EXAMINING CANOPY GAP DYNAMICS IN CENTRAL OREGON THROUGH A MULTI-TEMPORAL LENS

by

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ABSTRACT

Examining Canopy Gap Dynamics in Central Oregon Through a Multi-Temporal Lens

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In forest ecosystems, disturbances create variability through their influence on overstory and understory species. Canopy gaps created by smaller disturbances such as moderate to severe wildfires, snow, or wind, leading to the death or injury of one to several trees, can provide opportunities for niche diversification by encouraging regeneration of shade intolerant species to take advantage of increased sunlight, increasing overall species diversity. In early 2020, a severe snow event struck the Horace J. Andrews (HJA) Experimental Forest in central Oregon, leading to death and injury of many trees throughout several experimental watersheds. Here we analyze vegetation plot data and LiDAR data collected in 2008, 2016, and 2020, to determine influences on the presence, size, and frequency of canopy gaps over time in order to determine the effect of the 2020 snow event. We analyzed the influence of elevation, stand density, and canopy roughness on the presence of canopy gaps among three experimental watersheds containing impacted permanent study plots, as well as the influence of these variables as well as stand age on the size and frequency of gaps across all watersheds. The presence of canopy gaps increased with canopy roughness across all watersheds for all years, while elevation and density did not show consistent patterns, or clear influence due to the 2020 snow event. However, after the snow event, more gaps were detected at lower elevations, and the gaps that were detected at these lower elevations tended to be smaller than those found at higher elevations. The number of gaps increased with stand density and with canopy roughness. While our results do not depict a drastic change in how our study variables influence the presence, size, and frequency of canopy gaps before and after the snow event, the newly recorded increase of small canopy gaps at lower elevations in 2020 reflects the influence of the heavy, wet snow.

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Chapter 1: Introduction

Natural disturbances in forest ecosystems – such as fire, wind, snow – are key drivers in creating spatial heterogeneity in forest stand structures that support species diversity. Such disturbances are necessary for ecosystem functions, enhancing diverse structures in forest ecosystems by creating gaps in canopy cover through injury to branches or tree mortality. Sub-lethal tree damage results in heterogeneous conditions as stands recover, which can increase niche diversification (Franklin et al., 2002), and tree mortality can result in canopy gaps that have various impacts on vegetation such as influences on vegetation growth rates and population dynamics (Gray et al., 2012). Ranging from density-dependent tree mortality in early seral stages (Franklin et al., 2002), to stand-replacing wildfires and various other weather events, disturbances can vary in severity and their effects on forests. Here, we will focus on the formation of small canopy gaps ($<1000m^2$) that tend to be the result of mild to moderate severity disturbances that cause the fall of one to several dominant trees (Schliemann & Bockheim, 2011).

Historically, the measurement and characterization of canopy gaps has been executed through field-based measurements (e.g., stand density, crown volume, diameter at base height [DBH]), however these methods are time- and resource-consuming, requiring repeat visitation to remote sites to manually collect measurements. Our understanding of the mechanisms that drive canopy gap formation during various stages of forest succession and in stands of multiple ages continues to develop with the improvement of technologies (Vepakomma et al., 2011). Light Detection and Ranging (LiDAR) is a reliable tool that has been used for decades to create three-dimensional visualizations of forest structure by utilizing light through a pulsed laser that accurately measures distance to Earth's surface and can visualize many aspects of forest stand structures (US Department of Commerce, 2023; Kane et al., 2010; Pu et al., 2023). LiDAR data can be used to create Canopy Height Models (CHMs) or point-cloud-based methods to develop three-dimensional imagery of canopy structures (Pu et al., 2023) including stand density, crown height, and DBH (Vepakomma et al., 2008; Vepakomma et al., 2011; Kane et al., 2010).

While the use of single-flight LiDAR imagery to determine stand characteristics is widely practiced, the use of a series of LiDAR imagery to analyze changes in forest canopy structure over time has not been widely used (Vepakomma et al., 2011). Several studies have compared LiDAR data with ground-truthed field measurements, concluding that LiDAR is an accurate and reliable remote sensing technology (Kane et al., 2010; Senécal et al., 2018; Silva et al., 2019; Stitt et al., 2022). This study will use a multi-temporal lens to analyze LiDAR and vegetation plot data collected over time at the same locations to examine changes in canopy structure. To analyze canopy gap dynamics over time in the H.J. Andrews Experimental Forest following a severe snow event, this study asks, **"Did elevation, stand density, or canopy roughness influence the presence, size, or frequency of canopy gaps?"**, and **"Did stand age influence the size and frequency of canopy gaps?"**

Although validating LiDAR data using ground-truthed field data from vegetation plots is not a novel exercise (Kane et al., 2010), the comparison and use of these two types of data over the same area and over time has not been widely applied to illustrate changes in forest canopy structure. As noted by Kane et al. (2010), it is not possible to properly analyze structural development of a forest stand by looking at a single LiDAR image or field measurement. This research aims to help illustrate spatial variation in canopy structure over time in correlation with disturbances and landscape features by analyzing influences on the existence of gaps and their sizes and frequencies across the landscape. If we can accurately illustrate the responses of different stands to moderate or severe disturbances such as a heavy snow event, it could encourage the increased use of multiple LiDAR captures over time to inform forest management and research efforts regarding changes in stand structure on a landscape scale. Being able to visualize patterns in the development of canopy openings could help us to understand changes in canopy structure and their influences.

The study area for this research, the Horace J. Andrews Experimental Forest (H.J. Andrews Experimental Forest, hereafter referred to as HJA) located near Blue River, Oregon, is a Long-Term Ecological Research (LTER) site, and home to an array of research projects. Situated among steep hills ranging from about 400-1600 m in elevation, HJA comprises the Lookout Creek drainage basin, with nine experimental watersheds and gauging stations throughout (H. J. Andrews Experimental Forest, 2016). This experimental forest has experienced a multitude of disturbances of varying degrees over the decades since its establishment in 1948 by the United State Forest Service (USFS), from small scale windthrow events to stand-replacing wildfires including the recent Holiday Farm Fire in 2020, and the Lookout Fire in 2023. In the winter of 2019, HJA experienced a heavy snow event that resulted in significant tree injury and mortality within established LTER vegetation plots. In addition to vegetation data, LiDAR data has been collected over the same area at several points in time. With a substantial amount of tree plot vegetation data gathered in the field and numerous flights gathering LiDAR data over the same topographies over time, it may be possible to utilize these data to analyze the relationship between stand characteristics such as density, canopy roughness, and age, and the location and size of the gaps that were formed.

This forest provides a unique opportunity, supporting an enormous amount of field research that has been tracking the changes in these forests for decades. The advent of aerial LiDAR imagery and its continued development in recent years has only improved our capabilities to understand canopy gaps that increase and support species diversity in forest ecosystems. This research will support the improvement of canopy gap research by assessing a less resource-intensive alternative and enhancement of traditional field data collection. This study does not intend to promote the replacement of field data collection, as it is necessary that researchers have a physical connection to their study sites if possible. Rather, the goal of this study is to support remote alternatives to costly and time-consuming methods when resources are limited, or when sites are particularly difficult to visit due to remote access or topography.

The Introduction (Chapter 1) of this study will be followed by a Literature Review (Chapter 2), providing an in-depth contextualization of this research starting with an overview of forest ecosystems and succession, followed by the role and significance of canopy gaps in these systems, and finally a background on LiDAR imagery and data collection. Methods for this study (Chapter 3) will include descriptions of the methodology of field data collection by HJA researchers and how LiDAR imagery and data collected by HJA, the State of Oregon, and United States Forest Service (USFS) Region 6 was used in this study, as well as a description of the statistical analysis methods used to compare these datasets. The Results (Chapter 4) will thoroughly present the data and analyses while the Discussion (Chapter 5) will contextualize these results within the realm of existing research. The Conclusion (Chapter 6) will speak to the implications of the findings and present suggestions for further research.

Chapter 2: Literature Review

2.1 Introduction

Canopy gaps, the openings in tree canopies often caused by disturbances, play a critical role in the process of forest succession by increasing resource availability to understory vegetation and less dominant tree species. In old growth and second growth forests, the death or injury of larger "gap maker" trees can create substantial openings that increase light and nutrient availability in otherwise shaded areas, which encourages a diverse growth of species (Choi et al., 2023; Gray et al., 2012; Gray & Spies, 1997; Kuuluvainen, 1994; Schliemann & Bockheim, 2011) and increases heterogeneity in stand age and heights (Lu et al., 2023). Disturbances that can cause such mortality and injury include pest infestations, fungal decay, wind, snow, drought, fire, and timber operations (Tepley et al., 2013; Lutz & Halpern, 2006).

To assess forest dynamics and the effects of disturbance, there are multiple methods available to researchers and forest managers. Traditional field measurements of stand characteristics provide reliable assessments of forest ecosystems, however newer technologies are available to record these measurements on a landscape scale, quickly providing accurate measurements over large areas. One such method is LiDAR (Light Detection and Ranging), a remote sensing spatial analysis tool used in a multitude of applications, from visualizing urban areas to characterizing forest canopies by measuring distances using laser detectors. Aerial LiDAR, which will be the primary focus of this review, utilizes light in the form of a pulsed laser to capture "returns" from the Earth's surface that can visualize many aspects of forest stand structures (US Department of Commerce, 2023; Kane et al., 2010; Pu et al., 2023). These returns are used to create three- dimensional depictions of canopy structures either by creating a Canopy Height Model (CHM) or using point-cloud-based methods (Pu et al., 2023). By collecting accurate and remotely sensed ecosystem data in coniferous forests, LiDAR provides an alternative to traditional field measurements which are more resource consuming and more costly on a per hectare basis (Kane et al., 2010; Næssett, 2002).

The use of LiDAR imagery in ecological settings allows researchers to create highly detailed and accurate 3D visualizations of forest ecosystems on a landscape scale. While traditional field collection methods can assess canopy structure through manual measurements of diameter at breast height (DBH), count of trees per hectare (TPH) and basal area (BA), aerial LiDAR surveys can gather much of the same data using fewer resources (Vepakomma et al., 2008; Vepakomma et al., 2011; Kane et al., 2010; Næsset, 2002). In the study of forest ecosystems, accurately characterizing changes in forest structure at a landscape scale can provide crucial information regarding forest regeneration and changes in associated ecosystem processes. Changes in forest structure can inform our understanding of patterns of tree mortality and regeneration in natural and managed forest stands (Schliemann & Bockheim, 2011) that can be useful for forest managers and climate researchers alike.

This literature review will explain the role of canopy gaps in forest ecosystems and discuss the importance of using LiDAR as a tool to gather valuable information to efficiently and reliably analyze structural changes that are critical to forest succession. This review will focus on forest dynamics in the Western Hemlock Zone of the H. J. Andrews Experimental Forest in Central Oregon, USA following an extreme snow event. Following this introduction (Section 2.1), Section 2.2 will define forest succession and its role in a healthy forest ecosystem and describe the various types of disturbances that play important roles throughout the cycle of succession. Section 2.3 will discuss the complicated definition of canopy gaps, the various types of canopy gaps, and how we will define them for our study. Next, Section 2.4 will explore

LiDAR as a tool in the study of forest ecosystems and the application of multi-temporal LiDAR data to capture changes in forest structure over time, and finally, Section 2.5 will conclude this literature review with an overview of the topics discussed.

2.2 Understanding Forest Ecosystems

In forest ecosystems, biodiversity is a key indicator of forest health. Through analyzing the composition, function and structure of forest ecosystems we can understand the mechanisms that drive biodiversity and maintain healthy forests (Franklin et al., 2002). Here we will discuss forest ecosystems and biodiversity through their relationship with disturbances, particularly those that create canopy gaps and influence spatial diversity.

