Characterizing the Impacts of the Invasive Hemlock Woolly Adelgid on the Forest Structure of New England

Peter Brehm Boucher

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CHARACTERIZING THE IMPACTS OF THE INVASIVE HEMLOCK WOOLLY ADELGID ON THE FOREST STRUCTURE OF NEW ENGLAND

A Dissertation Presented

by

PETER BREHM BOUCHER

Submitted to the Office of Graduate Studies, University of Massachusetts Boston, in partial fulfillment of the requirements for the degree of

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ABSTRACT

CHARACTERIZING THE IMPACTS OF THE INVASIVE HEMLOCK WOOLLY
ADELGID ON THE FOREST STRUCTURE OF NEW ENGLAND

May 2020

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Climate change is raising winter temperatures in the Northeastern United States, both expanding the range of an invasive pest, the hemlock woolly adelgid (HWA; *Adelges tsugae*), and threatening the survival of its host species, eastern hemlock (*Tsuga canadensis*). As a foundation species, hemlock trees underlie a distinct network of ecological, biogeochemical, and structural systems that will likely disappear as the HWA infestation spreads northward. Remote sensing can offer new perspectives on this regional transition, recording the progressive loss of an ecological foundation species and the transition of evergreen hemlock forest to mixed deciduous forest over the course of the infestation. Lidar remote sensing, unlike other remote sensing tools, has the potential to penetrate dense hemlock canopies, and record HWA’s distinct impacts on lower canopy structure. Working with a series of lidar data from the Harvard Forest experimental site, these studies identify the unique signals of HWA
impacts on vertical canopy structure and use them to predict forest condition. Methods for detecting the initial impacts of HWA are explored and a workflow for monitoring changes in forest structure at the regional scale is outlined. Finally, by applying terrestrial, airborne, and spaceborne lidar data to characterize the structural variation and dynamics of a disturbed forest ecosystem, this research illustrates the potential of lidar as a tool for forest management and ecological research.
Remote Sensing

To define remote sensing and explain its overarching goals, I turn to the environmentalist, scientist, and writer Rachel Carson. In her book, *The Sea Around Us*, Carson describes the use of a sonar sensor by deep sea fishermen:

*Moving in fascination over the deep sea he could not enter, he found ways to probe its depths... he invented mechanical eyes and ears that could recreate for his senses a world long lost, but a world that in the deepest part of his subconscious mind, he had never wholly forgetting.*

(Carson, 1951: pp.15)

For Carson, remote sensing is the use of technology to extend our own senses into places we cannot go and perspectives we cannot see due to the limits of our bodies. The field of remote sensing focuses on expanding our perception of the natural world, by way of sending new “eyes” into orbit in the form of satellite sensors that monitor the earth’s cycles at scales we cannot observe and at wavelengths of light that we cannot see. Carson’s description implies that with remote sensing instruments, we are not discovering anything new. Instead, we are using technology, new “mechanical eyes and ears,” to remember where we came from. In Carson’s case, this is the deep sea, where life began. In this passage, Carson refutes the idea that mankind’s use of technology set us apart from the natural world. In fact, technology has brought us closer to our environment than ever before, with a deeper understanding and a remembrance of where we came from.
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TABLE OF CONTENTS

PREFACE AND ACKNOWLEDGEMENTS ....................................................... vi
LIST OF FIGURES ................................................................................................ xi
LIST OF TABLES .................................................................................................. xiii

CHAPTER

<table>
<thead>
<tr>
<th>CHAPTER</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTRODUCTION AND BACKGROUND</td>
<td>1</td>
</tr>
<tr>
<td>The Hemlock Woolly Adelgid (HWA): An Indicator of Global Change</td>
<td>1</td>
</tr>
<tr>
<td>Why monitor the inevitable? The value of HWA studies for science and society</td>
<td>3</td>
</tr>
<tr>
<td>Measuring Forest Disturbances with Lidar</td>
<td>5</td>
</tr>
<tr>
<td>Characterizing HWA’s Progressive Impacts</td>
<td>9</td>
</tr>
<tr>
<td>Field Data: The ForestGEO Plot at Harvard Forest</td>
<td>11</td>
</tr>
<tr>
<td>Chapter Summaries</td>
<td>13</td>
</tr>
<tr>
<td>Lidar Remote Sensing and Related Terminology</td>
<td>17</td>
</tr>
<tr>
<td>2. MONITORING FOREST HEALTH WITH WAVEFORM LIDAR</td>
<td>24</td>
</tr>
<tr>
<td>Introduction</td>
<td>24</td>
</tr>
<tr>
<td>What is Waveform Lidar Data?</td>
<td>26</td>
</tr>
<tr>
<td>Methods</td>
<td>28</td>
</tr>
<tr>
<td>Overview</td>
<td>28</td>
</tr>
<tr>
<td>Field Data on Hemlock Condition</td>
<td>28</td>
</tr>
<tr>
<td>ALS Data</td>
<td>30</td>
</tr>
<tr>
<td>Waveform Processing and Variable Creation</td>
<td>31</td>
</tr>
<tr>
<td>Variable Selection</td>
<td>36</td>
</tr>
<tr>
<td>Results</td>
<td>37</td>
</tr>
<tr>
<td>Field Data: Hemlock Condition</td>
<td>37</td>
</tr>
<tr>
<td>Waveform Processing</td>
<td>38</td>
</tr>
<tr>
<td>Variable Selection</td>
<td>39</td>
</tr>
<tr>
<td>Step-wise Models</td>
<td>42</td>
</tr>
<tr>
<td>Discussion</td>
<td>42</td>
</tr>
<tr>
<td>Canopy Layers and Waveform Variables</td>
<td>44</td>
</tr>
<tr>
<td>Challenges of Monitoring Forest Health with Waveform ALS Data</td>
<td>45</td>
</tr>
<tr>
<td>Attenuation in Infested Canopies</td>
<td>46</td>
</tr>
<tr>
<td>Conclusion</td>
<td>48</td>
</tr>
</tbody>
</table>
# 3. THE POTENTIAL FOR THE DETECTION OF THE HEMLOCK WOOLLY ADELGID FROM SPACE

<table>
<thead>
<tr>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction</td>
<td>65</td>
</tr>
<tr>
<td>Structural Signals of the Hemlock Woolly Adelgid Infestation</td>
<td>66</td>
</tr>
<tr>
<td>Lidar Remote Sensing for Monitoring Forest Health</td>
<td>66</td>
</tr>
<tr>
<td>Study Design</td>
<td>69</td>
</tr>
<tr>
<td>Methods</td>
<td>69</td>
</tr>
<tr>
<td>Overview</td>
<td>69</td>
</tr>
<tr>
<td>Airborne Lidar Scanner (ALS) Data</td>
<td>71</td>
</tr>
<tr>
<td>Simulated GEDI Data</td>
<td>71</td>
</tr>
<tr>
<td>Metrics</td>
<td>72</td>
</tr>
<tr>
<td>Field Data</td>
<td>74</td>
</tr>
<tr>
<td>Part I: Comparing ALS with the GEDI Simulator</td>
<td>75</td>
</tr>
<tr>
<td>Part II: Simulating GEDI Data</td>
<td>77</td>
</tr>
<tr>
<td>Results</td>
<td>79</td>
</tr>
<tr>
<td>Part I: Detecting Disturbance with Waveform Lidar</td>
<td>79</td>
</tr>
<tr>
<td>Part II: Simulating GEDI Data</td>
<td>83</td>
</tr>
<tr>
<td>Discussion</td>
<td>86</td>
</tr>
<tr>
<td>Overview</td>
<td>86</td>
</tr>
<tr>
<td>The Structural Impacts of Hemlock Woolly Adelgid</td>
<td>86</td>
</tr>
<tr>
<td>Toward Change Detection and Disturbance Monitoring with GEDI</td>
<td>89</td>
</tr>
<tr>
<td>Conclusion</td>
<td>90</td>
</tr>
</tbody>
</table>

# 4. SAMPLING STRATEGIES FOR CAPTURING FOREST STRUCTURAL VARIATION WITH TERRESTRIAL LASER SCANNING (TLS)

<table>
<thead>
<tr>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction</td>
<td>104</td>
</tr>
<tr>
<td>Methods</td>
<td>108</td>
</tr>
<tr>
<td>Part I: Biases in TLS Observations of Forests</td>
<td>108</td>
</tr>
<tr>
<td>Part II: Sampling Strategies for TLS</td>
<td>113</td>
</tr>
<tr>
<td>Results</td>
<td>116</td>
</tr>
<tr>
<td>Part I: Biases in TLS Observations of Forests</td>
<td>116</td>
</tr>
<tr>
<td>Part II: Sampling Strategies for TLS</td>
<td>121</td>
</tr>
<tr>
<td>Discussion</td>
<td>129</td>
</tr>
<tr>
<td>Overview</td>
<td>129</td>
</tr>
<tr>
<td>Correcting Biases in TLS Stem Counts</td>
<td>131</td>
</tr>
<tr>
<td>Representing Species Abundances</td>
<td>132</td>
</tr>
<tr>
<td>Future Challenges: Capturing Field Stem Diameters</td>
<td>133</td>
</tr>
<tr>
<td>Strategies for Surveying Forests with TLS</td>
<td>134</td>
</tr>
<tr>
<td>CHAPTER</td>
<td>Page</td>
</tr>
<tr>
<td>---------</td>
<td>------</td>
</tr>
<tr>
<td>Conclusion</td>
<td>136</td>
</tr>
<tr>
<td>5. CONCLUSION</td>
<td>156</td>
</tr>
<tr>
<td>Overview</td>
<td>156</td>
</tr>
<tr>
<td>Research Questions</td>
<td>157</td>
</tr>
<tr>
<td>Future Work</td>
<td>163</td>
</tr>
<tr>
<td>New Directions for Research in the ForestGEO plot</td>
<td>163</td>
</tr>
<tr>
<td>Regional-Scale Monitoring Tools</td>
<td>165</td>
</tr>
<tr>
<td>Advancing Forest Surveys with TLS</td>
<td>167</td>
</tr>
<tr>
<td>The Future of Forest Management</td>
<td>169</td>
</tr>
<tr>
<td>BIBLIOGRAPHY</td>
<td>174</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1, Lidar point cloud of a simulated insect infestation</td>
<td>20</td>
</tr>
<tr>
<td>1.2, Hemlock trees in the 35 hectare SI ForestGEO plot</td>
<td>21</td>
</tr>
<tr>
<td>1.3, Stem map of the 2016 Mortality Assessment</td>
<td>22</td>
</tr>
<tr>
<td>1.4, Spatial trends in the probability of hemlock tree mortality</td>
<td>23</td>
</tr>
<tr>
<td>2.1, Simple diagram of sampling with waveform lidar</td>
<td>50</td>
</tr>
<tr>
<td>2.2, Flowchart of study design</td>
<td>51</td>
</tr>
<tr>
<td>2.3, Aggregate waveform metrics from a single pixel of ALS data</td>
<td>53</td>
</tr>
<tr>
<td>2.4, Conversion of RH metrics from above ground heights to proportional heights</td>
<td>54</td>
</tr>
<tr>
<td>2.5, Hemlock mortality in the AOI</td>
<td>55</td>
</tr>
<tr>
<td>2.6, Results of Gaussian decomposition of waveform data</td>
<td>56</td>
</tr>
<tr>
<td>2.7, Point cloud colored by above ground height (AGH)</td>
<td>57</td>
</tr>
<tr>
<td>2.8, Point density and zenith angle of point cloud</td>
<td>58</td>
</tr>
<tr>
<td>2.9, Offset in ground heights between the NEON 2016 DTM and the processed point cloud</td>
<td>59</td>
</tr>
<tr>
<td>2.10, Spatial distribution of waveform variables and mortality</td>
<td>60</td>
</tr>
<tr>
<td>2.11, Plot of coefficients of variables selected by lasso logistic regressions</td>
<td>61</td>
</tr>
<tr>
<td>2.12, Scatter plots of waveform variables and hemlock mortality</td>
<td>62</td>
</tr>
<tr>
<td>2.13, The integral of returns from vegetation and hemlock mortality</td>
<td>63</td>
</tr>
<tr>
<td>Figure</td>
<td>Page</td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
</tr>
<tr>
<td>3.1, Simulated footprint locations within the ForestGEO plot</td>
<td>93</td>
</tr>
<tr>
<td>3.2, Simulated GEDI acquisitions within the ForestGEO plot</td>
<td>94</td>
</tr>
<tr>
<td>3.3, Simulated GEDI waveforms from G-LiHT 2012 and NEON 2016</td>
<td>95</td>
</tr>
<tr>
<td>3.4, Examples of Hemlock, Red Oak, and Red Maple PAI Change by Height</td>
<td>96</td>
</tr>
<tr>
<td>3.5, Profiles of hemlock and red oak PAI change by % height to max</td>
<td>97</td>
</tr>
<tr>
<td>3.6, Logistic regression of proportional hemlock mortality</td>
<td>98</td>
</tr>
<tr>
<td>3.7, Dominant species cover, change in PAI 11-12 m, and change in RH10 in ForestGEO plot footprints</td>
<td>99</td>
</tr>
<tr>
<td>3.8, Change in PAI 11-12m and RH10 by dominant species</td>
<td>100</td>
</tr>
<tr>
<td>3.9, G-LiHT 2012 as GEDI with varying beam sensitivities</td>
<td>101</td>
</tr>
<tr>
<td>3.10, GEDI’s proportion of false-positive ground returns by dominant species</td>
<td>102</td>
</tr>
<tr>
<td>3.11, ANOVA with simulated noise and spatial coverage of GEDI data</td>
<td>103</td>
</tr>
<tr>
<td>4.1, Visualization of pulse trajectories of simulated TLS scans</td>
<td>138</td>
</tr>
<tr>
<td>4.2, Stems observed by different sampling methods in the ForestGEO plot</td>
<td>139</td>
</tr>
<tr>
<td>4.3, Stem counts recorded by TLS scans</td>
<td>140</td>
</tr>
<tr>
<td>4.4, Stem counts recorded by low and high resolution TLS</td>
<td>141</td>
</tr>
<tr>
<td>4.5, Polygons showing the 5 different methods for estimating scan area</td>
<td>142</td>
</tr>
<tr>
<td>4.6, TLS stem densities compared to field stem densities</td>
<td>143</td>
</tr>
<tr>
<td>Figure</td>
<td>Page</td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
</tr>
<tr>
<td>4.7, Correlation between TLS and field stem densities with a varying radius.</td>
<td>144</td>
</tr>
<tr>
<td>4.8, Mean DBH (cm) of observed stems in TLS scans.</td>
<td>145</td>
</tr>
<tr>
<td>4.9, Histogram of the diameter of detected and undetected stems.</td>
<td>146</td>
</tr>
<tr>
<td>4.10, Number of tree species identified in TLS scans, simulated TLS, and field data.</td>
<td>147</td>
</tr>
<tr>
<td>4.11, Predicting species abundance from the TLS detection rate.</td>
<td>148</td>
</tr>
<tr>
<td>4.12, Species abundances of stems observed by TLS sampling strategies.</td>
<td>149</td>
</tr>
<tr>
<td>4.13, The proportion of similar KS tests with different size classes of field data.</td>
<td>150</td>
</tr>
<tr>
<td>4.14, Moving mean stem densities compared to the local field mean.</td>
<td>151</td>
</tr>
<tr>
<td>4.15, Moving mean stem diameters compared to the local field mean.</td>
<td>152</td>
</tr>
<tr>
<td>4.16, Moving mean Simpson Diversity index compared to the local field diversity.</td>
<td>153</td>
</tr>
<tr>
<td>4.17, Moving mean stem density, diameter, and diversity along the Row 23 Transect.</td>
<td>154</td>
</tr>
<tr>
<td>4.18, Local derivatives of the TLS moving means.</td>
<td>155</td>
</tr>
<tr>
<td>5.1, Abundance of size class against mortality of size class.</td>
<td>172</td>
</tr>
<tr>
<td>5.2, Cross-sections of TLS and ALS point clouds.</td>
<td>173</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.2</td>
<td>Summary of mortality metrics by size class of hemlock trees in 20 m pixels</td>
<td>37</td>
</tr>
<tr>
<td>2.3</td>
<td>Variables selected by lasso regression, grouped by dependent variable</td>
<td>39</td>
</tr>
<tr>
<td>2.1</td>
<td>Summary and explanation of all waveform variables</td>
<td>52</td>
</tr>
<tr>
<td>2.4</td>
<td>Results of step-wise regressions</td>
<td>64</td>
</tr>
<tr>
<td>3.1</td>
<td>Instrument and flight specifications of ALS data over the ForestGEO plot</td>
<td>71</td>
</tr>
<tr>
<td>3.2</td>
<td>Coefficients and fit of a logistic regression predicting hemlock mortality</td>
<td>81</td>
</tr>
<tr>
<td>3.3</td>
<td>ANOVA and post-hoc test results of change in PAI 11-12 m by species</td>
<td>82</td>
</tr>
<tr>
<td>3.4</td>
<td>ANOVA and post-hoc test results of change in RH10 by species</td>
<td>82</td>
</tr>
<tr>
<td>3.5</td>
<td>ANOVA results of PAI 11-12 m with GEDI’s noise and spatial coverage</td>
<td>85</td>
</tr>
<tr>
<td>4.1</td>
<td>Mean stem count in real and simulated TLS scans and field data</td>
<td>116</td>
</tr>
<tr>
<td>4.2</td>
<td>Linear regression fits of TLS and field stem densities</td>
<td>118</td>
</tr>
<tr>
<td>4.3</td>
<td>Acquisition statistics of TLS sampling strategies</td>
<td>122</td>
</tr>
<tr>
<td>4.4</td>
<td>Comparison of TLS and field stem density statistics by sampling strategy</td>
<td>123</td>
</tr>
<tr>
<td>4.5</td>
<td>Comparison of TLS and field DBH statistics by sampling strategy</td>
<td>124</td>
</tr>
<tr>
<td>4.6</td>
<td>KS Test results comparing the TLS distributions to field distributions</td>
<td>125</td>
</tr>
</tbody>
</table>
CHAPTER 1:
INTRODUCTION AND BACKGROUND

The Hemlock Woolly Adelgid (HWA): An Indicator of Global Change

In the modern era, the scale and severity of environmental disturbances are rapidly increasing due to anthropogenic drivers. The spread of invasive insects in the temperate forests of the United States exemplifies this global problem and the challenges that such disturbances pose to our society. Economic connectivity and trade in the last century have inadvertently brought an influx of invasive forest pests to the United States (Aukema et al., 2010; Lovett et al., 2016a, 2016b). These invasive insects suppress native tree species, downgrade ecosystems, and burden small municipalities with management costs (Aukema et al., 2011). The impacts of invasive pests are amplified by climate change, as warmer temperatures increase the rates at which invasive species reproduce and spread (Dukes et al., 2009). Together, the compound drivers of climate change and invasive insects are bringing about major transitions to forest ecosystems in North America.

The hemlock woolly adelgid (HWA; *Adelges tsugae*) is an invasive insect that exemplifies the threat posed to North American forests. HWA is an invasive insect from Japan that feeds on and eventually kills eastern hemlock (*Tsuga canadensis*) and Carolina hemlock (*Tsuga caroliniana*) trees. After arriving on ornamental hemlock trees in Virginia in
1951, HWA spread to nearby states and moved northward and southward along the Appalachian Mountain chain (Fitzpatrick et al., 2012; Ellison et al., 2010 and 2018). Now, HWA is reported in counties from Georgia to Maine, and is projected to expand into the full range of hemlock trees in the Northeast US in the coming century (Albani et al., 2010; Ellison et al., 2018).

The only major limiting factors to HWA’s expansion are the frequency, intensity, and variability of cold winter temperatures (Parker et al., 1998 and 1999; Skinner et al., 2003; Paradis et al., 2009; Mcclure and Cheah, 2002; Trotter and Shields, 2009; Elkinton et al., 2017). Cold snaps have previously prevented HWA from reaching the most northern range of hemlock trees in New England and southern Canada. However, climate change is reducing the frequency of these cold snaps in eastern North America, allowing HWA to move further northward (Dukes et al., 2009; Orwig et al., 2012). HWA undergoes asexual reproduction in the United States, meaning that a single surviving adelgid can multiply to infest a stand, and eventually an entire forest. Forest mortality rates for infested regions are high, and studies expect near-complete hemlock mortality in Connecticut and other New England states (Orwig and Foster, 1998; Orwig et al., 2002, 2012). Efforts to control HWA with biological agents and pesticides are ongoing (Onken and Reardon, 2011; Havill et al., 2016; Jubb et al., 2019; Foley et al., 2019), however, no population control methods have been successfully mobilized at the regional scale yet.

The loss of hemlock trees from the New England landscape has wide implications for both natural and human systems. Eastern hemlock trees are a foundation species, establishing a homogenous ecotype within temperate forests that supports a unique set of organisms and biogeochemical cycles (Ellison et al., 2005). Once established, stands of evergreen hemlock
maintain mild air temperatures, acidify soils, and regulate water cycles (Ellison et al., 2014). Hemlocks support a distinct set of fauna, cooling stream temperatures for brook trout (Sidehurst et al., 2010) and providing habitat for bird species (Tingley et al., 2002). HWA upends these unique environments, removing long-established hemlock stands and allowing pioneering deciduous tree species, such as black birch (Betula lenta) and maple (Acer) and oak (Quercus) species, to supplant them (Orwig and Foster, 1998; Orwig et al., 2002). The decline of hemlocks causes increased water yields (Kim et al., 2017) and a perturbation in carbon dynamics in the short term (Albani et al., 2010), although carbon cycles do stabilize in the long-term (Lemos, 2013). The HWA infestation ultimately results in the conversion of evergreen hemlock forest to mixed deciduous forests, altering the phenological, ecological, and biogeochemical cycles that hemlocks have maintained across their range for centuries.

From many perspectives, the spread and severity of HWA appears to be unstoppable. HWA has spread faster and further north than previous models had anticipated (Ellison et al., 2018). HWA is difficult to contain, spreading via multiple vectors including wind, deer, birds, and humans. In addition, anthropogenic emissions are projected to continue rising, and warming winter temperatures are facilitating HWA’s northward expansion (Dukes et al., 2009). While research efforts for biocontrol are still ongoing, it is increasingly likely that HWA will alter the New England landscape in the near-term, usurping an ecological foundation species and transforming hemlock stands into deciduous forest.

Why monitor the inevitable? The value of HWA studies for science and society

While the spread of the HWA disturbance may be inevitable, understanding its progression would be valuable for scientific research and for forest management. Ecological
theory states that forest ecosystems are shaped by past disturbances, influencing their structure, composition and productivity for the duration of a forest’s history (Oliver, 1981; Foster et al., 2008). While large-scale disturbances can be observed in long-term ecological records, such as tree rings (Hessl et al., 2013), preserved pollen grains (Foster et al., 1992), and even in canopy structure (Weishamphel et al., 2007), HWA provides the opportunity to record a forest disturbance as it unfolds in the present day. In this sense, research on HWA is valuable both for understanding the forces that construct our present environment and for anticipating future threats to temperate forest ecosystems.

The monitoring of the HWA infestation can also produce wider benefits to society. HWA exemplifies a current global problem, an indicator of the intensifying feedback loop between rising global temperatures and forest disturbances. The HWA disturbance is only one in a wave of invasive pests that are exponentially increasing in frequency in the United States (Aukema et al., 2010; Lovett et al., 2016a, 2016b). These invasive pests take an economic toll as well as an ecological one. The impacts of forest pests are estimated to cost small municipalities 1.7 billion dollars a year in the US (Aukema et al., 2011), a conservative estimate which underestimates the reduced value of ecosystem services in degraded ecosystems. As forest disturbances are projected to increase in frequency and severity in the coming decades (Dukes et al., 2009), studying HWA’s impacts can inform future efforts to manage and mitigate other infestation impacts.

In order to advance our ability to characterize ecological disturbances, this research aims to develop methods to both characterize HWA’s ecological impacts and to monitor the spread and severity of the infestation. These studies measure forest condition and composition in an HWA infested forest with light detection and ranging (lidar), an active
remote sensing technology that can record the 3-dimensional structure of forests. By studying the HWA infestation with lidar remote sensing, this body of work advances our understanding of ecological disturbances and lays a foundation for the development of future monitoring tools.

Measuring Forest Disturbances with Lidar

Ecological research has revealed how cyclic patterns of disturbance and recovery shape the composition and structure of forests (Oliver, 1981; White and Jentsch, 2001). Lidar remote sensing has a unique potential to record these stages of forest structure and use them to monitor disturbances at the landscape scale. However, it has yet to be shown whether the progression of particular disturbances, such as that of HWA, produce signals in lidar data that directly relate to disturbance severity. This research addresses the challenge of monitoring infestation severity by searching for the unique structural patterns of the HWA infestation.

Lidar is an active remote sensing technology that measures the structure of its surrounding environment by emitting pulses of light energy. Lidar instruments record the amount of time it takes for emitted pulses to reach a target and reflect back to the lidar sensor. Using the speed of light, the time of flight of an emitted pulse can be translated into the distance from the scanner. With knowledge of the orientation of the scanner and the emitted pulse, the location of a target object in space can be estimated. By emitting hundreds of thousands of pulses into a forest, a lidar instrument can sample the distribution of target objects (foliage, stems, and branches) in three dimensions. Lidar instruments can directly measure the structure of forest canopies, and thus, have the potential to capture the unique changes in forest structure that correspond with specific disturbances.
To identify the general progression of disturbance and recovery in forests, monitoring studies can turn to ecological theory, which outlines 4 stages of forest structure following disturbances (Oliver, 1981; White and Jentsch, 2001; Linke et al., 2007). After a disturbance opens up canopy gaps or clears a forested area, a \textit{stand initiation stage} begins in which “pioneer” understory trees compete for the newly available resources, such as sunlight and nutrients. Certain tree species will dominate this stage and create a closed canopy that blocks sunlight and smothers any new understory growth, marking the start of the \textit{stem exclusion stage}. Minor disturbances and site conditions will eventually allow shade-tolerant species to establish themselves again in the understory, marking the \textit{understory reinitiation stage}. Finally, competition between shade-tolerant stems and overstory trees leads to the \textit{old growth stage}, signified by a complex canopy structure and a diverse composition of tree species. These cycles of disturbance and recovery play out over the course of several centuries in temperate forests, although their timing and intensity vary by site and disturbance type (White and Jench, 2001).

