub-pixels in the array.

3. Compute the passive component (from sunlight, skylight, moonlight, and starlight) by using the “classic” DIRSIG radiometry engines. This is the step that DIRSIG would use for a hyper-spectral imagery (HSI) or multi-spectral passive sensor.

4. Combine the terms to generate the total received signal (see Figure 2.7c): The DIRSIG-generated passive and active components of the lidar signal can be combined into a wave-
form, $w$, by using

$$w = \text{active} + B \cdot |b| \cdot \Delta t \quad (2.33)$$

where $B$ is the DIRSIG-generated estimate of the background in units of photons $\cdot s^{-1}$, $|b|$ is the number of time bins, and $\Delta t$ is the temporal width of a single time bin in seconds.

5. (Optional) Generate discrete point clouds or photon counting signals by running the waveform signals through a detector model. DIRSIG provides a linear-mode, Geiger-mode, and photomultiplier tube detector models. The linear-mode detector operates by using a constant fraction discriminator (CFD) method (Amann et al., 2001). The Geiger-mode detector model was described by O’Brien and Fouche (2005). The photomultiplier tube detector model allows for the simulation of a photon-counting lidar system. If this step is omitted, the result will be the wlidar signal.

The DIRSIG-generated wlidar signal represents the best possible signal that could be detected as it assumes perfect optics and electronics. As mentioned above, it is possible to take the DIRSIG-generated wlidar signal and convert it into either a discrete signal or a photon counting signal.
Chapter 3

Literature Review

This section contains a brief literature review of extraction of biophysical structure from lidar (see Section 3.1) and simulation of lidar signals (see Chapter 3.2).

3.1 Extraction of biophysical structure from lidar

There have been many studies on the extraction of biophysical parameter extraction from lidar. Lim et al. (2003), Mallet and Bretar (2009), Maltamo et al. (2014), Roberts et al. (2007), van Leeuwen and Nieuwenhuis (2010), and Wulder et al. (2012) provide broad summaries of the state-of-the-art in forest parameter extraction from lidar systems. A large amount of the literature focuses on either discrete or large footprint waveform techniques. Wlidar has been used for forest structure assessment, including vegetation height (Nilsson, 1996; Lefsky et al., 1999a; Asner et al., 2007; Wagner et al., 2008), biomass (Kronseder et al., 2012; McGlinchy et al., 2014), landcover classification (Neuenschwander et al., 2009; Sarrazin et al., 2012; Wessels et al., 2011), tree classification (Brandtberg, 2007; Heinzl and Koch, 2011; Reitberger et al., 2006), and tree segmentation (Höfle et al., 2012; Reitberger et al., 2009). A brief description of some of the methods used to extract biophysical structural parameters follows.
Lefsky et al. (1999a) developed the canopy volume method (CVM) to extract canopy structure from large-footprint SLICER data over a *Pseudotsuga menziesii* (Douglas fir) and *Tsuga heterophylla* (western hemlock) forest in Oregon, USA. CVM involves finding the filled and empty space within the canopy. This information can lead to measures of canopy height, biomass, and LAI.

Morsdorf et al. (2006) used discrete lidar to estimate fCover (fractional cover) and LAI by looking at the ratio of vegetation to ground echoes. They found moderate agreement ($R^2$ of 0.69 and a root mean square error (RMSE) of 0.01) between lidar-estimated and hemispherical photography-measured LAI values.

Tang (2015) used the medium-footprint LVIS wLidar sensor to measure LAI in a Costa Rica forest. They decomposed the waveform signal into a series of Gaussians, which along with field-measured leaf and ground reflectances, were used to estimate gap probabilities, from which an estimate of LAI can be made. They found the gap-probability-based model of LAI had an $R^2$ of 0.63 when compared with tower-based LAI measurements.

Within the bigger picture of bridging the scales between plot-level and continental-scale ecology, there is a gap of trying to estimate the fine scale variability of forest structure across a site. ALS, and particularly wLidar may provide an opportunity to bridge this gap. However, due to the complex nature of forests, collection of field-data is impractical in many instances. To reduce these challenges, we will turn to simulation to provide insights into the complex nature of forest-lidar interactions.

### 3.2 Lidar Simulations

In order to (i) improve our understanding of the complex interactions occurring in lidar signals in forested environments, (ii) perform sensor trade studies, and (iii) have the ability to develop algo-
rithms prior to system launch, the forest remote sensing community has made use of a number of
simulation environments. These simulation environments in the literature include geometric op-
tical and radiative transfer (GORT), DIRSIG, lidar interception and tree environment (LITE), and
librat. Simulation allows for absolute knowledge of the scene geometric and radiometric truth,
which can lead to a better understanding of the complicated nature of radiometry in forested envi-
ronments. The findings from these simulations are discussed below, with the results summarized
in Tables 3.1 and 3.2. The details of these studies follow chronological order.

Gardner (1992) created a model of a space borne full-waveform laser altimeter (lidar) to eval-
uate the impact of surface properties, pointing jitter, and waveform digitizer properties on the
detected signal. This was done with simple diffuse ground targets (i.e., simple, unvegetated ter-
rain). They found that pointing accuracy has a large influence on ranging accuracy, particularly
in areas of steep terrain. For orbital altitudes of several hundred kilometers, single shot range
accuracies of a few centimeters could be achieved if the pointing jitter was less than 10 [µm].

Abshire et al. (1994) developed a one-dimensional (laser profilometer) model to simulate space-
borne lidar systems. The simulator allows for the setting of height and Lambertian reflectance
at each 1 [cm] step. To compute the backscattered signal, a Monte-Carlo method was used. The
output signal used a threshold for triggering the opening of a range gate.

Govaerts (1996) and Govaerts and Verstraete (1998) developed the RAYTRAN model for com-
puting light scattering in heterogeneous media. RAYTRAN is a Monte Carlo ray tracer that
interacts with geometry that potentially reflects, scatters, absorbs, or transmits. To validate RAY-
TRAN, the authors compared the results with another Monte Carlo model (Ross and Marshak,
1988), the discrete ordinance canopy model IAPI2A (Iaquinta, 1995), and laboratory measured bi-
directional reflectance factor (BRF) measurements. For forest simulations, they compared discrete
elements in a shell and pseudo-turbid canopies.
Tulldahl and Steinvall (1999) describe the creation of an analytical model for bathymetric lidar systems. They found good agreement in the simulated waveforms to data depth collected with a Hawk Eye lidar system.

Blair and Hofton (1999) modeled medium-footprint lidar signals as the spatial and temporal summation of the reflections from within-footprint surfaces convolved with a system response function. The within-footprint surfaces were from a FLI-MAP system (small-footprint, first return only discrete airborne lidar). The simulated waveform signals were compared to LVIS data. They found that this technique could be used to validate geolocation accuracies and evaluate ground finding algorithms of systems such as VCL and GLAS pre-launch. In addition, the high correlation between the simulated and LVIS waveforms indicated that the unmodeled multiple scattering did not significantly contribute to the waveform signal at a medium footprint scale.

Contrary to results of Blair and Hofton (1999), Sun and Ranson (2000) found higher order scattering does affect large-footprint waveform signals. The authors used tree primitives based on species, height, and maximum diameter to simulate a forest stand. The scene was then divided into small voxels from which a lidar system was simulated (see Figure 3.1). In order to validate the model, the simulated waveforms were compared to SLICER waveforms collected over a mature Pinus banksiana (jack pine) stand in Saskatchewan, Canada as part of the Boreal Ecosystem-Atmosphere Study (BOREAS) experiment (Gamon et al., 2004). They found that the average shape of measured waveforms were similar to the mean shape of simulated waveforms when an ellipsoid or hemi-ellipsoid shaped tree model were used. The model could be used to simulate the main lidar signatures; however, they found that sub-canopy structure (not modeled) also impacts the waveform shape.

Ni-Meister et al. (2001) adapted the GORT model (Ni et al., 1997) for simulating lidar. They found that leaf clumping has a significant effect on the large-footprint waveform signal. The model was validated using SLICER data of the BOREAS study area, with which there was good
In 2002, DIRSIG went from being able to simulate reflective and emissive phenomenology from 0.35 to 20.0 [$\mu$m] to adding lidar support with participating media. The prototype DIRSIG simulation environment, capable of simulating passive and active remote sensing, was conducted by Burton et al. (2002) and Burton (2002). Burton et al. (2002) describes the mathematics behind the DIRSIG lidar model, including interactions with the geometry, elastic atmospheric interactions, and addition of laser speckle to the simulations. Brown et al. (2005) demonstrated a more formalized version of lidar simulation within DIRSIG.

Holmgren et al. (2003) developed a discrete lidar simulation model. They modeled Picea spp. (spruce) and Pinus spp. (pine) trees as half ellipsoids with parameterized positions, tree heights, crown diameters, and height to living crowns. The simulations were compared to a TopEye lidar scan over a forest managed for timber production in Remningstorp, Sweden with Picea abies (Norway spruce), Pinus sylvestris (scots pine), and Betula spp. (birch) as the dominant species.
The virtual trees were placed in the same locations as field measurements. They found good agreement (0.96 correlation) between the proportion of canopy heights (PCH) at the 20th, 40th, 60th, 80th, and 90th percentiles of height from the real and simulated data. PCH is the percentage of lidar returns at a height, divided by the total number of returns. From these simulations, the authors were able to make predictions of what observed PCH values should be as a function of stem density, tree height, and scan angle.

Kotchenova et al. (2003) applied a numerical solution of a time-dependent stochastic radiative transfer equation. This model allowed for multiple scattering, which authors found led to a slower decay of the waveform and higher amplitude of the reflected signal. The modeled waveforms were compared to SLICER data from two conifer stands: one containing Pinus banksiana and the other containing Picea mariana (black spruce) and one broadleaf stand dominated by Liriodendron tulipifera (tulip poplar). The result was the \( x, y, z \) locations of the intersection of the laser beam with the geometry.

Blevins (2005) and Blevins et al. (2006) built on the work of Burton et al. (2002), Burton (2002), and Brown et al. (2005) by demonstrating lidar simulation of participating media, such as gas plumes, with DIRSIG. This work was a first-principles based method for using a differential absorption lidar (DIAL) system. DIAL is a technique in which two lasers with different wavelengths (one which will transmit through a medium and another which is absorbed by it) are used to extract optical depths of a medium by measuring the relative backscattered energy from the two lasers.

Harding and Carabajal (2005) simulated GLAS waveforms by extending the methods of Blair and Hofton (1999). Where Blair and Hofton (1999) used single return discrete lidar, this study used up to four return discrete lidar scans over Kisap Peninsula, WA, USA on top of a gridded DEM. This simulation provided a means to validate GLAS waveforms, elevation products, and geolocation.
Houldcroft et al. (2005) simulated a lidar system over *Zea mays* (maize) and *Helianthus annuus* (sunflower) crops. They used voxels with the statistical properties of the canopy (e.g., LAI and leaf angle distribution (LAD)) to define the within voxel structure. To generate a lidar signal, the authors started at the lower left corner of the voxel space. A return was created if the backscattered energy from a voxel was greater than a threshold. Once a return was generated, the beam was moved to an adjacent area of the canopy voxel space, until the entire voxel space was covered.

Lovell et al. (2005) investigate system parameters with a simulated discrete lidar system. They used a simple ray tracer to find the intersections of conical and ellipsoidal models of a *Pinus radiata* (Monterey pine) planation. They found that increasing scan density by using multiple flight lines provided better sampling than reducing scan angles; however, reducing scan angles improved ground detection.

Morsdorf et al. (2007) used the persistence of vision ray tracer (POVRAY) (Plachetka, 1998) with L-systems generated trees with leaf optical properties spectra (PROSPECT) (see Section 4.2.2.1) and field-collected spectra to simulate both discrete and wLidar. They later used this technique on *Pinus sylvestris* (see Figure 3.2) and *Picea abies* trees simulated from TREEGROW (Leersnijder, 1992) to investigate multi-spectral wLidar (Morsdorf et al., 2009). The authors performed simulations using 531, 550, 670, and 780 [nm] wLidar systems. They found that using multispectral wLidar could be used to pick up the seasonal and vertical distributions of normalized difference vegetation index (NDVI) within a canopy.

Goodwin et al. (2007) developed the LITE simulation environment for simulating discrete lidar systems. They defined a crown extent with measurements of tree height, height to living crown, and crown diameter. The optical properties within the crown extent were created using a probabilistic model of clumping (see Figure 3.3). Each 0.25 [m] on a side voxel was assigned a value for the effective transmission through that element (e.g., 0 for empty, 1 for trunk, < 1 for
3.2. LIDAR SIMULATIONS

The voxels within the canopy were filled such that outer shell voxels had low density (0.1) and the higher density (0.4) voxels were placed higher and towards the edge of the crown by using a lognormal distribution. To simulate a lidar system, forward ray tracing was used. For each interaction between a ray and a voxel, the location, scan angle, path length, and object type were recorded. The above parameters were used to calculate the probability of beam interception using a directional gap probability model to build the waveforms. A rasterized DEM can be placed under the tree geometries to produce the \( x, y, z \) locations of the ground. This model has as assumptions no beam divergence, with constant beam width, and a minimum resolution of the voxel size—0.25 [m]. Based on the work of Blair and Hofton (1999), the authors did not consider multiple scattering or returns from outside of the footprint. The model was verified using three Australian sites consisting of *Eucalyptus grandis* (flooded gum), *Eucalyptus pilularis* (blackbutt), *Corymbia maculata* (spotted gum), and *Eucalyptus microcorys* (tallowood). There was good agreement in the normalized height percentiles from the simulated point cloud and the point cloud from a Optech ALTM 3025 across the three sites.
3.2. LIDAR SIMULATIONS

Figure 3.3: Tree modeling process from Goodwin et al. (2007). (a) dividing a crown into 4 sectors, (b) calculating the number of modules from the Neyman type A distribution, (c) illustration of foliage clumping, and (d) modeled tree. Copyright © 2007, Elsevier.
Disney et al. (2010) used librat—a Monte Carlo ray tracer (Lewis, 1999; Disney et al., 2000; Disney et al., 2006)—to simulate discrete lidar returns to assess the impact of scan angle, footprint size, and discrete signal triggering threshold on tree parameters. They found that the choice of signal triggering method, scan angle, and footprint size all affected the lidar-retrieved canopy heights. This was tested on scenes containing Betula pubescens (downy birch) and Pinus sylvestris trees. These trees contained faceted geometry modeled using PINOGRAM (Leersnijder, 1992) and OnyxTREE (Bosanac and Zanchi, 2011).

North et al. (2010) extended the FLIGHT model (North, 1996) to be able to simulate lidar. FLIGHT is a Monte Carlo ray tracer that uses either voxelized properties (e.g., PAI, leaf angle distributions, reflectance, transmission) inside of envelopes (elliptical or conical) or facets to describe scene geometry (see Figure 3.4). To generate a waveform, rays are cast out spatially uniformly over the instantaneous field of view (IFOV) of the sensor and weighted by the backscattered energy from that path. FLIGHT allows for multiple orders of scattering; the authors typically used 6–9 interactions. The FLIGHT model was validated by comparing shapes of real and simulated GLAS waveforms over a single layer Quercus spp. (oak) canopy and a multi-layer Pseudotsuga menziesii canopy, both of which were found have good agreement.

Wu et al. (2011) investigated different deconvolution algorithms using DIRSIG-simulated and Carnegie Airborne Observatory (CAO) small footprint lidar data. They used virtual trees created from Arbaro (Weber and Penn, 1995; Arbaro 2013), while the CAO data were collected using an Optech ALTM3100. The modeled species were Sassafras albidum (white sassafras), Nyssa sylvatica (black tupelo), Populus tremuloides (quaking aspen), and Populus deltoides (eastern cottonwood). They found that the Richardson-Lucy deconvolution (Richardson, 1972; Lucy, 1974) outperformed Weiner filtering (Wiener et al., 1964) and non-negative least squares (Lawson and Hanson, 1974). This then became one component of a lidar pre-processing chain which included de-noising, deconvolution, ground registration, and angular rectification (Wu et al., 2012). Finally, they used a morphology-based approach to extract branching structure and stem location estimates from
small-footprint airborne lidar (Wu et al., 2013). These efforts were all described in the author’s dissertation (Wu, 2012).

Hancock et al. (2011) used librat to find canopy tops to address the well known problem of lidar underestimation of tree height (Hyde et al., 2005; Lefsky et al., 2002; Lefsky et al., 2005; Morsdorf et al., 2008). The authors used explicitly defined Picea sitchensis (sitka spruce) of different densities and ages in the simulations, which led to a new method of range gating called “noise tracking.” This in turn led to a lower error in estimating tree footprints than a more traditional threshold approach. librat was also used to evaluate the effect of terrain on large-footprint dual-wavelength lidar signals (Hancock et al., 2012). The authors placed Picea sitchensis and Betula spp. trees of different ages on sloped terrains and concluded that using a dual wavelength lidar system helped to better resolve the ground over a single wavelength system.

Calders et al. (2013) used librat to look at crown archetypes (conical, elliptical, and cuboid) and the impact that the simplification of geometries may have on lidar simulations. They found that
using generalized archetypes may not work for lidar simulation these structures may fail if within crown clumping is not taken into account. This shows the necessity to use high-fidelity geometric models for lidar simulations.

Huang and Wynne (2013) added a time-dependent component to the radiosity (Goral et al., 1984; Sillion and Puech, 1994) algorithm of Qin and Gerstl (2000). The authors used randomly-distributed multiple-scale triangles and rectangles to represent within-canopy structure. The scenes included defined trees, created from a crown shape structure (ellipsoids, cones, or cylinders), tree height, LAI, and LAD placed on a DEM. The authors found good agreement ($R^2 > 0.90$) between the real and simulated SLICER waveforms over BOREAS. Using the algorithm, they found that multiple scattering has a significant impact on the backscattered waveform by magnifying the returns in the upper canopy and resulting in a peak shift downwards in energy. The authors found that this impact was negligible for trees with an LAI of less than one.

Rosette et al. (2013) used FLIGHT to evaluate a range of system parameters. They found that a smaller (large) footprint of 25 [m] (as opposed to 70 [m]), will permit the detection of the ground for slopes up to 30 [°].

Finally, Morton et al. (2014) used FLIGHT to evaluate four possible reasons for Amazon forest green-up: increasing leaf area, increasing leaf reflectance, changing litter reflectances, or variability in the sun-sensor orientation. They tested these hypotheses by varying these parameters for simulated passive and lidar remote sensing collects. It was determined that the apparent optical green-up was caused by seasonal changes in near-infrared reflectance, which is a result of the sun-sensor geometry.

While there has been significant effort in the simulation of lidar signals, particularly at a large-footprint scale with primitive geometry, there are only a few simulation environments capable of simulating small-footprint signals in explicitly defined forested environments. These
### Table 3.1: Summary of lidar simulations (Part I)

<table>
<thead>
<tr>
<th>Paper Model Name</th>
<th>Method</th>
<th>Footprint</th>
<th>Digitization</th>
<th>Application(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abshire et al. (1994)</td>
<td>a</td>
<td>analytic</td>
<td>W</td>
<td>simulator manual</td>
</tr>
<tr>
<td>Blair and Hofton (1999)</td>
<td>b</td>
<td>O</td>
<td>medium</td>
<td>D</td>
</tr>
<tr>
<td>Blevins (2005)</td>
<td>c</td>
<td>DRSIG</td>
<td>PM</td>
<td>—</td>
</tr>
<tr>
<td>Burton et al. (2005)</td>
<td>d</td>
<td>DRSIG</td>
<td>PM</td>
<td>—</td>
</tr>
<tr>
<td>Burton (2002)</td>
<td>e</td>
<td>DIRSIG</td>
<td>PM</td>
<td>—</td>
</tr>
<tr>
<td>Calders et al. (2013)</td>
<td>f</td>
<td>librat</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Disney et al. (2010)</td>
<td>g</td>
<td>librat</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Gardner (1992)</td>
<td>h</td>
<td>DRSIG</td>
<td>PM</td>
<td>—</td>
</tr>
<tr>
<td>Goodwin et al. (2007)</td>
<td>i</td>
<td>RAYTRAN</td>
<td>MCRT</td>
<td>—</td>
</tr>
<tr>
<td>Hancock et al. (1998)</td>
<td>j</td>
<td>RAYTRAN</td>
<td>MCRT</td>
<td>—</td>
</tr>
<tr>
<td>Hancock et al. (2005)</td>
<td>k</td>
<td>RAYTRAN</td>
<td>MCRT</td>
<td>—</td>
</tr>
<tr>
<td>Harding et al. (2003)</td>
<td>l</td>
<td>small</td>
<td>D</td>
<td>D</td>
</tr>
<tr>
<td>Holmgren et al. (2005)</td>
<td>m</td>
<td>small</td>
<td>D</td>
<td>D</td>
</tr>
</tbody>
</table>

Methods are (A) analytic, (MRT) Monte-Carlo ray tracing, (O) combining other lidar signals, (PM) photon mapping, (R) radiosity, and (RT) ray tracing. Digitizations are (W) waveform, and (D) discrete. Geometries are (D) discrete points, (F) faceted, (L) line (1-D terrain model), (M) modeled e.g., cone, hemi-eliptical, etc., (S) simple targets, (VP) voxelized primitives, and (P) probabilistic.