In younger stands, particularly within plantation settings, tree mortality is often caused by self-thinning due to close proximity upon maturity (Larson et al., 2015). While individual mortality of these trees creates "openings" in the forest structure, they are quickly filled with branch growth and have less influence on increasing understory light availability and nutrient cycling (Franklin et al., 2002; Kuuluvainen, 1994). This density-dependent mortality also tends to create spatial uniformity in forest stands as surviving trees have similar ages (Larson et al., 2015). In old growth forests, even the loss of one tree can strongly influence understory dynamics and support vertical heterogeneity through increased light and water availability as well as nutrients from the decaying tree (Schliemann & Bockheim, 2011; Vepakomma et al., 2011). These dynamics not only play a vital role in vegetation growth dynamics, but also increase habitat for wildlife. The diversity of tree species increases through the enhanced growth of shade tolerant species associated with later stages of succession and can leave standing dead trees which create habitat for cavity nesting wildlife (Gutzat & Dormann, 2018) and understory forest species, resulting in increased biodiversity.

2.2.1 Forest Succession

In the context of this review, forest succession refers to changes in a forest's spatial structure and composition over time and can generally be described as the evolution of forest ecosystems. Historically, succession has been viewed as linear seral development of a forest following disturbance, however it may be helpful to understand forest development as a continuum (Franklin et al., 2002). This notion touches on the fact that it is a complex process that is difficult for researchers to succinctly model and find consensus on terminology, as many aspects of stand structural development classifications are arbitrary (Bell & Gray, 2016; Franklin et al., 2002). Forests are continuously experiencing disturbance of various degrees, which do not all result in a reset of a forest ecosystem to an early seral stage (Tepley et al., 2013) as many species and associated processes in these ecosystems are adapted to natural disturbance (Spies et al., 1991). As highlighted in this review and thesis research, small-scale disturbances create spatial heterogeneity through the development of canopy gaps that act as agents of succession (Gray et al., 2012) and are essential for a healthy forest ecosystem.

2.2.2 Western Hemlock Zones of Oregon

In the Western Hemlock Zones of Central Oregon, the primary focus area of this research, forest succession is largely dependent on shade tolerance or intolerance of species. This zone experiences development of canopy structural complexity faster than the higher elevation Pacific Silver Fir and Mountain Hemlock Zones, likely due to higher rates of growth and disturbance

(Kane et al., 2010). The Western Hemlock Zone refers to forest stands below 800 m, dominated by western hemlock (*Tsuga heterophylla* [Raf.] Sarg.), Douglas-fir (*Pseudotsuga mensiezii* [Mirb.] Franco), and some western redcedar (*Thuja plicata* Donn ex D. Don) (Kane et al., 2010). In this zone, Douglas-fir, a shade intolerant species, tends to quickly establish and take advantage of increased light availability following disturbances through colonization. Western hemlock, however, takes longer to establish and needs shade, often thriving in smaller canopy openings created by the falling of Douglas-firs, on top of which they tend to colonize (Gray and Spies, 1997). The Western Hemlock Zone is an interesting example of dynamic forest structure, with competition among species driven by minimal light reaching the forest floor enhancing the need for species to take advantage of any opportunity to establish. In this zone, the mortality of fast growing, shade-intolerant Douglas-firs creates canopy gaps that are essential for the establishment of western hemlocks.

2.2.3 Disturbances

In the Western Hemlock Zone and surrounding forested zones of central Oregon, moderate and severe disturbances caused by wildfire, disease, insect infestation, wind and snow events are frequent (Tepley et al., 2013). Disturbances of all kinds can change soil temperature and moisture, as well as light availability for forest microclimates (Atkins et al., 2023). Stand complexity, including spatial and species diversity, can influence the degree to which a forest ecosystem is influenced by these moderate disturbances (Choi et al., 2023). This region has experienced many of these disturbances over millennia, however the changing climate has increased the frequency and often the severity of these occurrences (Crausbay et al., 2017). This sustained exposure to disturbance has encouraged adaptation of many species resulting in resilience; however, levels of resilience may vary depending on disturbance type. Additionally, the degree of disturbance can influence the rate of regrowth and changes in forest structure and composition (Lutz and Halpern, 2006), with rates of change usually decreasing over time (Chang et al., 2019).

While timber harvests are a frequent recurring disturbance to these forest ecosystems, their behavior is much different and involves different processes as much of the biomass from logs is removed, which influences nutrient availability and regeneration. While patch-cut mosaic harvests can in some ways mimic natural forest dynamics (Spies et al., 1991), clear-cut timber harvests cannot. These large-scale extractions massively reduce biomass available for regeneration, as well as rapidly increase solar radiation reaching the exposed forest floor. Large openings in the forest canopy that are caused by severe fire or other climatological events, also result in increased solar radiation and reduced soil moisture (Schliemann & Bockheim, 2011); however, trees downed through these events usually remain in situ, providing increased soil moisture retention, nutrients through decay, and shade that is crucial for the establishment of seedlings (Gray and Spies, 1997).

2.3 Canopy Gaps

This section will review how canopy gaps are defined in forest ecosystems, as well as explore various types of gaps. Not only do the rates and mechanisms of disturbance vary in forest ecosystems, the rates and mechanisms of regeneration of trees within canopy gaps vary depending on the dominant tree species, stand age and stand density in a forest (Kuuluvian, 1994). Despite this variation, canopy gaps play an essential role in many different forest types (Gray and Spies, 1997). Here we will take a closer look at what canopy gaps are, how they are formed and why they are key drivers of forest succession (Gray et al., 2012), focusing on the Western Hemlock Zone.

2.3.1 Defining Canopy Gaps and Terminology

Stand density, crown volume, diameter at breast height (DBH), and other forest stand characteristics, have relatively finite definitions as well as measurement and analysis methodologies across forest types around the globe, but the definition of canopy gaps is highly forest type they can vary among tree species due to differing canopy structures. Various studies have reviewed the inconsistencies in terminology and definitions (Schliemann & Bockheim, 2011; Franklin et al., 2002), but it remains that the definition of a canopy gap may vary among forest stands (Gray & Spies, 1997; Gray et al., 2012; Lu et al., 2023; Schliemann and Bockheim, 2011). While acknowledging that a simple definition is convenient to establish consistency but may disregard important nuances of a complicated topic, Schliemann and Bockheim (2011) support the definition of a canopy gap as a hole through all foliage layers to an average regeneration level of 2 m, as defined by Brokaw (1982). Supporting this idea of regeneration height as an indicator, Vepakomma et al. (2011) define a gap as an opening in the canopy caused by the fall of one or several trees (Spies & Franklin, 1989), resulting in the height of the remaining stems falling below 5 m. In contrast, Lu et al. (2023) argue that a blanket height-based definition of a canopy gap may not be applicable across forest types, though they acknowledge that their own crown height ratio-driven methodology developed for deciduous stands should not apply to coniferous stands with low branches that can reach to the forest floor (Lu et al., 2023).

It is important to consider the classification of tree species when studying canopy structures due to the differences in behavior and architecture between deciduous and coniferous species (Gray et al., 2012). While deciduous trees tend to forage for light and are able to reach into openings with a more flexible structure, coniferous trees tend to have a more rigid structure and are not able to light forage in this way (Kuuluvainen, 1994). Appropriate consideration of the variance in canopy structure, overall architecture and behavior between deciduous and coniferous trees is an important step in determining the definition of a canopy gap. Establishing a consensus on what is defined as a canopy gap would increase consistency among studies and could highlight differences that should be noted among varying stand types and environments or climates.

2.3.1a Defining a Canopy Gap in a Western Hemlock Zone of Central Oregon

For this study, a canopy gap will be defined following parameters that apply to a conifer-dominated forest region in the Pacific Northwest. As we will be focusing on gaps created by a heavy snow event, it will be appropriate to define our gaps as openings that do not exceed an area of 1000 m^2, which tends to encompass openings created when one to several trees fall or are otherwise injured (Schliemann & Bockheim, 2011; Spies & Franklin, 1989; Vepakomma et al., 2011). For this study, our maximum height threshold was set at 2 m, as suggested by Brokaw (1982) and supported by Schliemann and Bockheim (2011), as our focus is on gaps created from a snow event causing the toppling of trees throughout experimental watersheds. Vepakomma et al. (2011) suggest that the height of remaining stems within a gap could reach up to 5 m, however the lower height threshold may better capture the toppling of larger trees that may also reduce understory and regeneration height.

2.3.2 Types of Gaps – Natural and Human Made

There are some basic similarities between naturally formed canopy openings and gaps that are created through timber harvests or other anthropogenic activities; however, there are substantial differences between the two that require proper consideration. This section will review variation in gap dynamics, where historically it was suggested that selective and patch-cut harvests in young forests could somewhat mimic natural succession processes and old growth forest dynamics (FEMAT, 1993); however, the most common natural gap size in the Pacific Northwest equates to the death or removal of a single dominant tree, which is clearly a different process (Franklin et al., 2002; Gray and Spies, 1997). Within forest ecosystems, canopy gaps generally increase light exposure, soil moisture and nutrient cycling (Gray et al., 2012; Schliemann and Bockheim, 2011), though the mechanism of gap formation and size of fallen trees influence these dynamics differently in natural vs. human made gaps (Kuuluvainen et al., 1994).

2.3.2a Naturally Formed Gaps

Naturally formed gaps are those created through a natural disturbance, such as wildfire, snow, wind, insects, pathogens, or other natural occurrences. Within this category, gap sizes can vary widely – as stand-replacing wildfires can dramatically reduce canopy coverage over large areas, while wind and snow storms tend to result in smaller openings in the canopy, often referred to as treefall gaps (Gray and Spies, 1997; Schliemann & Bockheim, 2011). In the Western Hemlock Zones of the Pacific Northwest, Douglas-firs often serve as gap makers as the falling of even just one Douglas-fir can create an opening large enough to influence microsite dynamics (Gray & Spies, 1997).

Canopy gaps created by natural disturbances can vary widely in size and degree of injury or mortality, resulting in various levels of change to forest ecosystem and microsite dynamics. In natural settings, disturbances cannot be planned, and their random occurrence or absence results in range of structural complexities (Kane et al., 2010). While the effect of small natural treefall gaps can have beneficial results for forest ecosystems and microsites, including increased spatial heterogeneity and species diversity, large gaps over roughly 1000 m^2 begin to result in negative effects (Schliemann & Bockheim, 2011). At those larger sizes, the level of increased solar radiation and reduced soil moisture make it very difficult for seedlings to establish unless they are able to quickly send deep roots that reach below the hot and dry top layer of soil and litter (Gray & Spies, 1997). Smaller regenerative treefall gaps also fill in much quicker than large gaps, both by vertical height growth of seedings and saplings and by lateral growth of branches at the gap edge (Schliemann & Bockheim, 2011; Lu et al., 2023). While this review focuses on canopy gaps and their role in forest ecosystems, it is important to note that some openings in the forest canopy are not considered canopy gaps in the same way. Canopy gaps are created by death or injury of trees following disturbance and are a part of forest succession, but some canopy openings exist due to such things as poor soil conditions or large topographical features like rock outcroppings or boulders. These permanent openings do not support regeneration and thus are referred to as non-regenerative openings (NROs) (Senécal et al., 2018).

2.3.2b Human Made Gaps

Human made gaps can refer to those that are created through timber extraction; however, they may also refer to silvicultural practices or research that intentionally aim to replicate natural openings and ecosystem processes. Small-scale timber extractions may closely simulate natural processes of a forest ecosystem by increasing light availability, but the removal of trees is a key difference that does not allow extraction to adequately simulate a natural gap. While thinning can be a vital part of effective forest management (Spies et al., 1991), selection for desired species or individuals reduces the ability for these openings to resemble natural processes.