Lidar sensors can record disturbance dynamics by detecting these stages of forest recovery, potentially enabling lidar data to document disturbance history across a landscape. Lidar measurements are intrinsically related to the vertical profiles of plant material and the gaps within forest plots (Lefsky et al., 1998, 1999; Harding et al., 2001; Ni-Meister et al., 2001, 2018; Armston et al., 2013). While these vertical profiles of forest structure can be measured with field methods (MacArthur and Horn, 1969), lidar enables their measurement at regional scales and with increasingly detailed spatial resolutions.

Vertical profiles have the potential to be utilized as identifiable structural signatures to predict plot age and estimate disturbance impacts. Using canopy height profiles (CHPs),
early studies with airborne lidar scanning (ALS) demonstrated an ability to differentiate
primary and secondary forests and to infer the age of plots across a region (Lefsky et al.,
1999; Harding et al., 2001; Drake et al., 2002). These studies demonstrated a strong
correspondence of lidar measurements with disturbance stage, but not necessarily with
disturbance severity.

Lidar’s sensitivity to changes in canopy structure shows the potential of deriving a
direct relationship with forest condition. With multiple collections of airborne lidar data,
studies have detected defoliation from insect infestations (such as that of the common pine
sawfly: Solberg et al., 2006, 2010; Vastaranta et al., 2013; Kantola et al., 2013), identified
gap formation in forest canopies (Vepakomma et al., 2008), measured growth dynamics and
phenological cycles (Kellner et al., 2009; Tang and Dubayah, 2007), and calculated changes
in aboveground biomass (Dubayah et al., 2010). Therefore, calculating structural change
from repeated lidar observations may offer opportunities to also elucidate structural signals
of disturbance.

However, comparing lidar data from different instruments and platforms can
introduce artifacts and unknowns into measurements of change. Every lidar system has
unique characteristics that affect its derived metrics, and as a result, calibration with field
data or with other lidar datasets (Shao et al., 2019; Kamoske et al., 2019) is often necessary
before calculating change metrics. In addition, differences in sampling pattern and view
angle can cause major differences in the observed area of different lidar datasets (Kukenbrink
et al., 2016). Therefore, a major challenge of studying forest change with multi-temporal
lidar data is to ensure that differences between datasets are the result of progressive
ecological conditions, rather than artifacts of the sensors and acquisitions being compared.
Studies with lidar have validated the past century of field-based ecological theory, demonstrating that disturbance dynamics are visible in the structure and composition of forest canopies. Future studies need to build upon this work to create unique identifiers for specific disturbances and to evaluate how forest structure relates to condition in each case. However, there are still challenges to overcome when comparing lidar data from different instruments, acquisition times, and sampling schemes. In order for lidar-based monitoring tools to succeed in identifying meaningful ecological change, methods of change analysis from multi-temporal lidar data need to be evaluated and further developed. Such new comparison methods will open up opportunities for using new public datasets of multi-temporal lidar data, such as the time-series of airborne data available from the NSF-funded National Ecological Observatory Network (NEON; Kampe et al., 2010), as well as new spaceborne lidar datasets, such as that of the NASA Global Ecosystem Dynamics Investigation (GEDI; Dubayah et al., 2020).

More research is needed to identify unique signatures of disturbances in lidar data and to test how they correspond with forest condition. In order for future monitoring tools to be successful, they will need to elucidate both the drivers and the severity of disturbances, especially during the initial stages of infestations, which are often the most important for forest management. As a well-studied ecological disturbance with a unique impact upon forest structure, the HWA infestation provides an ideal opportunity to address these challenges and develop methods for monitoring future disturbances with lidar.
Characterizing HWA’s Progressive Impacts

HWA’s unique progression through forest canopies poses a challenge for remote sensing studies, especially those that aim to detect HWA during the initial stages of disturbance. HWA causes defoliation from the inner crown and lower canopy layers of individual hemlock trees and moves outward (Orwig et al., 2002). During initial stages of the infestation, when HWA is contained within the crowns of hemlock trees, the tops and outer foliage may not prominently display infestation impacts. Thus, monitoring studies with more traditional passive optical imagers can misclassify trees as healthy, while HWA impacts are already present in mid-canopy forest structure.

However, lidar remote sensing can penetrate canopy gaps and record changes in lower canopy layers, giving it an advantage over passive remote sensing datasets when monitoring HWA’s sub-canopy impacts (Orwig et al., 2018). Lidar may also be able to capture the *stand initiation stage*, measuring the response of understory plants to new gaps in the forest canopy and thereby, inferring infestation severity. Studies with passive remote sensing have had trouble recording these changes in the past, as understory growth underneath defoliated canopies tends to saturate the spectral signal, causing misclassifications of forest condition (Pontius et al., 2017). If lidar could penetrate hemlock canopies to record the initiation of understory growth, then it could be used to mark a turning point in the HWA disturbance that may be applicable to other disturbances. The timing of this stage, however, can vary depending on site characteristics and infestation severity.

The Harvard Forest Hemlock Removal Experiment (HF-HeRE; Ellison et al., 2010, 2018) has offered some insight into the timing of these progressive changes and the structure
of forests after HWA. HF-HeRE was established to simulate an HWA infestation by maintaining girdled, logged, and control hemlock and hardwood plots in a mixed temperate forest at the Harvard Forest experimental site in Petersham, MA, USA. The HWA infestation was simulated by girdling hemlock trees in 2005 (Ellison et al., 2010). Within 2 years of the girdling treatment, all of the hemlock trees within the plot had died. The plot was scanned with a terrestrial lidar instrument in the summer of 2018 to illustrate the expected structure of a hemlock forest after HWA infestation.

Figure 1.1 shows the structure of one of the girdled hemlock plots 13 years after treatment, captured in a point cloud from 3 terrestrial lidar scans collected with the Compact Biomass Lidar (CBL; Paynter et al., 2016). A distinct understory canopy, primarily composed of black birch saplings, is visible up to 8 meters above ground level. Dead hemlock stems still stand, while other overstory tree species, such as eastern white pine (Pinus strobus), have taken over a more dominant role in the canopy.

Figure 1.1 also demonstrates the challenges of recording structure with lidar data. Scans were collected by raising the CBL on a mast above the understory canopy at increments of 5, 10, and 15 meters above ground height. While these elevated scan positions allowed the instrument to capture the overstory structure and the top of the understory structure, it also caused a gap in the data between the understory and the ground. This data-gap is a typical limitation for downward scanning lidar instruments, such as airborne lidar scanners (ALS), whose beams can be occluded and attenuated by dense canopies, causing them to under-sample lower canopy layers (Kukenbrink et al., 2016). In the case of Figure 1, the understory layer is also causing occlusion in TLS data, as it is raised above the canopy and is used to scan downward.
While the recovery of the deciduous trees in the HF-HeRE plots is representative of post-HWA forests, the mechanism of hemlock death, girdling, is not. Hemlock trees died too rapidly in girdled plots to accurately represent the long period of decline that HWA infested hemlock trees actually experience (Ellison et al., 2010). Colonies of HWA cause mortality by draining hemlocks of their stored sugars, causing death in 5-15 years (Orwig and Foster, 1998). During this period of decline, hemlock trees can even exhibit signs of recovery to stress, such as ramping up their primary productivity (Domec et al., 2013). If a lidar monitoring study is to accurately characterize the HWA infestation, it needs to capture the subtle changes in canopy structure that occur during this prolonged and dynamic period of decline.

Field Data: The ForestGEO Plot at Harvard Forest

Fortunately, a large long-term experimental plot at Harvard Forest, the Smithsonian Institute Forest Global Earth Observatory plot (ForestGEO plot; Orwig et al., 2015), provides an ideal example of a hemlock forest undergoing HWA infestation. The ForestGEO plot field data from the early stages of infestation are a valuable resource for developing new methods for monitoring disturbances with lidar (Orwig et al., 2018).

The ForestGEO plot is a 35 hectare forested site that is part of a global network of standardized field plots (CTFS; Anderson-Teixeira et al. 2015). The first census of the ForestGEO plot began in 2010 to document every stem above 1 centimeter in diameter within its boundaries (Orwig et al., 2015). The plot is organized onto a grid of 20x20 meter quadrants spanning 500 meters from the northern to the southern edge and 700 meters from the eastern to western edge. The plot also serves as a research hub that is the focus of
numerous field experiments, remote sensing datasets, and eddy flux towers that measure forest-atmosphere exchange.

Since HWA was already ubiquitous among hemlock trees at the time of the plot’s first census in 2010, the site has spurred a variety of work documenting the early impacts of HWA. Hemlock trees represent a dominant forest type in the plot (Figure 1.2), particularly in the western portion of the plot where mature hemlock forests have been established for several centuries. This hemlock-dominated section of the ForestGEO plot was reassessed for mortality during the summer of 2016 (Orwig et al., 2018). The 2016 assessment documented the status of 3595 hemlock trees in 72 of the quadrants that overlapped with mature hemlock forest (Figure 1.3). Hemlock stems that lacked any green foliage at the time of assessment were marked as dead, while stems with any amount of green foliage were marked as alive. During this 6 year time period, 435 of the 3347 hemlock stems that were alive in 2010 had died, representing a 13% mortality rate across the area.

When the spatial distribution of hemlock tree status was modelled with a trend surface analysis, a spatial gradient of hemlock condition was observed within the area (Figure 1.4). This analysis predicted probability of hemlock survival by location, using a logistic regression. The final model revealed that from 2010 to 2016, hemlock trees in the northern portion of the 72 quadrants had a higher chance of survival, while hemlock trees in the south-western portion had a higher chance of mortality (Figure 1.4). This spatial gradient provides an ideal foundation for monitoring studies to test the sensitivity of lidar data to subtle variations in condition within a small area (Orwig et al., 2018).

Airborne lidar scanner (ALS) data over the ForestGEO plot have been acquired on a biennial basis in late summer by the NEON Airborne Observation Platform since 2014.
(NEON AOP; Kampe et al., 2010). NEON plans to continue collecting data on a biennial basis, providing continuity for long-term studies of HWA infestation impacts. Additional ALS data collections by the NASA Goddard, Lidar, Hyperspectral, and Thermal instrument (G-LiHT; Cook et al., 2013) were acquired in June 2012. The NEON and G-LiHT datasets provide a valuable time series over the ForestGEO plot during early stages of the HWA infestation.

With the combination of detailed field measurements and the time-series of airborne lidar data, the ForestGEO plot data provides an ideal site for developing new methods for remote sensing technologies (Orwig et al., 2018). This research relies on the 2010 and 2016 field data for validating signals of disturbance and evaluating measurements from lidar data. By comparing lidar data to ecological field data, these studies create a positive feedback loop that both advances the development of new methods for remote sensing and provides new insight on the progression of the HWA disturbance within the plot.

Chapter Summaries

In a history of natural science, Donald Worster reflected on how past discoveries of ecological disturbances have shaped our modern worldview. Worster states that starting in the early 1800s,

...scientists began to realize how much time had transpired on the earth and how much had changed over that span of time. A static world of fixed, hierarchical relations began to give way to another nature, evolving, contingent, revolutionary, conflicted, catastrophic at times, always in a state of flux.

(Worster, 1977, pp. 421)
With this statement, Worster illustrates how ecological discoveries changed contemporary understanding and reframed how scientists, historians, and people saw the world. Environmental research propelled a new idea into society, that natural and human systems are undergoing a constant process of transformation, and it became a lens through which to understand nature. This history demonstrates that ecological ideas have a greater impact on society that extends beyond the boundaries of their field.

Research with lidar has the potential to transform the way that we value our environment. Lidar can give us insight into the current and future states of our ecosystems in real-time, providing new opportunities for forest management and disturbance mitigation. Offering a new perspective on forest change, research with lidar can contribute to greater understanding of global change and aid our response to it.

Collectively, these studies pursue two inter-related goals: 1) to adapt new technologies for monitoring temperate forests, and 2) to advance knowledge about the progression of forest disturbances. Each chapter addresses a research question related to these overarching goals.

1) How does raw waveform lidar data relate to forest condition during the HWA infestation at Harvard Forest?

Chapter 2 aims to classify forest condition from a single observation with waveform lidar data. It analyses lidar data from a flight by NEON AOP in August 2016 to predict field mortality data collected in summer 2016. Raw waveform lidar data is processed, lidar metrics are derived, and the relationship of waveform data to hemlock tree mortality is evaluated. In
the process, the study identifies lidar metrics that can expose differences in the condition of hemlock forests and outlines the future challenges that monitoring efforts will face.

2) How can multi-temporal and multi-spatial resolution lidar data be adapted to monitor forest change over the progression of the HWA infestation?

Rather than focus on a single instance of lidar observations, Chapter 3 calculates the change in forest structure in the ForestGEO plot from 2012-2016 to classify forest condition. Multi-temporal lidar data from NASA G-LiHT in 2012 is compared with data from the NEON AOP in 2016. The GEDI Simulator (Hancock et al., 2019) is used to make comparable metrics from these lidar datasets, collected by different sensors at different resolutions. Changes in the waveform metrics of the two datasets are calculated, uncovering a unique structural signal of the impacts of HWA that relates to the severity of the infestation. In addition, further tests demonstrate that HWA’s impacts can also be identified in new spaceborne lidar data from the NASA Global Ecosystem Dynamics Investigation (GEDI). Thus, this research outlines a method for scaling up monitoring studies to predict infestation severity across a region.

3) How can terrestrial lidar scanning (TLS) be used to augment and evaluate airborne lidar acquisitions and carry on the legacy of methods and tools for sampling forest ecosystems?

Chapter 4 returns to the basic relationship between lidar measurements and field data to develop new forest surveying methods with TLS. This section explores the use of TLS as a tool for forest inventory and ecological surveys. It evaluates the relationship between lidar
measurements and heterogeneous forest structure in the ForestGEO plot and offers solutions for overcoming biases in TLS data. The results of this study outline the challenges and benefits of adapting lidar technology for future surveys of forest environments.

This research is both applied, as it pursues tools for tracking the spread and severity of forest disturbances, and exploratory, as it evaluates the relationship of lidar data to properties of forest ecosystems. These studies are interdisciplinary pursuits that combine data, methods, and insights from ecology and remote sensing to characterize the HWA disturbance. By monitoring a forest disturbance with novel remote sensing methods and interdisciplinary techniques, this body of work opens up new opportunities for understanding and mitigating global environmental change.
DEFINITION OF TERMS

Lidar Remote Sensing and Related Terminology

As *active* remote sensing instruments, lidar sensors sample their surrounding environment by releasing pulses of energy, in contrast to *passive* sensors, which record radiation from an external source, usually the sun, that is reflected off and emitted from the environment. Lidar instruments use lasers, a concentrated and coherent form of light emission, to illuminate target objects and record their orientation in space. Pulse-based lidar instruments emit pulses of light of a known wavelength into their surrounding environment. Then, they record the timing and intensity of the returning radiation that was reflected by target objects at that wavelength. The time-of-flight recorded by lidar instruments can be translated into a distance by using the speed of light. With knowledge of the location of the instrument, the orientation of its emitted pulse, and the timing of returning radiation, lidar data can be used to estimate the position of target objects in surrounding space.

The most common form of lidar data is *discrete* data, also known as a *point cloud*, which is a series of points oriented by x, y, and z coordinates in 3-dimensional space. However, these discrete points (*returns*) are actually an abstraction of the raw measurement of the lidar sensor, the return *waveform*. A lidar waveform is the record of the entire distribution of returning radiation over time that resulted from a single emitted pulse. Waveforms can be composed of single or multiple pulses of return energy (*return pulses*) that correspond to reflected energy from objects that were hit along the trajectory of the lidar beam. These return pulses in lidar waveforms are processed and geo-registered to create a discrete point cloud. Thus, while point clouds of forests may look like raw measurements of
forest structure, they are actually a representation of the continuous distribution of energy in lidar waveforms.

Lidar beams do not produce infinitely precise measurements. Light is a wave as well as a collection of particles (photons), causing laser beams to diffract as they travel. Lidar beams can be understood as a cones of light that expand in diameter with increasing distance from their origin. When lidar instruments interact with a target object, they are sampling it with a circular *footprint* of a size that depends on instrument parameters and the distance to the object. This means that all lidar measurements have an uncertainty of position associated with the size of the beam that they use to sample environments. The *beam divergence* is the main parameter of lidar instruments that determines the size and expansion of the lidar beam.

In forests, this circular footprint allows lidar beams to record partial hits from foliage and branches and yet, potentially, to retain enough energy to still reach the forest floor. The density of vegetation and the frequency and size of canopy gaps determines how far a lidar beam can penetrate into a canopy. Lidar beams are *attenuated* as they travel, losing energy through processes of diffraction and from partial hits with canopy objects along the way. In this sense, lidar instruments measure the penetration of light through forest canopies with similar methods to that of spectroscopy. In fact, much of the theory of lidar sampling in forests is based on the Beer-lambert law, and assumptions made for measuring the concentration and content of a medium by passing a light of known wavelength through it.

Lidar beams cannot pass through target objects, they can only traverse through or diffract around canopy gaps. To this effect, lidar scanners are line-of-sight instruments that can be biased by *occlusion*, a topic extensively explored in the fourth chapter of this dissertation.
Lidar instruments can be categorized by the nominal footprint size of their beam, sorted into *small-footprint* or *large-footprint* instruments. Small-footprint instruments generally have footprint sizes from tens of centimeters in diameter down to the millimeter scale. Small-footprint instruments are also referred to as *high resolution* lidar instruments in this study. Large-footprint instruments, however, can measure entire stands of trees with a single beam, with footprints tens of meters wide.

Different platforms for deploying lidar scanners use different footprint sizes to optimize sampling over regions of interest. *Terrestrial lidar scanning* (TLS) instruments are mainly small-footprint instruments mounted on tripods just above ground level (Calders et al., 2014; Paynter et al., 2016). *Airborne lidar scanning* (ALS) instruments mounted on manned aircraft can be either small-footprint (Kampe et al., 2010; Cook et al., 2013) or large-footprint, depending on system hardware and sampling designs (Blair et al., 1999). *Space-borne lidar* instruments are generally large-footprint, since they have to operate in orbit above the Earth and make discrete samples of global forests (Dubayah et al., 2020).

While these explanations of lidar remote sensing are not comprehensive of the terminology and science of the field, they do provide context and explanation for this research effort. In addition to the explanations provided here, more detail is provided in the introduction sections of each chapter.
Figure 1.1, Lidar point cloud of a simulated insect infestation.

This figure shows a side-view of a point cloud representation of the Harvard Forest Hemlock Removal Experiment. (HF-HeRE; Ellison et al. 2010), 13 years after hemlock trees were girdled to simulate the HWA infestation. The understory tree layer, composed primarily of succeeding black birch (*Betula lenta*) trees, is highlighted in purple. Occlusion prevents the lidar instrument from recording points near the forest floor, causing a gap in the image at 0-3 meters. Visualized with the open-source software, CloudCompare (CloudCompare, 2018).
Figure 1.2, Hemlock trees in the 35 hectare SI ForestGEO plot.

Stems are colored by status in 2010.
Figure 1.3, Stem map of the 2016 Mortality Assessment.

Trees in 72 quadrats were reassessed for mortality over the course of the summer in 2016 (Orwig et al., 2018). Stems of all species are colored by status, with dead hemlocks (blue) highlighted.
Figure 1.4, Spatial trends in the probability of hemlock tree mortality.

A trend surface analysis models the spatial distribution of mortality within the 2016 assessment area, calculated as 1 minus the probability of survival. Hemlock survival was modelled as a binomial variable, with hemlock trees that survived from 2010-2016 representing successes, and the total number of live hemlocks representing the number of trials. The South-North distance (X in meters) and the East-West distance (Y and Y^2 in meters) were significant predictors of hemlock survival in the subplot, identifying a distinct spatial trend in the dataset.
CHAPTER 2
MONITORING FOREST HEALTH WITH WAVEFORM LIDAR

Introduction

In the last few decades, efforts to monitor forest disturbances have largely relied upon airborne surveys. A common method of disturbance monitoring employed by the USDA Forest Service is aerial sketch mapping (Ciesla, 2000), also known as Digital Mobile Sketch Mapping (DMSM; McConnell et al., 2000). These surveys rely on human observers sitting in aircraft to map the extent and severity of insect infestations, droughts, and fires across a region. They are effective in obtaining a wide coverage, and in combination with digital photography and satellite data, can obtain a high classification accuracy (Wulder et al., 2012; White et al., 2012). However, these surveys are limited in that they rely on changes in forest condition to be visible from the point of view of an aircraft. Disturbances are dynamic processes that can alter the forest structure and spectra of multiple canopy layers (Oliver, 1981; Linke et al., 2007). Often, during the initial stages of disturbances, healthy overstory trees can mask disturbance impacts in the middle and lower canopy. Limited by their ability to see below the canopy tops, aerial surveys may be missing subtle changes in the vertical profile of forest canopies that correspond with different stages of disturbance, such as the onset of an invasive insect infestation in a region.
The initial impacts of the hemlock woolly adelgid (HWA: *Adelges tsugae*) infestation exemplify this problem. HWA’s initial impacts occur in lower canopy layers (Orwig et al., 2002), posing a difficulty for detection by airborne surveys and satellite observations (Orwig et al., 2018). ALS is an active remote technology that should be well-suited for monitoring HWA’s sub-canopy impacts. ALS uses infrared laser energy to penetrate canopy gaps and record the vertical structure of a forest canopy as a set of discrete points in space, known as a point cloud (Gatziolis and Anderson, 2009; Wulder et al., 2008, 2012). Past research has shown the utility of ALS point clouds for mapping the impacts of invasive species infestations, improving estimates of tree mortality (Meng et al., 2018), measuring foliage loss (Kantola et al., 2013; Solberg et al., 2006, 2010), and measuring gap dynamics (Vepakomma et al., 2008).

However, even with small-footprint ALS data, complex forest dynamics and understory structure can be difficult to observe. ALS instruments are line-of-sight instruments that are occluded and attenuated by dense forest canopies, causing them to under-sample the understory and ground (Kukenbrink et al., 2016). ALS surveys are especially prone to this effect because they have a lower sampling density (point density) than that of other high resolution lidar instruments, such as terrestrial and UAV lidar. Therefore, either new sampling schemes or new processing techniques of ALS data are required to penetrate a healthy hemlock overstory and observe the impacts of the HWA infestation on lower canopy structure.

Fortunately, some airborne sensors record the entire waveform of the ALS data, not only retaining the discrete returns. Waveform data have been shown to improve characterizations of forest understory and lower canopy layers (Anderson et al., 2016;
Hancock et al., 2017). Also, lidar waveforms are sensitive to ecological variables that can characterize insect disturbances, such as the gap and foliage profile (Armston et al., 2013) and the exposure of dead biomass (Kim et al., 2009). While waveform data has been a standard product for large-footprint lidar instruments (e.g. Icesat/GLAS; LVIS; SLICER; GEDI), it has seldom been used for ecological studies (Anderson et al., 2016). The increasing availability and demonstrated applicability of waveform lidar data represents a potential for monitoring HWA and other sub-canopy forest disturbances.

What is Waveform Lidar Data?

Waveform data is the raw measurement received by all pulse-based lidar sensors. Lidar instruments are active remote sensing tools that sample the surrounding environment with pulses of infrared light. Emitted pulses reflect off objects in the surrounding space and return to the instrument, which records the distribution of returning energy over time (a return waveform; Figure 2.1). Discrete data is derived by fitting a model, usually a sum of Gaussian functions (Wagner et al., 2006), to the returning pulses in waveform data. The leading edge or the peaks of the modelled return waveform are then georeferenced and given an x, y, and z coordinate in space. In this sense, discrete data is actually a representation of the peaks in energy in the return waveform. One point in a point cloud is only a single sample from the continuous function of return energy, the waveform, that is recorded by the scanner.

Discrete ALS points clouds are easier to process, interpret, and take up considerably less storage space than waveform data. Because of their ease of use, they represent the majority of ALS data currently acquired. However, discrete data are often stripped of
potentially useful information about the return waveform (Anderson et al., 2016). Studies have shown that variables derived from waveform data can characterize the content and composition of the objects sampled by the lidar instrument (Zhou et al., 2018a, b). For instance, the mean integral of the first return in waveform data has been shown to improve a model of tree species classification (Brugisser et al., 2017) and to relate to the presence of dead biomass in forest plots (Kim et al., 2009). In addition, the width of return pulses has proved to be an important variable for identifying tree mortality (Shendryk et al., 2016).

New processing tools and datasets are making waveform data even more accessible, allowing users to directly process waveform data and produce metrics for applied ecological study (Anderson et al., 2016; Hancock et al., 2017; Zhou et al., 2019). The availability of waveform ALS data is also increasing, thanks to efforts by the National Ecological Observatory Network Airborne Observation Platform (NEON AOP; Kampe et al., 2010). NEON AOP gives public access to waveform lidar datasets from ecological sites across the United States. These recent developments ensure that data availability and processing tools are no longer a limitation for research studies with waveform lidar.