Continued in Table 3.2.
Table 3.2: Summary of lidar simulations (Part II). Unnamed models that are the same are marked with a lowercase letter. Methods are (A) analytic, (MCRT) Monte-Carlo ray tracing, (O) combining other lidar signals, (PM) photon mapping, (R) radiosity, and (RT) ray tracing. Digitizations are (W) waveform, and (D) discrete. Geometries are (D) discrete points, (F) faceted, (L), line (1-D terrain model), (M) modeled e.g., cone, hemi-elliptical, etc., (S) simple targets, (VP) voxelized primitives, and (P) probabilistic. Continued from Table 3.1.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Model name</th>
<th>Method</th>
<th>Footprint</th>
<th>Digitization</th>
<th>Geometry</th>
<th>Application(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Huang and Wynne (2013)</td>
<td>h</td>
<td>R</td>
<td>large</td>
<td>W</td>
<td>M</td>
<td>model development, multiple scattering</td>
</tr>
<tr>
<td>Kotchenov et al. (2003)</td>
<td>g</td>
<td>A</td>
<td>large</td>
<td>W</td>
<td></td>
<td>model development</td>
</tr>
<tr>
<td>Lovell et al. (2005)</td>
<td>h</td>
<td>RT</td>
<td>small</td>
<td>D</td>
<td>M</td>
<td>system parameter analysis</td>
</tr>
<tr>
<td>Morsdorf et al. (2007)</td>
<td>POVRAY</td>
<td>RT</td>
<td>small</td>
<td>W, D</td>
<td>F</td>
<td>model development</td>
</tr>
<tr>
<td>Morsdorf et al. (2009)</td>
<td>POVRAY</td>
<td>RT</td>
<td>small</td>
<td>W</td>
<td>F</td>
<td>multispectral lidar assessment</td>
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<tr>
<td>Morton et al. (2014)</td>
<td>FLIGHT</td>
<td>MCRT</td>
<td>large</td>
<td>W</td>
<td>M</td>
<td>Amazon forest hypothesis testing</td>
</tr>
<tr>
<td>Ni-Meister et al. (2001)</td>
<td>GORT</td>
<td></td>
<td>large</td>
<td>W</td>
<td>M</td>
<td>model development</td>
</tr>
<tr>
<td>Ni-Meister et al. (2008)</td>
<td>GORT</td>
<td></td>
<td>small</td>
<td>W</td>
<td>M</td>
<td>TLS model development</td>
</tr>
<tr>
<td>North et al. (2010)</td>
<td>FLIGHT</td>
<td>MCRT</td>
<td>large</td>
<td>W</td>
<td>V, F</td>
<td>model development</td>
</tr>
<tr>
<td>Rosette et al. (2013)</td>
<td>FLIGHT</td>
<td>MCRT</td>
<td>large</td>
<td>W</td>
<td>V, F</td>
<td>system parameter analysis</td>
</tr>
<tr>
<td>Sun and Ranson (2000)</td>
<td>i</td>
<td></td>
<td>large</td>
<td>W</td>
<td>VP</td>
<td>simulation validation</td>
</tr>
<tr>
<td>Tulldahl and Steinvall (1999)</td>
<td>j</td>
<td>A</td>
<td>—</td>
<td></td>
<td></td>
<td>bathymetric model development</td>
</tr>
<tr>
<td>Wu et al. (2011)</td>
<td>DIRSIG</td>
<td>PM</td>
<td>small</td>
<td>W</td>
<td>F</td>
<td>deconvolution analysis</td>
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<tr>
<td>Wu et al. (2012)</td>
<td>DIRSIG</td>
<td>PM</td>
<td>small</td>
<td>W</td>
<td>F</td>
<td>waveform pre-processing</td>
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<tr>
<td>Wu (2012)</td>
<td>DIRSIG</td>
<td>PM</td>
<td>small</td>
<td>W</td>
<td>F</td>
<td>see others</td>
</tr>
<tr>
<td>Wu et al. (2013)</td>
<td>DIRSIG</td>
<td>PM</td>
<td>small</td>
<td>W</td>
<td>F</td>
<td>branch estimation</td>
</tr>
</tbody>
</table>
include DIRSIG, librat, POVRAY, and RAYTRAN. Due to the complex nature of trees at this scale (the geometry changes at the centimeter scale), until recently, it was computationally infeasible to simulate lidar simulations with geometry at the leaf-level. Many of the other models make assumptions of archetypes (e.g., ellipsoid, hemi-ellipsoid, cone), which while useful for investigating large footprint systems, lack the fidelity to simulate small footprint lidar platforms.

With the exception of Morsdorf et al. (2007) and Disney et al. (2010) using TREEGROW (Leersnijder, 1992) and Wu et al. (2011), Wu et al. (2013), Wu et al. (2012), and Wu (2012) using Arbaro(Weber and Penn, 1995; Arbaro 2013) to create forest models, none of the other papers provide insight in the generation of explicitly-defined virtual tree models for insertion into a simulated forest. A workflow for addressing the construction of virtual forest scenes can be found in Chapter 4. As a part of understanding the creation of virtual forest scenes, there has not been a study to investigate the level of geometric complexity is necessary to get consistent lidar signals, i.e., which geometric components impact the signal and which geometric components have a negligible impact on the signal. This knowledge gap is addressed in Objective 2. in Chapter 5.

As a result of this lack of high-fidelity small-footprint lidar simulations, there is a knowledge gap for building high-resolution forested scenes.
Chapter 4

Scene Construction

4.1 Introduction

Simulated data generation models are an effective tool to provide insight into the complex interaction between a forest canopy and a lidar system. Typically, simulation models require three key components: (i) the lidar system, including the transmit and receiving capabilities, and their respective settings; (ii) the environmental conditions, including the atmospherics, time of day, etc.; and (iii) the scene being investigated. While existing tools can readily generate system and environmental characteristics, the development of virtual scenes is a much more complicated process. Moreover, the fidelity, or detail (both structural and radiometric) of the virtual scene is dependent upon the sensor of interest. For large-footprint systems, the use of primitives, e.g., ellipsoids and cones, provides a sufficient model of the canopy, e.g., Holmgren et al. (2003) and Sun and Ranson (2000). However, unlike large-footprint systems, which sample many trees with a single pulse, small-footprint system may only sample a portion of a single organism, and therefore require much more detailed virtual forest models. Therefore for small-footprint systems, tree models require individual components and leaves, rather than simple geometric primitives.
4.1. INTRODUCTION

Until recently, the modeling and ray-tracing of high-fidelity geometric forest models has been computationally intractable. In recent years, however, modern computing has offered a new opportunity to simulate small-footprint lidar sensing systems. While there has been an increase in studying virtual forest scenes in recent years, there is a lack of publicly available free virtual scenes. One key exception to this is the Radiation transfer Model Intercomparison (RAMI) initiative, which provides a set of abstract (see Figure 4.1) and actual canopies (see Figure 4.2) that are publicly available for comparisons of radiative transfer (RT) models in the passive domains, (Pinty et al., 2001; Pinty et al., 2004; Widlowski et al., 2006; Widlowski et al., 2011). As a result, one of the first steps toward increasing our understanding of the complex waveform-canopy interactions is to develop a method for constructing virtual scenes with which to develop algorithms and test hypotheses.

![Figure 4.1: RAMI-IV abstract scenes.](http://rami-benchmark.jrc.ec.europa.eu/HTML/RAMI-IV/RAMI-IV.php)

The construction of a virtual forest scene can be broken up into two main parts: the geometric...
Figure 4.2: RAMI-IV actual scenes. The RAMI scenes are (a) summer Järvselja pine stand, Estonia, (b) winter Ofenpass pine stand, Switzerland, (c) summer Järvselja birch stand, Estonia, (d) Wellington citrus orchard, South Africa, (e) winter Järvselja birch stand, Estonia, and (f) Lombardy short rotation forest, Italy. Images from http://rami-benchmark.jrc.ec.europa.eu/HTML/RAMI-IV/RAMI-IV.php.
part (Section 4.2.1) and the spectral part (Section 4.2.2). The requirements to build a forest scene are a DEM, aerial imagery, and field data including species, height, DBH, positions, crown extent, and spectral properties. The work contained in this chapter goes over the virtual forest scene construction process and an overview of the virtual forest scenes created within the scope of this dissertation. Parts of the work detailed in this chapter have been published and/or presented in Romanczyk et al. (2012), Romanczyk et al. (2013a), Romanczyk et al. (2013b), Yao et al. (2015a), and Yao et al. (2015b). The methods for scene construction contained in this chapter are my own, while the uses presented in Yao et al. (2015a) and Yao et al. (2015b) are part of algorithm development for a project related to NASA’s proposed Hyperspectral Infrared Imager (HyspIRI) mission.

4.1.1 Layout

The remainder of this chapter is broken up into three sections: Section 4.2 provides a method to produce virtual forest models, including geometric (see Section 4.2.1) and optical (see Section 4.2.2) properties, Section 4.3 provides details about a virtual scene that was created as part of this dissertation, and finally, Section 4.4 provides conclusions about scene construction and an outlook into future work that could improve the process. Additional virtual forest scenes that were developed, but not directly used within the scope of this dissertation, can be found in Appendix A.

4.1.2 Associated Publications and Presentations

4.2 Scene Construction

Figure 4.3 shows the basic workflow of building a DIRSIG forest scene. This process includes building tree models from either field inventory and/or high-resolution aerial imagery, “planting” the trees (and other objects in the scene) on a flat ground plane, adjusting the heights to the DEM, and assigning spectral properties to the geometry objects.

4.2.1 Scene Geometric Properties

4.2.1.1 OnyxTREE

Owing to the complicated nature of tree structure, it is desirable to programmatically build virtual tree models. For the work in this dissertation, the OnyxTREE (Bosanac and Zanchi, 2011) suite was used to build tree models. The OnyxTREE environment allows for trees to be built para-
4.2. SCENE CONSTRUCTION

Figure 4.3: Workflow for constructing a DIRSIG forest scene. **Bold** items are ones that are used in the DIRSIG simulations. Field data include tree species, species, position, height, height to living crown, DBH, spectra, etc.

metrically. OnyxTREE provides the OnyxGARDEN suite of vegetation modelers, which allows for the generation of broadleaves, conifers, grasses, palms, flowers, and bamboo. Unfortunately, the parameters required by OnyxTREE are not directly measurable by simple field inventories. In addition, more than one “knob” in OnyxTREE (see Figure 4.4) will influence field-measured inventory data, e.g., the Trunk Height and Bough Length adjustments both affect the total tree height, while the Bough Length will also affect the horizontal canopy extent. Creation of a single tree model will often require multiple passes through the same settings to generate a virtual tree model that approximately matches the field-measured parameters.

The OnyxTREE environment is capable of exporting faceted geometry of various components of a tree. The different components are summarized in Table 4.1 and shown in Figures 4.5 and 4.6. Leaf plates ($p$) are a two facet representation of leaves ($l$) for low-polygon count simulations. It is possible to UV-map a leaf to the leaf plates to produce realistically shaped leaves with fewer geometric facets. The leaves ($l$ or $p$) are connected to the leaf stems ($s$), which are in turn connected to the twigs ($w$), that are in turn connected to the branch-level-3 ($3$), etc. To prevent a photon from
Figure 4.4: Screen grab of the OnyxTREE Broadleaf user interface. Note that there are a number of menus on the right hand side from which the tree parameters can be adjusted. Many of these menus have sub-menus, which can be used to further refine the tree geometry.
rattling around on the inside of the woody tree geometry, end-caps, *i.e.*, opaque geometry with the same materials characteristics as the geometry they are associated with, are turned on for the geometries where it is available (*b*, *1*, *2*, *3*, *w*, and *s*).

Table 4.1: List of possible output geometries from OnyxTREE’s broadleaf and conifer geometry generators. Broadleaf and conifer refer to the ability for that geometry generator to model the particular component.

<table>
<thead>
<tr>
<th>Component</th>
<th>Name</th>
<th>Broadleaf</th>
<th>Conifer</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>t</em></td>
<td>trunks</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>b</em></td>
<td>boughs</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>1</em></td>
<td>branch-level-1</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>2</em></td>
<td>branch-level-2</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>3</em></td>
<td>branch-level-3</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>w</em></td>
<td>twigs</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>s</em></td>
<td>leaf stems</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td><em>l</em></td>
<td>leaves</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td><em>p</em></td>
<td>leaf plates</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td><em>e</em></td>
<td>envelope</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td><em>n</em></td>
<td>needles</td>
<td>×</td>
<td></td>
</tr>
</tbody>
</table>

To generate realistic trees, a minimum parameter set of species, crown height, height to living crown, DBH, and crown extent should be known. In addition, knowledge of more advanced tree attributes, such as branching structure and LAI, help to make more realistic tree models. However, knowledge of these additional attributes will significantly increase the time it takes to build a tree model, as many more iterations through the OnyxTREE adjustments will be required to match the desired tree parameters. In the end, the OnyxTREE model, will only be an approximation of any real-world tree.

4.2.1.2 Manual tree placement

Once the tree models are built, they need to placed within a scene. If coordinates of the trees were known, either from field measurements or from imagery, they were used directly for tree placement. Where tree coordinates were not known, the “lollipop” version of the trees (*te*),
Figure 4.5: OnyxTREE renderings of broadleaf tree components. See Figure 4.6 for a zoomed version. The component descriptions can be found in Table 4.1.
Figure 4.6: Zoomed OnyxTREE renderings of broadleaf tree components. See Figure 4.6 for the full trees. The component descriptions can be found in Table 4.1.
containing only tree trunks and envelopes were used. The lollipop version of the trees have relatively few facets, which is useful in terms of ease of manipulation within a 3D graphics package such as Blender (Blender Online Community, 2015). The lollipop trees were manually placed in the scene with the goal of having a relatively closed canopy (only small gaps, if any, between trees). Once the forest/forest stand has been built, the geometry can be changed from lollipop \((te)\) to a more complete tree model \((e.g., \text{tb123wsl})\) for some fine tuning of the positions.

### 4.2.1.3 Automated tree placement

For building large-scale forested scenes, \(e.g.,\) a square kilometer scene, it is useful to have an automatic way of placing tree models within a scene. One method with which to do this, is using Poisson-disk sampling (Yellott, 1983; Cook, 1986; Mitchell, 1987). This is a method to pseudo-randomly generate points with a blue noise frequency distribution. In other words, Poisson-disk sampling is a method of generating blue noise, where the distance between any pair of points is at least a set threshold apart. See Figure 4.7 for a comparison of sampling techniques. This is a reasonable approximation for many natural spacing scenarios, including homogeneous forests. A good rule of thumb for setting up a Poisson disk sampling for a closed canopy is to set the radius of the Poisson disk to the average radius of the tree models being used for the scene. It is possible to use a variable radii-poisson disk sampling method, \(e.g.,\) Mitchell \etal. (2012), to plant trees in a more heterogeneous way.

For each, location of the trees, a random assignment of a tree model can be given to each location. In order to reduce the computational load and tree geometry construction time, tree models should be used multiple times throughout a large-scale scene. It is recommended to have a few tree models per species, \(e.g.,\) a small, medium, and large model of each species, that can be instanced. Each instance can then have a random \(z\)-axis rotation and a small lean angle, which is also randomly added to it to help increase the scene variability. In addition, scale factors close to one may be used to increase the apparent variability of the scene. Large and small scale factors
4.2. SCENE CONSTRUCTION

Figure 4.7: Selected sampling methods: (a) uniform random; (b) gridded uniform random; and (c) Poisson disk. All three are shown with approximately the same point density: namely 66 points for uniform random and Poisson disk sampling and 64 for gridded uniform random. For the same density of points, Poisson disk sampling produces the most uniform distribution of points within the area. This distribution arguably also best represent the kind of spacing in forest, due to inter-tree competition and occupation of soil and light resources.

should be avoided to keep the leaf sizes within realistic bounds.

Once the tree models have been “planted,” additional manual relocation may be needed. Depending on the homogeneity of the forest, Poisson disk sampling alone may not be sufficient to create a closed canopy scene. For even-aged stands of conifers, Poisson disk sampling will produce an acceptable result with no manual adjustments. However, for broadleaf stands with mixed species and different dominance levels within the canopy, manual adjustment of the tree locations will be necessary to maintain a closed canopy. The Poisson disk sampling is still useful in this case, as it gives a good first estimate of a tree distribution within a scene.

4.2.1.4 Adjusting the heights of the scene objects

In order to have the tree locations follow a terrain surface, their locations need to be adjusted to the terrain. Previously, this involved a ray-tracing method to find the height of the ground at each \( x, y \) tree location. Starting with both the DIRSIG glist file, which contains the locations of the scene objects and a faceted DEM obj, the DEM was integrated using ray-tracing techniques to find the
height at each \( x, y \) tree location. This height, plus an optional bias, is added to the \( z \) value from the glist file to produce the height of the object on the DEM. The bias (usually negative) is to ensure that there are no (or minimal) gaps between the object and the DEM in sloped areas.

Since the initial efforts to automatically place geometry on terrains, DIRSIG has added functionality to perform this operation at runtime, called “drop placement”. To make use of drop placement, a named instance is needed for the reference, e.g., terrain, water, etc. location. See Figure 4.8 for an example glist file containing a named instance. Each tree instance is then given a \( x, y \) position relative to the reference location, and a height, \( z \), above or below the reference geometry. See Figure 4.9 for a sample glist static instance making use of drop placement. It is recommended to have a small negative \( z \) value for the translation to ensure there is no gap between the tree trunk and the terrain. Drop placement also provides the ability to rotate the instanced geometry, so that the \(+z\) axis of the geometry is aligned with the normal of the reference geometry via the \texttt{anchorrotation} extensible markup language (XML) tag. For trees this should always be set to “false” so that the trees grow upwards, rather than orthogonal to the terrain. All of this assumes that the origin, \( i.e., [0, 0, 0]^T \) of the tree geometry is the center of the bottom of the trunk, otherwise the above methods would need to be appropriately translated.

\[
\begin{xml}
<geometrylist enabled="true">
  <object>
    <basegeometry>
      <obj><filename>terrain.obj</filename></obj>
    </basegeometry>
    <staticinstance name="terrain">
      <translation>
        <point><x>0</x><y>0</y><z>0</z></point>
      </translation>
    </staticinstance>
  </object>
</geometrylist>
\end{xml}

Figure 4.8: A sample terrain glist file. This puts an instance of terrain.obj at the origin. It also names the instance “terrain,” which is required for making use of drop placement.
<staticinstance anchor="terrain" anchorrotation="false">
  <translation>
    <point><x>-7.0</x><y>8.0</y><z>-0.2</z></point>
  </translation>
</staticinstance>

Figure 4.9: Excerpt from a glist file showing how to make use of drop placement in a static instance. The anchor refers to the named instance (see Figure 4.8) which is used to anchor this piece of geometry. The anchor rotation being set to “false” tells DIRSIG to keep the orientation of the instanced glist, otherwise the orientation will be rotated to match the normal to the reference location at that geometry. In this example the origin of the tree geometry will be placed at -7, 8 [m] in the scene ENU coordinate space and placed 0.2 [m] below the the terrain.