2.4 LiDAR Imagery and Data Collection in Forest Ecosystems

Aerial Light Detection and Ranging (LiDAR) allows for the study and analysis of forest canopy structure from stand to landscape scales in ways that studies gathering field measurements from relatively small distributions of sample plots cannot (Kane et al., 2010). LiDAR pulses can catalog canopy heights, crown volumes and stand density among many other forest structure parameters that detail spatial patterns and structural complexity (Kane et al., 2010; Pu et al., 2023).

Terrestrial LiDAR data is another method of three-dimensional analysis of forest structure; however, it tends to focus on the lower portions of canopies as measurements are collected from the ground (Wassihun et al., 2019). Although terrestrial LiDAR data can provide valuable information, surveying large areas would be time consuming and expensive, likely running into the same limitations as traditional field measurements (Vepakomma et al., 2011). This section will review the value of LiDAR as a tool to gather data remotely, then explore the role LiDAR plays in understanding forest structure, and finally discuss how multi- temporal LiDAR data can characterize changes in forest stand structure over time at a landscape scale.

2.4.1 Value of Remote Sensing Data

While it may not be the goal of remote sensing technologies such as LiDAR to replace field measurements, it is certainly a valuable tool to help reinforce manually collected data and deepen findings, as well as provide an alternative methodology when field measurements may not be available. In managing forests at a landscape scale, LiDAR helps managers to gather important information, especially in regions that are heavily forested such as the cascade region of Oregon. Approximately 120,000 km^2 of Oregon is covered in forest, 64% publicly owned and managed, 34% privately owned, and 2% under tribal ownership (Oregon Forest Resources Institute, 2023). The larger tracts of these lands can be vast expanses, some of which are only accessible by small roads and can be quite remote. For forest managers and researchers, evaluating and studying these forest lands requires substantial resources and time, and surveys of forest stands is time consuming (Vepakomma et al., 2008; Vepakomma et al., 2011; Kane et al., 2010), and it has been established that LiDAR provides accurate, detailed data that can be used in lieu of field measurements if needed (Kane et al., 2010).

Several studies have compared stand structure data acquired through LiDAR with corresponding vegetation plot data to “ground truth” findings and assess the accuracy of LiDAR data and visualizations (Kane et al. 2010; Rex et al., 2023; Vepakomma et al., 2011). One such study determined that LiDAR data can be used to create predictive models that can accurately distinguish between canopy gaps and NROs (Senécal et al., 2018), and another study found that LiDAR-derived data improved their modelling methods in relation to identifying and quantifying canopy gaps found around individual trees (Stitt et al., 2022), further promoting the use of LiDAR data to improve traditional methodologies.

2.4.2 LiDAR's Role in Understanding Forest Stand Structure

LiDAR data analysis can provide a more thorough understanding of stand structure characteristics, such as identifying unexpected mixtures of primary and secondary stands within classification groups which suggests commonly accepted indicators of structural stage, such as stand age, may not be a sufficient proxy for structural stage (Kane et al., 2010). Because it is capable of accurately measuring ground elevations below forest canopy cover, it is a reliable method of detecting changes in tree canopy height across landscapes, as well as individual tree height growth through multiple LiDAR measurements taken over time (Vepakomma et al., 2011).

2.4.2a Multi- Temporal LiDAR Imagery

LiDAR data is widely used in a variety of applications from remote forest structure analysis to urban planning and development; however, the use of multi-temporal LiDAR data is limited. In forest ecosystem settings, the ability to conduct multiple LiDAR flights over the same area over time allows researchers to visualize changes in forest structure at the landscape scale, something that would take many hours and resources to accomplish through traditional methods (Vepakomma et al., 2011). Multi-temporal LiDAR data is an efficient tool in characterizing forest growth dynamics, and in the following thesis research, we will apply this notion to visualizing canopy structure to identify canopy gaps and investigate their behavior over time.

2.5 Conclusion

Forest ecosystems are constantly changing, through regeneration and death as part of the cycle we call succession. The elements of this phenomenon are much more complex than historic understanding suggests, functioning in a continuum rather than a linear fashion. Important aspects of this complex system, canopy gaps, could be easily overlooked as they are not as dramatic and headline worthy as high intensity wildfire, or as eye-catching as a vast clear-cut. But in reality, the role of canopy gap is powerful within forest ecosystems, and drives forest succession. Small-scale disturbances are constantly occurring, and the literature asserts that forest health is dependent on this disturbance regime.

In researching forest ecosystem dynamics, traditional field measurement methodologies are important; however, this is true for some forest measurements more than others. As accuracy of LiDAR continues to increase, and its applications expand, many forest measurements will be taken remotely. At a landscape scale, this ability increases efficiency in data collection, and can add depth to traditionally collected data. As canopy gaps fill in through regeneration and develop or grow through tree mortality and injury, LiDAR data collected over time can accurately account for these changes when it may not be possible or necessary to send researchers into the field, especially in topographies that are difficult to navigate or access.

This literature review illustrates the complexities and fine scale components of forest succession through examining canopy gaps and their role in forest ecosystems. Additionally, it identifies LiDAR data collection as an important tool in studying canopy gaps and other aspects of forest structure by collecting fine-scale and accurate elevation data, and describing how these data can be used to visualize and model forest ecosystem dynamics efficiently and accurately.

Chapter 3: Methods

Data detailing study sites and history in this chapter were provided by the H.J. Andrews Experimental Forest and Long-Term Ecological Research (LTER) program, administered cooperatively by Oregon State University, the USDA Forest Service Pacific Northwest Research Station, and the Willamette National Forest. This material is based upon work supported by the National Science Foundation under the grant LTER8 DEB-2025755. The HJA boundary layer used in the study area map was created by Jonathan Burnett (H.J. Andrews Experimental Forest), and the layer containing plot locations for each watershed is maintained by the Pacific Northwest Permanent Sample Plot Network.

3.1 Study Area

The H.J. Andrews Experimental Forest (HJA) is a highly studied research forest in central Oregon encompassing over 6,400 ha. With over 75 years of forest research since its establishment in 1948 by the U.S. Forest Service, HJA is primarily managed for research while some areas have been managed for timber production and hiking trails. The HJA is situated between 400 – 1600 meters above sea level (m.a.s.l.), just northeast of the Blue River reservoir, which is the meeting point of Blue River and Lookout Creek within the McKenzie River Ranger District. The HJA is composed of an array of forest stand ages due to timber harvests and natural disturbances as well as areas of forest that were intentionally not harvested in order to retain old growth. The HJA has historically been impacted by severe wildfires, with some areas being affected by recent wildfires including the 2020 Holiday Farm Fire and the 2023 Lookout Fire. The oldest trees within the old growth stands in this forest are recorded at 300 to 700 years old, with several standing over 75 m tall, and the tallest at over 90 m tall (H.J. Andrews Experimental

Forest, 2016). Dominant trees across HJA are representative of the western hemlock zone where the forest lies, including Douglas-fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*) and western redcedar (*Thuja plicata*). There are various understory communities present across the forest, dominated by rhododendron (*Rhodedendron macrophyllum* D. Don ex G. Don), vine maple (*Acer circinatum* Pursh), sword fern (*Polystichum munitum* [Kaulf.] C. Presl), Oregon grape (*Mahonia aquifolium* [Pursh] Nutt.), and salal (*Gaultheria shallon* Pursh).

The geology underlying the forest is representative of the volcanic makeup of the region, comprised entirely of three separate formations of volcanic bedrock. Lower elevations in the forest are underlain with Little Butte Formation bedrock, mid elevation areas are underlain with Sardine Formation bedrock, and above 1200 m.a.s.l., the Pliocascade Formation bedrock is found. The three watersheds included in this study have permanent plots within the lower (< 760 m.a.s.l.) and mid elevation (760-1200 m.a.s.l.) ranges, with variable soils. The HJA contains nine experimental watersheds within these varying forest ages, all with unique management histories (H.J. Andrews Experimental Forest, 2022). This study examines data collected from three watersheds, two of which are 60 year old plantations (WS01 and 03), and the other mature old growth forest (WS02), all of which have an estimated pre-management forest origin of around 1500 AD. Categorized as a transient snow zone, the HJA experiences snow annually, usually beginning in November, with the mean annual maximum snow-water equivalent measured at about 375 mm and 25% precipitation falling as snow at lower elevations within the experimental forest (H.J. Andrews Experimental Forest, 2017).

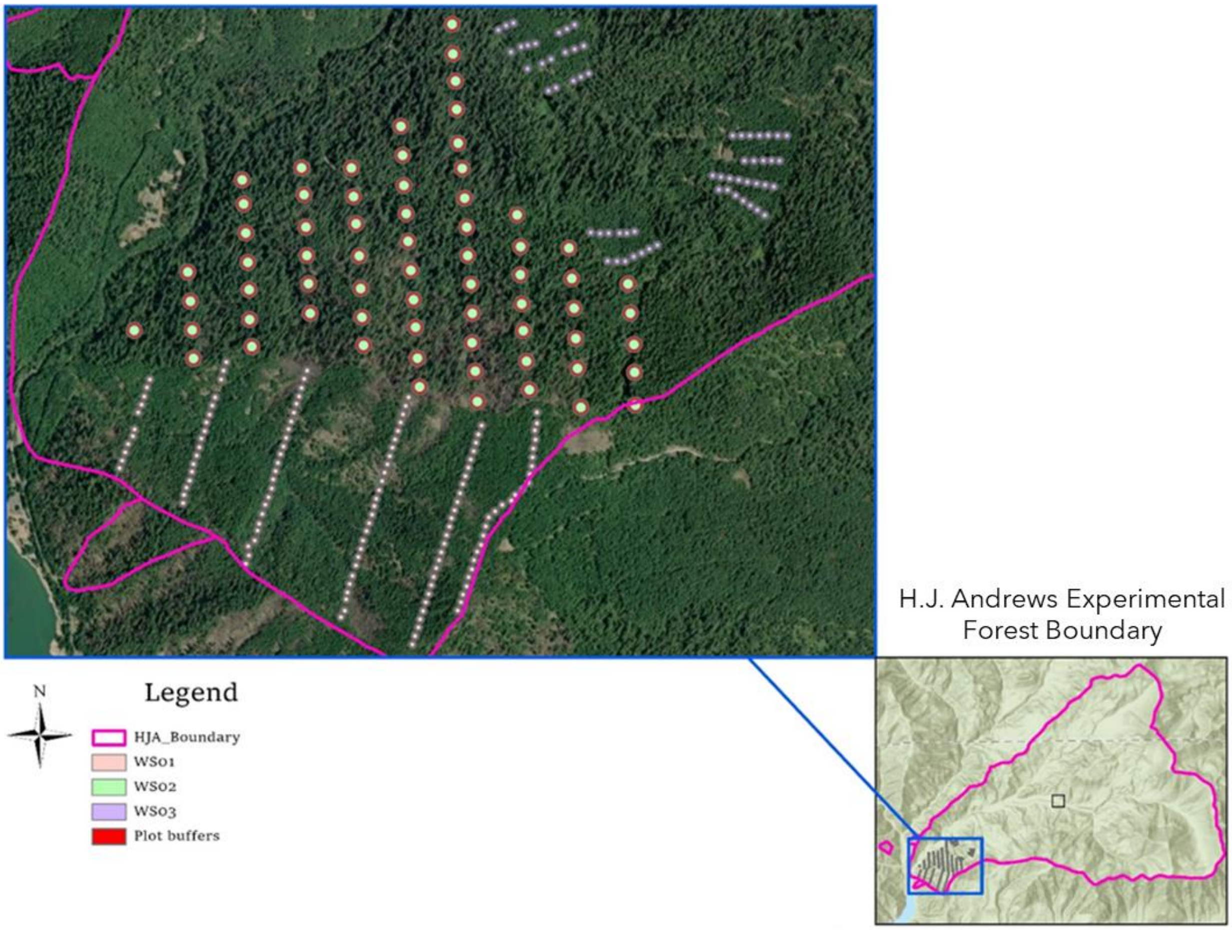
Researchers at HJA collected vegetation plot data for decades throughout the forest reserve, but for this study we are focusing on vegetation/tree plot data collected from 2008 to 2020 (Franklin, 2024; Halpern, 2022) in WS01, WS02, and WS03 (Figure 1). These watersheds include plots that were severely affected by a late 2019 snow event, and all three watersheds were included in this study to provide an age gradient that may have influenced mortality. Some plots lie above 800 m and some below, which is a threshold of interest for this study as researchers at HJA noticed a shift in snow make-up, with the snow below 800 m.a.s.l. being heavier and wetter, and the snow above 800 m.a.s.l. lighter and drier, which may have influenced the formation of canopy gaps and their distributions. WS01 is a 60-year-old plantation that was last 100% clear-cut in 1966, with elevations ranging from 439 to 1027 m.a.s.l.. Historic dominant species in this watershed were mature to old growth Douglas-fir and hemlock, with western redcedar present in drainages. Bigleaf maple (*Acer macrophyllum* Pursh) remains the dominant hardwood species. Today, Douglas-fir dominates this watershed, with some western hemlock and various other species recorded. The understory boasts six plant communities: hazel-salal, rhododendron-salal, vine-maple-salal, vine maple-Oregon grape, gold-thread, and sword fern. WS01 contains 132 permanent vegetation plots that are 250 m^2 circles spaced 30 m apart with a radius of 8.92 m (not corrected for slope) (Lutz & Halpern, 2006, Halpern & Lutz, 2013; H.J. Andrews Experimental Forest, 2017).