Before waveform data can be made operational for monitoring an infestation such as HWA, research is needed to identify relevant waveform variables that are sensitive to the impacts of forest disturbances. This study investigates whether waveform variables can determine the condition of infested hemlock stands in a mixed, temperature New England forest such as that at Harvard Forest, Petersham, MA. The ability of waveform variables to capture HWA’s lower canopy impacts is evaluated by relating waveform variables to hemlock mortality at different canopy layers. By investigating the ecological relevance of
waveform variables, this study aims to document the progressive impacts of HWA within a canopy and to develop new tools for aerial surveys of forest disturbances.

**Methods**

**Overview**

Waveform ALS data were acquired from a single NEON AOP overflight in August 2016, over an HWA-infested field site: the ForestGEO plot at the Harvard Forest experimental site (Orwig et al., 2015). Waveform data were clipped to an area of interest (AOI) within the ForestGEO plot that was assessed for hemlock tree mortality during the summer of 2016. Returning waveforms from the AOI were processed into a discrete point cloud with additional fields that contained waveform variables, such as the amplitude, width, and integral of the return pulse, using the `waveformlidar` R package (Zhou et al., 2019). Waveform metrics were rasterized onto a grid of 20 meter pixels to correspond with field data on hemlock tree mortality. Last, lasso logistic regressions and step-wise regressions were employed to select waveform variables that were related with the condition of hemlock stems of varying size classes (Figure 2.2).

**Field Data on Hemlock Condition**

The condition of hemlock plots was calculated within an AOI within the ForestGEO plot that overlapped with a mature hemlock forest that had been infested with HWA since 2008. Every stem greater than or equal to 1 cm in diameter at breast height (DBH) was
documented in the AOI in 2010 (Orwig et al., 2015). Hemlock trees accounted for 64% of the 5605 stems assessed and 62% of the total basal area in the AOI.

The AOI was re-assessed in 2016, and hemlock tree condition was recorded as a binary variable marking the presence (alive) or complete absence (dead) of foliage (Orwig et al., 2015, 2018). The field data was rasterized onto 72 pixels of 20 m resolution, and proportional hemlock tree mortality was calculated within each pixel. Hemlock tree mortality was defined as the number of live hemlocks in 2010 that had died by 2016, divided by the total number of live hemlock stems in 2010. Thus, this mortality metric did not include the status of hemlock trees that were dead at the time of the initial census in 2010 (and that had been decomposing for 6 years or more by the time of the airborne lidar survey). As these dead stems were not included, the mortality metric represented the pixel condition in 2016, rather than a measure of accumulated dead biomass.

In addition to the mortality of all hemlock stems within field pixels, the mortality of several size classes of hemlock stems was also derived from field data. Mortality was calculated for 4 tree size classes which represented the different canopy layers within field pixels: understory trees of 0-10 cm DBH, intermediate trees of 10-20 cm DBH, midstory trees of 20-30 cm DBH, and overstory trees of 30 cm DBH or more. To better understand how the condition of different canopy layers could be captured with waveform lidar variables, these 5 sets of mortality measures (4 size classes and 1 of all stems) were employed as dependent variables in lasso logistic regression models.

The variation of mortality of the different size classes could be an important factor for determining waveform variables. Changes in the understory layer (0-10 cm DBH) may cause different magnitudes and directions of change in the waveform signal variables than do the
changes in the intermediate (10-20 cm diameter) and midstory (20-30 cm diameter) canopy layers. In addition, while they may be less abundant than trees in smaller size classes, dominant trees of extreme size (>30 cm in diameter) can take up a larger proportion of the volume of field plots than do understory trees, and thus, may have a larger impact upon the waveform signal.

**ALS Data**

ALS waveform data was collected by the NEON Airborne Observation Platform (NEON AOP; Kampe et al., 2010) over the Harvard Forest ForestGEO plot on August 8, 2016. The ALS scanner was an Optech Airborne Laser Terrain Mapper (ALTM) Gemini, with a laser wavelength of 1064 nanometers (nm) and a Pulse Repetition Frequency (PRF) of 100 kHz (Krause and Goulden, 2015). Waveform data were acquired in NEON-binary file format as a set of arrays describing the outgoing pulse of the lidar instrument, the return waveforms, the geolocation of each return waveform, and ephemeris aircraft data.

Waveform data was recorded as a discrete distribution of return energy over time, recorded every 1 nanosecond (ns) from the start of detection. A 1 ns temporal resolution roughly corresponds to taking a sample at every 0.15 m of vertical distance (Zhou et al., 2019). Not all returning waveforms were of the same length or of the same minimum energy. To counter this, waveforms were zero-padded to a length of 500 bins, and a dark offset, calculated as the minimum intensity of the waveform, was subtracted from all points.

In addition, a Digital Terrain Model (DTM) was acquired to validate results and to produce above ground canopy heights (AGH). This DTM was created by NEON using discrete lidar data from multiple flights in August 2016. This study relied upon the NEON
DTM instead of directly processing ground heights, because the single flight of data used in this study did not acquire enough ground returns to create a high-quality DTM.

**Waveform Processing and Variable Creation**

Return waveforms were processed into point clouds with the `waveformlidar` R package (Zhou et al., 2019) with Gaussian decomposition and the Levenberg–Marquardt optimization method (Marquardt, 1963). Return waveforms were modelled as a sum of Gaussian functions. Before fitting, waveforms were smoothed with a moving window of 5 nanoseconds (ns). This discouraged the algorithm from fitting multiple Gaussian models to noisy waveforms. After fitting, peaks in returning energy were geolocated using the first time bin in the outgoing waveform, stored in the geolocation file, and in the first bin of the returning waveform. X and y coordinates were georeferenced in WGS-84 UTM-18N, and z coordinates were recorded as elevation in the NAVD-88 with the National Geodetic Survey Geoid12A height model (Krause and Goulden, 2015).

The processed point cloud contained extra fields for each point that described the Gaussian model of every return pulse. In addition, each discrete return contained a waveform identifier that allowed for complete models of return waveforms to be reconstructed. Waveform metrics were derived from individual returns and from complete waveforms for comparison with field data on hemlock condition.

Table 2.1 lists, categorizes, and describes all waveform variables used in this analysis. These variables generally fall into 3 categories: pulse-based metrics, waveform-based metrics, and aggregate waveform metrics. Each of these categories is explained below.
Pulse-based Metrics:

Pulse-based metrics were derived from Gaussian models of individual returns. These included the pulse integral, the full width at half maximum (FWHM), and the pulse amplitude (intensity), which were calculated for every return in the point cloud (see Table 2.1 for further detail).

The data were split into two sections. One section contained metrics from all returns, while the other selected for metrics from unimodal waveforms that produced a single identifiable return. In unimodal waveforms, return pulses are assumed to originate from a single target object, while returns from multi-modal waveforms are complex convolutions of multiple targets. Isolating unimodal returns in a separate dataset thus allowed for analysis on simple waveforms representing individual targets, rather than those with a complex composition of targets.

In addition, both the complete and unimodal dataset were split again by aboveground height (AGH). Vegetative (≥ 3 m above ground) and ground (< 3 m AGH) metrics for each dataset were produced, following the height thresholds used by similar studies (Zhou et al., 2019). This allowed for the separate comparison of return pulses from the canopy and the ground, which have been shown to have different waveform characteristics (Lefsky et al., 1998; Armston et al., 2013; Ni-Meister et al., 2001, 2018). Waveform metrics from each dataset were summarized by their mean and variance, and summarized metrics were rasterized onto a grid of 20 m pixels for further analysis.
Waveform-based Metrics:

The waveform-based metrics were calculated from individual ALS waveforms, rather than from individual returns within the waveforms. The slope, roughness, and total waveform integral metrics, were derived for every waveform (Table 2.1). The roughness measure represented the distance from the top of the waveform to the peak of the first return in meters, while the slope represents that angle of the start of the waveform to the first return of the Gaussian curve in degrees (Zhou et al., 2019).

In the same manner as the pulse-based metrics, the slope, roughness, and total waveform integral datasets were divided into datasets of unimodal returns and again into vegetative and ground datasets. The mean and variance of each metric were rasterized onto 20 m pixels.

In addition, the unimodal return ratio and the proportion of ground pulses were calculated for each 20 m pixel. These represented the proportion of waveforms with unimodal returns and the proportion of waveforms that reached the ground in each pixel.

Aggregate Waveform Metrics:

Aggregate waveforms were produced for each pixel by calculating the mean intensity of all waveforms within the pixel at 0.25 meter height intervals (Figure 2.3). Aggregate waveforms represented the average distribution of return energy by height within a pixel. They can be understood as the average waveform of a given pixel.

The integrals of the vegetative and ground portion of the aggregate waveforms (veg and ground) and their ratio (vegtoground) were calculated for all 20 m pixels (Figure 2.3).
Infested pixels were expected to have lower integrals of vegetated energy than do healthy canopies, since infested canopies are expected to have less foliage and more exposed wood than healthy pixels. At the 1064 nm wavelength of the NEON lidar instrument, trunks and branches are expected to reflect less laser energy than would vegetation (Kim et al., 2009). Thus, at near-nadir view angles and similar ranges from the scanner, return pulses from infested canopies can be expected to have lower amplitudes and smaller integrals than those from healthy canopies. In addition, infested canopies are expected to have more within canopy gaps that allow lidar beams to pass through and record the ground, resulting in higher integrals of ground energy.

Pixel-level relative height (RH) metrics were also calculated from aggregate waveforms (Figure 2.3). RH metrics describe the shape of the cumulative distribution of return energy using heights that correspond to percentiles of energy from the ground to the canopy top. For example, the $\text{RH}_{50}$ metric would correspond to the height at which 50% of the return energy in the waveform was reflected. $\text{RH}_{100}$ would represent the height of the top of the waveform at which 100% of all return energy was reflected. These metrics were originally developed for describing canopy structure with large-footprint lidar data (Drake et al., 2002a and 2002b; Dubayah et al., 2010), and they have been adopted for describing high resolution ALS waveforms (Kim et al., 2009; Zhou et al., 2019).

RH metrics can be used to describe the distribution of canopy structure (Drake et al., 2002a and 2002b). However, RH metrics are strongly related with canopy height, and thus, may not be comparable metrics of forest condition among pixels with different canopy heights. In order to compare pixels by condition, rather than canopy height, RH metrics in this study have been transformed into proportional heights (Figure 2.4).
To create proportional heights, RH metrics were normalized by the length of the aggregate waveform that they were created from. The length used to normalize RH metrics was calculated as the distance from the ground in the aggregate waveform, estimated as $RH5$, to the maximum height of the aggregate waveform, $RH100$. Using this normalization method, RH metrics were decoupled from canopy height, and instead, represented their proportional distance to the maximum height of the waveform. RH proportional heights allowed the analysis to focus on the relative differences in structure that corresponded with pixel condition, rather than absolute differences in structure between pixels.

Lower RH metrics ($RH50$ and lower) are expected to drop down to lower values after disturbances, as has been noted in other monitoring studies (Dubayah et al., 2010). A shift of an RH metric to a lower height indicates that the return energy of the lidar waveform is concentrated at lower canopy heights. This could be indicative of increased canopy structure near the ground, such as a high concentration of understory trees, or it could be indicative of increased gap formation, which allows laser energy to penetrate canopies and reach the ground. RH metrics would be expected to be lower in pixels with higher hemlock mortality. The HWA infestation is expected to defoliate lower portions of hemlock canopies before upper layers. This lower canopy defoliation allows more laser energy to reach the ground, making RH metrics lower in infested pixels than in healthy pixels.

RH metrics were calculated from the normalized, cumulative distribution of aggregate waveforms at 5% intervals from the start to the end of the waveform. Next, all of the RH metrics were converted into proportional heights, and the $veg$ and $ground$ integrals of the waveform were derived. Finally, aggregate waveform metrics were rasterized onto a grid of 20 meter pixels for comparison with other metrics and with field data.
Variable Selection

Lasso logistic regressions were applied to select for waveform variables with strong relationships to hemlock tree mortality. Logistic regressions modelled the condition of each pixel as a binomial variable, with a success (1) representing a hemlock stem that was alive in 2010 and died in 2016, and a failure (0) representing a stem that survived from 2010-2016. The number of live hemlock stems in 2010 represented the number of trials in each pixel. Lasso logistic regressions were fit using the Glmnet package in R (Friedman et al., 2010).

Lasso regressions use a penalty variable, lambda, that draws the coefficient values of weak fitting variables toward 0. A 5-fold cross-validation technique was used to iterate across a range of values to choose an optimal lambda. Optimal values of lambda were those that produced a model with the lowest statistical deviance compared to models fit with other lambda values (Friedman et al., 2010). The waveform variables of the model selected by this optimal lambda value were retained for further analysis.

Lasso regressions were run with 5 sets of dependent variables representing the condition of hemlocks of different size classes, and a set of 63 explanatory variables derived from the lidar waveforms (Table 2.1). Each set of dependent variables was run separately to select for the optimal waveform variables that best described the mortality of each size class of hemlock trees.

After lasso regressions were evaluated, step-wise regressions were performed upon the 5 models of hemlock mortality. Step-wise regressions iteratively removed variables to select a final model that minimized the Akaike Information Criterion (AIC), using the MASS package in R (Venables and Ripley, 2002).
Results

Field Data: Hemlock Condition

Between the first census of the ForestGEO plot in 2010 and the mortality assessment of the AOI in 2016, 449 of the 3316 hemlock trees that were alive in 2010 had died. This change represented a 13.5% average mortality across the AOI. When rasterized onto 20 meter pixels, mortality rates varied from a minimum of 0% to a maximum of 33% along a spatial gradient. All pixels were infested with HWA at the time of study, yet southern pixels had higher mortality rates than did the northern pixels (Orwig et al., 2018; Figure 2.5).

Mortality rates varied greatly among tree size classes within pixels in the AOI (Table 2.2). Trees of smaller diameter (DBH) had higher mean mortalities than did stems of larger size classes. This suggests that understory and midstory layers were most affected by HWA, while the upper layers of the canopy displayed relatively smaller impacts. While HWA impacts are expected to spread vertically from the bottom-up on individual trees, a progressive loss of vertical structure also appears to be occurring within vertical canopy layers across the AOI.

<table>
<thead>
<tr>
<th>Size Class (DBH)</th>
<th>Mean N Died</th>
<th>Mean N Survived</th>
<th>Mean Mortality</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Sizes</td>
<td>6.23</td>
<td>39.82</td>
<td>0.13</td>
</tr>
<tr>
<td>0-10 cm</td>
<td>27.7</td>
<td>22.79</td>
<td>0.20</td>
</tr>
<tr>
<td>10-20 cm</td>
<td>1.06</td>
<td>6.19</td>
<td>0.17</td>
</tr>
<tr>
<td>20-30 cm</td>
<td>0.43</td>
<td>5.69</td>
<td>0.10</td>
</tr>
<tr>
<td>&gt;30 cm</td>
<td>0.13</td>
<td>6.06</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 2.2, Summary of mortality metrics by size class of hemlock trees in 20 m pixels.
Waveform Processing

NEON waveforms from a single flight line (FL006 flown on August 16, 2016) were clipped to the AOI, and Gaussian decomposition was performed to model return pulses in each waveform (Figure 2.6). A point cloud was produced by geo-referencing the means of Gaussian pulses, using the corresponding time to the maximum amplitude of the return. Extra fields were added to the point cloud describing the Gaussian fit of each pulse in the return waveform. The Z-coordinates of all points were converted into aboveground height (AGH) by subtracting the values from the 1 m resolution NEON DTM (Figure 2.7).

To avoid side-viewing zenith angles from the analysis, returns from waveforms with angles greater than 15 degrees from nadir were removed. Zenith angles followed a spatial gradient across the ForestGEO plot, with lower zenith angles in the east and higher angles in the west (Figure 2.8).

After filtering for zenith angle, the point cloud was filtered for extreme outliers by removing waveforms with amplitudes greater than 250 DN and with widths greater than 50 bins. These outliers were chosen based on visual analysis, as the chosen threshold values removed the majority of points with extreme below-ground elevations (< -10 m AGH). The point cloud was also filtered based on AGH. Remaining waveforms that produced ground returns with heights below -3 meters as compared to the DTM were removed. In total, about 0.8% of waveforms were removed during this filtering process. The resulting point cloud consisted of 103,472 discrete points with an average point density of 3.5 points per m² (Figure 2.8) and a 0.5 meter spacing between points.
It should be noted that there was a systematic bias in the elevation of points compared to the NEON 2016 DTM (Figure 2.9). Ground points in the point cloud were on average $1.4 \pm 0.9$ meters below the height of the DTM. This offset is likely due to the differences in processing between the lidar data used to create the 2016 DTM and the waveform data used in this study, such as the use of the *leading edge* as opposed to the *amplitude* of the return waveform to perform geo-registration (Krause and Goulden, 2015). This offset was noted, but was not corrected as it did not have a significant impact upon the analysis in this study.

**Variable Selection**

Waveform, pulse-based, and aggregate waveform metrics were rasterized onto a grid of 72 individual pixels of 20 m resolution for comparison with field data (Figure 2.10). Lasso logistic regressions were performed with 5 sets of dependent variables (Table 2.1) representing hemlock condition at different canopy layers and for all stems within the pixel. Each lasso regression identified waveform variables that were related to the condition of a specific size class of hemlock trees.

<table>
<thead>
<tr>
<th>Model of Mortality of All Hemlock Stems</th>
<th>0-10 cm DBH</th>
<th>10-20 cm DBH</th>
<th>20-30 cm DBH</th>
<th>&gt;30 cm DBH</th>
</tr>
</thead>
<tbody>
<tr>
<td>peakintegral veg.mean</td>
<td>peakintegral veg.mean</td>
<td>uniretrat veg</td>
<td>peakintegral veg.mean</td>
<td>RH30</td>
</tr>
<tr>
<td>rough veg.mean</td>
<td>rough veg.mean</td>
<td>slope veg.var</td>
<td>FWHM veg.mean</td>
<td>RH95</td>
</tr>
<tr>
<td>peakintegral uniground mean</td>
<td>FWHM ground var</td>
<td>groundpulheratio</td>
<td>peakintegral ground.mean</td>
<td></td>
</tr>
<tr>
<td>intensity uniground mean</td>
<td>rough veg.var</td>
<td>slope univg.mean</td>
<td>intensity ground.mean</td>
<td></td>
</tr>
<tr>
<td>roughness univg.mean</td>
<td>roughness univg.var</td>
<td>uniretrat univg.var</td>
<td>roughness univg.var</td>
<td></td>
</tr>
<tr>
<td>peakintegral uniground mean</td>
<td>FWHM univg.var</td>
<td>intensity univg.var</td>
<td></td>
<td></td>
</tr>
<tr>
<td>slope uniground.mean</td>
<td>FWHM uniground.var</td>
<td></td>
<td></td>
<td>RH15</td>
</tr>
<tr>
<td>slope uniground.var</td>
<td></td>
<td></td>
<td></td>
<td>RH80</td>
</tr>
<tr>
<td>RH10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RH90</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.3, Variables selected by lasso regression, grouped by dependent variable.
Lasso regressions identified 26 waveform variables that were related to the condition of hemlock stems of varying sizes (Figure 2.11; Table 2.3). Waveform-based, pulse-based, and aggregate waveform metrics all displayed relationships with hemlock condition. The most common variable selected was the mean integral of returns from vegetation (peakintegral_veg.mean), which was correlated with the mortality of hemlock stems of 0-10 cm diameter, of 20-30 cm, and all sizes. The second most common variables were both the mean pulse integral of unimodal ground waveforms (peakintegral_ground.mean) and the mean roughness of vegetative returns (roughness_veg.mean). Both of these were related to the mortality of all size classes and of stems 0-10 cm in diameter.

The mean roughness of unimodal vegetative returns (roughness_univeg.mean) was also related to multiple sets of dependent variables. However, it displayed a direct relationship with the mortality of 20-30 cm trees, and it had a stronger, indirect relationship with the mortality of 0-10 cm trees. These opposing relationships highlight the sensitivity of waveform variables to conditions at multiple canopy layers.

Other than these 4 variables, waveform metrics were not selected in multiple models of dependent variables. For example, a unique set of variables was selected for trees of intermediate size class (10-20 cm), including the proportion of vegetative waveforms with unimodal returns (uniretrat_veg) and the proportion of pulses with ground returns in the pixel (groundpulseratio). However, neither of these variables were chosen in models of tree mortality for any other size class. This suggests that waveform metrics are uniquely sensitive to the mortality of trees of specific size classes.

Only RH30 and RH95 were selected for modelling the mortality of the largest trees (>30 cm in diameter). This suggests that while the crowns of large trees may make up a large
proportion of the volume within a pixel, their condition may not be as sensitive to pulse-based and waveform-based variables. However, the selection of aggregate waveform metrics as predictors suggests that the condition of large trees did have an impact on the average waveform attenuation within a pixel.

In a lasso regression model of hemlock mortality of all size classes, 4 variables were selected, all with a positive linear trend with hemlock mortality (Figure 2.12). A positive relationship was anticipated for ground integrals and ground intensities, as more gaps in infested pixels were expected to allow more direct ground hits without attenuation from canopy elements. Roughness also displayed a positive relationship with hemlock mortality, suggesting that the canopy surface in infested pixels is more variable than that of healthy pixels.

Selected variables did not always follow expected relationships with hemlock condition. In contrast to expectations, the mean pulse integral of vegetation had a direct relationship with hemlock mortality, with higher integrals from vegetation in pixels with higher mortality. The distribution of pulse integrals from vegetation confirms this trend (Figure 2.13). Pixels of high mortality had more returns with a higher frequency of integral values between ~2000-5000 DN, while pixels of low mortality had more returns with integrals less than 2000 DN. The observed relationship was opposite of what was expected, since pixels with more severe mortality and defoliation were anticipated to have more exposed woody components, which was anticipated to produce a higher frequency of returns with lower integrals. This finding suggests that differences in woody and vegetative reflectance are not driving the differences in waveform intensity, contrary to expectations.
Step-wise Models

Step-wise regressions were performed to further refine the variables selected by lasso regressions (Table 2.4). All models contained waveform variables that were significant ($p < 0.05$), however, not all waveform variables were significant predictors. The model of hemlock morality of stems of 0-10 cm DBH had the strongest fit, explaining 52% of the variation in mortality with waveform variables. All other models explained 20-30% of the variation in hemlock mortality, with the model of the mortality of all stems explaining the least amount of variation (22%) in mortality.

Discussion

Waveform variables derived from individual waveforms, from return pulses, and from aggregate waveforms all proved valuable for predicting condition at the 20 meter pixel scale. In particular, the mean integral of pulses from the ground and from vegetation were important variables that were selected by multiple models. The roughness of waveforms, which is related to canopy structure and permeability, was also frequently selected as a predictor of hemlock mortality.

Surprisingly, waveform variables were better predictors of the mortality of stems of small size classes than they were of any other dependent variables, despite the fact that small trees are more difficult for airborne lidar instruments to observe. Waveform metrics were also revealed to have different relationships with the condition of stems of different size classes. These findings demonstrate that specific waveform variables could be utilized by...
future studies to target disturbance impacts within specific canopy layers of forest ecosystems.

**Understanding the Progression of the HWA Infestation**

This study demonstrated how waveform lidar metrics can be influenced by ecological variables. In the process, it also revealed insights on the progressive nature of the impacts of the HWA infestation. HWA has been reported to affect individual tree canopies from the inner crown outward, causing defoliation in middle and lower crown before reaching the canopy top. HWA’s vertical progression of impacts through the canopy may also operate across the stand level, impacting the majority of understory and midstory hemlock trees before reaching those at the canopy top (Figure 2.5).

The strongest relationship of waveform variables and plot condition was found when predicting the mortality of the smaller 0-10 cm DBH hemlock stems ($R^2=0.52$). These results may seem counterintuitive, since smaller, understory trees reside near the ground, which is the most occluded area of the canopy for ALS sampling (Kukenbrink et al., 2016). Thus, given that ALS is more limited in its ability to sample understory vegetation, why were waveform variables in this study most strongly related to the condition of understory trees?

One explanation is that waveform lidar data provided a more comprehensive measurement of understory vegetation than did discrete data, as has been noted by numerous other studies (Anderson et al., 2016; Hancock et al., 2017). Another explanation is that the mortality of understory vegetation better represented the condition and disturbance stage of forest plots than did any of the other field mortality metrics. The mortality of understory vegetation could be acting as a proxy for defoliation and branch loss throughout the upper layers of the canopy. If understory mortality best represents the condition of a forest plot as a
whole, then waveform variables would be expected to correlate with the mortality of understory vegetation above all other mortality metrics. Either or both of these explanations could be causing the strong correlation between understory mortality and waveform metrics in this study.

**Canopy Layers and Waveform Variables**

This analysis highlighted how the conditions of different canopy layers can have unique effects upon waveform metrics. In the case of the `roughness_univeg.mean` metric (the mean roughness of unimodal returns from vegetation), the condition of different canopy layers had opposing effects upon the lidar signal. This result indicates that the variation in the condition of the canopy layers of forest plots could be negating or amplifying certain signals in waveform data.

The specificity of the relationship of waveform variables and canopy layers could explain why the model of mortality of all stems explained less variation ($R^2=0.2$) than did models of specific size classes of trees. Variations in condition at different canopy layers could have caused contrasting effects on waveform metrics. Thus, waveform metrics performed better when they targeted specific canopy layers, than when they predicted the overall condition of the plot. In order to classify condition at the plot-level, future studies need to differentiate the condition of various canopy layers and use that stratification of canopy structure to come to a consensus on the condition or disturbance stage of the entire forest plot.
Challenges of Monitoring Forest Health with Waveform ALS Data

While numerous waveform metrics showed potential for monitoring forest condition, this analysis also revealed a high amount of unexplained variation in the models of forest condition with waveform variables. The highest amount of variation explained by a step-wise model of hemlock mortality was 52%, with the majority of the models explaining only 20-30% of the variation in hemlock mortality.