### 4.2.2 Scene Optical Properties

Once the geometry has been constructed, its optical properties, *i.e.*, reflectance and transmission, need to be appropriately assigned. In many cases, DIRSIG optical properties were assigned by performing field collects to measure reflectance and transmission. In many cases, spectral properties will be reused over the years from previous DIRSIG scenes. These spectra may have been collected for previous scenes (many years ago) and be subject to noise from the atmosphere, may not have transmission spectra to go along with the reflectance spectra, or may be non-physical in that

$$\rho + \tau > 1,$$

where $\rho$ is the reflectance factor and $\tau$ is the transmittance factor. This is a violation of conservation of energy. In addition, the spectral measurement process can be time consuming, so only a few spectral samples per tree (if not per species) may have been collected. For leaves, it is possible to simulate reflectance and transmission properties based on concentrations of constituents. There are two main packages for simulating leaf spectra: PROSPECT for broadleaves (Section 4.2.2.1) and leaf incorporating biochemistry exhibiting reflectance and transmittance yields (LIBERTY) for conifers (Section 4.2.2.2).

It should be noted that for a narrow-band lidar system, a single reflectance and transmittance factor may be used per material instead of a full spectrum. This is due to the narrow spectral
distribution of a laser source. However, to make the scenes useful for other collection modalities, use of signal value optical properties is discouraged.

4.2.2.1 PROSPECT

The leaf optical properties spectra (PROSPECT) model was developed to simulate leaf optical properties bases on concentrations of constituents (Jacquemoud and Baret, 1990; Jacquemoud et al., 1996; Jacquemoud and Ustin, 2001; Fourty et al., 1996; Baret and Fourty, 1997; Bousquet et al., 2005; Féret et al., 2008). These constituents are leaf striation parameter ($N$), chlorophyll a+b content ($C_{ab}$), equivalent water thickness ($C_w$), dry matter content ($C_m$), carotenoids content ($C_{ar}$), and brown pigments content ($C_{brown}$). The output of PROSPECT are reflectance and transmittance spectra at a 1 [nm] spacing from 400 [nm] to 2500 [nm].

For the purpose of generating spectrally clean broadleaf optical properties (reflectance and transmittance), an inverse-forward pass through the PROSPECT model was used. The inverse PROSPECT model uses a non-linear optimization (Levenberg, 1944; Marquardt, 1963) to invert a reflectance and/or transmission spectra to leaf property concentrations. These concentrations are then fed into the forward PROSPECT model to generate reflectance and transmittance spectra. The non-linear optimization seeks to minimize the root mean square difference (RMSD) between the measured reflectance spectra and the PROSPECT-derived reflectance. The parameters are constrained within their typical ranges, of these parameters as stated by the authors (see Table 4.2). If both a reflectance and transmission spectrum are present, the model will seek to to minimize the RMSD between the measured and PROSPECT-derived reflectance and transmission spectra. In the presence of noisy spectra, the RMSD will only be computed for a set of good bands. The good bands are defined by omitting areas of the spectra where there are noisy features, e.g., the water absorption bands.

In order to build up spectral statistics, small amounts of noise may be added to each of the
4.2. SCENE CONSTRUCTION

Table 4.2: Ranges of variation of the PROSPECT parameters.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>C_{ab}</th>
<th>C_{ar}</th>
<th>C_{brown}</th>
<th>C_{w}</th>
<th>C_{m}</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>1.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.00005</td>
<td>0.002</td>
</tr>
<tr>
<td>max</td>
<td>3.5</td>
<td>100.0</td>
<td>30.0</td>
<td>1.0</td>
<td>0.05000</td>
<td>0.020</td>
</tr>
</tbody>
</table>

concentrations. This process can produce reflectance and transmission spectra, even if only one of them were measured. A sample PROSPECT run is shown in Figure 4.10. The workflow of the PROSPECT inversion process is shown in Figure 4.11.

Figure 4.10: Sample PROSPECT reflectance and transmittance spectra. The extracted parameters were: N = 1.92, C_{ab} = 45.04, C_{ar} = 3.94, C_{brown} = 0.57, C_{w} = 0.02, and C_{m} = 0.03. The original spectra were collected by the National Ecological Observatory Network (NEON) in the San Joaquin Experimental Range (SJER).

4.2.2.2 LIBERTY

Similar to PROSPECT, LIBERTY (Dawson et al., 1998) is a model for estimating optical properties of conifer needles. The liberty model has nine input concentrations: leaf cell diameter, intercellular air space, leaf thickness, baseline absorption, albino absorption, chlorophyll content, water content, lignin and cellulose content, and nitrogen content. Since conifers were not used in this dissertation,
Figure 4.11: Workflow for using PROSPECT to generate leaf reflectance and transmittance spectra. Dashed items are optional.
LIBERTY was not used. It is, however, included as a reference for future work including conifers in a scene.

4.3 Virtual Forest Scenes

For this work, three forest scenes were either created or used. The HarvardForest1 scene (Section 4.3.1) was used in the remainder of the dissertation. The HighPark1 (Appendix A.1) and SanJoaquin116 (Appendix A.2) scenes were created, but not utilized for the work presented in this dissertation.

4.3.1 HarvardForest1

HarvardForest1 was the first forest scene created for this project. The scene was created as a small broadleaf stand, based loosely on Harvard Forest inventory parameters from Munger and Wofsy (1999). The scene used only very basic forest inventory parameters (tree height, DBH, and species) for creating the tree models in OnyxTREE. Table 4.3 shows the parameters used for these trees and Table 4.4 shows some summary statistics of these parameters. The scene contained nine: *Acer rubrum* (red maple) trees and four: *Quercus rubra* (red oak) trees. The trees were hand-placed on a flat ground plane to create a closed-canopy environment (see Figures 4.12 and 4.13). The scene center was near Petersham, MA, USA (42.53° N, −72.19° W) with an elevation of 0 [m]. The optical properties used for this scene based on DIRSIG’s Megascene1 (Ientilucci and Brown, 2003) and the values at 1064 [nm] can be found in Table 4.5.
4.3. VIRTUAL FOREST SCENES

Figure 4.12: Position and extent of trees in the HarvardForest1 DIRSIG scene. Radii shown are the maximum of the “lollipop” tree model. The actual tree geometry falls inside of this maximum radius assumption. “AR” refers to *Acer rubrum* and “QR” refers to *Quercus rubra*.

Figure 4.13: Top-view DIRSIG RGB rendering of HarvardForest1. Note: despite red in their names, *Acer rubrum* and *Quercus rubra* leaves are green.
Table 4.3: Measured parameters for virtual trees in the HarvardForest1 scene. The parameters are measured from the “lollipop” version of the trees containing only the OnyxTREE trunks and foliage envelopes. DBH is defined at 1.3 [m] above the ground. The scene was constructed only using the species, DBH, and tree height parameters.

<table>
<thead>
<tr>
<th>Tree ID</th>
<th>Species</th>
<th>DBH [cm]</th>
<th>Crown extent [m]</th>
<th>Tree height [m]</th>
<th>Height to living crown [m]</th>
<th>x scene position [m]</th>
<th>y scene position [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR2</td>
<td><em>Acer rubrum</em></td>
<td>28.85</td>
<td>18.85</td>
<td>30.60</td>
<td>7.73</td>
<td>4.597</td>
<td>−15.914</td>
</tr>
<tr>
<td>AR3</td>
<td><em>Acer rubrum</em></td>
<td>38.19</td>
<td>11.84</td>
<td>15.64</td>
<td>2.40</td>
<td>−1.900</td>
<td>−4.400</td>
</tr>
<tr>
<td>AR4</td>
<td><em>Acer rubrum</em></td>
<td>16.32</td>
<td>12.84</td>
<td>18.17</td>
<td>2.22</td>
<td>13.700</td>
<td>1.300</td>
</tr>
<tr>
<td>AR5</td>
<td><em>Acer rubrum</em></td>
<td>23.84</td>
<td>11.17</td>
<td>19.06</td>
<td>4.35</td>
<td>−9.200</td>
<td>−10.300</td>
</tr>
<tr>
<td>AR6</td>
<td><em>Acer rubrum</em></td>
<td>28.26</td>
<td>7.94</td>
<td>15.17</td>
<td>4.25</td>
<td>7.100</td>
<td>−5.000</td>
</tr>
<tr>
<td>AR7</td>
<td><em>Acer rubrum</em></td>
<td>13.61</td>
<td>7.56</td>
<td>19.09</td>
<td>6.71</td>
<td>−0.341</td>
<td>13.815</td>
</tr>
<tr>
<td>AR8</td>
<td><em>Acer rubrum</em></td>
<td>27.23</td>
<td>10.82</td>
<td>12.36</td>
<td>2.16</td>
<td>4.378</td>
<td>2.468</td>
</tr>
<tr>
<td>AR9</td>
<td><em>Acer rubrum</em></td>
<td>13.00</td>
<td>7.12</td>
<td>15.85</td>
<td>2.94</td>
<td>6.712</td>
<td>7.915</td>
</tr>
<tr>
<td>QR1</td>
<td><em>Quercus rubra</em></td>
<td>51.19</td>
<td>17.04</td>
<td>20.70</td>
<td>4.37</td>
<td>−12.400</td>
<td>12.700</td>
</tr>
<tr>
<td>QR2</td>
<td><em>Quercus rubra</em></td>
<td>30.30</td>
<td>15.35</td>
<td>24.33</td>
<td>4.00</td>
<td>−15.000</td>
<td>0.000</td>
</tr>
<tr>
<td>QR3</td>
<td><em>Quercus rubra</em></td>
<td>30.30</td>
<td>15.35</td>
<td>24.33</td>
<td>4.00</td>
<td>−5.085</td>
<td>−18.296</td>
</tr>
<tr>
<td>QR4</td>
<td><em>Quercus rubra</em></td>
<td>38.42</td>
<td>16.00</td>
<td>31.68</td>
<td>8.11</td>
<td>−2.859</td>
<td>6.035</td>
</tr>
</tbody>
</table>

Table 4.4: Summary statistics for modeled tree parameters in HarvardForest1. “AR” refers to *Acer rubrum* and “QR” refers to *Quercus rubra.*

<table>
<thead>
<tr>
<th></th>
<th>DBH [cm]</th>
<th>Tree Height [m]</th>
<th>Crown extent [m]</th>
<th>Height to living crown [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR Min</td>
<td>13.00</td>
<td>12.36</td>
<td>7.12</td>
<td>2.16</td>
</tr>
<tr>
<td>AR Max</td>
<td>51.19</td>
<td>30.60</td>
<td>18.85</td>
<td>7.73</td>
</tr>
<tr>
<td>AR Mean</td>
<td>26.88</td>
<td>17.82</td>
<td>11.30</td>
<td>3.71</td>
</tr>
<tr>
<td>AR St. Dev.</td>
<td>11.72</td>
<td>4.01</td>
<td>3.70</td>
<td>1.38</td>
</tr>
<tr>
<td>QR Min</td>
<td>30.30</td>
<td>20.70</td>
<td>15.35</td>
<td>4.00</td>
</tr>
<tr>
<td>QR Max</td>
<td>51.19</td>
<td>31.68</td>
<td>17.04</td>
<td>8.11</td>
</tr>
<tr>
<td>QR Mean</td>
<td>37.55</td>
<td>25.26</td>
<td>15.94</td>
<td>5.12</td>
</tr>
<tr>
<td>QR St. Dev.</td>
<td>9.87</td>
<td>4.61</td>
<td>0.80</td>
<td>2.00</td>
</tr>
<tr>
<td>All Min</td>
<td>13.00</td>
<td>12.36</td>
<td>7.12</td>
<td>2.16</td>
</tr>
<tr>
<td>All Max</td>
<td>51.19</td>
<td>31.68</td>
<td>18.85</td>
<td>8.11</td>
</tr>
<tr>
<td>All Mean</td>
<td>27.24</td>
<td>20.90</td>
<td>12.68</td>
<td>4.56</td>
</tr>
<tr>
<td>All St. Dev.</td>
<td>11.25</td>
<td>5.93</td>
<td>3.75</td>
<td>2.01</td>
</tr>
</tbody>
</table>

The trees developed for the HarvardForest1 scene tend to be “park trees,” that is trees that could grow in the middle of a park with little to no competition. Trees such as these are unlikely
Table 4.5: HarvardForest1 optical properties used in the simulation at 1064 [nm]. The transmittances listed are the ones through the facet at normal incidence. Off-normal rays will have a lower transmittance due to a longer path length.

<table>
<thead>
<tr>
<th>Geometry</th>
<th>Reflectance</th>
<th>Transmittance</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Acer rubrum</em> leaf</td>
<td>0.39</td>
<td>0.52</td>
</tr>
<tr>
<td><em>Quercus rubra</em> leaf</td>
<td>0.36</td>
<td>0.52</td>
</tr>
<tr>
<td><em>Acer rubrum</em> bark</td>
<td>0.48</td>
<td>0.00</td>
</tr>
<tr>
<td><em>Quercus rubra</em> bark</td>
<td>0.41</td>
<td>0.00</td>
</tr>
<tr>
<td>Grass &amp; dirt (ground surface)</td>
<td>0.49</td>
<td>0.00</td>
</tr>
</tbody>
</table>

to exist in a true closed-canopy forest environment. This scene was built for the purpose of assessing what level of geometric complexity is needed to simulate small-footprint lidar signals. It was deemed adequate for these purposes, since we were interested in identifying meaningful geometry at the leaf-scale, and as such, the larger-scale deficiencies were negligible. However, to account for some of these deficiencies, additional scenes are being constructed, namely HighPark1 (Appendix A.1) and SanJoaquin116 (Appendix A.2).

### 4.4 Conclusions

To address the lack of high-fidelity forest scenes for small-footprint lidar simulation, we have developed a workflow to produce representative virtual forest models. The workflow includes using OnyxTREE to generate tree models, PROSPECT to generate optical properties, and Poisson disk sampling to plant the tree models on a DEM when tree positions are not known. As part of this thesis and other work three virtual forest scenes were created: HarvardForest1, HighPark1, and SanJoaquin116.

The process for scene creation is still far from perfect. The geometric tree models are the best that can be produced with limited field sampling data. In addition, OnyxTREE has a restrictive license on the tree models, making collaboration more challenging. To help address these limitations, future work includes using TLS-derived tree models for input into DIRSIG. In addition, a
rigorous validation of DIRSIG’s ability to simulate similar lidar signals as real world versions of the same scenes should be performed.

These scenes will be used to identify a minimum set of required geometry for a small-footprint lidar simulation (see Chapter 5), positional uncertainty analysis (see Chapter 6), and within-canopy attenuation correction (see Chapter 7).
Chapter 5

The impact of geometry on waveform lidar signals

5.1 Introduction

Approximations to reality (e.g., the classic physics problem of treating a cow as a sphere) are often made during the practice of science in order to simplify a complex problem sufficiently so that meaningful conclusions may be drawn. From the perspective of radiative transfer modeling in forests, it is desirable to have a geometry set that provides consistent results with a more complete model. A geometry set is a collection of explicitly defined triangular facets or primitives that when combined, make up a virtual tree model. Additional geometric complexity impacts random access memory (RAM) usage (performing simulations of some scenes are impossible on a smaller computeropen C ), and run time (there are more computations necessary to ray-trace into a scene with more facets). Furthermore, it is impractical to concern oneself with sub-cell structure within a leaf if the goal is to understand phenomenology at the forest scale. These interactions, however, are useful to drive models such as PROSPECT and LIBERTY, which produce reflectance and transmission spectra. At the forest scale, effective reflectance and transmission properties define
a much more efficient optical model for a leaf, opposed to focusing what individual chloroplasts are doing. This is achieved via construction of representative tree models at the scale of a small-footprint lidar system.

The OnyxTREE (Bosanc and Zanchi, 2011) virtual tree generating toolbox is capable of generating a number of geometries that make up a tree (e.g., trunks (t), boughs (b), and leaves (l)). Having knowledge of which of these geometries contribute in determining a meaningful way to a lidar signal is useful for two main reasons: (i) it provides a limit to the minimal detachable unit, and (ii) it allows simulations to be constructed with a minimal amount of geometry while avoiding statistical significant difference between the geometry and that of a full-geometry scene and associated computational cost. Knowledge of the minimal detectable units provide a sanity check for what types of parameters one can hope to make an inference about from a lidar signal. Finally, running radiative transfer models in complex environments, such as forests, is computationally expensive. If selected geometry can be ignored with a minimal impact on the signal, those simulations can be made more efficient. This knowledge can also be extended to determine the importance of the various geometric components to the backscattered waveform. It is hypothesized that the leaves will dominate the backscattered signal, due to their function as a tree’s solar cells, where they have a relatively large area to collect light and produce sugars.

The work described in this chapter has been published in Romanczyk et al. (2012) and Romanczyk et al. (2013a).

5.1.1 Layout

This chapter describes an experiment and results testing of which OnyxTREE geometry components are significant in terms of small-footprint lidar signals. The remainder of this chapter is broken up into six sections: Section 5.2 describes a method of comparing DIRSIG generated lidar
signals; Section 5.3 describing the methods of used to evaluate what level of geometry is sufficient; Section 5.4 describes the results of this study; Section 5.5 describes the implications of this study, and Section 5.6 offering a summary and conclusions.

5.1.2 Associated Publications and Presentations


5.2 Simulated Waveform Comparison

DIRSIG lidar generates an estimate of the mean sensor reaching photon count per time bin. A detailed description of the DIRSIG lidar signal generating process can be found in Section 2.3.2. It is up to the user to generate sample waveforms about the DIRSIG generated mean waveform signal to produce a possible waveform. Repeating this process results in a family of waveforms about the DIRSIG generated mean. In order to compare two DIRSIG generated waveforms, it is necessary to either compare a sample from each of the families, or to compare the entire family of waveforms. For this research, a confidence-interval-based comparison of the families was chosen.
5.2. WAVEFORM COMPARISON

5.2.1 Waveform overlap metric

For a given pair of waveforms, \( w_i \) and \( w_j \), where \( i \) and \( j \) are waveform identifiers, a probability-based waveform comparison metric \( O \) was created. Three assumptions were made about the DIRSIG-generated waveform signals:

1. The DIRSIG-generated mean signal is the population mean signal for the conditions (geometry, outgoing pulse width, etc.) of the signal. This was tested and confirmed by performing 30 DIRSIG simulations with the exact same parameters for HarvardForest1 (see Section 4.3.1) sites 0-9. The differences in waveforms were < 10 photons max in difference (out of a signal peaking at \( \approx 1000 \) photons).

2. The variance of the signal can be described by a Poisson distribution (shot noise) with \( \lambda_t = w^i_b \) for all time bins, where \( b \) is a time bin identifier.

3. All other sources of variance (noise) are negligible. This is useful because it allows for a relatively simple comparison between the families of waveforms that could be generated from a DIRSIG simulation.

As a result of these assumptions, a sample waveform could be drawn about the DIRSIG-generated mean, with variance described by the Poisson distribution.

