CHARACTERIZING POST-FIRE TREE ATTRIBUTES USING QUANTITATIVE STRUCTURE MODELS BASED ON DRONE AND MOBILE LASER SCANNING POINT CLOUDS

by

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B.Sc. Honours, The University of British Columbia, 2020

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

August 2022

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Characterizing post-fire tree attributes using quantitative structure models based on drone and mobile laser scanning point clouds

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the degree of  Master of Science
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Abstract

Wildfires burn with a mixture of severities across the landscape and create complex forest structures. Quantifying the structural changes in post-fire forests is critical to evaluating the ecological impacts of wildfires. Advances in drone laser scanning (DLS) and mobile laser scanning (MLS) have enabled the acquisition of high-density point clouds to better resolve detailed tree structures. Yet, few studies have examined their combined capability to describe forest structures. To characterize post-fire tree attributes in interior dry forests in British Columbia, nine study sites in the area burned by the 2017 Elephant Hill wildfire were scanned in 2019 using DLS and MLS. First, I examined the utility of DLS and MLS both individually and combined to estimate tree attributes using quantitative structure models (QSMs) across varying canopy cover levels. Second, I investigated the QSM-derived tree attributes to interpret the effects of burn severities at individual tree and plot scales.

The results showed that the fused laser scanning datasets outperformed single laser scanning datasets in estimating tree attributes across canopy cover levels. Specifically, with increasing canopy cover, diameter at breast height, crown diameter, and crown base height were best predicted using the fused data. Height was accurate regardless of canopy cover, which was independent of data collection platforms. Tree volumes could be best modelled by the fused data with increasing canopy cover. In terms of burn severities, the results suggested that smaller pre-fire trees tend to experience higher levels of crown scorch than larger pre-fire trees. Among trees with similar pre-fire sizes, those within mature stands experienced relatively lower levels of crown scorch than those within young stands. At the plot level, low-severity fires had minor effects, moderate-severity fires mostly decreased tree height, and high-severity fires significantly...
reduced diameter at breast height, height, and biomass. The results also revealed that stands dominated by trees with large crowns and relatively wide spacing could burn less severely than stands characterized by regenerating trees with high densities. The findings of this thesis facilitate forestry practitioners to select appropriate laser scanning tools in forest inventory assessment and develop site-specific management plans for fire-prone forests.
Lay Summary

Following a wildfire event, it is critical for forestry practitioners to assess its impacts on forest ecosystems. Drone and mobile laser scanning technologies produce three-dimensional point clouds with top-down and ground-up perspectives, respectively, to represent detailed forest structures. The combination of them, therefore, has the potential to improve our understanding of wildfire effects. In this thesis, I characterized post-fire tree structures using drone and mobile laser scanning data to examine the impacts of the 2017 Elephant Hill wildfire in British Columbia. Overall, the fusion of point clouds enhanced the quantification of tree structures. The results suggested that larger pre-fire trees could be more resistant to crown scorch than smaller pre-fire trees. My results also indicated that stands with trees of large crowns tend to burn less severely than stands with trees of high densities. The findings of this thesis can support the decisions on the management of fire-prone forests.
Preface

The body of this thesis is composed of two scientific papers written for peer review for which I am the lead author and investigator, as listed below. The research questions and objectives of this thesis were developed through discussions with Dr. Nicholas Coops, Dr. Lori Daniels, and Mr. Christopher Butson. I was primarily responsible for refining the research objectives, developing and implementing the methodology, processing and analyzing the data, interpreting and presenting the results, and preparing the manuscripts for submission. My supervisor and supervisory committee members also provided the project oversight and suggestions, edits, and feedback for the manuscripts. In addition, Jeremy Arkin provided advice on point cloud processing and editorial assistance for Chapter 3.


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List of Abbreviations

At  Trembling aspen
BC  British Columbia
CAD Canadian dollar
CBH Crown base height
CBI Composite burn index
CCC Concordance correlation coefficient
CPA Crown projection area
DBH Diameter at breast height
DLS Drone laser scanning
dNBR Differenced normalized burn ratio
EFA Exploratory factor analysis
Fd Douglas-fir
FRP Fixed-radius plot
GNSS Global navigation satellite systems
ICP Iterative closest point
KMO Kaiser-Meyer-Olkin
LiDAR Light detection and ranging
MLS Mobile laser scanning
NBR Normalized burn ratio
Pl Lodgepole pine
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<th>Abbreviation</th>
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<tr>
<td>Py</td>
<td>Ponderosa pine</td>
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<tr>
<td>QSM</td>
<td>Quantitative structure model</td>
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<td>RdNBR</td>
<td>Relative differenced normalized burn ratio</td>
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<td>Sx</td>
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<td>TLS</td>
<td>Terrestrial laser scanning</td>
</tr>
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<td>USA</td>
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Acknowledgements

This research was jointly funded by the British Columbia Ministry of Forests (2019FAIB501) and an NSERC (Natural Sciences and Engineering Research Council of Canada) Discovery Grant. I would like to thank FYBR Solutions Inc. for acquiring the drone laser scanning data and Lukas Jarron, Jeremy Arkin, and Felix Poulin for collecting mobile laser scanning data. I also thank the Forest Inventory in the Forest Analysis and Inventory Branch for funding to conduct fieldwork and Arial Eatherton and Spencer Bronson for field data collection. I thank Katlyn Wise for developing the calculations of the composite burn index and the classification of wildfire burn severities.

I owe so much of my academic success to Dr. Nicholas Coops for taking me on as an undergraduate research assistant in the lab and then supporting me as my MSc supervisor. I sincerely appreciate his mentorship, direction, immense support, and constructive feedback. I am also deeply grateful to my supervisory committee members, Dr. Lori Daniels and Mr. Christopher Butson, for their insights, guidance, and encouragement. Thank you for helping me improve and refine this research! In particular, I am thankful to Dr. Lori Daniels for guiding me to study wildfire science through this MSc project. Also, thank you for supervising me in the Directed Study to investigate the temporal trends in fire size and severity in BC over the last three decades. I am also thankful to Mr. Christopher Butson for his insightful support from the BC Ministry of Forests.

To all the members of the Integrated Remote Sensing Studio, thanks for your support, care, kindness, and good times! Specifically, I acknowledge the support from Brianne Boufford for manually measuring the basic and crown attributes to assist with the accuracy assessment in
Chapter 3. I would also like to thank Jeremy Arkin for helping with point cloud processing, answering my questions, reviewing the initial manuscript of Chapter 3, as well as providing editorial advice.

In addition, I would like to extend thanks to Michelle and Joris for their ongoing support and encouragement during my academic journey. I also thank my friends, Chen, Yufei, and Dani, for their patience, inspiration, and continued support. Lastly, a huge thank you to my family for their endless love and incredible support.
Dedication

This thesis is dedicated to my family and friends for their love, support, and encouragement.

Thank you!
Chapter 1: Introduction

1.1 Wildfires and forest ecosystems

Wildfires shape forest ecosystems by influencing the stand structure, species composition, nutrient cycling, as well as many other ecological processes (Reilly et al., 2006; Wieder et al., 2009; McGee et al., 2015; Koontz et al., 2020). Extreme wildfire events can result in extensive tree mortality, posing threats to the ecosystem’s biodiversity and resilience (Crockett and Westerling, 2018; Stevens-Rumann et al., 2018; Steel et al., 2021). With climate warming, rising temperatures and declining precipitation have facilitated the increased incidence of wildfires in many regions across the globe (Liu et al., 2010; Jolly et al., 2015; Davis et al., 2019). This increased number of wildfires releases a greater amount of greenhouse gases, which, in turn, exacerbates the effects of climate warming (Davis et al., 2019).

Over the past three decades, western North America, for example, has seen a significant rise in wildfire occurrences (Phillips et al., 2022). The catastrophic wildfires in recent years have triggered public concerns about the environmental (e.g., declined air quality, reduced forest recovery), economic (e.g., destroyed properties, loss of jobs), and social impacts (e.g., worries over the increased respiratory risks) (Bartels et al., 2016; Westerling, 2016; Coops et al., 2018; Cascio, 2018; Walker et al., 2019). In British Columbia (BC), Canada, over 17,500 wildfire events were reported in the last 10 years, impacting ~ 370,000 ha area annually (BC Wildfire Services, 2021). In the 2017 wildfire season alone, more than 1.2 million ha of land was burned in the province, resulting in a total cost of CAD 649 million in fire suppression (BC Wildfire Services, 2021).

The historical practice of fire suppression, in conjunction with climate warming, has altered the regime of contemporary wildfires (Prichard et al., 2017; Hanan et al., 2021). Consequently, wildfires are projected to increase in terms of frequency, extent, intensity, severity, and duration in
the next fifty years, adding barriers to emergency response, fire control, as well as management planning (Flannigan et al., 2013; Prichard et al., 2017; Hanan et al., 2021). Hence, there is an increasing need to ensure the effective monitoring and management of forest ecosystems in which fires are likely to occur as a primary disturbance agent (i.e., fire-prone forests).

1.2 Management of fire-prone forests

The ignition, development, and propagation of wildfires are controlled by complex interactions among forest fuels, weather, and topography (Kane et al., 2013; Foster et al., 2017; Walker et al., 2020). Of these variables, weather conditions are often considered a key driver of wildfire behaviours in many fire danger assessment systems (Pettinari and Chuvieco, 2017). Yet, the characteristics of forest fuels, such as the structure, bulk density (i.e., mass per unit volume), and moisture content, also play a vital role in driving wildfire behaviours (Ryan, 2002; Roger et al., 2007; Blauw et al., 2015; Paritsis et al., 2018). Under the same weather and topographic conditions, the variations in the fuel characteristics can influence the flammability of vegetation and lead to different responses to wildfires (Pettinari and Chuvieco, 2017). The forest structure, for example, determines the distribution and quantity of combustible biomass for fuel consumption in a fire event (Paritsis et al., 2018). Moreover, the structural complexity of fuels, together with the moisture content in live and dead fuels, affects the microclimate within a forest stand, which contributes to the heterogeneity of wildfire behaviours and impacts (Blauw et al., 2015; Pettinari and Chuvieco, 2017). For these reasons, the treatment of forest fuels is, therefore, critical to the mitigation of fire risks.

In fire-prone forests, the primary strategies of fuel treatment include prescribed burning and mechanical thinning. Both strategies aim to reduce the likelihood of devastating fires by removing or rearranging combustible fuels in forests (Pollet and Omi, 2002). Prescribed burning is conducted by
fire management agencies with the application of planned fires in forest stands to mainly remove surface fuels, such as needles and logging slash (Pollet and Omi, 2002). Mechanical thinning targets the reduction of fuel continuity and bulk density by removing ladder and crown fuels, such as shrubs and branches (Pollet and Omi, 2002). Together, these strategies can be effective to modify the structure of forest fuels, mitigate fire risks, and help maintain the health, biodiversity, and resilience of fire-prone forest ecosystems (Fernandes et al., 2013; Fernandes, 2015; Piqué and Domènech, 2018; Johnson and Kennedy, 2019; Hood et al., 2020).

However, prior to implementing these treatments, the conditions of forests need to be carefully evaluated (Reinhardt et al., 2008; Naficy et al., 2016). For example, in forest stands with high densities of ladder and crown fuels, the prescribed burning of surface fuels can be difficult to control and may require additional suppression efforts to prevent it from developing into crown fires (Stevens et al., 2020; Prichard et al., 2021). In addition, the use of mechanical thinning in certain temperate forests can increase sunlight exposure and wind speed in the lower canopy, leading to the reduction of fuel moisture (Hanan et al., 2020; Prichard et al., 2021). As a result, the altered stand condition may instead promote the propensity of subsequent fires (Hanan et al., 2020; Prichard et al., 2021).

Currently, a challenge in the management of fire-prone forests is that the practices of fuel treatment may not meet the management objectives (Kolden, 2019). For instance, to restore the historical wildfire regime and forest resilience in western North America, the fuel treatments need to be applied on a landscape scale (Kolden, 2019). Meanwhile, many stands often require periodic treatments to reduce the accumulated fuel loads (Lydersen et al., 2019; Prichard et al., 2021). Hence, the practices of large-scale and periodic fuel treatments can be operationally and financially challenging (Lydersen et al., 2019; Prichard et al., 2021). In the context of climate warming and
ongoing wildfire events, the understanding of wildfire impacts on fire-prone forests needs to be improved to support the planning for and decision-making of management practices.

1.3 Monitoring wildfire impacts on fire-prone forests using remotely sensed data

1.3.1 Satellite remote sensing of wildfire dynamics

The advent of satellite remote sensing has benefited the study of wildfire dynamics through the detection of fire activities, mapping of area burned, and assessments of pre-fire fuel load and post-fire forest recovery (e.g., Xu and Zhong, 2017; Hoff et al., 2018; Saulino et al., 2020; Skakun et al., 2021; White et al., 2022). In the last thirty years, a range of optical satellite imagery has been applied to characterize wildfire regimes (San-Miguel et al., 2017; San-Miguel et al., 2019; García et al., 2022), quantify the burn severity (French et al., 2008; Hall et al., 2008; Morgan et al., 2014; Edwards et al., 2018), and evaluate post-fire effects (Lentile et al., 2006; Chen et al., 2011; Chu et al., 2016; Fiore et al., 2020; de Oliveira et al., 2021). Previous studies highlighted that a comprehensive evaluation of wildfire effects is critical to improving our understanding of wildfire dynamics (Morgan et al., 2014). A series of satellite-based indices, such as the normalized burn ratio (NBR), differenced NBR (dNBR), and relative differenced NBR (RdNBR), have been developed to investigate wildfire effects over large forested areas (Wulder et al., 2009; Soverel et al., 2010; Boucher et al., 2016; Cardil et al., 2019). Yet, these indices only show the reflectance change of an area burned. Many other facets of wildfire effects, such as the forest structural change, may not be well-reflected. As the information on forest structural changes can be pivotal for the management of fuel loads, it should be integrated to enhance the monitoring of wildfire impacts.
1.3.2 Airborne laser scanning of fire-prone forests

Compared to optical satellite imagery, laser scanning or light detection and ranging (LiDAR) systems directly emit laser beams and measure their returns from the object (Lillesand et al., 2008). The three-dimensional point clouds generated by LiDAR allow researchers to identify the surface of objects and interpret their structures, thus providing more detailed spatial and structural information than optical satellite imagery (Lillesand et al., 2008; Wulder et al., 2008). Over the past two decades, airborne laser scanning (ALS) has supported the extraction of many forest structural attributes at the stand level, such as canopy height, basal area, canopy volume, and above-ground biomass (e.g., Cartus et al., 2012; Saremi et al., 2014; Bouvier et al., 2015; Garcia et al., 2017a; Hu et al., 2017; Chamberlain et al., 2021). On a broad scale, the use of ALS datasets can, thus, facilitate the monitoring of forest recovery and carbon dynamics following wildfire events.