WS02 is old growth forest, and is the control watershed for research conducted in the adjacent watersheds 1 and 3. With elevations ranging from 545 to 1079 m.a.s.l., WS02 has remained unharvested to act as a reference within the experimental forest, and displays expected characteristics of the western hemlock zone, dominated by Douglas-fir and western hemlock with the majority of trees reported to be around 450 years old, and a healthy understory comprised of rhododendron, vine maples, sword fern and Oregon grape (H.J. Andrews Experimental Forest, 2017). There are 67 permanent plots in WS02, each with a radius of 17.84 m (not corrected for slope), spaced 100 m apart with transects 200 m apart.

WS03 has elevations ranging from 476 to 1080 m.a.s.l., and contains a mix of ages with three clustered units of sample plots on alternate aspects of the watershed, the result of a harvest of 25% of the area in 1963. Despite these harvests, old-growth Douglas-fir and western hemlock that are 100-500 years old continue to dominate the overstory, with understory composition similar to WS02 (H.J. Andrews Experimental Forest, 2017). The permanent plots in WS03, in contrast, are all located within the harvested area of the watershed, so for the purpose of this study we will refer to it as a 60 year old plantation. The permanent plots are set up similar to those in WS01, with 66 plots spaced 30 m apart, each with a radius of 8.92 m (not corrected for slope). In addition to an age comparison, these watersheds provide an elevation gradient for comparison. The plots within the younger forests of WS01 and WS03 were measured using the same sampling protocol (see below), while the plots within the old growth forest of WS02 were measured using the Pacific Northwest Permanent Sample Plot Program (PNW-PSP) protocol (see below).

Figure 1

Study Area and Permanent Plot Transects Within H.J. Andrews Experimental Forest



Note. Map of the research study site within the H.J. Andrews Experimental Forest (HJA) in central Oregon, west of the Cascade Mountains. Permanent vegetation plots for each watershed included in this study are depicted with colored circles, and proportional buffers appear as red circles around each permanent plot. WS01 can be found in the southernmost area within the HJA boundary, WS02 adjacent to the north with larger research plots, and WS03 in the northeastern most area adjacent to WS02, with three permanent plot transect clusters Study area layout created by Ruth Mares using an HJA boundary layer created by Jonathan Burnett (H.J. Andrews Experimental Forest, and a permanent plot location layer maintained by the Pacific Northwest Permanent Sample Plot Network.

3.2 Field Measurements

3.2.1 Vegetation Plot Data

Field data used in this study were collected by various researchers at HJA as part of the LTER program, here focusing on data gathered from 2008 to 2020. Sampling protocols were established and conducted by HJA researchers, and here we outline the specific methods used to gather data used in this study (H.J. Andrews Experimental Forest, 2021).

Sampling Protocol for Watersheds 1 and 3

Tree plots within WS01 and WS03 each contain five 2 x 2 m understory vegetation plots (quadrats), named Q0, Q1, Q2, Q3 and Q4 which are corrected for slope. Only plot Q0, located at the center of each plot, was sampled by HJA researchers. Established in 1980 to boost the understory sampling dataset, the four "satellite" plots were dropped from the study as they could not be sufficiently maintained. There are 132 Q0 center plots in WS01 and 66 Q0 center plots in WS03, although data were only analyzed for 61 plots in WS03 due to insufficient LiDAR data extents in 2008 and 2016.

To reduce disturbance to understory species while sampling, vegetation quadrats were sampled before the larger tree plots. For each understory quadrat sampled, the following characteristics were recorded: two canopy cover (≥2m tall) estimates using a truck-mirror densiometer (with separate estimates made for conifer, hardwood, tall shrubs, and total canopy cover) to quantify cover on a scale of 1-4 and a visual estimate of growth form cover as a %, substrate type, burn severity, growth form for all species, species cover (%), height (cm), biomass – which could include basal diameter (DBA, cm), diameter at breast height (DBH, cm) for marked trees, length (for certain fern species) depending on the species (see Table 1 for more details on vegetation and tree characteristics). For each tree plot sampled, the following characteristics were recorded for live trees tagged at breast height: DBH, status, overall vigor, bark char, % canopy scorch, and any unusual features of the tree. For smaller live trees, the following characteristics were recorded: DBA, status, overall vigor. Trees too small to be tagged at breast height were measured for basal diameter, status, and overall vigor. Tagged trees that had died in recent years (since the last measurement) were measured for DBA or DBH depending on tagging mechanism, with status and overall vigor reflecting their death, as well as their probable cause of death (H.J. Andrews Experimental Forest, 2021).

Table 1

Categorical Vegetation and Tree Plot Characteristics

Measurement	**Description**
Substrate	Bare, stone, log, stump, butt, snag, litter
Burn severity	Black – lower severity fire White – higher severity fire
Growth form	Moss, tree, tall shrub, herbs
Status	1 = Present and alive, 2 = Ingrowth, 3 = Tree fused with another, 6 = Dead, 9 = Not found after search (NFAS)
Overall vigor	1 = good, 2 = fair, 3 = poor
Bark char	Light, moderate, deep

Note. This table details how vegetation and tree plot characteristics were categorized during sampling in WS01, WS02 and WS03.

Sampling Protocol for Watershed 2

There are 67 circular tree plots in WS02, spaced 100 m apart with transects 200 m apart. For these old growth plots, understory vegetation cover and biomass measurements were only taken on an as-needed basis. For tagged trees within these plots, tree status, DBH, overall vigor, main stem condition and rooting condition, lean angle, percent crown and percent tree were recorded. Percent crown refers to the estimated percent of a tree's live crown volume that is intact at the time of the assessment, while percent tree refers to the estimated percent of the entire main stem length that is intact. Ingrowth of new trees (≤1.37 m) were recorded; however, these trees fell below our threshold of 2 m to be assessed for canopy openings. To assess tree mortality, main stem condition and rooting condition were recorded for the standing portion of the tree. For the downed portion, % on the ground and % supported were recorded. For all dead trees, mortality cause was recorded, both the acute final suspected cause of death and any predisposed condition that may have increased the likelihood or rate of death (*PNW-PSP Measurement Protocol*, 2019).

3.2.2 Snow Damage Assessments

Due to the age difference between the young plantations and mixed aged stands of WS01 and WS03 and the old growth stands of WS02, slightly different snow damage assessment protocols were used. Protocols were developed and conducted by HJA researchers (H.J. Andrews Experimental Forest, 2019).

<u>2019 Snow Damage Assessment Protocol for Watersheds 1 and 3</u>

For this assessment, only tagged trees with DBH ≥ 5.0 cm were measured. Within plots, trees were noted as still alive or newly dead if they had died since the most recent measurement (2017). During these particular assessments, trees were only recorded with statuses of 1, 6 or 9. For live trees, status was recorded as 1, and assessed for tree damage. Trees were noted as either not impacted, scarred, stem broken but alive, down but alive, or crown sheared. Percent intact crown and percent tree were also recorded. For newly dead trees, status was recorded as 6 (dead), and physical characteristics as well as probable cause of death were recorded. For trees not found after search (NFAS) within the plot, status was recorded as 9. Physical characteristics could include notes such as broken top, uprooted, crushed, animal damage, while probable cause of death fell into five categories: suppression due to subordinate canopy position, mechanical damage, slope failure, pathogen, or unknown (H.J. Andrews Experimental Forest, 2019).

2019 Snow Damage Assessment Protocol for Watershed 2

For live trees with DBH ≥ 5.0 cm in WS02 sampling plots, tree status was recorded as 1, and a damage assessment was conducted to categorize the tree as: unimpacted, stem scarred, stem broken but alive, or down but alive. Percent intact crown and percent intact tree were recorded for trees that experienced damage from the snow event only, values were not recorded for previously noted injuries that were not caused by the snow. For newly dead trees that died since the last measurement in 2018, tree status was recorded as 6 (dead). New DBH measurements were not recorded for new dead trees, instead DBH from the last measurement was recorded. As part of the mortality data, main stem condition and rooting condition were recorded. For the standing portion of the tree, lean angle, percent crown and percent tree were recorded. Physical characteristics and proximate (immediate cause of death) and predisposing mortality causes were recorded (H.J. Andrews Experimental Forest, 2019).

3.3 LiDAR

LiDAR Data Collection

Countless studies have been conducted using aerial LiDAR data, however here we had a unique opportunity to utilize data from multiple LiDAR flights of the same area over time. Fixed-wing planes were used to obtain aerial lidar acquisitions (ALS) for all years analyzed in this study. The 2008 acquisitions were organized by HJA, while 2016 acquisitions were organized by the State of Oregon, and 2020 by United States Forest Service (USFS) Region 6. This collaboration resulted in ALS flights over HJA including WS01, WS02 and WS03 in the southeastern portion of the forest in our focus years of 2008, 2016 and 2020. Returns were captured on all surfaces and then filtered to thin the point cloud to only the first returns (in this case, vegetation canopy) and ground returns (as determined by ALS flight vendor) to calculate tree height and create canopy height models (CHMs).

3.3.1 Visualizing LiDAR Imagery

For each flight, several tiles were combined as a mosaic to encompass the entirety of watersheds 1, 2 and 3. Image files were uploaded as LAZ (laser zip) files into ArcGIS Pro version 3.2.0 and then converted to LAS (laser) files. After creating an LAS dataset, rasters were created with the point cloud data using the ground points to create a Digital Terrain Model (DTM). Digital Surface Models (DSMs) were created by filtering the point cloud data for non-ground points, focusing on the first of many (first returns) and single returns. Using the raster calculator geoprocessing tool, the DTM was subtracted from the DSM to calculate tree height.