Let \( S_b \) be a variable in the signal space for a time bin. The probability of observing a signal at level \( S_b \) is given by \( p_{\nu}(w^i_b) \), where \( \nu \cdot 100\% \) is the percentile of the Poisson distribution about the DIRSIG generated mean signal \( w^i_b \) for the time bin (see Figure 5.1b). We define a function, \( \psi \), with binary output values, to be the \((1 - \alpha) \cdot 100\% \) central region about the waveform (see Figure 5.1c).

\[
\psi(S_b|w^i_b, \alpha) \equiv \begin{cases} 1, & p_{\alpha/2}(w^i_b) \leq S_b \leq p_{1-\alpha/2}(w^i_b) \\ 0, & \text{otherwise} \end{cases}
\]  

(5.1)

The waveform overlap, \( O \), between two waveforms \( w^i \) and \( w^j \), is the area of the intersection divided by the area of the union of the waveform probabilistic space functions of the two
waveforms:

\[
O(w^i,w^j) = \frac{\sum_b \int_{S_b=0}^{\infty} [\psi(S_b|w^j,\alpha) \cap \psi(S_b|w^j,\alpha)] \, dS_b}{\sum_b \int_{S_b=0}^{\infty} [\psi(S_b|w^j,\alpha) \cup \psi(S_b|w^j,\alpha)] \, dS_b}
\]

For the purposes of computation:

\[
\int_{S_b=0}^{\infty} \psi(S_b|w^j,\alpha) \, dS_b = p_{1-\alpha/2}(w^j_b) - p_{\alpha/2}(w^j_b)
\]

The waveform overlap metric can be thought of the intersection divided by the union of the Poisson distributed confidence intervals about the DIRSIG-generated signals. The waveform overlap metric takes on values in the range [0, 1], where zero is no agreement between the waveforms and one is complete agreement between the waveforms. Figure 5.1 shows a schematic of a sample computation of an overlap value for a single time bin of a waveform. Figure 5.2 shows a sample computation of an \(O\) value.

### 5.2.2 Comparison with other metrics

To test the waveform overlap metric (\(O\)), it was compared to other metrics, including the correlation

\[
\text{corr}(w^i,w^j) = \frac{\sum_b (w^i_b - \bar{w}) \cdot (w^j_b - \bar{w})}{\sqrt{\sum_b (w^i_b - \bar{w})^2} \sqrt{\sum_b (w^j_b - \bar{w})^2}}
\]

the percent difference (PD)

\[
\text{PD}(w^i,w^j) = \frac{\sum_b |w^i_b - w^j_b|}{\sum_b |w^i_b| + |w^j_b|}
\]
Figure 5.1: Schematic showing the computations of the waveform overlap for two sample waveforms: \( w^i \) and \( w^j \): (a) shows two waveform means and the 95\% (\( \alpha = 0.05 \)) central region’s about the means (\( \psi \)); (b) shows the probabilities about the mean waveforms for a single time bin represented by the dashed line in (a). The central 95\% of this time bin is shaded; (c) shows the waveform probabilistic space function (\( \psi \)) for the same time bin as (b). The waveform overlap (\( O \)) is 0.38 for this example.
5.2. WAVEFORM COMPARISON

Figure 5.2: Waveform overlap between \(tb123w\) (leaf-off validation geometry) and \(tb123\) geometries at-nadir with a 4 [ns] outgoing pulse width: (a) shows the DIRSIG generated mean waveform from the \(tb123\) geometry; (b) shows the 95% central region of the Poisson distribution and difference waveform after subtracting the DIRSIG generated mean of \(tb123w\) (a). The sensor is 1000 [m] above the ground for this simulation. This subtraction is for display purposes. The x axis of (a) and (b) are the same. The waveform overlap between these waveforms is 0.50. This is Figure 5 in Romanczyk et al. (2013a).

The RMSD

\[
\text{RMSD}(\mathbf{w}', \mathbf{w}) \equiv \sqrt{\frac{1}{|b|} \sum_b (w'_b - w_b)^2},
\]  

(5.6)

and the vector angle (spectral angle mapper (SAM), (Richards and Jia, 2006))

\[
\text{SAM}(\mathbf{w}', \mathbf{w}) \equiv \cos^{-1}\left(\frac{\sum_b w'_b \cdot w'_b}{\sum_b (w'_b)^2 + (w'_b)^2}\right),
\]  

(5.7)

where \(\mathbf{w}'\) is the mean value of waveform \(\mathbf{w}'\) and \(|b|\) is the number of time bins in a waveform. The comparison between waveform similarity metrics was performed using all combinations of scan angle, outgoing pulse width, and geometry. As shown in Figure 5.3, there was a monotonic relationship between waveform overlap and other more standard vector comparisons. The waveform overlap metric has a much harsher falloff in similarity compared to the other metrics.
Figure 5.3: Comparison between waveform overlap (O) and (a) percent difference, (b) correlation, (c), spectral angle mapper: a measure of vector difference, and (d) root mean square difference. In all cases, waveform overlap had a monotonic relationship with the other metrics of waveform similarity. The analysis was performed across a range of geometry types, scan angles, and outgoing pulse widths.
5.2.3 Sensitivity

A brief study was conducted to determine the impact of $\alpha$ value on the percent overlap metric. Figure 5.4 shows waveform overlap metrics for different $\alpha$ levels. In general, the choice of $\alpha$ value used in the waveform overlap metric does not impact which geometry sets (see Table 5.1) are significant. For the studies in this dissertation, $\alpha$ was chosen to be 0.05, or comparing the overlap of the central 95% about a the Poison distributions. 95% is a common threshold to use for many statistical tests (Devore, 2007; Johnson and Wichern, 2007).

![Figure 5.4: Sample plots comparing percent overlap at different $\alpha$ values for different geometry combinations: (a) is for site 0 at 16ns outgoing pulse-width and 0° from nadir; (b) is for site 29 at 8ns outgoing pulse-width and 20° from nadir.](image)

5.3 Methods

5.3.1 Geometry sets

The HarvardForest1 DRSIG scene (see Section 4.3.1) was used to assess what level of OnyxTREE tree geometry is necessary to produce consistent small-footprint waveform lidar signals or stated differently, which tree geometry components have the largest impact on the backscattered lidar signal. For every scan location (see Section 5.3.2), scan angle, and outgoing pulse width (OPW)
5.3. METHODS

combination, a lidar simulation was performed for many geometry combinations. These geometry combinations can be broken up into four sets:

1. validation—sets of geometry that include all available components for either leaf-on \((\text{tb123wsl})\) or leaf-off \((\text{tb123w})\). All other sets are compared to this set.

2. incremental—add one more level of complexity from the previous, starting at just the trunk, then adding boughs, and then adding the next component, until all of the geometry is present.

3. single component—a single OnyxTREE-produced geometry type.

4. leave-one-out—all except a single OnyxTREE-produced geometry type. This set of runs is the compliment to the single component set.

A list of all of the geometry types used, the members of each set can be found in Table 5.1.

5.3.2 Spatial Sampling

In order to assess the impact of geometry on small-footprint wlidar signals, thirty pseudo-random sites were chosen from the original Harvard-Forest scene. This was done to keep the number of simulations reasonable, but still have a large enough sample for statistics. Since the Harvard-Forest1 scene is roughly circular with a 25 [m] radius, half the sites were drawn from a radially symmetric uniform distribution with radius 15 [m], and the other half from a radially symmetric uniform distribution with radius 25 [m]. This was done to ensure that most of the site locations fell in the interesting areas of scene \(i.e.,\) sample where the geometry is located and not on the ground plane. These locations provided the \(x,y\) location where the center of the lidar pulse intersected the ground. For off-nadir cases, a uniformly distributed random azimuth angle was chosen for each site. For a given sampling site, this azimuth was the same for any scan angle. The sensor position was adjusted so that given the zenith/scan-angle combination at the center of the laser footprint would intersect the same \(x,y\) location on the ground. See Figure 5.5 for the locations of the thirty randomly chosen sites.
Table 5.1: List of geometry subsets and facet counts used to assess the impact of geometry of small-footprint wliadar signals. The single component subsets contain only one component. The incremental subsets add a new component to the previous geometry. The leave-one-out subsets contain all but one component. The reference geometry of the leaf-on and leaf-off cases are $tb123wsl$ and $tb123w$, respectively. All facet percentages are with respect to the reference geometry except the leaf-off reference, which is with respect to the leaf-on reference.

<table>
<thead>
<tr>
<th>Set</th>
<th>Geometry</th>
<th># Facets</th>
<th>% Facets</th>
<th>Geometry</th>
<th># Facets</th>
<th>% Facets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference</td>
<td>$tb123wsl$</td>
<td>56,402,256</td>
<td>1.000</td>
<td>$tb123w$</td>
<td>23,542,506</td>
<td>0.417</td>
</tr>
<tr>
<td></td>
<td>$t$</td>
<td>39,344</td>
<td>0.001</td>
<td>$t$</td>
<td>39,344</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>$b$</td>
<td>326,279</td>
<td>0.006</td>
<td>$b$</td>
<td>326,279</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>$l$</td>
<td>965,066</td>
<td>0.017</td>
<td>$l$</td>
<td>965,066</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>$2$</td>
<td>2,790,126</td>
<td>0.049</td>
<td>$2$</td>
<td>2,790,126</td>
<td>0.119</td>
</tr>
<tr>
<td></td>
<td>$3$</td>
<td>10,439,904</td>
<td>0.185</td>
<td>$3$</td>
<td>10,439,904</td>
<td>0.443</td>
</tr>
<tr>
<td></td>
<td>$w$</td>
<td>8,981,787</td>
<td>0.159</td>
<td>$w$</td>
<td>8,981,787</td>
<td>0.382</td>
</tr>
<tr>
<td></td>
<td>$s$</td>
<td>18,995,934</td>
<td>0.337</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$l$</td>
<td>13,863,816</td>
<td>0.246</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only</td>
<td>$l$</td>
<td>13,863,816</td>
<td>0.246</td>
<td>$t$</td>
<td>39,344</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>$tb1$</td>
<td>14,229,439</td>
<td>0.252</td>
<td>$tb$</td>
<td>365,623</td>
<td>0.016</td>
</tr>
<tr>
<td>Incremental</td>
<td>$tb1l$</td>
<td>15,194,505</td>
<td>0.269</td>
<td>$tb1$</td>
<td>1,330,689</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>$tb12l$</td>
<td>17,984,631</td>
<td>0.319</td>
<td>$tb12$</td>
<td>4,120,815</td>
<td>0.175</td>
</tr>
<tr>
<td></td>
<td>$tb123l$</td>
<td>28,424,535</td>
<td>0.504</td>
<td>$tb123$</td>
<td>14,560,719</td>
<td>0.618</td>
</tr>
<tr>
<td></td>
<td>$tb123wl$</td>
<td>37,406,322</td>
<td>0.663</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leave-one-out</td>
<td>$b123wsl$</td>
<td>56,362,912</td>
<td>0.999</td>
<td>$b123w$</td>
<td>23,503,162</td>
<td>0.998</td>
</tr>
<tr>
<td></td>
<td>$tl23wsl$</td>
<td>56,075,977</td>
<td>0.994</td>
<td>$tl23w$</td>
<td>23,216,227</td>
<td>0.986</td>
</tr>
<tr>
<td></td>
<td>$tb23wsl$</td>
<td>55,437,190</td>
<td>0.983</td>
<td>$tb23w$</td>
<td>22,577,440</td>
<td>0.959</td>
</tr>
<tr>
<td></td>
<td>$tb13wsl$</td>
<td>53,612,130</td>
<td>0.951</td>
<td>$tb13w$</td>
<td>20,752,380</td>
<td>0.881</td>
</tr>
<tr>
<td></td>
<td>$tb12wsl$</td>
<td>45,962,352</td>
<td>0.815</td>
<td>$tb12w$</td>
<td>13,102,602</td>
<td>0.557</td>
</tr>
<tr>
<td></td>
<td>$tb123sl$</td>
<td>47,420,469</td>
<td>0.841</td>
<td>$tb123$</td>
<td>14,560,719</td>
<td>0.618</td>
</tr>
<tr>
<td></td>
<td>$tb123wl$</td>
<td>37,406,322</td>
<td>0.663</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$tb123ws$</td>
<td>42,538,440</td>
<td>0.754</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 5.5: RGB DIRSIG simulation showing the locations of the sampling locations of the 30 “sites” used. The footprint center is the cyan dot next to the site number. This simulation of the virtual HarvardForest1 scene covers a 50 [m] × 50 [m] extent.
5.3. METHODS

5.3.3 Virtual lidar sensor

Exact sensor specifications are difficult to obtain from sensor vendors, therefore we simulated a generic small-footprint waveform lidar system. Analyses were repeated for various combinations of outgoing pulse width and scanning angle to extend implications across a range of sensors and applications. The parameters used are similar to other small-footprint lidar sensors (e.g., see Tables 2.2 and 2.3). We attempted to keep the sensor settings general, so that the findings and implications of this study have broad use.

The sensor was placed 1000 [m] above the scene for each simulation. The lidar receiver parameters are shown in Table 5.2. The receiver parameters are listed in Tables 5.3 and 5.4. For these settings, the system has a 0.5 [m] footprint at-nadir and there is a backward projected ray cast from the sensor every 5 [mm].

Table 5.2: Settings used for the simulated lidar transmitter.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temporal pulse shape</td>
<td>Gaussian</td>
<td>—</td>
</tr>
<tr>
<td>Wavelength</td>
<td>1064</td>
<td>[nm]</td>
</tr>
<tr>
<td>Laser line width</td>
<td>0.01</td>
<td>[nm]</td>
</tr>
<tr>
<td>Spatial pulse shape</td>
<td>cylindrical</td>
<td>—</td>
</tr>
<tr>
<td>Spatial divergence half-angle</td>
<td>0.25</td>
<td>[mrad]</td>
</tr>
<tr>
<td>Pulse energy</td>
<td>0.2</td>
<td>[mJ]</td>
</tr>
<tr>
<td>Outgoing pulse width</td>
<td>4, 8, 16</td>
<td>[nm]</td>
</tr>
<tr>
<td>Maximum source bundles per pulse</td>
<td>250,000</td>
<td>—</td>
</tr>
<tr>
<td>Maximum bounces per photon bundle</td>
<td>4</td>
<td>—</td>
</tr>
<tr>
<td>Maximum events in photon map per pulse</td>
<td>500,000</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 5.3: Settings used for the simulated lidar receiver. See Table 5.4 for the range gate settings.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field of view</td>
<td>0.5</td>
<td>[mrad]</td>
</tr>
<tr>
<td>Array size</td>
<td>$1 \times 1$</td>
<td>—</td>
</tr>
<tr>
<td>Spatial subsampling type</td>
<td>regular grid</td>
<td>—</td>
</tr>
<tr>
<td>Spatial subsampling</td>
<td>$100 \times 100$</td>
<td>—</td>
</tr>
<tr>
<td>Temporal sampling</td>
<td>1</td>
<td>[ns]</td>
</tr>
<tr>
<td>Range sampling</td>
<td>15</td>
<td>[cm]</td>
</tr>
</tbody>
</table>
Table 5.4: Settings used for the simulated lidar receiver’s range gate. See Table 5.3 for the generic receiver settings. All ranges are sampled from 10 [m] below ground to 40 [m] above ground, based on the *a priori* knowledge of the scene of the scene having geometry up to $\approx 30$ [m] above ground.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>0°</th>
<th>10°</th>
<th>20°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range gate open</td>
<td>[µs]</td>
<td>6.738</td>
<td>6.6842</td>
<td>7.1704</td>
</tr>
<tr>
<td>Minimum range</td>
<td>[m]</td>
<td>960</td>
<td>974.775</td>
<td>1021.6</td>
</tr>
<tr>
<td>Maximum range</td>
<td>[m]</td>
<td>1010</td>
<td>1025.59</td>
<td>1074.82</td>
</tr>
<tr>
<td>Time bins</td>
<td></td>
<td>335</td>
<td>340</td>
<td>356</td>
</tr>
</tbody>
</table>

5.3.4 DIRSIG Runs

For every combination of geometry (see Section 5.3.1), site (see Section 5.3.2), scan angle (0°, 10°, and 20°), and outgoing pulse width (4 [ns], 8 [ns], and 16 [ns]) a DIRSIG run was performed. This led to a total of $31 \times 30 \times 3 \times 3 = 8370$ unique simulations. It took approximately 19.84 [days] of computer time to complete the final version of these simulations (and many more hours for the previous versions) on a system with two 6 core Intel® Xeon® X5680 CPUs (12 cores in total and hyper-threaded to allow for 24 effective cores) clocked at 3.33 [GHz] and 70 [GB] RAM. RAM is the limiting computational element for this simulation. See Table 5.5 for the RAM usage for the leaf-on incremental subset. The peak RAM usage of 27.8 [GB] would only allow two simultaneous DIRSIG runs if no one else was using the machine. Omitting the twigs and leaf-stems reduced the RAM usage by nearly half. Even the reduced RAM from these simulations requires a reasonably powerful machine to be able to run. The current DIRSIG4 builds are single-threaded. The forthcoming release of DIRSIG5 should allow for multi-threading instead of relying on “poor-man’s parallelization,” where the user runs multiple instances of DIRSIG simultaneously.

5.3.5 Comparing waveforms

Once all of the simulations were completed, the waveforms were compared in the geometry sets in Table 5.1 using the waveform overlap ($O$) metric. A waveform was only compared to the validation waveform (tb123ws1 or tb123w) with the same site, scan angle, and outgoing pulse
5.3. METHODS

Table 5.5: RAM usage for leaf-on incremental subset.

<table>
<thead>
<tr>
<th>Geometry Set</th>
<th>RAM [GB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>tb123wsl</td>
<td>27.8</td>
</tr>
<tr>
<td>tb123wl</td>
<td>18.5</td>
</tr>
<tr>
<td>tb123l</td>
<td>14.2</td>
</tr>
<tr>
<td>tb12l</td>
<td>10.2</td>
</tr>
<tr>
<td>tb1l</td>
<td>9.0</td>
</tr>
<tr>
<td>tbl</td>
<td>8.6</td>
</tr>
<tr>
<td>l</td>
<td>8.3</td>
</tr>
</tbody>
</table>

width, e.g., a waveform from Site 07 at 10° off-nadir, and an 8 [ns] outgoing pulse width was only compared to other waveforms from Site 07 at 10° off-nadir, and an 8 [ns] outgoing pulse width.

5.3.6 Comparing waveform overlaps

Since the distribution of waveform overlaps (O) are not necessarily normally distributed, a non-parametric statistic must be used to compare the distribution of waveform overlap metrics. To do this, the Kolmogorov-Smirnov test (Kolmogorov, 1933; Smirnov, 1948) was used to test if distributions of the waveform overlaps were the same with a 95% confidence level ($\alpha = 0.05$). The Kolmogorov-Smirnov test compares the distribution of the cumulative density functions (CDFs) of the two data sets. The null hypothesis is that the samples were drawn from the same distribution. The statistic for the Kolmogorov-Smirnov test is the maximum difference in CDFs between the two samples. For the two-sided case, the Kolmogorov-Smirnov statistic ($D_{n,n'}$) is given by

$$D_{n,n'} = \sup_x \left| F_{1,n}(x) - F_{2,n'}(x) \right|,$$

(5.8)

where $F_{1,n}(x)$ and $F_{2,n'}(x)$ are the discrete CDF of the two distributions defined on $x$ with $n$ and $n'$ samples, respectively, and sup represents the supremum function. The null hypothesis is rejected at a confidence level of $(1 - \alpha) \cdot 100\%$ if

$$D_{n,n'} > C(\alpha) \cdot \sqrt{\frac{n + n'}{n \cdot n'}},$$

(5.9)
where $C(\alpha)$ is given in Table 5.6 (Wessel, 2015).

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>0.10</th>
<th>0.05</th>
<th>0.025</th>
<th>0.01</th>
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<td>$C(\alpha)$</td>
<td>1.22</td>
<td>1.36</td>
<td>1.48</td>
<td>1.63</td>
<td>1.73</td>
<td>1.95</td>
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</tbody>
</table>

Within each geometry set (see Table 5.1), the distribution of $O$ for each geometry combination was compared to the mean of all others within the same set. To assess if scan angle or outgoing pulse width had an effect on which geometries are significant, an additional set of Kolmogorov-Smirnov tests were carried out across both of those parameters for a given geometry combination, e.g., for leaf-on at-nadir in the incremental subset, we compared the mean $O$ from the 4 [ns] scans to each of the 8 [ns] and 16 [ns] scans, as well as comparing the 8 [ns] scans to the 16 [ns] scans. Any of the comparisons that are statistically different from each other can be said to have meaningful impact on the backscattered waveforms.

