MEASURING HEIGHT GROWTH USING AIRBORNE LASER SCANNING AND DIGITAL AERIAL PHOTOGRAMMETRY IN A DISTURBED CANADIAN BOREAL FOREST

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Abstract

Enhancing forest inventories using airborne laser scanning (ALS) and digital aerial photogrammetry (DAP) is a spatially extensive means of providing accurate and consistent measures of forest stand structure. While the cost of multi-temporal ALS is still sometimes prohibitive to its integration for growth assessment, DAP point cloud data have been proposed as a cost-effective alternative to those from ALS for inventory re-measurement. As such, the primary objective of this thesis was to examine the capacity of ALS and DAP technologies to assess height growth (H_L) in a disturbed boreal forest near Slave Lake, Alberta.

First, this thesis determined the variables to be used in modeling height growth, and investigated how the predictive model errors responded to stand condition. To evaluate appropriate variables for predictive modeling, a model using only height metrics (*growth_single*) was compared with one using height, canopy cover and height variability metrics (*growth_multi*). The *growth_multi* model estimated height growth with an RMSE of 1.42 m (%RMSE = 164.18%) and the *growth_single* model estimated height growth with an RMSE of 1.76 m (%RMSE = 203.03%). To evaluate error response to stand condition, an iterative process was used to measure the accuracy of optimized height models while incrementing the mortality in the dataset. %RMSE increased with increasing plot-level mortality as a parabolic asymptotic curve. When the maximum allowable mortality was approximately 25% the %RMSE was just below 100%.

Second, this thesis determined growth patterns near Slave Lake with respect to eight ecological variables, ecosite type and ecosite phase. Analysis of variance (ANOVA) tests were conducted to test the significances of differences between the means of height growth (Δ H). Patterns demonstrated by the ecological variables were most apparent using nutrient regime,

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moisture regime, species dominance and the soils classification. Growth patterns among ecosites and ecosite phases followed the patterns of the ecological variables that describe them.

This research finds that, prior to utilizing multi-temporal remote sensing methods to assess stand-level height growth, forest managers must first understand local forest growth rates and mortality rates to ensure that the growth magnitudes and forest condition permit accurate height growth estimation using predictive models.

Lay Summary

Quantifying forest growth is necessary to estimate the capacity of forest stands to provide ecological goods and services. Remote sensing science offers a more spatially-extensive and accurate means of quantification as compared to manual methods. The capacity for airborne laser scanning (ALS) technologies to be utilized in the quantification of forest attributes has been well established. However, aerial photography can be utilized to develop similar spatial data products and has the advantages of providing spectral data, and requiring more flexible acquisition flight specifications. As such this thesis assesses whether an initial acquisition of ALS, and a subsequent acquisition of aerial photography can be used to generate estimates of forest height growth near Slave Lake, Alberta. This research first explores how different predictive modeling approaches and stand conditions impact the accuracy of growth predictions. Then, patterns among different types of forest sites that emerge from site-wide growth estimates are evaluated.

Preface

This thesis is the combination of one scientific paper written for peer-review of which I am the lead author, and a second analysis which will be formulated into a scientific paper following the completion of my graduate degree. Dr. Nicholas Coops and I were jointly responsible for defining the research objectives and developing a methodology, while I was also responsible for carrying out the data analysis and writing the manuscripts. Dr. Nicholas Coops, Joanne White, and Dr. Peter Marshall provided guidance, insight and editing suggestions for all components of the research on topics including forest ecology, forest attribute modeling and sampling theory. Dr. Piotr Tompalski developed the site-wide and plot-level point clouds from both of the remote sensing data sources, as well as technical advice for analytical procedures. Todd Bailey shared the Albertan forest inventory data, the raw remote sensing data from the initial and final airborne acquisitions, and reference growth and yield curves for different species and compositions around the study area. This research was developed for the Assessment of Wood Attributes from Remote Sensing (AWARE) project, which is an NSERC Collaborative Research and Development (CRD) project among universities, government and industry that seeks to use remote sensing to enhance Canada's forest inventory and to improve the modeling of forested ecosystems.

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List of Abbreviations

- AAC Allowable annual cut
- ABA Area-based approach
- ALS Airborne laser scanning
- ANOVA Analysis of variance
- AVI Alberta vegetation inventory
- BAP Best available pixel
- C2C Composite to Change
- CHM Canopy height model
- DAP Digital aerial photogrammetry
- DBH Diameter at breast-height
- DEM Digital elevation model
- DSM Digital surface model
- GDP Gross domestic product
- GIS Geographic information system
- GPS Global positioning system
- GYPSY Growth and yield projection system
- IMU Internal measurement unit
- MAI Mean annual increment
- NFI National forest inventory
- NTEMS National terrestrial ecosystem monitoring system
- PAI Periodic annual increment
- RMSE Root mean square error

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Chapter 1:

1.1 Boreal forests of Canada

Canada's 347 million ha of forests comprise 9% of the world's forest cover, containing 47 billion m³ of wood. The total forest area can be divided into managed (232 million ha), and unmanaged (115 million ha) regions. Canada's forests are relatively slow growing, producing an average wood volume of 136m³/ha (*The State of Canada's Forests: Annual Report 2017*). Approximately, 270 million ha of Canada's forests occur within the boreal zone, which have heterogeneous patterns of composition and structure, with stands frequently disturbed by wildfires (Brandt et al. 2013). Canadian mixedwood boreal forests are dominated by several genera including *Abies, Betula, Larix, Picea, Pinus* and *Populus*. Growth rates vary greatly between regions (Gutsell and Johnson, 2002; Lieffers et al., 1996; Martin and Gower, 2006). The boreal zone, which grows slower than the Canadian average, produces an average wood volume of 111m³/ha (*The State of Canada's Forests: Annual Report 2017*).

Differences in species dominance and successional patterns along an east-west gradient in the Canadian boreal forest ecosystems vary primarily with climate and disturbance. The western boreal has a drier continental climate, and is prone to higher frequency of severe fires (Brassard and Chen 2006), whereas the eastern is cooler and wetter with less or reduced severity fires. Within the western boreal, the focus of this thesis, successional patterns vary with climate. Warmer mesic sites are often initially colonized by shade-intolerant trembling aspen (*Populus tremuloides*) with some presence of white birch (*Betula papyrifera*) (Gauthier et al., 2000). During the stem exclusion phase, stands are typically dense with an even structure. As stands are thinned out by competition, more growing space is available for the understory species such as white spruce (*Picea glauca*) and balsam fir (*Abies balsamifera*), increasing the stand's structural complexity (Brassard and Chen, 2006; Cumming et al., 2000). The shade-intolerant species are generally shorter-lived and begin to die off, allowing the shade-tolerant species to grow more. Stands may also be initially recruited by white spruce if conditions are too moist for trembling aspen establishment, but not excessively so as to inhibit the white spruce (Archibald et al., 1996). Mixedwood stands are able to continue recruiting broadleaved species (typically trembling aspen) as long as gaps formed in the canopy are large enough to allow sufficient sunlight (Kabzems and García, 2004). Gaps in drier, wetter and cooler sites all generally recruit coniferous species more effectively. Drier sites are often initially dominated by Jack pine (Pinus banksiana) and replaced by black spruce (Picea mariana), as white spruce establishes more effectively on more mesic or hygric sites (Timoney, 2003). In more mountainous regions such as the Rockies, drier and/or cooler sites more often recruit lodgepole pine (*Pinus contorta*) initially, to be replaced by black spruce (Archibald et al., 1996). Very wet and bog-type sites are only able to recruit black spruce, resulting in its dominance at all seral stages of succession (Parisien and Sirois, 2003). Gradients exist between all of these successional patterns given the presence of microsites and the non-linear nature of stand succession (Oliver and Larson 1996).

Fire, windthrow and harvesting disturbances all modify boreal forest stand structures and successional patterns. Fires of varying severity have different effects on forest structure. While high-severity fires tend to bring about a new cohort of even-age colonizing species (Kipfmueller and Baker, 1998), low-severity fires are more frequent and often remove the understory along with a minority of overstory trees, leaving an open canopy (Schoennagel et al., 2004). Past research has affiliated stands previously affected by low-severity fires with structural attributes of late-successional stands, as partial burns cause stands to adopt multiple cohorts (Perry et al.,

2011). However, other work has found that differences in mixed-severity fire regimes only have subtle differences in their convolution of stand structure, and that other factors such as elevation and aspect more strongly control impact magnitude (Marcoux et al., 2015).

Most windthrow gaps in natural forests are smaller than 8 ha, and many are as small as a few trees (Nowacki and Kramer, 1998). Windthrow thus increases stand-level heterogeneity: overstory loss rates such that large windthrow gaps with many surviving trees often cannot be discerned from a mosaic of small gaps (Mitchell, 2013). Even-aged stands of new regeneration of trembling aspen and Jack pine tend to be the most susceptible (Rich et al., 2007). Wind-induced mortality in stands is generally greatest for relatively intermediate-sized stems. Shorter stems are sheltered by other trees, while taller veteran trees are often more effectively adapted (Mitchell, 2013). As windthrow preferentially damages overstory trees, resulting in recruitment of regrowth or the release of understory stems, windthrow is generally viewed as a process that accelerates succession (Rich et al., 2007). Repeated wind damage thus leads to complex, multi-cohort stands dominated by shade-tolerant species (Nowacki and Kramer, 1998). While stand-replacing windstorms tend to be quite rare in the boreal forest, smaller gap-scale disturbances can be quite frequent (Harper et al., 2002).

Harvesting can also modify the dynamics of a forest stand. The modifications incurred from selective harvesting depend on the species selected and the gap size created. Selective harvesting has historically targeted large, old stems. As such, gaps created from cutting these individuals were often large. Recruitment into these gaps are thus generally shade-intolerant species, namely trembling aspen in a boreal mixedwood context (Kabzems and García, 2004). Selective harvest over a stand thus generally pushes it towards an earlier seral stage in succession (Carleton, 2000). Alternatively, modifications from clearcut harvests depend on the stand type

that existed prior to harvest. Using mechanized harvesting methods, the overstory is removed while understory shrubs and saplings are often crushed by machinery, thus reinitiating the stand's succession and recruiting shade-intolerant species. Species with serotinous cones, such as Jack pine, are difficult to establish without fire to open their cones (Carleton, 2000).

The mosaicking of a forested landscape with cutblocks causes fragmentation and increases the amount of edges within the landscape. Forest edges in the boreal tend to have high levels of structural complexity due to the resulting openness of tree canopies, more downed logs and higher amounts of understory regeneration (Harper et al., 2015). Studies have shown that edge effects in boreal forests are less pronounced compared to temperate or tropical forests due to the natural patchiness occurring from regular, large-scale natural disturbances (Harper et al., 2015; Kneeshaw et al., 2011). However, the edge effects in conjunction with insect disturbances and the other disturbances discussed above all culminate to create a diverse and structurally complex landscape.

1.2 Drivers of growth in forests

Ecological factors affecting forest growth regulate the supply of light, water and nutrients to considered organisms (Ashton and Kelty, 2018). These factors can be divided into biotic and abiotic components. Some biotic factors related to the amount of interspecific competition within a site, include age, density and species composition. Some authors have argued that age is an unimportant factor as it is an ineffective proxy for diameter at breast height, as the age of a tree can be unrelated to its position in the canopy if the tree is tolerant or suppressed (Huang and Titus, 1994; Lynch and Moser, 1986.) However, stands consistently demonstrate a set of stages in stand development including stand initiation, stem exclusion, understory regeneration and

finally old growth, although it is possible for stands to pass over stages or to revert in their development as they are subject to disturbance (Bergeron et al., 2014). Density relates to the number of organisms an individual will be interacting with at a given site while seeking to acquire light, water and nutrients. As such, density indirectly measures competition and facilitation among organisms (Callaway and Walker, 1997). Competition is generally higher in denser stands. Though larger trees generally have a competitive advantage to acquire the three listed resources, they may also act as facilitators to smaller trees in a forest stand. Recent studies have shown that large trees in a stand can act as mother trees, transferring nutrients to trees recognized as genetically similar through the underground mycorrhizal network (Pickles et al., 2017). Mixed-species stands can be potentially facilitative environments. Certain trees may compliment others' uses of water and soil nutrients, and shade-intolerant species in the overstory may provide cover for shade-tolerant species in the understory (Oliver and Larson, 1996). The balance between competitive and facilitative effects of other trees around an individual tree, and their contributions to an organism's growth thus varies between individual organisms and their environments.

The most influential abiotic factors of a site are climate and landform. Climate is the predominant controller of light and water (precipitation) input into an ecosystem. At the forest stand scale, topographical features can modify climatic effects. The atmosphere cools according to the adiabatic cooling rate (9.8°C/km), and so increasing elevations have a comparable to effect on the ambient temperature to large changes in latitude. Orographic lifting can also induce precipitation events due to the cooling of air parcels by the adiabatic rate (Ahrens 2009). The steepness and orientation of a slope can alter the amount and direction of incoming solar radiation to an area (Ashton and Kelty, 2018). Landform characteristics also affect the dispersion

of inputs across a given site. Topographical features and elevation differences dictate patterns of overland flow, as well as soil water flow. However, quantities and flow directions of soil water are affected by other attributes, including the depth of the soil to the parent material and the texture of the parent material. These two variables determine the field capacity and the allowable rooting depth. Finer textured soils have stronger capillary rise and so often retain more water and have slower flow rates than coarser textured soils (Ward and Robinson, 2000). Any ecosystem factors that control hydrological inputs or flows will also relate to the ecosystems proneness to flooding (or excess moisture), and its duration. As different species have different flood or drought tolerances, the frequency and regularity of the flood, and adaptation of the organisms onsite to those events determine the magnitude of flood impacts on vegetation productivity.

Texture also relates the degree of weathering, an important factor in nutrient availability and exchange. Weathering rates depend on the type and exposure of the soil's parent material. However, most nutrients in the boreal forest soil profile come from the decomposition of organic matter. Decomposition rates are controlled by climate and the ease with which the substrate is broken down, generally dictated by the species of vegetation providing the substrate. The organic matter accumulation and extent of disturbance will also affect the soil temperature. In cold soils, the rate of root development and the ability of plants to draw water are much less than in warmer soils (Larcher, 2003). Warmer soils also facilitate seedling establishment and growth (Beckingham and Archibald, 1996).

1.3 Forest inventories in Canada

Forest inventories report on the quantity, extent, and location of forests in some defined area (Penman et al., 2003). The forest attributes measured, the methods used for measurement,

and the desired quantifications inferred from these measurements depend on the objectives of the inventory, as information needs for forest managers are increasingly complex and wide-ranging. For example, national forest inventories (NFIs) are undertaken to inform on national-scale resources for strategic planning and policy development. Desired quantifications for these inventories may include canopy cover, growing stock volume, biomass and carbon stock estimates (White et al., 2016). They are often based on field samples (Tomppo et al., 2010). Conversely, industry-realized inventories contemporarily focus on supply chain optimization of forest resources, for which field sampling methods alone are often inadequate for the desired accuracy (Shabani et al., 2013). Desired quantifications for these generally focus on attributes informing on wood procurement, stand classification, biodiversity assessment and potential for forest growth. For these finer-scaled inventories, data acquisition generally includes ground-plot assessment and remote sensing methodologies (White et al., 2016). This thesis will focus on industry-realized inventories.