Several extraneous factors could be limiting the predictive ability of waveform variables. One limitation could be the waveform post-processing techniques used in this study. Waveform processing only utilized Gaussian distributions to model the return pulses in waveform data. Gaussian models for return pulses could be misrepresenting the shape of certain pulses and missing details that correspond to infestation condition. Other ecological classification studies have found benefits to decomposing lidar waveforms with other distributions (Hancock et al., 2015), including using measures of waveform skewness to classify tree species (Brugisser et al., 2017). Future studies should test several models of return pulses to evaluate whether other distributions could provide relevant measures of waveform skewness for disturbance monitoring.

Artifacts in the raw waveform data also pose a challenge to waveform processing techniques. The multi-modal waveform in Figure 2.6 shows an example of one of the artifacts encountered by this study. In the raw waveform data, the multi-modal return pulse appears to cut off abruptly at the 48th time bin, before the end of 2nd return pulse. This artifact may be a result of the lidar instrument, as it appears that the detector shut off too early to finish collecting the full extent of the 2nd return pulse. While Gaussian decomposition
appears to have successfully reconstructed the pulse in this case, it is possible that this artifact caused omission errors in other waveforms with multiple return pulses, and thus, reduced the accuracy of some of the waveform metrics.

Lastly, environmental factors could also account for a portion of the unexplained variation in models of forest condition. This study assumed that the AOI had a relatively homogeneous tree species composition. Variations in the species composition of the plots were not controlled for, however, and could have introduced excess variation or outliers into their relationships with waveform data.

Attenuation in Infested Canopies

While it was expected that infestation impacts would change the vegetation and ground signal, the relationships between waveform variables and plot condition sometimes contrasted with expectations. For example, the mean integral of return pulses from vegetation was expected to have an indirect relationship with hemlock mortality. As the HWA infestation reduces the amount of foliage and exposes more woody targets in infested plots, integrals of pulses from the canopy were expected to be weaker at the wavelength of the lidar instrument (1064 nm). Contrary to expectations, the mean pulse integral from vegetation had a direct relationship with plot condition (Figure 2.13), and increased hemlock mortality produced higher mean integrals.

Previous work on separating leaf and woody elements has cited that differences in reflectance at the 1064 nm wavelength are small, and can also be dependent upon the tree species being measured (Douglas et al., 2012, 2015). For this reason, some research efforts have turned to dual-wavelength scanners to compare reflectance in the near infrared and the
shortwave infrared and to separate leafy and woody elements (Li et al., 2013, 2016, 2018). In light of these studies, it is possible that the differences in reflectance between foliage and trunks in hemlock stands were not significant, and thus, were overpowered by the effect of other structural differences in infested and healthy pixels. For instance, reduced attenuation in severely infested plots could be responsible for increasing the return integral. With less foliage, twigs, and other small obstructions, infested plots may have caused less attenuation to lidar beams than did healthy plots, with dense, foliated canopy structures. Thus, foliage loss in infested plots may have caused return pulses to be stronger and brighter than those in healthy plots.

This attenuation hypothesis is supported by the direct relationship between unimodal ground returns and hemlock mortality. Unimodal ground return pulses were brighter in infested plots when compared to healthy plots, with higher amplitudes and integrals (Figure 2.13). This direct relationship would be expected if defoliation was reducing attenuation in infested plots, allowing more laser energy to penetrate the canopy and reach the ground. This increased availability of energy at ground level could have amplified the strength of ground return pulses. In addition, the proportion of waveforms that reached the ground (groundpulseratio) also had a direct relationship with the mortality of 20-30 cm DBH stems (Figure 2.11). More waveforms were able to penetrate the canopy and to retain enough energy to reach the ground in infested plots, an indicator of reduced attenuation in plots with higher hemlock mortality.
Conclusion

Starting from raw waveform lidar data, this study processed return pulses, produced waveform metrics, and uncovered variables that were sensitive to the impacts of the HWA infestation. When summarized at the 20 meter scale, waveform variables showed promise in identifying the condition of infested hemlock plots. In addition, waveform metrics showed an ability to identify the condition of stems of varying size classes, suggesting that waveform lidar data can target infestation impacts at specific canopy layers. Future studies should exploit this finding to monitor forest condition and classify disturbance stage based on the severity of the infestation at specific layers in stratified canopies.

The finding that waveform variables are related with plot-scale condition, especially the condition of understory trees, bodes well for future monitoring efforts. Waveform ALS data are increasingly becoming a public resource, and with the launch of the NASA Global Ecosystem Dynamics Investigation (NASA GEDI; Dubayah et al., 2020), large-footprint waveform lidar data are being collected in temperate and tropical forests across the globe. Scaling up the relationships observed in this study to GEDI scale would allow HWA infestation severity to be recorded across the entire range of hemlock trees in the US.

Before monitoring efforts with waveform ALS can become operational, however, more research is needed to explain the variation in waveform metrics and understand how that variation relates to forest condition. Waveform variables for disturbance monitoring could be further refined by modelling the influence of other forest variables, such as species composition, on lidar waveforms. Another promising approach would be to remove excess variation by calculating the change in forest structure with multi-temporal lidar, rather than
relying on observations from a single flight to classify forest condition. By comparing the changes of waveform variables in disturbed forest plots, follow-up studies could negate confounding variables that should remain the same during the observation period, such as species composition. Recording changes in canopy structure would minimize excess variation in predictive models, potentially producing an operational method for classifying disturbance severity across regions with diverse canopy structures and compositions in the future.
Figure 2.1, Simple diagram of sampling with waveform lidar.

While a discrete return lidar instrument may only record the peak of the $1^{st}$ and $2^{nd}$ return pulses, waveform lidar would record the entire return waveform.
Figure 2.2: Flowchart of study design.

- **ForestGEO Plot Field Data**
  - **Mortality Calculated** as:
    - N = number of live hemlocks in 2010
    - Ndied = number of live hemlocks in 2010 that died in 2016
    - Hemlock Mortality = Ndied / Ntotal

- **Raw Waveform Data**
  - NSF NEON Flight-006, August 2016
  - **Processed into a point cloud** with Gaussian decomposition in the waveformidar R package (Zhou et al., 2019)
  - **Added Extra fields** with waveform variables.

- **Grouped by diameter** at breast height (DBH):
  - All stems
  - 0-10 cm
  - 10-20 cm
  - 20-30 cm
  - >30 cm

- **Rasterized onto 20 meter pixels in AOI**
  - Mortality by size class
  - Summarized Waveform Variables (mean and variance)

- **Selected variables** with Lasso Logistic regression and 5 dependent variables:

  \[
  \text{logit(Mortality)} = \text{Intercept} + B1 \times \text{peakintegral_veg.mean} + B2 \times \cdots
  \]
<table>
<thead>
<tr>
<th>Category</th>
<th>Summary Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Return Pulses</strong></td>
<td><strong>Intensity</strong></td>
<td>Amplitude of Gaussian model of return pulse.</td>
</tr>
<tr>
<td>Ground (&lt; 3 m)</td>
<td><strong>Pulse Integral</strong></td>
<td>Integral of Gaussian pulse.</td>
</tr>
<tr>
<td>Vegetative (≥ 3 m AGH)</td>
<td><strong>Normalized Pulse Integral</strong></td>
<td>Integral of Gaussian pulse normalized by the total waveform integral.</td>
</tr>
<tr>
<td><strong>Return Pulses from Unimodal Waveforms</strong></td>
<td><strong>Full Width at Half Maximum (FWHM)</strong></td>
<td>Width of the pulse at half the amplitude in units of time.</td>
</tr>
<tr>
<td>Ground (&lt; 3 m)</td>
<td><strong>Rising Slope</strong></td>
<td>Slope in degrees from the start of the waveform to the amplitude of the first peak (Zhou et al., 2019).</td>
</tr>
<tr>
<td>Vegetative (≥ 3 m AGH)</td>
<td><strong>Roughness</strong></td>
<td>Distance in meters from the top of the waveform to the amplitude of the first peak (Zhou et al., 2019).</td>
</tr>
<tr>
<td><strong>Aggregate Waveform Metrics</strong></td>
<td><strong>Unimodal Return Ratio</strong></td>
<td>Proportion of the number of waveforms with unimodal returns to the total number of pulses in a plot.</td>
</tr>
<tr>
<td>Based on the mean intensities of all pulses in a pixel, by height.</td>
<td><strong>Proportion of Ground Pulses</strong></td>
<td>The number of pulses reaching the ground divided by the total number of pulses in a plot.</td>
</tr>
</tbody>
</table>

| | **RH1-RH100** | R.H heights describe the height distribution of cumulative return energy in a pixel. RH100 corresponds to the top of the signal, while RH0 to the bottom. RH50 refers to the height at which 50% of the return energy in the pixel has been reflected. |
| | **Proportional Height to Max Canopy Height** | |
| | **Ground Fraction** | Integral of the aggregate waveform corresponding to ground (< 3 m AGH). |
| | **Vegetated Fraction** | Integral of vegetative portion of aggregated waveform (≥ 3 m AGH). |

Table 2.1, Summary and explanation of all waveform variables.
Figure 2.3, Aggregate waveform metrics from a single pixel of ALS data.

Ground and vegetative integrals of aggregate waveforms (left) are plotted by aboveground height (AGH). In addition, RH metrics (right) are labelled along the distribution of cumulative, normalized distribution of return energy of the aggregate waveform by height.
Figure 2.4, Conversion of RH metrics from above ground heights to proportional heights.

This conversion removed variation in plots that originated from differences in canopy height. RH90 aboveground heights are correlated with max canopy heights ($R^2 = 0.92$), and the proportional height adjustment reduces that correlation (0.47).
Figure 2.5, Hemlock mortality in the AOI.

The spatial distribution of mortality of hemlock trees of all sizes from 2010-2016 is plotted for all 20 meter pixels (top). A kernel density plot of hemlock mortality shows distributions of pixels (frequency) with different mortality rates by size class across the plot (bottom).
Figure 2.6, Results of Gaussian decomposition of waveform data.

A single Gaussian model of a unimodal return with amplitude of 170 is plotted (top). Multiple Gaussian functions are summed together to model multiple return peaks (bottom). X1 and X2 correspond to Gaussian models of the 1st and 2nd return pulses.
Figure 2.7, Point cloud colored by above ground height (AGH).

Top-down view (top) and size view (bottom) of point cloud in the AOI.
Figure 2.8, Point density and zenith angle of point cloud.

(Left) Raster of point density (points per m$^2$) at 1 meter resolution. (Right) Top-down view of point cloud colored by zenith angle.
Figure 2.9, Offset in ground heights between the NEON 2016 DTM and the processed point cloud.

(top) Histogram of point cloud aboveground heights from -3 to 1 meter.
(bottom) Point cloud colored by ground and canopy returns. White points are canopy returns, while colored points are ground.
Figure 2.10, Spatial distribution of waveform variables and mortality.

Plots show waveform variables and mortality summarized at the 20 meter pixel scale. A north-south gradient in waveform variables can be observed that roughly corresponds to the north-south gradient observed in hemlock mortality.
Figure 2.11, Plot of coefficients of variables selected by lasso logistic regressions.

The color of the bar graph corresponds to the DBH size class of the dependent variable (hemlock mortality).
Figure 2.12, Scatter plots of waveform variables and hemlock mortality.

These plots show the mean integral of ground and vegetation returns, the mean roughness, and the mean intensity of unimodal ground returns against the mortality of hemlock stems of all size classes.
Figure 2.13, The integral of returns from vegetation and hemlock mortality.

Scatter plot (top) of mean pulse integral by mortality, and kernel density plot (bottom) of distribution of integrals from vegetative returns, grouped by pixel and colored by mortality.
Table 2.4, Results of step-wise regressions.

Coefficients are shown for the final variables in 5 models of mortality of hemlock trees of varying size classes. Bold text marks variables that were significant at the 0.05 level.
CHAPTER 3
THE POTENTIAL FOR THE DETECTION
OF THE HEMLOCK WOOLLY ADELGID FROM SPACE

Introduction

Insect infestations cause unique changes in the structure of forests over time, opening up gaps in the canopy and triggering growth among understory species (Oliver, 1981). Active remote sensing instruments, such as spaceborne and airborne lidar scanners (ALS), can penetrate dense forest canopies to observe these subtle changes in structure. Thus, lidar has potential to detect the spread and to monitor the severity of infestation impacts at the regional scale.

An invasive insect, the hemlock woolly adelgid (HWA; Adelges tsugae), is currently bringing about distinct and lasting impacts on the forest structure of the eastern United States (Orwig and Foster, 1998; Orwig et al., 2013). HWA is spreading northward as climate change warms New England winters and reduces the frequency of cold snaps, which are the major limiting factor to adelgid populations in the US (Parker et al., 1998, 1999; Skinner et al., 2003; Paradis et al., 2007; Dukes et al., 2009). As multiple time series of lidar data over HWA infested sites have become publically available, new opportunities have emerged to track the spread of this insect infestation and to characterize its impacts upon forest structure.
A new spaceborne lidar sensor, the Global Ecosystem Dynamics Investigation (GEDI; Dubayah et al., 2020), is now collecting data of vertical canopy structure over the New England region, providing the regional scale coverage that could capture HWA’s northern expansion. This study explores the use of lidar waveforms and the future potential of GEDI data for monitoring the spread of the HWA into New England.

**Structural Signals of the Hemlock Woolly Adelgid Infestation**

HWA’s impacts are widespread upon eastern and carolina hemlock trees (*Tsuga canadensis* and *Tsuga caroliniana*) in the eastern United States, extending across the Appalachian Mountains from Georgia to Maine. While HWA does not directly defoliate hemlock trees, colonies of HWA bring about progressive needle loss and branch death by draining hemlocks of their stored sugars (Domec et al., 2013). Infested trees die within 5-15 years from the onset of infestation, and are replaced primarily by deciduous tree species (Orwig and Foster, 1998). Studies project that HWA will spread into the full range of hemlock in New England and southern Canada (Fitzpatrick et al., 2012; Ellison et al., 2018), potentially eliminating this ecological foundation species from the landscape in the coming decades.

**Lidar Remote Sensing for Monitoring Forest Health**

Repeat measurements from lidar remote sensing instruments can detect disturbances and record structural change in forests (Tang and Dubayah, 2017; Kellner et al., 2009; Calders et al., 2015; Solberg, 2010; Meng et al., 2018). Lidar sensors are active remote sensing instruments that emit pulses of light to characterize the structure of targets in 3-dimensional
space (Wulder et al., 2012). Emitted light reflects off target objects and returns to the instrument, which records the distribution of returning energy over time, a waveform, to measure the range to targets. Most lidar instruments decompose these waveforms into a set of 3-dimensional points that correspond to peaks in the distribution of returning energy, known as discrete lidar data or a point cloud. Small-footprint lidar instruments sample a small area with each beam, from the millimeter to centimeter scale. In contrast, a large-footprint lidar instrument might measure a stand of trees with a single beam, capturing vertical structure in a circular footprint of tens of meters in diameter. While waveform and discrete lidar instruments record structure with the same physical system, the specific parameters of the sensor, the sampling scheme, and the data type can make a time series of lidar data from different sensors difficult to compare.

The recent launch of a spaceborne lidar instrument, the Global Ecosystem Dynamics Investigation (GEDI) lidar, presents new opportunities for monitoring forest disturbances with vertical profiles of forest structure (Dubayah et al., 2020; Hancock et al., 2019). GEDI may be particularly well suited to monitor HWA infestation impacts because of its ability to penetrate through the forest canopy and record lower canopy structural change. Large-footprint waveform lidar data like that of GEDI has proven useful for observing distinct canopy structures related to disturbances: inferring past hurricane damage (Weishampel et al., 2007), identifying developmental stages of forest plots (Harding et al., 2001; Drake et al., 2002), observing phenological cycles (Tang and Dubayah, 2017), and calculating biomass change (Dubayah et al., 2010; Huang et al., 2013).

While GEDI’s resolution could be useful for pursuing ecological research, its spatial coverage is limited by the physics of an active optical system. GEDI relies on large-footprint
(19-25 meter diameter) samples to maximize the coverage that it can achieve at the given pulse rate. Operating from the International Space Station (ISS), GEDI samples forests with 3 beams that are split into 8 parallel tracks, spaced 600 meters apart on the ground (Coyle et al., 2015; Stysley et al., 2015). Each of GEDI’s tracks samples the Earth’s surface with a waveform every 60 meters along its path. By gridding these discrete samples at the 1 kilometer scale, the mission will produce global data products of vegetation structure for regions between 51.6 degrees N and S latitude (Patterson et al., 2019).

Due to the orbital constraints of the ISS, GEDI will only be able to sense forests in the temperate and tropical regions. Forested regions will be sampled multiple times during the 2-year mission, but it is rare that GEDI footprints will overlap, making it infeasible to calculate structural change over a region with GEDI data alone. Other lidar or field datasets could be compared with GEDI to calculate change, but the geolocation accuracy of GEDI waveform data presents an obstacle to comparison. After processing, the geolocation error for each waveform is still expected to be 8-11 meters (Dubayah et al., 2020), which may be too high for accurate comparisons with individual field plots or other coincident datasets.

Fortunately, the obstacles to change detection with GEDI can be overcome with the GEDI Simulator (Hancock et al., 2019), an open-source software developed to calibrate GEDI’s data products before launch. The GEDI simulator uses discrete and waveform ALS lidar data to produce large-footprint lidar waveforms. By processing ALS data, the simulator corrects for the specific characteristics of the ALS datasets and the instruments that collected them. In addition, the simulator software provides tools for geo-locating GEDI waveforms to within 2-3m using a waveform shape-matching technique (Blair and Hofton, 1999). As long as a site has spatially overlapping ALS and GEDI data available, studies can use the
simulator to (1) geolocate GEDI waveforms, (2) simulate comparable waveforms from ALS data at the same footprint locations, and (3) output measurements of vegetation structure that are comparable between ALS and GEDI. Thus, the simulator enables the calculation of structural change for a set of ALS and/or GEDI data at the scale of a 19-25 meter footprint. If this change detection method proves viable for real GEDI data, the ecological applications of GEDI could vastly increase, enabling future studies of forest disturbance and structural change for any site with ALS data within GEDI’s coverage.

Study Design

GEDI waveforms were simulated from ALS data collected in 2012 and 2016 over a mixed temperate forest infested by HWA, the 35-hectare Smithsonian Institute Forest Global Earth Observatory (ForestGEO) plot at the Harvard Forest experimental site in Petersham, MA, USA (Orwig et al., 2015). By comparing changes in simulated waveforms over an established field site with a well-studied infestation, this study outlines a viable method for change detection in temperate forests with GEDI waveforms. It aims to extract ecologically meaningful observations of the impacts of HWA upon New England forest structure, and to test the viability of GEDI waveforms for detecting disturbance.

Methods

Overview

GEDI waveforms were simulated with the GEDI Simulator (Hancock et al., 2019) from ALS data collected by a Riegl VQ-480 sensor on the NASA Goddard Lidar
Hyperspectral and Thermal instrument (G-LiHT) in 2012 (Cook et al., 2013) and by an Optech ALTM Gemini sensor as part of the NSF funded National Ecological Observatory Network (NEON) Airborne Observation Platform in 2016 (Kampe et al., 2010). To compare waveforms between years, waveform metrics were derived with the GEDI Simulator and LibCLidar software packages (Hancock et al., 2017, 2019). The change in waveform metrics from 2012 to 2016 was calculated for each footprint (2016 – 2012 = Change). The importance of waveform metrics for observing the impacts of the HWA disturbance was assessed by relating metrics to the ForestGEO plot field data (Orwig et al., 2015). Metrics were assessed with 2 statistical methods: 1) One-way analysis of variance (ANOVA) grouped by the dominant tree species of each footprint; and 2) Logistic regression of hemlock tree mortality on the change in waveform metrics.

The analysis is divided into two sections. The first section aims to assess the utility of a large-footprint lidar simulation for comparing ALS acquisitions from different sensors and acquisition times. Waveforms are simulated without noise and at high spatial coverage to identify waveform metrics that correlate with the structural impacts of the HWA disturbance.

The second section evaluates how the noise parameters and spatial coverage of real GEDI data might obscure the relationship between waveform metrics and forest condition. Waveforms are simulated with varying degrees of noise based on pre-launch signal-to-noise estimates and at sparse spatial coverage in order to mimic the parameters of real GEDI acquisitions. Statistical relationships between waveform metrics and forest condition are reevaluated to measure the impact of noise and spatial coverage. Thus, this section tests whether the method outlined in this study could be viable for future disturbance studies with real GEDI data.
Airborne Lidar Scanner (ALS) Data

The 2 ALS data sets were collected with different sensors (Table 3.1): the Riegl VQ-480 on NASA G-LiHT (Cook et al., 2013) and the Optech ALTM Gemini on the NSF funded NEON AOP (Kampe et al., 2010 and 2016). To mitigate potential sensor biases in simulated waveform data, such as those caused by different ALS scan angle and point density distributions, an analysis was performed using waveforms that had the most similar sets of input data between years. The waveform dataset was filtered so that only waveforms with similar distributions of scan angle and pulse density in input ALS datasets would be compared. Other sensor differences, such as sensor wavelength, were not investigated in this study, since they were shown to be negligible in previous studies of simulated data (Hancock et al., 2019).

<table>
<thead>
<tr>
<th>Instrument</th>
<th>GLIHT 2012</th>
<th>NEON 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beam divergence (mrad)</td>
<td>0.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Altitude (m)</td>
<td>~300</td>
<td>~1000</td>
</tr>
<tr>
<td>Wavelength (nm)</td>
<td>1550</td>
<td>1064</td>
</tr>
<tr>
<td>Pulse Repetition Frequency (PRF; kHz)</td>
<td>300</td>
<td>100</td>
</tr>
<tr>
<td>Max Number of Returns per Pulse</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Max Scan Angle Used (degrees)</td>
<td>36</td>
<td>18</td>
</tr>
<tr>
<td>Point Density (points/m²)</td>
<td>29.9</td>
<td>6.6</td>
</tr>
<tr>
<td>Month of Acquisition</td>
<td>June</td>
<td>August</td>
</tr>
</tbody>
</table>

Table 3.1, Instrument and flight specifications of ALS data over the ForestGEO plot.

Simulated GEDI Data

Each lidar instrument has a specific footprint and pulse shape that affect the derived metrics. To prevent any differences in these properties between GEDI and ALS data, the GEDI Simulator aggregates small-footprint lidar data and convolves a large-footprint
waveform of return energy based on the vertical distribution of points within a specified footprint. Simulated GEDI data has been shown to be highly comparable with real large-footprint lidar data, having been validated with the NASA Land Vegetation and Ice Sensor (LVIS) and other large-footprint lidar instruments (Hancock et al., 2019). The simulated waveforms used in this study are structured as a sum of Gaussian components, and waveform features, such as ground elevation, are extracted following Hofton et al. (2000). Because GEDI’s ground elevation is derived directly from this smoothed waveform, there can be discrepancies between GEDI’s ground elevation and ALS ground elevation that impact derived metrics. The waveforms are plotted as height above ground against normalized intensity. The highest peak is characteristic of the forest canopy shape, while the lowest peak identifies the ground.

**Metrics**

Vertical profiles of changes in Plant Area Index (PAI) and Relative Height (RH) metrics are derived to compare waveforms between years. The PAI describes the horizontal projected area of plant elements (foliage, branches, and trunks) per unit of ground area (m²m⁻²) within a volume of canopy (Chen et al., 1997). PAI is derived from the vertical distribution of gaps within the canopy (gap fraction; \( P_{gap} \)) to PAI distribution with a widely used method (Ni-Meister et al., 2010; Armston et al., 2013; Tang et al., 2012, 2014; Dubayah et al., 2020). The PAI at any given height is calculated from waveform data with the equations:
\( P_{gap}(\theta, z) = 1 - \frac{R_v(z)}{R_v(0) + \frac{\rho_v}{\rho_g} (R_g)} \)

\[ PAI(z) = -1[ \ln(P_{gap}(\theta, z + \Delta z)) - \ln(P_{gap}(\theta, z)) ] \frac{G(\theta) \Omega(\theta)}{} \]

\( R_v(z) \) is the integral of reflected energy from canopy elements from the canopy top down to the given height (z). \( R_g \) is the integral of reflected energy from the ground. \( \Delta z \) is the height increment at which PAI is calculated. Constants are set as: a nadir view angle (\( \theta = 0 \)), a spherical leaf angle distribution (\( G = 0.6 \)), a random spatial distribution of canopy elements (\( \Omega = 1 \)), and a canopy-to-ground reflectance ratio (\( \rho_v/\rho_g \)) of 1.425.

RH metrics describe the vertical distribution of energy in a returned waveform. Heights are derived from the normalized cumulative distribution of the waveform summed from the ground to the canopy top (Drake et al., 2002). For example, \( RH10 \) is the height of a waveform at which the integral of waveform energy, from the ground-up, is 10% of the total waveform energy. Changes in RH metrics over time can be indicative of changes in canopy structure, including growth, gap formation, and disturbance (Dubayah et al., 2010). The HWA infestation is hypothesized to shift RH values lower over time in hemlock forests, as foliage loss from HWA increases canopy permeability and allows more laser energy to reach the ground. In order to compare tree stands of varying heights, PAI change was calculated at 1 meter height intervals and binned to percent height relative to the maximum canopy height recorded in 2012 (\( RH100 \)).
Field Data

The CTFS-ForestGEO plot at Harvard Forest is part of an international network of forest sites (Anderson-Teixeira et al. 2015). It is a georeferenced 35 hectare plot divided into a grid of 20 meter sided quadrats. The first census of the ForestGEO plot began in 2010 (Orwig et al., 2015), and all quadrats containing hemlock trees in the plot were found to be infested by HWA in 2012. A subset of the plot was reassessed for hemlock tree mortality in 2016 (Orwig et al., 2018). This 2016 assessment of hemlock mortality only revisited select quadrats (72 quadrats in total) in the mature hemlock area to assess tree condition. Tree condition was recorded as a binary value (alive or dead) based on the presence or complete absence of foliage.