### 5.4 Results

The analyses of the different geometry subsets (see Table 5.1) were performed separately. Different geometry combinations have a distinct impact on the resultant waveform, as seen in Figure 5.6. Specifically, reduced geometry waveforms from the incremental set tended to have similar shapes to the validation waveform in terms of the locations of the peaks, with different amplitudes of backscattered energy. In addition, removing geometries caused a shift in return signal amplitude towards the ground.

For all geometry subsets, the waveform overlap ($O$) was computed between a waveform at a reduced geometry and its validation waveform, i.e., the leaf-on waveforms were all compared to the ones with *tb123wsl* geometries and the leaf-off waveforms were all compared to the corresponding *tb123w* waveform. In order to assess the effect of geometry complexity, $O$ statistics were computed and analyzed using box-and-whisker plots. This analysis was repeated for all
Figure 5.6: Figure 6 from Romanczyk et al. (2013a). Sample waveforms from the leaf-on incremental subset, along with the leaf-on (tb123wsl) and leaf-off (tb123w) validation geometries. The maximum amplitude of the ground tb123w peak is 1481 photons and is cut off for better scaling of the leaf-on waveforms. Waveforms are from a 4 [ns] outgoing pulse width at-nadir for site 18. A 2.5× zoom of a set of peaks around 10 [m] above ground is also shown. The waveform overlap with tb123wsl is: tb123w: 0.16, tb123wl: 1.00, tb123l: 0.99, tb12l: 0.58, tbl: 0.30, tbl: 0.27, and l: 0.27. For this site, there are two sets of geometries that have almost the same DIRSIG waveforms: 1.) tb123wsl, tb123wl, and tb123l and 2.) tbl and l. The sensor is 1000 [m] above the ground.
combinations of site, outgoing pulse width, and scanning angle.

5.4.1 Leaf-on

Figure 5.7 shows the distributions of waveform overlap (O) for the incremental, single, component, and leave-one-out subsets of the 4 [ns] at-nadir simulations with leaf-on validation geometry (tb123ws). Figure 5.8 shows the distributions that are significantly different from each other. For both of the preceding figures, part (a) refers to the incidental subset, part (b) refers to the single-component subset, and part (c) refers to the leave-one-out subset.

In the incremental set (see Figure 5.7a), the O value increased as geometry was added. As shown in Figure 5.8a, there was no statistical difference (at a 95% confidence level) in the distribution of the l to either the tbl or tb1l sets, from the tb1l to the tb12l subset, or from the tb12l to tb123l subset. This implies that there was no statistically-detected change waveform overlap distrution by adding trunks (t), boughs (b), and first order branches (1) to only the leaves (l), adding second order branches (2) to tb1l, or by adding twigs (l) to tb123l. Figure 5.7b shows the single component geometry subset. The leaf-only geometry (l) performed much better than any other single component, i.e., the leaves were the most important geometry component. As shown in Figure 5.8b, the difference in mean waveform overlap between the leaf-only geometry (l) was statistically different from any other single component geometry. In addition, the trunks and twigs both were statistically different from all three levels of branches. Figure 5.7c shows the leave-one-out geometry subset. The everything-but-leaves geometries (tb123ws) performed the worst, further validating the claim that leaves are the most important geometry for a backscattered waveform. Similar results (not shown) were found for the other scan angles and pulse widths.
Figure 5.7: Waveform overlap ($O$) for 4 [ns] at 0° from nadir: (a) is for the incremental subset; (b) is the single component subset; and (c) is the leave-one-out subset of the leaf-on validation geometry. Each waveform was compared to the leaf-on validation geometry set containing all components ($tb123wsl$) for that site.
### Figure 5.8: Two-sample Kolmogorov-Smirnov test between waveform overlap (O) means for 4 [ns] at 0° from nadir for the leaf-on case:

- **(a)** is for the incremental subset;
- **(b)** is the single component subset; and
- **(c)** is the leave-one-out subset of the leaf-on validation geometry.

Comparisons marked with a ✓ are statistically different from each other, comparisons marked with a × failed to meet the requirements to reject the null hypothesis, and comparisons marked with a — are repeats from another entry in the table.
5.4.2 Leaf-off

Figure 5.9 is the leaf-off version of Figure 5.7. Figure 5.9a shows the incremental geometry subset. Once again, the overlap statistics increased as additional components were added. The distribution of the trunk subset was not statistically different from the \(tb\) subset and the \(tb\) subset was not statistically different from the \(tb1\) subset. Figure 5.9b shows the single component geometry subset. The branch-level-3 (3) geometry subset had a slightly larger mean and median than other geometry combinations, implying that there is not a dominant geometry in the leaf-off case like leaves (l) are for the leaf-on case. The difference in distribution was significant between the third order branches and all other leaf-off single component geometries except the second order branching. Although the results are not shown, similar results were found for the other scan angles and pulse widths.

5.4.3 Effect of scan angle

Figure 5.11 shows overlap statistics for the 4 [ns] outgoing pulse width of the leaf-on incremental geometry subset at different scan angles. At each geometry set, the difference in waveform overlap distribution for different angles were not statistically different from each other at a 95% confidence level using the Kolmogorov-Smirnov test. Since we failed to reject the null hypothesis that these came from the same distribution, we can conclude that it is statistically unlikely at a 95% confidence level, that the scan angle will have impact which geometries are significant.

5.4.4 Effect of pulse-width

Figure 5.12 shows the overlap statistics for the nadir leaf-on incremental geometry set. For the incremental data set, in each geometry set the 16 [ns] outgoing pulse width performed better in terms of increased overlap than the 8 [ns] pulse width, which in turn performed better than the 4 [ns] pulse width. The difference in distributions from 16 [ns] to 8 [ns] and 8 [ns] to 4 [ns] were
Figure 5.9: Leaf-off waveform overlap ($O$) for 4 [$\text{ns}$] at $^\circ$ from nadir: (a) is for the incremental subset; (b) is the single component subset; and (c) is the leave-one-out subset of the leaf-on validation geometry. Each waveform was compared to the leaf-off validation geometry set containing all components ($tb123w$) for that site.
Figure 5.10: Two-sample Kolmogorov-Smirnov test between waveform overlap (O) means for 4 [ns] at 0° from nadir for the leaf-off case: (a) is for the incremental subset; (b) is the single component subset; and (c) is the leave-one-out subset of the leaf-on validation geometry. Comparisons marked with a ✓ are statistically different from each other, comparisons marked with a × failed to meet the requirements to reject the null hypothesis, and comparisons marked with a — are repeats from another entry in the table.
Figure 5.11: Waveform overlap (O) comparison for 0°, 10°, and 20° scan angles for the incremental leaf-on subset at 4 [ns] outgoing pulse width. Each waveform was compared to the leaf-off validation geometry set containing all components (\textit{tb123ws}) for that site.

not statistically significant. The difference in distributions from 16 [ns] to 4 [ns] were significantly different from each other at a 95% confidence level. Failing to reject the null hypothesis that the two distributions are the same from 16 [ns] to 8 [ns] and 8 [ns] to 4 [ns] means that it is unlikely that there is a difference in which geometries are needed at these confidence levels. The statistical difference from 16 [ns] to 4 [ns] implies that a smaller geometric subset might produce similar results at 16 [ns] outgoing pulse width, when compared to a 4 [ns] signal. This is likely due to the smearing of the geometry response due to the broad (\approx 4.8 [m] full width half max (FWHM)) outgoing pulse width at 16 [ns].
5.5 DISCUSSION

5.5.1 Effect of Geometry

Figure 5.6 shows the incremental leaf-on subset along with the leaf-on validation waveform (\textit{tb123wsl}) and the leaf-off validation waveform (\textit{tb123w}). As more geometry is removed from the scene, more photons are free to propagate closer to the ground, thereby causing a downward shift in the backscattered energy distribution and further verifying the findings of Huang and Wynne (2013), Kotchenova et al. (2003), and Sun and Ranson (2000). For example, when comparing \textit{tb123wsl} to \textit{tb123w}, the amplitude and width of the peak at approximately 979 [m] from the sensor are much larger for the leaf-on case. There is a much larger signal for the leaf-off case than for leaf-on at the ground, due to having fewer facets to intercept photons. The locations of the peaks generally remain the same across the different geometries, with a change in amplitude. Similar results were obtained from the other 29 sites.
As shown in Figures 5.7b and 5.8b, the leaf-only geometry is the single dominant geometry component. The hypothesis that the back-scattered waveform is dominated by leaves at the 1064 [nm] wavelength is further proven by considering the leave-one-out geometries (see Figures 5.7c and 5.8c). The trunk ($t$) component should be included in simulations, despite having a small value in the single component geometries. This is especially true for large angles from nadir (i.e., terrestrial lidar simulation), where the trunks will occupy a significant portion of the scene.

The inclusion of twigs ($w$) and leaf stems ($s$, petioles) result in a 75% increase in RAM usage ($\approx 18 \text{Gb}$ to $\approx 32 \text{Gb}$), and do not significantly impact the backscattered signal. The likely reason for the low backscattered contribution of these geometries is due to the small size relative to the 0.5 [m] footprint. Currently, DIRSIG is a single thread process and a single CPU was maxed out for each simulation. For a leaf-on simulation, the $tb123l$ subset (i.e., no twigs or leaf stems) is recommended and for the leaf-off case, the $tb123$ subset (i.e., no twigs) is recommended for future simulations at 1064nm full-waveform small-footprint lidar sensors.

### 5.5.2 Effect of Scan Angle

Different scan angles ($0^\circ$, $10^\circ$, and $20^\circ$ from nadir) were considered to ensure that the results would be valid for a range of ALS systems. There was no statistical difference in mean waveform overlap between the different scan angles at a 95% confidence level for any of the simulated combinations (geometry, outgoing pulse width). This is not to say that the waveforms are the same (see Figure 5.13), but that there is not an angular dependance of geometry over the range of angles simulated. In this example, there is a decrease in ground return as scan angle increases. Note that this is a single example and not indicative of a trend relating foliage penetration and scan angle. We therefore concluded that any choice of geometry for future simulations with similar conditions will not be influenced by scan angle. This is useful for our work on simulating more
realistic scan patterns, as the the twigs and leaf stems do not become a significant contributor when a scan is acquired off-nadir. This further allows for a single geometric representation of a scene to be used for scans taken anywhere from 0°–20° off-nadir, rather than having a separate scene for nadir shots than off-nadir shots. It is likely, although not confirmed, that the twigs and leaf stems could be omitted at even larger scan angles, e.g., 90°, without loss of simulation fidelity.

Figure 5.13: DIRSIG simulations of the same location on the ground from 0°, 10°, and 20° from nadir. Notice that the ground backscatters different amounts of energy depending for different scan angles.
5.5.3 Effect of Outgoing Pulse Width

Figure 5.14 showed that the 16 [ns] pulse width had larger waveform overlap values than the 8 [ns] pulse width, which in turn had larger waveform overlap values than the 4 [ns] pulse width waveforms. However, the difference in mean (O) was not statistically different from zero at a 95% confidence level for any geometry-scan angle combination. Once again, this is not to say that different outgoing pulse widths do not lead to different backscattered waveforms (see Figure 5.14), but rather that there is no change in which geometry components are significant over the range of simulated pulse widths. Larger outgoing pulse widths will produce more similarity between waveforms, since the ability to resolve small changes in the direction of beam propagation is reduced. The practical implication of this result is that narrower outgoing pulse widths may enable researchers to achieve a finer resolution in terms of the level of structural complexity that is assessed. This will be particularly useful for deconvolution algorithms, which have a better chance of extracting the underlying signal with a delta-like system function.

5.6 Conclusions

We presented a first principles, physics-based simulation study to assess the effect of different tree geometry components on a near infrared (1064nm) full-waveform small-footprint lidar signal. As part of this study, we: (i) simulated the collection of small-footprint lidar signals on the HarvardForest1 virtual forest scene; (ii) introduced and analyzed a probabilistic waveform difference metric for comparing simulated waveform signals; and (iii) investigated how different simulation conditions, namely geometry, scan angle and outgoing pulse width, affect the simulated waveforms. We found that the back-scattered signal is indeed dominated by leaves (l), confirming our initial hypothesis. The next most important component was branch-level-3 (3). It was also found that the outgoing pulse width of 4 [ns], 8 [ns], or 16 [ns], and the scan angle of 0°, 10°, or 20° from nadir do not have a statistically significant impact on the means of waveform overlap. The
Figure 5.14: DIRSIG simulations of the same location with 4, 8, and 16 [ns] outgoing pulse widths. The scan was taken at 1000 [m] above the ground at a scan angle of 20°. This puts the ground at a range of \( \approx 1064.2 \, [m] \). Notice that the shorter wavelengths retain more structural detail.
and \(tb123\) geometry subsets, \(i.e.,\) those geometries that exclude twigs (\(w\)) and leaf stems (\(s\)), were found to be a good approximation of the truth geometries in the leaf-on (\(gls\)onyx:\(tb123awol\)) and leaf-off cases (\(gls\)onyx:\(tb123aw\)), respectively. It should be noted that these simulations were only performed on broadleaf deciduous trees, and that there may not be a direct extension to conifers. In addition, caution should be used when extending these results outside of the parameters simulated (\(e.g.,\) the optical properties may vary greatly at other wavelengths (\(e.g.,\) green-532 [nm]); and trunks will have a much higher contribution for a terrestrial system, etc.) leading to a potentially different set of geometries that contribute to the backscattered waveform signal.

The implications of this study are four-fold: (i) a specific geometry was defined for high fidelity simulation in each of the leaf-on and leaf-off scenarios; (ii) these identified geometries will enable faster simulation run times due to a non-linear decrease in the scene size/complexity; (iii) we now have a better understanding of the complex light-target interactions that occur in a physically- and radiatively-realistic forest scene for a generic full-waveform small-footprint lidar sensor, and (iv) future algorithm development will be facilitated by our knowledge of (i)-(iii).

Next steps include the assessment of a larger variety of off-nadir geometry interactions and the use of high-fidelity scenes at the identified geometry levels to develop algorithms for assessment of complex vegetation structure using full-waveform small-footprint lidar (identifying the locations and sizes of branches within the canopy, assessing fine-scale spatial distributions of biomass). In order to move closer to this goal, the within-canopy attenuation of the lidar signal must be characterized and compensated for (see Chapter 7). Our next steps are to investigate the impact of positional and rotational uncertainties on the received waveform signals within a forest canopy (see Chapter 6), which has implications for the utility of waveform-to-waveform comparisons of lidar signals.

We believe that this and previous efforts by other researchers will broaden the use of full-waveform small-footprint lidar scanners across various domains ranging from forest inventory and carbon accounting to detailed structural analyses for ecological applications.
5.6. CONCLUSIONS
Chapter 6

The impact of sensor positional uncertainty on lidar-derived parameters

6.1 Introduction

Once estimates of vegetation bio-physical structure have been made from lidar data, it is desirable to know more about the sensitivity and repeatability of the estimates, so that they can be used over time, i.e., in multi-temporal or time series analysis. In the hyper- and multi-spectral remote sensing change detection literature, it is common to find the difference between two pixels (either in radiance or reflectance space), e.g., Bruzzone and Prieto (2000), Eismann et al. (2008), Mas (1999), and Meola et al. (2011). While the optical properties of forests are often relatively homogenous at meters to large fractions of a meter scales, the structure of the forest at these scales is more heterogenous. This may introduce challenges in comparing year-to-year lidar scans of the same ecological regions, as proposed by National Ecological Observatory Network (NEON)
(Kampe et al., 2010), particularly for structural change detection in forested environments, e.g., has a tree fallen over or lost leaves due to biotic or abiotic shock? While spectral time-series studies typically evaluate change on a per-pixel basis, it is hypothesized that the structural heterogeneity of forest environments is too great to allow a similar pixel-based (or waveform-based) comparison at the small-footprint (≈0.5 [m] scale). We content that such multi-temporal comparisons would need to be performed at the object-level.

A high level of confidence that two waveforms are from the same location is required in order to accurately perform change detection on a per-waveform basis. Sensor position, obtained from a GPS and sensor orientation, obtained from an INS and scan-mirror location, are used to geolocate the lidar signal. Each of these positioning measurements has an associated uncertainty. Once again, the assessment of positional uncertainty is not practical in a real-world experiment—it is nearly impossible to fly a plane back to the exact same location, in the same orientation, and with the scan mirror pointed in the same direction. On top of that, environmental effects, such as changing atmospheric conditions or the wind blowing and changing the orientation of the leaves, may have an effect on the observed signal.

### 6.1.1 Layout

This chapter describes a study that evaluates the effect that sensor-positioning error has on a lidar signal through the use of simulation. The remainder of this chapter is broken up into three sections: Section 6.2 which describes the two experiments performed for this study, Section 6.3 states the results of this study, and finally Section 6.4 is a discussion of the these results and their implications. This work was published in Romanczyk et al. (2013c).
6.1.2 Associated Publications and Presentations


6.2 Methods

This study used the HarvardForest1 (Section 4.3.1) DIRSIG scene with the *tb123l* geometry subset, found in Chapter 5 and Romanczyk *et al.* (2012) and Romanczyk *et al.* (2013a).

6.2.1 Virtual lidar sensor

Once again, generic system parameters were chosen in order to extend the applicability of this study to a broad range of airborne lidar sensors. The footprint was 0.5 [m] at 1000 [m] flying altitude. All simulations were at-nadir and had a wavelength of 1064 [nm]. The outgoing pulse width was 4 [ns] with 1 [ns] (15 [cm]) time bins.

6.2.2 GPS/INS error analysis

The same thirty random locations (sites) within the HarvardForest1 DIRSIG scene (Section 4.3.1), as used in the geometry experiments (Chapter 5), were used to test the effects of system positioning (GPS) and pointing (INS) uncertainties on wlidar signals. A “truth” waveform was generated based on the known position and rotation information for each site. For this experiment, all simulations were taken at-nadir. In order to assess the effect of positioning error on the repeatability of waveform signal generation, additional waveforms were generated with positional or rotational jitter added. These additional waveforms could be captured when the GPS/INS read the desired location as at-nadir, but the actual location/orientation is different. The resulting jitter values encompass the typical, commercial-grade positioning errors (see Table 6.1). The jitter values were modeled with uncorrelated Gaussian random variables with mean zero and predefined variance.
levels.

Table 6.1: Accuracy specifications for Applanix POS AV GPS and INSs (Applanix, 2012). All values are RMS error. A checkmark (✓) in the “Post-Proc.” row refers to the accuracies after post-processing. H– and V–position refer to the horizontal and vertical position, respectively. The true-heading accuracies are for a typical mission profile, maximum RMS error.

<table>
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<th>RTX</th>
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</table>

As mentioned previously, the same thirty sites were used as in the geometry studies (shown in Figure 5.5). For each site, uncorrelated normally-distributed positional jitter, with zero mean and either 10 [cm], 25 [cm], 50 [cm], or 100 [cm] standard deviation (σ), was added to the x-y position of the sensor in order to assess the effect of positioning error on full-waveform small-footprint lidar signals. The jitter in position is given by

\[
\begin{bmatrix}
  x_i \\
  y_i \\
  z_i
\end{bmatrix} = \begin{bmatrix}
  x_0 \\
  y_0 \\
  z_0
\end{bmatrix} + \begin{bmatrix}
  \eta_1 \\
  \eta_2 \\
  0
\end{bmatrix},
\]

(6.1)

where

\[
\eta_1, \eta_2 \sim N(0, \sigma),
\]

(6.2)
and \([x_0, y_0, z_0]^T\) is the true location of the platform. Separately, to assess the effect of angular positioning error, a normally distributed rotational jitter (zero mean, and 0.001 \(^\circ\), 0.005 \(^\circ\), 0.01 \(^\circ\), 0.05 \(^\circ\), 0.1 \(^\circ\), or 0.5 \(^\circ\) standard deviation) was added about each of the \(x\)-, \(y\)-, and \(z\)-axes. The jitter in angle is given by

\[
\begin{bmatrix}
\theta_x \\
\theta_y \\
\theta_z 
\end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix}, \tag{6.3}
\]

where

\[
\eta_1, \eta_2, \eta_3 \sim \mathcal{N}(0, \sigma), \tag{6.4}
\]

and \((\theta_x, \theta_y, \theta_z)\) is the rotational jitter about the \(x\), \(y\), and \(z\) axis, respectively. The rotational vector \([0, 0, 0]^T\) corresponds to a sensor that is looking directly down, \(i.e.,\) at-nadir. Once again, thirty angle samples per site were drawn for each of the standard deviations. For all of the angular jitter simulations, the position of the lidar was fixed at 1000 [m] directly above the target location.