Forest management in Canada is a provincial/territorial responsibility and each jurisdiction implements its own methods to conduct forest inventories according to their respective requirements. Jurisdictions themselves are divided into forest management units and/or forest licenses, and inventories are often conducted over individual units or regions. Derived inventory data are provided to direct forest agencies and companies for use in management planning of each unit (Leckie and Gillis, 1995). Prior to the development of geographic information systems (GIS), Canadian forest inventories were conducted using a combination of ground plot data acquired from field campaigns along with manual interpretation of stereo aerial photography. The development of a forest inventory in a given province generally was implemented as follows: photo acquisition and processing, stand delineation,

photointerpretation of required attributes for delineated stands, transferring and drafting delineations and interpretations to new map sheets, and (following the implementation of GIS) digitizing (Leckie and Gillis, 1995). Stands were delineated on the photos based on the perceived homogeneity of species composition, density, height, and age characteristics. Attributes were then estimated for each stand. Species composition was estimated based on apparent crown cover and stand volume, and the latter three characteristics were all quantified categorically, with some characteristics being interdependent. For example, age is estimated using interpreted height categories, as well as site characteristics. Ground and air calls are often used to aid in calibrating photo interpreters. Accuracy assessment of photo-interpreted information is difficult and is rarely undertaken (Magnussen and Russo, 2012) although audits may be done to assess specific attributes, namely timber volume. Quality is evaluated using a combination of aerial photography and field plot information, but the rigorousness of the evaluations are dependent on the expertise of the interpreters (Kangas and Maltamo, 2006). More experienced interpreters are faster, more accurate, and require less field work to calibrate their interpretations in a given forested region. However, inconsistencies between interpreters sometimes makes inventory comparisons within and between jurisdictions problematic. As well, acquiring experienced interpreters has historically been a major problem for forest agencies (Leckie and Gillis, 1995). Regardless, as the first form of remotely sensed data implemented into forest inventories (Smith, 1976), aerial photography has been a staple data source for operational inventories since the 1950s, so the costs are low and the step sequence for inventory development is familiar with personnel adequately prepared to train newcomers to the industry (Leckie and Gillis, 1995). To estimate growth, permanent sample plots were established in many

provinces and remeasured at 10-year intervals, while standard re-inventory was conducted at anywhere between 5- and 20-year intervals depending on the region (Smith, 1976).

The introduction of new geographic information systems (GIS) in the 1980s revolutionized forest inventories by facilitating the transfer and drafting processes of the inventory step sequence, and greatly reducing the labour and time inputs required. Outcomes of these facilitations included improved capability for modelling, ease of data manipulation and display, improved data storage, and advancements in decision support systems (Leckie and Gillis, 1995). However, the technological advent of GIS and the changing demands of forest managers began to impact the precision of the data recorded. For example, age or height, which were formally recorded as classes are now more frequently recorded as actual values. GIS also increased the capacity of forest agencies to store inventory data and facilitated data sharing, allowing other agencies to make use of data collected for forest inventories. For example, management inventory data began to be used for operational planning where appropriate (e.g., estimating logging costs or the costs of road construction) (Leckie and Gillis, 1995).

1.4 The role of remote sensing in forest inventories

Currently, changing demands of forest managers reflect the changing global economic climate of forest products. The Canadian forest products industry must maximize the value of timber and other forest products, and improve supply chains. To accomplish this, enhanced forest inventories containing timely, accurate and consistent measures of forest stand structure, composition and productivity is required (Alam et al., 2014). Recent remote sensing advances, such as the development and use of three-dimensional point clouds to measure forest structural variables, have shown marked promise as a cost-effective and spatially extensive means of

supplementing traditional modes of inventory using the area-based approach (ABA) (White et al., 2013a). This two-step approach first develops predictive models from ground plot inventories and plot-level point cloud data, then applies them across the region of interest to generate wall-to-wall estimates of forest inventory attributes (Næsset, 2002). The required point clouds are commonly developed using airborne laser scanning (ALS) technology. ALS is an active remote sensing technology that utilizes a near-infrared laser to emit pulses that return to a sensor to measure the location of targets (Lim et al., 2003). The laser is able to penetrate forest canopies at depth to construct a three-dimensional distribution of vegetation through the canopy (Wehr and Lohr, 1999). The discrete return ALS systems can now measure multiple returns per pulse emitted (Lim et al., 2003), and precise locations for ALS returns are enabled by an inertial measurement unit (IMU) and Global Positioning System (GPS) (White et al., 2016). A pulse density of 0.5-1 point/m² is low but considered adequate for the application of ABA in most forest environments (Jakubowski et al., 2013).

The ABA is now a proven concept (Wulder et al., 2012b), and currently applied operationally in a variety of forest types and for a range of managerial requirements (Bouvier et al., 2015; Næsset, 2007; Woods et al., 2011). Although ALS data may provide less accurate estimates of individual tree heights relative to field measurements, the loss in accuracy is easily offset by the extensive coverage afforded by the technology (Andersen et al., 2006). Remote sensing technologies also offer economies of scale, with acquisition costs per unit area decreasing as the area of interest increases (Franklin et al., 2002). Operationally, the ABA has become an agency-standard through which to produce predictive models for forest attributes from ALS point cloud data (White et al., 2013a). However, barriers still exist to the full integration of ALS, including the cost and complexity of the data acquisition and the availability

of trained and reliable personnel for subsequent processing (White et al., 2016). For example, trade-offs exist between the area covered by an acquisition flight and issues such as point density and scan angle (Jakubowski et al., 2013), thus optimizing the flight parameters for the best cost and to provide the necessary quality of data requires complex statistical analyses. As well, it is difficult for many managers to understand the value of ALS as a data source due to the lack of cost-benefit analyses in the literature (Holopainen et al., 2010).

Extensive research has been conducted to assess survey design for growth monitoring of height increment with ALS (Hopkinson et al., 2008; Næsset and Gobakken, 2005; St-Onge and Vepakomma, 2004; Yu et al., 2008). However, two matters to address are how to link growth estimates derived from ALS to traditional growth and yield curves (Tompalski et al., 2018), and how to assess the error magnitudes associated with growth estimates relative to actual measured growth increments (Wulder et al., 2008).

1.5 Assessing forest height growth with remote sensing

One proposed method of addressing the issue of cost for repeat ALS acquisitions for growth assessments is to use ALS for an initial acquisition, primarily to obtain a detailed and accurate digital terrain model (DTM) under canopy, followed by the use of digital aerial photogrammetry (DAP) point cloud data at subsequent time steps (White et al., 2016). Stereo photogrammetry allows the measurement of an object's position when imaged from two different perspectives. Applying this to the many objects that compose a surface on overlapping images produces an image-based point cloud from which a digital surface model (DSM) can be created (St-Onge et al., 2008). Flights for photogrammetric image acquisition are typically conducted at a higher altitude and faster than ALS flights, with a wider field of view, consequently image

platforms can cover a much larger area for a given number of flying hours. In all, the cost of image acquisition is estimated at one-half to one-third that of ALS data (White et al., 2013b). However, pixel-matching algorithms are only applicable to objects that are directly visible in the images themselves and therefore image-based point clouds can only describe the upper canopy surface (Zimble et al. 2003). Oversmoothing and reduction of local variance between points in the point cloud distribution can hide canopy gaps and architectural details (Baltsavias et al., 2008). A digital elevation model (DEM) can be subtracted from these point clouds to obtain the elevations of returns from vegetation, but DEMs of adequate resolution for normalization are usually available exclusively from ALS data (Reutebuch et al., 2003), particularly underneath forest canopies.

DAP is currently infrequently used for forest inventories. However, research has established the potential for forest inventory applications (e.g. Korpela, 2006; Véga and St-Onge, 2008; St-Onge et al., 2008). Comparisons of ALS and DAP derived point clouds using ABA for predictions of stand height, basal area and volume have generally concluded that ALS data provides more accurate estimates (Gobakken et al., 2015; Vastaranta et al., 2013; White et al., 2015). Imagery is also affected by illumination conditions and viewing angles, limiting the optimal flying hours per day (White et al., 2013b). Overall, optimal photo acquisition parameters and their impacts on the resulting data quality are uncertain (White et al., 2016). However, using the data is convenient, as it can be stored and manipulated similarly to ALS once processed (Leberl et al. 2010). The data is comparatively inexpensive to collect, and provides spectral data not afforded by non-multispectral ALS sensors. Preliminary studies have shown the potential for combined structural and spectral metrics to be useful for predicting species composition (St-Onge et al., 2015). Finally, photo-derived data complement the pre-existing expertise of photo-

interpreters in the inventory process; the imagery can be used to create point clouds, as well as interpreted.

1.6 Research objectives and questions

Given the aforementioned context, the primary objective of this thesis was to examine the capacity of ALS and DAP technologies to assess Lorey's height growth (ΔH_L) over approximately eight years in the managed and highly disturbed mixedwood boreal forests near Slave Lake in central Alberta, Canada. Through this analysis, the following two research questions were addressed:

- Question 1. How can ALS and DAP point clouds be utilized to derive measures of height growth at Slave Lake, AB, Canada?
- Question 2. What patterns of growth are apparent in stands near Slave Lake, AB with respect to ecological factors available from the Albertan AVI and ecosite-scale inventories?

To address the research objective and the two research questions presented here, this thesis has been broken down into the following chapters.

Chapter 2 introduces the study site of Slave Lake, AB as well as the data used to derive estimates of ΔH_L . As such, it outlines the specifications of the data acquisition and the required processing steps for the ALS and DAP point clouds. It also outlines the executed procedures for field data collection.

Chapter 3 addresses the first research question by dividing it into two sub-questions. The first sub-question focuses on the optimization of the modelling approach used to produce

estimates of ΔH_L . The second sub-question implements a sensitivity analysis with respect to plotlevel mortality to determine the effect of disturbance on ΔH_L estimation accuracy.

Chapter 4 addresses the second research question using a simple predictive model to extrapolate estimates of ΔH_L across the Slave Lake study site. Spatially-explicit estimates of ΔH_L were then analyzed using various ecological factors to determine that factors that were determinant in the apparent patterns of growth across the study area.

Chapter 5 concludes the thesis by outlining some of the key findings from chapters 3 and 4. Those findings are then used to contextualize this research for use by forest managers. The potential applicability of a multi-sensor approach to forest growth monitoring in a disturbed boreal site are discussed, and directions for future research in the application of a multi-sensor approach for forest growth assessments.

Chapter 2:

2.1 Study area

The focus site for this thesis is a 700,000 ha forest area located near the township of Slave Lake, Alberta (Figure 1), directly south of Lesser Slave Lake. The climate ranges between subarctic and humid continental. Winters are cold, summers are cool, and year-round precipitation averages about 600 mm (Natural Regions Committee, 2006). The site lies within three natural sub-regions: boreal mixedwood, lower foothills, and upper foothills, with a maximum elevation of 1375 m and a minimum elevation of 546 m above sea level. The relief is generally undulating. The Slave Lake forest is mixedwood boreal forest, including trembling aspen, white spruce, balsam poplar (*Populus balsamifera*), Jack pine and black spruce as some of the most common species (Natural Regions Committee, 2006). Forest dynamics are characterized by natural and anthropogenic disturbances, including wildfires, wind damage, harvesting activities, and oil exploration (Figure 1b). A large fire occurred in 2011 that burned 40% of the township. The study area is bordered to the north by Highway 2 and split by Highway 33. West Fraser Mills Ltd. manages the forest for spruce-pine-fir lumber, bleached chemical thermos-mechanical pulp, and bio-products such as wood chips.





Figure 1: Location of the Slave Lake study site in Alberta Canada. The study site is shown a) Outlined in red within the province of Alberta. b) Overlain with the Composite-to-Change (C2C) forest change product (Hermosilla et al., 2016) and outlined in Section 3.2.1. Shown are stand-replacing disturbances (fire and harvesting) that have occurred since 1985. Field plots are marked as black dots. The light gray area is the regional subset studied in Chapter 3. c) Overlain with species dominance data available from the AVI outlined in Section 2.3. The central area highlighted is the regional subset studied in Chapter 4.

2.2 Field plot measurement

Twenty-seven plots were established and measured between 2004 and 2006 and remeasured in 2012 or 2016. The plots were circular with a radius of 11.28 m and an area of 400 m^2 . For each tree in the plot, location, species, diameter at breast height (DBH), height and height-to-live-crown were measured. Crown class was recorded by visually classifying the location of each tree crown within the vertical canopy structure as dominant, codominant, intermediate or suppressed. Lorey's height (H_L) was calculated for each plot as per Equation 1:

$$H_L = \Sigma h_i^* g_i / \Sigma g_i \tag{1}$$

where h_i is the height of the ith tree and g_i is the basal area of the ith tree on a plot. ΔH_L was calculated as the difference between T1 and T2 values for a plot. Only trees with an initial DBH above 7 cm were used in this calculation. The H_L data are summarized in Table 1.

	Minimum	1 st Quartile	Median	3 rd Quartile	Maximum	Mean	Standard Deviation
T1 Measurement	6.75	12.70	14.03	17.06	23.38	14.67	3.89
T2 Measurement	7.36	13.19	15.16	17.96	24.86	15.54	3.90
ΔH_L	-1.16	0.16	0.61	1.42	4.14	0.87	1.26

Table 1: Summary statistics of H_L for the twenty-seven ground plots from T1, T2, and the change in H_L . All units are in meters.

Of the many height-based measures used in forest inventories, Lorey's height was used in this study as it is the most easily relatable to canopy surface height. If the canopy surface is an outer envelope containing vegetation underneath, then the canopy surface height is the vertical distance from of any point along this idealized surface to the ground (Magnussen and Boudewyn, 1998), and the mean canopy surface height is the mean height of all points along this surface (StOnge et al., 2003). An ALS acquisition over a forest canopy can be thought of as a sample of points from the canopy surface (Magnussen et al., 1999). As most canopy surface points from an ALS or DAP point cloud are not directly on tree apices, the average height of a sample of surface points is then an estimator of mean canopy height rather than any measure of mean tree height (St-Onge et al., 2003). As larger trees occupy a larger area, point clouds should then better approximate mean height metrics that give more weight to these larger trees such as Lorey's height (Magnussen and Boudewyn, 1998). Lorey's height is also stable as it is minimally affected by the mortality or harvesting of smaller trees. However, Lorey's height is still sensitive to overstory mortality. Nelson (1997) notes that stand height estimations are sensitive to canopy shape factors such as species and structure. Extending this notion, the impact of tree mortality on estimates of Lorey's height therefore depends on the extent to which the canopy shape is modified by the mortality. Canopy surface points along non-defoliated dead trees that have retained their upper branches can cause estimation discrepancies between Lorey's height estimates derived from remote sensing and field-measured estimates if the field estimates are calculated only from live trees. Conversely, surface points over canopy gaps around defoliated snags can cause similar estimation discrepancies in the case that field estimates are calculated from both live and dead trees. Regardless, due to the link between canopy surface points and Lorey's height, it continues to be a commonly used metric in remote sensing studies that quantify forest attributes (Gobakken et al., 2015; White et al., 2015; Yu et al., 2015).

