USING AIRBORNE LASER SCANNING TO ASSIST IN SUSTAINABLE FOREST MANAGEMENT DECISIONS FOR SECHELT'S COMMUNITY FOREST ON BRITISH COLUMBIA'S SUNSHINE COAST

by

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Abstract

As of 2016, there were 57 community forestry organizations in British Columbia apart of various community forest agreements (CFA). Community forests allow for the development of multi-use management plans to reflect a diverse set of values. The availability of detailed information of the forested area is vital to maximizing a community's benefits and profits. Airborne laser scanning (ALS) can provide estimates of conventional forest attributes, advance inventory attributes along with spatially describing ecosystem services (ES). This thesis combines ALS data, ground sampling data and vegetation resource inventory (VRI) data for the Sunshine Coast Community Forest (SCCF) located near Sechelt, British Columbia in a case study of the application of ALS data to benefit a community forest.

Primary attributes (height, diameter at breast height, stem number, quadratic mean diameter, Lorey's height, volume and biomass) were calculated using an area-based-approach. A secondary attribute (stem size distribution) was calculated using a two-parameter Weibull probability density function. Finally, a tertiary attribute - site indices - was calculated using maximum height from ALS. The reliability of primary attributes predictions varied, with stem number being the poorest (R^2=0.51, p-value<0.001) and Lorey's height (R^2=0.92, p-value<0.001) the most precise. Stem size distribution was predicted with reasonable accuracy using the two-parameter Weibull approach (R^2=0.43 and 0.65 for shape and scale, respectively). Site index (RMSE%=35.09), derived from ALS and VRI data was used to predict growth and yield for a timber supply analysis. ALS derived estimates of site indices increased the predicted amount of harvestable timber on the landscape.

The spatial description of ES has been identified as a key area where information is lacking, hampering efforts to better manage ES. This thesis describes the ability of ALS to map and monitor ES by reviewing existing ALS research and discussing the applications, limitations, and knowledge gaps for spatially describing ES. I conclude with recommendations for SCCF for using ALS data to map ES.

The research in this thesis advances the use of ALS in community forest agreements and demonstrates the feasibility of using ALS data to augment traditional forestry inventory, conduct a timber supply and map a variety of ES.

Preface

In this thesis, I was responsible for determining the research question and methods, as well as, writing of manuscripts and this thesis. Dr. Nicholas Coops provided guidance throughout the entire project as well as editorial help. My research committee provided insight related to their various fields of expertise. Dr. Verena Griess assisted with my understanding of forest operations and the rules and regulations of forest management. Dr. Jeanine Rhemtulla assisted with my understanding of ecosystem services classification. Dave Lasser provided me with a history of Sunshine Coast Community Forestry and assisted in guiding the research questions of this thesis to focus on community forestry. Dr. Piotr Tompalski and Douglas Bolton provided insight and assistance with developing ALS modelling of forest inventory attributes. All co-authors on the following potential manuscripts derived from my thesis work for publication in scientific journals gave insight and editorial assistance.

- Chapter 3: **Anna Yuill**, Piotr Tompalski, Nicholas C. Coops, Douglas Bolton, Marie-Eve Leclerc, Verena C. Griess, Dave Lasser. 2016. Enhancing sustainable forest management decisions with Sechelt's Community Forest through the integration of advanced inventory obtained by airborne laser scanning.

- Chapter 4: **Anna Yuill**, Nicholas C. Coops. 2016. Can LiDAR map ecosystem services? Application and valuation.

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List of Abbreviations

ABA – Area Based Approach

AAC – Allowable Annual Cut

ALS – Airborne Laser Scanning

BC – British Columbia

BCCFA – British Columbia Community Forest Association

CFA – Community Forest Agreement

CFO – Community Forest Organizations

CV – Coefficient of Variation

CWH – Costal Western Hemlock

DBH – Diameter at Breast Height

DEM – Digital Elevation Model

DSM – Digital Surface Model

ES – Ecosystem Services

FRPA – Forest Range and Practices Act

GDP – Global Domestic Product

GIS – Geographic Information Systems

GLAS – Geoscience Laser Altimeter System

ICESat – Ice, Cloud and land Elevation Satellite

LiDAR – Light Detection and Ranging

MEA – Millennium Ecosystem Assessment

MFLNRO – Ministry of Forests, Lands and Natural Resource Operations

MH – Mountain Hemlock

NASA - National Aeronautics and Space Administration

NDY – Non Declining Yield

PDF – Probability Density Function

QMD – Quadratic Mean Diameter

RF – Random Forest

RMSE – Root Mean Square Error

RS – Remote Sensing

S1 – Scenario 1

S2 – Scenario 2

S3 – Scenario 3

S4 – Scenario 4

SBL – Space borne laser scanning

SCCF – Sunshine Coast Community Forest

SCPI – Sunshine Coast Projects Inc.

SI – Site Index

SQ – Site Quality

TASS – Tree and Stand Simulator

TIPSY – Table Interpolation for Stand Yields

TFL – Tree Farm License

TLS – Terrestrial Laser Scanning

TSA – Timber Supply Analysis

VDYP – Variable Density Yield Projection

VRI – Vegetation Resource Inventory

VS – Variable Selection

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Dedication

To my family and PAL

Chapter 1: Introduction

1.1 Community Forests in BC

British Columbia (BC) is one of Canada's most ecologically and biologically diverse provinces with temperate rainforests, dry pine forests and alpine meadows (Council of Forest Industries, 2016). The diversity of BC's climate and topography supports a variety of ecosystems. The forests of BC cover approximately 62% or 55 million hectares of land. They are predominately coniferous (83%) followed by mixed (6%) and broadleaved (6%) forests. This large forest coverage has resulted in BC being economically reliant on forestry with less than 1% (200,000ha) of the forested land mass harvested annually (Council of Forest Industries, 2016). The forest industry contributes $12 billion annually to the provincial gross domestic product; 1 in 16 jobs in BC are tied to forestry and 40% of BC's regional economies are dependent on the forest industry (Council of Forest Industries, 2016). Throughout the past 20 years the role of communities and their local forest resource has been marked by change with the development of legislation allowing for community forest initiatives to be established. The idea of community forest agreements and their practicality started to develop in the 1990's as a result of economic instability and a need for local community employment (McIlveen and Bradshaw, 2009). In 1998, amendments to the Forest Act created a new form of tenure to increase the participation of communities and First Nations in the management of local forests (Wouters, 2000; B.C. Ministry of Forests, Lands and Natural Resource Operations [MFLNRO], 2016a). The government has recognized that the forest industry is important for communities and organizations. Over the last two decades approximately 1.7 million cubic meters of timber has been allocated by the B.C. Ministry of Forests, Lands and

Natural Resource Operations (MFLNRO) to community forest agreements (CFA) and Woodlots (MFLNRO, 2015a). As of 2016, there are 57 community forest organizations in BC, representing nearly 100 individual communities involved at some stage of planning or operating a CFA. These 57 community forest organizations account for approximately 2% of the provincial annual harvest (British Columbia Community Forest Association [BCCFA], 2016).

Traditionally, large industrial forestry agreements (Forest Licenses and Tree Farm Licenses) involved large scale operations with a primary focus on profit maximization through extensive production of timber (Beckley, 1998). Tree Farm Licenses (TFL), Woodlots and CFA operate as area-based tenures that can range between 25 and 99 years with the license replaceable every ten years. (MFLNO, 2015a). Community forests are substantially smaller than TFL and the holder of a CFA has non-exclusive rights to harvest, manage and charge for botanical and other non-timber products (Mulkey and Day, 2012). CFA are still subject to provincial regulations, the province determines the allowable annual cut (based on an upper limit of sustainable harvest) and the agreement holders pay stumpage fees for harvested timber (Furness et al., 2015). The philosophies behind a community forest, are inherently different from those of TFL. CFA are based on the premise that the forest directly benefits communities in a number of ways, by: providing long-term opportunities for numerous community objectives, diversifying uses and benefits of the tenure, providing local social and economic benefits, increasing community involvement and incorporating aspects of ecosystem based management (Beckley, 1998; MFLNRO, 2014c; BCCFA, 2016). Three principals are often associated with CFA: 1) local residents have access to forested lands, 2) opportunities exist for local residents to participate in management decisions relating to forest lands, and 3) an effort is made by communities to protect and maintain the forest they are responsible for (Brendler and Carey, 1998). Additionally, CFA have other responsibilities that go beyond the scope of traditional forest management in BC, such as, conflict mitigation over valuable environmental resources, community empowerment, and the implementation of ecosystem-based management to restore the environment (Bullock and Hanna, 2007; Bullock et al., 2009).