Hemlock mortality from 2010-2016 was calculated for 39 GEDI footprints that overlapped with the area of the ForestGEO plot that was reassessed in 2016. Mortality was defined as the number of live hemlock trees that died from 2010-2016 divided by the total number of live hemlock trees within the footprint in 2010.

The times of observation of hemlock tree mortality (summer 2010 and summer 2016) are offset from the time of lidar observations (June 2012 and August 2016). This offset was unavoidable, since these data acquisitions were planned with different research goals in mind.

To compare waveform metrics by tree species, the dominant species of each GEDI footprint was derived across the ForestGEO plot with field data. Dominant species were calculated by summing the total Basal Area (BA) of each species within a lidar footprint and assigning the dominant tree species as that with the majority BA. The top 5 dominant species
used in this analysis were: eastern hemlock (Tsuga canadensis; 38% of the 560 total footprints), red oak (Quercus rubra; 32%), red maple (Acer rubrum; 16%), white pine (Pinus strobus; 8%), and red pine (Pinus resinosa; 5%). These species comprised the majority of footprints (~99%) in the ForestGEO plot. Part I: Detecting Disturbance with Waveform Lidar

Part I: Comparing ALS with the GEDI Simulator

ALS acquisitions from 2012 and 2016 were compared with the GEDI simulator to identify waveform metrics that correlate with the structural impacts of the HWA disturbance. A total of 560 GEDI waveforms were simulated within a rectangular grid for each ALS acquisition, G-LiHT in 2012 and NEON in 2016 (Figure 3.1). Simulated GEDI footprints were spaced along a 25 meter rectangular grid in order to maximize coverage within the 35 hectare ForestGEO plot (500 x 700 meters). Waveform footprints were 22 meters in diameter and did not overlap in space. Relative Height (RH) metrics at 10% energy intervals and Leaf Area Index (PAI) values at 1 meter height intervals were calculated for all footprints.

Relating Waveform Metrics to HWA Disturbance

The top disturbance metrics were assessed for their correspondence with HWA infestation condition. First, each metric was run through a one-way ANOVA with a Tukey-Kramer post-hoc test grouped by dominant species. Waveform change metrics within hemlock-dominated footprints were expected to be significantly different from those of other species, since HWA only affects hemlock trees and was ubiquitous in the field site at the time of study.
Next, field-measured hemlock condition was regressed on waveform change metrics with a logistic (logit) model. The dependent variable, hemlock mortality, was modelled with a binomial distribution. The number of live hemlocks that died from 2010-2016 represented the number of observations, and the number of live hemlocks in each footprint in 2010 represented the number of trials. Independent variables were normalized before input into the model in order to better compare coefficient magnitudes.

**Variable Selection**

A lasso regression of hemlock tree mortality was employed to identify the important variables for predicting HWA disturbance impacts. Lasso regressions were fit with the subset of 35 hemlock dominant footprints (Figure 3.1) that were assessed for hemlock mortality in 2016 and that also had comparable ground heights (less than 1 meter difference between G-LiHT and NEON waveforms). Lasso regression employs a penalty parameter, lambda, to reduce the magnitude of insignificant coefficients in a model to 0 (Tibshirani, 1996). RH and PAI change metrics at different canopy heights (42 independent variables in total) were then selected with a 10-fold cross-validation method (Friedman, 2009). Cross-validation results identified an optimal model by using the largest lambda value within 1 standard deviation of the minimum statistical deviance of all models.
Part II: Simulating GEDI Data

Simulating GEDI’s Noise

First, the effect of noise on the relationship between waveform metrics and forest condition was investigated. Gaussian noise was incrementally added to the simulated waveforms used in Part 1. The NEON 2016 waveforms were simulated without noise, while G-LiHT 2012 waveforms were simulated with varying degrees of noise. Noise was incrementally added using the beam sensitivity, a metric that describes the canopy cover at which a noised waveform would have a 90% probability of detecting the ground with a 5% probability of causing a false positive (GEDI ground height > true ground; Hancock et al., 2019). Noise was simulated from 90% to 99% beam sensitivity to cover the range of real GEDI data, estimated to be 92-99.6% beam sensitivity. Then, noised waveforms were filtered using a variable threshold set at 3 standard deviations above the mean noise value (Hancock et al., 2019), smoothed with Gaussian convolution, and PAI metrics were calculated.

A total of 11 simulations were run with the G-LiHT dataset by degrading beam sensitivity values from 0.99-0.90. An ANOVA tested the effect of species, eastern hemlock and red oak, on the PAI change of each dataset with degraded beam sensitivity.

Simulating GEDI’s Noise and Spatial Coverage

Second, waveforms were simulated with the sparse spatial coverage and average noise parameters of GEDI’s beams. Simulated GEDI tracts were acquired for the Northeastern United States region, and a set of 80 footprints (Figure 3.2) that intersected the study site were selected for further analysis. Waveforms were simulated at these 80 footprints.
realistically spaced footprint locations in the ForestGEO plot. In addition, realistic noise was added to simulated waveforms using the estimated parameters of the link margin for GEDI’s power beam at night (Link Margin = 4.956 at 95% canopy cover) and coverage beam during the day (Link Margin = -2.039 at 95% canopy cover).

The real noise parameters of GEDI will vary depending on the power of the laser beam and the time of acquisition. Of GEDI’s 3 laser beams, 2 are used at full power (power beams), while 1 is split into 2 beams (coverage beams) (Dubayah et al., 2020). Waveform noise will be lowest when the power beam is operating during the nighttime, and noise will be the highest while using the weaker coverage laser during the daytime. Noise was added to simulated waveforms to represent the best (night-power) and worst (day-coverage) scenarios of future GEDI acquisitions.

Noise was added to both G-LiHT 2012 and NEON 2016 waveforms. Change metrics were calculated relative to their noiseless counterpart (i.e., NEON 2016 noiseless - G-LiHT 2012 night-power, or NEON 2016 day-coverage - G-LiHT 2012 noiseless). An ANOVA tested the effect of species on the change in PAI 11-12m with each set of noised change metrics.
Results

Part I: Detecting Disturbance with Waveform Lidar

Simulation Results

Waveforms were simulated for 2012 and 2016 in 560 footprint locations along a rectangular grid within the ForestGEO plot. Waveforms were simulated in footprints located within hemlock stands that were assessed for mortality in 2010 and 2016 (Figure 3.3).

Footprints containing higher hemlock mortality showed increased amplitude in the ground peaks in 2016 (blue) compared to the ground peaks in 2012 waveforms (orange). The middle portion of the waveforms, from about 10-20 meters above ground, appears to have declined between years. In addition, the upper canopy tops increased slightly from 2012-2016, a change indicating growth in the overstory during this time period.

Plotting the vertical PAI profiles of healthy and infested hemlock footprints in comparison to those of red oak and red maple shows distinct mid-canopy foliage loss in hemlock dominated footprints (Figure 3.4). Plots of 4 representative footprints for each species show how a healthier hemlock footprint (with 0% mortality) displays similar increases in PAI compared to that of other species, which gained PAI from 2012-2016. In contrast, a footprint with severe hemlock mortality (36%) displays distinct decreases in PAI in its middle and lower canopy.

A plot of the vertical profile of PAI change for eastern hemlock and red oak footprints showed that the trend in PAI loss in the mid-canopy is ubiquitous within the ForestGEO plot (Figure 3.5). PAI change at 1 meter height intervals was binned to percent
height relative to the maximum canopy height recorded in 2012 (RH100). While both tree species displayed a slight loss of PAI in the lower canopy (10-40% of max height) and a gain of PAI in the upper canopy (above 70% height), hemlock dominated footprints showed a distinct loss of PAI in the mid-canopy (40-70% height).

**Variable Selection**

A series of lasso logistic regressions were used to identify waveform metrics that could be important predictors of mortality. Out of 42 independent variables, the negative changes in PAI 11-12 m, PAI 17-18 m, and RH10 were selected as optimal variables. Decreases in RH10 are indicative of increased permeability throughout the canopy, while decreases in PAI highlight foliage and branch loss at specific heights in the canopy.

All 3 variables were further evaluated in a variety of combinations, and a final model was produced with PAI 11-12 m and RH10. This model had the lowest RMSE, the highest R2, and the lowest correlation between independent variables. In a final model, the change in PAI 11-12 m and RH10 both had coefficients with significant fits (p < 0.01) of relatively equal magnitude (Figure 3.6; Table 3.2). The independent variables were not highly correlated ($R^2 = 0.07$). The variation in PAI 11-12m and RH10 explained 60% of the variation in hemlock mortality, with a predictive accuracy of 8% mortality (RMSE = 0.08).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( B_{RH10} )</td>
<td>-0.23 ± 0.08</td>
<td>0.002</td>
</tr>
<tr>
<td>( B_{PAI11-12m} )</td>
<td>-0.29 ± 0.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.89 ± 0.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.60</td>
<td>-</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.08</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3.2, Coefficients and fit of a logistic regression predicting hemlock mortality.

**Waveform Change Metrics**

Mid-canopy PAI 11-12 m change showed a loss (brown) in areas dominated by hemlocks, whereas it generally showed an increase (green) or no change (white) in footprints dominated by other tree species (Figure 3.7). In addition, areas dominated by hemlock trees showed decreases in RH10 between years, while areas dominated by healthy tree species, particularly red oak, showed positive increases in RH10 between years (Figure 3.7). Decreases in RH10 in hemlock areas are indicative of increased canopy permeability and foliage loss. In contrast, the increases in RH10 in areas of healthy deciduous trees signify growth and increased canopy cover.

To test the effect of species on waveform variables, ANOVA tests were run on 470 footprints with comparable ground heights between years (within 1 meter). There was a significant effect of species on PAI 11-12 m change (F(4,466) = 10.8, p < 0.001; Figure 3.8 and Table 3.3). A Tukey-Kramer post hoc test revealed a significant difference (p < 0.001) between hemlock and red oak, red maple, and red pine, but not with white pine (p = 0.12). There was also a significant effect of species on RH10 change (F(4,466) = 54.7, p < 0.001).
A post hoc test revealed a significant difference (p < 0.001) between the RH10 change of hemlock and that of all other tree species (Figure 3.8 and Table 3.4).

The ANOVA results indicate that unique structural changes are occurring in infested hemlock stands, demonstrated by a loss of PAI at 11-12 m and a decrease in RH10. These distinct changes even separate infested hemlock stands from stands of evergreen trees of similar structure, such as white pine and red pine.

<table>
<thead>
<tr>
<th>Species</th>
<th>Median</th>
<th>Mean</th>
<th>N</th>
<th>Post-Hoc p-value from Hemlock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemlock</td>
<td>-0.072</td>
<td>-0.064 ± 0.012</td>
<td>186</td>
<td>-</td>
</tr>
<tr>
<td>Red Oak</td>
<td>0.001</td>
<td>0.020 ± 0.013</td>
<td>138</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Red Maple</td>
<td>0.003</td>
<td>0.041 ± 0.017</td>
<td>82</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>White Pine</td>
<td>-0.020</td>
<td>0.001 ± 0.025</td>
<td>40</td>
<td>0.15</td>
</tr>
<tr>
<td>Red Pine</td>
<td>0.051</td>
<td>0.057 ± 0.031</td>
<td>25</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Table 3.3, ANOVA and post-hoc test results of change in PAI 11-12 m by species

<table>
<thead>
<tr>
<th>Species</th>
<th>Median</th>
<th>Mean</th>
<th>N</th>
<th>p-value from Hemlock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemlock</td>
<td>-0.085</td>
<td>-1.563 ± 0.263</td>
<td>186</td>
<td>-</td>
</tr>
<tr>
<td>Red Oak</td>
<td>3.610</td>
<td>4.200 ± 0.305</td>
<td>138</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Red Maple</td>
<td>0.995</td>
<td>2.166 ± 0.396</td>
<td>82</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>White Pine</td>
<td>2.070</td>
<td>2.507 ± 0.567</td>
<td>40</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Red Pine</td>
<td>1.760</td>
<td>1.695 ± 0.717</td>
<td>25</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Table 3.4 ANOVA and post-hoc test results of change in RH10 by species.

_Evaluating Potential Sensor Bias_

Scan angle and point density distributions differed greatly between both sets of input data. G-LiHT ALS data had a greater range of scan angles per footprint (max scan angle of 36 degrees in G-LiHT vs. 18 degrees in NEON), as well as a higher average point density per footprint (29.6 points per m2) compared to NEON data (6.8 points per m2; Table 3.1).
To mitigate potential biases caused by the different scan angle and point density distributions in the input ALS datasets, the PAI 11-12 m change was compared by species (hemlock, red oak, red maple, and white pine) for a subset of footprints with the most similar distributions of input data. When the data were subset to 157 footprints (1/3 of the dataset) with similar scan angle distributions, an ANOVA with Tukey-Kramer post-hoc tests still found significant differences between hemlock and red oak, red maple, and white pine (p < 0.05). When the data were subset to those with similar point density distributions, PAI 11-12 m changes in hemlock footprints were also significantly different from those of red oak, red maple, and white pine (p < 0.05). These results reinforce the findings of this study, showing that the changes observed in waveform variables are not the result of sensor differences, but rather, have ecological origins.

Part II: Simulating GEDI Data

*Simulating GEDI’s Noise*

An ANOVA test was performed upon a series of noised files to test the effect of species (hemlock and red oak) upon PAI 11-12 m change with added noise. For beam sensitivities 0.99-0.94, there was a significant effect of species on PAI change on the 3 dominant species tested (p < 0.05; Figure 3.9). At beam sensitivities below 0.94, dominant tree species were not significant as a grouping factor. The mean canopy cover of these footprints was 0.90 ± 0.18.

Dominant tree species reacted differently to added noise. This variability can be illustrated by plotting the proportion of false-positive ground returns in noised GEDI data by
dominant species (Figure 3.10). A false positive was defined as the number of instances in which GEDI finds ground to be >1m above ground compared to the ground determined by ALS. Different species accumulate errors at different rates with added noise, likely a result of their structural properties of their canopies. With added noise, hemlock footprints tend to accumulate a higher proportion of false-positive ground returns than do other species, indicating a higher rate of failure to penetrate the canopy and reach true ground.

### Simulating GEDI’s Noise and Spatial Coverage

Next, the realistic spatial coverage of GEDI and the noise parameters of the best (night-power) and the worst (day-coverage) signal-to-noise ratio scenarios of GEDI were applied. When G-LiHT 2012 waveforms were degraded with GEDI’s noise parameters and spatial coverage, the PAI change of waveforms using the power beam at night were significantly different by species (night-power: F(2,60) = 6.79, p = 0.002), while waveforms using the coverage beam during the day were not significantly different (day-coverage: F(2,32) = 0.43, p = 0.65; Figure 3.11 and Table 3.5). In the night-power scenario, there was a significant difference between the PAI change of hemlock and red oak (p = 0.002) and between that of hemlock and red maple (p = 0.03). In the noisier day-coverage scenario, there was no significant difference between hemlock and red oak (p=0.66), nor with red maple (p=0.96).

When NEON 2016 waveforms were degraded with GEDI’s noise parameters, waveforms using the power beam at night could be separated by species at the 5% significance level (night-power: F(2,58) = 5.39, p = 0.007), while waveforms using the coverage beam during the day could not (day-coverage: F(2,24) = 1.47, p = 0.25; Table 5).
the night-power scenario, there was a significant difference between hemlock and red oak (p = 0.02), as well as hemlock and red maple (p = 0.02). However, again in the day-coverage scenario, there were no significant differences between hemlock and red oak (p = 0.62), nor with red maple (p = 0.27).

With night-power GEDI waveforms, the effect of species explained 19% (NEON as GEDI) and 16% (G-LiHT as GEDI) of the variation in PAI 11-12m, compared to the 22% of variation explained by noiseless waveforms. In contrast, species did not account for a large proportion of the variance in day-cover waveforms (3% for G-LiHT as GEDI, and 11% for NEON as GEDI).

<table>
<thead>
<tr>
<th></th>
<th>Day-Coverage Noise</th>
<th>Night-Power Noise</th>
<th>Noiseless</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>G-LiHT 2012</td>
<td>NEON 2016</td>
<td>G-LiHT 2012</td>
</tr>
<tr>
<td>F-statistic</td>
<td>0.43</td>
<td>1.47</td>
<td>6.79</td>
</tr>
<tr>
<td>p-value</td>
<td>0.65</td>
<td>0.250</td>
<td>0.002</td>
</tr>
<tr>
<td>η²</td>
<td>0.03</td>
<td>0.11</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Table 3.5, ANOVA results of PAI 11-12 m with GEDI’s noise and spatial coverage.
Discussion

Overview

This study evaluates the ability of above-canopy lidar sensors, including the newly launched GEDI spaceborne lidar, to detect distinct changes in canopy structure brought about by an invasive insect infestation in a temperate New England forest. ALS datasets acquired with different lidar instruments, with varying pulse densities and scan angles, were successfully compared at the scale of a large-footprint lidar instrument (22 m diameter) with the GEDI simulator (Hancock et al., 2019). Waveform metrics were significantly correlated with the hemlock crown condition of HWA infested forest quadrats. The unique structural changes identified by this study, particularly the PAI loss in the midstory and the increased permeability of the canopy indicated by RH10 change, reveal the utility of lidar data for detecting the unique lower canopy impacts of the HWA disturbance.

The relationship between lidar metrics and forest condition also held true when ALS and simulated GEDI waveforms were compared, provided that the acquisitions were high quality: greater than 0.93 beam sensitivity or with the power beam at night. While these analyses are limited to specific datasets and environmental conditions, they outline a viable method for change detection and disturbance monitoring with real GEDI data for any temperate field site with spatially coincident lidar datasets.

The Structural Impacts of Hemlock Woolly Adelgid

Analysis with lidar waveforms confirmed that initial HWA impacts occur in the middle canopy and understory of hemlock-dominated forests. The loss of PAI at 11-12 meters above
ground and the drop in RH10 from 2012-2016 were both found to be significantly related to hemlock tree condition.

The change in PAI at 11-12 meters successfully distinguished infested hemlock quadrats from those of other healthy tree species, including evergreen species such as white pine that might be expected to be of similar structure. Vertical profiles of PAI change showed that that the upper and lower portions of hemlock canopy are similar to those of a healthy deciduous species, red oak, while the middle portion of the canopy (40-70%) reveals a signal of structural change that is unique to hemlocks. Long-term observations in infested hemlock quadrats in southern New England corroborate these results, documenting foliar loss initially in the lower and central portions of tree crowns, then on interior branches and exterior branch tips, and finally at the top of the crowns (Orwig et al. 2002).

The change in RH10 also had a strong correlation with HWA impacts. The negative change in RH10 in infested hemlock quadrats indicates that more laser energy was able to pass through the canopy and trigger a ground return of higher amplitude. This finding supports the hypothesis that the HWA infestation increases canopy permeability through defoliation. The importance of RH10 as a disturbance metric corresponds with the findings of other studies with large-footprint lidar data (Dubayah et al., 2010) that linked positive changes in RH metrics with canopy growth and negative changes in RH metrics with canopy loss.

Waveform metrics were also able to model the condition of hemlock stands in the ForestGEO plot. The strong correlation ($R^2 = 0.60$) between forest condition and the change in $PAI_{11-12m}$ and $RH10$ further suggests that the HWA infestation produces unique structural impacts that could be exploited to monitor the insect infestation at a regional scale.
The most important indicators of the HWA disturbance in lidar waveforms were found in the mid-canopy and near the ground. However, growth in the overstory was also seen in hemlock dominated plots with severe mortality.

Clearly, some large trees in infested hemlock quadrats are continuing to grow. Potentially, this growth is led by dominant, less impacted trees that are taking advantage of the new resources made available by the HWA infestation. The healthiest foliage remains at the top of the tree and if not yet severely impacted by HWA, conditions are still adequate for canopy growth in some trees. Growth in the upper canopy could also be indicative of a ramping up of production in response to the stress of the insect, as has been observed in individual hemlock trees by Domec et al. (2013). Another possible explanation is that eastern white pine trees (*Pinus strobus*) within the infested hemlock stands are growing rapidly and taking a more dominant position in the canopy. Whatever the ecological driver may be, this finding makes an argument for monitoring studies to rely on measurements from the entire profile of forest canopies, rather than solely on top-of-canopy metrics.

Subsequent and predicted forest dynamics could also pose a problem for the lower RH metrics used in this study. While RH10 has been found to be significant predictor of HWA impacts, this metric could be potentially be confounded by the growth of understory plants that compete for the light and space in the aftermath of forest disturbances (Oliver, 1981). The distinct signal of a drop in *RH10* during initial stages of the infestation could be dampened by understory growth, which would have the effect of raising or negating change in *RH10*. Rapid birch establishment is commonly a part of vegetation dynamics following HWA infestation in New England (Orwig and Foster, 1998; Stadler et al., 2005) and birch seedlings are already starting to become established in the impacted areas of the ForestGEO.
plot (Orwig et al. 2018). Since RH metrics rely upon the entire distribution of energy in a waveform, they may be increasingly impacted by these dynamic changes, gains and losses, along the vertical profile of the forest canopy.

**Toward Change Detection and Disturbance Monitoring with GEDI**

The general method applied in this study for monitoring the HWA disturbance could be expanded to other disturbances in temperate or tropical forests around the world with GEDI data acquisitions. If ALS data is available for the site of interest, GEDI waveforms can be geolocated and ALS waveforms can be simulated for comparison with real GEDI data. Structural change along the entire vertical profile of the canopy can be calculated for individual GEDI waveforms between time points: the instance of GEDI acquisition and that of the ALS data. With additional field data on forest condition and canopy structure, a model could be trained to classify forest condition for a wide area.

This simulation study had the advantage of control over the noise parameters, sampling coverage, and location of the GEDI waveforms. Results of noise analyses showed that GEDI waveforms with beam sensitivities of greater than 0.93 and data acquisitions made at night with the power laser are suitable for monitoring HWA in forests with comparable structure (mean canopy cover of 0.90). However, night-power waveforms had different capabilities depending on which input ALS data was degraded with noise. For instance, the effect of species on PAI change was more significant when using noisy NEON waveforms and noiseless G-LiHT waveforms, compared to using noiseless NEON and noisy G-LiHT (Table 3.5). This result suggests that even high-quality GEDI data will react differently when compared to specific datasets in other environments. Future studies will need to develop their
own quality thresholds to fit the structural complexity of the target site, the ALS datasets being compared, and the tree species of interest.

Forests with different structures and species compositions will vary in their sensitivity to noise, but hemlock forests seem to be particularly affected. Added noise caused hemlock stands to accumulate ground errors at a faster rate than those of other species. This difference is likely due to the unique structural properties of hemlock stands, including their dense canopy covers. Regardless, this study showed that the HWA disturbance could be detected despite the accumulation of ground error with added noise. However, future studies could easily adjust for these errors by using the true ground elevation from coincident ALS datasets.

The sparse spatial coverage of GEDI also posed an issue for the regression model used in this study, since only 8 footprints overlapped with the western portion of the ForestGEO plot that was sampled for mortality in 2016. However, had the entire 35 hectare ForestGEO plot been resurveyed in 2016, enough training data may have been available to fit an initial model (21 hemlock dominated footprints). Future studies with GEDI data would benefit from drawing on large field plots, such as the entire 35 hectare ForestGEO plot and others in the CTFS network (Anderson-Teixeira et al., 2015), and focusing on sites with the highest density of high quality GEDI shots, such as those locations planned for GEDI’s validation studies.

**Conclusion**

By linking the change in simulated GEDI waveforms with the deteriorating condition of hemlock stands in a New England forest, this study highlights how a time series of lidar
waveforms can capture structural change and classify disturbance. The GEDI Simulator (Hancock et al., 2019) successfully enabled an analysis of structural change between ALS datasets and simulated GEDI data. Lower canopy PAI and RH metrics from simulated GEDI waveforms emerged as significant predictors of the severity of the HWA infestation. In addition, overstory growth was observed in infested hemlock plots, revealing that infested stands are undergoing a complex shift in the vertical distribution of leaf matter, with loss in the lower canopy and growth in the upper canopy. These structure-condition relationships held true even when the quality of GEDI waveforms was degraded with noise and the sparse coverage of GEDI acquisitions was applied.

GEDI data is just becoming available, and it will continue to be collected and released over the course of the next 2 years. Following the method of this study, a time series of ALS data and/or GEDI data can be compared for other forested sites and disturbances. The findings of this study open up new opportunities for ecological research and disturbance monitoring in temperate and tropical forests around the world.

By predicting forest condition with temporal changes in waveform metrics, instead of focusing on a single year of data collection, this study was able to reduce excess variation that arises from differences in the species compositions and structures of forest plots. While there is a strong relationship between forest structure and condition in this study, there are still residuals in predictions of mortality that warrant further investigation. These residuals may arise because of discrepancies between lidar observations of forest plots and the records of forest plots recorded in field data. With a better understanding of how lidar metrics are impacted by variations in field data, these residuals could potentially be minimized.
Furthermore, field data remain invaluable to the evaluation of airborne or spaceborne determinations of change and disturbance. Both traditional forestry measures and terrestrial lidar scanning (TLS) can support these studies with detailed characterizations of forest environments. In particular, with its unique view of the understory and lower levels of the canopy, TLS could focus on forest structures that are less accessible to airborne and spaceborne lidar. However, the use of TLS data also requires a thorough understanding of how these data differ from traditional forestry measures. In support of future airborne, spaceborne, and field missions, the following chapter explores new methods for sampling forests with TLS.
Figure 3.1, Simulated footprint locations within the ForestGEO plot.