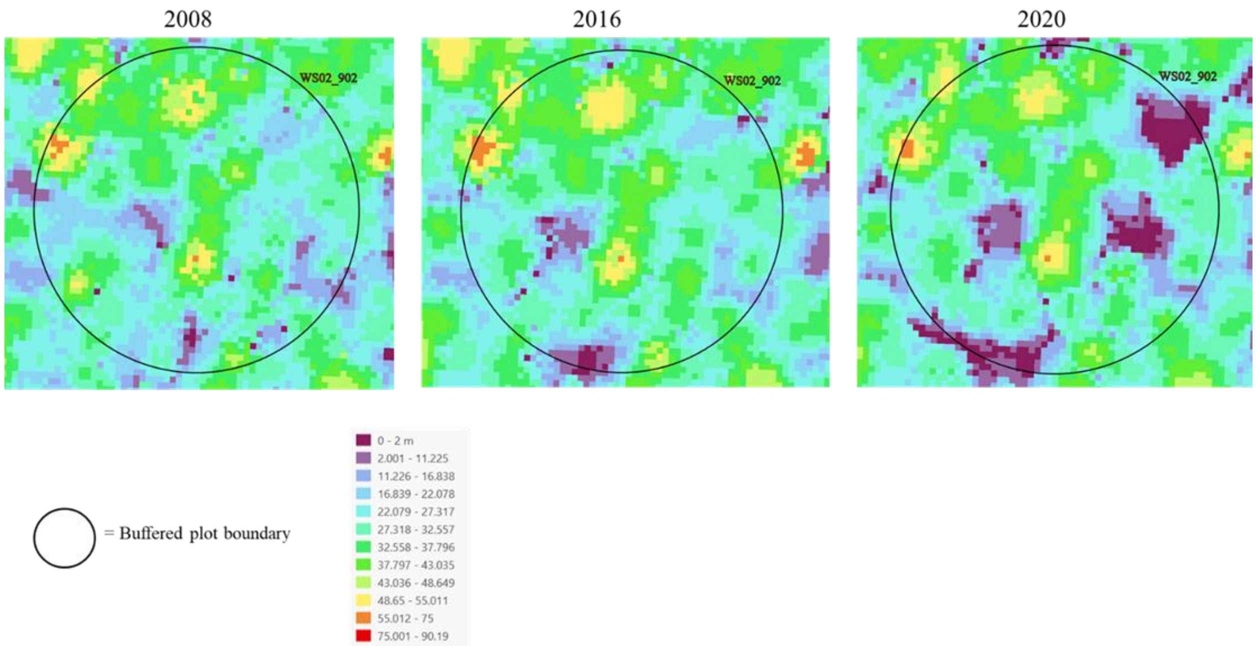
3.3.2 Measuring Height and Gap Identification

Using ArcGIS Pro, a buffer was applied from the center of each plot at 1.5 times the radius of the plot (Rex et al., 2023). For WS01 and WS03, this buffer was 13.38 m, and for WS02 the buffer was 26.76 m. This fixed-area approach allowed for analysis of the area of the canopy around the plot center rather than the height of individual trees (Næsset et al., 2002), leading to a more reliable representation of canopy height variability between plots. As returns between years may lack precision in tracking individual trees, this approach uses the LiDAR-derived canopy height measurements at a plot level.

Buffered plots were classified to have a gap ("yes gap") if the portion of the gap within the buffered plot was at least 10 m^2, but the total area of the contiguous gap did not exceed 1000 m^2 (Schliemann & Bockheim, 2011). Plots were visually identified from height calculation rasters created in ArcGIS Pro, and measured using the Measure Area tool. Gaps were measured by identifying 1 m^2 pixels that fell into the 0-2 m^2 height category as per our canopy gap parameters for this study, and the Measure Area tool was used to trace those pixels. Gap area measurements were rounded to the nearest square meter. Buffered plots that had gaps $\leq$ 10 m^2, or gaps whose contiguous area exceeded 1000 m^2 were classified to not have a gap ("no gap"), and areas were not measured. Larger gaps were also cross- referenced with the World Imagery layer within ArcGIS Pro to ensure they were not part of a more permanent meadow or bluff. These types of openings do not experience the same ecosystem processes of forest succession, and were not created due to the falling of one or several trees. If a buffered gap contained an opening larger than 1000 m^2 (meadow/other feature) as well as a canopy gap $\leq$ 10 m^2, the plot was classified at "yes gap," and the smaller gap was measured.

Figure 2

Canopy Height Model Change Over Time



Note. Sample of canopy height models across the three study years for the same permanent plot in WS02 (WS02_902). Dark purple pixels indicate areas that fall within our height parameters for canopy gaps (< 2 m), but were only recorded as a gap if they fell between 10 m^2 and 1000 m^2. This side-by-side comparison highlights regeneration and gap formation over time, with this 2020 example displaying large new gaps, which likely resulted from the heavy snow event.

3.4 Multi-temporal Statistical Analysis and Comparison of Field and LiDAR Data

Field and LiDAR data collected from vegetation plots within the years of the LiDAR flights were used with the LiDAR point cloud data for statistical analysis. LiDAR data collected in 2008, 2016, and 2020 were paired to the most recent corresponding field measurements. LiDAR data collected in 2008 were used to create a baseline, with LiDAR data collected in 2016 establishing a rough idea of forest characteristics and growth under normal conditions. LiDAR data collected in 2020 revealed the impacts of the snow event and were the focus of this analysis. Stand density was calculated from field data that recorded trees per plot, here normalized to trees per hectare, while elevation and canopy roughness were calculated from the LiDAR data using ArcGIS Pro. Canopy roughness was determined using the standard deviation from the mean height recorded across raster tiles in ArcGIS Pro (Rex et al., 2023). Because canopy roughness was calculated based off of plot areas in square meters, these data were normalized to reflect roughness per hectare to account for varying plot sizes between the watersheds. For our analysis using data collected during the 2019 Snow Damage Assessment, we focused on mortality, which was recorded as % basal area for each plot. This metric was arcsine square root transformed to allow for linear regression analysis.

Testing Normality

Under the parameters of our research and the variables we were testing, these data did not meet the assumptions of parametric ANOVA testing (gap frequency data among watersheds derived from ArcGIS Pro CHM analysis), so we used a permutational ANOVA (permANOVA) approach. We compared means using permANOVAs in JMP (JMP Pro 16.0), with a random seed of 363. We used permANOVAs to test for differences in numbers of gaps and average gap size among watersheds in each year (2008, 2016, and 2020).

Logistic Regression Plot Analysis: Multi-Temporal Data

To test the effects of elevation, stand density, and canopy roughness on the presence or absence of canopy caps, we created logistic regression models in JMP (figures were created in the R package ggplot2).

Linear Regression Plot Analysis: Multi-Temporal Data

To test the effects of elevation, stand density, and canopy roughness on the average size and frequency of canopy gaps, we created linear regression models for each sampling year using

JMP Graph Builder software. All plots with canopy gaps were pooled together and separately analyzed for each study year (2008, 2016, and 2020).

Linear Regression Plot Analysis: Snow Damage Assessment

To test the effect of canopy roughness on the percent mortality of trees within plots following the snow event, we first performed an arcsine transformation on the percent mortality of basal area recorded in each plot. We then created a linear regression model using the transformed 2019 mortality data with the 2020 LiDAR data using JMP Graph Builder software.

Chapter 4: Results

4.1 Influences on the Presence or Absence of Canopy Gaps in 2008, 2016, and 2020

Elevation

Logistic regressions revealed that canopy gap presence or absence was positively associated with elevation in Watersheds 2 and 3 (Figure 3; $P = 0.03$, $P = 0.04$, respectively) in 2008, with presence of canopy gaps increasing with elevation, while negatively associated with elevation in Watershed 1 in 2020 ($P < 0.0001$; Table 2). No significant associations were found in Watershed 1 in 2008, in Watersheds 1, 2, or 3 in 2016, or in Watersheds 2 or 3 in 2020 ($P > 0.05$).

Linear regressions showed that among all plots with canopy gaps recorded across watersheds, the average size of canopy gaps in 2020 had a strong positive association with elevation (Figure 4; $P = 0.02$), and the frequency of gaps decreased with elevation (Figure 4; $P = 0.005$). The mean elevation at which gaps were recorded was 686.6 m, and the average gap size was 0.004 ha (39.9 m^2). No significant associations were observed between elevation and the size or frequency of canopy gaps in 2008 or 2016 ($P > 0.05$).

Table 2

Effects of Elevation, Stand Density, and Canopy Roughness on the Presence of Canopy Gaps Across Watersheds and Study Years.

		Elevation	Stand Density	Canopy Roughness
Year	Watershed	*p*	*p*	*p*
2008	1	0.06	0.37	**<0.0001**
2008	2	**0.03**	**0.04**	**0.02**
2008	3	**0.04**	0.89	**0.02**
2016	1	0.63	0.052	**0.0002**
2016	2	0.06	0.28	**0.02**
2016	3	0.71	**0.02**	**0.003**
2020	1	**<0.0001**	**0.03**	**<0.0001**
2020	2	0.71	0.11	0.05
2020	3	0.32	**0.001**	**0.001**

Note. Results from logistic regression models for each variable tested for all years and for all watersheds. Significant results ($P < 0.05$) are highlighted in bold. Results shown in Figure 3.

Table 3

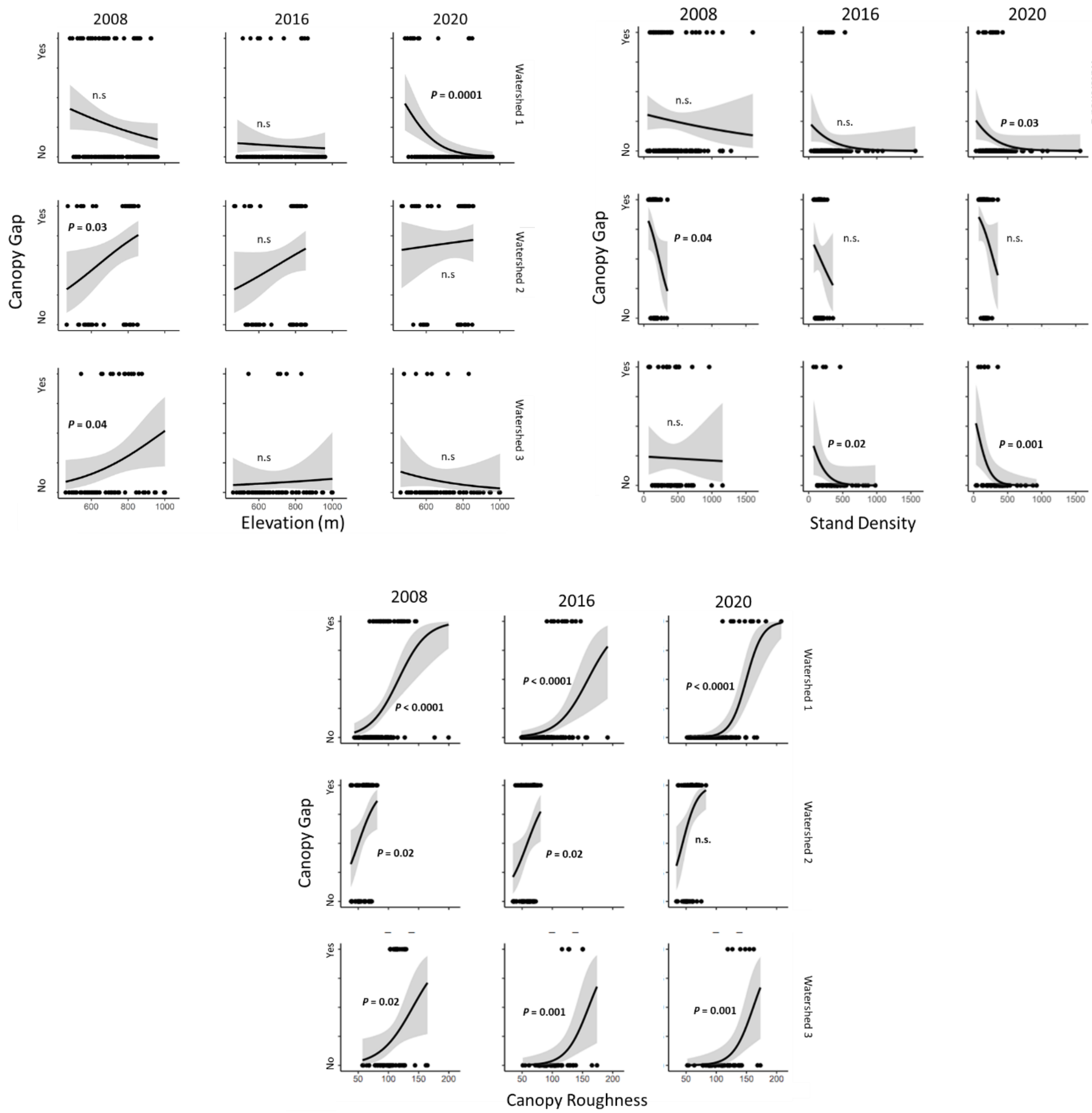
Effects of Elevation, Stand Density, and Canopy Roughness on the Size and Frequency of Gaps in All Plots With Gaps Recorded Across Study Years.