Each jittered waveform was compared to the “truth” \((i.e.,\) no jitter) waveform using the waveform overlap \((O)\) metric (Section 5.2). In addition, the waveform overlap was computed for just the passive terms in order to improve our understanding of linking the effect of positional errors in lidar data, when compared to the more established multi- and hyperspectral imaging modalities.

### 6.2.3 Spatial evolution of errors

For the second uncertainty experiment, a profiling lidar was “flown” in a straight, north-south line 1000 [m] above the scene, to assess the effect that these errors may have on measurements. The pointing was fixed at-nadir (no mirror rotation, or aircraft roll \((\omega)\), pitch \((\phi)\), or yaw\((\kappa)\). There was a large overlap in adjacent footprints with a 50 [cm] footprint center being captured every 5 [cm]. A lidar-derived tree height was compared to the DIRSIG truth maximum height for each footprint. After collecting the simulated waveforms, a Gaussian decomposition (Wagner et al.,
2006) was performed. The lidar-derived height for each waveform was the distance from the peak of the highest Gaussian to the ground (which was assumed to be known exactly, i.e., 1000 [m] from the sensor). The correlation between the true tree height and the lidar-derived tree height was computed for offsets between the two signals from 0–100 [cm].

6.3 Results

6.3.1 The effect of GPS errors

Figure 6.1 shows the sample waveforms with 10 [cm], 25 [cm], 50 [cm], and 100 [cm] positional uncertainty added in the x- and y-directions. It shows that very different waveforms can be obtained from small shifts in x-y position. This is true for even a 10 [cm] standard deviation jitter, where there is a significant overlap between the 0.5 [m] footprints. Figure 6.2 is a box and whisker plot of the waveform overlaps (O) that were used to compare the effect of jitter on the similarity of waveforms. As was expected, with increased positional uncertainty, the overlap decreased. The passive (solar/sky) terms were constant across the range of jitters simulated and outperformed the lidar signal in terms of waveform overlap (O) at each jitter level.

6.3.2 The Effect of INS Errors

Figure 6.3 shows possible waveforms from x-, y-, and z-axis rotational jitter standard deviations of 0.001°, 0.005°, 0.01°, 0.05°, 0.1°, and 0.5°. Once again, as more rotational uncertainty is added, the discrepancy in waveforms becomes larger. There is noticeably reduced waveform variability at 0.001° of angular jitter. These results are quantified in Figure 6.4, which shows a box and whisker plot of waveform overlap between the “truth” waveforms and the jittered waveforms. An increase in jitter standard deviation led to a decrease in waveform overlap (O). As with the positional jitter experiment, the passive terms were constant across the range of jitters simulated and significantly outperformed the lidar signal.
6.3. RESULTS

Figure 6.1: DIRSIG simulated mean waveforms from a site with (a) 10 [cm], (b) 25 [cm], (c) 50 [cm], and (d) 100 [cm] standard deviation of sensor position jitter in both the x and y axes. The thick black line is the true signal for this location if there were no jitter. The colors represent individual trials. As positional uncertainty increases, there is a wider range of waveform signals.

Figure 6.2: Box and whisker plot of the waveform overlaps (O) of the waveform signals (red) and passive term (blue) for various standard deviations of x- and y-axis positional jitter. Asterisks represent the mean waveform overlap. As the uncertainty increases, the similarity of the waveforms to the “truth” decreases. Note that the passive terms are more similar to the truth than the lidar signals.
Figure 6.3: DIRSIG simulated mean waveforms from a site with (a) 0.001°, (b) 0.005°, (c) 0.01°, (d) 0.05°, (e) 0.1° and (f) 0.5° standard deviation jitter in $x$, $y$, and $z$-axis rotations. The thick black line is the “truth” signal for this location. The colors represent individual trials. As the angular uncertainty increases, there is a wider range of waveform signals.

Figure 6.4: Box and whisker plot of the waveform overlaps ($O$) of the waveform signals (red) and passive term (blue) for various standard deviations of $x$, $y$, and $z$-axis rotational jitter. Asterisks represent the mean waveform overlap. As the uncertainty increases, the similarity of the waveforms to the “truth” decreases. The passive terms are more similar to the truth than the lidar signals.
6.3.3 Spatial evolution of errors

Figure 6.5 shows a scatter plot of true heights, computed from a DIRSIG truth collector, and lidar-derived heights for various offsets in position. This comparison is especially useful to assess the impact of positional uncertainty on a typical forest structure variable assessment, namely height. There is a correlation (blue diagonal line) between the two heights for small positional offsets, but as the distance between the truth and the lidar derived product increases, there is reduced correlation in the data. These correlations between true height, extracted from the virtual DIRSIG scene, as a function of offset between lidar position to position of the lidar-measured height, can be visualized in Figure 6.6. There was a high correlation (≈0.99) between the lidar-derived height and the DIRSIG true height in the absence of positional offset. At 50 [cm] of misregistration, or one waveform “pixel”, the correlation decreased to about 0.83. At 100 [cm] of disagreement, the correlation decreased to about 0.77. There arguably was some amount of error caused by the height finding process. The correlation of the lidar-derived heights tended to approximate the cube of the correlation of the true heights.

6.4 Discussion

Even small uncertainties in the position (≈10 [cm]) or orientation parameters (≈ 0.005°) of a lidar sensor may lead to large differences in the small-footprint waveforms, as shown by Figures 6.1–6.4. The larger similarity in the passive optical signals, compared to the structural lidar signals, are clearly shown in Figures 6.2 and 6.4. The 1064 [nm] passive part of the lidar signals was used as a proxy for a more extensive multi- or hyperspectral sensor, where it is a common practice to spatially interpolate signals. Furthermore, Figures 6.5 and 6.6 show that there is a decreased correlation in the ability to match lidar-derived tree heights to the true height as positional error increases. This decrease in correlation shows that the lidar-derived tree height from a single waveform may not be well-matched to the lidar-derived tree height a few years later. Direct
Figure 6.5: Lidar-derived height vs. true height for positional offsets from 0-100 [cm], in 5 [cm] increments.

Figure 6.6: Correlation of the true height and the lidar-derived height at offsets from -100 [cm] to 100 [cm] in 5 [cm] intervals.
waveform-to-waveform comparison for change detection will only be possible if the aircraft is positioned in the same location (positional standard deviation <10 [cm]) and with the same pointing direction (roll, pitch, yaw, scan mirror angle standard deviation <0.005°). It should be noted that the positional uncertainties used are relatively large fractions of the small-footprint ground sample distance (GSD). The smallest positional standard deviation of 10 [cm] is 10% of the 1 [m] footprint. These same results are not likely to affect a large footprint sensor such as the 25 [m] footprint of ICESat-2. Using today’s flight technology, these conditions will be challenging to achieve.

The differences in waveform signals due to small positioning/pointing uncertainties may pose challenges for doing year-to-year, waveform-to-waveform comparisons. Due to the heterogeneous tree-to-tree branching structure, even in a relatively homogeneous forest, it may prove challenging to perform these waveform-to-waveform comparisons, akin to pixel-level change detection of passive optical imagery. The addition of ground control points, the use of the entire “waveform-cloud” and not just isolated signals, and analysis at object- or tree-level, should help to mitigate the impact of these errors. It is more likely that geolocated products derived from waveform data, e.g., stem maps, canopy height models, etc. will be more robust against the fine scale waveform differences and allow for year-to-year comparisons. Although this may seem like an expected result, it remains useful to assess the exact impact of platform noise on year-to-year data collections. These results point to the need to assess multi-temporal structural changes at coarser scales, a topic which is recommended for future research.

6.5 Conclusions

We presented a study to evaluate the effect of positional uncertainties on full-waveform, small-footprint lidar systems. We found that even small positional errors (<10 [cm] in x-y axis translation) or angular errors (∼ 0.005° in x-, y-, and z-axis rotation) can cause significant dissimilarities in
the waveforms for a small-footprint system. The effect of angular error were comparable to the
effect of positional error over the range of jitters that were simulated. This has implications for the
ability to perform waveform-to-waveform comparisons from either a multi-temporal, e.g., year-
to-year, or multi-flightline collect. It is likely that combining waveform signals together to perform
analysis at at object level will help reduce the impact of these variabilities in the backscattered
signal. Future work will include simulating the same types of experiments with a scanning lidar,
adding z-axis positional jitter, looking at individual jittering individual components, e.g., just the
along-track positional, and combinations of components to determine weak links, performing
simulations on other scenes, and using off-nadir scans for the truth scan with jitter around them.

From this last chapter, we concluded that the uncertainty in GPSINS makes it intractable to per-
form waveform-to-waveform comparisons of the underlying structure, from either overlapping
flight-lines or multi-temporal (year-to-year) observations. In an effort to mitigate this limitation,
the subsequent chapter (Chapter 7) developed a methodology for correcting the attenuation of the
lidar signal. This calibration will provide a view-invariant description of the underlying canopy
structure, thus opening the door to multi-temporal forest structure comparison.
Chapter 7

Attenuation Correction

7.1 Introduction

Wlidar is a technology where a pulse of light is emitted from a transmitter, interacts with objects in its path, and the return pulse is digitized by the receiver. Waveform lidar differs from discrete lidar in that it digitizes the entire backscattered signal, whereas discrete lidar returns point measurements of position and intensity (Neuenschwander et al., 2008). Such an instrument can acquire detailed information on 3D structure. Wlidar has been used for vegetation mapping (Wagner et al., 2008; Neuenschwander et al., 2008), modeling canopy structure (Wagner et al., 2008; Koetz et al., 2006; Lefsky et al., 1999a), estimating biomass (Lefsky et al., 1999a), canopy height (Lefsky et al., 2007; Sun et al., 2008) and foliage density (Adams et al., 2012), and for tree species classification (Reitberger et al., 2008). For many of these applications, an accurate DEM is also needed (Adams et al., 2012).

As the light travels through various geometry components, from top- to sub- to lower-canopy regions, some forward propagated energy is reduced with each interaction, resulting in fewer photons reaching the ground. Ni-Meister et al. (2001) modeled wlidar interactions and state that
such attenuation is dependent on spatial (density, size, position) and spectral (reflectance, transmission) properties of the leaves and branches. This causes difficulties in detecting the ground for DEM estimation, biases when investigating sub-canopy vegetation structures and parameters, and an impaired understanding of vertical canopy behavior for height-stratified models.

The impact that within-canopy attenuation can have on a lidar signal is shown in Figure 7.1. In this case, the canopy was divided into 1 [m] segments. Starting from the top of the canopy, a segment was removed, and the received waveform was simulated with DIRSIG. As the geometry was removed from the top of the canopy, the distribution of received photons shifts towards the ground, as photons are able to penetrate further into the canopy. It is worth noting that the locations and widths of the returns are mostly independent of the proceeding geometry, with only their amplitudes changing.

In this study, we have specifically evaluated the ground response, in conjunction with preceding light-structure interactions, in order to understand attenuation. Recent papers have been published that show an improvement in the ground response or detection when compared with discrete return lidar. Magruder and Neuenschwander (2009) amplified faint ground returns in a pine forest by using adjacent Gaussian responses within the waveform in a stacking technique. This method was validated against discrete lidar data. Adams et al. (2012) designed a synthetic model of a tree, where the transmissivity was modeled as “gas or needles and small elements”. The decay of individual Gaussians was modeled using the Beer-Lambert Law. Lefsky et al. (2007), in turn, used parameters within the waveform, i.e., leading and trailing edge extents, to improve height estimates without addressing attenuation. Forest canopy height was successfully estimated with a RMSE of 5 [m].

These studies show the importance of correcting the effects of attenuation, but Adams et al. (2012) contended that attenuation will only be fully understood with in-depth laboratory testing. We believe that a realistic and physics-based simulation is an appropriate testing environment,
Figure 7.1: Example of the within-canopy attenuation. The colors represent the height in meters above which the geometry was removed. Note that as geometry at the top of the canopy are removed, the distribution of received photons shifts towards the ground.
since all parameters, such as the spectral responses, the exact size and location of the trunk, branches and leaves, etc. are specified and thus explicitly known.

Mathematically, a simple case of attenuation through a series of specular reflecting and direct transmitting parallel plates (ignoring scattering and refraction, and assuming negligible attenuation through air) may be explained using the Beer-Lambert law (Telle et al., 2007):

\[ I_{d}^{\eta} = I_{d}^{0} \cdot \exp(-\eta \cdot \delta \cdot \beta), \]  

(7.1)

where \( I_{d}^{\eta} \) is the downward intensity after \( \eta \) intersections of identical objects with thickness \( \delta \) and effective extinction \( \beta \). The initial downward intensity is given by \( I_{d}^{0} \).

Figure 7.2: A schematic showing energy interactions between two identical plates. All plates are assumed to have the same upward reflectance, \( \rho_u \), downward reflectance, \( \rho_d \), thickness, \( \delta \), and extinction, \( \beta \). The transmission through a single plate, \( \tau \), can be calculated by \( \tau = \exp[-\delta \cdot \beta] \). The total downward energy entering the top plate from above is \( I_{d}^{0} \). The total downward energy entering the top of the second plate from above is \( I_{d}^{1} \). The total upward energy entering the second plate from below, resulting from scattering and reflectance off objects beneath the plate, is \( I_{u}^{2} \).

Given two identical plates with specular reflectance, \( \rho_u \), off the upward facing surface, \( \rho_d \), off the downward facing surface (shown in Figure 7.2), then the total intensity incident on the second
plate may be given by

\[ I_1^d = \text{downward transmitted energy} + \rho_d \cdot \text{upward transmitted energy} \]  
\[ = I_0^d \cdot e^{-\delta \beta} \cdot \left(1 + \rho_u \cdot \rho_d + \rho_u^2 \cdot \rho_d^2 + \ldots\right) + \rho_d \cdot I_2^u \cdot e^{-\delta \beta} \cdot \left(1 + \rho_u \cdot \rho_d + \rho_u^2 \cdot \rho_d^2 + \ldots\right) \]  
\[ \to \frac{I_0^d + \rho_d \cdot I_2^u}{1 - \rho_u \cdot \rho_d} \cdot \exp(-\delta \cdot \beta) \]  

for infinite scattering events. The upward energy may be written in terms of the effective reflected energy, \( \rho_{\text{eff}} \in [0, 1] \), so that

\[ I_2^u = \rho_{\text{eff}} \cdot I_1^d \cdot e^{-\eta \cdot \delta \beta}. \]  

Therefore,

\[ I_1^d \to \frac{I_0^d \cdot e^{-\delta \beta}}{1 - \rho_u \cdot \rho_d - \rho_{\text{eff}} \cdot \rho_d \cdot e^{-2 \delta \beta}} \]  

More complex interactions, including non-identical interactions, may not be written in a closed-form solution without prior knowledge of the exact location and spectral properties of each object encountered. Therefore, we first evaluated attenuation events in a simulation environment in order to understand this behavior.

The DIRSIG simulation environment (Schott et al., 1999) has been used to study wLIDAR interactions with tree or forest geometry in recent studies. The impact of tree geometry components on the returned waveform for a small-footprint system has been studied (see Chapter 5) and it was found that the twigs and leaf stems contribute insignificantly to the returned waveform (Romanczyk et al., 2012; Romanczyk et al., 2013a). Wu et al. (2012) designed a pre-processing chain for wLIDAR in DIRSIG, using knowledge of the simulated trees in order to determine the best methods for denoising, deconvolution, waveform registration, and angular rectification (described in more detail in Wu et al. (2011)). This simulation environment was also used to design a method to derive 3D tree structure from wLIDAR (Wu et al., 2013) and has undergone significant verification.
and validation (Brown and Schott, 2010). A more detailed description of DIRSIG is presented in Section 7.2.1. So while simulated studies need to be tested on real data to evaluate the effect of the true scene complexity on the outcome, many experiments can only be evaluated in terms of known truth, i.e., by using simulations where all parameters are known and have been specified. This is true because in a real world scenario we cannot realistically and empirically measure all vegetation structural components and their interactions with an airborne, inbound laser.

In a related study, DIRSIG was used to evaluate the effects of attenuation on a simple synthetic dataset consisting of stacked plates with leaf properties (Cawse-Nicholson et al., 2013). After each waveform had been decomposed into Gaussians using Wagner’s method (Wagner et al., 2006) and normalized to unit area, the effects of varying the amount of geometry, size of geometry, vertical positioning, and absorption properties were investigated. The attenuation was found to be linearly related to the sum of the area under preceding Gaussians in the waveform. This elegant relationship meant that waveform attenuation theoretically may be corrected, or at least accounted for in this relatively simple synthetic scenario.

7.1.1 In-canopy attenuation correction

As a lidar pulse propagates through a medium, scattering and absorption reduce the signal that will travel a further distance into the medium. The implication of this is for a columnated laser beam, where there is no decrease in signal due to beam divergence, a target further away from the lidar system will have a lower signal than if the same target was closer to the lidar system. The reason for this is that some of the photons that were emitted from the lidar system did not make it to the target, and some of the photons that reflected off of the target did not make it back to the sensor. In order to work towards the objective of a range-varying estimate of LAI, the within canopy attenuation must be accounted for in order to get unbiased estimates of the subsequent leaf area.
While there has been a significant amount of work characterizing the laser attenuation in the atmosphere (Chepfer et al., 2008; Hamilton, 1969; Klett, 1981) and in water (Churnside et al., 1998; Churnside et al., 2001; Mitra and Churnside, 1999), there has been relatively little work investigating the within forest canopy attenuation. These environments have well mixed scatters that are much smaller than the footprint of the laser, e.g., sediments in water or aerosols in the atmosphere. As a result, relatively simple extinction models may be used to characterize the within-medium attenuation (Kunz and de Leeuw, 1993; Walker and McLean, 1999). The scattering elements in forest canopies, i.e., leaves and needles, however, are clumped (Myneni et al., 1997) together within the canopy. Furthermore, for small-footprint lidar systems, the leaves occupy a significant portion of the beam, violating the assumptions of the extinction-based atmospheric and oceanographic attenuation models.

Richter et al. (2014a) and Richter et al. (2014b) used a voxel-based method to correct for within canopy attenuation. They modeled a waveform as a series of Gaussians and then applied an attenuation based on a set of predefined layer transmittances. For the attenuation correction, they performed a Gaussian decomposition and followed by computing the area under the $j$-th Gaussian of the $i$-th waveform, $B^i_j$. They then used an unattenuated, i.e., a ground response with no previous interactions, as a reference $B_{ref}$. For each interaction, they computed the proportion of the reflected signal $p^i_j$:

$$p^i_j = \frac{B^i_j}{B_{ref}}$$ \hspace{0.5cm} (7.7)

Moving down the waveform, a new reference value ($B_{ref,j+1}$) was computed as

$$B_{ref,j+1} = B_{ref,j} \cdot (1 - p^i_j)$$ \hspace{0.5cm} (7.8)
The correction factor, \( c_i^j \) for the \( j \)-th Gaussian of the \( i \)-th waveform was given by

\[
    c_i^j = \frac{B_{\text{ref},j}}{B_{\text{ref},j+1}} \tag{7.9}
\]

They found that on the simulated data set, the correction, was able to reconstruct the unattenuated waveform, however quantitative results were not presented. In addition, this study lacks the simulation of multiple bounce effects within the canopy. We will now present an attenuation correction method on a more-complex set of simulated data.