A grid of 22 meter diameter footprints, spaced 25 meters apart, is laid out within the boundary of the ForestGEO plot. Footprints used in the logistic (logit) model of hemlock mortality are highlighted. Footprints are overlaid a 1 meter resolution canopy height map derived from the G-LiHT 2012 ALS data. The map is rendered in WGS-84 UTM 18N.
Figure 3.2, Simulated GEDI acquisitions within the ForestGEO plot.

These 80 footprints were produced from the pre-launch simulated orbits of GEDI over New England. Footprint locations are spaced to mimic the real parameters of GEDI’s spatial coverage. Each set of footprints corresponds to a different GEDI acquisition time, although all acquisitions were combined and treated as one time-step in this analysis.
Figure 3.3, Simulated GEDI waveforms from G-LiHT 2012 and NEON 2016.

Simulated waveforms from G-LiHT 2012 and NEON 2016 from the mature hemlock section of the ForestGEO site are plotted by above-ground height. Plots are titled and sorted by the live hemlock mortality within the footprint of each waveform (ex: 0.1 = 10% mortality from 2012-16). An increase in the amplitude of ground returns can be observed in 2016 waveforms (blue) compared those of 2012 (orange), a trend associated with the severity of hemlock mortality.
Figure 3.4, Examples of Hemlock, Red Oak, and Red Maple PAI Change by Height.
Figure 3.5, Profiles of hemlock and red oak PAI change by % height to max.

Vertical profiles of PAI Change for footprints dominated by hemlock (N=176) and red oak (N=213) follow similar trends in the lower and upper canopy, but not in the mid-canopy. Both hemlock and red oak follow similar trends of loss of PAI from 10-40% height and gain in PAI above 70% height, while hemlock displays a distinct pattern of PAI loss at 45-70% height. To make the PAI change comparable between plots of different heights, PAI is calculated at 1 meter height intervals and binned to percentile heights, relative to the max height observed in 2012.
A logistic regression modelled proportional hemlock mortality with PAI change at 11-12m and RH10 change from 2012-2016, accounting for 53% of the variation in mortality. Hemlock mortality was treated as a binomial variable, with the number of live trees in 2010 that died in 2016 being as an observation and the total number of live hemlock trees in 2012 in each footprint as the number of trials. Correlation between the independent variables was low (R2 = 0.03). Variables were z-score normalized before modelling for comparability.
Figure 3.7, Dominant species cover, change in PAI 11-12 m, and change in RH10 in ForestGEO plot footprints.

The dominant species cover per GEDI footprint (top) compared to plots of change in PAI 11-12m (middle) and RH10 (bottom) from 2012-2016 over a grid of footprints in the 35 hectare ForestGEO plot. A negative RH10 change (shift down in 2016: brown) occurs within the infested hemlock area (western portion of the plot), while a positive RH10 change (shift up in 2016, green) appears to be associated with healthy hardwood areas (center of the plot). Losses of PAI (brown) also highlight hemlock dominated footprints, while deciduous tree species display primarily no change (white) or gain in PAI (green) in the mid-canopy. The swamp, near the center of the site and dominated by red maple trees and shrubs, shows comparatively little to no change in structure between years.
Figure 3.8, Change in PAI 11-12m and RH10 by dominant species.

Dominant tree species are compared by PAI change (top) in the midcanopy and RH10 change (bottom). When footprints were subset to those with comparable ground heights (within 5 meters), a one-way ANOVA with a Tukey-Kramer post-hoc test showed a significant difference between the rank sums of PAI change and RH10 change of hemlock dominated footprints and those of Red Oak, Red Maple, White Pine, and Red Pine. Species boxplots are colored by their significant difference from hemlock (magenta; p<0.05), as determined by the post-hoc test.
Figure 3.9, G-LiHT 2012 as GEDI with varying beam sensitivities.

F-test results are plotted against depreciated beam sensitivity values (x-axis). Higher beam sensitivities represent higher quality data files with little added noise, while lower beam sensitivities represent low quality data with larger amounts of added Gaussian noise. At the 5% significance level, the effect of species as a grouping factor stops becoming significant below a beam sensitivity of 0.94.
Figure 3.10, GEDI’s proportion of false-positive ground returns by dominant species.

A scatter plot with smoothing spline curve fits illustrates the accumulation of false-positive ground returns in GEDI data with varying beam sensitivities. Hemlock dominated footprints tend to accumulate ground errors at a higher rate than that of other species.
Figure 3.11, ANOVA with simulated noise and spatial coverage of GEDI data.

Boxplots of PAI change at 11-12m are plotted by species for best (night-power) and worst (day-coverage) case scenarios of GEDI’s noise parameters and laser power. Noise was added to one dataset at a time and change metrics were calculated in comparison to a noiseless set of waveforms. The analysis used 80 footprints laid out in the sparse spatial coverage of real GEDI footprints in the ForestGEO plot. Species boxplots are colored by a significant difference from hemlock (magenta; p<0.05), as determined by post-hoc tests.
CHAPTER 4

SAMPLING STRATEGIES FOR CAPTURING
FOREST STRUCTURAL VARIATION
WITH TERRESTRIAL LASER SCANNING (TLS)

Introduction

Terrestrial lidar scanning (TLS) instruments are anticipated to revolutionize forest inventory and ecological analysis by bringing automation to the standard survey methods in forestry and ecology (Danson et al., 2018). In the past, foresters relied on a variety of instruments and survey techniques for recording the distributions of stem count, tree species, tree size, and timber volume over a large forested area (Wenger, 1984), and TLS technology seems poised to continue this trend. However, the transition from human-based survey practices to automated surveys with lidar instruments still poses uncharacterized uncertainties. Many of the properties that make TLS so promising for large-scale forest characterization: their speed, consistency, and the detail of the data captured, may also be masking biases that beckon further investigation.

TLS are also active instruments that record the structure of their surrounding environment by emitting pulses of light with a near-infrared laser. A typical pulse-based TLS instrument operates by line-of-sight, rotating from a fixed position and emitting pulses at set
of vertical and horizontal angular steps to generate a hemisphere of samples (Calders et al.,
2014; Paynter et al., 2016). Pulses reflect off targets in the surrounding environment and
return to the instrument, which measures the distribution of returning energy over time,
known as a lidar waveform. To conserve memory, TLS instruments often store waveforms as
a set of discrete points with x, y, and z coordinates (a point cloud) that correspond to the
peaks of energy in the returning waveforms. Depending on the instrument, millions of points
can be derived from a few minutes of scanning, enabling the rapid assessment of the structure
of forest environments.

TLS instruments have been compared to standard forestry tools, such as wedge
prisms, relascopes, and dendrometers because of their fixed position, line-of-sight sampling
technique (Strahler et al., 2008; Newnham et al., 2015). However, TLS and human surveyors
have critical differences in the way they observe stems in a forest. Often, surveyors are sent
to conduct “timber cruises,” surveying a large-area of forest by sampling from a series of
fixed positions around a forest (Wenger, 1984). At a sample location, a surveyor would rotate
360 degrees and count the number of trees of a designated size and distance from their
position. A series of these measurements allows a surveyor to estimate the volume of timber
in the forest as well as the variation in structure that might be indicative of forest age and
ecotype. Up to this point, this process is very similar to that of sampling with a TLS
instrument. After taking each sample, however, surveyors are encouraged to move from their
fixed position to count trees that may have been obscured by foliage, understory, or trees in
the foreground (Wenger, 1984). While TLS instruments can make discrete samples of forests
in a similar manner, they do not have the flexibility of human surveyors to slightly adjust
their position and investigate occluded areas of their surroundings. TLS can only assess their

105
environment via straight-line paths originating at their optical center and cannot adjust for missed information on-the-fly. In their current design, TLS instruments will always miss information due to occlusion by the trunks of trees and foliage in the foreground. In order to capture these additional details in forests, TLS would require both multiple scan angles and high scan densities. For this reason, some studies have discouraged the use of TLS as a surveying instrument (Newnham et al., 2015). However, by modelling occlusion and correcting for its bias in TLS data, TLS data can potentially be repurposed as a surveying instrument.

Occlusion in scan data is not only dependent upon the structure of the environment, but also upon the resolution, range, and accuracy of the lidar instrument. In particular, two instrument parameters can cause instruments to be particularly sensitive to occlusion: the angular resolution, which determines the distance between each emitted pulse, and the beam divergence, which determines the width of the footprint of the emitted pulse as it travels from the scanner.

The operator of a TLS instrument could account for the impacts of occlusion by adjusting the instrument position and sampling pattern, but the interaction of scanner and its environment poses a complex problem that is difficult to adjust for in the field. Most TLS studies have relied on plot-based sampling strategies that treat a set of small areas (plots) as samples to represent the structure of the larger environment. Practitioners usually scan plots with a standardized pattern, usually a square grid, in attempt to maintain consistency between plot samples (Wilkes et al., 2017; Newnham et al., 2015). Plot-based sampling in forestry relies on the assumption that all the information in a plot (such as the stems count, tree species, foliage distribution, etc.) can be observed with equal weight and without omission so
that the metrics of the plot can be scaled up to represent the metrics of a larger area. While
this assumption might be more true for human observers, it does not hold true for TLS plot-
based sampling, where the distribution of information is limited by the line-of-sight of the
scan positions and is biased by occlusion.

Recently, studies have begun to explore sampling techniques that can change in
response to their environment. Abegg et al. (2017) modelled the effect of scanner positions
on a variety of tree structures, producing a set of ideal plot-based sampling strategies. Other
studies have identified the need for dynamic sampling techniques that can quantify missed
information on the fly, potentially enabling an operator to adjust for occlusion as they scan
(Paynter et al., 2016; 2018). Sampling techniques for large-area characterization with TLS
are an ongoing field of research, and more work is needed to understand how the interaction
between a particular TLS instrument and its environment impacts derived forestry metrics.

Therefore, the present study aims to address 2 related research questions about
producing a representative sample of an area of unknown forest structure with TLS scans.
First, can the biases in current TLS sampling methods be accounted for? To address this
question, forestry metrics derived from simulated and real TLS scans are compared to field
data at the Harvard Forest ForestGEO site in order to uncover trends in TLS observations of
stem density, tree diameter at breast height (DBH), and tree species abundances. Second, can
TLS sampling strategies be improved in order to account for biases and to better represent
forest structure in an area of interest? To address the second question, 3 sampling strategies
are evaluated for their ability to capture the distributions of stem density, size, and species
abundance of an area of interest (AOI). By comparing TLS derived forest metrics to a
detailed field dataset, this study develops methods for correcting bias in TLS measurements.
and produces recommendations for surveying large areas of forest with various TLS instruments.

Methods

This study was concerned with the ability of TLS to capture a representative sample of stem count, size, and species across the AOI in the ForestGEO plot. It did not focus on the direct measurement of these properties from TLS data, such as directly classifying species or measuring diameters from point clouds. Instead, it solely focused on the samples of the stems that were observed by TLS. Thereby, this study compared the sample population of TLS stems to the true population of stems within the ForestGEO plot.

The study was split into 2 parts. The first part of this study aimed to characterize the relationships between the information content of real and simulated TLS scans and field data. The second part evaluated how sampling strategies with TLS can capture the population statistics of stems within an AOI as well as within the local vicinity of the scans.

Part I: Biases in TLS Observations of Forests

Overview

Part 1 utilized 294 scan locations collected along 3 transects to compare forest metrics derived from TLS scans to simulated data and field data. The stem count, density (stems per m²), size (DBH in centimeters), and species abundances observed by the TLS scanner were compared.
The DBH and species of stems was not directly derived from TLS point clouds. Rather, the information content of TLS scans was compared to that of field data. Stems identified in TLS scans were matched to field stems with a stem detection algorithm. Then, the size and species abundances of the stems observed by TLS were compared to those of field data within a 40 meter radius of the scanner position, the maximum range of the TLS instruments primarily used in this study (Paynter et al., 2016). Relying on the field data for forest metrics allowed the analysis to focus on the difference in information content between TLS and field data, rather than on errors in the derivation of forestry metrics from point cloud data. This approach ensured that biases in TLS forest metrics were solely the result of occlusion.

To correct for biases in TLS observations of stem count, TLS stem densities were calculated by estimating the observed area of a scan directly from point cloud data. Stem densities were produced by dividing the number of stems observed by the estimated area sampled by each scan. A variety of methods for deriving observed area from point cloud data were evaluated for their correspondence with field data.

Site

Field data were obtained for the 35 hectare CTFS-ForestGEO plot (Anderson-Teixeira et al., 2015) at the Harvard Forest and Long Term Ecological Research (LTER) site in Petersham, MA, USA. Since 2010, every stem in the ForestGEO plot with a diameter greater than 1 centimeter has been documented in a dataset of over 116,227 stems (Orwig et al., 2015). The 500x700 meter area is divided into a grid of 20x20 meter plots, with a marker
placed every 10 meters. This extensive grid provided an ideal space to geo-reference TLS scan positions and to compare TLS with field data (Orwig et al., 2018).

The ForestGEO plot is a mixed temperate forest composed of a distinct set of forest structures and compositions. The upland areas are primarily dominated by eastern hemlock (*Tsuga canadensis*; 22.2% of all stems) and red maple trees (*Acer rubrum*; 12.6%), while a lowland swamp to the northeast of the plot’s center is dominated by winterberry holly (*Ilex verticillata*; 15.5%).

**TLS Data**

TLS data were collected with the Compact Biomass Lidar (CBL) in August 2017. The CBL is a portable, rapid-scanning instrument that creates a point cloud in a 33-second scan (Paynter et al., 2016). Its beam divergence is 0.4 milliradians, which is large compared to most other TLS instruments. The CBL is capable of registering multiple returns from a single pulse, and both 1st and 2nd returns were kept in this study’s analysis. Its maximum range is 40 meters. All scans were levelled to ground and aligned to true north along the ForestGEO plot grid. Unless otherwise mentioned, “TLS data” refers to data collected by the CBL in this study.

CBL scans were taken every 5 meters along 3 transects. The transect along column 8 followed a North-South trajectory in the western portion of the ForestGEO plot, the row 23 transect traversed East-West near the northern edge of the plot, and the column 29 transect travelled South-North along the eastern portion of the plot. Transects were placed to capture a horseshoe-shaped Area Of Interest (AOI) that is defined in the second section of the analysis.
The CBL data were also compared with 9 scans from high-resolution TLS data collected with the Leica BLK360 to test the trends observed in TLS stem detection. The Leica BLK360 collected data at a higher angular resolution (<0.2 milliradians) and with a smaller beam divergence that gives it a higher accuracy (4 mm accuracy at 15 m range) than that of the CBL. These 9 high-resolution TLS scans were obtained on a 10 meter grid within a single 20 meter quadrat (plot 1024) in the ForestGEO plot.

*Stem Detection*

Stem detection was performed with a simple, conservative algorithm designed to have a low rate of false-positive detections. First, TLS point clouds were sorted by horizontal and zenith angles. Then, the algorithm iterated through TLS returns near the optical plane, searching for vertical stacks of points with similar zenith angles. Vertical stacks of points were recorded as stems if they were composed of at least 10 points within 5 centimeters horizontal distance from each other, and if they could be matched within 0.5 meters to a stem in the field data.

*Simulated TLS Data*

TLS data can miss forest stems due to occlusion by foliage and understory plants in the foreground of the scanner position. Offsets between the scanner position and field data can also produce errors when comparing TLS and field metrics. To control for the impacts of these field conditions, TLS data was simulated at every scan position in the ForestGEO plot. Simulated TLS scans followed the line-of-sight sampling method of the real TLS scans, and were impacted by occlusion from the trunks of stems at the optical height of the instrument.
but not by the foliage, understory plants, or geolocation errors. In addition, simulated scans tested a range of angular resolutions to evaluate how scan angles impacted stem detection and occlusion.

TLS scans were simulated in the 2-dimensional space of the field stem maps with a method that mimicked the data collection of real TLS scanners. TLS pulses were represented by vectors that originated at the center of the scan position and traversed a straight-line path to the 40 meter range of the instrument (Figure 4.1). These simulated pulses were emitted at various angular steps (0.01-0.5°) as they rotated 360° around the scan center, representing the horizontal angular resolutions of high and low resolution TLS instruments.

The simulator modelled the impacts of occlusion from field stems at the optical plane of the instrument. Stems were placed in the simulated scans according to their position and diameter in the field data. Each stem was represented as a flat target, a straight-line centered at the position of the field stem with a length corresponding to its diameter. Stem axes lay perpendicular to a vector originating from the scanner origin. Stems in the foreground of the simulated scan were allowed to occlude trees in the far-field. If a single simulated pulse hit a stem along its trajectory without hitting another first, the stem was marked as observed. Otherwise, stems were marked as occluded, either because they were missed by the angular steps of the simulated scan, or because pulses were blocked by stems in the foreground.

Pulses had no width as they travelled from the scanner origin and could only interact with stems that were directly in their line of sight. Thus, the beam divergence of simulated scans was modelled to be infinitesimally small. In reality, the footprint of a TLS pulse expands as it travels. As a result, even the highest quality TLS instruments sample a volume of space with a single pulse rather than a discrete vector, leading to the diminished positional
accuracy of targets with added distance from the scanner. The simulated data in this study thus represents scanning with an ideal instrument, with pulses that are perfectly accurate at high angular resolutions. While conical beams do provide real TLS scanners with a slightly higher observation density than is simulated here, this ideal model closely approximates the performance of high-resolution TLS instruments with small beam divergences in an environment without obstructions or occlusion from understory.

Part II: Sampling Strategies for TLS

Overview

The second section of the study evaluated how the information collected by a series of TLS scans corresponded with the global statistics and the local variation of a sampled area of forest. TLS data were originally collected with the CBL (Paynter et al., 2016) in the ForestGEO plot with 3 additional sampling strategies in August 2016 and 2017. Figure 4.2 displays the patterns of the 3 sampling strategies overlaid on the ForestGEO plot stem map (black) and the area of interest (AOI; dark blue). The AOI encapsulated a particular forest type dominated by eastern hemlock trees while also avoiding a swamp near the center of the plot. Its irregular shape is characteristic of that of a real land survey in a fragmented rural landscape.

The Transect sampling strategy (magenta) employed 2 North-South transects and 1 East-West transect for a total of 294 scans, spaced 5 meters apart along a cardinal direction. Each transect location was randomly selected using the established columns and rows of the ForestGEO plot and the boundaries of the AOI.
The Grid sampling strategy (*light blue*) consisted of 323 total scans within the AOI. Grid scans were collected at the center of the established 20 meter plots. The coverage of Grid scans represented a majority of the plots (82%) within the AOI.

The Plot sampling strategy consisted of 74 TLS scans collected on a 5 meter square grid at 3 randomly chosen 20 meter plots in the AOI. Only the stems observed within the boundaries of the 3 plots were used in the derivation of Plot forest metrics. The Plot sampling strategy has traditionally been used in the majority of TLS studies (Newnham et al., 2015). The Plot strategy ensures highly detailed point clouds by scanning single plots from a variety of angles. However, the plot strategy covers less area in the AOI than the other sampling methods.

**Evaluation of Sampling Strategies**

First, each sampling strategy was evaluated for its ability to capture the global population statistics of stems in the AOI. Statistics were derived from the distributions of stem density, DBH, and species abundances for each sampling method. The mean, median, standard deviation, maximum, minimum, and range of each forest metric were compared to the statistics of field stems in the AOI. For each sampling strategy, a Kolmogorov–Smirnov Test (KS Test) for similarity of distributions (KS Test; Massey 1951) compared TLS observations of stem density, DBH, and Simpson Diversity Index (Simpson, 1949) to all field stems within the AOI. The KS Test compared distances between the cumulative probability distributions of TLS and field data to determine whether there was a significant difference between the distribution shape and scale.
Second, the Transect and Grid sampling strategies were evaluated for their information gain per unit effort (one scan) and their ability to approach the local field mean. The local field mean in this section was defined as the mean of all field stems within a 20 meter radius of scan positions.

The stem density, DBH, and Simpson Diversity Index were then also compared for Transect and Grid sampling methods with a moving mean. Each of the 3 transects was evaluated separately by calculating a moving mean along the trajectory of the given transect. With each step (one scan) along the trajectory, new observations of stems were accumulated and the mean forest metrics were calculated. A similar method was followed for the Grid scans, but without a fixed trajectory. Instead, the order of Grid scans was randomly shuffled 100 times, and the mean of all 100 iterations with a 95% confidence interval (from a student’s T-distribution) was calculated for each step.

Testing the Impact of Size Class on TLS Observations

To test if TLS observations did better at representing larger size classes of field data, a series of KS Tests compared distributions of Grid scans to those of field data, with the minimum threshold for tree size in field data iterated from 5 cm to 35 cm. For each size class, the order of Grid scans was shuffled 500 times, and KS Tests were run on each iteration to compare sets of 5, 10, 50, 100, 150, 200, 250, 300, and 325 scans to the field data DBH distribution of the AOI. Thus, the proportion of the 500 KS tests that resulted in significantly similar results could be calculated. This proportion is akin to the probability of achieving the correct distribution of field stem size with successive numbers of TLS scans.
Results

Part 1: Biases in TLS Observations of Forests

Stem Counts

Both TLS instruments had mean stem counts that were an order of magnitude lower than simulated TLS scans (Table 4.1). The dramatic difference between real and simulated stem counts signifies the strong influence that occlusion has upon scan data.

<table>
<thead>
<tr>
<th>Stem Count [stems per scan]</th>
<th>Field (40 meter radius)</th>
<th>Simulated High Angular Res. (0.001°)</th>
<th>Simulated Low Angular Res. (0.25°)</th>
<th>TLS Low Res. (CBL)</th>
<th>TLS High Res. (Leica BLK)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1236 ± 414</td>
<td>713 ± 196</td>
<td>709 ± 194</td>
<td>69 ± 39</td>
<td>96 ± 25</td>
</tr>
</tbody>
</table>

Table 4.1, Mean stem count in real and simulated TLS scans and field data. The mean number of stems observed within 40 meters of the 294 transect scan positions was calculated for field, TLS, and simulated data. Stem counts represent the total number of stems observed at each position, allowing for repeated observations of stems from nearby scan locations.

The distribution of stem counts derived from simulated and real TLS scans were shifted considerably lower compared to field stem counts within a 40 meter radius of the scan location (Figure 4.3; histogram). The distribution from simulated TLS (yellow) had a bimodal shape with a long tail similar to that of the field distribution (red), but shifted lower and with a shorter tail. The distribution of real TLS stem counts was shifted toward 0 and did not match the shape of the simulated or the field stem count distributions. Field stem counts were higher than simulated and TLS estimates.
When simulated and real TLS scans were plotted against those of field data (Figure 4.3; scatter plot), simulated data (red and yellow) consistently underestimated field stem counts, but identified more stems than did real TLS (blue). Even when simulated data was subset to stems detected at the angular resolution of the TLS instrument (yellow; 0.25 degrees), simulated data performed better than real TLS. Real TLS scans (blue) located far fewer stems than did simulated TLS data.

The wide beam divergence of the CBL (0.4 mrad), which is at the coarser end of the spectrum for commercial TLS instruments, could have accentuated the impacts of occlusion in a manner that is not representative of other TLS instruments. To test the ability of the CBL to generalize the properties of higher resolution TLS instruments, stem maps were also derived from a TLS instrument with finer beam divergence and higher angular resolution, the Leica BLK360.

However, stem counts from 9 Leica BLK scans produced stem counts that were comparable to that of CBL scans (Figure 4.4). Although the BLK produced a higher mean stem count than did the CBL, the BLK also underestimated the stem counts of both simulated and field data at a similar order of magnitude (Table 4.1).

**Stem Density**

In order to correct for the underestimation of stem counts in TLS scans, stem counts were adjusted by the area observed in each scan to produce a stem density metric. Figure 4.5 displays the 5 area models that were tested.

Stem densities (stems per m²) were derived with each area method. Stem densities from real TLS were compared to actual field stem densities (Figure 4.6). Field stem densities
were calculated as the number of stems greater than 1 centimeter in diameter within a 40 meter radius of the scan location.

Out of the 5 stem density calculation methods, 3 greatly underestimated the stem density of the plots: the convex hull area of observed stems (blue; CHull), the circular area with radius set by distance to furthest stem identified (red; FurthestStemCircle), and a circular area with radius equal to the max range of the TLS instrument (yellow; 40m Range). The area methods that came closest to estimating a one-to-one relationship with the field stem densities were the Optical Plane Area (OPA) and the Modified Optical Plane Area (MOPA). MOPA yielded results closest to a one-to-one relationship with the field stem densities, although it consistently overestimated stem densities. In every method, the discrepancies between TLS and field stem densities were more pronounced at higher stem densities.

In order to test the relationship of each stem density metric to the field stem density, linear regressions were fit (Table 4.2). The stem convex hull (CHull) method explained the highest amount of the variation in field data (62%) with the lowest error (RMSE = 0.05).

<table>
<thead>
<tr>
<th></th>
<th>OPA</th>
<th>Stem Convex Hull</th>
<th>Furthest Stem Circle</th>
<th>40m Range</th>
<th>MOPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.34</td>
<td>0.62</td>
<td>0.59</td>
<td>0.41</td>
<td>0.49</td>
</tr>
<tr>
<td>p</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.09</td>
<td>0.05</td>
<td>0.05</td>
<td>0.06</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table 4.2, Linear regression fits of TLS and field stem densities.

To further test the ability of TLS area methods to represent scan area, the radius of inquiry from each scan location was iterated from 3-40 meters, and linear regressions of the field stem density on the CHull and MOPA stem densities were fit for every 1 meter increase in radius.
in the field radius. The correlation between TLS and field stem densities of varying radius were plotted to show how well the CHull and MOPA stem densities represented their surrounding area (Figure 4.7).