More than simply prompting economic growth, CFA can increase social and ecological benefits for a community. Many community forest organizations (CFO) have numerous focuses and values of their tenure area, some CFA exist for stewardship of watersheds and forest habitats others exist for the creation of economic opportunities in their community (Reed and McIlveen, 2007). The majority want to achieve steady revenues and employment which is typically the primary aim of CFA in BC. Most of the revenue is derived from timber harvesting through traditional forest management practices that can be seen within TFL. However, many CFO struggle to remain economically viable as they suffer from a lack of economic security and diversification away from conventional forestry models is considered risky (Furness et al., 2015). Almost all CFO in BC are dependent on timber harvesting and selling of raw logs (McIlveen and Bradshaw, 2009; Furness et al., 2015). Currently, there is a need to understand how to better support and expand the opportunities within a CFO; including the improvement of returns from timber harvests and moving towards an ecosystem based management approach.

1.2 Ecosystem Based Management and Community Forestry

The concept of stewardship and sustainability draws many people into community-based management as a way to protect and restore natural ecosystems from large scale industrial use. Good land stewardship often involves processes that encompass a diverse set of perspectives that are not limited to a single individual or organization (Gray et al., 2008). Community based management, in this case CFA, have emerged as a means to move beyond output-based resource management and focus on ecosystems as a whole. Thereby encouraging adaptive, innovative approaches to management decisions (Gray et al., 2008). A number of CFO are using ecosystem-based management (EBM) to integrate a full array of interactions within an ecosystem, including both environmental and socioeconomic sustainability. EBM takes into consideration a spectrum of management issues and tries to be effective in incorporating scientific and practical information (Christensen et al., 1996; Granek et al., 2010). It emphasizes the protection of ecosystem structure, function, processes, as well as, incorporating ecological, social and economic values into management (Granek et al., 2010). In order to assess and compare various management objectives and alternatives EBM uses the concept of ecosystem services to provide a common language (Granek et al., 2010).

Ecosystems provide a variety of goods and services to society; we rely heavily upon these services as they contribute to our economic wealth, physical and emotional well-being (Ostrom, 1990; Fisher et al., 2009; de Groot et al., 2010; Andrew et al., 2014). The ways in which humans rely upon and are supported by ecosystems services (ES) are numerous and complex. Our physical and mental well-being is directly and indirectly linked to the goods and services provided by ecosystems (Millennium Ecosystem Assessment [MEA], 2005). Using EBM as tool to focus on ES allows for CFO to use local resource wisely while managing the landscape, providing other economically viable incentives rather than solely relying on timber harvesting (Furness et al., 2015). Understanding the various ES present within a landscape can assist with expanding the management practices and addressing community values.

1.3 Remote Sensing and Community Forestry

Remotely sensed data has provided forest managers with the ability to deliver a suite of information regarding forest characteristics and spatial attributes of vegetation cover, while decreasing costs of ground based inventories and in many cases increasing accuracy of predicted forest attributes (Coops et al., 2007 and Wulder et al., 2012). Light Detection and Ranging (LiDAR) is a recent remote sensing technology that has been shown to be extremely valuable in assessing forest attributes within a tenured area. A particular form of LiDAR known as Airborne Laser Scanning (ALS), is used to penetrate the vertical profile of a forest canopy. This provides estimates of stand attributes such as height, basal area, stand volume and biomass, as well as underlying terrain information, all gathered remotely (Bater et al., 2007; Gatziolis and Andersen, 2008). These estimates can be used to generate approximations of the above attributes for an entire forested area (Næsset and Økland, 2002). ALS data can be further used to analyze the distribution of attributes across the landscape, such as, stem diameter distribution, and can be used to determine an assortment of management implications such as site quality, harvest yield, age class, value of timbers, and extraction costs (Gobakken and Næsset, 2005). With the advancement and increased accessibility of ALS technology it has become an important tool in the development of forest inventories for forest planning. As a result, many forestry companies, both industrial and community-based, have been increasingly receptive to using ALS to provide accurate assessments of their land base. ALS technology can augment current forest inventory methods in a number of unique ways, including:

1) Providing cost effective and timely assessment of the forest landbase by describing traditional forest inventory attributes (e.g., volume, basal area, mean diameter breast height

(DBH), height and stem volume) and advanced forest inventory attributes (e.g., stem distribution, piece size, stand health and condition).

2) Estimating additional forest ecosystem services (e.g., fresh water supply, viewsheds, carbon assessment and detection of iconic tree species (old growth cedars))

The ability of ALS to estimate forest stand attributes accurately and timely at a comparably lower cost than that of ground based inventories makes it a desirable technology for forest managers. Providing forest attribute data at the landscape level will not only inform decision making on harvesting practice but also provide detailed, quantitative data on forest resources. Thus allowing improved support to expand business opportunities to ensure that CFA have the potential to grow and fulfill community needs. This includes improving existing timber returns from timber sales, a vital part of successful CFA. Accurate, spatially explicit forest information creates the possibility to promote the stewardship of standing timber by assessing alternative sources of income from forest management such as selling carbon credits and non-timber resources, while also creating the capacity to manage the forests habitats and watersheds.

1.4 LiDAR

LiDAR is an active form of remote sensing that utilizes light in the form of a pulse laser to measure the distance to the Earth’s surface and surface structures. The light emissions are used to generate three-dimensional information about the shape and size of the Earth’s surface characteristics. There are two types of LiDAR: one which utilizes the near-infrared spectrum to capture surface structures and is readily reflected by vegetation and soil but almost entirely absorbed by water (Baltsavias 1999; Aschoff and Spiecker 2004; Lefsky et al., 2005b; van Leeuwen and Nieuwenhuis

2010). This makes LiDAR and exceptional tool for assessing the structural characteristics of vegetation (Lefsky et al., 2002). The other form of LiDAR commonly known as bathymetric LiDAR uses a green light source making it possible to measure the seafloor and riverbed elevations and structures. LiDAR instruments consist of a laser scanner and a specialized global position system (GPS) receiver that can discern the location of each laser pulse. Using any of these platforms it is possible to gather structural information of the Earths' surface by using the speed of light and the elapsed time to calculate the distance to an object which can then be used to produce information on the various surface attributes (Vierling et al., 2008). There are three main platforms which LiDAR data is collected upon: space borne laser scanning (SBL), airborne laser scanning (ALS), and terrestrial laser scanning (TLS). Work has been done on integrating ALS data with TLS data to enhance ALS abiltiy to predict understory cover, but still remains a challenge (Jupp et al., 2009; Hilker et al., 2010) . LiDAR can provide information on both terrain and above ground structures (Figure 1). Terrain data can be used to describe stream morphology (Hohenthal et al., 2011) and geomorphology (Lloyd and Atkinson, 2006). Above ground structural information can be used to derive measures of forest volume, above-ground biomass (Nilsson, 1996; Næsset et al., 2004; Wulder et al., 2008) and archeological information.