		Size	Frequency
	Year	*p*	*p*
Elevation	2008	0.09	0.09
	2016	0.23	0.54
	2020	**0.02**	**0.005**
Stand Density	2008	**0.04**	**0.001**
	2016	0.08	**0.0003**
	2020	0.18	**0.02**
Canopy Roughness	2008	0.29	**<0.0001**
	2016	0.47	**<0.0001**
	2020	0.76	**0.002**

Note. Results from linear regression models for each variable tested across watersheds for each year. Significant results ($P < 0.05$) are highlighted in bold. Results shown in Figures 4, 5, 6, and 7.

Figure 3

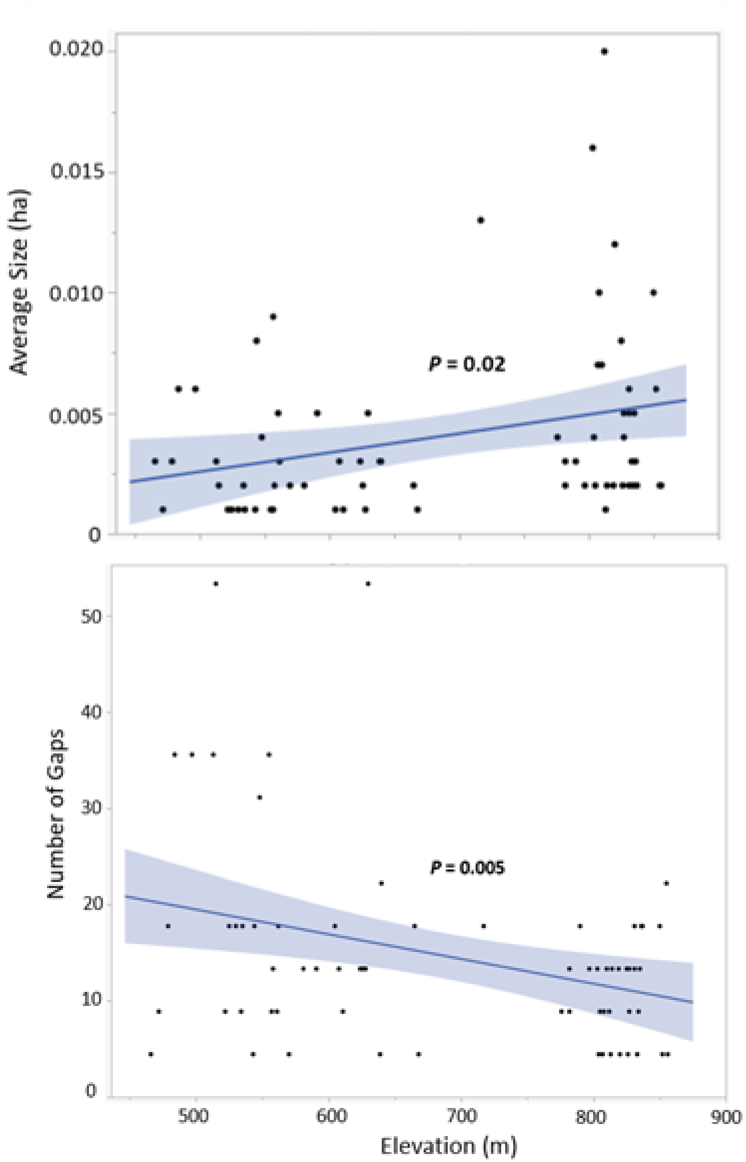
Influences on the Presence or Absence of Canopy Gaps



Note. Logistic regressions of the influence of elevation (m), stand density (trees per hectare), and canopy roughness (standard deviation of canopy height) on presence or absence of canopy gaps in 2008, 2016, and 2020. Plots with canopy gaps recorded are represented by black plot points at the top of each graph, and plots with no canopy gaps recorded are represented by black plot points at the bottom of each graph. Least squares fit is represented by a solid black line, and 95% CI on fit prediction is represented in gray. Regressions with significant results include *p*-values in bold, n.s. for non-significant results, further detailed in Table 2.

Figure 4

Influence of Elevation on Gap Size and Frequency in 2020



Note. Linear regressions of the influence of elevation (meters) on average gap size (hectares) and gap frequency (gaps per hectare) across all plots with gaps recorded in 2020. Study plots with gaps are represented by black dots, line of fit is presented as a solid blue line, and 95% CI on fit prediction is represented in light blue.

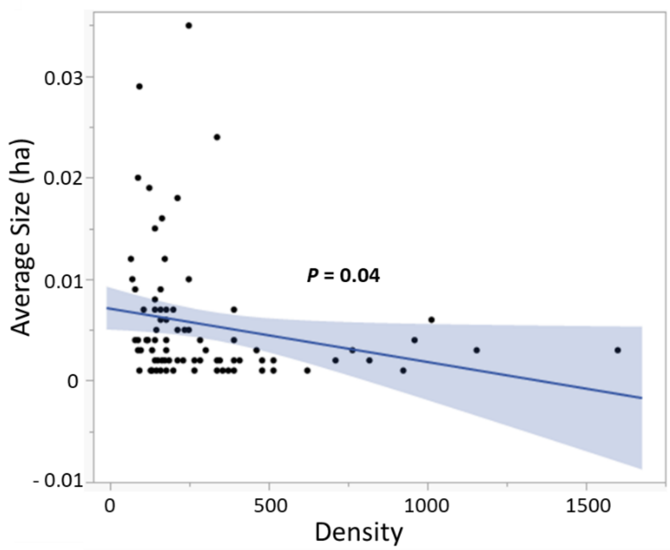
Stand Density

Logistic regressions showed that in 2008, stand density had a significant negative influence on the presence or absence of canopy gaps in Watershed 2 (Figure 3; $P = 0.04$) with gap presence decreasing with density. In 2016, stand density had a significant influence on the presence or absence of canopy gaps in Watershed 3 (Figure 3; $P = 0.02$) with gaps decreasing with density. In 2020 stand density had a significant influence on the presence or absence of gaps in Watershed 1 and in Watershed 3 (Figure 3; $P = 0.03$, $P = 0.001$, respectively), with gap presence again decreasing with stand density.

Linear regressions showed that among all plots with canopy gaps recorded across watersheds, average gap size decreased with stand density in 2008 (Figure 5, $P = 0.04$). Stand density did not influence gap size in 2016 or 2020 (Table 3, $P > 0.05$). Gap frequency based on plot data for number of trees per hectare increased with stand density in 2008, 2016, and 2020 (Figure 6, $P = 0.001$, $P = 0.003$, and $P = 0.02$, respectively) overall across watersheds. Although logistic regressions showed the number of plots with gaps present consistently decreasing with stand density between watersheds, linear regressions showed more canopy gaps per hectare at higher stand densities when looking at all plots with canopy gaps present across watersheds.

Figure 5

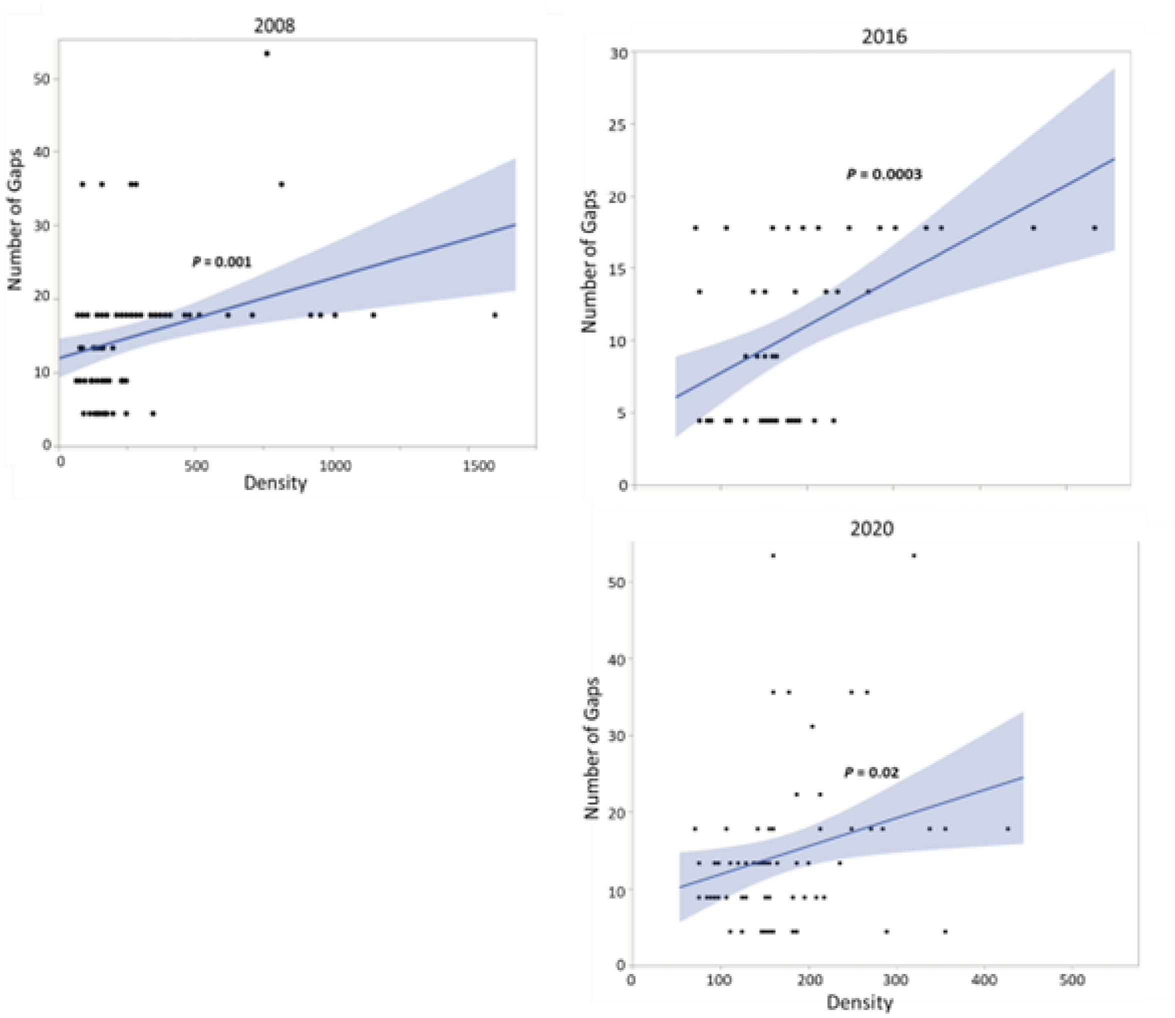
Influence of Stand Density on Gap Size 2008



Note. Linear regression of the influence of stand density (gaps per hectare) on average gap size (ha) in 2008. Study plots with gaps are represented by black dots, line of fit is presented as a solid blue line, and 95% CI on fit prediction is represented in light blue.