CHull and MOPA stem densities both reached their peak correlation with field data at about 10 meters from the scanner position. The CHull stem density explained a maximum of 66% of the variation in field stem density at a 10 meter radius, while the MOPA stem density explained 67% of the variation at a 10 meter radius. The CHull stem density was more consistent with the expansion of the field radius, explaining above 60% of the variation in field stem density with a radius of 6-40m from the scan center. MOPA stem density depreciated more rapidly than the CHull stem density. Overall, the CHull stem density method more consistently correlated to field stem densities of varying radius than did the MOPA stem density metric.

*Stem Diameter (DBH)*

Histograms of the distributions of the diameters of trees identified in real TLS data (blue), simulated data (red), and field data (yellow) showed that mean stem diameters from TLS were much more variable than those of simulated or field data (Figure 4.8; histogram). A scatter plot of the mean stem diameter by scan location (Figure 4.8; scatter plot) showed that simulated TLS consistently overestimates the mean stem diameter. Real TLS data, however, both overestimated and underestimated mean diameter. This suggests that factors other than tree size, such as occlusion from foliage, branches, and understory plants, are having a major impact upon tree detection.
The means of real (12.7 ± 11.6 cm) and simulated TLS (12.7 ± 12.1 cm) both overestimated the true mean DBH (11.25 ± 11.25 cm) of field data. In a linear regression comparing mean TLS diameters to field diameters, TLS data explained 32% of the variation in field data with an RMSE of 1.9 cm.

To further investigate the impact of size upon stem detection by real TLS, histograms of the distribution of the diameters of detected (blue) and undetected (red) trees were plotted for 294 scans (Figure 4.9). TLS detected more trees of a higher size classes (8-40 cm in diameter) and missed more trees of a lower size class (6 cm or less in diameter). The inverse was true of the distribution of undetected stems. Stems of 6 cm or less in diameter were missed more often, and larger stems (greater than 8 cm) were more likely to be detected by TLS.

**Stem Species Abundance and Diversity**

The number of unique species observed per scan from simulated (red) and real (blue) TLS data was compared to that of field data (yellow; Figure 4.10). The simulated data was similar to the distribution of field data in shape, with three distinct peaks in the histogram, but with an overall distribution shifted lower than that of field data. Real TLS data had longer tails than the field data distribution, especially in lower stem densities.

A scatter plot emphasizes TLS’s tendency to underestimate the number of species in a scan (Figure 4.10). Real TLS data did not closely match the field distribution, greatly underestimating the number of unique tree species in each scan. In contrast, simulated data matched closely to field data, with a general underestimation bias. The mean number of unique tree species for simulated data (20.2 ± 5.2 species) slightly underestimated that of
field data (22.7 ± 5.5 species), while the mean of real TLS was much lower (8.4 ± 3.0 species).

To test the correlation of the species distribution of real TLS data to that of field data, the field abundance of each tree species was compared to the detection rate by real TLS. The field species abundance was calculated as the total stems of a given tree species divided by the total number of stems within a 40 meter radius of the current scan position. Detection rate was calculated as the number of scans in which the tree species was observed divided by the total number of scans taken.

When the detection rate of tree species in real TLS scans was plotted against the abundances of each species in field data, a statistical relationship between the TLS and field abundances can be seen. A logistic regression was fit to predict field species abundance from the TLS detection rate (Figure 4.11). The TLS detection rate accounted for 78% of the variation in the field data with an RMSE of 0.03.

Part II: Sampling Strategies for TLS

Capturing the Population Statistics of the AOI with TLS

Sampling strategies for surveying the AOI with TLS were evaluated for their ability to capture the global population statistics of stems in the AOI. TLS statistics were calculated using the total number of unique stems observed by each method. Statistics from the TLS distributions of stem density, DBH, and species abundance were compared by their difference from AOI field statistics in Tables 4.3-4.5 and Figure 4.12.
First, acquisition statistics for the 3 TLS sampling strategies were compared (Table 4.3). Grid sampling was the most efficient at gaining new information, with the highest number of unique stems observed per scan and the highest total coverage (33%) of the 37,924 stems in the AOI.

<table>
<thead>
<tr>
<th></th>
<th>Transect</th>
<th>Grid</th>
<th>Plot</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Number of Scans</strong></td>
<td>294</td>
<td>323</td>
<td>74</td>
</tr>
<tr>
<td><strong>Number of Unique Stems per Scan</strong></td>
<td>27.7</td>
<td>38.9</td>
<td>3.09</td>
</tr>
<tr>
<td><strong>Total Unique Stems Observed</strong></td>
<td>8,148</td>
<td>12,573</td>
<td>229</td>
</tr>
<tr>
<td><strong>% Stems Observed in AOI</strong></td>
<td>21.5%</td>
<td>33.2%</td>
<td>0.6%</td>
</tr>
</tbody>
</table>

Table 4.3, Acquisition statistics of TLS sampling strategies.

Stem Density

Stem density was calculated for the Grid and Transect sampling strategies with the CHull area method and a linear regression (Table 4.4). For the Plot sampling strategy, a single stem density calculation was made for each 20 meter plot, rather than for each scan. Field stem densities were calculated using the 20 meter square plots in the AOI.

Grid sampling performed the best in capturing the mean (0.1% difference from field), median (3.5%), and range (11.9%) of field stem density. However, Transect sampling best captured the standard deviation (12.8%) and the maximum (13.3%) of the field distribution. Plot stem densities were the least representative of the field population statistics.
Table 4.4, Comparison of TLS and field stem density statistics by sampling strategy. Colors highlight the magnitude and direction of the difference from field statistics (blue highlights underestimation, orange highlights overestimation). Stem density was calculated using a linear regression of the Convex Hull stem density with field data 20 meters from the scan location, defined as: \( Stem\ Density = 7.594 \times CHull + 0.1172 \).

Stem Diameter (DBH)

When DBH population statistics were compared (Table 4.5), both Grid and Transect sampling greatly overestimated the mean, median, and standard deviation of the field DBH distribution. Grid sampling performed best in identifying the maximum (a 5.1% difference from field) and the range (5.2% difference) of field DBH. Plot scans were the most representative of the mean, median, standard deviation, and minimum statistics of the field distribution. This result reflects the advantage of the Plot sampling strategy, able to observe all of the stems, regardless of size, with a high density of scans and multiple scan angles focused on a bounded area.
Table 4.5, Comparison of TLS and field DBH statistics by sampling strategy. Colors highlight the magnitude and direction of the difference from field statistics (blue highlights underestimation, orange highlights overestimation).

Species Abundance

Species abundances from the total population of observed stems of each sampling strategy were plotted against the true species abundances in field data (Figure 4.12). Grid and Transect sampling characterized the field species abundances with the highest accuracy (Grid RMSE: 0.007; Transect: 0.007), while the Plot sampling strategy had the most error from field abundances (Plot RMSE: 0.012). This result reflects the disadvantage of the Plot sampling strategy, which only covers a small portion of the AOI (0.6%; Table 4.3), and thus is less accurate in representing the abundances of tree species across the AOI.

Similarity of Distributions

KS Tests evaluated whether the distributions of forest metrics from TLS data approximated the distributions of field data in the AOI. Field data was defined as all stems
within the AOI, and field stem densities were calculated from 20 meter square quadrats within the AOI. KS Tests compared distributions of TLS stem density, DBH, and tree species abundances to those of field data (Table 4.6). The species abundance distributions of Transect and Grid sampling strategies were found to be statistically similar to the species abundance distributions of field data. All other metrics had distributions that significantly differed (p<0.001) from the distributions of field data.

<table>
<thead>
<tr>
<th>CHull Stem Density</th>
<th>Transect</th>
<th>Grid</th>
<th>Plot</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>1.000</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>-</td>
</tr>
<tr>
<td>KS Statistic</td>
<td>0.230</td>
<td>0.267</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DBH</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>KS Statistic</td>
<td>0.44</td>
<td>0.45</td>
<td>0.150</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Species Abundance</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>p-value</td>
<td>0.77</td>
<td>0.91</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>KS Statistic</td>
<td>0.119</td>
<td>0.102</td>
<td>0.475</td>
</tr>
</tbody>
</table>

Table 4.6: KS Test results comparing the TLS distributions to field distributions. Stem density, DBH, and species abundance distributions from each TLS sampling strategy are compared to distributions of field data. Bold text highlights KS Test results that indicated statistically similar distributions of TLS and field data. Plot data had to be excluded from the stem density comparisons because of its small sample size (n = 3 stem densities).

*Impacts of Size Class on TLS Distributions*

To investigate the influence of stem size on the ability of TLS to capture the correct field distribution, a series of KS tests of similarity were run with field distributions of varying size classes. The proportion at which KS Tests identified similarity between the TLS and field stem diameter distributions was plotted (Figure 4.13). It showed that limiting the size
class of observed stems has a major impact upon the ability of TLS to observe accurate distributions of stem size.

When stems less than 10 cm in diameter were included in the analysis, TLS scanning would identify an inaccurate distribution of stem size. When size classes were limited to above 10 cm in diameter, TLS would eventually achieve an accurate distribution of field stem sizes, provided that numerous scans had been taken.

There were also chances of false-positives and false-negatives for surveys of any size class. For example, if only 100 TLS scans were made in an AOI and field data were subset to stems greater than 5 cm in diameter, there was a 60% chance that the TLS stem size distribution would be found to be statistically similar to that of field data (Figure 4.13). However, that conclusion would be akin to a false-positive result. With additional scans, the proportion of similar KS Test results approaches 0%, showing that the TLS distribution is in fact significantly different from that of field data for the 5 cm DBH size class.

Larger size classes had the opposite problem of having a high chance of false-negative results unless many scans were taken or the size class was restricted above 30 cm in diameter. For example, after with 100 scans, TLS will correctly estimate the size distribution of field stems greater than 10 cm diameter 80% of the time, while 20% of the time, significantly different distributions of stem size will be produced (Figure 4.13).

_Capturing Local Variation in Field Data with TLS_

TLS sampling strategies were also evaluated for their ability to capture the local population statistics of field data in the vicinity of scan locations. Moving means were calculated for the Transect and Grid sampling methods along their trajectories. The moving
mean stem density (Figure 4.14), DBH (Figure 4.15), and Simpson Diversity Index (Figure 4.16) showed the unique properties of the Transect and Grid sampling strategies.

Each set of figures shows the progressive change in content per scan for each sampling strategy, along the 3 trajectories of Transect strategy and drawing from 100 iterations of the order of Grid scan locations. Moving means are compared with the local mean of field stems within a 20 meter radius of each scan location (red line).

Stem Density

The moving mean Stem Density was plotted for each Transect and for the set of Grid scans (Figure 4.14). Unlike Grid scans, the Transect scans showed a high sensitivity to variation in their local environment, diverging from and converging upon the local mean stem density several times along their trajectory. The Column 8 South-North transect and the Row 23 East-West transect both resulted in a mean stem densities that overestimated the local field mean. By contrast, the Column 29 North-South transect resulted in an underestimation of the local mean. The Grid sampling method converged in less than 50 scans, but also underestimated the local field mean.

Stem Diameter (DBH)

Moving means were calculated and plotted for the Transect and Grid sampling methods (Figure 4.15). Given that TLS data showed a bias toward detecting trees of high DBH (Figure 4.9), TLS was expected to overestimate the mean DBH of local field data. Each sampling method confirmed this expectation by ending in an overestimate of the local field mean diameter. Transect scans showed high variability in mean DBH over the course of their
trajectories. Grid sampling overestimated field diameters for the majority of its trajectory, gradually approaching the local mean and converging with it after 300 scans.

**Species Diversity**

A moving Simpson Diversity Index was calculated and plotted for each sampling strategy (Figure 4.16). Given that TLS underestimates the number of unique tree species in a plot (Figure 4.10), TLS was also expected to underestimate the Simpson Diversity of local field data.

Both the Transect and Grid sampling methods underestimated diversity in their local area. Transect scans were highly sensitive to change in diversity along their trajectories, showing high variation around the mean, while Grid scans converged toward a mean value within 50 scans.

**Summary of Sampling Strategy Results**

Across all 3 metrics, the Transect sampling strategies were the most variable along their trajectories, an indicator that transect scans were especially sensitive to gradients of structure and species in their local environment. Transects varied in their ability to approach the local mean, indicating that the ability to approach a mean value may be dependent upon starting point and direction of the transect. In contrast, Grid sampling converged quickly toward its mean value, even though that mean value was biased. Grid sampling underestimated the mean DBH, overestimated mean stem density, and underestimated species diversity.
Because they are done in close succession, 5 meters apart, Transect scans sampled fewer unique observations of stems per scan than did Grid scans, which gathered completely new information from a 20 meter area with each scan. While Grid sampling often stabilized on a mean within 50 scans, Transect sampling produced highly variable mean values along their route and sometimes resulting in unexpected end values. For example, the Row 23 transect overestimated its Simpson Diversity, while other transects and Grid sampling underestimated diversity.

To further show the ability of Transect scans to capture variation in their local environment, the moving mean Stem Density, DBH, and Simpson Diversity of TLS and field data along the Row 23 East-West transect were plotted (Figure 4.17). While TLS data displayed a systematic bias from that of field data in all of the metrics, TLS matched the change in the field data along the trajectory of the transect.

To further show how the variation in field data was captured by TLS data, the derivatives of the moving means were calculated for each metric along the trajectory of the Row 23 transect (Figure 4.18). The closeness of the field and the TLS derivatives demonstrates the ability of TLS data to record local structural change in its surrounding environment.

Discussion

Overview

This study evaluated the performance of TLS as a forest surveying tool and revealed biases in the content of stem maps derived from TLS data. TLS data consistently underestimated stem counts and densities, overestimated tree size, and under-represented tree
species diversity. TLS has a high rate of failure in observing stems, resulting in underestimations of stem counts and therefore stem density. Unsurprisingly, there is a tendency for TLS to miss rare tree species and to miss smaller stems, resulting in overestimations of tree size. While these biases were expected and observed in both real TLS and simulated data, the magnitude of the difference between real TLS and simulated data was surprising. This difference demonstrates that field conditions and occlusion are altering TLS metrics to a considerable degree. Furthermore, increasing the angular resolution of real lidar instruments and of simulated data was not able to mitigate these biases, showing that stand conditions, not TLS hardware specifications, are the limiting factors for conducting forest inventories with TLS. Thus, the means to overcome occlusion is to respond dynamically to an environment by way of altering the sampling scheme.

While this study revealed major challenges in TLS forest surveys, it also revealed strong relationships between TLS observations and field data that could be further developed for the purposes of forest inventory. For example, the rate of TLS detection explained 78% of the variation in field species abundances. When adjusted, the TLS distributions of species abundances were shown to be statistically similar to those of field data. On the other hand, even though corrected TLS stem densities explained 66% of the variation in field stem densities, the distributions of field and TLS stem densities were never statistically similar. While bias corrections were not universally successful in this study, future studies could build off of this initial work to produce more accurate metrics for forest inventory.
Correcting Biases in TLS Stem Counts

TLS was expected to underrepresent stem counts within the 40 meter range of the instrument due to occlusion by stem trunks, which is unavoidable with the current design of these line-of-sight instruments. The magnitude of this underestimation bias, when compared to field data, was far greater in the real TLS data than in the simulated TLS data, regardless of the angular resolution or the accuracy of the lidar sensor being used (Figure 4.4). The discrepancy between real and simulated TLS data suggests that occlusion from other environmental variables, such as foliage, branches, and understory plants, had a greater impact upon the information content of TLS observations than did instrument parameters. Thus, the limiting factor of TLS sampling is its surrounding environment, not the resolution of the instrument.

Several strategies for overcoming TLS’s stem count bias were investigated in this study, including correcting stem observations by scan area to produce a stem density. Stem density corrections did improve the underestimation bias. In particular, the convex hull (CHull) and modified optical plane area (MOPA) methods both emerged as promising estimates of TLS scan area (Figure 4.5-4.6). Interestingly, both scan area methods had their maximum correlation with field data at a 10 meter radius from the scanner position. This finding demonstrates that regardless of the range of a TLS instrument, the structure of the surrounding environment will constrain its field of view and limit its representation of the environment. Based on the correlation of CHull area with field data, TLS data in the ForestGEO plot is most representative of the surrounding forest within 10-20 meters of scan locations, much lower than the 40 meter range specified by the instrument hardware. Future
research could build upon this finding to test how the observational range changes with different forest types and make recommendations for sampling different environments with TLS.

**Representing Species Abundances**

TLS representations of tree species abundances tended to underestimate the number of unique species present (Figure 4.10). As a result, TLS tends to under-represent the Simpson Diversity across a surveyed area, regardless of the sampling strategy employed (Figure 4.16). This impact was more pronounced in real TLS data than in simulated data, suggesting that occlusion from other environmental factors, such as foliage and understory, were the major cause of this bias.

However, among tree species that were observed by TLS, abundances were strongly related to the TLS detection rate. In addition, the species abundances in the total population of TLS observed stems matched closely with those of the field population (Figure 4.12). The Grid and Transect sampling methods did particularly well at characterizing these, with a mean error of 0.7% abundance (RMSE = 0.007).

The species abundance distributions of the Grid and Transect scans were the only TLS-derived distributions that were found to be statistically similar to field data distributions (Table 4.6). If tree species could be identified in TLS scans, then the abundances of observed species can be accurately estimated in a TLS forest survey. Even if species detection for TLS does not become a viable option in the future, this finding demonstrates that TLS will observe the correct distribution of the dominant species in an area, while it will miss some rare species.
Future Challenges: Capturing Field Stem Diameters

Capturing accurate stem sizes was a major challenge for TLS forest surveys in this study. TLS had a strong bias toward identifying trees of larger diameter and missing small trees. In addition, the size distributions of TLS and field data were significantly different, regardless of the sampling method employed. However, these results were dependent upon the minimum size class of the field data, which was set to include all stems greater than 1 centimeter in diameter.

When field data was subset to size classes above 10 cm, TLS was able to correctly estimate the size distribution of field stems, provided that numerous scans were taken (Figure 4.13). However, when trees smaller than 10 cm diameter were included in field data, TLS observations had a high chance of being different from those of field data. Alarmingly, the discrepancy between TLS data and field data was not apparent in many cases until numerous scans were taken. Even among large size classes, sample sizes had to be high, often on the order of 100 or more scans, to confidently confirm or reject that TLS was measuring the correct size distribution of field stems.

These findings demonstrate that with discrete samples across an area, TLS can effectively estimate the size distribution of large trees. However, unless many scans are taken and analysis is restricted to trees of larger size classes (greater than 10 cm DBH), there is a chance of misrepresenting the true size distribution of a forest with TLS data.
Strategies for Surveying Forests with TLS

If TLS is to revolutionize forestry and automate forest surveys, sampling strategies will need to be optimized to account for the biases in TLS data as well as to meet the specific goals of a surveying effort. This study explored how the Grid, Transect, and Plot sampling strategies performed at surveying an unknown area of forest and at overcoming the impacts of occlusion in scan data.

Grid sampling consistently obtained a representative sample of field data with the fewest number of scans. With 20 meter spacing between randomized scan locations, Grid sampling produced independent samples and captured more unique observations of stems than did Transect and Plot sampling (Table 4.3). The high rate of information gain per scan allowed Grid sampling to converge to a local mean within 50-100 scans (Figures 4.14-4.16).

Transect sampling did not converge toward the mean at the same rate or consistency as Grid sampling, but it was able to capture variation in structure across the AOI and to respond to environmental gradients in local field data (Figure 4.17). Also, Transect sampling performed slightly better than did Grid sampling with a lower magnitude of bias, which is likely a result of the 5 meter spacing of Transect scans. The close spacing of Transect scans meant that successive scans would resample areas with different view angles along their route, updating their baseline of local forest structure with each step. The benefit of area resampling was minimal compared to the impacts of the size bias in TLS data, but the effect still shows that sampling strategies that use this technique can mitigate bias in TLS data.

While Plot sampling did display some advantages over Grid and Transect sampling in that it was less affected by TLS biases, it performed worse in capturing the variation in field data.
data across the AOI. Its high density of scans and multiple scan angles allowed for the
detection of all stems within the plot boundaries, regardless of size class. However, the stems
within the 3 Plots chosen for analysis were not representative of the distribution of field
stems in the AOI. As a result, the Plot data still produced stem density, size, and species
distributions that significantly differed from those of the field data. Because they covered a
larger portion of the AOI, both the Grid and Transect sampling did better in identifying the
population statistics of field stem densities than did Plot sampling. This finding suggests that
the sampling patterns of Grid and Transect methods are of benefit to the accurate
characterization of field data. Their ability to cover a wide area gave them an advantage over
Plot sampling in observing variation and rare instances of forest structure.

This finding represents a trade-off in TLS sampling schemes. When given the job of
surveying an AOI with TLS, sampling plans can either minimize bias in TLS data, with scan
positions clustered together in close-proximity (as in Plot sampling), or to maximize the
variation captured, with multiple scans spread across an AOI (as in Grid and Transect
sampling). Hybrid samplings schemes could be created to balance these 2 goals, both
reducing bias in TLS observations and producing a representative sample of variation in the
AOI. These hybrid sampling plans could be tailored to specific survey needs, such as that of
exploring a new environment or of locating trees of specific size classes. Hybrid sampling
plans also could optimized for the forest structure of a particular area, such as planning closer
scan positions in areas with high amounts of understory vegetation, where the impacts of
occlusion in TLS data will be worse.

In fact, hybrid sampling schemes could even be created and adjusted on-the-fly by
using the information present in TLS data. If TLS data was processed into forest metrics as it
scanned, TLS software could be trained to choose a next set of scan positions based on the information gain of its current trajectory. It could adjust for occlusion by detecting changes in its nominal range, using a metric such as the CHull area. In addition, scanner software could be trained to seek out specific forest structures, relying on methods such as a moving mean (Figure 4.17) or a derivative of a moving mean (Figure 4.18) to identify changes in the variation of forest structure along the sampling trajectory. Building off of the findings of this study, future work should focus on the potential of dynamic sampling for optimizing and automating forest surveys in the future.

**Conclusion**

While there are still major challenges to conducting forest inventories with TLS data, there are also myriad opportunities for developing tools that adjust biases in TLS data and that optimize sampling schemes. A major finding of this study is that the major limitation to TLS surveys is not dictated by sensor hardware. Instead, stand conditions that cause occlusion are the factors that limit TLS data. While occlusion is a major challenge, the findings of this study suggest it can be overcome by developing novel sampling schemes and by employing bias corrections.

One of the most common contemporary roles of TLS in forestry is that of aboveground biomass (ABG) assessment (Calders et al., 2015; Disney et al., 2019), which is most often conducted using Plot sampling on a uniform grid with high-resolution scans. This study demonstrates that while it does reduce bias in TLS forest metrics, Plot sampling does not produce a representative sample of the variation in forest structure within a larger region.
Hybrid sampling schemes could provide new avenues for conducting biomass assessment, reducing bias while also capturing a representative sample of a region.

Future studies should explore combinations of hybrid sampling strategies to reduce the biases inherent in TLS data. For instance, a Grid scan with overlapping view angles and repeated sampling at each Grid location could provide the benefits of Plot sampling, (by observing all nearby trees regardless of size), as well as the benefits of Grid sampling, (by being able to capture the variation in forest structure across a large AOI). Future studies could also investigate dynamic sampling techniques that use metrics from lidar data to update scanner positions on-the-fly. The development of these flexible and adaptive sampling techniques could enable the automated exploration of forests by UAVs or autonomous vehicles in the future.
Simulated pulse trajectories are shown overlaid on the ForestGEO plot stem map at a 20 meter radius from scan centers. *Red points* represent trees observed by simulated TLS, while *blue points* were unobserved stems. *Blue lines* represent pulses that hit trees along their trajectory, while *red lines* represent pulses that did not. *Green lines* go to the centers of the trees that were observed. High-resolution scanners are shown at 0.01 degree angular resolution (top), while coarse resolution scanners are shown at 0.5 degree angular resolution (bottom).
Figure 4.2, Stems observed by different sampling methods in the ForestGEO plot.

Stems observed by Transect (magenta), Grid (sky blue), and Plot (red) sampling strategies are highlighted. Stems outside of this study (black) and the area of interest (dark blue) used in Part II of this study are also marked.
Figure 4.3, Stem counts recorded by TLS scans.

A histogram (top) displays stem counts of real TLS, simulated data, and field data for 294 transect scan locations. A scatter plot (bottom) displays the relationship between stem counts from simulated data of varied angular resolutions and TLS data in comparison to field stem counts within a 40 meter radius of the scanner.
Figure 4.4, Stem counts recorded by low and high resolution TLS.

A histogram displays stem counts from 294 low-resolution TLS Scans (CBL) compared that of 9 scans from a high-resolution scanner (Leica BLK360).
Figure 4.5, Polygons showing the 5 different methods for estimating scan area.

The Optical Plane Area (OPA) is calculated as the convex hull polygon of the point cloud at the optical plane of the instrument. The Modified OPA (MOPA) is similar to OPA, but with a vertical tolerance for points above or below the optical plane. The Convex Hull of stems (CHull) is the area described by the convex hull polygon of observed stems. The Furthest Hit Circle is the circular area defined by a radius equal to the distance of the furthest stem observed. The 40m Circle describes a circular area equal to the specified range of the TLS instrument, with a radius of 40 meters.
Figure 4.6, TLS stem densities compared to field stem densities.

Stem densities produced with the 5 area methods are plotted against field stem densities. With the exception of the Optical Plane Area (OPA) stem density, these methods tend to underestimate field stem densities within a 40 meter radius of the scan.
Figure 4.7, Correlation between TLS and field stem densities with a varying radius.