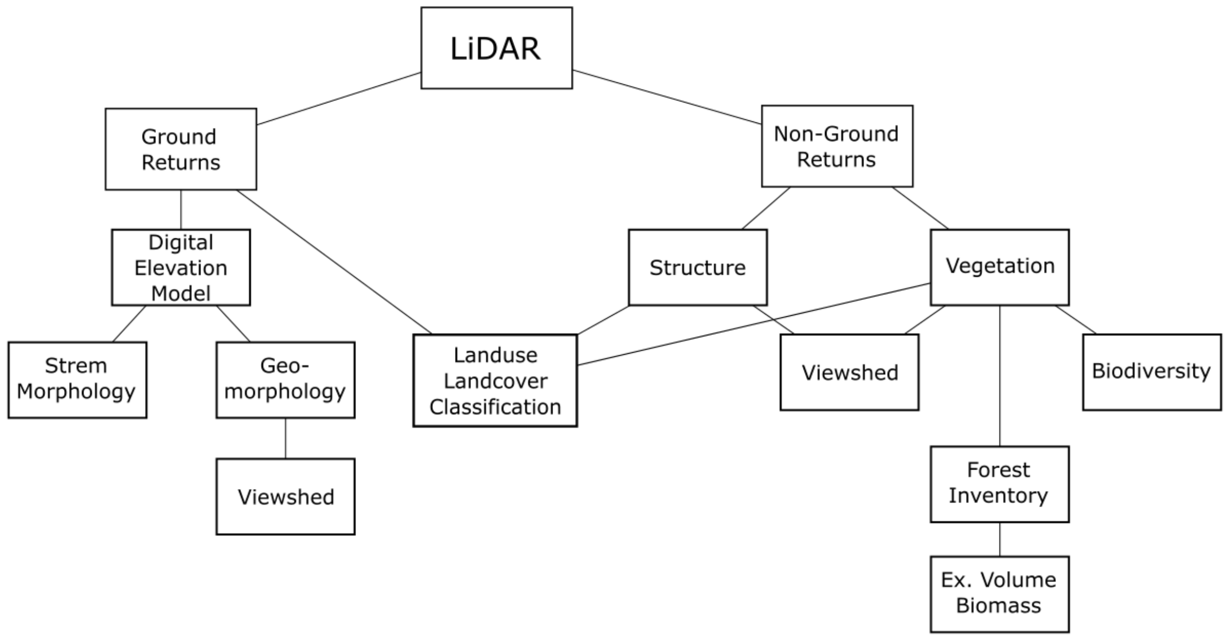

Figure 1: Flow diagram of various Light Detection and Ranging (LiDAR) derived products that can be used to map a variety of ecosystem services such as forest inventory, geo-morphology, stream morphology and biodiversity using ground returns and non-ground returns.

1.4.1 Geoscience Laser Altimeter System

The Geoscience Laser Altimeter System (GLAS) on the NASA Ice, Cloud and Land Elevation Satellite (ICESat) is an example of a space borne laser scanner used for structural measures of the earth's surface, it was operational from 2003 to 2009. GLAS is a large footprint instrument, the diameter of one of the laser pulse is approximately 65m, except when cloud coverage obscures the pulse (Schutz et al., 2005). Each pulse is separated by 172m on the Earth's surface (Schutz et al., 2005). GLAS data is freely available from the US snow and Ice Data Center and has been used for a variety of purposes including the characterization of vertical vegetation structures of forests and biomass, determining the mass balance of polar ice sheets and assessing global sea level change (Zwally et al., 2002; Schutz et al., 2005; Nelson et al., 2010; National Aeronautics and Space Administration [NASA], 2014). Due to its large footprint size the data poses significant challenges when trying to model fine scale structural parameters. The data is too broad to provide useful information in ecosystems that have rugged terrain, but can be beneficial for analyzing vertical structure in areas of gentle terrain (Vierling et al., 2013).

1.4.2 Terrestrial Laser Scanning

Terrestrial laser scanning (TLS) usually involves a laser mounted on a tripod that allows for the rapid collection of dense data (<1cm resolution). It can also be made to be mobile and used to acquire data across the whole or part of the hemispherical field of view (Hyyppä et al., 2012). The use of TLS systems for surveying continues to increase with the increase availability of the technology. TLS is commonly employed for recording archelogy sites, measuring natural processes, tree defoliation and the structural measurements of buildings. The primary use of a TLS system within forestry is to investigate the structure of a forest stand from within providing millimeter-level detail of the surrounding area, allowing for the derivation of forest attribute information (Liang et al., 2016). TLS systems, like ALS can record one or a number of discrete returns per emitted laser pulse, or can be full waveform, as a result, TLS is capable of acquiring detailed information regarding vegetation below the forest canopy. Links between TLS point clouds and forest inventory/forest structure parameters have focused principally on measurements of the trunk, such as DBH and taper, with errors in measuring stem diameters ranging between 1.5 – 3.3 cm (Hopkinson et al., 2004; Thies et al., 2004; Maas et al., 2008; Tansey et al., 2009). Important factors that limit the use of TLS data is the relatively high cost of the instrument, limited software and a lack of individuals capable of processing the data (Liang et al., 2016).

1.4.3 Airborne Laser Scanning

Airborne laser scanning (ALS) is the most common form of LiDAR collection used. It has the ability to provide information over large areas, at a relatively cost effective price (Næsset, 1997; Coops et al. 2007; Wulder et al. 2008). An ALS instrument is comprised of three main components: a laser device, an inertial navigational measurement unit (IMU), and a GPS unit linked through a computer interface. Using either a helicopter or airplane as a platform, the sensor emits pulses of light which are used to determine the time elapsed between the object and the sensor, this is then used to determine the range or the distance to the object (Vierling et al., 2008; Gatziolis and Andersen, 2008). Typically, data acquisition is flown between an elevation of 500-3,000 meters depending on the resolution and point density desired (Hilker et al., 2010). ALS laser pulse footprints can range from 0.1m-2.0m in diameter (Lim et al., 2003; Wulder et al., 2008) and can achieve sub-meter accuracy of terrain surface heights (Blair et al., 1994; Lefsky et al., 2002). There are two main data products that can be derived from ALS, a highly accurate DEM model and detailed forest attributes. The DEM generated from ALS is one of the most effective and reliable means for collecting terrain data, and in many cases is the primary purpose for acquiring ALS data (Liu, 2008; Bater and Coops, 2009). Structural characteristics of vegetation are another product that can be estimated at a higher or similar level of accuracy using ALS data when compared to field-based inventory (Næsset and Økland, 2002). ALS does have certain limitations; due to upper canopy foliage, it can be poor at observing lower canopy foliage and understory vegetation (Lovell et al., 2003). ALS data has become an operational tool for supporting the development of forest inventories and assisting with decision making (Næsset et al., 2004; Lefsky et al., 2005a; Bater et al., 2007; Wulder et al., 2008; Woods et al., 2011; White et al., 2013). It is the most common form of LiDAR collection used and has the ability to provide information over large areas at a relatively cost effective price (Coops et al., 2007; Næsset and Nelson, 2007; Wulder et al., 2008). Recently, ALS data has also been applied to developing more advanced forest inventory attributes which can form the basis of growth and yield estimates, individual tree lists, spacing and volumes (Tompalski et al., 2015a), diameter distributions (Saad et al., 2014), forest health assessment (Solberg et al., 2004; Thomas et al., 2008) and stand age (Racine et al., 2014). The ability of ALS to predict site quality has also recently been explored (Tompalski et al., 2015b), which will influence growth and yield estimates allowing them to be developed at finer scales which will aid with the development of accurate long term management plans.

1.5 Research Objectives

The overall objective of this research is to examine how ALS data can improve decision making in sustainable forest management within a community forest environment with a focus on social and environmental issues. Two main research questions are posed to address this objective:

1. Is it possible to accurately predict allowable annual cut and other advanced inventory forest attributes such as stem size distribution using ALS data?
2. Is it possible to identify and map ecosystem service indicators using ALS data?

1.6 Thesis Overview

To answer the above research questions my thesis is structured into 5 chapters: following the introduction (Chapter 1), Chapter 2 presents in detail Sunshine Coast Community Forest, data collection, the vegetation resource inventory data and the ALS data used to investigate the integration of ALS data into a community forest.

Chapter 3 provides the methodology, results and discussion on how ALS data can be used to determine various levels of forest attributes and develop a timber supply analysis.

Chapter 4 investigates applications of ALS data that might contribute to the mapping of ecosystem services.

Chapter 5 concludes by discussing the research implications, applications, innovations, and limitations of Chapter 3 and 4 while also providing recommendations for future research.