In this study, we have evaluated the attenuation through more complex simulations of a tree canopy. A better understanding of this attenuation of lidar will lead to important advancements in digital terrain mapping under dense canopy. This in turn would result in more accurate models for forestry applications; e.g., tree height, biomass estimation, sub-canopy structure, tree structure analysis (LAI), and many others. We hypothesize that, as with the simple experiments described by Cawse-Nicholson et al. (2013), attenuation is linearly related to the area under the waveform. Portions of this work have been published in Cawse-Nicholson et al. (2013) and presented in Romanczyk et al. (2013b). This work is a collaboration with Dr. Cawse-Nicholson.

### 7.1.2 Layout

The remainder of this chapter is broken up into four sections. Section 7.2 details the methods used, including data sets (Section 7.2.1), and preprocessing steps (see Section 7.2.2). The results of the various simulations can be found in Section 7.3, with associated discussion in Section 7.4. Finally, conclusions and an outlook of future work can be found in Section 7.5.
7.2 METHODS

7.1.3 Associated Publications and Presentations


7.2 Methods

To develop and assess an attenuation correction algorithm, a number of virtual scenes were used. The virtual scenes used (Section 7.2.1), preprocessing steps (Section 7.2.2), and experimental methods (Section 7.3) for the attenuation correction algorithm will follow.

7.2.1 Data

We simulated several scenes containing different levels of geometric complexity in order to study attenuation. Each scene was modeled within the DIRSIG simulation environment, where the truth parameters, e.g., true ground and geometry locations and their spectral properties, were known. As a recap, DIRSIG allows users to create realistic scenes and sensors to simulate images or lidar returns using first-principles, physics-based ray-tracing. The wlidar simulation follows photon paths using a two-pass forward and backward Monte Carlo ray-tracing, called photon mapping (Jensen, 2001). The rays are cast into the scene and perform a random walk, interacting with geometry that have been assigned spectral transmission, reflectance, and absorption properties (Burton et al., 2002; Brown et al., 2005; Blevins, 2005). These properties dictate the behavior of each ray, and backwards ray-tracing is used to map the total photons that will be received by the detector. The output of DIRSIG is an estimate of the mean number of sensor-reaching photons for each time bin, across the detector array.
All scene simulations were performed at a wavelength of 1064 [nm], where the laser had a Gaussian outgoing pulse shape. Digitization of the waveform at a resolution of 1 [ns] resulted in a 0.15 [m] temporal bin width. The sensor parameters were chosen to approximate real, operational systems, although many of these parameters vary in our experiments to simulate a range of potential systems. Details are provided for each simulation case.

This study evaluated attenuation based on the change in the amplitude of the Gaussians at ground level, and so each synthetic experiment contained at least one waveform response that did not interact with geometry above ground. This waveform was labelled as the ground reference waveform and was used to inform the true Gaussian amplitude at ground level. Finally, the virtual scenes were developed with increasing structural complexity in order to assess the attenuation in a stepwise fashion.

### 7.2.1.1 Simple geometry

In the simplest case, thin plates were stacked in different configurations to analyze interactions at the leaf-level. Plates were assigned reflective and transmissive properties based on field measurements of a *Quercus rubra* and were placed over a flat plane that was assigned a reflective spectrum of mixed grass. The simulated sensor was placed at 2000 [m] above ground. At this altitude, a 0.5 [mrad] beam divergence resulted in 1 [m] lidar footprint size at ground-level. The spectral pulse width was 2 [nm] (around a mean of 1064 [nm]) and the spatial shape of the outgoing laser was uniform rectangular, to evenly sample the 1 [m] × 1 [m] geometric plates. Only a single “pixel” or footprint was considered for each experiment. Many of these parameters are taken from the RIEGL LMS-Q680i specifications (Riegl, 2012), although a 2 [ns] temporal pulse width was implemented in this case for better representation of each interaction (*i.e.*, to detect interactions in more detail with finer vertical resolution). The pulse width parameter was varied
more in the subsequent experiments of increasing structural complexity.

### 7.2.1.2 A single simulated tree

To study realistic geometry, a full *Acer rubrum* tree was exported from OnyxTREE (Bosanac and Zanchi, 2011), using the default *Acer rubrum* tree model (see Figure 7.3). Spectral properties of tree components were again assigned based on field data. The tree geometry consisted of a trunk, boughs, three levels of branching, and leaves. These were represented as a collection of facets, and the leaves were assigned reflective and transmissive properties. At 1064 [nm], the field spectrum applied to each leaf resulted in reflectance of approximately 43% and transmission of approximately 52% of the received light. Tests were also run on two artificially altered spectra with transmittance 40% and 60% (reflectance 55% and 35%, respectively). It is challenging to assign “typical” spectral properties, since these vary significantly according to leaf age, canopy position, season, tree health, *etc.* (Yang *et al.*, 2013), so we chose to use field samples as representative spectra. Yang *et al.* (2013) found that forest reflectances average between 40% and 60% at 1064 [nm] for a terrestrial lidar, and the United States Geological Survey (USGS) spectral library (USGS, 2013) contains leaves with a large range of reflectances, varying between 30% and 90% at 1064 [nm].

For rapid processing, and to guarantee that random behavior was consistent throughout the scene, the entire scene was captured instantaneously by a sensor with a grid detector, which resulted in an output reminiscent of an image. We considered each return a pixel, where each pixel had a 0.25 [m] spatial resolution at an altitude of 20,000 [m] (a high altitude was used so that angular effects would be negligible). *Sub-sampling* is a DIRSIG term referring to the fine-scale evaluation of a single pixel. Higher sub-sampling increases the likelihood of detecting sub-pixel structures, allocating fuller photon coverage of each pixel, but increases the load on computational resources. In this case, we used $10 \times 10$ sub-sampling per “pixel”, *i.e.*, 0.025 [cm] sub-pixels, which allowed adequate coverage of the geometry. Each outgoing pulse had a rectangular uniform
Figure 7.3: Blender (Blender Online Community, 2015) rendering of the default OnyxTREE *Acer rubrum*.
spatial shape and the energy over the entire $40 \times 40$ pixel scene was 0.02 [J]. Three pulse widths were tested: 2 [ns], 4 [ns], and 8 [ns]. The range gates were set to collect responses between 10 [m] below- and 30 [m] above ground.

7.2.1.3 A simulated forest

In order to understand the attenuation behavior across different trees, the HarvardForest1 simulated forest scene was considered (see Section 4.3.1). Nine Acer rubrum and four Quercus rubra trees were placed on a flat ground plane. The individual trees were designed in OnyxTREE, with properties such as DBH and height acquired from basic inventory data from a plot in Harvard Forest. The trees contained the following OnyxTREE-defined structures: trunk, boughs, branch level-1, branch level-2, branch level-3, and leaves. As shown in Romanczyk et al. (2013a), smaller components, such as twigs and leaf stems, did not contribute to the waveform in a statistically significant way. The tree locations were assigned manually in order to simulate a closed canopy, and 30 sites were selected pseudo-randomly to ensure that the majority of the sites fell within canopy.

The simulated sensor, created by Romanczyk et al. (2013a), was designed to be realistic, although sensor vendors do not make all system parameters publicly available. The sensor was simulated at 1000 [m] altitude with a radially uniform footprint of 0.5 [m] (due to a 0.25 [mrad] divergence half-angle). Three pulse widths were considered, namely 4 [ns], 8 [ns], and 16 [ns], with a pulse energy of 0.2 [mJ]. An individual pulse was emitted towards each site. The detector had a field of view of 0.5 [mrad] and had $100 \times 100$ “pixel” subsampling. Three zenith angles were considered for the 4 [ns] simulation: at nadir; 10 [$^\circ$] off-nadir; and 20 [$^\circ$] off-nadir. The azimuth angle was chosen from a uniform distribution over [0 $^\circ$, 360 $^\circ$]) for each sample, and the same azimuth angle was used for the nadir, 10 [$^\circ$] and 20 [$^\circ$] simulations for each sample.

The Acer rubrum trees in this scene had an approximate reflectance of 39% and transmission
of 52%, while the Quercus rubra trees had an approximate reflectance of 36% and transmission of 52% at 1064 [nm].

### 7.2.2 Preprocessing

Each of the $N$ waveform responses was first decomposed into Gaussian curves using Wagner’s method (Wagner et al., 2006). Each waveform, $\mathbf{w}_i \in \mathbb{R}^{|b|}$, $i = 1, \ldots, N$, over $|b|$ time bins, was first normalized by a specific value to standardize the decomposition for different sensor parameters. The normalization factor in each case was chosen to be the area under the curve of a representative waveform, defined as a waveform representing a single ground-only interaction. Next, first order differentiation was used to find inflection points in the waveform, and those $K_i$ points that were centers of gravity (local maxima) were used to inform initial conditions for the mean and amplitude of each of the Gaussian curves. Levenburg-Marquardt optimization (Levenberg, 1944; Marquardt, 1963) was used to determine the mean/position ($\mu_j$), amplitude ($\alpha_j$), and standard deviation/width ($\sigma_j$), $j = 1, \ldots, K_i$ for each Gaussian, where $\tilde{\mathbf{w}}_i$ provided the best fit to the waveform $\mathbf{w}_i$, and

$$\tilde{\mathbf{w}}_i = \sum_{j=1}^{K_i} \alpha_j \cdot \exp \left\{ -\frac{1}{2} \left( \frac{\mathbf{b} - \mu_j}{\sigma_j} \right)^2 \right\}, \tag{7.10}$$

where $\mathbf{b} \in \mathbb{R}^{|b|}$ is the vector spanning the time bins of $\mathbf{w}_i$.

The amplitude of each Gaussian at ground-level was determined by finding the Gaussian in each waveform whose mean (vertical height) matched that of the ground reference waveform. The amplitude of these were compared and the difference between each Gaussian amplitude at the ground level and the amplitude of the ground reference waveform was calculated. This difference is the correction necessary in order to remove the effects of attenuation.

In the simple experiment described in Section 7.3.1, the correction for each interaction was analyzed. For more complex scenes, the ground was considered sufficient validation, since the correction depends on all previous interactions. In other words, if above-ground interactions are
7.3. RESULTS

poorly decomposed or understood, then the error in the correction will have the greatest impact at the last interaction, \( i.e. \), the ground, in most cases.

7.3 Results

7.3.1 Simple geometry

An experiment was carried out in a related study, where thin plates were assigned leaf properties and attenuation was studied while varying four parameters: plate size, number of plates, vertical distance between neighboring plates, and spectral reflectance (Cawse-Nicholson et al., 2013). Each waveform was decomposed into Gaussians using Wagner’s method (Wagner et al., 2006) and the difference between the observed Gaussian amplitude and the reference amplitude was evaluated for each Gaussian in each pulse. This was a simple experiment that showed a linear relationship between an additive correction factor for each Gaussian and the sum of the area under the preceding Gaussians. Specifically, for the \( j \)-th Gaussian in the \( i \)-th waveform, it was shown that

\[
c_i^j \propto \sum_{k=1}^{j-1} \sigma_k^i \cdot \alpha_k^i
\]  

(7.11)

where \( c_i^j \) is the difference between the observed and reference amplitude of the \( j \)-th Gaussian, and \( \sigma_k^i \) and \( \alpha_k^i \) are the standard deviation and amplitude, respectively, of the \( k \)-th Gaussian in the \( i \)-th waveform. Note that the product of standard deviation and amplitude is proportional to the area under the \( j \)-th Gaussian:

\[
B_i^j = \sqrt{2 \cdot \pi \cdot \sigma_k^i \cdot \alpha_k^i}
\]  

(7.12)

Further experimentation in this study has shown that this linear relationship is also independent of plate angle; this relationship is illustrated in Figure 7.4. Although only returns at nadir
were considered in this experiment, the independence of the results to plate angle implies that off-nadir returns will exhibit similar behavior. The parameters considered in the simple geometry experiment are listed in Table 7.1.

Table 7.1: Parameters considered in the simple geometry experiment. The initial reflectance factor $\rho$ represents a spectral curve determined by field data. The angle of the top plate is relative to horizontal.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of plates</td>
<td>2, 3, 4, 5, 6</td>
</tr>
<tr>
<td>Reflectance</td>
<td>$\rho$, 0.9-$\rho$, 0.8-$\rho$, 0.7-$\rho$, 0.6-$\rho$, 0.5-$\rho$</td>
</tr>
<tr>
<td>Size of intercepting plate</td>
<td>100%, 90%, 80%, 70%, 60%, 50%</td>
</tr>
<tr>
<td>Vertical distance between plates</td>
<td>1 [m], 0.8 [m], 0.6 [m], 0.4 [m], 0.2 [m]</td>
</tr>
<tr>
<td>Angle of top plate</td>
<td>0°, 15°, 30°, 45°</td>
</tr>
</tbody>
</table>

Figure 7.4: It has been shown that, when varying the parameters described in Table 7.1, there is a linear relationship between the additive correction factor for each Gaussian and the sum of the products of standard deviation and amplitude for all the preceding Gaussians in each waveform (Cawse-Nicholson et al., 2013).
In order to investigate the effect of atmosphere on our experiments, we simulated a mid-latitude summer atmosphere in MODTRAN5 (Berk et al., 2005), with rural extinction and a perceived horizontal visibility of 10 [km]. The intensity of the backscattered lidar at 1064 [nm] differed by less than 0.1% in the range 0–30 [m] above ground, showing that attenuation through air may be ignored at this wavelength and typical tree canopy height. Therefore, for increased processing time, a simple atmosphere (ideal transmission with no scattering) was assumed throughout this study, without loss of generality.

The linear relationship described in Eq. (7.11) was still observed when the experiment was replicated with a different transmission value for all plates, but the slope of the linear regression was different. This is reasonable, since the waveform response is determined by the reflected light only, but a decreased transmission will result in smaller amplitudes of the following Gaussians; \textit{i.e.}, a larger correction factor is necessary, even though the initial Gaussian looks the same.

This means that correction of waveform attenuation appears to be viable, although some prior knowledge of the transmission may be required. While the results were promising, this simple experiment did not adequately represent all the complexities of a realistic scene. The following experiment therefore evaluated attenuation through the canopy of a simulated tree.

### 7.3.2 A single simulated tree

The \textit{Acer rubrum} instance used in this study was designed with realistic geometry, while branches and leaves were assigned different spectral properties, as described in Section 7.2.1.2. Attenuation was therefore evaluated for different proportions of leaves (which transmit light) and branches (which obscure light).

The linear relationship described in Eq. (7.11) is evident in Figure 7.5, but the slope of the linear
Figure 7.5: For 1600 waveforms acquired over a simulated *Acer rubrum* on a flat grass plane, there was a linear relationship between the additive correction factor for the Gaussian at ground level and the sum of the products of standard deviation and amplitude for all the preceding Gaussians in each waveform. For this example, the standard field leaf spectra with 52% transmittance was used, with a pulse width of 2 [ns].
regression is different to that seen in Figure 7.4. This is because the first experiment contained only *Acer rubrum* plates (*i.e.*, leaves) and no branches. The linear relationship in the single tree experiment exists due to the structural relationship between leaves and branches (*i.e.*, leaves only grow on branches). The cluster of points around zero represents the noise or intensity variation present in the ground-only responses, including gaps in the tree canopy.

Three different transmission properties and three different outgoing pulse widths were tested in this experiment, with the slope of the linear regression given in Table 7.2. In Section 7.3.1 we showed that the slope is affected by the effective transmission of the object, but in this experiment we found that this effect is negligible when considering more realistic, complex geometry. Specifically, this is due to the difference between component and effective transmission. There are slope differences due to the different pulse widths—this is due to the nature of the additive correction and the fact that amplitude is reduced for larger pulse widths, since energy is constant, resulting in a “stretched” waveform. This effect is discussed in Section 7.4.

The results therefore show that an attenuation correction may be possible on a per-tree basis, even though the tree contains objects with different transmissive properties. Finally, we extended the results to an even more complex scene, described in the following section.

Table 7.2: Different transmission values show insignificant differences in slope for this particular geometry. Wider pulse widths resulted in smaller additive corrections due to the lower initial amplitudes of the waveform, resulting from a conservation of energy.

<table>
<thead>
<tr>
<th>Transmission</th>
<th>2 [ns]</th>
<th>4 [ns]</th>
<th>8 [ns]</th>
</tr>
</thead>
<tbody>
<tr>
<td>40%</td>
<td>0.95</td>
<td>0.49</td>
<td>0.25</td>
</tr>
<tr>
<td>52% (field)</td>
<td>0.97</td>
<td>0.49</td>
<td>0.24</td>
</tr>
<tr>
<td>60%</td>
<td>0.95</td>
<td>0.49</td>
<td>0.24</td>
</tr>
</tbody>
</table>
7.3. RESULTS

7.3.3 A simulated forest

The simulated HarvardForest1 forest scene (see Section 4.3.1) contains two different species (Acer rubrum and Quercus rubra), where each tree was constructed from height and DBH inventory data collected from Harvard Forest, Petersham, MA, USA. See Table 4.5 for the 1064 [nm] optical properties used for this scene.

Ten of the original thirty laser pulses intersected with non-transmissive targets (branches or trunk) or were absorbed during that trajectory through the canopy, and their energy did not reach the ground. Therefore, we considered only the remaining twenty waveforms. Two of these did not interact with geometry above ground and these were used as reference returns to describe the correct ground response with no attenuation effects.

Despite the different properties of each tree, the linear correlation between the additive correction and area under preceding Gaussian curves remains (see Figure 7.6). Observations that do not fit the linear correlation line represent waveforms that were ill-suited for Gaussian decomposition. These waveforms are complex with multiple potential decomposition solutions that may correspond to different geometric structures.

When using a robust regression to reduce the weight of outliers, the slope is 0.495 for nadir acquisitions, 0.492 for 10°, and 0.489 for 20° off-nadir. The spatial location of the lidar pulse is determined by the point at which it intersects with the ground plane, and so the off-nadir simulations will interact with different geometries. Different pulse widths had a larger impact: the 8 [ns] simulation resulted in a slope of 0.26 and the 16 [ns] simulation resulted in a slope of 0.12. However, these values are consistent with the 4 [ns] simulations when considered in proportion to the true ground response under the specific system parameters. This is discussed in more detail in Section 7.4.
Figure 7.6: For three angular acquisitions (nadir, 10° and 20°) over a simulated forest, there was a linear relationship between the additive correction factor for the Gaussian at ground level and the sum of the products of standard deviation and amplitude for all the preceding Gaussians in each waveform.
7.4 Discussion

Normalization was used throughout for consistent Gaussian approximation across simulations with potentially different energy settings. However, different parameters will result in different waveforms—for instance, a wider pulse width results in Gaussians with lower amplitude, but an equal integral under the curve. The results for each scenario should be understood in terms of such parameters. In this study we have simulated different sensor altitudes, wavelengths, scan angles, and geometries, including clumping and angular distribution. Figure 7.7 shows that the slope of the correction is directly related to the normalized amplitude of the true ground response. Thus, the additive correction may be understood as a proportional correction.

Figure 7.7: The linear relationship in Eq. (7.11) may be described by the slope of the regression. This slope is linearly related to the amplitude of the normalized true ground response for 14 cases: the simulated forest with a 4 [ns], 8 [ns], and 16 [ns] pulse widths at nadir, the simulated forest with 4 [ns] pulse width at 10° and 20° off-nadir, and the single tree simulation with three pulse widths (2 [ns], 4 [ns], and 8 [ns]) and three transmission values (40%, 52%, and 60% at 1064 [nm]).
This correction may be applied to a real scene that has similar transmission values and leaf-branch ratios to the simulated trees in the single tree and forest simulations. A ground-only response would be necessary for the relative slope calculation, which may be estimated from Figure 7.7. This slope is representative of certain system parameters and may then be used to successively correct each Gaussian in the original waveforms, based on the relationship illustrated in Figures 7.4, 7.5, and 7.6.