2.3 Stand-level attributes from forest inventories

Stand-level attributes were obtained from the AVI (Alberta Vegetation Inventory Interpretation Standards, 2005). AVI data is developed using a series of interpreted photos obtained between 1949 and 2012, supplemented with field campaigns for the assignment of stand-level attributes to delineated polygons. AVI attributes include stand density and mean height, percent species composition, stand structure, stand age, natural land cover, disturbance information, and a timber productivity rating (Alberta Vegetation Inventory Interpretation Standards, 2005). Each of the attributes, and their corresponding codes and legends, are listed in Table 2. The polygon-level inventory for the study area subset contained 13499 forested polygons (Figure 1c). A summary of counts and sizes of these polygons by species dominance are presented in Table 3.

Ecosites are ecological units that are defined through an environmental stratification of climate, moisture, and nutrient regimes. Ecosite names convey ecological information about the unit, frequently referring to the common plant species present (Lawrence et al., 2005). An ecosite phase is a subdivision of the ecosite that incorporates information on dominant tree species. Ecosites also have characteristics attributed to them through photointerpretation. Some of these include excess moisture, moisture regime, nutrient regime, soil temperature, a soil classification according to the Canadian system of soil classification, and soil texture. Excess moisture and soil temperature are categorized as limitations; meaning that categorical values indicate the extent to which quantified values are perceived to prohibit plant growth and establishment (Archibald et al., 1996). For example, a "high" rating for soil temperature implies that the soil temperature is expected to inhibit growth or establishment more than a "low" rating. Each of these eight attributes' categories and their corresponding codes and legends are listed in Table 2. Ecosite phases are identified by the ecosite letter, name, and number representing the phase within the ecosite. Ecosite types and phases are specific to each of the natural sub-regions in Alberta (Lawrence et al., 2005). Ecosites, their respective phases and their names for each of

the three natural sub-regions within the study area are listed in Table 4. The ecosite-scale data in the subset contained 32441 forested polygons. A summary of counts and sizes of these polygons by ecosite is presented in Table 5.

Table 2: Description of select forest attributes forest attributes at Slave Lake available from the AVI polygons and ecosite polygons available from the Alberta provincial government. Categories are those existing in the area shown in Figure 1c. An AVI polygon's dominant species was considered the species with the highest percent composition. Excess moisture is categorized based on soil permeability derived from soil texture, and moisture regime to generalize surface moisture conditions. Soil temperature ratings are based on moisture regime, topographic position, surface texture and disturbance of surface layers. Soil classes are categorized based on the Canadian System of Soil Classification. Soil texture is categorized using a two or three-character code. The first is always an "S" that stands for "soil". The second is a capital letter indicating either moisture content, or that the soil is organic (in which case the code is only two letters). The final character indicates either grain coarseness for soils ranging from very dry to moist with a value between 1 and 4, or substrate type for wet soils

Ecological Variable	Data Source	Categorical Values	Code Legend
Canopy Cover	AVI	A, B, C, D	A: 6% - 30%, B: 31% - 50%, C: 51% - 70%, D: 71% - 100%
Species Dominance	AVI	Aw, Bw, Pb, Pl, Sb, Sw	Alberta tree codes
Excess Moisture	Ecosites	L, L-H, M-H, H	L: Low, M: Medium, H: High
Moisture Regime	Ecosites	Xeric, Subxeric, Submesic, Mesic, Subhygric, Hygric, Subhydric	-
Nutrient Regime	Ecosites	Very Poor, Poor, Medium, Rich, Very Rich	-
Soil Temperature	Ecosites	L, L-H, M, H	L: Low, M: Medium, H: High
Soil Class	Ecosites	BR.GL, CU.R, E.EB, O.EB, O.GL, O.HR., O.HR, O.LG, R.G, T.M, TY.M	Canadian System of Soil Classification

Ecological Variable	Data Source	Categorical Values	Code Legend
Soil Texture	Ecosites	SV1, SV4, SD4, SM4, SWm, SR	V: Very dry, D: Dry, M: Moist, W: wet, R: Organic, m: mineral, p: peaty, 1: Sandy, 2: Coarse-Loamy, 3: Silty-Loamy, 4: Fine-Loamy- Clayey

Table 3: Summary of AVI polygon counts and areas by species dominance at Slave Lake. Counts and percentages are relative to the polygons included within the subset outlined in Figure 1c.

Dominant Species	Number of Stands		Total	Mean Stand Area	
	#	%	ha	%	ha
Aw	2876	21.31	39659.77	25.12	13.79
Bw	270	2.00	1902.97	1.21	7.05
Fb	31	0.23	485.55	0.31	15.66
Lt	32	0.24	248.42	0.16	7.76
Pb	255	1.89	2529.25	1.6	9.92
Pl	5163	38.25	70501.76	44.65	13.66
Sb	3539	26.22	29056.70	18.4	8.21
Sw	1333	9.87	13503.31	8.55	10.13
TOTAL	13499	100	157887.70	100	

Table 4: Ecosite names and corresponding codes, and ecosite phase names are their corresponding codes. Boreal mixedwood ecosites and their phases are identified as per Beckingham and Archibald (1996), lower foothills ecosites and phases as per (Lawrence et al. 2005), and upper foothills ecosites and phases as per (Willoughby 2007). This list only incorporates ecosites and ecosite phases occurring within the subset outlined in Figure 1c.

Natural sub-	Facita anda	Foosito nomo	Ecosite phase	Ecosite phase
region	Ecosite coue	Ecosite name	code	name
	0	lichen	a1	lichen-Pj
Dagaal	a	(subxeric/poor)		
Boreal	b b		b2	blueberry -
Mixeuwoou		blueberry		Aw(Bw)
		(submesic/medium)	b4	blueberry - Sw-
				Pi
Natural sub- Ecosite code Ecosite name		Ecosite phase	Ecosite phase	
---	-----	--------------------	---------------	------------------
region			code	name
			d1	low-bush
				cranberry - Aw
		low-bush cranberry	d2	low-bush
	d	(mesic/medium)		cranberry - Aw-
		()		Sw
			d3	low-bush
				cranberry - Sw
			el	dogwood - Pb-
		dogwood		Aw
	e	(subhygric/rich)	e2	dogwood - Pb-
		(subliggile, nell)		Sw
			e3	dogwood - Sw
	f	horsetail	f1	horsetail - Pb-
	I	(hygric/rich)		Aw (Bw)
	C		c1	hairy wild rye -
		hairy wild rye		Pl
-	c	(submesic/medium)	c3	hairy wild rye -
				Aw-Sw-Pl
	d		d1	Labrador tea-
		Labrador tea -		mesic - Pl-Sb
	u.	mesic (mesic/poor)	d2	Labrador tea-
				mesic - Pl
			e1	low-bush
Lower Foothills				cranberry - Pl
			e2	low-bush
		low-bush cranberry		cranberry - Aw
	e	(mesic/medium)	e3	low-bush
		(meshe, mearann)		cranberry - Aw-
				Sw-Pl
			e4	low-bush
				cranberry - Sw
			f1	bracted
				honeysuckle/fern
				- Pl
	f H	bracted	f2	bracted
		honeysuckle		honeysuckle/fern
		(subhygric/rich)		- Aw-Pb
			f3	bracted
				honeysuckle/fern
				- Aw-Sw-Pl

Natural sub- region	Natural sub- region Ecosite code Ecosite name		Ecosite phase code	Ecosite phase name		
			f4	bracted honeysuckle/fern - Sw		
	h	Labrador tea (subhygric/poor)	h1	Labrador tea- subhygric - Sb- Pl		
			i1	horsetail - Pb-		
	i	horsetail (hygric/rich)	i2	Aw horsetail - Pb- Sw		
			i3	horsetail - Sw		
	k	bog (subhydric/poor)	k1	treed bog		
	а	grassland	al	shrubby grassland		
	с	hairy wild rye	c1	hairy wild rye - Pl		
		(submesic/medium)	c4	hairy wild rye - Sw		
	d	Labrador tea-mesic (mesic/poor)	d1	Labrador tea- mesic - Pl-Sb		
	els		e1	tall bilberry/arnica - Pl		
Upper Foothills		tall bilberry/arnica (mesic/medium)	e2	tall bilberry/arnica - Aw-Sw-Pl		
opper i coumis			e3	tall bilberry/arnica - Sw		
			f1	bracted honeysuckle - Pl		
	f	bracted honeysuckle	f3	bracted honeysuckle - Pb-Sw-Pl		
		(subhygric/rich)	f4	bracted honeysuckle - Sw		
	h	Labrador tea- subhygric (subhygric/poor)	h1	Labrador tea- subhygric - Sb- Pl		

Natural sub- region	Ecosite code	Ecosite name	Ecosite phase code	Ecosite phase name	
	j	horsetail (hygric/rich)	j1	horsetail - Sw	
	k	bog (subhydric/poor)	k1	treed bog	

Natural Sub-	Ecosite	Number	of Units	Total	Mean	
region	Code		<u> </u>			Area
		#	<u>%</u>	ha	<u>%</u>	ha
	a	113	0.35	29.41	0.02	0.26
	b	2233	6.88	1386.95	0.93	0.62
	С	8	0.02	21.63	0.01	2.7
	d	867	2.67	13694.09	9.21	15.79
Boreal	e	984	3.03	1679.1	1.13	1.71
Mixedwood	f	233	0.72	803.98	0.54	3.45
	g	6	0.02	5.25	0	0.87
	i	116	0.36	1986.5	1.34	17.13
	j	4	0.01	40.04	0.03	10.01
	TOTAL	4564	14.07	19646.95	13.21	
	b	62	0.19	15.61	0.01	0.25
	с	1370	4.22	4570.25	3.07	3.34
	d	3539	10.91	26234.21	17.64	7.41
	e	4301	13.26	30756.16	20.68	7.15
	f	5002	15.42	4940.96	3.32	0.99
T T (1'11	h	850	2.62	644.29	0.43	0.76
Lower Footnills	i	1314	4.05	5209.31	3.5	3.96
	j	42	0.13	43.06	0.03	1.03
	k	1120	3.45	16575.87	11.15	14.8
	1	52	0.16	591.73	0.4	11.38
	m	11	0.03	118.49	0.08	10.77
	TOTAL	17663	54.45	89699.94	60.32	
	а	160	0.49	43.5	0.03	0.27
	с	3316	10.22	2211.49	1.49	0.67
	d	681	2.1	5806.44	3.9	8.53
	е	2702	8.33	25340.16	17.04	9.38
	f	2017	6.22	1673.62	1.13	0.83
	ff	227	0.7	874.58	0.59	3.85
Upper Foothills	g	70	0.22	86.43	0.06	1.23
	ĥ	444	1.37	287.19	0.19	0.65
	i	27	0.08	18.62	0.01	0.69
	i	356	1.1	761.87	0.51	2.14
	k	214	0.66	2245.33	1.51	10.49
	TOTAL	10214	31.48	39349.22	26.46	
	TOTAL	32441	100	148696.1	100	

Table 5: Summary of ecosite polygon counts and areas at Slave Lake. Counts and percentages are relative to the polygons lying within the subset outlined in Figure 1c.

2.4 ALS data collection

ALS data were acquired for the Slave Lake region between 2006 and 2008 using an Optech ALTM 3100 with a dual frequency Applanix POSAV 510 GPS receiver and inertial measurement unit. Data were acquired with a maximum scan angle of $\pm 25^{\circ}$ from nadir, a beam divergence of 0.3 mrad The average point density was 1.27 points/m² within the 27 plots. In 2006, the laser scanner operated at an altitude of 1250 m with a pulse repetition rate of 50 kHz and a scanning frequency of 30 Hz. In 2007 and 2008 the laser scanner operated at an altitude of 1400 m with a pulse repetition rate of 70 kHz and a scanning frequency of 33 Hz. Data were collected in July 2006, in October 2007, and July through September, in 2008 and included both leaf-on and leaf-off conditions.

2.5 DAP data collection

A total of 1527 aerial images were acquired on 26 April, 9 May and 13 May 2015 using a Z/I DMC® II230 at nadir including blue, green, red and near-infrared spectral bands. The ground sample distance was 0.3 m and along-track and across-track overlaps were 60% and 30%, respectively. Using the ALS-derived DSM as a reference, 134 ground control points were used to register the image data.

2.6 Point cloud data processing

The DAP data were processed using the Agisoft PhotoScan software. The software first detected points in the source photos that were stable under viewpoint and lighting variations and generated a descriptor for each point based on its local neighborhood. It then used a greedy algorithm to find initial, approximate camera locations and which were later refined using a

bundle-adjustment algorithm similar to Bundler (Snavely et al., 2006). Photoscan then reconstructed the surface using the pair-wise depth map computation (Kamencay et al., 2012). Finally, the software parameterized a surface and blended the source photos to form a texture atlas. This resulted in a point cloud with an average point density of 0.82 points/m² within the 27 plots.

A DEM was developed using returns from the ALS dataset at a 1 m spatial resolution. Ground classifications were based on adaptive triangulated irregular network (TIN) models (Axelsson, 2000). The DEM was then used to normalize both the ALS and DAP point heights and respectively generate T1 and T2 canopy height models (CHMs). Studies have shown that ALS can accurately and precisely be used to normalize DAP point clouds assuming the terrain surface is invariant between fly-overs (St-Onge et al., 2008).

Chapter 3:

3.1 Introduction

Forest managers require the development of a cost-effective inventory cycle using remotely sensed data (Pitt and Pineau, 2009). Research has shown that area-based forest attribute predictions can accurately be made from DAP on simple boreal sites (Bohlin et al., 2012; Järnstedt et al., 2012), as well as complex coastal environments with varying slope and canopy cover conditions(White et al., 2015). However, few studies have explored the accuracy of forest attribute estimates from image-based point clouds in highly disturbed forest environments. If such estimates are sufficiently robust, then the data could plausibly be used to realize more frequent inventory cycles at a lower cost (White et al., 2016). Accurate estimates are especially vital for change evaluation as predictions are based on assessments at two points in time.

Two methods for assessing forest growth using three-dimensional point cloud datasets are commonly applied: direct and indirect methods (Cao et al., 2016; Goodbody et al., 2016). Direct methods are those that estimate growth from differences in common metrics acquired from two datasets at two different points in time. Indirect methods compute growth by differencing two estimates (e.g. of height), an initial and final, with the two models not requiring the same predictor variables (McRoberts et al., 2014). The direct method tends to minimize prediction errors by minimizing the number predicted values used as input. However, the indirect method avoids the assumption that ALS and DAP point cloud metrics are comparable to one another. The indirect method is therefore necessary for the application of a multi-sensor approach to estimating growth, but can only be effective if the prediction errors of the input values can be minimized.