Chapter 2: Sunshine Coast Community Forest and Data Collection

2.1 Sunshine Coast Community Forest

The District of Sechelt located on the Sunshine Coast of BC. It was one of the first municipalities in the province granted a Community Forest Agreement (Sunshine Coast Community Forest [SCCF], 2013) known as the Sunshine Coast Community Forest Inc. (SCCF). It is owned and operated by Sechelt Community Projects Inc. (SCPI) with the District of Sechelt being the sole shareholder of the corporation. SCPI holds and manages the licenses to harvest as a BC company under the provincial Community Forest Agreement #K3F (SCCF, 2013). The allowable annual cut (AAC) for SCCF is set at 20,000m^3/year. The AAC is the rate of timber harvested from a specified area of land, this is determined by the chief forester from the BC Ministry of Forest Land and Natural Resources Operations (MFLNRO) in accordance with the Forest Act (MFLNRO, 2014c). The AAC is determined by a body of guiding principles set by the Chief Forester to minimize environmental and economic risk, assess changes in social values and incorporation of current information and knowledge through analyzing timber supply available across the landscape (Snetsinger, 2012). Table 1 shows the company's harvest volume from 2011 to 2015 along with the profits generated and returned back to the community shareholders. The company's mission is to create a legacy for their citizens by being exceptional stewards of the forest while maintaining a balance between environmental, economic, and social aspirations of the community (SCCF, 2013).

Table 1: Financial summary of Sunshine Coast Community Forest from forest harvest from 2011-2015 (Source: Sunshine Coast Community Forest Annual Report, 2015)

Achievements					
	2015	**2014**	**2013**	**2012**	**2011**
Harvest volume (m^3)	32,519	30,169	18,818	18,701	5,376
Sale (m^3):					
To local independent mills	612	169	253	386	149
To Howe Sound Pulp & Paper	3,051	1,951	0	2,722	752
Within Canada (BC)	26,697	24,362	13,726	13,468	3,573
Export outside Canada	2,159	3,687	4.839	2,125	902
Seedlings planted	13,440	43,020	33,835	34,100	35,890
Revenues ($)	2.80M	2.95M	2.13M	1.59M	0.55M
Dollars invested in our community	2.3M	1.8M	1.3M	1.1M	0.46M
Profits earned/(lost)	869,575	706,499	660,858	226,321	169,913
Dividends paid to Shareholders	525,890	525,890	225,890	25,890	0

2.1.1 Community Goals in Forest Management

Since coming into effect SCCF has benefited the community of Sechelt in a multitude of ways. A legacy fund was created to assist with community based projects, using the profits from timber sales from the community forest. The community is able to invest in a wide variety of community projects because of the legacy fund, for example: bus shelters, upgrades to community use and day care buildings, addition of accessibility ramps and the renovation of the community arts center, along with the contribution of funds to assist with GPS mapping of local trails. Additionally, to monetary benefits, the community forest provides opportunities for forest-based recreation and is a significant attraction for many visitors to the Sunshine Coast. SCCF directly supports the recreation industry by assisting with local projects such as the Hidden Grove trail and parking lot develop, mapping and inventorying recreational features such as old-growth trees. SCCF creates transparency between recreational groups and individual's through consultations to minimize interference between the community's needs and harvesting activities (SCCF, 2016).

2.1.2 Area

SCCF covers 10,790 ha encompassing the areas: Halfmoon Bay (1,191ha), Wilson Creek (1,048ha), Angus (2,957ha) and Chapman/Gray Creeks (5,600ha) located near the municipality of Sechelt (Figure 2). All three areas are located within the Coastal Western Hemlock (CWH) and Mountain Hemlock (MH) biogeoclimatic zone. The CWH is characterized by high annual precipitation (2,228 mm), mild winters and cool summers (Meidinger & Pojar, 1991). The highly productive temperate rainforest is dominated at lower and mid elevations by Douglas fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*) and western red cedar (*Thuja plicata*). The MH zone is characterized by short, cool summers and long, cool wet winters, with moderate to heavy snow cover for many months. The annual precipitation ranges from 1,700 to 5,000mm as a mix of snow and rain. Mountain hemlock (*Tsuga mertensiana*), amabilis fir (*Abies amabilis*) and yellow-cedar (*Cupressus nootkatensis*) are the most common tree species in the MH zone (Meidinger & Pojar, 1991). Common occurrences of shore pine (*Pinus contorta*) and western white pine (*Pinus monticola*) are observed on various micro-sites within the study area. The average age of stands according to the vegetation resource inventory provided by the Ministry of Forests, Lands and Natural Resource Operations was 118 years. The oldest stands were estimated to be over 600 years of age, mainly comprised of hemlock.

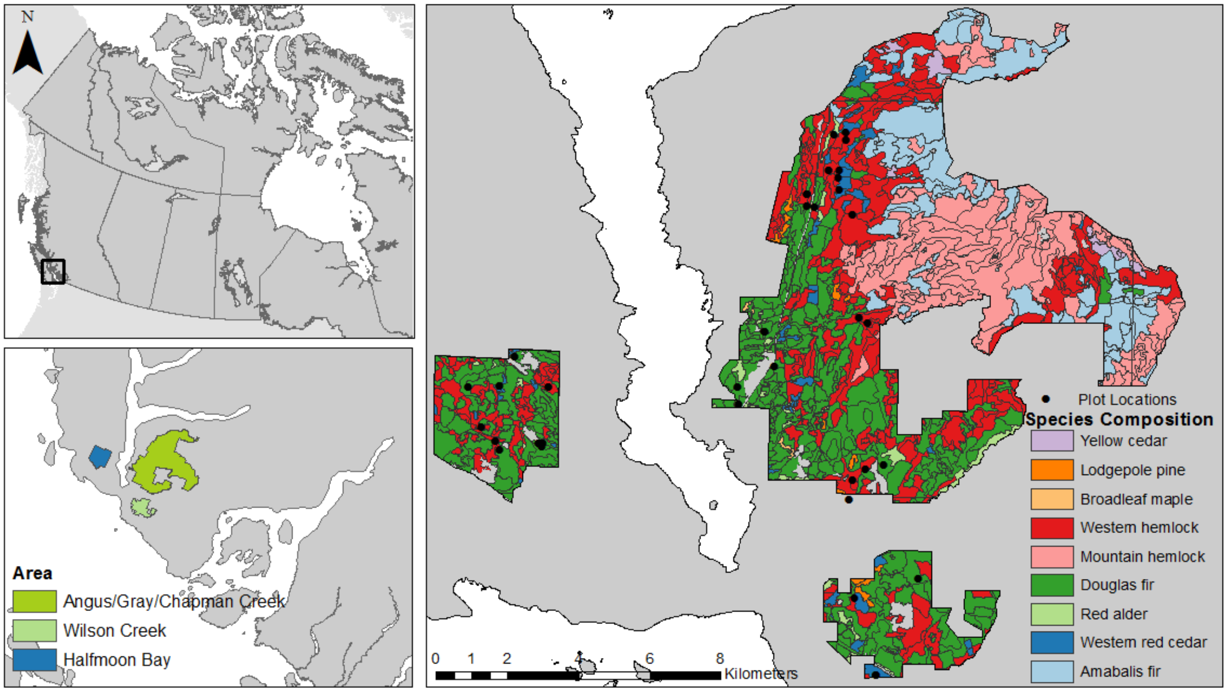

Figure 2: Map of Sunshine Coast Community Forest tenure located on the coast of British Columbia, Canada. Large insert shows dominate species defined by the Vegetation Resource Inventory developed by the Ministry of Land Forests and Natural Resource Operations along with the location of all 32 field plots.

2.2 Data Collection

To answer research question 1) *"Is it possible to accurately predict AAC and other advance inventory forest attributes such as stem size distribution using ALS data?"* Three data sources were employed: first, data from the vegetation resource inventory was obtained, second ground sampling was conducted and third, ALS was provided. Each data set played a critical role in estimating various forest attributes and conducting a timber supply analysis, from determining species and age to describing height and DBH measurements. Data collection and specifics are explained in detail below.