The structural attributes extracted from the ALS data are predominantly at the canopy level, which can be suitable for analyzing the impacts of crown fires on forest stands. For fires that primarily burn understory vegetation and younger trees, their impacts may not be well detected (Kane et al., 2013; Kramer et al., 2016; Hu et al., 2019). To account for this, researchers examined point clouds by separating them into different height strata (e.g., 2m, 8m, 16m, 32m, etc.) (Kane et al., 2014). In sites with a high degree of canopy closure, however, this method may not be effective since the number of ALS returns is mostly limited by canopy structures (Skowronski et al., 2011; Hyyppä et al., 2012). As the sub-canopy structure can be relatively poorly represented, the impacts of wildfires could be underestimated by ALS data (Hu et al., 2019). Point clouds with greater densities are, therefore, needed to investigate wildfire effects with enhanced representations of both canopy and sub-canopy forest structures.
1.3.3 Drone, terrestrial, and mobile laser scanning of fire-prone forests

As laser scanning technologies continue to evolve, it is possible to utilize these devices on an increased variety of platforms, specifically with advances in drone laser scanning (DLS), terrestrial laser scanning (TLS), and mobile laser scanning (MLS). These three platforms, enable researchers to obtain point clouds of high densities (e.g., > 500 points/m²), which can capture the structural information of stands and trees at much finer spatial scales than conventional piloted ALS datasets, thus opening up new possibilities for studies of wildfire effects. Compared to ALS, DLS systems fly much lower to the ground and can be deployed with greater flexibility, allowing the improved detection of post-fire crown structures (Bruggisser et al., 2019; Vandendaele et al., 2021). Using DLS data, studies have estimated various tree attributes, such as leaf area density, crown volume, and crown area, to promote the assessment of crown fuels (e.g., Viedma et al., 2020a; Arkin et al., 2021; Hillman et al., 2021). With these attributes, researchers can differentiate crown fires from surface fires by comparing the degree of damage to vegetation structures at different height strata (Viedma et al., 2020a).

To enhance the representation of sub-canopy structures from laser scanning data, an increasing number of studies also explore the utility of TLS systems as they acquire highly dense point clouds from the ground upwards. In comparison with the airborne systems, recent TLS instruments are characterized by smaller laser beam divergence (e.g., ~ 0.30 mrad) and footprint size (e.g., ~ 5 cm) that produce high-resolution data with less noise (Calders et al., 2020). These characteristics enable TLS to be suitable for mapping structurally complex forests. Hence, it has been used to derive stem diameters, resolve fine branches, identify the foliage, and augment the use of ALS/DLS (e.g., Kankare et al., 2013; Murgoitio et al., 2014; Srinivasan et al., 2015; Liang et al., 2016, 2018; Ma et al., 2018). However, TLS requires multiple scans to fully capture desirable tree
attributes, which hinders the efficiency of data acquisition, especially in dense forests (Shao et al. 2020). Likewise, performing multiple scans and registering each scan can also impede the efficacy of TLS data processing (Bauwens et al., 2016; Shao et al., 2020).

To help resolve some of the aforementioned issues, MLS is a practical option (Lin et al., 2012; Liang et al., 2014, 2018). MLS collects ultra-high-density point clouds (e.g., > 10,000 points/m²) on a mobile platform (e.g., hand-held, vehicle-based). Increased mobility and flexibility allow researchers to collect point clouds faster and easier in comparison with static TLS (Liang et al., 2014; Bauwens et al., 2016). The MLS data, thus, support the retrieval of vital attributes of fire-prone forests and allow a refined characterization of fuel loads horizontally and vertically. Yet, in stands with high tree densities, the environmental complexity can reduce the quality of MLS data (Liang et al., 2018). As the sensor is in motion during data collection, it may not completely capture individual tree structures when high levels of occlusions exist (Liang et al., 2018).

To improve the characterization of forest attributes in stands with complex structures, two major methods have been applied to laser scanning point clouds. The first method proposes to densify the point cloud by scanning the stand repeatedly following different viewing perspectives or trajectories (Wang et al., 2021). The repeated scanning, thus, increases the time and cost of operations, undermining the efficiency of data collection (Wang et al., 2021). In forests with relatively open canopies, this method can be effective. However, in forests with closed canopies, DLS data may still have relatively limited representations of sub-canopy structures even after repeated scanning.

The second method offers a solution via fusing the point clouds collected by different laser scanning instruments (Wang et al., 2021). Particularly, the fusion of point clouds between ALS/DLS and TLS/DLS combines the benefits of both aerial and terrestrial scanning perspectives, allowing a
comprehensive representation of forest structures. As this method requires high-quality data from different laser scanning instruments, it presents challenges in terms of equipment availability and data acquisition (Wang et al., 2021). Therefore, it is important to evaluate the effectiveness of both single and fused laser scanning point clouds in representing forest structures.

However, the extent to which the fused point clouds can retrieve accurate structural information is not fully understood. Only a limited number of studies have combined ALS/DLS with TLS point clouds or merged TLS with MLS point clouds to investigate the accuracy of tree structure representation. The majority of studies have used a single laser scanning system to examine forest structural attributes, likely due to the challenges in acquiring desirable data and performing image registration. (Murgoitio et al., 2014; Shao et al., 2020). With fused ALS-TLS data, the modelling of tree structures (e.g., stems, branches, etc.) can be significantly improved (Murgoitio et al., 2014; Paris et al., 2017; Dai et al., 2019). Lin et al. (2014) noted that the combination of MLS and TLS data could better inform the modelling of tree biomass and crown attributes. Shao et al. (2020) fused MLS with TLS point clouds to accurately derive tree attributes, such as the stem position and diameters, with the relative mean bias error < 0.02 m and 0.01 m, respectively. Although promising, more research is needed to explore the combined utility of ALS/DLS and TLS/MLS datasets in characterizing the structural attributes of fire-prone forests.

1.4 Research objectives

Overall, the objective of this thesis was to characterize post-fire tree attributes in interior dry forests in BC using the drone and mobile laser scanning point clouds both individually and combined. Understanding the strengths and weaknesses of different laser scanning datasets can inform forestry practitioners in selecting appropriate tools to manage fire-prone forests. The first research question
focused on the fusion of DLS with MLS point clouds to compare a number of tree attributes extracted from different laser scanning datasets. The second research question focused on using the derived tree attributes to improve our understanding of the ecological impacts of wildfires across a range of burn-severity levels. Specifically, to address the overall research objective, this thesis posed the following research questions:

(1) What tree attributes can be accurately derived from DLS and MLS point clouds across a range of canopy conditions?

(2) How can the effects of burn severity be assessed using the attributes of post-fire tree structures derived from DLS and MLS point clouds?
1.5 Thesis overview

This thesis consists of five chapters: an introduction, one chapter about the study area and data, two research chapters, and a concluding chapter.

Chapter 2 describes the Elephant Hill wildfire in 2017 as well as the pre-fire field information in the study sites. It also describes the provincial monitoring programs in BC. Additionally, it provides information about the pre-fire forest inventory data and post-fire drone and mobile laser scanning data.

Chapter 3 addresses the first research question by comparing the accuracy of a number of tree attributes derived from single and fused laser scanning datasets. This chapter proposes a new fusion method based on the probability density of vertical point distribution. It also characterizes canopy conditions using canopy cover levels and examines the impacts of canopy cover on tree attribute extraction from different laser scanning datasets.

Chapter 4 addresses the second research question by assessing the wildfire impacts on individual tree structures using pre-fire field measured attributes as well as post-fire attributes derived from the fused laser scanning data. It examines the effects of burn severity at individual tree and plot scales and also infers the burn-severity patterns.

Chapter 5 concludes the thesis with a summary of key findings in Chapters 3 and 4. It also discusses the implications, limitations of this thesis, and directions for future research.
Chapter 2: Study area and data

2.1 Study area

The Elephant Hill wildfire started on July 6\textsuperscript{th}, 2017, near Ashcroft, BC, Canada, and was not contained until the end of September 2017 (BC Wildfire Services, 2022). This wildfire burned a total area of 191,865 ha, representing one of the largest fires in the 2017 wildfire season (BC Wildfire Services, 2022). It burned across a broad range of elevations and forest types, including naturally regenerating forests dominated by interior Douglas-fir (\textit{Pseudotsuga menziesii var. glauca}) and young plantations of lodgepole pine (\textit{Pinus contorta}). Ponderosa pine (\textit{Pinus ponderosa}) co-dominates at the lowest elevations, while hybrid spruce (\textit{Picea engelmannii X Picea glauca}) commonly occurs at mid- and high elevations (Meidinger and Pojar, 1991). Trembling aspen (\textit{Populus tremuloides}) is also distributed across the elevation range (Meidinger and Pojar, 1991).

Natural disturbances and forest management, together with the terrain features, have created forests with diverse stand ages and canopy closure conditions (Meidinger and Pojar, 1991). Historically, lower elevations in the study area experienced frequent fires with low-to-moderate severity, while higher-elevation forests burned at longer intervals but with higher severity (Meidinger and Pojar, 1991). However, fire suppression after the 1940s greatly reduced the annual area burned and effectively eliminated fires with lower severities, while industrial forest management increased. From 2000 to 2010, lodgepole pine forests were highly impacted by the mountain pine beetle and forest plantations were established after salvage logging.

In BC, the status of forest resources is regularly assessed through three monitoring programs based on permanent sampling plots on a gridded network, including the Change Monitoring Inventory program, the Young Stand Monitoring program, and the National Forest Inventory program (Government of BC, 2022). These plots provide temporal re-measurements of forest stands.
throughout the province using consistent sampling methods to inform disturbance impacts, timber
supply, silviculture practices, and growth and yield modelling (Government of BC, 2022). The
Elephant Hill wildfire burned 23 permanent plots, nine of which were located near the center of the
fire and could be safely accessed for re-sampling (Figure 1). These nine study sites ranged in
elevation from 1014 to 1219 m above sea level and all were located in the Interior Douglas-fir
biogeoclimatic zone (Meidinger and Pojar 1991). Pre-fire forest inventory data provided by the BC
Ministry of Forests showed that six sites included mature forests (age class: > 50 years) and three
were regenerating plantations (age class: 15 – 50 years); all were dominated or co-dominated by
interior Douglas-fir and lodgepole pine (Table 1). In the summer of 2019, fieldwork was conducted at
these nine study sites to evaluate wildfire impacts at individual tree and plot scales, and each study
site was scanned using both DLS and MLS, as described below.
Figure 1 The location of the study area (A) in the Elephant Hill wildfire that burned in 2017. The distribution of the study sites was highlighted using circles and dots in (B) and (C). The area burned was visualized using a Sentinel-2 image (true colour composite) with a 0.5 percent minimum-maximum clip and 1.3 gamma stretch to differentiate burned (magenta) and unburned (green) regions.

2.2 Data

2.2.1 Pre-fire forest inventory data

The most recent field measurements of the study sites before the Elephant Hill wildfire were used as the pre-fire forest inventory data. Among the nine study sites, 36 trees were measured in fixed-radius plots (r = 11.28m) in 6 mature forests and 172 trees were measured with prisms in 3 regenerating forests (Table 1). For each tree, its key attributes, including species, diameter at breast
height (DBH in cm) and height (H in m) were measured in the field; basal area (BA in m²) for each
tree was calculated from DBH (BA = \( \pi (DBH/2)^2 \)). To assess the pre-fire biomass of stems and
branches of individual trees, I used species-specific allometric equations from Ung et al. (2008):

\[
y_{\text{wood}} = \beta_{\text{wood}} DBH^{\beta_{\text{wood}}_1} H^{\beta_{\text{wood}}_2} + e_{\text{wood}} \\
y_{\text{bark}} = \beta_{\text{bark}} DBH^{\beta_{\text{bark}}_1} H^{\beta_{\text{bark}}_2} + e_{\text{bark}} \\
y_{\text{stem}} = y_{\text{wood}} + y_{\text{bark}} + e_{\text{stem}} \\
y_{\text{branches}} = \beta_{\text{branches}} DBH^{\beta_{\text{branches}}_1} H^{\beta_{\text{branches}}_2} + e_{\text{branches}}
\]

where the dry mass (kg) of tree compartments (i.e., wood, bark, stem, and branches) is
represented as \( y \), DBH (cm) and height (m) were manually measured in the field, the species-specific
allometric parameters are denoted as \( \beta \), and estimation errors are represented as \( e \).

<table>
<thead>
<tr>
<th>Site</th>
<th>Sampling method</th>
<th># of trees measured</th>
<th>Elevation (masl)</th>
<th>Age class (years)</th>
<th>Density (trees/ha)</th>
<th>DBH (cm) (mean ± SE)</th>
<th>Height (m) (mean ± SE)</th>
<th>Species composition (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>VRP</td>
<td>8</td>
<td>1156</td>
<td>&gt; 50</td>
<td>2177</td>
<td>21.7 ± 3.7</td>
<td>16.9 ± 2.3</td>
<td>25 63 0 0 12</td>
</tr>
<tr>
<td>2</td>
<td>VRP</td>
<td>3</td>
<td>1049</td>
<td>&gt; 50</td>
<td>308</td>
<td>36.9 ± 4.9</td>
<td>22.2 ± 3.1</td>
<td>67 0 33 0 0</td>
</tr>
<tr>
<td>3</td>
<td>VRP</td>
<td>3</td>
<td>1189</td>
<td>&gt; 50</td>
<td>244</td>
<td>37.6 ± 7.6</td>
<td>24.3 ± 3.5</td>
<td>67 33 0 0 0</td>
</tr>
<tr>
<td>4</td>
<td>VRP</td>
<td>10</td>
<td>1126</td>
<td>&gt; 50</td>
<td>1382</td>
<td>23.5 ± 1.8</td>
<td>16.1 ± 0.6</td>
<td>0 80 10 0 10</td>
</tr>
<tr>
<td>5</td>
<td>VRP</td>
<td>8</td>
<td>1219</td>
<td>&gt; 50</td>
<td>1901</td>
<td>28.6 ± 5.3</td>
<td>16.9 ± 1.4</td>
<td>75 13 12 0 0</td>
</tr>
<tr>
<td>6</td>
<td>VRP</td>
<td>4</td>
<td>1103</td>
<td>&gt; 50</td>
<td>241</td>
<td>34.3 ± 3.6</td>
<td>15.4 ± 4.4</td>
<td>100 0 0 0 0</td>
</tr>
<tr>
<td>7</td>
<td>FRP</td>
<td>35</td>
<td>1014</td>
<td>15 – 50</td>
<td>876</td>
<td>14.9 ± 1.0</td>
<td>10.5 ± 0.5</td>
<td>57 34 0 9 0</td>
</tr>
<tr>
<td>8</td>
<td>FRP</td>
<td>103</td>
<td>1199</td>
<td>15 – 50</td>
<td>2577</td>
<td>11.5 ± 0.7</td>
<td>12.0 ± 0.4</td>
<td>37 21 39 0 3</td>
</tr>
<tr>
<td>9</td>
<td>FRP</td>
<td>34</td>
<td>1132</td>
<td>15 – 50</td>
<td>851</td>
<td>17.7 ± 1.8</td>
<td>12.1 ± 0.6</td>
<td>100 0 0 0 0</td>
</tr>
</tbody>
</table>

2.2.2 Post-fire laser scanning data

2.2.2.1 Drone laser scanning data

DLS point clouds (Figure 2 (A)) were acquired using a LiAir S200 scanner (https://www.greenvalleyintl.com/) mounted on a DJI Matrice 600 drone. The LiAir S200 uses the Hesai Pandar40 laser sensor with a 200 m maximum range and a range accuracy within 2 cm horizontally and 5 cm vertically (Alsadik, 2020). The sensor has a beam divergence of 3.0 mrad with an angular resolution of 0.2° (horizontal) and 0.33° (vertical) (Alsadik, 2020). The laser scanning system uses the global navigation satellite systems (GNSS) and the inertial navigation system to ensure that the point clouds are georeferenced with a relative horizontal accuracy within 5 cm. The drone was flown at ~ 80 m above ground over the study sites on July 29th and 30th, 2019. The average point density of the DLS data was ~ 2,072 points/m².
2.2.2 Mobile laser scanning data

MLS point clouds (Figure 2 (B)) were acquired with a GeoSLAM ZEB Horizon (https://geoslam.com/solutions/zeb-horizon/) concurrently with the DLS data on July 29th and 30th 2019. The GeoSLAM ZEB Horizon is a survey-grade laser scanner that uses the Velodyne VLP-16 sensor with a 100 m ranging capability and a range accuracy within 3 cm (Alsadik, 2020). It has a collection rate of > 300,000 points/sec with a beam divergence of 3.0 mrad (Alsadik, 2020). The sensor has a horizontal angular resolution of 0.38° and a vertical angular resolution of 2° (Alsadik, 2020). To achieve accurate positioning and attitude estimation, the system relies on a simultaneous localization and mapping (SLAM) algorithm based on the geometric features of scanned environments (Sammartano and Spanò, 2018). With SLAM, the system senses unknown environments consistently by adding each scanning result to the previous point clouds (Sammartano and Spanò, 2018). During the data collection, an iterative closest point (ICP) algorithm based on the estimation of continuous trajectories was integrated to improve the correspondence of matched...
surface points and reduce the biased estimations from inertial measurement units (Bosse et al., 2012; Sammartano and Spanò, 2018). Overall, the SLAM algorithm allows a point-to-point accuracy of $6 \pm 4$ mm (GeoSLAM, 2021).