We believe that, if structure can be estimated from the waveform so that it is independent of prior interactions, then a better understanding of sub-canopy structure will be enabled from airborne data. Specifically, there is the potential for sub-canopy biomass estimation, stratified biomass and leaf area estimates (at different vertical heights throughout the canopy), etc. Accurate 3D structure estimates throughout the canopy will also enable improved modeling of trees and sub-canopy vegetation.

We assume that our simulation adequately represents the complexities present in real data, including tree geometry, sensor parameters, and transmission behavior. While the simulations in this study have shown the correction to be robust to variations in many parameters, implementation of such a procedure in a real environment would first require understanding of the exact impact of these parameters, particularly effective transmission, and a way to establish the “truth” of the amplitude of the ground response. We therefore contend that a logical next step is validation of the approach in a real world case, which is planned for the near future using data from the NEON lidar sensor.

7.5 Conclusions

In this chapter, we have evaluated the use of a true ground-only signal to correct for attenuation caused by multiple geometric components through a forest canopy in three simulated datasets.
of increasing complexity. The first dataset consisted of stacked leaf plates of known geometry and known reflectance as per Cawse-Nicholson et al. (2013), the second contained a single tree consisting of leaves and branches arranged in a realistic configuration, and the third consisted of a simulated forest derived from field-based inventory and spectral measurements.

We have tested the effect of reflectance, transmission, geometry, pulse width, and scan angle, while varying sensor parameters such as altitude and outgoing pulse width. In all three datasets, we have shown that the effects of attenuation may be understood with knowledge of the amplitude of a single ground return. The effects of geometry and reflectance are adequately represented in the waveform itself. In other words, the additive correction to be applied to the amplitude of each Gaussian is proportional to the sum of the product of amplitude and standard deviation of the preceding Gaussians.

Future work should include developing a fuller understanding of the sensitivity of this correction to different transmission values and different topographies. Also, this method should be tested on real lidar data to see how the algorithm performs. This could result in a correction that would allow improved ground detection in waveform responses to inform DEM estimation, as well as improved understanding of sub-canopy structure, e.g., forest gaps, sub-canopy biomass, and perhaps even vertically-stratified LAI. Our ability to correct for lidar attenuation essentially could enable more realistic 3D forest representation and quantification.
Chapter 8

Final Conclusions and Future Work

8.1 Conclusions

This dissertation has laid the groundwork for the development of a method for extracting biophysical complex and detailed tree structure from full-waveform small footprint lidar signals. There were four objectives for this dissertation:

1. To assess the ability of DIRSIG to simulate full-waveform small-footprint lidar signals in forested environments, i.e., determine the ability to construct representative virtual forest scenes.

2. To assess the necessary geometric complexity of virtual forest scenes to produce consistent small-footprint lidar signals.
   2.1. To determine the most important geometric component to the backscattered signal.
   2.2. To determine the smallest component contribution that a lidar system has a chance of detecting.

3. To assess the ability of small-footprint lidar to consistently measure structure due to variability in platform positioning.
4. To determine the feasibility of correcting for within canopy attenuation of the lidar signal, \textit{i.e.}, to quantify the impact that leaf optical properties have on the propagation of a lidar pulse through the canopy.

As part of this dissertation, and as part of other collaborations, a number of virtual forest scenes were created, including HarvardForest1, HighPark1, and SanJoaquin116 (see Chapter 4). The scene creation involved developing methods for spectral attribution, automatically planting trees according to minimum separation, and adjusting geometry to a DEM. This is a vital contribution to future research efforts related to vegetation biophysical characterization from lidar. In addition, this work has helped to pave the way for the creation of other virtual forest scenes, to help validate the performance of NASA’s next generation of Earth-observing satellites. Parts of this work have been published in Romanczyk \textit{et al.} (2012), Romanczyk \textit{et al.} (2013a), Yao \textit{et al.} (2015a), and Yao \textit{et al.} (2015b).

Using the HarvardForest1 scene, it was determined that twigs (\textit{t}) and leaf stems (\textit{s}) do not have a significant contribution to a small-footprint lidar system (see Chapter 5). These results held true for 4, 8, and 16 [ns] outgoing pulse widths and at scan angles of 0°, 10°, and 20° off-nadir. This has two main implications: (i) these geometries are not needed for simulations and (ii) at the typical small-footprint lidar scales, it will be nearly impossible to extract information about these geometries from a lidar signal. In addition, it was found that the most important type of geometry are the leaves (\textit{l}). This work was published in Romanczyk \textit{et al.} (2012) and Romanczyk \textit{et al.} (2013a).

Again using the HarvardForest1 scene, it was shown that positional and angular uncertainties may play a larger role for lidar systems than for passive optical systems due to complexity of forests at the small-footprint scale (see Chapter 6). Even small positional (10 [cm] standard deviation in the \textit{x}-\textit{y} plane) or angular (0.005° standard deviation about the \textit{x}, \textit{y}, and \textit{z} axes) can lead to a dramatically different waveform. Due to positional and angular uncertainties it may prove
8.1. CONCLUSIONS

challenging to perform waveform-to-waveform comparisons as part of multi-temporal studies when compared to the traditional pixel-level change detection from passive optical systems. This work was published in Romanczyk et al. (2013c).

Finally, an additive attenuation correction method was proposed and tested on a variety of scenes (see Chapter 7). It was shown that after performing a Gaussian decomposition on the lidar signal, the attenuation correction factor was linearly proportional to the sum of the area under the proceeding Gaussians. The use of the this attenuation correction will enable future work towards extracting unbiased vegetation biophysical structure from within the canopy. Parts of this work were published in Cawse-Nicholson et al. (2013) and presented in Romanczyk et al. (2013b).

This dissertation has highlighted many challenges associated with the extraction of fine-scale vertically-stratified LAI. Some of the key challenges are the validation of any algorithms that were developed solely in a simulation environment and the effect that even small positional offsets have on a small-footprint full-waveform lidar signal. In addition, the current lidar technology with a 4 [ns] outgoing pulse width corresponds to roughly 1.2 [m] of range. This impacts the ability detect the fine-scale branching and leaves within the canopy volume. The broader pulses are intended to provide more photons in the scene while keeping power densities lower on the optics and to help maintain eye-safety requirements. Furthermore, spatial differences in the outgoing pulse shape and receiver optics cause uncertainty in what the answer truly is. Despite these challenges, a foundation has been laid towards the big-picture objective of fine-scale vertically-stratified forest structure assessment. As technology improves, we may one day see the generation of fine-scale forest structure products, which will help increase our understanding of forest function, as well as allow for the characterization of forest change.
8.2 Future Work

8.2.1 Forest scene generation

The current method of building forest scenes requires a large amount of manual inputs, including stem locations, DBH, tree heights, and species. OnyxTREE is not the easiest piece of software to create a tree for a given set of parameters. In addition, it has a restrictive license agreement that does not allow the sharing of tree models, unless the other party also has a copy of OnyxTREE.

Some initial work towards the automatic generation of forest scenes builds off of Kelbe et al. (2015a), Kelbe et al. (2015c), Kelbe et al. (2015b), and Kelbe (2015). This work used a TLS scanner to extract tree stems and register point clouds. The tree stems were used as the tree stems in a virtual model and then used to drive a Voronoi tessellation to establish competition bounds. Arbaro (Arbaro 2013) was then programmatically called to generate tree models that fit the parameters given from the TLS data. Initial models can be found in Figures 8.1 and 8.2. This work should be extended in order to develop robust virtual scene creation, based on actual forest scene TLS scans.

8.2.2 Additional Attenuation Analysis

The majority of the analysis was performed using Lambertian reflection and delta (direct-only) transmission for the leaf optical properties. Another model for the leaf optical properties is bi-Lambertian, i.e., the leaves are both a Lambertian reflector and Lambertian transmitter. This is the model that is called for in the RAMI RT comparison scenes (Pinty et al., 2001; Pinty et al., 2004; Widlowski et al., 2006; Widlowski et al., 2011). Initial work shows that under a bi-Lambertian model, it is there is a very low probability of a photon transmitting though a leaf, traveling a “large” distance, reflecting of a target, and scattering back to the the sensor. For small-footprint lidar systems, leaves separated by distances of a few 10’s of centimeters, will be approximately opaque to the sensor. This is contradictory to the behavior of large-footprint systems and passive sensors, where there is a high probability of multiple-interaction photons being detected by the
8.2. FUTURE WORK

Figure 8.1: A TLS-derived virtual scene. The grey areas are TLS lidar points. Note that the tree model on the right has longer branches where there is not modeled data to constrain its growth. See Figure 8.2 to see a zoom of this scene.

Figure 8.2: A zoom of a TLS-derived virtual scene. The grey areas are TLS lidar points. See Figure 8.1 for the full scene.
sensor. In these systems, on average, there is a photon that gets added to the field of view for everyone that leaves it. The implications of this appear to be that lower returns are mostly made up of photons that did not interact with the earlier geometry. This “feature” might be exploited for use in the extraction of range varying biophysical structure, e.g., vertically stratified LAI. Additional future work should consider the footprint size at which the multiple scattering start to have an impact on the signal.

To show the impact of this, consider the following experiment. There is a scene consisting of two parallel plates: the top one a 100% Lambertian transmitter and the bottom a 100% Lambertian reflector. Just due to the “magic pi” relating exitance to radiance at each interaction (lentilucci and Schott, 2009; Schott, 2007) there is a decrease of $1/\pi^3 \approx 3.2\%$ as a result of the Lambertian surfaces (two transmissions and one reflection). This does not take into account the inverse square law term relating the distance between the plates or the area of the plates, both further reducing the sensor-reaching signal.

There are two currently available transmission methods in DIRSIG: Lambertian and delta transmission. In reality, leaves probably have a transmittance somewhere in between. A further study should be conducted to measure the bi-directional transmission distribution function (BTDF) and bi-directional reflectance distribution function (BRDF) of leaves and a BRDF of the woody parts of the trees. This may help produce even more realistic DIRSIG simulations.

### 8.2.3 DIRSIG Validation

To improve the reliability of DIRSIG simulations of wlidar in forested environments, additional work will need to be performed in comparing DIRSIG-generated wlidar signals to real-world data. At this time, there is a lack of waveform data over sites that also have a virtual version of them. As NEON moves closer to being fully operational, the availability of wlidar data will
8.2. FUTURE WORK

vastly expand. As shown, in the geolocation uncertainty experiments (see Chapter 6), even small changes in position can have a large difference on the backscattered waveform. Therefore, a statistically-based comparison will need to be performed, rather than a waveform-to-waveform one.

In addition to the validation of small-footprint simulations that would be needed to help enhance the reliability of simulation-derived biophysical parameter extraction, it is useful to validate other parts of DIRSIG. A virtual evergreen site from BOREAS, could be used in conjunction with SLICER data to help verify DIRSIG’s ability to simulate large-footprint waveforms. Participating in the RAMI RT comparison studies (Pinty et al., 2001; Pinty et al., 2004; Widlowski et al., 2006; Widlowski et al., 2011) will allow comparisons between different radiometry engines’ ability to simulate passive sensing. Finally, a laboratory experiment with a TLS or a lidar system that does not shut itself off if the power is too high due to eye safety constraints, may be the best way to validate the simulation of a wlidar system. In this case carefully controlled primitives or even a few tree branches may be used to directly compare a simulated and real waveform system. Particularly in the primitives case, known BRDF, BTDF, position, orientation, and sizes can be used to create a virtual replica of the lab experiment.

8.2.4 Vegetation Biophysical Structure

Finally, these virtual scenes and the attenuation correction method should be extended to be part of the preprocessing step towards extracting fine-scale, vertically stratified, vegetation structure. Vertically stratified LAI is one such example product. These future efforts will be made more tractable by the increasing computer power that we see every year. In addition, the forthcoming DIRSIG5 simulation looks promising for providing both easier and more efficient simulations of wlidar signals. These efforts may be boosted by the emergence of multiple wavelength lidar systems and fusion of wlidar data with hyperspectral imagery.
The validation of a simulation-derived biophysical structure parameter assessment method will pose a problem without real data to confirm its robustness. Having a well verified and validated model can go a long way to helping with this challenge. Additionally, comparisons with related, “easily” obtained field-based measurements will help with the validation. One example of this is that the sum of the vertically-stratified LAI should be equal to the field-measured total LAI for the same location. These comparisons will most likely not be able to be performed at the small-footprint lidar scale as shown, due to the conclusions from the positional uncertainty study (see Chapter 6). A more appropriate scale might be the tree-level or the large-footprint scale. These scales may be obtained by averaging waveforms together or looking at the distributions of these waveforms within a larger footprint.
Appendix A

Additional Scenes

This appendix describes two additional scenes that were created as part of this dissertation. Two additional scenes are HighPark1 (Appendix A.1) and SanJoaquin116 (Appendix A.2). The SanJoaquin116 scene was developed as part of a collaborative effort to investigate the impact of sub-pixel structure on hyperspectral vegetation indices for NASA’s proposed HyspIRI mission (Yao et al., 2015a; Yao et al., 2015b).

A.1 HighPark1

The HighPark1 scene was built to help the NEON assess the impact that lidar sensor parameters have on extracting forest structure. The site is monitored by Colorado State University (CSU) to measure erosion rates and new growth in a post-fire environment. NEON is interested in detecting snags, or standing dead trees in the recently burned (High Park fire) near Poudre Park, Coloardo, USA in 2012. The scene has its origin at 40.683858° N, 105.296475° W, with an altitude of 1952.08 [m] above WGS-84. The site consists of mountainous terrain containing severely burnt Pinus ponderosa (ponderosa pine) and Pinus contorta (lodgepole pine) trees. See Figures A.1 and A.2 for sample RGB simulations of the scene.
To build the scene, twenty OnyxTREE tree models were generated using field measurements and images. Summary properties of these base trees are found in Table A.1. Each model had two variants, namely $tb$ and $tb1$. An additional tree, bent over from the temperatures of fire, was programmatically created. The trees were randomly placed at $(x, y)$ locations within the $\approx 2 \text{ [km]} \times 2 \text{ [km]}$ scene by using Poisson disk sampling with a minimum distance between tree stems of 5 [m]. A total of 141,317 tree models were automatically placed in the scene. Each of the 40 base trees was randomly assigned a NEON-collected spectral property (different severities of burnt bark). Each of the trees were shifted up to the height of the DEM. For each tree location, a random tree model was drawn with uniform probability. The tree was given a random lean

$$\text{lean [°]} = \frac{1}{2} \cdot \prod_{i=1}^{4} \eta_i$$

(A.1)

$$\eta_i \sim \mathcal{N}(0, 1),$$

(A.2)
Figure A.2: Visible (RGB), nadir DIRSIG rendering of the central 345 [m] HighPark1. Note the relatively uniform spacing of the tree models caused by the Poisson disk sampling. The blocky nature of the ground from the low resolution DEM that was used in this scene.
A.2 SANJOAQUIN116

rotation

\[ \text{rotation}[^\circ] = \mathcal{U}(0, 360), \quad (A.3) \]

and scale

\[ \text{scale} = \mathcal{N}(\vec{1}, \Sigma), \quad (A.4) \]

where

\[ \Sigma = \sigma^2 \begin{bmatrix} 1 & \rho & \rho \\ \rho & 1 & \rho \\ \rho & \rho & 1 \end{bmatrix}, \quad (A.5) \]

\[ \mathcal{N} \] is a normally-distributed random variable, \( \mathcal{U} \) is a uniformly distributed random variable, \( \rho \) is the correlation between the scale terms, and \( \sigma^2 \) is the variance of a given scale term. For this scene, a scale variance (\( \sigma^2 \)) of 0.2 and correlation (\( \rho \)) of 0.9 were used. The product of four normally-distributed random variables (equation A.1) produces a high probability of getting a near zero lean angle. The probability density function (PDF) of this distribution is shown to have a high probability of a near-zero value by use of a Monte-Carlo simulation with 10,000,000 trials (see Figure A.3).

A.2 SanJoaquin116

The SanJoaquin116 scene is a 80×80 [m] scene surrounding the NEON Pacific Southwest domain (domain 17) site 116 in the San Joaquin Experimental Range (SJER). This site is located in an oakland savannah, consisting of mostly Quercus douglasii (blue oak) and Quercus wislizeni (interior live oak) trees on a grass carpet. The locations of the tree models can be found in Table A.2. Visible DIRSIG renderings are shown in Figures A.4 and A.5. The scene contains nineteen unique tree models and has options for faceted grass or just “glueing” grass spectra onto the DEM. The leaf optical properties were derived by using PROSPECT inversion of NEON-measured spectra. The grass and bark spectra were collected in-field during the summer 2013 NEON/HyspIRI flights (Kampe
Figure A.3: Probability density functions of the product of random variables, each drawn from a standard normal distribution. These distributions were computed using a Monte-Carlo simulation with 10,000,000 trials. Note that as more Gaussian-distributed variables are multiplied, the resultant PDF has a larger probability of a near-zero value.
Table A.1: Height, canopy extent (mean diameter), and instance count for the base versions of the trees used in the HighPark1 scene. These parameters were derived from field-measured estimates of tree height and canopy extent. The parameters of both the \( tb \) and \( tb1 \) instances of each tree are shown.

<table>
<thead>
<tr>
<th>Tree</th>
<th>Extent [m]</th>
<th>Height [m]</th>
<th>Count</th>
<th>Extent [m]</th>
<th>Height [m]</th>
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<td>16.99</td>
<td>3539</td>
<td>5.14</td>
<td>17.42</td>
<td>3537</td>
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*et al.*, 2013). The scene was developed in part to help with the pre-launch science questions related to NASA’s proposed HyspIRI mission. This scene will be used in the future to assess the ability for DIRSIG to simulate small-footprint wLIDAR data in a discontinuous tree canopy environment, such as a savannah, as well as for the validation of DIRSIG’s ability to simulate a wLIDAR signal within a tree canopy.
Table A.2: Positions of the trees in the SanJoaquin116 scene. The positions are in scene ENU coordinates in meters from the origin. The origin of each tree, i.e., the center of the bottom of the trunk, is placed 10 [cm] below the terrain height at that location.

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<th>Instance 3</th>
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Figure A.4: Top view of current visible DIRSIG rendering of SanJoaquin116 scene. The area with the trees correspond to the field-measured locations of trees within NEON’s domain 17 site 116. These trees occupy an 80 [m] × 80 [m] area surrounding the site center. See Figure A.5 for an oblique view of this site.

Figure A.5: Oblique view of visible DIRSIG rendering of SanJoaquin116 scene. See Figure A.4 for a nadir view of this site.
Appendix B

Code, Data, and DIRSIG Scenes

Rather than having an appendix full of \LaTeX{}ed code, the code used for this dissertation has been uploaded to GitHub. This allows for easier use of the code, rather than copying it out of an Appendix and changing all of the formatting that got changed, or tracking down a copy of the code on a hard-drive somewhere. The code, data, and DIRSIG scenes related to this dissertation can be found in two repositories.

B.1 DIRSIG-related code

The DIRSIG-related code can be found at https://github.com/pavdpr/DIRSIG. It provides code to read DIRSIG lidar bin files, convert geometry files to a newer version, and parallelize DIRSIG runs. The code provided are written in a combination of MATLAB and python. This code is separate from the rest of the dissertation’s code to make it more-easily accessible to the broader DIRSIG community.
B.2 Dissertation-related code and DIRSIG simulations

The remainder of the code and DIRSIG simulation files can be found in https://github.com/pavdpr/disseration.

B.2.1 Code

This contains the functions to perform the analysis as well as the scripts that call them can be found in the code directory within this repository.

B.2.2 DIRSIG simulations

Elements of the DIRSIG simulations used in this dissertation can be found in the dirsig directory within this repository. Due to OnyxTREE’s restrictive license, tree models cannot be shared. However, the proprietary OnyxTREE binary files can be shared to allow others with a valid OnyxTREE license to use the same tree models.
Bibliography