2.2.1 VRI Data

The Vegetation Resource Inventory (VRI) provides information on the status of BC's provincial forests and is publically available on BC's MFLNRO website (MFLNRO, 2016b). Data collection for the VRI is overseen by the Forest Analysis Inventory Branch of the MFLNRO and conducted in a two-phase process, comprising of 1) photo interpretation and 2) ground sampling. Due to the extremely large size of BC and the remoteness of many of BC's forest locations, aerial photography and photo interpretation are the main sources of forest inventory used to estimate forest attributes (MFLNRO, 2015b). According to the VRI forest attributes located with SCCF tenured area were predominately estimated using photo interpretation, silviculture surveys and ground calls. Silviculture surveys and ground calls are used to provide a level of certainty and validity regarding forest attributes that cannot be sampled everywhere. Ground calls in particular are used for calibration of photo interpretation (Ministry of Sustainable Resource Management, 2004). Attribute estimates are made at the stand level which are represented in a Geographic Information Systems (GIS) as polygons. As of June 2, 2015 the information provided by the VRI was considered up to date with all forest activities according to the MFLNRO (2015b). The inventory is updated continuously each year. However, it is the responsibility of the licensees to update the inventory through electronic submission of inventory data following harvesting activities, fire and other catastrophic events. Discrepancies in data are bound to exist because of small ground sampling and limited resources.

Data primarily used from the VRI for this thesis was the spatial extent of stand types classified by dominant species. Other information obtained from the VRI was age, height, site indices and land cover classification. This information provided by the VRI was used to conduct ground sampling and data analysis in Chapter 3. Figure 3 shows the distribution of age class for each species and the distribution of site indices per species.

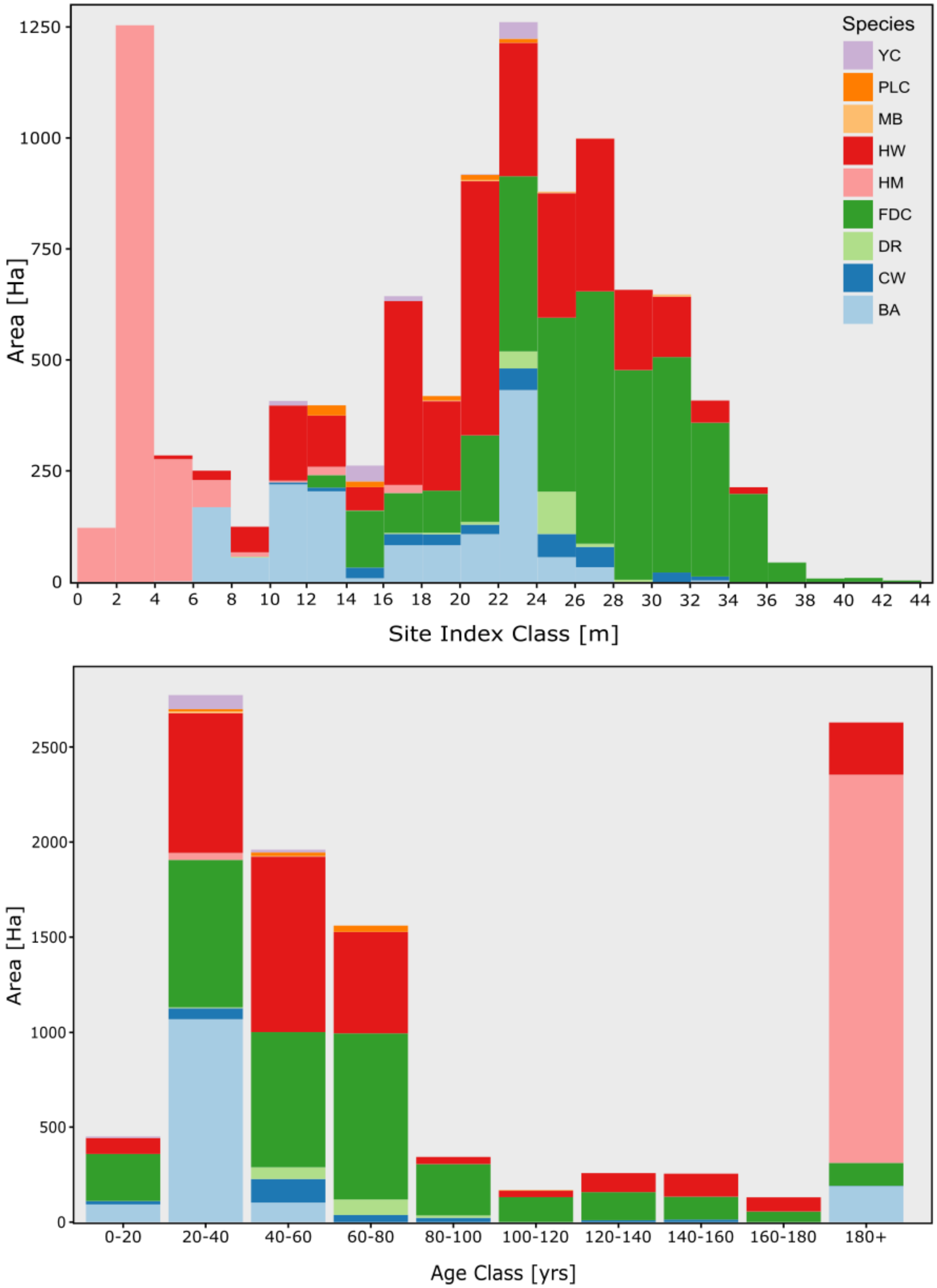

Figure 3: Distribution of age class and site indices for each species (YC-yellow cedar, PLC – lodgepole pine, MB – bigleaf maple, HW – western hemlock, HM – mountain hemlock, FDC – Douglas-fir, DR – red alder, CW - western redcedar, BA – amabilis fir) across the entire tenure area, information obtained by the VRI (MFLNRO, 2016b).

2.2.2 Ground Sampling

Ground data was collected in the spring 2015 on a total of 32 circular plots of 0.04 ha each, following the guidelines developed by White et al., (2013) for generating forest inventory attributes from ALS data. Plots were randomly located within nine strata defined by three height classes from the ALS data (5-10m, 10-20m and 20-30m) and 3 dominant species classes from the VRI. Within each plot a range of attributes were measured including DBH, height and species, for all trees larger than 10cm in diameter. Height measurements were determined using a laser hypsometer. A random sample of tree heights were measured within each plot based upon the distribution of DBH measurements and canopy position. Heights for all trees were then interpolated using DBH-height specific equations provided by the lmfor R-pacakage using the Naslund function (Mehtatalo, 2015). Additional field measurements were also made within each plot, including length and diameter of course woody debris (DBH > 10cm), leaf area index which was measured using a spherical densitometer, understory species identification and percent crown cover estimates, presence and absence of large mammals though pellet observations (i.e., *Ursidae spp*. (bears) and *Cervidae spp.* (deer)), aspect and slope. Timber volume (m^3/ha) and biomass (kg/ha) were calculated using DBH, height and species information. Volume was calculated by creating a relationship between DBH and height to describe the area that a whole tree would occupy. Biomass was calculated using the Canadian National Biomass equations developed by Ung et al., (2008) to convert DBH and height into the mass of the whole tree. Figure 4 shows a sample of the diversity of plots measured while Figure 5 shows the distribution of height and DBH measured and calculated volume. Table 2 shows the minimum, maximum, mean and standard deviation (STD) of measurements made within the field.

Figure 4: Sample of three plots showing the diversity of stands within SCCF.

Table 2: Forest attributes derived from data collection of ground plots, height, DBH, and steam number are calculated per plot. Total volume and Total biomass are calculate per hectare.