For each study site, 10 ground markers were placed 3 m away from one another along a line that bisected the plot center (Figure 3). The operator then activated the scanner and walked outwards in a spiral pattern following the ground markers and returned to the plot center to close the loop (Figure 3). The average point density of the MLS data was $\sim 20,274$ points/m$^2$.

![Figure 3](image.png)

**Figure 3** The illustration of the walking route for MLS data collection
Chapter 3: Comparing tree attributes derived from quantitative structure models based on drone and mobile laser scanning point clouds across varying canopy cover conditions

3.1 Introduction

Wildfires burn heterogeneously across the landscape and create complex canopy conditions in forest ecosystems. To measure the canopy conditions in forests, canopy cover can be used as it quantifies the vertical projection of tree crowns on the forest floor (Jennings et al., 1999). Across forest stands, the variations in canopy cover can reflect the changes in vegetation productivity, inter-tree competition, disturbance impacts, as well as microclimate (Canham et al., 2006; Stephens et al., 2009; De Frenne et al., 2013; Conenna et al., 2017; Majasalmi and Rautiainen, 2020). Assessing tree attributes in stands with different canopy cover is, therefore, crucial to various applications in the management of fire-prone forests, including fuel load treatment, growth and yield modelling, merchantable volume projection, and wildlife habitat evaluation (Mahoney et al., 2018; Grulke et al., 2020; Penner, 2021).

The diverse and complex canopy cover conditions in post-fire forests, however, often challenge forestry practitioners in acquiring accurate measurements of many tree attributes. Although conventional field-based approaches have been widely used to measure tree attributes, these methods are critiqued for being cost-ineffective, time-consuming, and limited in terms of spatial extent (Moran and Williams, 2002; Liu et al., 2011; Luoma et al., 2017; Jurjević et al., 2020). As a result, new approaches and techniques are needed to effectively obtain tree attributes accurately under a range of canopy cover conditions.
The use of ALS has supported the estimation of many stand-level forest attributes. However, ALS datasets are typically acquired using $< 20$ pulses/m$^2$ from a high flight altitude, yielding a near nadir perspective and point clouds that are difficult to detect tree-level attributes (Lee and Wang, 2018; Bruggisser et al., 2019). Although higher density point clouds ($> 60$ pulses/m$^2$) can be obtained by multiple flight passes, reliable segmentation of individual trees can still be problematic (Bucksch et al., 2014; Kandare et al., 2017; Marinelli et al., 2018). In forests with moderate-to-high canopy cover, for example, sub-canopy attributes and individual branches are not well resolved using ALS data (Roussel et al., 2017). Higher density point clouds are, thus, required to resolve detailed internal tree structures.

The acquisition of high-density point clouds is now readily available from new remote sensing platforms, such as DLS, TLS, and MLS. Particularly, advances in DLS allow the collection of higher density point clouds (e.g., $> 1000$ points/m$^2$) at a lower flight altitude and wider scan angles, compared to conventional ALS (Kellner et al., 2019; Resop et al., 2019; Puliti et al., 2020). The resulting point clouds improve the resolution of canopy structures as well as the detection of individual trees (Balsi et al., 2018; Kellner et al., 2019; Kuželka et al., 2020). For example, tree height, crown size and depth, upper branch location, size, and biomass, have been shown to be better detected from DLS data than ALS data with increased accuracy and precision (e.g., Kellner et al., 2019; Corte et al., 2020; Hartley et al., 2020; Puliti et al., 2020). In forests with multi-layered canopies, however, DLS remains limited when representing sub-canopy structures mainly due to the low return of light pulses, which can result in the biased estimation of both stand- and tree-level attributes, such as stem density, basal area, and diameter at breast height (DBH) (e.g., Skowronski et al., 2011; Hyyppä et al., 2012; Hyyppä et al., 2020; Pascu et al., 2020).
Unlike DLS, MLS collects point clouds with a ground-up perspective. With the ultra-high-density point clouds, fine individual tree features can be resolvable, especially the features at the sub-canopy level. Therefore, the use of MLS enhances the measurement of diverse structural attributes at fine spatial scales (Marselis et al., 2016; Vatandaşlar and Zeybek, 2021). For example, Liang et al. (2014) found that the accuracy of MLS-derived DBH and stem position can be as high as 87.5% with relatively low RMSE (i.e., 2.36 cm for DBH and 0.28 m for stem position). Zhou et al. (2019) also reported highly accurate MLS-derived DBH ($R^2 > 0.95$; RMSE < 1 cm), similar to other recent studies (e.g., Tang et al., 2015; Forsman et al., 2016; Marselis et al., 2016; Vatandaşlar and Zeybek, 2021).

Despite the potential for MLS to retrieve forest attributes, its accuracy may not outperform that of DLS or static TLS, especially in forests with complex canopy and understory conditions (Ryding et al., 2015; Liang et al., 2018; Shao et al., 2020). For example, Liang et al. (2018) found that the completeness of stem mapping using MLS data decreased from 90% in sparse forests to less than 60% in dense forests. The accuracy of stem detection from MLS (50–80%) was also lower than that from static TLS (90%), similar to studies reporting that MLS alone did not minimize the occlusion impacts as expected (Ryding et al., 2015; Forsman et al., 2016; Liang et al., 2018). In general, researchers have explained this lower accuracy of MLS-derived attributes to three factors: the geometrical complexity of a forest stand, the noise of the point clouds, and the positioning errors of the system (Tang et al., 2015; Forsman et al., 2016; Liang et al., 2018; Shao et al., 2020).

The fusion of high-density DLS and MLS point clouds may offer a solution to increase the robustness and accuracy of tree attribute estimation. Yet, little is known about the effectiveness of the data fusion between DLS and MLS point clouds in supporting tree attribute estimation in stands with varying canopy cover conditions. Therefore, this chapter aims to examine the impacts of canopy
cover on tree attribute estimation using both single and fused laser scanning datasets. The main objective of this chapter is to compare the accuracy of a number of tree attributes derived from low, moderate, and high canopy cover sites. I focus on the following questions: (1) What tree attributes can be accurately retrieved from single and fused laser scanning datasets? (2) By fusing the DLS and MLS point clouds, which tree attributes are better estimated? (3) How does the estimation of tree attributes differ across stands of varying canopy cover conditions? By quantifying the impacts of canopy cover conditions on tree attributes estimation, researchers and forestry practitioners can better choose appropriate laser scanning tools when conducting fieldwork. Understanding the effectiveness of single and fused laser scanning datasets in accurately extracting tree attributes can offer insights into the improved growth and yield modelling, assessment of fuel loads, as well as the sustainable management of fire-prone forests.
3.2 Methods

3.2.1 Point cloud processing

Figure 4 The overall workflow of data processing for single and fused laser scanning datasets
3.2.1.1 **Point cloud registration, fusion, and canopy cover classification**

The workflow of point cloud processing is presented in Figure 4. First, the raw DLS and MLS point clouds for each study site were clipped to circles with a 20 m radius (Figure 5). The clipped MLS point clouds were manually shifted to approximately overlap with their corresponding DLS point clouds. During this process, key point cloud features based on the patterns of horizontal point distribution were identified from the DLS data and used as guidance for the approximate alignment (Figure 5). After the manual shifting and alignment, a rigid transformation using the ICP algorithm from CloudCompare was performed to precisely register the MLS point clouds with DLS point clouds (CloudCompare, 2015). With the fine registration (Figure 5), the correspondence between the paired point clouds was calculated and the distances between them were minimized (Besl and McKay, 1992).

![Figure 5](image_url) The approximate alignment and fine registration for MLS point clouds based on DLS point clouds
To examine the quality of fine registration, the cloud-to-cloud distances were computed between the MLS data and their corresponding DLS data. Since the reference clouds (i.e., DLS data) have much lower point densities compared to the target clouds (i.e., MLS data), the local modelling strategy (least square plane method) of cloud-to-cloud distance computation was enabled to create a local model based on the nearest points from the reference clouds (Fuad, 2018). The cloud-to-cloud distances must be minimal to ensure a well-aligned MLS dataset, as demonstrated in Table 2, which shows that the distances ranged between 0.01 and 0.04 m.

<table>
<thead>
<tr>
<th>Site</th>
<th>Cloud-to-Cloud Distance (m)</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>0.0099</td>
<td>0.0301</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0.0144</td>
<td>0.0699</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>0.0181</td>
<td>0.0822</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0.0431</td>
<td>0.1444</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>0.0175</td>
<td>0.0805</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>0.0121</td>
<td>0.0619</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>0.0263</td>
<td>0.1070</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>0.0259</td>
<td>0.0991</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>0.0123</td>
<td>0.0636</td>
</tr>
</tbody>
</table>

Once precisely registered, the MLS point clouds were merged with their corresponding DLS point clouds to form the fused datasets using two methods. First, I directly combined the DLS and MLS data to create the fused DLS-MLS clouds (Figure 6 (A)). The average point density of the fused clouds was ~ 22,342 points/m². Second, considering the scanning characteristics of DLS and MLS, I proposed a new fusion strategy using a relative weighting scheme based on the probability density of the vertical point distribution (Figure 6 (B)). For each study site, I investigated the probability density curves of DLS and MLS data and identified the height of their intersection point. Next, I calculated ±
30% of the intersection height to divide DLS and MLS data into three sections: (1) lower (≤ 0.7 intersection height), (2) middle (0.7 – 1.3 intersection height), and (3) upper (> 1.3 intersection height). For each section, I applied voxel grids with varying sizes (e.g., 1 cm\(^3\), 8 cm\(^3\), 27 cm\(^3\), etc.) to sample the point clouds based on a series of relative weighting coefficients (\(\lambda_{1,2,3}\) for DLS and \(\gamma_{1,2,3}\) for MLS). For DLS data, a decreasing percentage of point clouds were sampled from upper to lower sections, whereas for MLS data, an increasing percentage of point clouds were sampled from upper to lower sections. To select the relative weighting coefficients, I tested a combination of options and visually examined the quality of the resulting point clouds. For DLS data, \(\lambda_1\), \(\lambda_2\), and \(\lambda_3\) were determined to be 90%, 60%, and 30%, respectively. For MLS data, \(\gamma_1\), \(\gamma_2\), and \(\gamma_3\) were determined to be 30%, 60%, and 90%, respectively. For each pair of DLS and MLS data, the sampled point clouds in each section were merged to create the weighted clouds. The average point density of the weighted clouds was ~ 17,951 points/m\(^2\).

Using the fused clouds, I calculated the canopy cover for each study site using the percentage of first returns above 2 m. I categorized the study sites into three canopy cover levels (Table 3): (1) low (< 20%), (2) moderate (20 – 40%), and (3) high (> 40%). Figure 7 shows the cross-sections of DLS, MLS, fused, and weighted DLS-MLS point clouds in low, moderate, and high canopy cover sites.
Figure 6 The illustration of (A) direct fusion and (B) fusion with a relative weighting scheme

Table 3 The canopy cover classes and related field information

<table>
<thead>
<tr>
<th>Canopy Cover</th>
<th>Number of Sites</th>
<th>Mean DBH (cm)</th>
<th>Mean Height (m)</th>
<th>Average Density (trees/ha)</th>
<th>Observed Tree Species</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>3</td>
<td>13.8</td>
<td>12.3</td>
<td>167</td>
<td>Lodgepole pine, Douglas fir</td>
</tr>
<tr>
<td>Moderate</td>
<td>3</td>
<td>13.7</td>
<td>10.7</td>
<td>1044</td>
<td>Lodgepole pine, Douglas fir, ponderosa pine, hybrid spruce, trembling aspen</td>
</tr>
<tr>
<td>High</td>
<td>3</td>
<td>27.1</td>
<td>14.2</td>
<td>1634</td>
<td>Lodgepole pine, Douglas fir, hybrid spruce, trembling aspen</td>
</tr>
</tbody>
</table>
3.2.1.2 Individual tree segmentation

I applied a bottom-up tree segmentation separately for each of the four datasets using the same set of parameters in Computree (Computree, 2021). First, digital terrain models were generated to classify ground points and isolate vegetation clouds (Figure 8). Next, the vegetation clouds were thresholded at breast height (1.3 m) above ground to identify individual stems. The Dijkstra-based tree segmentation algorithms were next applied to vegetation clouds to segment trees based on the
locations of the stems (Figure 8; Dijkstra, 1959; Hackenberg et al., 2015). Statistical outlier removal and radius outlier filters were used to denoise the segmented tree clouds (Hackenberg et al., 2015). For each study site, the segmented point clouds representing the same trees were matched among DLS, MLS, fused, and weighted datasets to allow further comparison.

3.2.1.3 Quantitative structure models

A quantitative structure model (QSM) is a group of geometric primitives (e.g., cylinders) that are hierarchically ordered to store the information about an entity’s topology, geometry, and volume (Hackenberg et al., 2014; Calders et al., 2015; Torresan et al., 2018). For each dataset, 20 tree clouds were selected from each of the three canopy cover classes (60 trees total) for QSM reconstruction. The number of trees was governed by the maximum number of trees observable in the point clouds of the lowest canopy cover sites that had the lowest tree density. To match the species composition
across study sites based on field observations (Table 3), 90% of tree clouds were randomly selected from coniferous trees and 10% of tree clouds were randomly selected from deciduous trees. QSMs representing the same tree based on the four datasets were matched and compared with each other.

I used the SimpleForest plugin in the Computree platform to generate QSMs based on the methods developed by Hackenberg et al. (2014) and (2015). For each denoised tree cloud, I first generated initial cylinders using the basic sphere following function (Torr and Zisserman, 2000; Hackenberg et al., 2015). During this process, a search sphere was created to partition each tree cloud into small segments from the base to the treetop (Figure 8; Côté et al., 2011, 2012; Torresan et al., 2018). Initial cylinders were then generated inside the search sphere to match the surface points of each segment. As the search sphere moved upwards to the treetop, the initial cylinders were linked following a topological order to form the basic QSM. Meanwhile, the tree clouds were classified into stem and branch points using the QSM-based tree clustering function (Hackenberg et al., 2015). Following the clustering, the advanced sphere following function was applied to improve the modelling accuracy of initial cylinders with an iterative process (Hackenberg et al., 2015). For each cylinder, the minimum cloud-to-model distance was identified to choose the best-fitting one. When a cylinder’s radius was 15% larger or smaller than the median radius of its three adjacent cylinders, the QSM median filter was used to replace the original radius with the median radius (Hackenberg et al., 2015). Next, the shoot correction function was applied to improve the cylinder quality of fine branches (Hackenberg et al., 2015). Finally, I performed the allometric correction algorithm, as proposed by Hackenberg et al. (2015), to correct QSMs based on the relationship between cylinder radius and accumulated volume. All QSMs were produced using a Windows 10 64-bit operating system (2.60 GHz, 64.0 GB memory).
3.2.2 Tree attribute extraction and validation

Computree generated a list file to store the following information for each cylinder in each QSM: start and end coordinates (x, y, z), radius, branch order, length, volume, and generated method (Hackenberg et al., 2015). The list files were exported to RStudio (RStudio Team, 2020) for the extraction of target tree attributes. The seven tree attributes examined in this chapter are listed in Table 4.