Past studies investigating the use of multi-temporal datasets to monitor forest height growth with ABA are presented in Table 6. St-Onge and Vepakomma (2004) assessed average dominant height growth in stands divided by hardwood/softwood dominance and by height classes of 5-10 m, 10-15 m, and >15 m. Average differences in the upper height percentiles were near to average observed growth in the "medium" age category in hardwood and softwood stands. Height increases were generally close to the reference age-height table values (average deviation = 0.42 m). Næsset and Gobakken (2005) assessed growth in Lorey's height at the plot and stand levels, stratified by age and site quality. Observed plot growth was close to the root mean square error (RMSE) in the young stand. Hopkinson et al. (2008) assessed mean height growth in a temperate coniferous plantation. Trends of observed stand height growth and DSMbased height growth estimates were nearly parallel. Yu et al. (2008) produced estimates of Lorey's height growth on plots, first using only dominant trees then with all trees, using three methods: individual tree crown differencing, DSM differencing and ABA. ABA produced models with the lowest R^2 value and the highest RMSE of the three methods for all-tree and dominant-tree height estimates ($R^2 = 0.53$, RMSE = 0.29). Véga and St-Onge (2008) used an archive of aerial photos and validation data derived from growth curves to develop height models for plots. Large time intervals facilitated accurate height estimates despite large errors in height estimates at individual times. Stepper et al. (2015) used bi-temporal DAP data to assess the periodic annual increment (PAI) of stand height in three different age classes. Derived PAI values were used as truth data, and PAI was shown to decrease as age class increased. Tompalski et al. (2018) assessed height growth using projections from plot-specific yield curves. Applied yield curves were calculated as the weighted mean of an array of candidate curves produced from a growth and yield projection system that best corresponded to each of the modeled

structural attributes at T1 and T2: top height, basal area, total volume and number of trees. The %RMSE of projected values at T2 was 13.2%.

Overall, results have been better in forests with relatively taller mean stand heights. Consequently, results from temperate zones were generally good, while results from boreal zones varied. In boreal studies, success was facilitated by the use of large growth intervals (Véga and St-Onge 2008) and comparatively simpler stand structures (Yu et al. 2008). No patterns of success were apparent regarding scale or sensor choice. Of the studies that have evaluated height growth, few validated their models against independent data sources, and only two used a multisensor approach (i.e., Tompalski et al., 2018; Véga and St-Onge, 2008). A multi-sensor approach can reduce the costs of acquiring multi-temporal point cloud data for stand-level growth assessments, by leveraging the ALS-derived DTM from an initial acquisition of ALS data for the subsequent processing of DAP data acquisitions (White et al. 2013b), but it also can increase the uncertainty associated with the growth estimate. **Table 6**: Results of studies on height growth modelling using the ABA with multi-temporal ALS and/or DAP point cloud data.

Reference	Site Location	Forest Type	Acquisition Years	Sensor	Scale	Mean Tree/Plot Heights (m)	R ²	RMSE (m)	Bias (m)
St-Onge & Vepakomma, 2004	Lake Duparquet, QC	Mature boreal mixed forest	T1 = 1998 T2 = 2003	ALS ALS	Stand- level	Low: 5-10 Med: 10-15 High: 15+	-	Not Report	ted
Næsset & Gobakken, 2005	Våler, Norway	Managed boreal regeneratio n and plantation	T1 = 1999 T2 = 2001	ALS ALS	Plot- and stand- level	Young: 13.7 Mature, poor: 16.0 Mature, rich: 19.2		0.47 – 1.28	-0.23 – 0.27
Hopkinson et al., 2008	Toronto, ON	Temperate coniferous plantation	T1 = 2000 T2 = 2002 T3 = 2004 T4 = 2005	ALS ALS ALS ALS	Plot- and stand- level	23.8 - 24.6		0.5 (41%)	
Yu et al., 2008	Kalkkinen, Finland	Mature boreal mixed forest	T1 = 1998 T2 = 2003	ALS ALS	Plot- level	7.2 – 28.7	0.51	0.36	
Véga & St- Onge, 2008	Lake Duparquet, QC	Managed even-aged boreal forest	T1 = 1945 T2 = 1965 T3 = 1983 T4 = 2003	DAP ALS	Plot- level	Coniferous: 22.3 Deciduous: 26.4	-	Not Report	ted
Stepper et al., 2015	Traustein, Germany	Temperate mixed forest	T1 = 2009 T2 = 2012	DAP DAP	Plot- and stand- level	27.7	-	Not Report	ted
Tompalski et al., 2018	Slave Lake, AB	Managed boreal mixedwood	T1 = 2006- 2008 T2 = 2015	ALS DAP	Plot- and stand- level	17.7		2.23 (13.23%)	0.64 (9.81%)

I examine the capacity of ALS and DAP technologies to assess ΔH_L over approximately eight years in the context of managed yet highly disturbed boreal forest stands near Slave Lake in central Alberta, Canada by answering the following specific questions.

1. Does the predictive capability of linear models for Lorey's mean height growth improve when including canopy cover and/or canopy height variability metrics in the T1 and T2 models? Studies that have developed predictive models for forest stand height using threedimensional point cloud data have often used only height metrics as predictor variables (e.g., Bohlin et al., 2012; Hopkinson et al., 2008; Stepper et al., 2015; Tompalski et al., 2018; Véga and St-Onge, 2008; Yu et al., 2008). However, canopy cover and canopy height variability metrics could be useful for three reasons. First, estimation errors from the T1 and T2 height models are compounded when making growth predictions. Second, growth estimates could be overwhelmed by noise if they are imprecise, as mean annual increments (MAI's) are small. Third, canopy cover and height variability metrics can provide additional information in stands with high densities of large snags as they could obscure structural quantifications of live trees (Bollandsås et al., 2013).

The forests around Slave Lake are highly disturbed and have high mortality rates. To assess the significance of including these additional predictor variables, I compared models using only height metrics with those using combinations of height, canopy cover and height variability metrics.

2. How is the predictive capability for Lorey's mean height growth impacted by increasing plot-level mortality?

Stand-level mortality has been shown to alter forest structure as detectable in threedimensional point clouds (Coops et al., 2009). However, models developed for ABA estimates of mortality-related forest attributes, and which use statistics from three-dimensional point clouds as predictor variables, have generally included spectral intensity (Bright et al., 2013; Kim et al., 2009). Intensity metrics have often been of limited use due to lack of calibration and differences in optimal flying conditions for structural data and spectral data acquisitions. Without a means of quantifying mortality, there is a need to assess the impacts of plot-level mortality on the predictive accuracy of stand-level forest attribute models to determine what stand conditions can be modeled (Yoga et al., 2017). To assess the impacts of plot mortality on ΔH_L estimates in Slave Lake, I iteratively measured the accuracy of optimized height models, while incrementing the mortality in the dataset.

3.2 Methods

3.2.1 Field plot selection

Plots were omitted from this analysis if they had mortality rates of 100%, if there was evidence of harvesting or fire, or if they decreased in live volume over the measurement period.. These disturbances were identified using an updated version of the change history of forested ecosystems product developed by Hermosilla et al. (2016). This product was developed for the National Terrestial Ecosystem Monitoring System (NTEMS) project that characterizes the recent change history of Canada's forests using freely available data from the Landsat archive (White et al., 2014). The product was developed using the Composite2Change (C2C) time series-based change mapping method presented in (Hermosilla et al., 2015), which utilizes best-availablepixel (BAP) composites of surface reflectance values derived from Landsat image archives. These composites are then used to produce a database of annual change occurring over Canada's forests, including amounts, types, and rates of disturbances from fire, harvesting, non-standreplacing disturbances, and construction of infrastructure. Results from the Canada-wide

assessment revealed the ability of spectral-trend analysis to identify forest changes with extremely high accuracy (Hermosilla et al., 2016).

After removal of the plots for the disturbances noted above, twenty-seven plots remained, all of which were located roughly in center of the study area. The minimum bounding rectangle containing these plots was approximately 200,000 ha (Figure 1b).

3.2.2 Metric comparison

As the timing of the T1 and T2 field measurements did not correspond exactly to the respective airborne data acquisitions, a correction factor was applied to field-measured plot-level H_L as per Eq. 2:

$$H_{adj} = H_L + (H_{T2} - H_{T1}) / (t_{FT2} - t_{FT1})^* (t_A - t_F)$$
⁽²⁾

where t is the acquisition year, and A and F correspond to airborne and field campaigns, respectively. All subsequent references to field-measured H_L on plots are H_{adj} .

Statistical metrics describing forest stand structure were extracted from the ALS and DAP point clouds within the sample plots. Metrics were generated using returns above 2 m (Nilsson, 1996), and using only first returns in case of the ALS. Metrics were divided into three categories based on the canopy structures they describe: height, canopy cover and variability in height (Lefsky et al., 2005; White et al., 2013a). To evaluate the relationships of height, canopy cover, and height variability metrics with field-measured H_L , we calculated the Spearman rank correlation coefficient (r) between H_L at T1 and T2, and the suite of candidate metrics (Table 7) from each sensor.

Variable Category	Metrics				
Height (9)	Mean Height, Mode of Height Height Percentile Values (10 th , 25 th , 50 th , 75 th , 90 th , 95 th , 99 th)				
Canopy Cover (3)	Percentage of 1 st returns above: Mean Height, Mode of Height, 2 m Height Threshold				
Height Variability (8)	Interquartile Range, Skewness, Kurtosis, Variance, Standard Deviation, Coefficient of Variation (of height) Canopy Relief Ratio, Upper Surface Area				

Table 7: Metrics calculated for both ALS and DAP plot-scale point clouds. The numbers in brackets indicate the number of metrics in each category.

3.2.3 Modeling Lorey's height and growth

Two approaches were used to assess the influence of including canopy cover and variability metrics in the predictive models. First, multiple linear regression was used to develop each of the models, dividing the potential predictor variables into categories to reduce redundancy in the models (Table 7). A forward stepwise variable selection approach was used, resulting in models with the lowest AIC and where all predictors were statistically significant (p < 0.05). Hereafter, these models are referred to as the *multi* models, since they are based on multiple predictor variables. For the second approach, we developed models using the height percentile with the strongest correlation with H_L as the single predictor variable for a linear regression. These models will subsequently be referred to as the *single* models. The RMSE, bias and % bias for each model were calculated as per Equations 3 to 6:

$$RMSE = \sqrt{(\Sigma((\mathbf{y}_{i} - \hat{\mathbf{y}}_{i})^{2})/n)}$$
(3)

$$\% RMSE = RMSE/\bar{y}_i^*100$$
(4)

$$bias = \Sigma(\mathbf{y}_i - \hat{\mathbf{y}}_i)/n \tag{5}$$

$$\% bias = bias/\bar{\mathbf{y}}_i^* 100 \tag{6}$$

where \mathbf{y}_i is an observed value, $\bar{\mathbf{y}}_i$ is the mean of observed values and $\hat{\mathbf{y}}_i$ is a predicted value for the i^{th} sample plot.

We used the indirect method to assess forest growth. Predicted values for ΔH_L were derived by differencing the predicted values from selected height models at T1 and T2. RMSE for ΔH_L were estimated from the RMSEs for the height models at times T1 and T2 as per Equation 7, adapted from (Hughes and Hase, 2010):

$$RMSE_{G} = \sqrt{(RMSE_{T1}^{2} + RMSE_{T2}^{2})}$$
(7)

where RMSE_{G} is the prediction error of the growth model and RMSE_{T1} and RMSE_{T2} are the errors of the T1 and T2 models. Pearson product moment correlation coefficients were also calculated between measures of observed and predicted ΔH_L .

3.2.4 Model sensitivity to stand condition

An exploratory assessment of the relationship between plot-level mortality and \mbox{RMSE}_{G} was executed as per Workflow 1 below. Plots were ordered according to tree mortality (defined as the percentage of dead trees in a plot) observed during the T2 field campaign. Model error for ΔH_L was then evaluated iteratively for a subset of plots with increasing sample size (one additional plot at each iteration), and incremental mortality. At each iteration, predictions and RMSEs were generated from the optimized T1 and T2 H_L models, and \mbox{RMSE}_G was estimated. The %RMSE_G values developed from subsets ordered by T2 tree mortality are hereafter referred to as %RMSE_{GM}. The trend was assessed between %RMSE_{GM} and the plot-level mortality at T2.

To determine whether the trend was an artefact of subset size (n), and to assess the utility of minimizing plot-level mortality to reduce $\mbox{\sc RMSE}_G$, a Monte Carlo simulation was used. The method explained in Table 8 was repeated for N = 100 random arrangements of the plot list to develop a distribution of $\mbox{\sc RMSE}_G$ for each value of n. The $\mbox{\sc RMSE}_G$ values developed from these randomizations of plot subsets will subsequently be referred to as $\mbox{\sc RMSE}_{GR}$. The distributions of $\mbox{\sc RMSE}_{GR}$ were then overlain with $\mbox{\sc RMSE}_{GM}$ values to visually compare them, and linear, quadratic and square root curves were fit to each to determine the similarity of the observed trends with respect to n.

Table 8: Iterative calculations for the development of distributions of $\[mmodeRMSE_{GR}\]$. i goes to 27 which is the total number of remeasured plots at the study site near Slave Lake, AB.

1	Arrange all plots by increasing T2 mortality
2	for $i = 2$ to 27 do:
3	Select i plots from the top of the plot list
4	Generate T1 and T2 H_L predictions, and calculate RMSE
5	Propagate RMSEs from T1 and T2
6	End

3.3 Results

3.3.1 Metric comparison

ALS height metrics showed the strongest correlations to H_L . Correlation strength increased with increasing height percentiles, but the degree of correlation was very similar between the 90th and 99th percentiles. Correlation values were consistently around 0.6 across canopy cover metrics. Correlation values for variability metrics were moderately high (>= |0.6|) for standard deviation, variance, skewness and canopy relief ratio, but lower for the other three metrics (Table 9).

Correlations were lower for DAP than for ALS across all variables and categories. Correlation values followed the same trend as ALS with height percentiles, and were nearly the same from 90% to 99%. Correlation values were low for all canopy cover metrics, with the highest values for the percentage of points above the mode. Correlation values were also low for all variability metrics with the highest being for the interquartile range and the standard deviation (Table 9).

Variable Category	Metric	ALS	DAP
Height	P10	0.72	0.72
	P25	0.81	0.75
	P50	0.86	0.79
	P75	0.91	0.88
	P90	0.96	0.93
	P95	0.96	0.93
	P99	0.95	0.93
	Mean of Height	0.90	0.83
	Mode of Height	0.73	0.73
Canopy Cover	1 st Returns Above 2m	0.66	-0.09
	(%)		
	1 st Returns Above	0.59	-0.22
	Mean of Elevation		
	(%)		
	1 st Returns Above	0.61	0.35
	Mode of Elevation		
	(%)		
Height Variability	Standard Deviation	0.72	0.29
	Variance	0.61	0.24
	Coefficient of	-0.17	0.00
	Variation		
	IQ Range	0.47	0.37
	Skewness	-0.60	0.08
	Kurtosis	0.36	0.03
	Canopy Relief Ratio	0.69	0.14

Table 9: Spearman rank correlation coefficients for ALS (T1) and DAP (T2) metric correlations with field-based measures of H_L . Height metrics denoted by "P" are height percentile values.