Attribute	Min	Max	Mean	STD
Height (m)	3	59	20	7
DBH (cm)	10	127	24	13
Stem Number (n/ha)	43	262	138	60
Total Volume (m^3/ha)	0.4	433	13	23
Total Biomass (kg/ha)	145	192,837	5,191	9,644

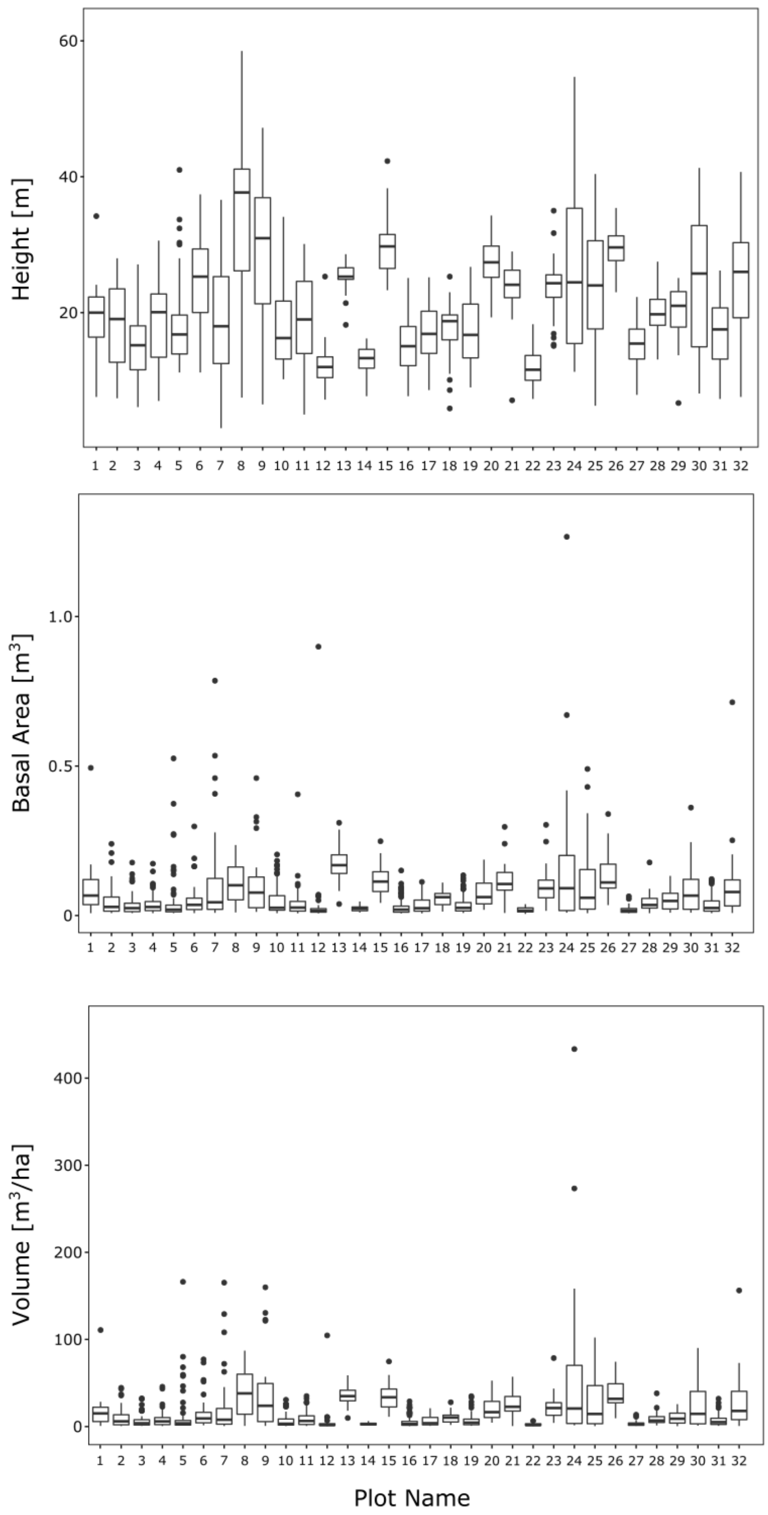

Figure 5: Distribution of field measured height (m) and basal area (m^3) for each plot. Derived distribution of volume (m^3/ha) for each individual tree per plot.

2.2.3 ALS Data

ALS point cloud data was acquired on November 5, 2015 using a Riegl LMS-Q1560 scanner. The average point density was 12 pts/m^2. The vendor provided a digital elevation model along with the classification of ground returns and vegetated returns.

As the collection of ground data and ALS data occurred within the same year, no transformation of ground data was need to match growth that would occur if data was collected in different years. ALS data was then processed according to Chapter 3 Section 3.2, Data Processing.

Chapter 3: Using LiDAR to Enhance Plot Based Forest Inventories

3.1 Introduction

Sustainable forest management requires detailed and accurate knowledge of a tenured land base including forest inventory information, such as species, height, diameter at breast height (DBH), volume and biomass as well as additional information such as the topography, hydrology and disturbance regimes. In particular, operational level forestry relies heavily upon accurate and up to date forest inventory information to determine harvestable areas. Traditionally, aerial photography and ground based surveys were used to develop estimates of forest inventory on the landscape. Lately there has been an increased need for timely, spatially explicit, and accurate information, driving forest managers to consider alternatives to augment traditional forest inventory approaches. As such ALS has become an important tool for the development of forest inventories assisting with decision making (White et al., 2013; Woods et al., 2011; Wulder et al., 2013). ALS data is an accurate tool for assesing structural characteristis of forest stands, delivering data compareable to, or better than field-based assessments (Næsset and Økland, 2002).

Data derived from ALS can augment current forest inventory methods, by providing estimates of traditional forest attributes (Næsset et al., 2004; Lefsky et al., 2005b; Bater et al., 2007; Wulder et al., 2008). With the increasing use of EBM resulting in uneven-aged forest stands the area based approach used to derive average stand attributes is becoming less useful for forest managers (Tompalski et al., 2015a). As such, research into advanced forest inventory attributes derived from ALS data, such as, individual tree lists, information on spacing and volume (Tompalski et al., 2015a), diameter distribution (Saad et al., 2014), forest health assessments (Solberg et al., 2004; Thomas et al., 2008) and stand age (Racine et al., 2014) is becoming increasing more useful.

Recently, estimates of stand index using ALS data along with species and age data has been explored (Tompalski et al., 2015b). A forest inventory derived from ALS data, in combination with a reduced number of ground plots, can provide estimates of the timber volume, basal area, mean DBH, and stem volume, amongst others. These characteristics of a forest stand are crucial for calculating timber volume for AAC, site potential and silvicultural treatments.

While the application of ALS for forest inventory assessments is common place for some industrial forest companies, its use in smaller CFA is less common. Accurate and spatially explicit forest information creates the possibility of promoting stewardship of standing timber by assessing other economically viable approaches through carbon offsets and non-timber resources, while also creating the capacity to manage forest habitats and watersheds. Three levels of attributes were derived (Figure 6): primary attributes (height, DBH, stem number, Lorey`s height QMD, biomass and volume), which have been successfully derived from ALS data before; a secondary attribute, stem size distribution, which can provide detailed information on stand level distribution used for silvicultural assessments; and finally, a tertiary attribute, site index, which is critical for accurate growth and yield predictions. All three attributes can then be combined in a forest decision and planning framework to provide long-term estimates of forest growth and development. I conclude with a discussion on the usefulness of these datasets for community forests in general and in particular a costal British Columbia community forest.

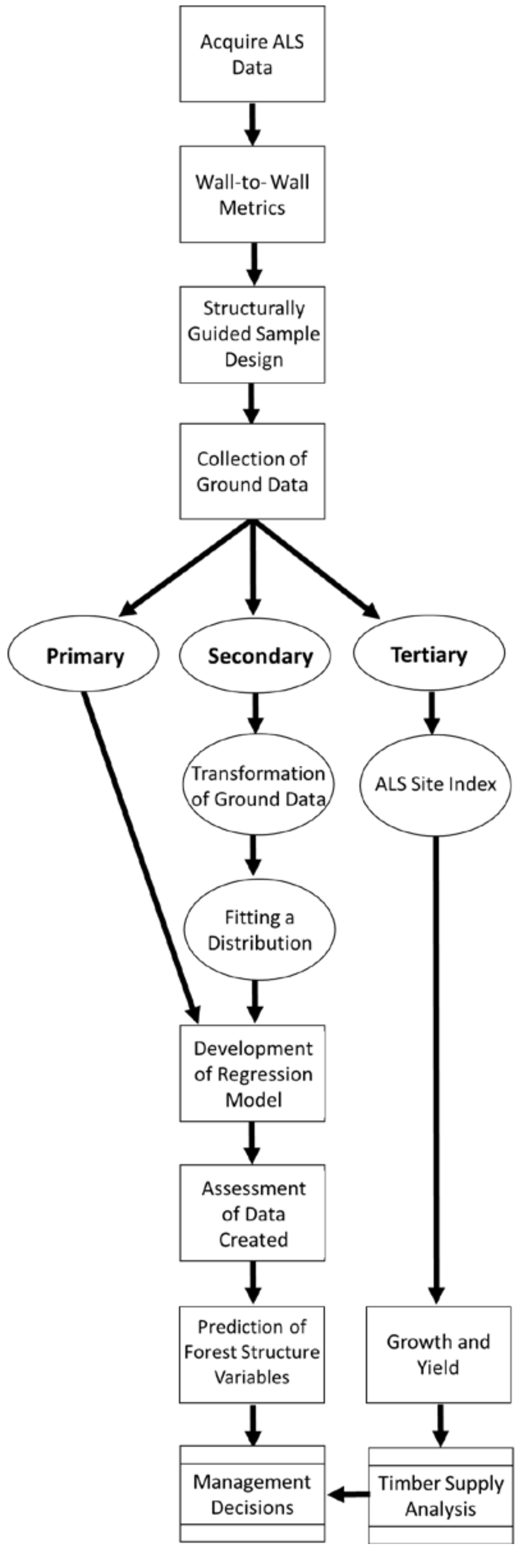

Figure 6: An outline of the methodology used in this study.