The diameter of the stem cylinder with a height of 1.3 m was used as the DBH. The tree height was calculated by subtracting the minimum value of the start z coordinate from the maximum value of the end z coordinate. The crown diameter was identified by finding the largest distance of the crown from one end to the other using the x and y coordinates of branch cylinders. The crown base height (CBH) was set as the height of the lowest base cylinder among all branch cylinders. The volumetric attributes were computed by summing the values of the target cylinders’ volumes. The stem volume was the sum of the volume of all stem cylinders; the branch volume was the sum of the volume of all branch cylinders; the total volume was the combination of the stem and branch volume.

Table 4 The target tree attributes derived from single and fused laser scanning datasets

<table>
<thead>
<tr>
<th>Tree attributes</th>
<th>Descriptions and related work</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic attributes</strong></td>
<td></td>
</tr>
<tr>
<td>DBH (cm)</td>
<td>The diameter at breast height (1.3 m) of a tree (Lin et al., 2012; Brede et al., 2017; Yin and Wang, 2019)</td>
</tr>
<tr>
<td>Tree height (m)</td>
<td>The total height of a tree (Brede et al., 2017; Zhou et al., 2019)</td>
</tr>
<tr>
<td><strong>Crown attributes</strong></td>
<td></td>
</tr>
<tr>
<td>Crown diameter (m)</td>
<td>The diameter of a living crown (Wannasiri et al., 2013; Brede et al., 2017; Yin and Wang, 2019)</td>
</tr>
<tr>
<td>CBH (m)</td>
<td>The distance between the ground and the lowest live or dead branch (Popescu and Zhao, 2008; Vauhkonen, 2010; Maltamo et al., 2018)</td>
</tr>
<tr>
<td><strong>Volumetric attributes</strong></td>
<td></td>
</tr>
<tr>
<td>Total volume (m³)</td>
<td>The total volume of the stem and branches (Kankare et al., 2013; Hyyppä et al., 2020)</td>
</tr>
<tr>
<td>Stem volume (m³)</td>
<td>The volume of the stem (Kankare et al., 2013; Hyyppä et al., 2020)</td>
</tr>
<tr>
<td>Branch volume (m³)</td>
<td>The volume of all branches (Hosoi et al., 2013)</td>
</tr>
</tbody>
</table>
For tree attribute validation, an independent operator conducted the measurement of basic and crown attributes using the raw point clouds segmented from the fused DLS-MLS point clouds in the open-source CloudCompare software (CloudCompare, 2015). The point-picking tool was used to measure the distance between a pair of selected points (CloudCompare, 2015). Four tree attributes, DBH, height, crown diameter, and CBH, were manually measured. I used the manually measured values as the reference data. As the field data did not contain estimations of stem and branch volumes for each individual tree, I validated the volumetric attributes by comparing the ratio of stem-to-branch volume with the ratio of stem-to-branch biomass. The biomass of stems and branches was calculated from the aforementioned allometric equations for tree species in BC (Ung et al. 2008).
3.2.3 Data analyses

For tree diameter, height, and crown attributes, the concordance correlation coefficient (CCC) was used to examine the agreement between the QSM-derived data and their corresponding reference data. CCC was also used to compare the agreement between the stem-to-branch volume ratios derived from QSMs and the stem-to-branch biomass ratios calculated from allometric equations. The CCC enables the measurement of reproducibility between two methods by quantifying their Euclidean distance to the 45° line (Lin, 1989). As a standardized coefficient, the CCC ranges between -1 to 1, with 1 meaning perfect agreement, 0 meaning no agreement, and -1 meaning perfect disagreement (Lin, 1989).

\[ \rho_{CCC} = \frac{2\sigma_{12}}{\sigma_1^2 + \sigma_2^2 + (\mu_1 - \mu_2)^2} \]  

where \( \sigma \) means the covariance of the variables, \( \sigma^2 \) is the variance of the data, and \( \mu \) represents the mean of the data.

In addition, the relative mean bias error (RMBE) and relative root-mean-square error (RRMSE) were considered to evaluate the accuracy of QSM-derived attributes.

\[ MBE = \frac{\sum_{i=1}^{n} (y_i - y'_i)}{n} \]  

Relative MBE (%) = \( \frac{MBE}{\bar{y}_i} \times 100\% \)  

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y'_i)^2}{n}} \]  

Relative RMSE (%) = \( \frac{RMSE}{\bar{y}_i} \times 100\% \)
where $y_i$ represents the measured data and $y'_i$ represents the corresponding data extracted from the QSMs. The mean value of the measured data is denoted as $\bar{y}_i$.

To compare the same types of tree attributes generated from the QSMs based on different laser scanning sources, I used CCC for measuring the agreement and conducted the Wilcoxon rank-sum test for pairwise comparisons (Cuzick, 1985; Wilcoxon, 1992).

3.3 Results

3.3.1 QSM reconstruction

The examples of QSMs produced from the four datasets are presented in Figure 9. The average processing time per QSM from DLS point clouds (~1.4 min) was the lowest among the four datasets regardless of canopy cover levels (Figure 10). In general, using weighted point clouds, the average processing time per QSM was reduced by ~19% compared to that of MLS point clouds, and by ~24% compared to that of fused point clouds.

![Figure 9](image-url)  
*Figure 9* Examples of the QSMs of a deciduous tree reconstructed from its corresponding (A) DLS, (B) MLS, (C) fused, and (D) weighted point clouds
Figure 10 The average processing time per QSM across laser scanning datasets under (A) overall, (B) low, (C) moderate, and (D) high canopy cover levels
3.3.2 **Assessment of basic and crown attributes**

Overall, QSMs generated from the fused laser scanning datasets (QSM\text{fused} and QSM\text{weighted}) outperformed those from the single laser scanning datasets (QSM\text{DLS} and QSM\text{MLS}) in estimating almost all basic and crown attributes across canopy cover levels. Comparable results were found between QSM\text{fused} and QSM\text{weighted}. As canopy cover increased, the advantages of the fused datasets emerged. Under high canopy cover, for example, attributes extracted from QSM\text{fused} exhibited excellent agreements with their corresponding reference values (CCC > 0.90) and had relatively low errors (Figure 11). Yet, the consistently negative RMBE values for QSM\text{fused}-derived attributes suggested a systematic underestimation.

Of the attributes derived from the fused datasets, the best results were for the estimation of tree height (CCC ~ 0.98, RMBE ~ -3%, and RRMSE ~ 5%), followed by the estimation of crown diameter (CCC ~ 0.93, RMBE ~ -8% and RRMSE ~ 12%). The estimation errors of DBH and CBH varied among canopy cover levels (Figure 11 (D), (H), (L)), indicating the impacts of canopy cover on the detection of sub-canopy attributes. The results for DBH and CBH from the fused datasets were still better than those from the single datasets.

Similar to QSM\text{fused} and QSM\text{weighted}, QSM\text{MLS} estimated tree heights and crown diameters relatively accurately. Although the CCC values and estimation errors were similar in sites with low and moderate canopy cover, they declined markedly when the canopy cover was high (Figure 11 (J), (K)). In terms of DBH, it was overestimated by 13% in sites with moderate canopy cover, but underestimated by 8% in sites with high canopy cover. Conversely, CBH was underestimated by 6% in sites with moderate canopy cover, but overestimated by 23% in sites with high canopy cover.

In comparison, QSM\text{DLS} accurately detected tree heights in different canopy cover levels (CCC > 0.90). Under high canopy cover, height estimation from QSM\text{DLS} was more accurate than that
from QSM$_{\text{MLS}}$. QSM$_{\text{DLS}}$-derived crown diameters showed moderate to strong agreements with the reference values (CCC > 0.60) across canopy cover levels, but were negatively biased with RMSE ranging from -31% to -12%. Both QSM$_{\text{DLS}}$-derived DBH and CBH agreed poorly with the reference data and had large estimation errors.
Figure 11 The agreements and estimation errors between reference and QSM-derived values of DBH, height, crown diameter, and CBH across canopy cover levels (the red line represents the 1:1 line)
3.3.3 Assessment of volumetric attributes

In Figure 12, the stem-to-branch volume ratios computed from QSMs are compared with the stem-to-branch biomass ratios computed from the allometric equations for lodgepole pine (*P. contorta*), one of the major tree species across the study sites. The stem-to-branch volume ratios from most of the QSMs were greater (> 300%) than their reference stem-to-branch biomass ratios, mainly due to the poorly modelled stem cylinders, and are not shown in Figure 12.

At low canopy cover sites, I found high agreements (CCC > 0.90) between QSM-derived stem-to-branch ratios and allometric stem-to-branch ratios (Figure 12 (A)). As canopy cover increased, the estimation of volumetric attributes varied markedly, with the CCC values sharply decreasing from > 0.90 to ~ 0.35 (Figure 12 (B), (C)). With moderate and high canopy cover, the scatter plots also exhibited large variability of QSM-derived stem-to-branch ratios, indicating mixed species composition (Table 3). Compared to low canopy cover sites, the stem-to-branch ratios at moderate-to-high canopy cover sites had a narrower range, implying that trees in forests with greater canopy cover have larger branches than trees in forests with relatively open canopies.
3.3.4 Comparison of basic and crown attributes

Figure 13 summarizes the agreements between pairs of QSMs for seven tree attributes across canopy cover levels. For pairs of QSM\textsubscript{fused} and QSM\textsubscript{weighted}, the values for basic and crown attributes agreed strongly (CCC > 0.80), except for CBH values under high canopy cover (CCC < 0.70). Between pairs of QSMs, the agreement patterns for height and crown diameter values were similar across canopy cover conditions. For DBH and CBH values, however, the agreement patterns varied differently. For example, the agreement of DBH values between QSM\textsubscript{fused} and QSM\textsubscript{MLS} decreased from CCC > 0.80 to CCC < 0.55 with increasing canopy cover. For CBH, the agreement between QSM\textsubscript{fused} and QSM\textsubscript{MLS}-derived values increased from CCC of 0.67 to 0.94 at sites with low and moderate canopy cover, respectively, but decreased to only 0.12 at high canopy cover sites. Both DBH and CBH values between QSM\textsubscript{fused} and QSM\textsubscript{DLS} generally had poor agreements across canopy cover levels.
Several significant differences were detected when comparing QSM-derived tree attributes (Figure 14). The median values of DBH and CBH derived from QSM$_{DLS}$ were greater than those from other QSMs across canopy cover levels. At low canopy cover sites, the median values of height and crown diameter derived from QSM$_{DLS}$ were smaller than those from other QSMs (Figure 14 (C), (D)). At high canopy cover sites, the median values of DBH, height, and crown diameter derived from the fused datasets were greater than those from QSM$_{MLS}$ (Figure 14 (I), (J), (K)).

![Figure 13](image)

**Figure 13** The agreements of tree attributes extracted from QSMs based on the fused, weighted, MLS, and DLS point clouds (the greater the CCC, the stronger the agreement)
Figure 14 The violin and box plots showing the distribution and pairwise comparisons of QSM-derived basic and crown attributes in different canopy cover classes; the significant differences (p < 0.05) between the median of the two groups are indicated using different letters.
3.3.5 Comparison of volumetric attributes

Overall, the agreement patterns between pairs of QSMs for volumetric attributes across canopy cover levels were similar to those observed for basic and crown attributes (Figure 13). For total and stem volumes, the QSM$_{\text{fused}}$-derived values agreed substantially (CCC ~ 0.95) with corresponding values from QSM$_{\text{weighted}}$ and QSM$_{\text{MLS}}$ under low and moderate canopy cover. As canopy cover further increased, the CCC values sharply decreased to ~ 0.65 for pairs of QSM$_{\text{weighted}}$ and QSM$_{\text{MLS}}$, and ~ 0.45 for pairs of QSM$_{\text{fused}}$ and QSM$_{\text{MLS}}$. Between QSM$_{\text{fused}}$ and QSM$_{\text{DLS}}$, the agreements for values of total and stem volumes decreased with increasing canopy cover. In contrast, the agreements of branch volumes derived from different types of QSMs improved steadily as canopy cover increased.

By comparing QSM-derived volumetric attributes, I found multiple significant differences (Figure 15). Under low canopy cover, the median values for total and stem volumes were largest from QSM$_{\text{DLS}}$, followed by QSM$_{\text{MLS}}$, QSM$_{\text{weighted}}$, and QSM$_{\text{fused}}$ (Figure 15 (A), (B)). The median values for branch volumes, however, were largest from QSM$_{\text{MLS}}$, followed by QSM$_{\text{weighted}}$, QSM$_{\text{fused}}$, and QSM$_{\text{DLS}}$ (Figure 15 (C)). With moderate and high canopy cover, the median values of total and stem volumes derived from QSM$_{\text{DLS}}$ were significantly larger than those from QSM$_{\text{fused}}$, QSM$_{\text{weighted}}$, and QSM$_{\text{MLS}}$ (Figure 15 (D), (E), (G), (H)).
Figure 15 The violin and box plots showing the distribution and pairwise comparison of QSM-derived volumetric attributes across three levels of canopy cover; the significant differences (p < 0.05) between the median of the two groups are indicated using different letters.
3.4 Discussion

This chapter quantified the effectiveness of DLS, MLS, fused, and weighted DLS-MLS point clouds in extracting individual tree attributes using a QSM approach. The impacts of canopy cover on tree attribute estimation uncovered the benefits and shortcomings of different laser scanning data in forestry practices. This chapter refines existing studies on DLS and MLS point clouds in forest mapping. The findings of this chapter can also be applied to regions with similar forest types across North America. Here, I discuss the factors that influence the modelling of QSMs, as well as the effects of canopy cover on the estimation of the basic, crown, and volumetric attributes.

3.4.1 QSM reconstruction

Well-reconstructed QSMs, as I found in this chapter, can provide effective estimates of the basic, crown, and volumetric attributes across canopy cover levels. The results show that the fusion method based on the relative weighting scheme improved the modelling efficiency of QSMs, especially at sites with low and moderate canopy cover (Table 5). The fusion of DLS and MLS point clouds presents opportunities to benefit the reconstruction of QSMs and allow better estimates of tree attributes compared to single laser scanning datasets. In addition, the (1) individual tree segmentation, (2) point cloud denoising, and (3) characteristics of laser scanning instruments are also critical for the accurate reconstruction of QSMs (Kaasalainen et al., 2014; Hackenberg et al., 2015; Gonzalez de Tanago et al., 2018; Brede et al., 2019). Below, I examine how each of these processes was addressed in this chapter.

Segmented tree clouds provide input data for reconstructions and directly affect the quality of QSM outputs. To minimize the influence of occlusion, researchers have manually corrected tree clouds generated by automatic segmentation algorithms (Calders et al., 2015; Brede et al., 2019).
While this manual correction optimizes the reconstruction of QSMs, it poses challenges when processing a large number of tree clouds. Thus, before applying the QSM approach to retrieve tree attributes on a large scale, the effectiveness and accuracy of current automatic segmentation algorithms require further investigation. In this chapter, I used an automatic bottom-up segmentation algorithm that might not be the best option for DLS data. However, Vandendaele et al. (2021) examined similar algorithms and found that over 70% of trees from DLS data could be correctly identified during leaf-off conditions. This suggests that bottom-up segmentation algorithms can achieve optimal results from DLS point clouds, depending on forest conditions and the attributes of interest. For future work, I suggest researchers evaluate the quality of tree segmentation results prior to reconstructing QSMs.