3.3.2 Plot-level estimations of Lorey's height and growth

Predictive models were developed for H_L at T1 and T2 (Table 10, Figure 2). All *single* models were developed using the 90th percentile of height as a predictor variable as it demonstrated a strong correlation with H_L for both the ALS and DAP datasets (Table 9). The T1 ALS *multi* equation included 3 variables with positive parameter coefficients. The adjusted R^2

and %RMSE_{T1} were very similar between the two ALS models, although the T1 ALS *single* equation was slightly less accurate. The T2 DAP *multi* equation also included 3 variables, although the percentage of points above the mean had a negative coefficient. The adjusted R² and %RMSE_{T2} were also very similar between the two DAP models, although the difference in fit measures was slightly larger than between the ALS models, with the T2 DAP *single* equation being less accurate than T2 DAP *multi* equation. All parameters were statistically significant (p < 0.01) for all models.

Table 10: Equations and predictive accuracy measures of linear regression models for H_L at T1 and T2. Models labeled multi are built using stepwise multiple linear regression and models labeled single are built using simple linear regression. Model scatterplots are shown in Figure 2. *p < 0.01. **p < 0.001.

Model	Explanatory Variables	Parameters	Intercept	\mathbb{R}^2	Adjusted R ²	RMSE (m)	RMSE (%)	Bias (m)	Bias (%)
T1	Standard	1.89 **	2.61	0.94	0.94	0.90	6.11	0	0
ALS	deviation of								
multi	height								
	10th Percentile	0.60 **							
	of Height								
	1st Returns	0.05 *							
	Above Mode								
	(%)								
T1	90th Percentile	0.75 **	3.26	0.92	0.92	1.07	7.26	0	0
ALS	of Height								
single									
T2	Mean of Height	0.84 **	7.11	0.92	0.91	1.10	7.10	0	0
DAP									
multi									
	Coefficient of	11.36 **							
	Variation of								
	height								
	1st Returns	- 0.09 *							
	Above Mean								
	(%)								
T2	90th Percentile	0.73 **	4.40	0.87	0.86	1.40	9.00	0	0
DAP	of Height								
single									



Figure 2: Scatterplots of linear regression models for H_L at T1 and T2. A) T1 ALS multi, B) T1 ALS single, C) T2 DAP multi, D) T2 DAP single. Model equations and predictive accuracy measures are shown in Table 10.

The *growth_multi* model estimated height growth with an RMSE of 1.42 m (%RMSE_G = 164.18%) and correlation was strong between the observed and predicted values (r = 0.75). The growth_single model estimated height growth with an RMSE_G of 1.76 m (%RMSE_{GM} =

203.03%) and correlation between the observed and predicted values was weather than that of the *growth_multi* model (r = 0.65) (Figure 3).



Figure 3: Scatterplots for observed and predicted values of ΔH_L by the indirect approach. Growth shown using models built from A) multi equations and, B) single equations. Models input to the indirect approach are illustrated in Figure 2, and equations are available from Table 10.

3.3.3 Model sensitivity to stand condition

Sensitivity to mortality was assessed for the *growth_multi* model exclusively, as its predictions had a lower RMSE_G and %RMSE_G than the *growth_single* model. The plot of %RMSE_{GM} versus mortality rate showed an asymptote located approximately at the optimized model's %RMSE_G value (Figure 4).

Within the %RMSE_{GR} distributions derived from 100 randomizations of plot order, the median of %RMSE_{GR} was greater than 100% when the sample size was seven (Figure 5). %RMSE_{GM} falls within the 1st quartile of %RMSE_{GR} distributions at all sample sizes except 26

and 27, and from 16 - 20 where it falls outside of the distributions. The values of %RMSE_{GM} best fit a linear trend while the median values of the %RMSE_{GR} distributions best fit a square root curve.



Figure 4: Mortality sensitivity of the *growth_multi* model. $\[Mathebaacking] RMSE_{GM}$ is the error for ΔH_L . Mortality rate is the ratio of dead stems to total stems in the plot.



Figure 5: % RMSE_{GR} by sample size for N = 100 random orders of plots and comparison with % RMSE_{GM}. The boxes present the interquartile range of the distributions of % RMSE_{GR} while bars show the medians. The upper and lower tails of the boxes show the 1st and 4th quartiles of the distributions respectively. The grey circles present values of % RMSE_{GM}.

3.4 Discussion

This study had two main objectives, first to assess whether predictions for ΔH_L are more accurate when including canopy height and height variability metrics in the T1 and T2 models,

and second to assess the impact of plot-level mortality on the accuracy of ΔH_L estimates. Predictive models were developed for H_L at T1 and T2 using three categories of point cloud metrics. Including additional categories of predictor variables reduced %RMSE_G, although %RMSE_G was high for both *multi* and *single* equations. These results were attributed to slow height growth and to high amounts of plot-level mortality and disturbance.

Correlations between T1 H_L values and height metrics were expectedly lower for height percentiles below the 90th than for those above the 90th. Correlations between T2 H_L values and height metrics followed the same pattern as those from T1, while correlations with canopy cover and variability in height were much weaker. These results are similar to the findings of White et al. (2015), except for the correlation they found between H_L and coefficient of variation (r = -0.59 there, and r = 0 here). DAP-based point clouds only represent the outer canopy envelope by the nature of how they are generated (White et al., 2013b). As such, cloud metrics derived from DAP point clouds contain little information regarding the vertical distribution of canopy cover through the canopy and height variability.

The T1 ALS *multi* model ($R^2 = 0.94$) explained slightly more variance than the T2 DAP *multi* model ($R^2 = 0.91$), and the differences in RMSE between the *single* and *multi* models were small at both T1 (0.17 m, 1.15%) and T2 (0.3 m, 2.90%). Including canopy cover and height variability in the predictive height models for T1 and T2 provided only minor improvements in accuracy. Both *multi* models performed comparably to each other and favorably to many other studies that have compared model accuracy for height growth with ALS and DAP for single dates. Studies with reported %RMSEs include Järnstedt et al. (2012); ALS = 11.79%, DAP = 18.17%, Pitt et al. (2014); ALS = 7.30%, DAP = 10.8%; Tompalski et al. (2015); ALS = 8.96%, DAP

= 14.00%. However, the RMSE_G of the *growth_multi* model was 0.336 m (38.85%) less than the *growth_single* model and the correlation with the observed ΔH_L was 0.09 greater than the *growth_single model*. Due to the slow growth observed in the plots (mean ΔH_L of 0.87m over 8 years), the differences in RMSE between *single* and *multi* models at T1 and T2 were large relative to the growth. Other studies that have performed growth analyses at the plot level have been in relatively homogenous, even-aged, comparatively fast-growing sites (e.g., Hopkinson et al., 2008; Næsset and Gobakken, 2005; Véga and St-Onge, 2008). In the context of growth analysis using the indirect method, minimizing the RMSE at T1 and T2 is crucial to discern the growth signal from RMSE_G. The direct method can minimize growth estimation errors (Hopkinson et al., 2008; Yu et al., 2008), but is likely better suited to single-sensor approaches where derived point-cloud metrics are more equivalent (Yu et al., 2008).

%RMSE_G was high for both the *growth_single* and *growth_multi* models. This can be explained firstly by slow height growth and the resultant small increments to be predicted. Secondly by having not stratified the data by species/forest type prior to modeling. White et al. (2017) noted that coniferous/deciduous splits or splits by species dominance are suggested for ABA modeling, as done by Næsset and Gobakken (2005). Such stratification was not feasible for this study due to the limited plot size. Thirdly, tree mortality causes discrepancies between field measurements and modeled estimations if the deaths occur between the field and remote data acquisitions (White et al., 2013a). Finally, points from snags in or above the canopy may have affected the point cloud metrics used in modeling, by either obscuring live trees or by modifying the plot's canopy surface (Bollandsås et al., 2013).

The mortality sensitivity assessment showed that \mbox{RMSE}_{GM} increased with increasing plot-level mortality. The trend between model error and mortality indicated that when the

maximum allowable mortality was approximately 25%, the %RMSE_{GM} was just below 100%. Given a mean growth rate of 0.11 m yr⁻¹ in this set of plots, approximately 12.79 years (an additional ~5 years beyond what was used in this study) would be required for the growth to exceed the modeling error (Eq. 6). The overlay of %RMSE_{GM} with distributions of %RMSE_{GR} showed that minimizing plot-level mortality successfully minimized the prediction errors, particularly at sample sizes where n > 15. Small sample sizes were subject to variable RMSE magnitudes, making the error reduction more prominent as the sample size increased from five. When the subset included nearly all possible plots (n > 23), %RMSE_{GM} converged back into the distributions of %RMSE_{GR}. Though %RMSE_{GM} and medians of %RMSE_{GR} showed similar trends with sample size, their fitting to different curves supported the approach that minimizing plot-level mortality reduces prediction error. As single-date models were already quite accurate and error magnitudes were comparable to those found in previous works comparing ALS and DAP derived estimates of forest structural attributes, a multi-sensor approach to growth monitoring may be better suited to less disturbed boreal sites or faster growing sites such as temperate forests.

Despite technological advancements over the past few decades, ALS data acquisition remains a relatively expensive option for monitoring forest growth. However, value in the application of ALS in a forestry context comes in the full suite of applications that are enabled by these data including forest operations, inventory, planning, and management for a broad suite of ecosystem goods and services. ALS acquisitions are also necessary for the production of a quality and highly detailed DEM, and high-quality attribute estimates, which together can largely balance the costs from the data's collection and processing (Lacriox and Charette, 2013). The province of Alberta, where this study area was located, has invested in near wall-to-wall

acquisition of ALS data between 2003 and 2014 and is interested in maximizing the utility of the existing data set (Coops et al., 2016). By supplementing ALS data acquisitions with DAP, the forest industry can save on costs (White et al., 2013b) and provide other predictive statistics including spectral tone, texture, and pattern (Pitt et al., 2014). These metrics have been valuable in quantifying other forest attributes that are challenging to resolve using ALS, such as species composition and health status (Wulder et al., 2008; White et al. 2013b). They also serve well for many forest monitoring applications including the monitoring of mountain pine beetle (Wulder et al., 2012a), monitoring forest fires (Rufino and Moccia, 2005) or tree species identification (Gini et al., 2012). These recommendations must also be considered with respect to the study site itself, where higher quality acquisitions are needed for disturbed, slow-growing, dense stands.

Chapter 4:

4.1 Introduction

In Chapter 3 of this thesis, I showed that both ALS and DAP can successfully derive forest attributes using the ABA, in complex and disturbed sites such as Slave Lake (Figure 1b). The results also indicated that using the indirect method to estimate growth, in this environment where stands are slow-growing was most effective in areas where mortality was low. Given individual tree dynamics and mortality typical of boreal environments, tree-level differences over time are hard to quantify (Yoga et al., 2017). However, forest inventories typically summarize forest characteristics at the stand level (Leckie and Gillis, 1995). Despite a high error-to-growth ratio on a per-plot basis in disturbed environments, if pixel-wise estimates were summarized to the stand-level and a sufficient sample size used, then general landscape-scale patterns in height growth should be apparent.

In forest inventories, landscape-scale growth patterns can inform on, and help quantify ecosystem services provided by different forest types, such as carbon sequestration, biodiversity conservation and forest product provision. Canada calculates carbon flux magnitudes for forest ecosystems using stock value estimates at different times (Penman et al., 2003). Stand growth estimates can allow fluxes to be estimated directly from changes in stock. Reporting on these fluxes is essential to different global coalitions seeking to address climate change, such as the requirements imposed by the criteria and indicator processes of the Montreal Process (Gillis et al., 2005). Forest structure, in particular, has been used as a biodiversity indicator in many forests. Various disturbances that induce stem mortality, removal, or that defoliate live or dead stems modify canopy structure and microclimate. These modifications impact the species present to varying extents, and so quantifying changes in these structures has conservation value (Guo et al., 2017). Finally, wood quality of individual stems, including species and size, inform on the product mixes available from them (Murphy, 2008). Quantifying growth can help inform predictions of future product mixes at the stand level and improve forecasting algorithms. In turn, drivers of growth inform forest managers on how to optimize the different ecosystem services provided by different site types. Quantifying growth patterns is an essential step in determining growth drivers.

Landscape-scale growth summaries can be used to study growth patterns, as well as for inventory purposes. The Albertan ecosite phase and ecosite-level stand summaries contain information regarding lesser-investigated ecological variables, such as soil temperature (Larcher, 2003) or excess moisture (Ward and Robinson, 2000). However, other growth patterns are not well-established. For example, there is ongoing debate over whether monospecific or mixedspecies sites have higher growth rates (Harper, 2015). The same debate persists for coniferous sites versus mixedwood sites in the Canadian boreal forest. Given that results from growth and productivity comparisons between sites differing in species composition in the Canadian boreal tend to be regionally dependent (Filipescu & Comeau, 2007; MacPherson et al., 2001; Man & Lieffers, 1999), determining growth patterns around the area of Slave Lake, Alberta is important for industry and jurisdictional forest managers to optimize harvesting operations and improve decision making in sustainable forest management.

In this chapter I examine the capacity of ALS and DAP technologies to assess ΔH over a subset of the Slave Lake study site in central Alberta (Figure 1c). Through the generation of these estimates, I seek to evaluate growth patterns across this study site with respect to ecological variables available from the AVI- and ecosite-scale inventory information.

4.2 Methods

4.2.1 Modeling height growth

In order to derive a spatially-explicit characterization of height growth for the stands considered in this analysis, the T1 ALS and T2 DAP canopy height models were adjusted to ensure they represent maximum stand height at each time step, as the focus was to assess the growth of the overstory trees. These two CHMs were then differenced and resampled to a spatial resolution of 10 m. The resulting wall-to-wall 10 m Δ H raster was then used as the basis for the spatially-explicit investigation of variations in height growth. Field data for individual trees were obtained from the twenty-seven plots established and measured between 2004 and 2006 and remeasured in 2012 or 2016 (Section 2.2). ALS data were acquired for the Slave Lake region between 2006 and 2008, and aerial images were acquired in 2015 (Sections 2.4 and 2.5). Despite the temporal mismatch between field and remote sensing datasets at both T1 and T2, fieldmeasured individual tree heights were not modified accordingly as done in Section 3.2.2. A detailed description of the modeling process is defined below.

Matching:

Individual trees (with DBH > 9 cm) within plots identified in Chapter 2 and used in Chapter 3 were isolated by either selecting locally tallest trees or spatially isolated trees on the ALS and DAP CHMs. The maximum height value within a 3 x 3 pixel window around each tree top was then matched to the corresponding field-measured heights. In total, sixty-four individual trees were matched.

Modeling:

A simple linear regression model was then developed to adjust the CHM to the heights of the field-measured trees. Separate models were developed for the T1 ALS and T2 DAP CHMs (Figure 6). Matches for each of the two models were filtered based on the magnitude of differences between field-measured heights and the CHM heights: the T1 matches were filtered for trees where this measured difference was > 1 m (n = 55); and the T2 matches were filtered for trees where this measured difference was > 1 m and < 8 m (n = 53). The modeled adjustments were then systematically applied to ALS and DAP CHMs (CHM_{adj}). As the focus was to assess the growth of the overstory trees, both CHMs were filtered to remove cells with heights < 5 m and outliers > 40 m prior to model adjustment.