3.2 Data Processing

Data processing was divided into three approaches depending on the methodology used: primary, secondary and tertiary attributes. Primary attributes were developed to provide generalized stand-level forest attribute. A secondary attribute was developed to provide a fine scale description of the DBH distribution at the plot level. Finally, site index was calculated directly from ALS data providing a tertiary attribute.

3.2.1 Primary Attributes

ALS data was processed using an Area-Based-Approach (ABA). ABA is used to estimate a range of forest inventory attributes based on the statistical dependency between ALS metrics (predictor variables) and plot-level measurements (response variables) (Vastaranta et al., 2012; White et al., 2013). ABA is able to deliver accurate wall-to-wall predictions on various forest stand level attributes, such as biomass, volume, tree height, DBH, and canopy cover (Wulder et al., 2012). The ABA combines ALS and plot data to develop predictive models through a variety of methods such as regression or non-parametric approaches (Vastaranta et al., 2012; White et al., 2013).

To process the data we derived a normalized ALS point cloud for each plot. A range of descriptive metrics using FUSION (McGaughey et al., 2014), including, minimum height, maximum height, standard deviation, coefficient of variation (CV), skewness and percentage of canopy returns above a certain threshold value were derived (Næsset and Økland 2004; Hopkinson et al., 2006; Vastaranta et al., 2012). The threshold value was calculated using first returns greater than 2m in height to clearly distinguish between vegetative returns and ground returns (Nilsson 1996; Næsset and Økland, 2004; Mora et al., 2013).

A number of standard plot based forest inventory attributes were modeled, including mean stand height, DBH, quadratic mean diameter (QMD), volume, biomass and stocking. For height and DBH individual tree heights measured were averaged by plot. Lorey's height weights the contribution of trees to the stand height by their individual basal area, it was calculated because it is more stable estimate of height and is less affected by mortality and harvesting of smaller trees than calculating raw height. QMD was calculated using average plot DBH weighted by the number of trees in the plot. All forest inventory attributes were tested for normality, stem count was transformed using a natural log to ensure residuals were normally distributed using the Shapiro-Wilk test (p=0.21).

3.2.2 Secondary Attributes

The prediction of primary tree attributes using ABA does not always provide sufficient information, resulting in poor decisions and economic losses (Bergseng et al., 2015). Tree level inventory data can provide additional information to augment primary tree attributes. Deriving an additional attribute - secondary attribute - from ALS data, such as, stem size distribution can augment primary attribute information derived from ALS. Stem size distribution in particular can be used to determinate various stand characteristics and subsequent management implications such as value of timber and extraction costs (Gobakken and Næsset, 2005). A number of previous studies have demonstrated the use of Weibull parameters to estimate stem size distribution (Gobakken and Næsset, 2004; Gobakken and Næsset, 2005; Thomas et al., 2008). Following an approach by Tompalski et al., (2015a) a two-parameter Weibull probability density function (shape (k) and scale (λ)) was fitted to the DBH field measurements. The k parameter provides a description of the distributions shape (which can range from an inverse J-shape curve, unimodal skewed curve and unimodal symmetrical curve) whereas the λ provides a description of distributions range (Coops et al., 2007; Tomaplski et al., 2015b). Using ALS-derived metrics and linear regression following the same methodology as primary attributes, λ and *k* were predicted across the entire study area. Both λ and *k* parameters were not normally distributed, the natural log was used to transform the parameters and the Shapiro-Wilk test confirmed *k* ($p=0.33$) and λ ($p=0.20$) were normally distributed.

Primary and secondary attributes were modelled using the software “R” (version 3.3.1) (R Core Team, 2012) and statistical packages, Random Forest (RF) (Liaw and Wiener, 2002) and Variable Selection (VS) (Lumley, 2009). RF is a machine learning method that is based on the construction of multiple decision trees used to determine the most important ALS metrics derived from FUSION. VS was performed on a subset of the top 10 most important predictor metrics determined from RF using a stepwise selection process to find the model of best. VS produced the three best models which were then assessed based on their coefficient of determination (R^2), bias and root mean square error (RMSE). Reliance of model estimations were calculated using the minimum and maximum values observed in the field +/- 10% the minimum/maximum values (Woods et al., 2011).

3.2.3 Tertiary Attribute

Site index (SI) is a common measurement of relative site productivity and an important attribute in forest inventories. SI is defined as the stand dominant height (m) at a given reference age (usually 50years). There are 3 common methods used to estimate SI in BC (British Columbia Ministry of Forests, 1999): the Site Index Biogeoclimatic Ecosystem Classification, growth intercept method and the height-age curve method. The height-age curve method is the most used method to calculate SI for stands between 30 to 140 years (based on species-specific equations for age and stand dominant height). The height-age curve method is the most applicable method to determine site indices as the majority of stands are between the ages of 30-140.

The research and implications of using ALS point cloud data to derive measures of SI is relatively new (Gatziolis, 2007; Wulder et al., 2010; Chen and Zhu 2012; Ham et al., 2013; Tompalski et al., 2015b). The approach used in this thesis follows the largely accepted definition of dominant height used in BC, where dominant height is defined as the average height of the 100 largest trees by DBH (British Columbia Ministry of Forests, 1999). Estimates of dominant stand height were calculated based upon the weighted mean of ALS point cloud data. First a 10x10m grid was overlaid the ALS point cloud data and the maximum return height was calculated for each grid cell with the average non-ground return count used as the weight. The dominant tree height was slightly modified using the spatial area of the VRI polygons, so that each polygon had a SI estimate. The maximum height estimations were then imported into the software SiteTools developed by the BC provincial government (British Columbia Ministry of Forests and Range, 2004). SiteTools contains height-growth equations for all major tree species in BC, and calculates SI as a function of stand age and dominant stand height.

3.2.4 Timber Supply Analysis

To predict future forest conditions and determine harvestable timber volumes a robust timbers supply analysis is needed. Timber supply analysis (TSA) are traditionally completed by the MFLNRO at least once every five years and combined with a variety of management consideration to determine a sustainable AAC. Under-, or overestimation of timber volume available for harvest can have a profound effect on long-term economic, ecological and social sustainability and subsequent management options. For a CFA that depends on the revenue generated from harvesting activates for community infrastructure and economic security this could affect the success of a CFA.

A TSA for SCCF was carried out using WOODSTOCK (Remsoft Inc., 2009). The purpose of conducting this analysis was to see how variable the differences between VRI data and ALS data would affect a TSA for a community forest. Forest inventory data derived from ALS as well as traditional forest inventory data was included into the analyses. WOODSTOCK allows for the building of spatially explicit models that concede the evaluation of harvest schedules and treatment regimes for large areas over an unlimited timeframe. WOODSTOCK has been used previously to calculate an optimum AAC based upon optimal harvest levels and schedules in accordance with particular actions and constraints (Canadian Council of Forest Ministers; 2005, Hossain and Robak, 2010). WOODSTOCK is highly flexible, allowing multiple forest management scenarios to be solved using various approaches, such as, Monte Carlo simulations, binary searches and linear programming techniques (Walters, 1993; Gunn, 2009). In order to undertake a simulation, three sets of input variables are required: forest inventory data, landscape information and information on forest dynamics in the area under consideration. Forest inventory data includes information about the forest landscape (age of stands and site indices), tree rotation age and growth rate. Landscape level information describes the site specific attributes of the area containing forest type, stocking level, seral stage and site quality (Walters, 1993; Remsoft Inc., 2009). Management dynamics are defined by a series of management actions such as different levels of harvesting, which will influence the harvestable yield (Walters, 1993; Remsoft Inc. 2009).