Brede et al. (2019) reported that point cloud denoising is a key step to reducing the impacts of foliage on the modelling of woody structures. In previous work, researchers have scanned trees during the leaf-off season, relied on point cloud filtering functions, or skipped this step (e.g., Hackenberg et al., 2014; Raumonen et al., 2015; Brede et al., 2019). Fundamental point cloud filtering functions may have limited efficacy on foliage removal when the tree clouds have large crowns or complex branching structures. Brede et al. (2019) suggested that foliage classification methods should be adopted before building QSMs. Although advanced foliage classification algorithms have been developed recently, most apply to specific tree species and require point clouds to have ultra-high-density that can resolve foliage (Vicari et al., 2019; Moorthy et al., 2020; Wang et al., 2020). Hence, methods to more effectively separate foliage from woody structures in tree clouds are needed to advance this area of research.

Differences in the characteristics of laser scanning instruments, such as scanning frequency, ranging accuracy, and beam divergence, yield point clouds of different accuracies that influence the
reconstruction of QSMs. With larger beam divergence, for example, point clouds would have lower resolution and greater ambiguity, adding difficulties to the cylinder modelling (Brede et al., 2019). In this chapter, both the DLS and MLS instruments use multi-beam sensors with similar angular resolutions and beam divergence. Yet, DLS scans the forest further away at a faster rate than MLS, producing lower-density point clouds that may not be suitable for QSM reconstructions. For MLS, the environmental complexity of forests tends to reduce the accuracy of scan positions and orientations while the sensor is in motion, which contributes to the degradation of data quality (Liang et al., 2018). Future research should explore methods, such as graph-based trajectory optimization (Kukko et al., 2017) and odometry drift compensation (Liu et al., 2022), to account for and correct the deformations within MLS data.

3.4.2 Canopy cover impacts on the estimation of basic and crown attributes

The results suggest that canopy cover conditions can have a direct impact on the estimation of basic and crown attributes using single laser scanning datasets. The increasing canopy cover particularly challenged the detection and estimation of sub-canopy attributes for both DLS and MLS data. The low accuracies of QSM_{DLS}-derived sub-canopy attributes can be related to the cylinder modelling procedures. Since the modelling of cylinders starts at the tree base, it does not favour DLS data with insufficient points close to the ground, especially in areas with high canopy cover. When the lower stem is poorly modelled, the errors of cylinders would accumulate to upper levels. This error accumulation, in turn, impedes the accurate extraction of sub-canopy attributes. I recommend that different cylinder fitting and correction functions should be developed for building QSMs from DLS data. Under-canopy DLS may also improve the data quality close to the ground and facilitate the estimation of sub-canopy attributes (Wang et al., 2021).
While I expected MLS data to resolve sub-canopy structures well, the DBH estimation was highly accurate only in the low canopy cover sites. Similarly, Heo et al. (2019) found that, as canopy cover increased, the accuracy of MLS-derived DBH decreased. This decreased accuracy was explained by the inadequate scans of stems caused by the structural complexity in dense forests (Heo et al., 2019). Yet surprisingly, the DBH estimation at moderate canopy cover sites had the lowest accuracy (Figure 11 (E)), which is likely related to the stand characteristics. As I observed, the moderate canopy cover sites were occupied by a mixture of regenerating and mature trees following disturbances. The competition among regenerating trees over light and nutrients created a complex sub-canopy structure with suppressed young trees and overlapping branches. These characteristics, therefore, complicated the mapping of individual stems, leading to a biased estimation of DBH. In addition, the MLS pulses may not always reach the treetop due to the effects of off-nadir scan angles, resulting in missing points in the upper canopy. This may explain the lowest accuracy (CCC = 0.81) of MLS-derived tree height in high canopy cover sites (Figure 11 (J)). Forestry practitioners, therefore, need to account for this impact when surveying tall trees at sites with high canopy cover.

In comparison with single datasets, the fused datasets were less impacted by canopy cover conditions. DBH, height, and crown attributes derived from the fused datasets showed excellent agreements with the reference data. The findings in this chapter suggest that the data fusion improves the estimations of multiple basic and crown attributes in coniferous-dominated forests, similar to findings of several previous studies that fused ALS with TLS point clouds to improve attribute estimates (e.g., Murgoitio et al., 2014; Paris et al., 2017; Dai et al., 2019). Future studies should examine the effectiveness of the fused datasets in extracting tree attributes in different types of forests. For forestry practitioners, however, the question remains: is it worthwhile to perform data fusion to estimate basic and crown attributes? Since the process of data registration and fusion is
time-consuming and challenging, determining the degree to which fused datasets outperform single datasets when extracting a variety of target attributes is an important application of the findings in this chapter.

Using fused ALS-TLS point clouds, Paris et al. (2017) accurately estimated tree height and crown diameter ($R^2 > 0.85$) and concluded that the fused dataset improved the evaluation of crown structures. Their finding corresponds to my results that the fused datasets performed well in extracting accurate heights and crown diameters. Yet, this chapter further revealed that, for height and crown diameter, single DLS/MLS datasets can achieve accurate estimations. Several other studies that used single datasets of laser scanning point clouds also support this finding (Wannasiri et al., 2013; Unger et al., 2014; Brede et al., 2017; Yin and Wang, 2019). If forestry practitioners only need to predict tree heights and crown diameters, the benefits of fused laser scanning datasets would be minor and may not justify the extra time and cost of fusion.

In forests with high canopy cover, my results show that the fused laser scanning datasets were more advantageous over single laser scanning datasets in estimating sub-canopy attributes, especially for CBH. Although CBH is important for understanding the wildfire impacts, few studies have investigated its estimation at an individual tree level using point clouds. A common strategy is to predict CBH using allometric regression models based on the relationships between tree attributes (e.g., height, DBH, crown width, etc.) and field-measured CBH (Næsset and Økland, 2002; Holmgren and Persson, 2004; Andersen et al., 2005; Solberg et al., 2006). As the performance of regression models depends on the input data, and CBH has proven difficult to consistently measure in the field, the accuracy of CBH estimation using this strategy varies greatly (Vauhkonen, 2010; Kelly et al., 2017). Another strategy directly estimates CBH from point clouds using the inflection point of the vertical profile of return signals (Popescu and Zhao, 2008; Maltamo et al., 2010). This strategy can
allow accurate estimations of CBH (RMBE < 15%; RMSE < 2.0 m) but still faces challenges in correctly locating the inflection point (Luo et al., 2018). Compared to previous work, the fused datasets achieved similar results. In this regard, the QSM approach has the potential to advance the estimation of CBH.

### 3.4.3 Canopy cover impacts on the estimation of volumetric attributes

Complex canopy cover conditions can influence laser scanning instruments’ capability in differentiating fine features of individual trees, which challenges the cylinder modelling and the subsequent extraction of volumetric attributes. Meanwhile, validating QSM-derived volumes has been difficult since it typically involves destructive measurements (Putman et al., 2018). In this chapter, I compared the ratio of stem-to-branch volumes from QSMs to the ratio of stem-to-branch biomass based on species-specific allometric equations (Ung et al., 2008). The lack of the species information of each segmented tree cloud limited the tree attribute validation, especially in moderate and high canopy cover sites with diverse species compositions. Thus, future studies should incorporate tree species data into the assessment of QSM-derived volumes across canopy cover levels.

Under low canopy cover, I found that the values of tree volumes derived from QSM\textsubscript{fused}, QSM\textsubscript{weighted}, and QSM\textsubscript{MLS} agreed strongly with each other, but the median values of QSM\textsubscript{weighted} and QSM\textsubscript{MLS} were greater than those of QSM\textsubscript{fused} (Figure 15 (A), (B), (C)). With increasing canopy cover, the agreements among the total and stem volumes sharply reduced, although their median differences became non-significant. These discrepancies could result from variations in the modelling of branches and boles. At low canopy cover sites, trees have more space to develop horizontal structures due to low inter-tree competition. As a result, these trees have large crowns close to the ground.
When the laser scanning data cannot discriminate fine branches and boles along the stems, the size of stem cylinders tended to be overestimated and caused an increase in tree volumes.

The results in this chapter suggest that QSMs perform well in estimating large stems and branches across canopy cover conditions, similar to previous research (Hackenberg et al., 2014). When modelling fine branches (e.g., diameter < 5 cm), however, the performance of QSMs can be relatively poor (Hackenberg et al., 2014; Kaasalainen et al., 2014; Hackenberg et al., 2015; Gonzalez de Tanago et al., 2018). The cylinder fitting for fine branches can be problematic mainly due to the limited point coverage around them (Hackenberg et al., 2014). These incorrectly fitted cylinders, consequently, undermine the modelling performance as a whole and contributed to discrepancies in volumes estimated by different types of QSMs in this chapter. Further research should, thus, optimize the modelling of small-diameter branches.

In the upper canopy, MLS data alone may not well differentiate branching structures. After the integration of DLS data, the fused laser scanning datasets combined information on upper and lower branches, enhancing the representation of branching structures. As canopy cover increased, DLS data detected fewer branches in the sub-canopy and the branch information mainly came from MLS data. These patterns explain why the agreements among $QSM_{\text{fused}}$, $QSM_{\text{weighted}}$, and $QSM_{\text{MLS}}$-derived branch volumes increased with increasing canopy cover. Previous studies similarly found that the modelling accuracy of QSM-derived volumes decreased in dense forests where branching structures were complex (Torresan et al., 2018; Brede et al., 2019). Fusing MLS with DLS point clouds, however, can partially resolve the issue of insufficient point coverage on branches. Under-canopy DLS, repeated scanning, alternative QSM modelling strategies, as well as species-specific allometric corrections, might alleviate the negative effects of high canopy cover on the tree volume estimation.
Overall, the fusion of DLS and MLS point clouds improved the reconstruction of QSMs as well as the estimation of the basic, crown, and volumetric attributes at an individual tree level. With the well-reconstructed QSMs, it is possible to extract a variety of post-fire tree attributes and advance the understanding of wildfire impacts on individual trees and forest stands. Therefore, in the next chapter, I applied the QSM approach to the fused DLS-MLS point clouds to investigate the effects of the 2017 Elephant Hill wildfire on post-fire tree structures across a range of burn-severity levels.
Chapter 4: Assessing the effects of burn severity on post-fire tree structures using the fused drone and mobile laser scanning point clouds

4.1 Introduction

Post-fire assessments provide pivotal information about the magnitude of wildfire impacts on forest ecosystems (Robichaud et al., 2014; Klauberg et al., 2019). At an individual tree level, wildfire impacts can be estimated using crown scorch which measures the proportion of discoloured foliage following a fire (Hood et al., 2018; Varner et al., 2021). Thus, it is commonly used to indicate a fire’s consumption of foliage and the heat damage to individual trees (Wallin et al., 2003; Hood et al., 2018; Varner et al., 2021). With increasing crown scorch, for example, the foliage colour can change from green and yellow (minor damage) to brown and black (complete damage), suggesting an external fire-induced injury (Hood et al., 2018; Varner et al., 2021). Based on crown scorch, the internal injury of individual trees due to fires can also be interpreted since the reduced foliage is associated with many physiological processes, such as water uptake, photosynthesis, and carbon assimilation (Alonso et al., 2002; Wallin et al., 2003; O’Brien et al., 2010).

At a plot level, wildfire impacts can be categorized into different burn-severity levels, such as low, moderate, and high. A low-severity fire (i.e., surface fire) partially consumes the surface fuel, with most of the trees unscorched or lightly scorched (Keeley, 2009). Following a moderate-severity fire, forest structure is altered due to the burning of multiple vegetation strata from ground to canopy (Keeley, 2009; Ager et al., 2013; Kramer et al., 2016). Low- and moderate-severity fires may benefit residual trees with reduced competition and increased seed germination and sprouting (Collins et al., 2018; Jean et al., 2019; Cannon et al., 2021). By contrast, high-severity fires (i.e., crown fires) are characterized by a major loss in the above-ground biomass due to the consumption of surface, ladder,
and crown fuels (Chambers et al., 2016; Jones et al., 2016; Garcia et al., 2017b). Meanwhile, the prolonged droughts associated with high-severity fires can also cause delayed mortality of remaining trees, further challenging the survival and recovery of trees in forested habitats (Savage et al., 2013; Ruffault et al., 2018; Rodman et al., 2020).

Due to the interacting effects of fuel availability, weather conditions, and topographic features, wildfires burn with a mixture of severities, generating a mosaic pattern of burned and unburned patches within the fire perimeter (Kane et al., 2013; Foster et al., 2017; Crockett and Westerling, 2018; Walker et al., 2020; Churchill et al., 2022). As a result, wildfires can create complex forest structures with high spatial heterogeneity (Bassett et al., 2017; Carlson et al., 2017; Foster et al., 2017). During the post-fire assessment, the evaluation of wildfire impacts on forests can be based on visual estimations (e.g., percentage of ground scorch) and field measurements (e.g., char height) (Robichaud et al., 2007; Chuvieco, 2009). Many structural attributes of forests that are important to examining post-fire biomass, such as crown volume, can be hard to measure in the field (Karna et al., 2019). Therefore, the post-fire assessment may not fully reflect the structural condition of forest ecosystems. Quantifying the post-fire forest structure is, in this case, critical to improving our understanding of wildfire impacts, especially for large and severe fires.

The use of laser scanning technologies allows the acquisition of three-dimensional point clouds to accurately represent the structure of forest stands and individual trees (Goodwin et al., 2006; Wulder et al., 2008). Previous studies conducted across a range of forest types have utilized airborne laser scanning (ALS) data to examine the characteristics of post-fire vegetation (e.g., Botequim et al., 2019; Kane et al., 2019; Gelabert et al., 2020), evaluate the wildfire effects by comparing burned with unburned forest plots (e.g., Alonzo et al., 2017; Hoffman et al., 2018; Hu et al., 2019; Karna et al., 2020), and assess the mortality and recovery of remaining trees with the aid of
multispectral satellite imagery (e.g., Kane et al., 2014; Bolton et al., 2015; McCarley et al., 2017; Klauberg et al., 2019). From ALS data, researchers have examined post-fire forest structures across a wide range of forest types globally to improve our local understanding of the impact of wildfires across landscapes (Botequim et al., 2019; Kane et al., 2019; Karna et al., 2019, 2020). Research has shown, for example, that ALS-derived forest canopy cover decreased by ~30% after moderate- and high-severity fires (Karna et al., 2020). High-severity fires also impacted the spacing of dominant vegetation, leading to stands with decreased canopy height, increased canopy gaps, and increased habitat fragmentation (Karna et al., 2020). At the individual tree level, several structural attributes (e.g., crown dimensions) can also be calculated (Casas et al., 2016; Hu et al., 2019; Klauberg et al., 2019), with researchers finding that, after high-severity fires, trees had significantly smaller crown width, cover, and biomass compared to trees burned by low- or moderate-severity fires (Karna et al., 2019). Tree crowns burned by high-severity fires also became more elongated and conical-shaped instead of round-shaped, implying their reduced recovery and primary productivity (Karna et al., 2019).

The majority of research on the post-fire stand and tree structures, in general, has been undertaken from piloted airborne systems. New laser scanning instruments, such as DLS and MLS, offer unique information on the post-fire forest structure. However, to date, there have been a limited number of studies exploring how DLS and MLS datasets can be used together to provide both a ground-up and top-down assessment of post-fire forest structure. In the previous chapter, I explored the effectiveness of DLS and MLS point clouds in extracting post-fire tree attributes with a QSM approach. In this chapter, I used the QSMs generated from the fused DLS-MLS dataset to further quantify the effects of wildfires on individual trees across a range of burn-severity levels.
To do so, I sampled trees that experienced a range of crown scorch levels from low-, moderate-, and high-severity sites. I investigated the following questions: (1) At the individual tree level, how is crown scorch related to pre-fire tree size and post-fire tree attributes? (2) At the plot level, how does tree size change in response to wildfires with different burn severities? And finally, (3) from the structural attributes of post-fire trees, what can be inferred about the wildfire burn-severity pattern? By examining the differences in post-fire tree structures, this chapter aims to improve the understanding of relationships between burn severities and tree-level responses, therefore informing fire behaviour modelling, fire risk mitigation, and fire-prone forest management.