TLS and field stem densities were compared to the stem density of field data with a series of increasing radii, from 3-40 m, from the scan position. The Convex Hull and MOPA stem density methods both maximize their correlation with field data at 10 meters from the scan position.
Figure 4.8, Mean DBH (cm) of observed stems in TLS scans.

Histogram and scatterplot of the mean size of stems in real TLS data, simulated data, and field data by scan location. TLS data can both tend to overestimate and underestimate mean stem diameters, while simulated data systematically overestimates stem sizes.
Figure 4.9, Histogram of the diameter of detected and undetected stems.

TLS has a bias toward observing larger stems (>6 cm in diameter) and missing smaller stems (<6 cm in diameter).
Figure 4.10, Number of tree species identified in TLS scans, simulated TLS, and field data.

A histogram and scatterplot show TLS’s tendency to miss species within scans. Simulated data also systematically underestimates the number of unique species in each scan, but with a minimal bias of lesser magnitude and variability.
Figure 4.11, Predicting species abundance from the TLS detection rate.

A scatterplot of TLS detection rate and field stem species abundances, with the top 18 most abundant stem species labelled. A logistic regression was fit to predict the field stem abundances from the TLS detection rate. The detection rate was treated as a binomial variable in the model. For each species, the number of scans in which a given species was detected represented the number of successes, and the total number of scans represented the number of trials. The model shows a strong relationship between the TLS detection rate and the abundance of stems of that species in field data.
Figure 4.12, Species abundances of stems observed by TLS sampling strategies.

TLS species abundances calculated from their detection rate in TLS data are compared to the real abundances of species in field data. Each point represents the abundance of a single species observed by TLS. Tree species had to be observed at least once by TLS to be included in the analysis.
Figure 4.13, The proportion of similar KS tests with different size classes of field data.

For each size class of field data, KS Tests were run to identify similarities between the TLS and field stem diameter distributions. The proportion of significantly similar KS tests (y-axis) is akin to the probability of achieving the correct distribution of field stem size, given a certain number of scans (x-axis) and the size class of the field data. The figure shows that when sampling size classes greater than 10 cm with TLS, there is a high chance of producing the correct distribution of stem size, even with a small number of scans. However, when surveying smaller trees, of 5 cm DBH or less, there is a high chance of generating an incorrect distribution of stem sizes. The more scans that are taken, the more it is confirmed that TLS has either successfully captured the correct distribution (for stem classes >10 cm DBH), or that TLS is capturing a biased distribution that is dissimilar from field data (DBH<10cm).
Figure 4.14, Moving mean stem densities compared to the local field mean.

Each plot follows the moving mean of a specific transect or Grid sample as it moved along its trajectory (blue). Grid scans were randomized and bootstrapped to compute a confidence interval around their mean. The moving mean is compared to the local field mean of all stems along their trajectory. TLS observations are shown to be sensitive to changes in stem density. Grid sampling methods show an ability to converge near the local mean within 50-100 scans, while Transect sampling methods are highly sensitive to changes in stem density, and do not converge as quickly.
While Transect estimations of mean stem size are sensitive to changes in DBH along their trajectory, they result in an overestimation of DBH compared to the local mean. Grid scans eventually converge toward the local mean stem size, but not until over 300 scans have been taken.
Figure 4.16, Moving mean Simpson Diversity index compared to the local field diversity.

Transect scans show a high sensitivity to changes in diversity along their trajectory. All methods result in an underestimation of Simpson Diversity due to the tendency of TLS to miss less abundant species.
Figure 4.17, Moving mean stem density, diameter, and diversity along the Row 23 Transect.

Moving averages of metrics from TLS data are compared to that of field data along the East-West trajectory of the transect. While TLS data may underestimate or overestimate metrics, it shows an ability to match the variations of field metrics along a specified trajectory. Field data are all stems within a 20 meter radius of scan positions.
Figure 4.18, Local derivatives of the TLS moving means.

TLS shows an ability to capture the derivatives of the moving mean stem densities, diameters, and diversity of field data along the Row 23 Transect trajectory.
CHAPTER 5

CONCLUSION

Overview

This research set out to apply lidar technologies to problems in forest ecology, including monitoring the progressive impacts of the HWA disturbance in the forests of the eastern USA. Collectively, these studies have shown how different interpretations of lidar data, such as raw waveforms, point clouds, foliage profiles, and simulated waveforms, have specific applications in ecology and disturbance monitoring. Chapter 2 and 3 identified structural signals of HWA’s progressive impacts using lidar data. In particular, Chapter 3 showed that changes in forest structure relate directly to changes in disturbance severity, showing the promise of using structural signals to monitor HWA across a wider region.

These studies also highlighted challenges faced by lidar surveys, and explored solutions for overcoming biases to meet the particular needs of foresters and ecologists. Chapter 4 discussed how forest metrics derived from TLS could be adapted for large-area forest surveys, while Chapters 2 and 3 experimented with methods for monitoring forest condition using lidar measurements of forest structure. These studies laid a foundation for future studies to continue to develop disturbance monitoring and forest survey tools with discrete and waveform lidar.
Collectively, this research achieved its primary goals of generating new applications for lidar data and of using lidar data to gain new understandings of an ecological disturbance. These studies repeatedly demonstrated that lidar data can capture subtle variations in forest structure at the landscape scale. In addition, lidar measurements of structure strongly related with stand-level ecological variables, such as mortality, stem density, and species abundances. Thus, these findings open up numerous applications for this data that go beyond the scope of this study, and build an understanding of the larger role of lidar remote sensing in ecology.

Research Questions

1) How does raw waveform lidar data relate to forest condition during the HWA infestation at Harvard Forest?

Chapter 2 explored how the progression of the HWA disturbance appeared in airborne lidar waveforms at multiple canopy layers. It revealed a variety of waveform variables from the canopy and ground layer that related to forest condition in the mature hemlock section of the ForestGEO plot. It showed that waveform variables, particularly the integrals of return energy from waveforms, were positively related to hemlock mortality and the progressive impacts of HWA. Results suggested that differences in the attenuation of hemlock canopies, rather than differences in reflectivity, were driving the changes in waveform variables that corresponded to forest condition.

Waveform variables had the strongest relationship with the mortality of small trees, with diameters between 0-10 cm. This finding suggests that either waveform variables do particularly well at explaining variation in understory trees, or that the mortality of
understory trees best represents the greater condition of forest plots. Most likely, both of these explanations are valid. Numerous other studies have shown that waveform lidar data offers a better characterization of lower canopy layers than does discrete lidar data (Anderson et al., 2016; Hancock et al., 2017), supporting the finding that waveform variables were detecting understory trees.

In addition, field data showed that the progression of HWA impacts was more advanced in understory trees than in trees of larger size classes. The mortality of small hemlock trees was higher than that of other size classes of stems in the field data, and thus, their disturbance signal was stronger.

A closer examination of the field data provides further evidence for this explanation. When plotting the relationship between the abundance of a size class of stems and the mortality observed in that size class, an indirect relationship between abundance and mortality is revealed (Figure 5.1). Within 20 meter quadrants in the ForestGEO plot, when the abundance of hemlock stems of a given size class is high, the mortality within that size class is low. While mortality may be, on average, much higher for trees of 0-10 cm in diameter across the plot, trees of larger size classes, particularly 10-20 cm and 20-30 cm in diameter, also showed a similar indirect relationship with abundance. This finding suggests that while HWA infests all trees at similar rates, smaller trees die sooner than do larger tree size classes. In this sense, the condition of understory trees be may the precursor or “canary in a coal mine” for HWA monitoring studies, an indicator of the wider impacts occurring in the plot.
2) How can multi-temporal and multi-spatial resolution lidar data be adapted to monitor forest change over the progression of the HWA infestation?

By relating changes in forest structure, rather than a single observation, to predict hemlock condition, Chapter 3 aimed to minimize the residual variation that arises from differences between plots, rather than differences in the severity of HWA’s impacts. Calculating change did improve the relationships between structure and condition that were observed in the ALS waveform variables in Chapter 2. In addition, Chapter 3 presented a method for comparing multi-temporal lidar data by simulating large-footprint lidar waveforms. Simulated waveforms made comparable metrics out of the 2 discrete datasets from different airborne lidar sensors and sampling schemes. These methods were also applicable to future acquisitions from the GEDI spaceborne lidar sensor, offering opportunities to scale up the results of the ForestGEO plot and monitor the greater New England region.

One of the most exciting findings of this study was that the infested hemlock stands displayed signals of structural change that allowed them to be identified from other stands of tree species. Increased canopy permeability and a loss of plant material in the mid-story were only identified in hemlock dominant plots. In addition, this structural signal was directly related to the severity of the infestation, as measured by hemlock mortality.

Understory growth, however, was not identified during this period. It is possible that because this was the initial stage of the infestation in the ForestGEO plot, the plot had not reached the stand initiation stage (Oliver, 1981). It is also possible that understory trees were
beginning to grow, but they were not yet dense or tall enough to appear in the lidar signal from 2012-2016.

Fortunately, the monitoring method outlined in Chapter 3 could be used to continue a time series of forest structure in the ForestGEO plot and to detect the onset of the stand initiation stage in future years. The NEON AOP team plans to continue collecting lidar data from the ForestGEO plot on a biennial basis, providing a steady data stream to continue this study. In addition, the methods discussed in Chapter 3 enable any future overflights by NASA G-LiHT (airborne) or acquisitions by NASA GEDI (spaceborne) to be included in the time series with the NEON data. Thus, this study enables numerous future applications for monitoring ecological change in the ForestGEO plot and the wider region.

Interestingly, the waveform metrics that were identified by large-footprint simulated waveform data in Chapter 3 were not the same as those identified for high-resolution ALS waveform data in Chapter 2. This may well be governed by the difference in scale between the two datasets. Small-footprint waveform data measures a small sample of space with each beam, less than 1 m in diameter for NEON, while large-footprint lidar measures an entire stand, about 19-25 meters for GEDI (Dubayah et al., 2020). This is a classic example of how ecological processes have different properties at different scales of observation (Woodcock and Strahler, 1987), with different signals resulting from the same ecological disturbance when measured at 1 m and at 25 m.

With the recent release of GEDI data, future work will further test how lidar signals of forest change differ by resolutions and by processing techniques (i.e. actual GEDI vs NEON waveform data). However, these findings highlight the value of multi-temporal lidar datasets and also, the importance of making multi-temporal, multi-resolution lidar datasets
comparable by using tools such as the GEDI simulator (Hancock et al., 2019). Future work should continue to develop these comparative methods, as they are critical for creating an ecologically meaningful time series of forest structure from lidar data.

3) **How can terrestrial lidar scanning (TLS) be used to augment and evaluate airborne lidar acquisitions and carry on the legacy of methods and tools for sampling forest ecosystems?**

Terrestrial scanners are most often understood as plot sampling instruments (Newnham et al., 2015), confined to a grid of sampling locations in order to capture accurate details of a small section of forest (Wilkes et al., 2017). The study in Chapter 4 challenged that notion by examining the utility of TLS for surveying a larger region, in the manner of Bitterlich or prism sampling. When employed as a surveying instrument, TLS produced forest metrics that captured more of the variation in a region of forest than did typical plot sampling efforts. However, due to the impact of occlusion on scan data, TLS observations were greatly skewed from field metrics that were collected manually.

Even high-resolution terrestrial scanners suffered from the impacts of occlusion in dense foliage, showing that environmental conditions, not hardware, are the limiting factors for TLS surveys. This notion is perhaps contrary to conventional thinking about technological development. It is often assumed that data quality will automatically improve with increased instrument resolution. In real-world environments, however, when lidar sensors encounter complex forest structures with dense patches of understory plants, the methods with which scanners are deployed become more important than do the specifications of the instruments.
These findings argue for an expansion of the methods under which TLS sampling is typically conducted (Wilkes et al., 2017; Abegg et al., 2017). Sampling on a uniform grid is not the only option for using TLS. When other sampling strategies were employed, such as transect sampling, TLS observations displayed a sensitivity to subtle variations in forest structure, such as changes in stem density, size, and species compositions. Despite biases in TLS observations, TLS from other sampling strategies produced better estimates of the global mean than did sampling with a uniform grid. Future studies could exploit the sensitivity of TLS by balancing the methods of uniform sampling and other surveying patterns, developing hybrid sampling strategies that achieve a more representative understanding of a particular forest region.

In addition to new sampling strategies, methods need to be developed for correcting the known biases in TLS observations. One solution would be to create new post-processing techniques that regress TLS survey data onto a subset of field data to produce a corrective model for subsequent TLS scans. Also, the information within TLS scans could be drawn upon to correct biases on a site-specific and scan-specific basis. For example, in Chapter 4, the estimated area observed by each scan was able to correct biases in stem counts from TLS by translating TLS stem observations into stem density metrics. These area corrections also showed the potential to act as estimators of the occlusion of the site as a whole. Corrected TLS stem densities agreed best with field data within a 10-20 m radius of scanner positions at Harvard Forest. This radius could be understood as a nominal range for TLS instruments within a specific environment, determined by the unique effects of occlusion within that environment. Using metrics such as the nominal range, a system could be developed for
optimizing sampling strategies, on-the-fly, to meet the needs of a forest survey while adjusting for site-specific occlusion parameters.

With a better understanding of the strengths and limitations of terrestrial lidar, TLS deployments can serve both to provide evaluations of airborne acquisitions and to obtain incremental change information in between airborne/spaceborne acquisitions. By adding frequent TLS acquisitions of the ForestGEO plot at Harvard Forest, improved time-series can be developed leading to more nuanced monitoring of the HWA infestation.

**Future Work**

Viewing the forest surveying methods of Chapter 4 in context with the disturbance detection methods from Chapters 2 and 3, this work as a whole demonstrates the sensitivity of lidar data to subtle variations in forest structure and condition. These findings open up a variety of avenues for future research on HWA’s progressive impacts, novel tools for automated forest surveys, and new ways to inform policy on the management of forest pests.

**New Directions for Research in the ForestGEO plot**

The possibilities for future studies of the structural change ongoing in the ForestGEO plot and Harvard Forest are greatly enhanced by the future acquisitions of lidar data already planned by NEON AOP, NASA G-LiHT, and the GEDI mission. As an LTER site, Harvard Forest supports a variety of other coincident time series of ecological data that can be compared with lidar data. For instance, multi-temporal lidar data could be especially beneficial when combined with the long-term record of carbon and water exchange in the ForestGEO plot. Together, these datasets have the potential to precisely measure how the
HWA disturbance is influencing the emergent properties of hemlock-dominated ecosystems in New England.

With the GEDI simulator (Hancock et al., 2019), lidar data from any instrument can be compared in a time-series, regardless of differences in platform (terrestrial, airborne, or spaceborne) or in sensor parameters. The simulator not only provides the capability to compare future ALS acquisitions from NEON AOP, it could also bring in past lidar datasets that were collected pre-HWA infestation. For instance, the NASA Land Vegetation and Ice Sensor (LVIS; Blair et al., 1999) collected large-footprint lidar data over Harvard Forest in 2002 and 2009 (prior to and coincident with the outbreak of the infestation). With the GEDI simulator, these LVIS waveforms should be compared with ALS, TLS, and GEDI data collected over the course of the HWA infestation. This spatial understanding of structural change would be a boon to many ecological studies in the ForestGEO plot.

To reveal more about HWA’s biogeochemical impacts, a time series of lidar data could be compared alongside the long-term record of carbon and water exchange collected by eddy-covariance flux towers at the Harvard Forest. Studies using eddy-covariance data have already shown that the decline of hemlocks initially releases water reserves (Kim et al., 2017) and temporarily reduces carbon uptake (Albani et al., 2010). Both water and carbon cycles could change again once deciduous trees replace hemlock stands in decline (Kim et al., 2017; Lemos et al., 2013; Finzi et al., 2014), and new phenological cycles become established (Kim et al., 2019). Changes to the water cycle, in particular, could have larger impacts upon New England watersheds and water supplies.

In anticipation of the regional-scale changes due to HWA, future studies should use a combination of lidar and eddy-flux data in the ForestGEO plot to predict transitions in
biogeochemical cycles. The structural change and infestation severity observed from lidar could be used to mark important turning points in biogeochemical cycles that have impacts upon the wider region. In addition, this research would benefit other research studies, as lidar can improve the accuracy of flux models (Antonarakis et al., 2014), enabling better estimates of the forest-atmosphere exchange at Harvard Forest.

These comparative studies are initial examples of the myriad possibilities for collaboration and synthesis at the ForestGEO plot and the Harvard Forest LTER. As a hub for a variety of research on disturbance ecology and biogeochemical cycling, the ForestGEO plot provides a model forest to evaluate the impacts of HWA disturbance and assess its wider impacts.

Regional-Scale Monitoring Tools

This dissertation explored a variety of methods for measuring forest condition with lidar data. With further development, some of these methods could be made into regional-scale tools for forest management. Before that future is possible, however, more research is needed to generalize monitoring methods for the New England region.

By finding a structural signal that was unique to the HWA infestation, Chapter 3 opened the door to regional scale monitoring using a combination of airborne and spaceborne lidar. The study in Chapter 3 benefited from detailed field data, which allowed for lidar data from hemlock stands to be compared with those of other tree species. At the regional scale, however, such a detailed understanding of species composition is not as accessible as it is in the ForestGEO plot. In order for regional scale monitoring studies with ALS and GEDI to
become operational, hemlock tree stands need to be identified at the same time that their condition is measured.

Fortunately, forest types can also be estimated directly from large-footprint lidar waveforms, even in complex tropical forests (Marselis et al., 2018). Chapter 3 showed that changes in mid-canopy leaf area and canopy permeability differentiated infested hemlock trees from those of all other dominant tree species in the ForestGEO plot. This finding suggests that the structural signal of loss from HWA may be used to identify infested hemlock dominant plots without a preliminary species classification, although more research is needed to evaluate whether structural change profiles are unique enough to perform such a classification. Expanding to other Harvard Forest tracts, as well as other experimental sites known to contain hemlock stands, such as Bartlett Experimental Forest in New Hampshire or Howland Cooperating Experimental Forest in Maine, could allow for a model to be trained to predict both the presence and condition of hemlock stands.

Identifying hemlock trees at the regional scale could also be accomplished by combining lidar data with other passive remote sensing datasets. For instance, studies using multi-spectral data from NASA/USGS Landsat have developed methods to predict the presence of hemlock trees (Dunckel et al., 2015) and detect the more advanced stages of HWA infestation with spectral indices (Bonneau et al., 1999; Royale and Lathrop, 2002; Jones et al., 2015; Williams et al., 2016; Pontius et al., 2005, 2017; Hanavan et al., 2015). A model combining both of these data sources would likely produce more accurate estimates of hemlock severity than could be achieved with either dataset alone, as has been demonstrated by a HWA monitoring study using high resolution imagery (Kantola et al., 2016). Future
research should explore how measuring both structural change from lidar and spectral change from satellite or airborne imagers could improve regional monitoring of HWA.

Last, the methods explored for disturbance monitoring in this dissertation could be generalized for other invasive insect infestations and other disturbances. As the economic and ecological impacts of invasive forest pests are increasing in the US (Aukema et al., 2010; 2011; Lovett et al., 2016a, 2016b), there is a need for monitoring systems that can simultaneously discern the drivers and the severity of disturbances. Lidar shows promise as a comprehensive data source for classifying hemlock condition, but it is unknown whether such distinct signals of structural change could be observed for other pest infestations and other types of disturbances. Future work could expand on these methods and use the GEDI simulator to document other disturbances in search of unique signals of structural change that correspond to forest condition.

**Advancing Forest Surveys with TLS**

When engineered to be durable, portable, and fast-scanning, TLS instruments have the potential to become a standard tool for forest inventory in the future (Paynter et al., 2016; Disney et al., 2019). However, their utility for forest monitoring currently faces a major challenge: sampling bias from occlusion within a forest. For this reason, it is unlikely that human observers will be replaced by TLS in the near future (Newnham et al., 2015). However, Chapter 4 does show that biases in TLS data can be addressed with new post-processing corrections and sampling strategies. If tools can be developed to process and update TLS forest metrics on-the-fly, TLS instruments could detect forest variation in the field, and thereby, update sampling strategies in real-time, in order to guide surveyors and
airborne remote sensing teams toward a specific goal. These findings show that with further
development, TLS has great potential to augment traditional methods for surveying forests.

Evaluating the ability of TLS to capture forest environments also provides additional context for other emerging surveying technologies, such as lidar mounted on Unmanned Aerial Vehicles (UAVs; Kellner et al., 2019). The flexibility of movement of UAVs may allow them to avoid some of the biases encountered by TLS, since UAVs can surmount obstacles that occlude their line-of-sight, such as understory plants. The ability to circumvent occlusion may give UAVs an advantage over TLS for large-scale forest surveys, while the physical principles of the lidar instruments remain the same. Future studies should explore comparisons of forest inventories conducted with UAVs, TLS, and human observers to specify the role that each can play in forest surveys.

In addition to forest inventory, TLS could also assist future disturbance monitoring efforts from airborne and spaceborne sensors. While calculating change with the GEDI simulator provides many benefits for data continuity and comparability, there are also opportunities to use TLS to develop change products with NEON waveform lidar data that have a higher spatial resolution and a better characterization of understory structure.

TLS provides a particularly detailed view of sub-canopy forest structure that can complement the views of airborne and spaceborne lidar, which mainly record detailed information from the upper canopy layers (Kukenbrink et al., 2016). Figure 5.2 illustrates the complementary information provided by TLS, by better capturing the lower canopy and understory structure that is occluded by ALS. In support of ALS monitoring efforts, TLS can help produce better characterizations of understory structure by calibrating the gap and foliage profiles of waveform ALS data (Hancock et al., 2017). As the condition of understory
hemlock trees was revealed to be particularly important for monitoring the HWA infestation, combinations of TLS and ALS datasets could improve methods for observing understory structure and condition, which could aid in the early detection of the HWA infestation.

**The Future of Forest Management**

In the US, the number of invasive pests and the damage that they cause is growing (Aukema et al., 2010; Lovett et al., 2016a and b), a trend that is being accelerated by anthropogenic climate change (Dukes et al., 2009). This increase of invasive pests poses a seemingly unstoppable threat not only to forest ecosystems, but also to the ecosystem services that they provide to New England communities. Fortunately, history shows us that detrimental ecological changes are not imminent or predetermined, and that human communities can change the course of natural systems through conversion and management. Modern technologies, such as lidar remote sensing, present new opportunities for New Englanders to sustainably manage their natural resources, just as they have done in the past.

Since the 1800s, the historical narrative of ecological change in New England has been one of regional scale recovery. As colonial era farms were abandoned and large-scale agriculture moved west, forests reclaimed much of the empty agricultural land (Hall et al., 2002; Foster et al., 2008). While contemporary thinking might attribute this regrowth of forests in the northeast to a coincidence of history, the historian, Ellen Stroud, demonstrates that is was the people and institutions of New England who protected these forests and allowed them to grow to the mature state they are in today (Stroud, 2012).

During the 19th and 20th century, scientific research on the ecosystem services of forests began to emerge. With these new advances in forest research, agricultural and urban
communities began to recognize that protected forests could provide clean water, fresh produce, and increased revenue from tourists, escaping from Boston, New York, and Philadelphia. To safeguard these ecosystem services, numerous public works projects and policies were established that protected forests so that they could reach their mature state in the present day (Stroud, 2012). For example, the Quabbin reservoir, which supplies water to Boston, was established with a buffer of preserved forest in order to protect and maintain a supply of clean drinking water for the city’s expanding population. The large-scale planning efforts made by urban centers during this time-period exemplify how scientific research can lead to environmental policies that benefit both natural ecosystems and human communities.

By putting people at the center of the history of northeastern forests, Stroud reminds us that humans remain the major drivers of environmental change in natural environments. The trend of forest recovery in New England was the result of policies fought for by people, not historical circumstance, nor technological development alone.

This body of work has demonstrated how lidar remote sensing can offer new ecological insight on forest disturbances, as well as new tools for monitoring and managing forests. In the case of HWA infestation, monitoring campaigns with airborne and spaceborne lidar could contribute to HWA control efforts by tracking the spread of the adelgid and providing advanced warning to landowners. In addition, the response of landowners to HWA, such as clear-cutting hemlock stands, can cause even more ecological damage than does HWA (Kizlinski et al., 2002). Thus, advanced warning of HWA’s spread into a region would offer the chance to communicate about a proper response, preventing excess ecological damage. Finally, using lidar to communicate the scale of HWA’s impacts can also influence regional decision-making. If people see the scale of hemlock decline in their towns
and national parks, they may be convinced to support conservation efforts and to campaign for environmental policies that prevent the spread of invasive species in the US, such as the policies outlined by Tree-SMART Trade (Lovett et al., 2016a and b).

By advancing methods for monitoring forests, this research contributes to the legacy of conservation that is central to the society and environment of New England. This work develops tools that can help New Englanders to better understand the ecological value of their forests and to address the threat posed by an invasive species. However, while lidar remote sensing can provide timely measurements of disturbance impacts in unprecedented detail, this promising technology will not be the sole saving grace of New England ecosystems. Instead, it ultimately will be up to people- universities, landowners, companies, and governments -to employ these tools to protect forests and carry on the legacy of ecosystem recovery in New England.
Figure 5.1, Abundance of size class against mortality of size class.

Hemlock trees with higher abundance in a given size class tend to have lower mortality. Quadrats with 0% mortality are not displayed. Lines display a loess smoothing function.
Figure 5.2, Cross-sections of TLS and ALS point clouds.

(top) Side-view of an ALS point cloud, colored by height above ground.
(bottom) TLS points (*white*) primarily measure the mid-story and understory of forest environments, while ALS points (*purple*) primarily observe the tops of the canopy and the forest floor. Data was visualized using the CloudCompare (2018) software package.
CloudCompare (version 2.11), 2018.


176


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