Figure 6: Simple linear models used to adjust T1 and T2 CHMs developed from CHM pixel values to individual trees. Black line is the 1:1 line. Blue line is the line of best-fit.

Differencing/Filtering:

The T1 ALS CHM_{adj} was subtracted from the T2 DAP CHM_{adj} to generate the wall-towall, spatially explicit estimate of growth for each 2 m x 2 m grid cell (Δ H).

Aggregating:

The Δ H layer was aggregated to a 10 m spatial resolution using a fixed window and selecting the maximum 2 m x 2 m pixel value of Δ H within each 10 m x 10 m cell. Areas with negative growth (defined as < -2m), such as stands that had been harvested or burnt between T2 and T1 were set to no data. A 10 m buffer was applied to all stand boundaries to exclude edge pixels. Finally, areas of spatial mismatch where height growth exceeded 10 m (e.g. due to canopy gaps in T1 that were not captured by the DAP in T2) were excluded. Stand-level estimates of height growth were then developed by calculating the mean value for all of the 10 m Δ H pixels within each AVI stand or ecosite polygon.

Product validation is critically important prior to the application of any model. Growth validation requires field-derived estimates that are spatially-explicit, that represent the diversity of forest types existing over the landscape, and that temporally match the aerial data acquisition (White et al., 2013a). Error estimates derived in Chapter 3 were developed based on point cloud metrics at the plot-scale, and so are not applicable here. While growth values of individual trees were not calculated, validation was available from individual trees at each time. The T1 adjusted CHM had an RMSE of 1.44 m and the T2 adjusted CHM had an RMSE of 1.85 m. While the mean growth of the trees used in the models is not calculated here, the mean growth in the 27 plots presented in Chapter 3 was 0.87 m, suggesting that the error of the growth value of a given

pixel from the product is, on average, likely much higher than the actual growth of the represented in the pixel.

4.2.2 Evaluating patterns of growth

The height growth patterns across categories within each of the eight ecological variables (Table 2), and across/within ecosites within each of the three natural sub-regions (Table 4) were evaluated. The subset of Slave Lake included three natural sub-regions: boreal mixedwood, lower foothills, and upper foothills. Stand age was used to stratify the growth increments, and was derived from the AVI polygons: (1, young) < 60 yrs; (2, middle-aged) 60 yrs; > 120 yrs; > 120 yrs; (3, mature).

A stratified proportional sampling method was used to sample polygons (Figure 7). A sample of 1500 polygons was selected in each of three age strata using the *sample_n* function in the "dplyr" package within the R statistical software package. An ecological class was required to have a minimum size of 50 polygons in order to be included in the analysis. In total, eight ecological variables were used, representing 47 categories (Table 2). If all categories were represented in each age strata, and if all of these samples were sufficiently large, then this would result in 141 samples.

To sample stands within each ecosite type or ecosite phase, the same proportional sampling method was used as outlined above, except that ecosite units were split by natural sub-region prior to age stratification (Figure 7). This was necessary as ecosite types and phases are specific to natural sub-regions. A sample of 1500 polygons was selected in each of three age strata and per natural sub-region using the *sample_n* function in the "dplyr" package within the R statistical software package, and the minimum threshold number of required stands including a

category in the analysis was again 50. Growth among ecosite phases was only compared within ecosites, therefore ecosite types consisting of a single ecotype phase were excluded from the comparison of ecosite phases. In total, three natural sub-regions were used, representing 20 ecosite types and 23 ecosite phases. If all ecosite types were represented in each age strata, and if all of these samples were sufficiently large, then this would result in 60 samples of ecosite types. If each of these ecosite types further consisted of >1 ecosite phase (notably already known to be false, Table 4), and if each of these samples were sufficiently large, then this would result in 69 samples of ecosite phases.

One-way analysis of variance (ANOVA) was conducted to test for significant differences in mean canopy height growth. For the eight ecological variables, one ANOVA was performed per age strata for a theoretical total of 24 such comparisons. For ecosite types within each of the three natural sub-regions, one ANOVA was performed per age stratum for a theoretical total of 9 ANOVAs. For ecosite phases, one ANOVA was performed per stratum of age, natural subregion and ecosite type combination. Tukey's HSD post-hoc tests were used to determine which groups had significant differences.



Figure 7: Workflow illustrating the sampling methodology used for the proportional sampling of AVI and ecosite polygons to assess growth patterns across the landscape near Slave Lake. The green trajectory shows the steps involved in sampling the AVI stands and ecosite polygons to obtain samples categorized according to the eight considered ecological variables. The blue trajectory shows the steps involved in sampling the ecosite polygons to obtain samples categorized according to ecosite types and ecosite phases. The tan coloured shapes and arrows show steps and datasets involved in sampling for the ecological variables, ecosite types and ecosite phases. The "Samples" box (last of the three) shows a) samples by ecological variables, and b) samples by ecosite and ecosite phase obtained from each of three age strata.

4.3 Results

The sampling criteria outlined in Section 4.2.2 caused some samples to be excluded from the analysis. The eight ecological variables representing 47 categories from three different age strata included 103 samples, the 20 ecosite types from the different age strata included 39 samples, and the 23 ecosite phases from the different age strata included 39 samples. Restrictions caused all boreal mixedwood ecosite samples from age strata 2 and 3 to be excluded from the analysis. Height growth distributions from each of the eight ecological variables are shown in Figure 8. The one-way ANOVA result for each ecological variable and age class is presented in Table 11. Summary statistics of the height growth distributions describing each category of each ecological variable in each age class, and grouping results from the Tukey HSD post-hoc tests are presented in Table 12.

While patterns across age classes varied among ecological variables, the samples overall presented minimal variability in growth. Over eight years, the range of growth rates in these samples was from 0.29 m/year to 0.68 m/year. Categorization by canopy cover, revealed few trends. Samples in age classes < 60 years and > 120 years demonstrated small increases in growth with increasing canopy cover. In the comparison of samples taken by species dominance, black spruce stands demonstrated the lowest mean growth across all age classes. The sample of black spruce stands < 60 years had mean = 2.35 m, sd = 1.20 m, black spruce stands 60 – 120 years had mean = 2.70 m, sd = 1.07 m, and black spruce stands > 120 years had mean = 3.57 m, sd = 1.47 m. The sample of trembling aspen stands < 60 years demonstrated the highest mean growth of samples taken by species dominance and in that age class, with mean = 4.17 m, sd = 1.17 m. Few trends were apparent from the categorization by excess moisture. Height growth among samples in the < 60 years strata minimally increased from low limitation to medium-high
limitation. Growth was lowest in the high limitation category among stands > 120 years. In the comparison of samples taken by moisture regime, among samples from units < 60 years, submesic units demonstrated the least growth with mean = 3.5 m, sd = 1.32 m. Among samples 60 - 120 years mean growth and standard deviation increased from submesic to hygric. Subhydric-classified units demonstrated the least growth among samples 60 - 120 years (mean = 2.59 m, sd = 1.02 m), and among samples > 120 years (mean = 3.41 m, sd = 1.39 m). Growth patterns examined by nutrient regime showed that mean growth and standard deviation increase with increasing nutrient availability. Among samples < 60 years, mean growth increased from poor to rich, and in samples 60 - 120 years, mean growth increased from very poor to rich. In samples 60 - 120 years and > 120 years, measures of mean growth in very poor-classified units were lowest among their respective age strata. Very poor-classified units in the 60 - 120 years strata had mean = 2.44 m, sd = 0.91 m, while those in the > 120 years strata had mean = 3.16 m, sd = 1.54 m. No clear trends were apparent from samples taken by categories of soil temperature. Units classified as high-limitation demonstrated the lowest mean growth in all age strata. From assessing growth patterns demonstrated by categories of primary Canadian soil classification, mean growth was highest in units with orthic eutric brunisols among samples < 60 years (O.EB, mean = 5.11, sd = 1.44 m), and among samples > 120 years (mean = 5.43, sd = 1.49 m). Mean growth was lowest in terric mesisol-classified units among samples 60 - 120 years (T.M, mean = 2.65, sd = 1.14 m), and among samples > 120 years (mean = 3.59, sd = 1.57 m). Across age classes, mean growth measures in units with organic soils were lower than units with other soil classes. No growth trends were apparent across soil great groups, or subgroups. In examining units by categories of prevalent soil texture, in samples < 60 years, units with very dry sandy soils showed the lowest mean growth (SV1, mean = 3.39, sd = 1.23 m) while units with dry

clayey soils showed the greatest mean growth (SD4, mean = 4.86, sd = 1.37 m). Units with organic soils demonstrated the lowest mean growth among samples 60 - 120 years (SR, mean = 2.65, sd = 1.04 m) and among samples > 120 years (mean = 3.26, sd = 1.43 m).

Ecological Variable	Age Class	F-statistic	Degrees of Freedom	p-value
Conony Cover	1	56.58	3	***
Canopy Cover	2	2.96	3	
	3	4.4	3	**
Species	1	76.23	3	***
Dominance	2	118.13	4	***
	3	54.91	3	***
Nutrient Desires	1	10.85	2	***
Nutrient Regime	2	48.15	3	***
	3	23.66	3	***
Moisture	1	9.84	3	***
Regime	2	35.49	4	***
-	3	16.1	4	***
Europe Maisture	1	11.09	2	***
Excess Moisture	2	4.65	3	**
	3	14.78	3	***
Soil	1	7.18	3	***
Temperature	2	10.44	3	***
-	3	17.4	3	***
Soil	1	32.91	4	***
Classification	2	12.4	6	***
	3	10.47	5	***
Coll Torrer	1	34.17	2	***
Son rexture	2	25.82	4	***
	3	20.96	3	***

Table 11: One-way ANOVA results describing categorical mean differences for each ecological variable and ageclass. *p < 0.05. **p < 0.01. ***p < 0.001.</td>



Figure 8: Stand growth distributions in categories of ecological variables. Distributions describe stands stratified by age class. Y-axis units for Δ H are estimated mean growth in m. Black horizontal bars within the boxes show the medians of the distributions. Boxes show the and 3rd and 2nd quartiles of the distributions, while limits of the upper and lower tails are (Q3 + 1.5 * IQR) and (Q2 - 1.5 * IQR) respectively. Q signifies quartile and IQR stands for interquartile range.

Table 12: Summary statistics of the height growth distributions describing each category of each ecological variable in each age class, and grouping results from the Tukey HSD post-hoc tests. Different letters under Tukey's HSD group indicate significant difference between groups at α =0.05 determined with Tukey's HSD test. Groups that share the same letter are not significantly different. For example, AVI polygon samples selected to compare stands with canopy cover classes A and B are not significantly different, while samples selected to compare stands with classes A and C are significantly different.

Ecological Variable	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD Group
		А	3.21	1.37	453	а
	1	В	3.41	1.29	318	а
		С	3.88	1.27	454	b
		D	4.43	1.34	273	c
Conorri		А	3.58	1.32	513	а
Canopy	2	В	3.54	1.52	225	а
Cover		С	3.74	1.39	419	а
		D	3.8	1.11	340	а
		А	4.14	1.47	572	а
	3	В	4.38	1.69	256	ab
		С	4.32	1.59	389	ab
		D	4.52	1.37	282	b
		Sb	2.35	1.2	78	а
	1	P1	3.44	1.29	551	b
		Aw	4.17	1.17	693	c
		Bw	3.17	1.45	78	b
	2	Sw	4.09	1.43	81	ab
Species		Sb	2.7	1.07	446	с
Dominance		P1	3.93	1.01	420	а
		Aw	4.19	1.16	437	b
		Bw	3.8	1.25	56	ab
	3	Sw	4.59	1.41	219	а
		Sb	3.57	1.47	455	b
		P1	4.62	1.51	670	а
		Aw	4.76	1.48	138	а
	1	Poor	2.88	1.02	50	а
	1	Medium	3.7	1.37	1017	b
		Rich	3.88	1.69	414	b
Nutriant		Very Poor	2.44	0.91	76	а
Regime	2	Poor	3.7	1.23	287	b
Regime		Medium	3.93	1.39	627	b
		Rich	4.43	1.7	505	с
	3	Very Poor	3.16	1.54	85	a
	3	Poor	4.68	1.53	361	b
		Medium	4.78	1.7	580	b

Ecological Variable	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD Group
		Rich	4.72	1.81	469	b
		Submesic	3.5	1.32	625	а
	1	Mesic	3.93	1.5	433	b
		Subhygric	3.92	1.63	338	b
		Hygric	3.95	1.99	61	ab
		Submesic	3.64	1.36	286	а
	2	Mesic	4.04	1.18	548	b
Moisture	Z	Subhygric	4.35	1.67	461	с
Regime		Hygric	4.45	1.77	101	bc
		Subhydric	2.59	1.02	84	d
		Submesic	4.78	1.64	201	а
	2	Mesic	4.92	1.59	647	b
	3	Subhygric	4.56	1.83	458	с
		Hygric	4.73	2.15	97	bc
		Subhydric	3.41	1.39	87	d
	1	Ĺ	3.56	1.36	970	а
	1	L_H	3.92	1.65	116	b
		M_H	3.95	1.64	367	b
	2	Н	3.75	1.87	174	а
Excess		L	3.88	1.28	770	а
Moisture		L_H	3.76	1.23	82	ab
		M_H	4.14	1.61	472	b
	3	Н	3.9	1.68	182	а
		L	4.79	1.58	699	b
		L_H	4.87	1.72	157	b
		M_H	4.58	1.84	460	b
	1	L	3.61	1.37	970	а
	1	L_H	4	1.66	116	b
		М	3.97	1.69	337	b
		Η	3.45	1.82	75	ab
S all		L	3.78	1.25	770	а
S011 Temperature	2	L_H	3.98	1.3	82	ab
Temperature		Μ	4.25	1.7	398	b
		Η	3.74	1.67	248	а
		L	4.81	1.53	699	a
	3	L_H	4.98	1.74	157	а
	-	Μ	4.58	2.05	372	а
		Н	3.98	1.72	270	b
Soil	1	O.EB	5.11	1.44	78	a
Classification	1	E.EB	3.39	1.07	358	b
		O.LG	4.11	1.6	168	с

Ecological Variable	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD Group
		O.GL	3.25	1.22	183	b
		BR.GL	3.79	1.54	636	с
		O.EB	4.02	1.39	72	ab
		E.EB	4.11	1.64	77	ab
	2	O.LG	4.52	1.7	110	а
	Z	O.GL	4.2	1.71	111	ab
		BR.GL	3.96	1.4	940	b
		CU.R	4.46	1.89	74	ab
		T.M	2.65	1.14	60	с
		O.EB	5.43	1.49	65	а
		O.LG	4.56	1.67	96	bc
	3	O.GL	4.27	1.92	124	bd
		BR.GL	4.8	1.7	1001	c
		CU.R	4.78	2.19	68	abc
		T.M	3.59	1.57	71	d
	1	SV1	3.39	1.23	357	а
	1	SD4	4.86	1.37	75	b
		SM4	3.76	1.49	1012	c
		SV1	3.95	1.52	76	а
	2	SD4	4.25	1.3	58	ab
Soil Texture	Z	SM4	3.98	1.42	1172	а
		SWm	4.77	1.89	91	b
		SR	2.65	1.04	86	c
		SD4	4.82	1.61	61	а
	3	SM4	4.61	1.69	1228	а
		SWm	4.97	1.84	92	а
		SR	3.26	1.43	92	b

Height growth distributions categorized by ecosite type compared to units separated by each of the three natural sub-regions are shown in Figure 9. The one-way ANOVA result for each natural sub-region and age class is presented in Table 13. Summary statistics of the height growth distributions describing each ecosite of each natural sub-region in each age class, and grouping results from the Tukey HSD post-hoc tests are presented in Table 14. In the boreal mixedwood, among samples < 60 years, mean and standard deviation of height growth increased

from site types "a" to "f". In the lower foothills, among samples < 60 years, mean growth decreased while the standard deviation of growth increased from site types "c" to "i". Among samples 60 - 120 years, the mean growth increased from site types "d" to "f", peaking at "i" (mean = 4.71, sd = 1.73 m). Site type "k" units demonstrated the lowest mean growth (mean = 2.83, sd = 0.86 m). Samples > 120 years showed little variation in growth. Only site type "k" showed significantly less growth than the other samples (mean = 3.33, sd = 1.31 m, group = "b"). In the upper foothills, in samples < 60 years, mean growth decreased from site types "e" to "ff". Among samples 60 - 120 years, a trend of increasing mean growth was apparent from site types "a" to "j". In samples > 120 years, no trend was apparent.