4.2 Methods

4.2.1 Burn severity classification

The post-fire conditions of the nine study sites were examined in August and September 2019 by relocating the permanent sample plots and assessing fire effects at both individual tree and plot scales. To measure the tree-level burn severity, the percentage of crown scorch for each tree that could be matched in the pre-fire inventory data was evaluated. In total, 86 trees were recorded with crown scorch, with 80 coniferous trees (i.e., interior Douglas-fir, lodgepole pine, and hybrid spruce) and 6 trembling aspens.

To estimate the plot-level burn severity, I calculated the Composite Burn Index (CBI) using the post-fire field data by considering the average impacts of wildfires on five vertical vegetation strata (Key and Benson, 2006; De Santis and Chuvieco, 2009). To do so, I used the CBI concept from Key and Benson (2006) and modified some strata to minimize the assumptions of pre-fire conditions. The five strata were: (1) substrates, (2) understory plants (mosses, bryophytes, herbs and ferns), (3) shrubs, (4) sub-canopy trees, and (5) canopy trees. For this study, the modified CBI is
referred to as CBI. On the forest floor, I examined the degree of ground scorch, percentage of exposed soil, and depth of burn classes (Ryan, 1982). I also estimated the percentage of understory plants and shrubs affected by the fire. For sub-canopy and canopy trees, I estimated the percentage of crown scorch and measured the char height on individual trees and averaged them to represent each study site. Table 5 shows the CBI scores for each study site across the five vertical vegetation strata. Finally, I categorized the plot-level burn severity into three classes: (1) low (CBI $\leq 1.5$), (2) moderate (1.5 < CBI $\leq 2.25$), and (3) high (2.25 < CBI $\leq 3$). Examples of study sites from different plot-level burn-severity classes are presented in Figure 16.

Table 5 The burn severity classification of study sites with CBI scores by vertical vegetation stratum and plot (the dash symbol indicates that there are no sub-canopy trees at the site)

<table>
<thead>
<tr>
<th>Site</th>
<th>Substrates</th>
<th>Understory plants</th>
<th>Shrubs</th>
<th>Sub-canopy trees</th>
<th>Canopy trees</th>
<th>Plot</th>
<th>Burn severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.80</td>
<td>1.00</td>
<td>1.00</td>
<td>0.60</td>
<td>0.00</td>
<td>0.68</td>
<td>Low</td>
</tr>
<tr>
<td>2</td>
<td>0.30</td>
<td>1.50</td>
<td>1.50</td>
<td>-</td>
<td>0.00</td>
<td>0.83</td>
<td>Low</td>
</tr>
<tr>
<td>3</td>
<td>1.50</td>
<td>3.00</td>
<td>2.50</td>
<td>-</td>
<td>1.60</td>
<td>2.15</td>
<td>Moderate</td>
</tr>
<tr>
<td>4</td>
<td>1.80</td>
<td>2.00</td>
<td>2.00</td>
<td>-</td>
<td>1.80</td>
<td>1.90</td>
<td>Moderate</td>
</tr>
<tr>
<td>5</td>
<td>1.20</td>
<td>2.50</td>
<td>3.00</td>
<td>2.40</td>
<td>2.00</td>
<td>2.22</td>
<td>Moderate</td>
</tr>
<tr>
<td>6</td>
<td>2.00</td>
<td>3.00</td>
<td>3.00</td>
<td>2.50</td>
<td>2.50</td>
<td>2.60</td>
<td>High</td>
</tr>
<tr>
<td>7</td>
<td>2.20</td>
<td>3.00</td>
<td>3.00</td>
<td>-</td>
<td>2.40</td>
<td>2.65</td>
<td>High</td>
</tr>
<tr>
<td>8</td>
<td>2.00</td>
<td>3.00</td>
<td>3.00</td>
<td>2.40</td>
<td>2.40</td>
<td>2.56</td>
<td>High</td>
</tr>
<tr>
<td>9</td>
<td>2.70</td>
<td>3.00</td>
<td>3.00</td>
<td>2.40</td>
<td>2.40</td>
<td>2.7</td>
<td>High</td>
</tr>
</tbody>
</table>
4.2.2 Point cloud processing

The point clouds were grouped based on the plot-level burn-severity classes of their corresponding plots (Figure 17). As the pre-fire plots were sampled using both fixed- and variable-radius methods, the point clouds were clipped to reduce their geometric inconsistencies compared to the sizes and shapes of field plots. For fixed-radius plots, I directly clipped the fused point clouds to circles with a radius of 11.28 m. For variable-radius plots, I identified the horizontal distance between the plot center and each tallied tree from the field data (Figure 18). The largest center-to-tree distance in each field plot was used as the clipping radius for the point clouds (Figure 18). The resulting clipping radii ranged from 6.4 to 10.78 m. The average point density of final fused point clouds ranged from 25,498 to 32,743 points/m² across the plot-level burn-severity classes.
Figure 17 Examples of laser scanning data that are classified as different burn-severity classes
Figure 18 The workflow of matching point clouds with fixed- or variable-radius field plots

4.2.3 Tree attribute extraction

Using the final fused point clouds, I reconstructed QSMs for individual trees in each study site using the methods proposed by Hackenberg et al. (2014) and (2015), as described in Chapter 3. The QSMs were grouped based on the burn-severity levels of their study sites (Figure 19). To pair individual tree QSMs with post-fire field measurements, I compared their spatial coordinates and used a buffer range of the average crown size in each plot to match the corresponding tree datasets. With the QSMs, I extracted post-fire biometric, crown, and volumetric attributes at the individual tree level using QSMs (Table 6). In terms of biometric attributes, I retrieved the diameter of stem cylinders at 1.3 m above ground as an estimate of DBH. The coordinates of the highest and lowest
cylinders were used to calculate the tree height. Using the DBH and tree height, I computed the biomass using the aforementioned allometric equations (Ung et al., 2008). Eight crown attributes were examined in this chapter to quantitatively describe the horizontal and vertical structure of tree crowns. The horizontal attributes include crown diameter, crown projection area (CPA), crown compactness, and crown evenness. The vertical attributes include CBH, crown length, crown ratio, and crown elongation. To extract the crown attributes, I isolated the branch cylinders from QSMs. The coordinates of the branch cylinders were used to compute the crown diameter, CBH, and crown length. With these three attributes, I further derived crown ratio and crown elongation. Of all the branch cylinders from a QSM, I identified the outermost ones and connected their locations to delineate the 2D shape of crowns on the horizontal plane. From this 2D shape, I calculated the CPA and crown compactness. The crown evenness index was adapted from Åkerblom et al. (2017) to evaluate the lateral distribution of branches. In addition, I also summarized the stem, branch, and total volumes of individual trees using the volumetric information provided by QSMs.
Figure 19 Examples of individual tree QSMs from low-, moderate-, and high-severity study sites

Table 6 The structural attributes of individual trees examined in this chapter

<table>
<thead>
<tr>
<th>Type</th>
<th>Tree attribute (units)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biometric</td>
<td>DBH (cm)</td>
<td>The outside bark diameter of a tree at breast height (1.3 m)</td>
</tr>
<tr>
<td></td>
<td>Tree height (m)</td>
<td>The height of a tree from the ground to treetop</td>
</tr>
<tr>
<td></td>
<td>Biomass (kg)</td>
<td>The weight of the dry mass of tree stem and branches (Ung et al., 2008)</td>
</tr>
<tr>
<td>Crown</td>
<td>Crown diameter (m)</td>
<td>The maximum width of the crown of a tree</td>
</tr>
<tr>
<td></td>
<td>CPA (m²)</td>
<td>The projected area of the crown of a tree on the horizontal plane (Xu et al., 2013; Karna et al., 2019)</td>
</tr>
<tr>
<td></td>
<td>Crown compactness (0-1)</td>
<td>The ratio of the crown projection area to its perimeter (Kunz et al., 2019; Madsen et al., 2021)</td>
</tr>
<tr>
<td></td>
<td>Crown evenness (0-1)</td>
<td>The branch cylinders were separated into four angular bins. Crown evenness measures the ratio of maximum and minimum heights of the lowest branches across the bins (Åkerblom et al., 2017).</td>
</tr>
<tr>
<td></td>
<td>CBH (m)</td>
<td>The height from the ground surface to the lowest live or dead branch</td>
</tr>
<tr>
<td></td>
<td>Crown length (m)</td>
<td>The distance from the treetop to the lowest branch</td>
</tr>
<tr>
<td></td>
<td>Crown ratio (0-1)</td>
<td>The ratio of the crown length to tree height</td>
</tr>
<tr>
<td></td>
<td>Crown elongation (0-1)</td>
<td>The ratio of the crown width to crown length</td>
</tr>
<tr>
<td>Volumetric</td>
<td>Total volume (m³)</td>
<td>The volume of the stem and all branches of a tree</td>
</tr>
<tr>
<td></td>
<td>Stem volume (m³)</td>
<td>The volume of the stem of a tree</td>
</tr>
<tr>
<td></td>
<td>Branch volume (m³)</td>
<td>The volume of all branches of a tree</td>
</tr>
</tbody>
</table>
4.2.4 Data analyses

I performed an initial Kruskal-Wallis test (Kruskal and Wallis, 1952) using the field data and did not find significant differences among interior Douglas-fir, lodgepole pine, and hybrid spruce in terms of pre-fire DBH, height, and biomass (see Appendices). These coniferous trees also experienced similar levels of crown scorch (see Appendices). Since there were only six trembling aspens recorded in the field data, their impact on the analyses of post-fire tree structure was anticipated to be minor. Overall, this pre-fire analysis suggests that pre-fire tree species should not be a significant confounding factor in the subsequent analyses.

To understand the impacts of wildfires on individual tree structures, I first examined the relationship between crown scorch and trees of different pre-fire sizes (DBH, height, and biomass) in mature (age class: > 50 years) and young (age class: 15 – 50 years) stands. I quantified the relationship using Spearman’s rank correlation coefficient considering the non-normal distribution of the data (Gauthier, 2001). This coefficient measures both the direction and strength of the correlation between two variables based on the ranks of the data (Gauthier, 2001).

\[
R = 1 - \frac{6 \sum d_i^2}{n^3 - n} \tag{10}
\]

where \(d_i\) denotes the difference between the ranks of each pair of observations and \(n\) represents the number of observations. The coefficient (R) ranges between -1 and +1, with \(R > 0\) indicating a positive correlation, \(R = 0\) indicating no correlation, and \(R < 0\) indicating a negative correlation. The stronger the correlation, the greater the absolute value of R.

To compare the post-fire tree structures across a range of crown scorch levels, I used pre-fire DBH to separate individual trees into three groups according to the provincial standards of timber
cruising (Government of BC, 2021): (1) small (DBH < 12.5 cm), (2) medium (12.5 \leq DBH < 30 cm), and (3) large (DBH \geq 30 cm). For each group of trees, I examined the relationship between crown scorch and post-fire tree attributes using Spearman’s rank correlation coefficient (Gauthier, 2001).

To further understand the effects of burn severity at the plot level, I aggregated individual trees based on the CBI score of their study sites. I examined the changes in pre-and post-fire tree attributes using the paired Wilcoxon rank-sum test. This test is a non-parametric technique to compare the ranking of observations of two groups of paired samples (Cuzick, 1985; Wilcoxon, 1992). The three biometric attributes investigated were DBH, tree height, and biomass. DBH and height were manually measured in the field before the fire and were derived from QSMs after the fire. Pre- and post-fire biomass were calculated from species-specific allometric equations based on DBH and height, as described above.

Exploratory factor analysis (EFA) is a multivariate technique that aims to uncover the underlying patterns and relationships among the variables (Taherdoost et al., 2014). In this chapter, I performed EFA on tree attributes to infer the burn-severity pattern of wildfires at the plot level. Before extracting common factors, I assessed the data adequacy and suitability using Kaiser-Meyer-Olkin (KMO) and Bartlett’s tests. The KMO test measures the correlations among variables in the correlation matrix for EFA, which provides information on the sampling adequacy that is important for the grouping of variables (Kaiser, 1970; Taherdoost et al., 2014). The statistic of KMO ranges from 0 to 1, with values below 0.5 meaning that the data are not adequate for EFA (Taherdoost et al., 2014). Bartlett’s test of Sphericity examines whether the correlation matrix is the same as an identity matrix (Bartlett, 1950). A significant result (p < 0.05) is needed to ensure that the data are suitable for EFA (Taherdoost et al., 2014). After confirming the data adequacy and suitability, I extracted
uncorrelated factors using a principal component method and they were further rotated using the equamax rotation technique (Manly, 2005). With this orthogonal rotation technique, the data variance was re-distributed across the common factors to minimize the complexity between them and the variables (Akhtar-Danesh, 2017). Using the common factors, I compared their loadings across burn-severity levels to study their correlations with the variables. The meanings of the common factors were then interpreted as each of them encompassed a unique set of relationships with the post-fire tree attributes. I used 0.80 as the cut-off value for strong correlations when defining the meanings of common factors from their loadings. The meanings of common factors across burn severities may indicate the differences in the burn-severity pattern of wildfires.

All statistical analyses were conducted in RStudio (RStudio Team, 2020).
4.3 Results

4.3.1 Crown scorch and pre-fire tree size

Figure 20 shows the correlations between crown scorch and trees in mature and young stands with different pre-fire sizes. Overall, I found significant and negative correlations between crown scorch and pre-fire DBH, height, and biomass, indicating that trees with smaller pre-fire sizes tend to experience higher levels of crown scorch than trees with larger pre-fire sizes. In addition, the scatter plots also show that young stands (age class: 15 – 50 years) were mostly occupied by small trees, whereas mature stands (age class: > 50 years) included trees of a range of sizes. Among trees within young stands, the majority of them were severely scorched, while trees within mature stands experienced relatively lower levels of crown scorch (Figure 20 (A), (B), (C)).

![Figure 20](image)

**Figure 20** The scatter plots and trend lines between crown scorch (%) and pre-fire (A) DBH, (B) height, and (C) biomass of trees at mature and young stands

4.3.2 Crown scorch and post-fire tree attributes

The correlations between crown scorch and post-fire biometric, crown, and volumetric attributes are presented in Figure 21 and Table 7. Among small-diameter trees, post-fire volumetric and crown attributes exhibited significant and moderate correlations with crown scorch levels. The
negative trends indicate that trees that experienced higher levels of crown scorch had smaller post-fire volumes, especially the branch volumes (Table 7). Their post-fire crown structures were also smaller both horizontally and vertically, as well as more compacted and uneven (Figure 21; Table 7). Among medium-diameter trees, I found similar patterns in the relationships between crown scorch and post-fire attributes compared to small-diameter trees. Specifically, post-fire DBH, biomass, total and branch volumes, and most crown attributes were significantly correlated with crown scorch levels (Table 7). In contrast, I did not find any significant correlations between crown scorch and post-fire attributes among large-diameter trees (Figure 21; Table 7). These non-significant correlations indicate that large-diameter trees were relatively more resistant to different levels of crown scorch than small- and medium-diameter trees.
Figure 21 The scatter plots and trend lines between crown scorch (%) and post-fire (A) DBH, (B) height, (C) biomass, (D) crown diameter, (E) crown evenness, and (F) CBH among small-, medium-, and large-diameter trees classified using pre-fire DBH.