Figure 6

Influence of Stand Density on Gap Frequency in 2008, 2016, and 2020



Note. Linear regressions of the influence of stand density (trees per hectare) on the frequency of gaps (gaps per hectare) across all plots with canopy gaps in Watersheds 1, 2 and 3 in 2008 (P = 0.001), 2016 (P = 0.0003) and 2020 (P = 0.02). Study plots with gaps are represented by black dots, line of fit is presented by a solid blue line, and 95% CI on fit prediction is represented in light blue.

Canopy Roughness

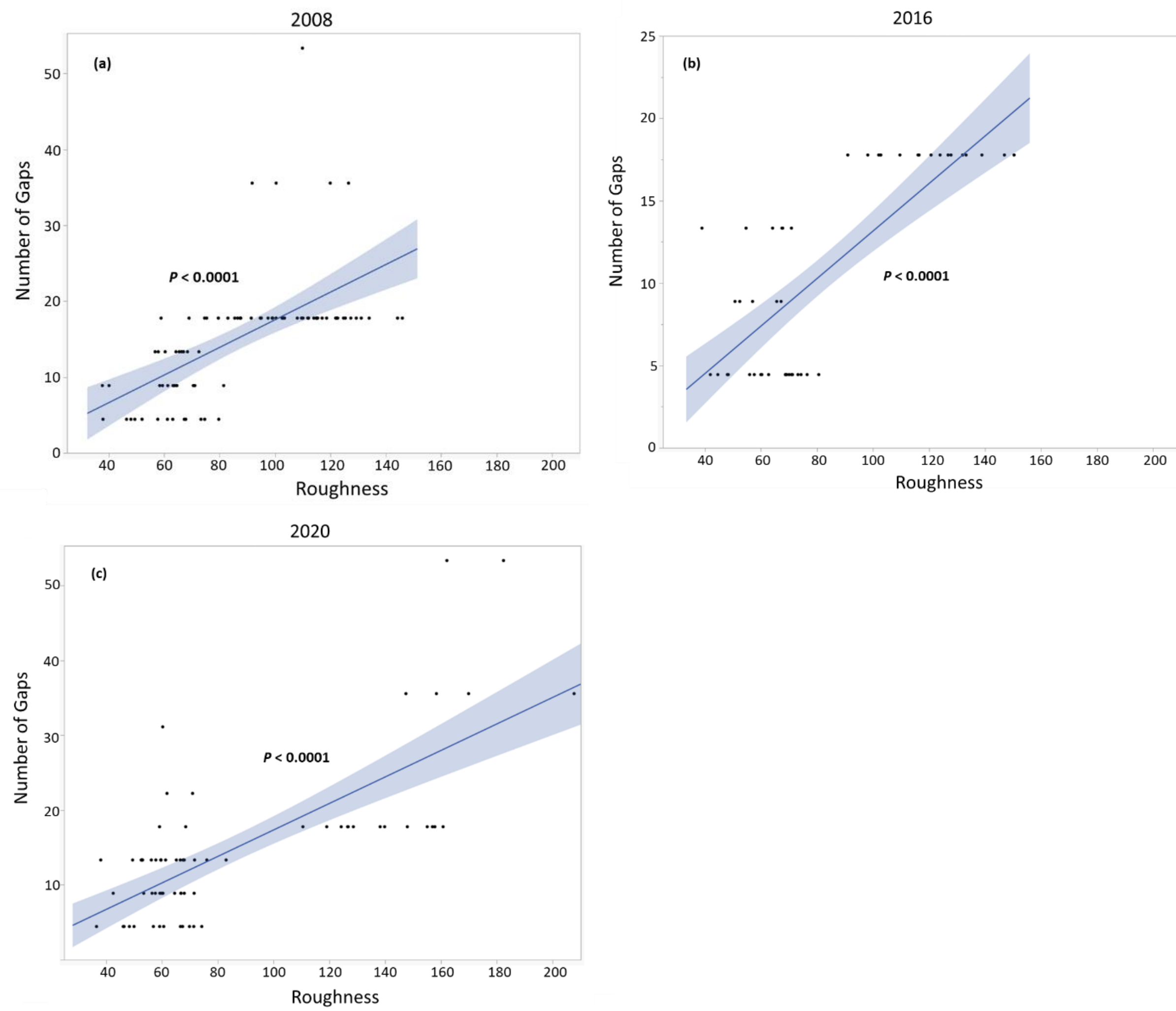
Canopy roughness was consistently positively associated with the presence or absence of canopy gaps across all Watersheds (Figure 3; $P < 0.05$), apart from Watershed 2 in 2020 ($P = 0.05$). Watershed 1 had the strongest associations, with $P < 0.0001$ in both 2008 and 2020 (Table 2).

Higher variation in standard deviation from the mean tree height within plots (canopy roughness), was found in plots with canopy gaps recorded, however it could also be inferred that the presence of canopy gaps increases canopy roughness.

Among plots that had gaps recorded, linear regressions revealed positive correlations between canopy roughness and frequency of gaps in 2008, 2016 and 2020 (Figure 7a, b, and c, respectively, $P < 0.05$, Table 3). This result is consistent with logistic regressions analyzing the watersheds individually, and here we find that the number of gaps detected based on gaps per hectare increases with canopy roughness. No significant relationships were found between canopy roughness and average size of gaps in any study year ($P > 0.05$).

Figure 7

Influence of Canopy Roughness on Gap Frequency



Note. Linear regressions of the influence of canopy roughness on the frequency of gaps (gaps per hectare) across all plots with canopy gaps in Watersheds 1, 2 and 3 in 2008 (a), 2016 (b) and 2020 (c). Study plots with gaps are represented by black dots, line of fit is presented by a solid blue line, and 95% CI on fit prediction is represented in light blue. Standard deviation from the mean height of each plot was used as a proxy for canopy roughness.

4.2 Stand Age Influences on Gap Size and Number of Gaps

Permutative ANOVAs

When using watersheds as proxies for stand age (WS01 = 60 year old plantation, WS02 = old growth, WS03 = 60 year old plantations), no significant differences in average gap size were found in 2008, 2016, or 2020 ($P > 0.05$); however gap frequency varied in all three years (Figure 8a, b, and c; Table 4). The average number of gaps varied significantly among watersheds ($F_{(2,82)} = 41.72$, $P < 0.0001$) in 2008; with significantly fewer canopy gaps per plot in WS02 (mean = 8.5) than both WS01 (mean = 21.6) and WS03 (mean = 17.8). In 2016, the average number of gaps also varied significantly among stand ages ($F_{(2,49)} = 70.2$, $P < 0.0001$), with WS02 (mean = 7) having significantly fewer gaps recorded than WS01 (mean = 17.8) and WS03 (mean = 17.8). In 2020, the average number of gaps again varied significantly with different stand ages ($F_{(2,67)} = 23.1$, $P < 0.0001$) with significantly fewer canopy gaps again in WS02 (mean = 10.6) than WS01 (mean = 26) and WS03 (mean = 23.7).

Table 4

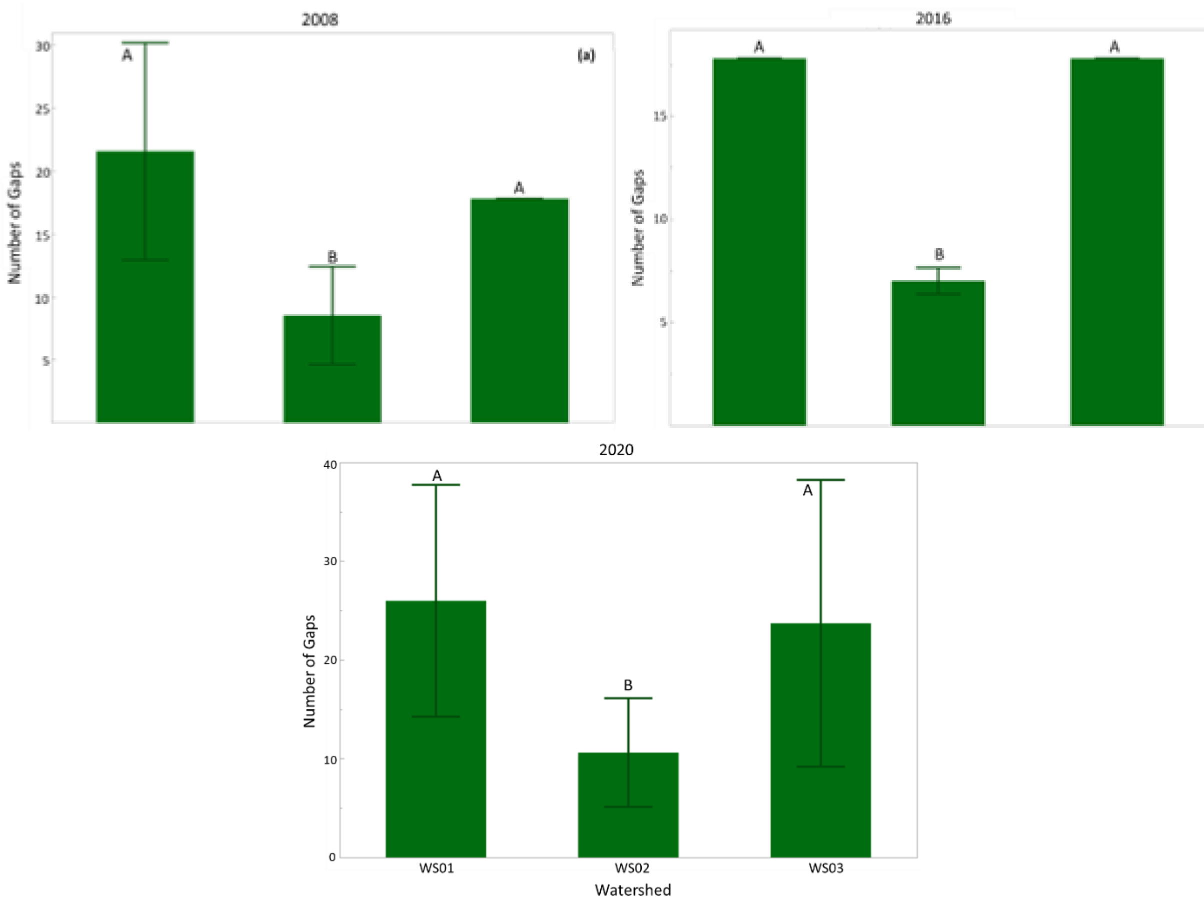
Variance of Gap Frequency Between Three Experimental Watersheds

	Number of gaps		
	F	dfs	*p*
2008	41.72	2, 82	**< 0.0001**
2016	70.2	2, 49	**< 0.0001**
2020	23.1	2, 67	**< 0.0001**

Note. Results of permutative ANOVAs comparing the mean number of gaps per hectare derived from gaps detected in buffered research vegetation plots and stand age (watershed) for each year.