Natural Sub- region	Age Class	F-statistic	Degrees of Freedom	p-value
Boreal Mixedwood	1	41.85	4	***
Lower	1	11.39	3	***
Foothills	2	25.98	6	***
	3	14.68	6	***
Upper	1	30.68	3	***
Foothills	2	30.62	5	***
	3	4.9	5	***

Table 13: One-way ANOVA results describing ecosite mean differences for each natural sub-region and age class.*p < 0.05. **p < 0.01. ***p < 0.001.



Figure 9: Stand growth distributions categorized by ecosite type. Distributions describe stands stratified by age class. Y-axis units for Δ H are estimated mean growth in m. Black horizontal bars within the boxes show the medians of the distributions. Boxes show the and 3rd and 2nd quartiles of the distributions, while limits of the upper and lower tails are (Q3 + 1.5 * IQR) and (Q2 - 1.5 * IQR) respectively. Q signifies quartile and IQR stands for interquartile range.

Table 14: Summary statistics of the height growth distributions describing each ecosite of each included natural sub-region and age class, and grouping results from the Tukey HSD post-hoc tests. Different letters under Tukey's HSD group indicate significant difference between groups at α =0.05 determined with Tukey's HSD test. Groups that share the same letter are not significantly different. For example, ecosite polygon samples selected to compare boreal mixedwood natural sub-region stands with ecosite types "b" and "d" are not significantly different, while samples selected to compare stands with ecosite types "a" and "b" are significantly different.

Natural Sub-region	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD group
		a	2.67	0.98	56	а
Boreal	1	b	3.44	1.05	796	b
Mixedwood	1	d	3.30	1.17	229	b
		e	4.20	1.51	331	с
		f	4.45	2.05	68	с
		с	4.81	1.41	281	а
	1	e	4.49	1.41	668	b
Lower		f	4.22	1.78	392	с
Foothills		i	3.91	1.94	88	с
_	2	с	3.91	1.30	94	ab
	2	d	3.70	1.09	294	a
		e	4.31	1.18	336	bc

Natural Sub-region	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD group
		f	4.34	1.61	460	bc
		h	3.89	1.34	82	ab
		i	4.71	1.73	119	с
		k	2.83	0.86	93	d
-		с	5.05	1.56	98	a
		d	4.69	1.62	356	а
	2	e	5.00	1.52	324	а
	3	f	4.70	1.92	406	a
		h	4.60	1.68	79	a
		i	4.78	1.92	111	a
		k	3.33	1.31	111	b
		с	3.18	1.27	689	a
	1	e	3.91	1.52	369	b
		f	3.24	1.42	279	a
		ff	2.68	0.97	69	с
-		a	2.70	1.00	53	а
	2	с	3.28	1.28	587	b
I Iron on		d	3.33	1.03	90	ab
Upper		e	3.97	1.35	314	с
FOOLIIIIS		f	4.04	1.70	272	с
		j	4.91	1.77	53	d
-		с	4.75	1.54	351	ab
		d	4.27	1.29	134	ac
	3	e	4.75	1.70	450	b
		f	4.29	1.85	315	с
		h	4.60	1.86	102	abc
		j	4.27	1.92	61	abc

Height growth distributions categorized by ecosite phase from units separated by each of the three natural sub-regions are shown in Figure 10. The one-way ANOVA result for each natural sub-region, age class, and ecosite is presented in Table 15. Summary statistics of the height growth distributions describing each ecosite phase of each natural sub-region in each age class, and grouping results from the Tukey HSD post-hoc tests are presented in Table 16. In the categorization by ecosite phase, in the boreal mixedwood, broadleaf-dominant phases demonstrated larger mean growth than conifer-dominated phases in site types "b" and "c". In the lower foothills, the mixedwood phase demonstrated higher mean growth than the lodgepole pine-dominated phase in ecosite type "f" among samples < 60 years and 60 - 120 years. The mixedwood phase also demonstrated higher mean growth than the lodgepole pine-dominated phase in ecosite type "e" among samples 60 - 120 years. In the upper foothills, among samples < 60 years, the mixedwood phase again demonstrated higher mean growth than the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase again demonstrated higher mean growth than the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase again demonstrated higher mean growth than the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite type "e". Among samples 60 - 120 years, the lodgepole pine-dominated phase in ecosite types included in this stratum: "c", "e", and "f". No significant differences were found among phases in sites > 120 years.

Natural Sub- region	Age Class	Ecosite	F-statistic	Degrees of Freedom	p-value
Boreal	1	b	71.33571	1	***
Mixedwood		d	58.78036	1	***
	1	с	1.035431	1	
	1	e	0.509704	2	
		f	5.865129	2	**
Lower	2	d	1.770373	1	
Foothills	2	e	0.903013	2	*
		f	12.18725	2	***
-	2	d	7.316688	1	**
	5	e	1.725258	1	
		f	1.717684	2	
	1	e	54.10336	1	***
Ummon	2	С	23.50248	1	***
Upper Footbills	2	e	39.97021	1	***
Footinits		f	38.73211	1	***
-	3	e	16.87644	1	
		f	0.624205	1	

Table 15: One-way ANOVA results describing ecosite phase mean differences for each natural sub-region, ageclass, and ecosite type. *p < 0.05. **p < 0.01. ***p < 0.001.</td>



Figure 10: Stand growth distributions categorized by ecosite phase. Distributions describe stands stratified by age class. Y-axis units for Δ H are estimated mean growth in m. Black horizontal bars within the boxes show the medians of the distributions. Boxes show the and 3rd and 2nd quartiles of the distributions, while limits of the upper and lower tails are (Q3 + 1.5 * IQR) and (Q2 - 1.5 * IQR) respectively. Q signifies quartile and IQR stands for interquartile range.

Table 16: Summary statistics of the height growth distributions describing each ecosite phase of each included natural sub-region and age class, and grouping results from the Tukey HSD post-hoc tests. Different letters under Tukey's HSD group indicate significant difference between groups at α =0.05 determined with Tukey's HSD test. Groups that share the same letter are not significantly different. For example, ecosite polygon samples selected to compare lower foothills natural sub-region stands with ecosite phase types "f2" and "f3" are not significantly different, while samples selected to compare stands with ecosite phase types "f1" and "f2" are significantly different.

Natural Sub-region	Age Class	Category	Mean	Standard Deviation	n	HSD group
D		b2	3.56	1.07	645	a
Boreal	1	b4	2.67	0.91	124	b
Mixedwood		d1	3.71	1.19	112	а
		d3	2.63	1.01	82	b
		c1	4.88	1.39	148	а
		c3	5.01	1.30	115	а
		e1	4.50	1.61	133	а
	1	e2	4.40	1.45	260	а
	1	e3	4.58	1.33	263	а
		f1	3.55	1.40	61	а
		f2	4.43	1.72	214	b
		f3	4.32	1.72	114	b
		d1	3.68	0.93	103	а
	_	d2	3.77	1.05	190	а
Lower		e1	3.73	1.19	56	а
Foothills	2	e2	4.05	1.01	159	а
	-	e3	4.63	1.29	95	b
		f1	4.00	1.42	209	а
		f2	4.67	1.54	158	b
		f3	4.85	1.41	79	b
		d1	4.13	1.30	95	а
		d2	4.87	1.50	261	b
	3	e3	4.87	1.47	119	а
	5	e4	4.97	1.80	128	а
		f1	4.78	1.73	197	а
		f3	5.09	2.03	97	а
		f4	4.81	1.74	77	а
	1	e1	3.61	1.32	210	а
		e2	4.51	1.55	143	b
Upper		c1	3.39	1.18	446	а
Foothills	2	c4	2.70	1.26	137	b
	2	e1	4.25	1.22	176	a
		e3	3.24	1.18	105	b
		f1	4.76	1.60	132	a

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Natural Sub-region	Age Class	Category	Mean	Standard Deviation	n	Tukey's HSD group
		f4	3.53	1.46	123	b
		e1	5.00	1.63	187	а
	3	e3	4.63	1.51	209	а
		f1	4.54	1.70	119	a
		f4	4.14	1.79	168	а

4.4 Discussion

The growth patterns seen across ecosites and natural sub-regions can be used to contextualize the possible relationships between the considered ecological variables and height growth (Figures 8 and 9). Generally, the links between patterns demonstrated by ecosite and by patterns demonstrated by the ecological variables were most apparent using nutrient regime, moisture regime, species dominance and the soils classification. First, bog type ecosites ("k") had distinctly lower growth than other ecosites. This is expressed through trends in the ecological variables, including low growth in the very nutrient-poor units, in subhydric units, on sites dominated by black spruce, and units with organic soils (soil type = "SR", soil classification = "T.M"). The second trend was the generally increasing mean growth across ecosites in the boreal mixedwood, and in units 60 - 120 years in the lower and upper foothills. The trend of increasing growth with increasing nutrient and moisture regime was apparent from "very poor" to "rich", and from "submesic" to "hygric" respectively in corresponding age classes. However, the trend was not consistent. Thirdly, in young units in the lower and upper foothills, rich and moist ecosite types demonstrated comparatively lower mean growth than might be expected. One reason for this could be that the water table height has a large impact on the time required for seedling establishment in these natural sub-regions. When trees are removed due to disturbance,

the water table may rise significantly on wetter sites. In sites that are also more eutrophic, shrub, forb and grass species are often effective colonizers, further impeding tree establishment (Lawrence et al., 2005, Willoughby, 2007, Moisey et al., 2016). Following establishment, these sites may be highly productive, but the time required for establishment is variable. Leading from this, another possibility is that the observed decreasing trends were a result of the chosen limits for the age classes. Other studies on succession in this area of Alberta used different age limits for their designation of young and mature forests. Morgantini & Kansas (2003) studied successional rates in the upper foothills and subalpine natural sub-regions of Alberta and found that elevation and water table depth strongly influenced the progression of a site towards maturation. Stands included in their sample of a 70 - 130 year age class were described with qualities characteristic of young forests including high stem density, low proportion of shadetolerant species, and low volume of downed woody debris. Corns, Downing, & Little (2005) assessed top height in the lower foothills and upper foothills in stands up to 40 years old. The patterns shown there generally match the growth patterns presented here in stands < 60 years. The authors found that top height in the lower foothills generally decreased from drier, more mesotrophic sites to wetter, more eutrophic sites ("c" to "i"): top height in the upper foothills was low in "c", higher in "d", "e", and "f", and lower again towards "i".

Stands composed of a deciduous/coniferous mix generally showed greater mean height growth than lodgepole pine stands, while the mean height growth of mixed stands was variable in comparison to trembling aspen stands. Other studies that have compared the productivity of monospecific stands to mixed-species stands within the natural sub-regions considered here came to different conclusions. MacPherson, Lieffers, & Blenis (2001) assessed biomass and periodic annual biomass increment (PAI) in trembling aspen stands, with and without white

spruce present in the understory, in northeastern Alberta. They found that both biomass and PAI were greater in mixed plots when summed over both species. Man & Lieffers (1999) provide an overview of ecological theory supporting why mixes of trembling aspen and white spruce would be expected to be more productive than monospecific stands of either species based on competitive reduction through differential utilization of resources and facilitative production through improved nutritional conditions, mitigation to pest attacks, and increased resistance to blowdown. However, Filipescu and Comeau (2007) studied competitive interactions between trembling aspen and white spruce in stands up to 60 years old in the boreal mixedwood natural sub-region. Their competition indices were able to predict spruce growth with an R^2 of 0.7; however, they found that a separate model was required for the prediction of growth in stands 10 -20 years than for stands 20-60 years, suggesting that differences in competitive effects on growth exist between stands of different ages. Contextualized by Man & Lieffers (1999), this is likely due to differences in structural complexity of the stands in these age classes. In younger stands, competition was likely higher as the trembling aspen and white spruce trees would have been much closer in height, and nutritional inputs from organic matter would have been lower. Harper (2015) compared growth interactions in mixes of trembling aspen and lodgepole pine in stands 22 - 39 years in the Sub Boreal Spruce biogeoclimatic zone of northern interior British Columbia and found that pine growth was a linear function of competitive reduction, since pine volume, basal area, and merchantable volume were very sensitive to changes in aspen competition. This result suggests that the composition of the species mix may also affect the productivity in a comparison with monospecific stands.

Growth distributions in units > 120 years were poorly differentiated using the ecological variables, the ecosites, and ecosite phases. As well, the mean height growth values in this age

class were similar to those of the first and second age classes, which is contrary to the understanding that stand height growth is initially rapid, and then slows with senescence (Ryan et al., 1997) (Tables 12, 14, 16). There are at least two potential explanations for this. First, the ranges of age classes were chosen to reflect the full range of ages present in the AVI data. As previously explained, successional rates are variable in this region as they are dependent on a number of ecological factors. If successional rates in the region are slow, then overall height growth in this age category may not have decreased yet. Second, it is possible that these data reflect the inability of DAP to record forest canopy gaps (Vastaranta et al., 2013; White et al., 2018). In the presence of gaps, ALS is able to penetrate down into the canopy. When differencing the two CHMs, canopy gaps are likely to be locations of maximum local growth, which would be emphasized upon aggregation of the growth layer to a coarser resolution. As younger stands tend to be denser with fewer gaps, the growth of older stands may appear inflated in contrast (Chen and Popadiouk, 2002).