Table 7 Spearman’s rank correlation coefficients (R) between crown scorch (%) and each post-fire tree attribute among small-, medium-, and large-diameter trees (significant correlations (p < 0.05) are highlighted in bold)

<table>
<thead>
<tr>
<th>Type</th>
<th>Post-fire attribute (unit)</th>
<th>Spearman’s rank correlation coefficient (R)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Small-diameter trees</td>
</tr>
<tr>
<td>Biometric</td>
<td>DBH (cm)</td>
<td>-0.30</td>
</tr>
<tr>
<td></td>
<td>Tree height (m)</td>
<td>-0.19</td>
</tr>
<tr>
<td></td>
<td>Biomass (kg)</td>
<td>-0.35</td>
</tr>
<tr>
<td></td>
<td>Crown diameter (m)</td>
<td>-0.60</td>
</tr>
<tr>
<td></td>
<td>CPA (m²)</td>
<td>-0.68</td>
</tr>
<tr>
<td></td>
<td>Crown compactness (0-1)</td>
<td>-0.35</td>
</tr>
<tr>
<td></td>
<td>Crown evenness (0-1)</td>
<td>-0.58</td>
</tr>
<tr>
<td>Crown</td>
<td>CBH (m)</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>Crown length (m)</td>
<td>-0.46</td>
</tr>
<tr>
<td></td>
<td>Crown ratio (0-1)</td>
<td>-0.50</td>
</tr>
<tr>
<td></td>
<td>Crown elongation (0-1)</td>
<td>-0.54</td>
</tr>
</tbody>
</table>
### Volumetric

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Pre-Fire</th>
<th>Post-Fire</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total volume (m³)</td>
<td>-0.42</td>
<td>-0.38</td>
<td>0.14</td>
</tr>
<tr>
<td>Volumetric</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stem volume (m³)</td>
<td>-0.38</td>
<td>-0.32</td>
<td>0.31</td>
</tr>
<tr>
<td>Branch volume (m³)</td>
<td>-0.50</td>
<td>-0.56</td>
<td>0.20</td>
</tr>
</tbody>
</table>

#### 4.3.3 Plot-level burn severity and biometric attributes

Impacts of wildfires with different plot-level burn severities on individual tree DBH, height, and biomass are presented in Figure 22. Overall, low-severity fires had negligible effects on individual tree biometric attributes, moderate-severity fires mostly influenced tree height, while high-severity fires significantly reduced the DBH, height, and biomass of individual trees. At low-severity sites, I found no significant differences between pre- and post-fire biometric attributes. At moderate-severity sites, I observed a significant decline (p < 0.05) between pre- and post-fire tree height, with the median values decreasing from 12.5 m to 9.7 m (Figure 9. (B)). By contrast, at high-severity sites, all three biometric attributes were significantly different post-fire from their corresponding pre-fire values. The median values of individual tree DBH, height, and biomass decreased by 16%, 25%, and 29%, respectively (Figure 22 (A), (B), (C)).
**Figure 22** The comparisons between pre-fire field-measured and post-fire laser scanning-derived (A) DBH, (B) tree height, and (C) biomass across plot-level burn-severity classes. The violin plots show the data range of each attribute, with the curves representing the probability density distribution, the boxes representing the interquartile range, the bars representing the median, and the dots representing outliers. Significant differences among medians ($p < 0.05$) are indicated with different letters.
4.3.4 Wildfire burn-severity patterns

The exploratory factor analyses (EFA) (Kaiser-Meyer-Olkin > 0.65; p of Bartlett’s test < 0.05) with the equamax rotation revealed a clear factor pattern across the plot-level burn-severity classes. Four common factors emerged from the EFA, accounting for ~ 80% of the total data variance. Factors 1 and 2 were dominant factors with ~ 50% combined contribution to the total data variance, and factors 3 and 4 jointly explained ~ 30% of the total data variance. The correlation coefficients between common factors and the post-fire tree attributes (i.e., factor loadings) are summarized in Figure 23.

At low-severity sites (Figure 23 (A)), factor 1 exhibited strong and positive correlations with two crown attributes (i.e., crown diameter and CPA). This factor, thus, reflected the relationship between horizontal crown size and burn severity. Factor 2 showed strong correlations with total, stem, and branch volumes (loadings = ~ 0.90), which served as an indicator of post-fire tree volumes. Factor 3 was positively correlated with crown ratio (loading = 0.86) and negatively correlated with crown elongation (loading = - 0.83), indicating the vertical crown size of post-fire trees. The last factor recorded great correlations with DBH and biomass, which provided information on the sub-canopy tree size.

At moderate-severity sites (Figure 23 (B)), factor 1 directly correlated with tree height and crown length (loadings > 0.89), suggesting an indicator of vertical crown size. Similar to trees from low-severity sites, factor 2 was also strongly and positively correlated with tree volumes, with loadings ranging from 0.89 to 0.94. Factor 3 indicated the sub-canopy tree size as it exhibited substantial correlations with DBH and biomass, with loadings > 0.96. Factor 4 reflected the amount
of crown fuel as it was positively correlated with CBH (loading = 0.86) and negatively correlated with crown ratio (loading = -0.82).

At high-severity sites (Figure 23 (C)), the strongest factor became an indicator of tree volumes, with positive loadings ranging from 0.80 (branch volume) to 0.92 (total volume). The next strongest factor offered information on the sub-canopy tree size with direct correlations with DBH and biomass (loadings > 0.93). I found no post-fire tree attribute strongly correlated with factor 3 but moderate correlations with crown compactness and elongation, which can be viewed as a reflection of crown shapes. Similar to trees from moderate-severity sites, the last factor also indicated the amount of crown fuel as it was strongly correlated with CBH (loading = -0.94) and crown ratio (loading = 0.87).

In general, following low-severity fires, I found that the variations in tree characteristics were mainly driven by large horizontal crown sizes and tree volumes, which reflected the relatively greater size and wider spacing of trees in low-severity sites. Following moderate-severity fires, the dominant factors driving the variations in tree characteristics changed to vertical crown sizes and tree volumes, indicating a more prevalent fire impact along the stem. Following high-severity fires, the dominant factors further changed to reduced tree volumes and sub-canopy tree sizes, emphasizing the remaining tree structures with deeply burned crowns.
Figure 23 The loadings of common factors for post-fire attributes in (A) low, (B) moderate, and (C) high plot-level burn-severities. The loadings represent the correlation coefficients between each post-fire attribute and each factor. The factors are ordered in terms of their contribution to the data variance from high to low.

| Biometric Attributes: a - DBH, b - tree height, c - biomass; |
| Volumetric Attributes: d - total volume, e - stem volume, f - branch volume; |
| Crown Attributes: g - crown diameter, h - CPA, i - crown compactness, j - crown evenness, k - CBH, l - crown length, m - crown ratio, n - crown elongation. |
4.4 Discussion

In this chapter, I used the fused DLS-MLS point clouds to examine the structure of post-fire trees using QSMs. QSMs have been demonstrated to be an effective methodology to extract detailed information on the tree structure, allowing accurate measurements of various attributes at an individual tree scale (e.g., Raumonen et al., 2013, 2015; Gonzalez de Tanago et al., 2018; Brede et al., 2019). Through QSMs, I retrieved biometric, volumetric, and crown attributes of post-fire trees to compare the effects of varying burn severities. This method can, thus, be complementary to studies that investigated wildfire impacts on stand and tree structures via computing metrics (e.g., height percentiles, skewness, kurtosis, etc.) directly from ALS point clouds. The findings of this chapter refine our understanding of the variation in wildfire impacts on dry forests at both individual tree and plot scales.

4.4.1 Effects of burn severities on tree structures

At the individual tree level, the results of this chapter suggest that trees with smaller pre-fire sizes tend to be more susceptible to higher levels of crown scorch than trees with larger pre-fire sizes. Among small- and medium-diameter trees (DBH < 30 cm) that were severely scorched, they tend to have smaller post-fire volumes and crowns compared to the ones that were slightly scorched or unburned. A potential explanation is that, as crown scorch levels increased, a greater amount of branches and foliage was consumed by fires which may result in the compacted and uneven shape of post-fire crowns. I also observed that many small- and medium-diameter trees had relatively low CBH after experiencing low to moderate crown scorch (< 60%). The low CBH indicates that fires may have resulted in a degree of crown kill, which triggered basal and epicormic resprouting of trees (Hood et al., 2018; Woodward et al., 2020; Varner et al., 2021). Yet, as the crown scorch level further
increased, small- and medium-diameter trees could have post-fire crowns with high CBH and little to no branch volumes. This implies that high crown scorch could damage trees with top-kill and reduce the occurrence of epicormic resprouting (Hood et al., 2018; Bär et al., 2019). Thus, the structure of smaller and younger trees could be simplified by high levels of crown scorch, and their post-fire survival and recovery could also be threatened due to the severe injury. Larger and more mature trees, however, could be more resistant to fires, which is likely related to the protection of their thick bark.

At the plot level, low-severity fires had relatively minor impacts on tree structures as they mostly consumed surface fuels. Although younger trees may be charred during the burn, their subsequent growth can mask fire effects (Kane et al., 2014; Hoffman et al., 2018). This finding is similar to multiple studies (e.g., Becker et al., 2016; Kauffman et al., 2019; Klauberg et al., 2019). Yet, it is contrary to the findings of Kane et al. (2013) who found that low-severity fires significantly modified the canopy structure of coniferous forests in comparison with unburned sites in Yosemite National Park, USA. The major difference between the two studies is that I examined the effects of a single fire, whereas they analyzed the combined effects of fires over two decades. As Kane et al. (2013) noted, the unburned reference sites that they selected outside fire perimeters may not fully represent the pre-fire conditions of burned forests, which can contribute to the differences in post-fire tree structures. Additionally, the tree species composition, topography, and the classification of burn severities can also contribute to the different interpretations of burn severity effects on tree structures.

Principally, low- and moderate-severity fires burn more surface than crown fuels, and may remove small-diameter trees (Keeley, 2009; Kane et al., 2013). Consequently, the average post-fire DBH and tree height increase due to the larger residual trees. In this study, two years post-fire, I did not find changes in DBH but detected a decreasing trend in tree height following moderate-severity fires, similar to several studies (Kane et al., 2014; Hoffman et al., 2018; Karna et al., 2019). This
suggests that tall trees can also be affected by moderate-severity fires. Possible explanations include that, during the stem exclusion phase, trees invested in vertical growth to compete for growing space and resources (Agee and Huff, 1987), yet their bark may not be thick enough to tolerate moderate-severity fires. As a result, in places with aggregated ladder fuels, shorter trees may help fires spread into the canopy, causing the adjacent taller trees to be charred, snapped off, or killed. With moderate burn severity, fires could remove thin-bark trees, which might lead to greater dominance of thick-bark trees (e.g., Douglas-fir) in post-fire forests.

In contrast, following high-severity fires, the study sites were characterized by abundant standing dead trees (i.e., snags) that were completely or near-completely charred. These trees had significantly smaller DBH, height, and biomass after the fire, implying that high-severity fires might have substantially altered their structures, similar to findings from multiple studies that were conducted across different types of forests (Kane et al., 2014; Kauffman et al., 2019; Karna et al., 2019, 2020). The decreased DBH after high-severity fires was likely due to the removal of large-diameter trees, and the damage to roots and boles causing hydraulic dysfunction of xylem (i.e., the inability of water transport) in the remaining trees (Midgley et al., 2011; Hood et al., 2018; Bär et al., 2019).

4.4.2 Tree characteristics and wildfire burn-severity patterns

The interactions among vegetation, weather, and topography influence the burn-severity pattern of wildfires (Kane et al., 2013; Foster et al., 2017; Walker et al., 2020). Research has demonstrated that pre-fire vegetation has a vital impact on burn-severity patterns and post-fire vegetation resembles its pre-fire condition (Kane et al., 2014; Viedma et al., 2020a; Walker et al.,
2020). Yet, I also acknowledge that both weather and topography could have critical impacts on burn-severity patterns.

Across the nine sites in this study, trees from mature stands (age class: > 50 years) experienced relatively lower levels of crown scorch compared to trees of similar sizes in young stands (age class: 15 – 50 years). This is broadly consistent with previous work (e.g., Lydersen et al., 2016; Alonzo et al., 2017; Stephens and York, 2017; Bowd et al., 2021). At the plot level, the results of EFA also imply that burn severities were lower in stands dominated by mature trees with low densities and large horizontal crown structures. In contrast, stands that tended to burn more severely were those occupied by regenerating trees with high densities of vertical crown fuels. This finding implies that the differences in fuel abundance and configuration could play a critical role in driving the burn-severity patterns across the study sites.

In general, a primary factor that likely contributed to the different burn-severity patterns between mature and young stands is related to pre-fire tree size and fuel density. In the six mature stands, trees had larger pre-fire sizes and were less densely distributed compared to those in the three young stands. For large-diameter trees, their thick bark can resist heat during the fire, which increases their survival following the fire (Agee, 1993). In addition, trees from the six mature stands had probably experienced stem exclusion and reached a relatively closed canopy. High canopy closure blocks sunlight from directly infiltrating the understory, and limits the growth of sub-canopy trees and ladder fuels (Hoffman et al., 2018; Karna et al., 2019), which did not favour the vertical or horizontal spread of high-severity crown fires. Yet, during the understory re-initiation phase of closed-canopy stands or in open-canopy stands, the increasing abundance of understory vegetation and surface fuels could make them more susceptible to moderate-severity fires due to torching or passive crown fires.
Among the three young stands, I noticed that they were characterized by trees of smaller sizes and higher densities. As these stands also had a low canopy closure, surface fuels might be exposed to sunlight and wind, decreasing their moisture content and increasing their flammability (Lyons-Tinsley and Peterson, 2012). Meanwhile, short tree heights and the closeness of adjacent tree crowns enhanced the fuel continuity vertically and horizontally, allowing fires to spread into and across the canopy. As a result, these trees- and stand-level characteristics could support the incidence and propagation of fires with increasing burn severities.
Chapter 5: Conclusion

5.1 Overview addressing main research goals

The overall research objective of this thesis was to characterize post-fire tree attributes in interior dry forests in BC using drone and mobile laser scanning point clouds. To do so, I reconstructed QSMs to represent post-fire tree structures in nine study sites within the central area burned by the Elephant Hill wildfire. I compared the accuracy of a number of tree attributes derived from QSMs based on single and fused laser scanning datasets. Secondly, I examined the impacts of the Elephant Hill wildfire on tree structures across a range of burn-severity levels using the QSM-derived attributes.

In Chapter 3, I compared single and fused laser scanning datasets in estimating seven attributes of individual trees under low, moderate, and high canopy cover levels. Considering the scanning characteristics of DLS and MLS, I proposed a new data fusion strategy using a relative weighting scheme based on the probability density of vertical point distribution. The results showed that, in comparison with single datasets, the fusion of DLS and MLS point clouds improved the estimation of the basic, crown, and volumetric attributes across canopy cover levels. In particular, the fused datasets enhanced the representation of complex structures for trees from sites with moderate and high canopy cover. Single DLS or MLS datasets may still perform well in estimating certain tree attributes (e.g., height, crown diameter) across canopy cover levels. Therefore, forestry practitioners need to evaluate the trade-offs in selecting the most appropriate platform for laser scanning data based on their needs.

In Chapter 4, I investigated the impacts of wildfire on post-fire tree structures at both individual tree and plot scales. Using the fused DLS-MLS point clouds, I applied the QSM approach to reconstruct the tree structures and extracted 14 post-fire biometric, volumetric, and crown
attributes. At the individual tree level, the data suggested that smaller pre-fire trees tend to experience higher levels of crown scorch than larger pre-fire trees. Among trees with similar pre-fire sizes, those within mature stands had lower levels of crown scorch than those within young stands. Among pre-fire small- and medium-diameter trees, those experiencing high crown scorch had smaller post-fire crowns with unevenly distributed branches compared to unburned trees. In contrast, pre-fire large-diameter trees were more resistant to crown scorch. At the plot level, low-severity fires had minor effects, moderate-severity fires mostly decreased tree height, and high-severity fires significantly reduced diameter at breast height, height, and biomass. The exploratory factor analyses further revealed that stands dominated by trees with large crown sizes and relatively wide spacing could burn less severely than stands characterized by regenerating trees with high crown fuel density and continuity.