Figure 8

Permutative ANOVAs



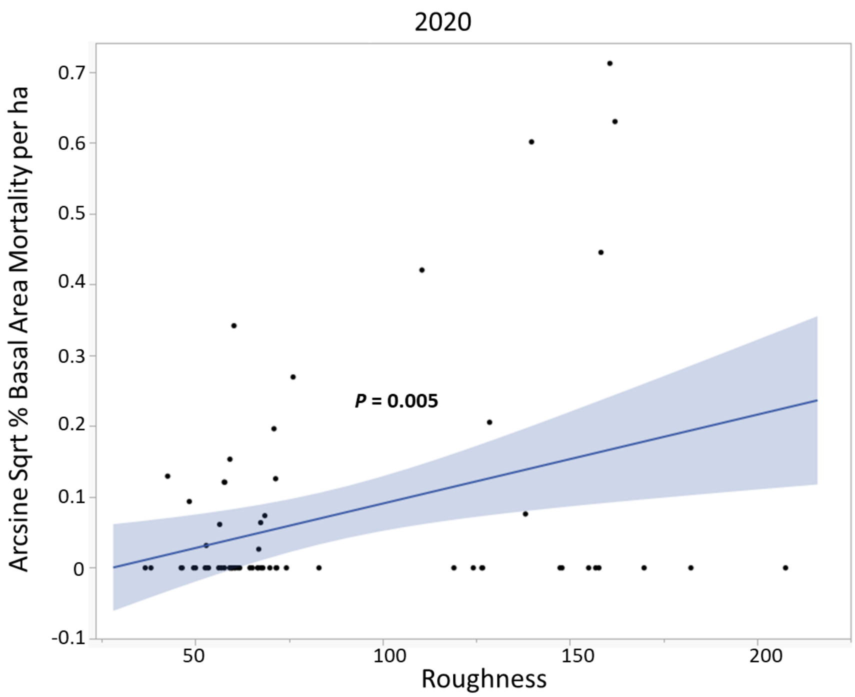
Note. Permutative ANOVAs comparing the mean number of gaps per hectare derived from gaps detected in buffered research vegetation plots and stand age (watershed) in (a) 2008, (b) 2016, and (c) 2020 using watershed as a proxy for stand age; WS01 = 60 yr old, WS02 = Old Growth, WS03 = 60 yr old. Bars with different letters indicate significant differences ($P < 0.05$), error bars represent one standard deviation from the mean.

4.3 Influence of Canopy Roughness on Percent Mortality

Our linear regression showed that among all plots with canopy gaps recorded across watersheds in 2020, mortality (arcsine square root % basal area mortality per hectare) increased with canopy roughness (Figure 9, $P = 0.005$).

Figure 9

Influence of Canopy Roughness on Mortality



Note. Linear regression of the influence of canopy roughness on tree mortality following the 2019 severe snow event. Mortality was calculated as the arcsine square root of the recorded % basal area mortality per hectare based off of field data collected in 2019, and canopy roughness was calculated using 2020 LiDAR data. Study plots with gaps are represented by black dots, line of fit is presented as a solid blue line, and 95% CI on fit prediction is represented in light blue.

Chapter 5: Discussion

The primary objective of this study was to identify canopy gaps using multi-temporal LiDAR-based canopy height models and combine them with field-based forest metrics to better understand canopy gap distributions and characteristics following a severe snow disturbance to the forest canopy. While our goal was to look for distribution and growth patterns of the canopy gaps over the three study years, our main interest was to investigate the damage following the 2020 snow event.

5.1 Effect of Elevation on Gap Presence, Size and Frequency

We hypothesized that more gaps would be found at elevations below 800 m, where it is generally expected to see heavier, wetter snow. While we did not see this pattern strongly supported in Watersheds 2 and 3, our hypothesis was supported in Watershed 1, where we found a strong pattern of gap presence decreasing with higher elevations, and the majority of plots with canopy gaps detected located below 800 m. We found our hypothesis again supported with the result that the gap frequency would be higher at lower elevations in 2020 due to the heavy snow, however canopy gap size tended to increase at higher elevations.

5.2 Effect of Stand Density on Gap Presence, Size and Frequency

Elevation was expected to have the greatest influence on canopy gap dynamics following the snow event, however other variables were considered. Stand density measurements were available for the permanent research plots in this study and thought to have potential influence on where gaps would form following moderate to severe disturbance, as well as the size of canopy gaps. Because dense stands can result in competition-based self-thinning (Knapp et al., 2021; Lu et al., 2023) which could result in more standing dead trees within plots, we expected more gaps to form in stands of higher density (more trees per hectare) following the severe snow event in 2020. We found that in all years, plots with lower stand densities were more likely to have gaps recorded – with 2020 showing a significant negative relationship between stand density and the presence of a gap or gaps within a plot in both Watershed 1 and Watershed 3. While we found that average gap size was larger at lower stand densities in 2008, we did not find relationships between stand density and gap size in other years. Han et al. (2023) found higher density of seedling regeneration to be associated with larger canopy gaps due to increased light availability, however as we were focusing on established trees and their mortality, it is understandable that the pattern we observed would vary from that finding.

After running linear regressions, we were surprised to find that the number of gaps recorded per hectare generally increased with stand density in 2008, 2016, and 2020. Gaps were mostly found in stands with densities of 500 trees per hectare and lower, which is consistent with the density where gaps were found to be present based on logistic regression models; however, the paradoxical results between our logistic and linear regressions may be indicators that pooling stand density data among differently sized research plots may have negative effects on analysis results.

5.3 Effect of Canopy Roughness on Gap Presence, Size and Frequency

Because canopy gaps tend to increase vertical heterogeneity in forest ecosystems (Gray et al., 2012), we expected to find positive correlations between canopy roughness and presence of gaps, as well as number of gaps per hectare based off of gaps detected within buffered study plots. We were curious to see if gap size correlated with canopy roughness – however our finding that roughness did not correlate with gap size for any year may support the idea that canopy roughness and the presence of canopy gaps are circular indicators that have little to do with gap size.

Our findings that show canopy roughness is positively associated with the presence of canopy gaps for all watersheds in all years ($P < 0.05$ in 2008, 2016, and 2020) apart from Watershed 2 in 2020 ($P = 0.05$), support the hypothesis that canopy gaps are associated with increased canopy roughness – but it may be more accurate to assert that the presence of canopy gaps increases canopy roughness. Following this trend, when our data was combined and normalized for all watersheds, the number of gaps present increased as canopy roughness increased. This, again, supports the hypothesis that canopy gaps are important indicators of canopy roughness, as they add vertical heterogeneity to the canopy structure through injury or mortality of trees. While the buffered plot data were normalized to number of gaps per hectare within watersheds, it can be asserted that the method of deriving canopy roughness from the standard deviation of mean height within each buffered plot (Rex et al., 2024) is effective at characterizing the overall watershed landscapes. LiDAR data enhances the ability to examine at canopy height models at a landscape scale, though the relatively small sizes of research plots within this study should be acknowledged as they may not always be able to capture broader patterns (Kane et al., 2010).

5.4 Effect of Canopy Roughness on Percent Basal Area Mortality

To contextualize our findings from the logistic and linear regressions conducted with the 2020 LiDAR data, it was important to conduct multi-temporal analyses. Following these analyses, we were interested in examining whether canopy roughness had an influence on basal area (BA) mortality within the study plots using only the 2019 data collected during the snow damage assessment. Our findings show that canopy roughness had a strong positive correlation with % BA mortality (arcsine square root transformed) (P = 0.005). This result reinforces that our method of canopy gap identification is consistent with field measurements, as increased mortality should be expected in areas with higher numbers of gaps.

5.5 Analyzing Variance in Gap Frequency

At the outset of this study, each watershed (01, 02 and 03) was understood to represent a different age group of forested stands within HJA, with W01 study plots located within a 60 year old plantation, WS02 study plots located in old-growth forest, and WS03 study plots located in stands comprised of mixed ages, including old-growth and another 60 year old plantation. Through further analysis it was determined that while WS03 contains old growth, all vegetation plots in WS03 are located in harvest units that are the same age as WS01, 60 years old. As such, here we tighten our scope to compare the variance between two 60-year-old plantation stands and old-growth forest.

When normalized to number of gaps per hectare, our permutative ANOVAs revealed an overall increase in number of gaps across all watersheds in 2020, likely a result of the severe snow event. The significantly lower gap numbers in WS02 in all years may indicate the resiliency of old-growth forests, and supports research observing higher rates of tree death in younger forests than in old growth forests (Larson et al., 2015). Higher gap numbers recorded in WS01 and WS03 in all years may be reflective of higher vulnerability of plantations to severe weather events, such as snowfall, but may also be attributed to density-dependent mortality that decreases with stand maturity (Larson et al., 2015; Franklin et al., 2002). From this we may assume that disturbances to younger forest stands may result in higher rates of structural change, consistent with previous research proposing that disturbance may be a stronger driver of structural development in second-growth forests (Kane et al., 2010).

5.6 Detecting Canopy Gaps Using Canopy Height Models in ArcGIS Pro

While considering the limitations of this study, the accuracy of LiDAR derived data and canopy height models (CHMs) derived from point-cloud data (Kane et al., 2010) should produce a reasonable representation of the forest canopy and gaps within our study parameters, defined as areas at least 10 m^2 and no larger than 1000 m^2 in size with canopy heights below 2 m (Schliemann & Bockheim, 2011). Without the capabilities of gap detection software such as R programs ForestGapR or lidR, this study likely presents a higher risk of human error in manual gap detection, as well as an increase in the time spent detecting gaps. ForestGapR is not only capable of automating canopy gap detection and compute statistics, but also it is able to utilize multi-temporal LiDAR data to map canopy gap dynamics (Silva et al., 2019), which is highly relevant to this research.

Although this study aimed to discount larger non-regenerative openings (NROs), this was limited to known roads or streams and large balds and openings that were likely alpine meadows at higher elevations. Using an adaptive height thresholding algorithm (Senécal et al., 2018) within ArcGIS Pro may also have increased accuracy of the detection and measurement of canopy gaps, as well as distinguishing regenerative openings that can increase diversification (Franklin et al., 2002) from non-regenerative openings that do not support regrowth (Senécal et al., 2018).

Chapter 6: Conclusion

This study aimed to identify patterns in canopy gap dynamics (presence, size, and frequency) over time in order to better understand the influence of a severe snow event on canopy gap formation. Across study years, canopy roughness had the most consistent positive influence on the presence of canopy gaps among the three watersheds, with significant correlations confirmed in each watershed each year. This finding, although not surprising or unexpected, reinforces the assumption that the presence of canopy gaps is associated with vertical heterogeneity in forest systems which provides diversity of microhabitats for dependent species (Han et al., 2023). Elevation appeared to have overall positive significant relationships with the presence of canopy gaps, and although these results were not consistent across years or watersheds, the significant positive correlations in WS01 and WS03 in 2020 are reflective of the 2019 snow event. While we were unable to find consistent trends across our variables for 2020, we were able to confirm that canopy roughness had a strong positive correlation with tree mortality as recorded in % basal area mortality. Although these findings are significant, it would be interesting to run these data through gap identification software that may increase accuracy (Silva et al., 2019).

Through the process of this thesis research, I felt fortunate for the opportunity to apply new skills learned through Evergreen's MES Program to a place that is very important to me. The knowledge that the H.J. Andrews Experimental Forest has decades of archived research and data that continues to be conducted and collected was exciting, however homing in on a specific topic to research proved to be quite difficult. My main goals in entering the MES program were to learn skills that could be applied to my professional development and focus my research on forest ecosystems, and I am happy to say that I accomplished that goal. Initially intimidated by the prospect of entering a multi-quarter GIS certification course, I ended up getting comfortable enough with ArcGIS Pro to apply GIS as an integral part of my thesis with the LiDAR data provided by the USFS Northwest Research Station. This was in part made possible by Evergreen’s support of Independent Learning Contracts (ILCs), as I was able to create an ILC focusing on the use of LiDAR in GIS to independently expand my learning while conducting my thesis research. I value the interdisciplinary experiences and skills that I have gained, research into forest succession, management of field survey data, remote sensing data analysis, a reintroduction and understanding of statistical analyses and proficiency in ArcGIS Pro.

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