The trends and distributions shown in this study support the use of a multi-sensor approach to observing growth patterns over an eight-year period in Alberta's foothills and in the south of the boreal mixedwood sub-region in young and mature sites. In the first two age classes, growth trends across ecosite distributions generally followed the expected patterns, with logical ecological variables that differentiated them: species dominance, nutrient regime and moisture regime. However, caution must be taken when using this approach in this region to describe the expected growth of a given stand. The stands are slow-growing with high levels of mortality. As shown in Chapter 3, even optimized models for Lorey's height growth had a high %RMSE as the model error was relatively large as compared to the growth magnitudes of the stands (Figure 3). While these data are suitable for characterizing large-area trends in height growth, to describe

individual stands with a multi-sensor approach using the quality of data presented here, the approach would either be best applied to more rapidly-growing stands, or the time between remotely-sensed data acquisitions would need to increase.

Chapter 5: Conclusion

5.1 Overview

The Canadian forest products industry aims to maximize the value of timber and other forest products, and improve supply chains. To accomplish this, enhanced forest inventories containing timely, accurate and consistent measures of forest stand structure, composition and productivity are required (Alam et al., 2014). The development and use of ALS point clouds to measure forest structural variables offer a spatially efficient means of complimenting existing methods of forest inventory. Barriers such as cost and complexity of data acquisition still impede the full integration of ALS technologies into data acquisition methods for forest inventories. DAP point clouds have been proposed as a cost-effective alternative to ALS point clouds for inventory re-measurement. The primary objective of this thesis was to examine the capacity of ALS and DAP technologies to assess Lorey's height growth (ΔH_L) in a disturbed boreal forest near Slave Lake in central Alberta. Findings from each of the research questions derived to fulfill this objective are outlined below.

Question 1. How can ALS and DAP point clouds be utilized to derive measures of height growth at Slave Lake, AB, Canada?

This question was investigated in Chapter 3 of this thesis. As few studies have explored the accuracy of forest attribute estimates from image-based point clouds in highly disturbed environments (White et al., 2015), this question had to be divided into two subquestions. The first determined which variables to use in modeling height and the second investigated how the predictive model errors responded to stand condition. Findings from each of these subquestions are summarized below.

a) Does the predictive capability of linear models for Lorey's mean height growth improve when including canopy cover and/or canopy height variability metrics in the T1 and T2 models?

To assess the utility of including additional predictor variables in the predictive models for ΔH_L , I compared models using only height metrics with those using combinations of height, canopy cover, and height variability metrics. Predictor variables were selected using forward step-wise multiple linear regression.

Including additional categories of predictor variables reduced the %RMSE_G, although %RMSE_G was high for both *multi* and *single* equations. These results were attributed to slow height growth and to high amounts of plot-level mortality and disturbance. Given a mean growth rate of 0.11 m yr⁻¹ in this set of plots, approximately 12.79 years (an additional ~5 years) would be required for growth to exceed the modeling error (Eq. 6). Given the DAP correlation strengths with H_L the results indicate that metrics of canopy cover and height variability should not be included for H_L modeling using DAP point clouds in disturbed boreal environments. However, given the results of comparative studies (e.g., White et al., 2015), the utility of including canopy cover and height variability metrics may depend on forest type and structure.

b) How is the predictive capability for Lorey's mean height growth impacted by increasing plotlevel mortality? To assess the impacts of plot mortality on ΔH_L estimates in Slave Lake, I iteratively measured the accuracy of optimized height models while incrementing the mortality in the dataset. Plots were ordered according to tree mortality (defined as the percentage of dead trees in a plot) observed during the T2 field campaign. Model error for ΔH_L was then evaluated iteratively for a subset of plots with increasing sample size (one additional plot at each iteration), and incremental mortality.

The mortality sensitivity assessment showed that \mbox{RMSE}_{GM} increased with increasing plot-level mortality. The trend between model error and mortality indicated that when the maximum allowable mortality was approximately 25%, the \mbox{RMSE}_{GM} was just below 100%. The overlay of \mbox{RMSE}_{GM} with distributions of \mbox{RMSE}_{GR} showed that minimizing plot-level mortality successfully minimized the prediction errors, particularly at sample sizes where n > 15.

Question 2. What patterns of growth are apparent in stands near Slave Lake, AB with respect to ecological factors available from the Alberta AVI and ecosite-scale inventories?

This question was investigated in Chapter 4 of this thesis. Quantifying growth patterns is an essential step in determining growth drivers. Landscape-scale growth patterns can also inform on, and help quantify, ecosystem services provided by different site types. Landscape-scale growth summaries can be used to study growth patterns, which can be used to inform on distributions of many ecosystem goods and services (Section 5.2). ALS and DAP point clouds at Slave Lake were used to determine site-wide patterns of Δ H with respect to eight selected ecological variables, ecosite types and ecosite phases.

Building on the findings from Chapter 3, wall-to-wall height models for T1 and T2 were developed by systematically adjusting the T1 and T2 CHMs. A simple linear model for adjusting each CHM was developed by matching pixel values to heights of individual trees. The models were then extrapolated over the study sub-region (Figure 1c), and the difference was taken between the two adjusted CHMs to estimates ΔH . Pixel values were then aggregated (from 2 m to 10 m) and averaged generate a stand-level estimate of ΔH . ANOVA tests were conducted to test the significances of differences between the means of ΔH across eight ecological variables, ecosite types and ecosite phases.

Patterns demonstrated by the ecological variables are most apparent using nutrient regime, moisture regime, species dominance, and the soil classification. Increasing height growth with increasing nutrient and moisture regime is apparent from "very poor" to "rich", and from "submesic" to "hygric", respectively, in young and mature units. Stands composed of a deciduous/coniferous mix generally showed a greater mean height growth than lodgepole pine stands, while mean height growth was variable in comparison to trembling aspen stands. Growth distributions in the oldest age class were poorly differentiated for all categories tested. Two suggested explanations were: a) the age ranges for the chosen classes were too broad to capture variability in growth patterns within younger age classes, b) stands in this age class possibly contain more gaps in which growth values were overestimated. The results from this study support the use of a multi-sensor approach to observe growth patterns in young and mature stands over an eight-year period in Alberta's foothills and in the south of the boreal mixedwood sub-region.

5.2 Implications

Forest managers should be cautious when utilizing multi-temporal remote sensing methods for assessing stand-level height growth if growth is slow and they have high levels of mortality on their landbase. Prior to use, forest managers must have a solid understanding of local forest structural attributes, including mortality rates, expected levels of growth, and gap dynamics. As the error magnitudes of predicted growth values are propagated when using an indirect modeling approach, estimates become more reliable as growth increases. Thus, multitemporal remote sensing of height growth is best suited either to faster-growing forests or to slow-growing forests with long re-measurement intervals. In either context, the key is that the timing of data acquisition should be guided by expectations of height growth, unless some other imperative drives the inventory cycle.

DAP continues to show promise as a complementary source of 3D data to ALS for sites where mortality is low. The primary motive for implementing DAP for forest inventory remeasurement is the significant cost savings over ALS acquisition flights, though the need for an ALS acquisition for the development of a high resolution DEM remains. From a forest management perspective, cost-savings translates into a greater ability to allocate resources towards quantifying forest attributes. This, in-turn, expands the data available to inform decision making by permitting analyses that relate forest attributes to ecosystem goods and services provided by forests. Below, I have divided some motivations behind forest attribute quantification into four categories: ecological, economic, cultural and sustainability.

Ecological:

Two valuable ecosystem services provided by Canadian boreal forests include carbon sequestration and biodiversity conservation. Canada estimates its forest carbon budgets by calculating the difference between gains and losses, which requires detailed stock estimates at different times (Penman et al., 2003). Uncertainties are high in the above and below-ground estimation of carbon stocks and fluxes in Canada's forests. Reducing the uncertainties of Canada's current and future carbon balance requires addressing gaps in monitoring, observation and quantification of carbon cycling in forested ecosystems (Kurz et al., 2013). Forest vertical structure has also been used as a biodiversity indicator in a broad range of forest ecosystems. Structure is affected by disturbances such as wildfires, harvesting and road development and will in turn favour certain species. Variations in canopy structure create microclimates with differing habitats. Quantifying changes in forest structure therefore also has conservation value (Guo et al., 2017).

Economic:

In 2016, the forest industry contributed over \$23.1 billion (1.2%) to Canada's GDP. The industry accounted for 211,075 direct jobs, and approximately 95,000 indirect jobs in related activities, demonstrating that many peoples' livelihoods and the well-being of the Canadian economy heavily depends on the industry's performance (*The State of Canada's Forests: Annual Report 2016*, 2016). Since the industry hit its lowest real-GDP contribution in 2009, it has been growing steadily with the Canadian economy. Some products derived from harvesting include lumber, newsprint, printing paper, wood panels, wood pulp and bioproducts. As forest products differ with respect to optimal desired wood quality, different forest compositions and site types

lend themselves to different product mixes (Murphy, 2008). As a means of assessing forest attributes and the supply of raw materials available from them, a means of quantifying forest attributes is necessary.

Cultural:

An estimated 70% of Indigenous people in Canada live near forests (The State of Canada's Forests: Annual Report 2017, 2017), and hundreds of Indigenous communities are within the boreal region. The boreal landscape is extremely valuable to these populations for providing food and medicine, maintaining social structure and for spiritual connection with both ecosystem communities and the land itself. Edible plants provide vital nutritional supplements to many communities whose diets are often predominately meat-based. Different plant types can provide vitamins C, A, calcium, and fibre (Karst, 2010). Medicines are fundamental to holistic healing methods and come from a variety of plant types. As the economies of many communities depend on goods acquired from the forest, maintaining relationships between and within them rely on the quality and consistent availability of these goods (Parlee et al., 2006). Inherently, the belief system of many Indigenous communities is such that if you take care of the land through the respectful use of resources, then the land will take care of you. This ideology carries with it an understood meaning of "respectful use", which although complex and often community specific, often includes the avoidance of overharvesting, waste, destruction of the land and generally responsible stewardship (Andre & Fehr, 2002; Marles et al., 2000; SENES Consultants Limited, 2008). In accordance with the laws around consultation and negotiation with Indigenous communities, a means of quantifying forest attributes related to food availability and sustainable harvest is required.

Sustainability

It is necessary to provide comparable forest information in response to national and international concerns about sustainable forest management, including the assessment of forest health, biodiversity and forest productivity. It follows that Canada must address the criteria and indicator processes of the Montreal process to report on climate change (Gillis et al., 2005).

To ensure sustainable forest harvest over the long term, harvesting volumes are regulated by the provincial and territorial governments through the specification of allowable annual cuts (AAC). AAC indicates the level of harvest permitted on a particular area of crown land over a set number of years (*The State of Canada's Forests: Annual Report 2017*, 2017). Harvesting practices are subject to ongoing forest monitoring to ensure that specifications are followed. Forest inventories thus also have a vital role in temporal forest monitoring and sustainable forest management planning.

5.3 Limitations

There are a few general limitations to implementing DAP as compared to ALS which were factors in the DAP acquisitions in this study. First, pixel-matching algorithms that produce the point cloud are highly sensitive to ambient light and weather conditions (Baltsavias et al., 2008; Gobakken et al., 2015). Data collection for DAP should be restricted to certain times of day and favorable weather conditions for image consistency if acquisition occurs over many days. This is slightly offset by the rapid rate of acquiring DAP, as flights can be higher and faster than ALS flights (Leberl et al., 2010). However, given the large size of the Slave Lake site, acquisition occurred over three days, and light and weather conditions varied slightly.

Caution should be taken when using the method for height growth estimation presented in Chapter 4 to describe the expected growth within a given unit. The stands around Slave Lake are slow-growing with high levels of mortality. As shown in Chapter 3, even optimized models for Lorey's height growth using a multi-sensor approach in this region have a high %RMSE, as the model error is relatively large as compared to the growth magnitudes of the stands (Figure 3). As such, the following must be considered upon assessing the confidence in estimates from the wall-to-wall height growth product. First, height at each time was estimated by adjusting CHMs according to individual tree heights rather than by modeling height using suites of point cloud metrics. This approach was very rough as trees were matched to the maximum height of a 3 pixel by 3 pixel window on a grid over the individual stems. The uncertainty associated with this matching process was not evaluated. Furthermore, errors from height estimates at each time were not propagated, thus only the RMSE values from models at each time can be used to inform on the accuracy of growth values. Growth validation requires field-derived estimates that are spatially-explicit, that represent the diversity of forest types existing over the landscape, and that temporally match the timing of the aerial data acquisition (White et al., 2013a). Limitations to validation data meeting these criteria include costs of organizing field excursions, accessibility or remoteness of sample plot locations, and weather conditions (Köhl et al., 2006). In the assessment of growth, these challenges and limitations are compounded by the necessitation of more field excursions, the additional challenge of accurately relocating field plots, eliminating plots that experienced stand-replacing disturbances, and the required organization of more aerial data acquisitions that are temporally congruent with the field data. Model validation must also be performed at the scale at which the model was developed. Validation for the product shown

here could therefore be performed using growth measured from trees used to model the CHM adjustments, or preferably using cross-validation (White et al., 2017).

5.4 Future Research

Future work in multi-sensor growth studies should continue to focus on attribute estimation and modeling optimization. The majority of studies assessing growth using 3-D remotely sensed data and DAP for inventory cycle optimization have been in less complex Scandinavian boreal sites. More research is required as an extension to Chapter 3 to evaluate the combination of ALS and DAP data to estimate forest growth in unmanaged, natural boreal forests, particularly for basal area and gross total volume. In the continued interest of reducing the costs of updating forest inventories, the refinement of growth estimation can be incorporated into growth and yield models for optimizing harvesting rotations (Tompalski et al., 2016).

Future work assessing the utility of a multi-sensor approach to assess growth patterns on a landscape scale can be extended to identify the drivers of growth. Identifying growth patterns can be seen as a step in a larger workflow to develop predictive models for growth, which account for the spatial correlation of the considered environmental variables (Bontemps and Bouriaud, 2014). Patterns could also be identified among different ecological variables, and utilizing different data sources and methodologies than those presented in Chapter 4. Other variables that may be worth testing include insolation, canopy cover, and wet areas mapping data. Canopy cover is available from the AVI polygons; however, this product is estimated from aerial photo interpretation. A canopy cover product derived using ALS and summarized at the polygon scale may differentiate growth patterns more effectively. Wet areas maps are also a product derived from ALS that estimates depth to the water table based on landscape topography

and hydrographic features present on the surface. This product has already shown value for categorizing productivity and predicting regrowth in harvested stands (Nijland et al., 2015), and so may be able to provide different information than the available moisture regime classification from the AVI.

In Chapter 4, the decision to aggregate growth using the maximum value was hypothesized to contribute to the increase in observed growth across all age classes. Three possible alternative methods to resolve this are as follows. First, aggregation could be avoided altogether and growth could be summarized at the AVI and ecosite polygon level by the mean of values obtained from the finer-resolution growth layer within the polygon boundaries. Second, a filter could be applied using an ALS-derived canopy cover product to ensure any method to summarize growth at a polygon scale excludes canopy gaps. Finally, a mask could be applied to remove the non-forested components of polygons identified as forest using spectral data available from the DAP prior to calculating the stand-level averages.

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