5.2 Significance of research and key findings

This thesis examined the capability of high-density DLS and MLS point clouds in characterizing post-fire tree attributes in interior dry forests under varying canopy cover conditions. Through the quantification and comparison of post-fire tree attributes, this thesis investigated the ecological impacts of wildfires across a range of burn-severity levels. The fused DLS-MLS point clouds enabled the retrieval of comprehensive tree-level information, which can be used in many applications in the management of fire-prone forests, such as forest inventory assessment, fuel load treatment, and wildfire risk mitigation.

In Chapter 3, I compared the accuracy of seven individual tree attributes derived from QSMs based on DLS, MLS, fused, and weighted DLS-MLS point clouds across a range of canopy cover levels. In general, the weighted data achieved comparable results with the fused data and
outperformed DLS/MLS data in estimating tree attributes. Moreover, the weighted data also presented opportunities to improve the modelling efficiency of QSMs compared to the fused and MLS data. In terms of specific tree attributes, the results showed that: (1) DBH can be accurately retrieved from the fused, weighted, and MLS data under low canopy cover. With increasing canopy cover, DBH can be well estimated by the fused and weighted data. (2) Height was accurate across canopy cover levels, which was independent of data collection platforms. (3) Crown diameter can be accurately extracted from the fused, weighted, and MLS data regardless of canopy cover. (4) CBH can be well identified by the fused, weighted, and MLS data with low-to-moderate canopy cover, yet it is most accurately extracted from the fused data under high canopy cover. (5) The total and stem volumes could be well detected by weighted and MLS data, except under high canopy cover. The fused data can be suitable for deriving these two attributes across all canopy cover levels. (6) The branch volumes can be best modelled by the fused data, particularly for trees with complex branching structures. (7) DLS data did not estimate volumetric attributes well using the QSM approach, mainly due to the poorly modelled cylinders resulting from insufficient point coverage around stems and fine branches.

Chapter 4 compared pre-fire field measurements with QSM-derived post-fire tree attributes to assess the effects of burn severity of the 2017 Elephant Hill wildfire at both individual tree and plot scales. At the individual tree level, I found significant and negative correlations between crown scorch and pre-fire DBH, height, and biomass, suggesting that smaller pre-fire trees tend to experience higher levels of crown scorch than larger pre-fire trees. Meanwhile, I also noticed that trees at mature stands (age class: > 50 years) experienced relatively lower levels of crown scorch than trees with similar pre-fire sizes at young stands (age class: 15 – 50 years). Among pre-fire small- and medium-diameter trees, I found that many post-fire volumetric and crown attributes were
significantly and negatively correlated with crown scorch, indicating that trees following high crown scorch could have smaller volumes and crowns compared to the ones that were slightly scorched or unburned. In contrast, among pre-fire large-diameter trees, no post-fire attribute exhibited significant correlations with crown scorch, indicating that they can be more resistant to fires. At the plot level, the effects of low-severity fires were probably masked by the subsequent growth of trees since I did not detect structural changes in DBH, height or biomass. At moderate-severity sites, I observed a major reduction in tree height, implying that moderate-severity fires could consume tall trees with thin bark in places where aggregated ladder fuels existed. At high-severity sites, I found a large number of completely charred trees with smaller DBH, height, and biomass compared to their pre-fire condition. Further, the results suggested that stands with trees of low densities and large crown sizes tend to burn less severely than stands with trees of high crown fuel density and continuity. Overall, the results demonstrated that fused DLS-MLS point clouds can be effective in quantifying post-fire tree structures, which facilitates foresters to develop site-specific management plans.

5.3 Implications

Accurate assessments of wildfire risks rely on the accurate characterization of fuel availability, distribution, and condition in fire-prone forests. The methodology presented in this thesis provides guidance on using high-density point clouds from DLS and MLS to reconstruct the structure of individual trees. The fusion of DLS and MLS point clouds enhanced the representation of post-fire tree structures, which supports the monitoring, evaluation, and treatment of fuel loads in forest ecosystems.

The work in Chapter 3 offers a framework to extract individual tree attributes that are critical to forest inventory assessment in a non-destructive manner. It also quantifies the utility of single and
fused laser scanning datasets in extracting tree attributes across varying canopy cover levels. The findings of this chapter, therefore, assist forestry practitioners in selecting appropriate laser scanning instruments for fieldwork. For example, DLS or MLS could be useful for estimating basic and crown attributes in sites with low canopy cover. As canopy cover increases, neither DLS nor MLS datasets might be suitable for estimating sub-canopy attributes mainly due to occlusions in forested environments. In addition, in sites with high canopy cover, MLS can also be influenced by off-nadir scanning and its light pulses may not reach the treetop. In comparison with MLS, DLS can be operated remotely to promote the safety of fieldwork. Advances in under-canopy DLS may strengthen the characterization of sub-canopy structures at sites with moderate and high canopy cover. Thus, forestry practitioners need to account for the benefits and limitations of DLS and MLS technologies when surveying forests in the future.

The advantages of the fused laser scanning datasets emerged in sites with moderate and high canopy cover. In comparison with single laser scanning datasets, the fused datasets would lead to more accurate and robust estimations of the basic, crown, and volumetric attributes. Particularly, the fused DLS-MLS point clouds can accurately estimate CBH regardless of canopy cover, which is vital for assessing crown fuels and understanding wildfire impacts. Forestry practitioners, however, should note that using fused datasets to predict tree height and crown diameter can only lead to slight improvements, which does not justify the additional time and cost of acquiring both DLS and MLS datasets. For these two attributes, single datasets can also produce accurate estimations across canopy cover levels (CCC > 0.80). Therefore, forestry practitioners should carefully consider their needs as well as the strengths and weaknesses of each laser scanning dataset when making decisions for forest inventory assessment.
Chapter 4 provides an examination of burn-severity effects on tree structures using the attributes derived from QSMs. The findings in this chapter inform the management of fuel loads as well as the changes in post-fire carbon dynamics due to varying burn severities. For instance, in sites with aggregated ladder fuels, fires can spread into the canopy and consume crown fuels. Hence, reducing the density of ladder fuels would be helpful to prevent surface fires from developing into crown fires. Similarly, in sites with high density and continuity of crown fuels, fires can also spread into and across the canopy relatively easily. The management of the abundance and configuration of crown fuels in fire-prone forests could be critical to controlling fire propagation and burn severities. In this regard, the use of fused DLS-MLS point clouds can facilitate the evaluation of site conditions as well as the decision-making and implementation of fuel treatment practices.

5.4 Limitations

The QSMs used in this thesis were overall effective in characterizing post-fire tree structures and burn-severity effects. However, several limitations should be considered before applying QSMs to extract tree attributes on a large scale. Here, I discuss the limitations in terms of point cloud processing and burn severity assessments.

5.4.1 Point cloud processing

The differences in the point density between DLS and MLS data could influence many steps of point cloud processing, such as registration, fusion, individual tree segmentation, and QSM reconstruction. The point density difference, therefore, may result in differences in the estimation of tree attributes. To fully understand the impacts of point density on point cloud processing and tree
attribute estimation, a sensitivity analysis could be beneficial. Yet, performing the sensitivity analysis would be beyond the scope of this thesis.

The QSM reconstruction, for example, requires good-quality segmented tree clouds as input data. Ideally, the segmented tree clouds should not have missing features or extra points from adjacent trees. In this thesis, I relied on an automatic bottom-up segmentation algorithm in the Computree platform to process all laser scanning datasets. In stands with moderate and high canopy cover, DLS data had a relatively low density of points at the sub-canopy level, which hindered the process of individual tree segmentation. The resulting tree clouds, therefore, may not be suitable for QSM reconstruction and subsequent tree attribute extraction. This partly explained the relatively poor results of QSM$_{DLS}$-derived attributes in Chapter 3.

Meanwhile, the points representing the foliage should also be removed to minimize their impacts on the reconstruction of branching structures. To do this, I used a combination of point cloud filtering functions in the Computree platform. Yet, these functions were limited in terms of foliage removal, especially for the tree clouds with complex branching structures. As a result, the estimation of total and branch volumes could be affected.

Additionally, I also used the allometric algorithm proposed by Hackenberg et al. (2014) and (2015) to optimize the radius and volume QSMs at the end of point cloud processing. As this allometric algorithm was not initially designed based on the tree species in BC, it might not be suitable for all QSMs. Hence, the estimation of diameters and volumes for some trees could be influenced to some extent.
5.4.2 **Burn severity assessments**

I recognize that this thesis is focused solely on a single wildfire event in BC. With nine study sites in the area burned by the Elephant Hill wildfire, the extrapolation of burn severities within the fire perimeter was not possible. The inferences on the burn-severity patterns could also be limited. To better understand the wildfire impacts on forest ecosystems in BC, long-term data on forest inventory and historical wildfires will need to be integrated.

I also acknowledge that a major limitation of this thesis is related to the measurements of pre-fire forest conditions (e.g., vegetation structure, wind, temperature, moisture, etc.). As with other studies that investigate the chronological impacts of wildfires, this thesis cannot completely rule out the potential influence of pre-fire conditions on post-fire forests (Kane et al., 2013, 2014). Therefore, to minimize the impacts of limited measurements of pre-fire conditions, I focused on the general trend when interpreting wildfire effects as well as the burn-severity patterns in Chapter 4.

Ideally, bi-temporal laser scanning data are required to compare forest structures pre- and post-fire. Since wildfires have legacy effects on coniferous forests that persist over decades (Bolton et al., 2015), multi-temporal laser scanning data are needed to monitor the long-term change in forest structures. To my knowledge, however, only a few studies have obtained bi-temporal or multi-temporal laser scanning data when investigating wildfire impacts (e.g., Alonzo et al., 2017; McCarley et al., 2017; Hu et al., 2019; Karna et al., 2020). This is mainly because of the operational challenge in acquiring high-quality data before wildfires (Viedma et al., 2020a), as they tend to be unpredictable in space and time.

Since I did not have the laser scanning data for the pre-fire forest structure, I relied on the field measurements to examine the pre-fire stand and tree structures. Consequently, I could only compare the changes in DBH, tree height, and biomass to understand wildfire effects in Chapter 4. In
addition, both fixed- and variable-radius sampling strategies were employed in the field measurements and data were collected under different provincial monitoring programs in BC. As a result, inconsistencies existed between variable-radius plots in the field and the inclusion of the relevant laser scanning data. Although I accounted for this during data processing, it still influenced the comparison between pre- and post-fire tree attributes to some extent. Since variable-radius sampling can be efficient in the field, methods that can reduce errors in matching the shape and size of these plots with laser scanning data need to be developed.

5.5 Future research

For future work, the QSM approach presented in this thesis should be further tested in other types of forests to understand its effectiveness in quantifying tree structures. Considering the importance of individual tree segmentation on QSM reconstruction, I suggest that researchers should examine the quality of segmented tree clouds before extracting the structural attributes on a large scale. For tree cloud denoising, the algorithms of leaf-wood separation should also be integrated into future studies to improve the modelling accuracy of woody structures.

For single laser scanning datasets, the current QSM approach does not work well with DLS point clouds. Thus, I recommend researchers develop different cylinder fitting and correction functions to optimize DLS-based QSMs. Meanwhile, alternative modelling methods with different geometric primitives (e.g., circular cone, polyhedron, etc.) could also be investigated to advance the reconstruction of QSMs using DLS point clouds (Åkerblom et al., 2015). For MLS, forested environments could complicate the scanning position and orientation during the motion of the sensor. More studies could consider exploring methods to improve the scanning accuracy of MLS in forests with complex environmental conditions.
For fused laser scanning datasets, the two fusion strategies enhanced the representation of tree structures and allowed the accurate estimation of many tree attributes. Particularly, the fusion strategy with the relative weighting scheme generated point clouds with a reduced density compared to the directly fused point clouds while maintaining the advantages of DLS and MLS data. Thus, this weighted fusion strategy can facilitate the modelling of QSMs when processing a large number of tree clouds. Yet, the voxel grid sampling method used in this strategy simplifies point clouds uniformly and does not maintain the geometry of forests, which may result in point clouds with missing features and influence the estimation of tree attributes. To improve the weighted fusion strategy, future studies should examine more advanced sampling methods to preserve the geometric features of individual trees based on the shape description of point clouds (Zhang et al., 2019) or deep learning networks (Dovrat et al., 2019).

In terms of tree attribute estimation, future research also needs to improve the performance of QSMs for reconstructing trees with complex branching structures. Particularly, as Chapter 3 found, the increasing canopy cover can reduce the modelling accuracy of sub-canopy and volumetric attributes. With high canopy cover, fusing DLS and MLS point clouds may partially resolve the issues of insufficient point coverage on stems and branches. Therefore, I suggest future research investigate under-canopy DLS, repeated scanning, alternative modelling strategies, and advanced allometric corrections to minimize the effects of high canopy cover on tree attribute estimation.

Additionally, I was not able to differentiate tree species or their mortality using laser scanning data alone. To consider this, I used pre- and post-fire field data to broadly evaluate the impacts of wildfires on recorded tree species and their mortality status. Since changes in tree species composition and mortality can be crucial to understanding forest recovery and fire-caused secondary succession (Kane et al., 2013; Hood et al., 2018; Steady et al., 2019), I recommend that future studies
should combine DLS/MLS data with high-resolution optical images from satellites or drones to distinguish fire effects or other tree mortality drivers (e.g., infestation, drought) on different species. This would, therefore, allow forestry practitioners to identify species-specific plans in terms of forest management and restoration.

To compare pre- and post-fire biomass, I used species-specific allometric equations developed by Ung et al. (2008). As these equations were based on unburned trees, they may not reflect the actual change in biomass due to wildfires. Thus, new allometric equations should be developed in the future to compute post-fire biomass using field measurements or to transform QSM-derived volumes into biomass.

In Chapter 4, I also inferred the wildfire burn-severity patterns using post-fire tree attributes. As several studies pointed out, the role of vegetation on burn-severity patterns could be overwhelmed if fires propagated under extreme weather conditions (Schoennagel et al., 2004; Viedma et al., 2020b). Hence, for future research, detailed weather information during fire propagation should be integrated to investigate the interactions among weather, vegetation, and burn-severity patterns. In addition, as I mainly focused on trees that represent ladder and crown fuels, the role of surface fuels was not fully considered. Research has shown that the abundance and moisture in surface fuels may determine fire behaviour and burn severities (Lyons-Tinsley and Peterson, 2012). With highly dense TLS/MLS data, I suggest that future work also extract point clouds of forest floor and understory vegetation to examine the effects of surface fuels on driving burn-severity patterns.
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Appendices

Appendix A: Supporting material for Chapter 4

A.1 Comparison of pre-fire DBH across species

Figure A1 The comparison of pre-fire DBH across Douglas-fir (Fd), lodgepole pine (Pl), and hybrid spruce (Sx)
A.2 Comparison of pre-fire height across species

Figure A2 The comparison of pre-fire height across Douglas-fir (Fd), lodgepole pine (Pl), and hybrid spruce (Sx)
A.3 Comparison of pre-fire biomass across species

Figure A3 The comparison of pre-fire biomass across Douglas-fir (Fd), lodgepole pine (Pl), and hybrid spruce (Sx)
A.4 Comparison of crown scorch across species

**Figure A4** The comparison of crown scorch levels across Douglas-fir (Fd), lodgepole pine (Pl), and hybrid spruce (Sx)