Four scenarios were developed using linear programming within WOODSTOCK to assess how conventional forest inventory data (VRI) and ALS derived data would influence a TSA. Table 3 provides a summary of the four scenarios (S1, S2, S3, S4) created and the data used for each category of WOODSTOCK. In order to reduce model complexity and understand how ALS data alone would influence a TSA complex management decisions, such as, cut block proximity, old growth management areas and wildlife habitat were not included in this analysis. The only management considerations was the rotation age of each species and the inclusion of riparian management areas (RMA). RMA were inclued to meet the minimum requirements set by the Forest Ranges and Practices Act (FRPA).

Table 3: Comparison of input data used in the four scenarios (S1, S2, S3 and S4) for timber supply analyses in WOODSTOCK. Site quality is the classification of site index into three categories based upon site index values; poor (SI<20m), medium (20<SI<35m) and good (SI>35m).

WOODSTOCK		**Conventional Scenarios**		**ALS Scenarios**	
		S1	**S2**	**S3**	**S4**
		Site Quality	Site Index	Site Quality	Site Index
Forest Inventory	**Landscape Themes**	VRI	VRI	VRI and SI ALS	VRI and SI ALS
	Areas	VRI	VRI	VRI	VRI
	Yields	MFLNRO	Species – VRI Managed - VRI Site Index - VRI	MFLNRO	Species – VRI Managed - VRI Site Index - ALS
	Lifespan	VRI	VRI	VRI	VRI
Management Dynamics	**Actions**	Clearcut - 100%	Clearcut - 100%	Clearcut - 100%	Clearcut - 100%
	Outputs	Volume, Area and Standing Inventory	Volume, Area and Standing Inventory	Volume, Area and Standing Inventory	Volume, Area and Standing Inventory
	Transitions	Managed to managed Unmanaged to managed	Managed to managed Unmanaged to managed	Managed to managed Unmanaged to managed	Managed to managed Unmanaged to managed
Objectives	**Objective**	Maximum Harvest	Maximum Harvest	Maximum Harvest	Maximum Harvest
	Constraints	Non-declining standing inventory Even harvest	Non-declining standing inventory Even harvest	Non-declining standing inventory Even harvest	Non-declining standing inventory Even harvest
	Time Span	160 years	160 years	160 years	160 years

For all four scenarios the timber harvesting land base and non-timber harvesting landbase were defined within WOODSTOCK. Defining the non-timber harvesting landbase was done by identifying areas that were non-vegetated, using the land cover classification scheme provided by the VRI. Since WOODSTOCK assumes that stands have the same density, polygons were removed from the timber harvesting landbase if less than 10% of the landscape unit consisted of trees. Each polygon defined as being harvestable was linked to a combination of unique stand attributes represented by management type, species and site index. Defined species units were based upon the dominant species obtained from the VRI; management type were determined by site history from the VRI: stands that had a previous history of harvesting were considered “managed stands”, those with no prior harvest were considered “unmanaged stands.” To meet the minimum requirements of FRPA, stream data was obtained from the National Hydrological Network for Jervis Inlet from the Natural Resources Canada data bank. Stream and lake classification was unknown as this data was not made available, as such a 30m buffer was applied to all streams and a 10m buffer was applied to all lakes creating RMA. No harvesting activities were allowed to take place within these areas.

Scenario 1 (S1) and Scenario 3 (S3) used volume estimates obtained from the MFLNRO Timber Supply Analysis from the Forest Analysis of the Sunshine Coast Timber Supply Area (MFLNRO, 2014). For Scenarios 2 (S2) and 4 (S4) I derived volume estimates based on site index (SI) values from the VRI (SI_{VRI}) and SI obtained from the acquired ALS data (SI_{ALS}). Volume estimates within the MFLNRO TSA were produced using the software packages TIPSY (table interpolation for stand yields) and VDYP (variable density yield prediction) developed by the BC Forest Service, Resource Inventory Branch and were assumed to be stands of mixed composition (MFLNRO, 2014a). TIPSY provides yield tables for managed single-species or mixed species stands by providing access to the tree and stand simulator (TASS) which in turn models tree growth dynamics (MFLRO, 2014a). VDYP is similar to TIPSY but is intended for unmanaged pure or mixed stands (MFLNRO, 2104b).

For S1 and S3 volume estimates were linked to landscape units based on site quality (SQ). SQ is the categorization of SI, making it easier for forest managers to describe site productivity. SI is divided into three categories: poor (SI<20m), medium (20<SI<35m) and good (SI>35m) (British Columbia Ministry of Forests, 1999). Whereas, S2 and S4 used SI_{VRI} and SI_{ALS} to establish landscape units and create growth and yield predictions to estimate volume. Yield estimates were produced using the batch mode for both TIPSY and VDYP from SI_{VRI} and SI_{ALS}. The site index curve for bigleaf maple (*Acer macrophyllum*) was not available within TIPSY but was available within VDYP. As a result managed stands of bigleaf maple were left out of the analysis. Due to limitations within TIPSY and VDYP certain growth and yield predictions were not calculated as the age of certain stands were outside calculated ranges for certain species. These stand types were removed from both models to avoid errors of commission. The processing extent for S2 and S4 was reduced to 9,060ha. SI for S2 and S4 was rounded to a full meters for each landscape unit and yield curves, this reduced the processing time.

The rotation age for all four scenarios were based on the peak mean annual increment (MAI), all harvesting activities were allowed to occur following the peak MAI. The modelling timeframe was set to 160 years and calculated in 5 year periods. The objective for all scenarios was to maximize harvest volume over the length of the simulation. Two flow constraints were applied; a non-declining yield (NDY) was applied to the standing inventory and an even-flow to harvest volume.

The NDY constraint forced the simulation to only consider actions that allow standing inventory to remain at a similar level or increase from period to period over the entire planning horizon and never decline. The even-flow constraint forced the harvest level to remain constant throughout the planning horizon while still trying to maximize harvest levels.

3.3 Results

3.3.1 Primary and Secondary Attributes

Predicted plot-level linear regression models for primary attributes are presented in Table 4. Most of the models required multiple ALS metrics related to height percentiles (p05, p20, p25, p95 and p99) and structural measures (standard deviation and skewness) with Lorey's height being the only exception. Model performance varied for each model, with the poorest results for DBH (R^2=0.57; $p<0.001$), QMD ($R^{2=}$0.62; $p<0.001$) and stem count ($R^{2=}$0.51; $p<0.001$). All models directly related to height (mean height and Lorey's height) produced the best results (RMSE%=8.85 and RMSE%=7.92, respectively). Attribute models were then applied across the entire SCCF tenure. The VRI polygon was then overlaid to examine the visual comparison between area heterogeneity from model results (Figure 7).

Table 4: Developed predictive models for primary attributes (height, DBH, stems Lorey's height, QMD, biomass and volume). Adjusted R^2 value, p-value and RMSE% indicating significance and model results are reported.

Primary Attributes				
Dependent Variable	Predictive Model	Adjusted-R^2	p-Value	RMSE%
Height	$4.20 - 4.95 * skewness - 0.27 * P05 + 0.48 * p99$	0.92	<0.001	8.85
DBH	$-3.91 - 12.34 * skewness - 1.83 * p20 + 1.57 * p99$	0.57	<0.001	19.16
Stem Number*	$9.00 + 1.18 * skewness + 0.24 * p25 - 0.16 * p99$	0.51	<0.001	35.53
Lorey's Height	$0.35 + 0.91 * p95$	0.92	<0.001	7.92
QMD	$-6.35 - 10.42 * skewness - 1.77 * p20 + 1.77 * p99$	0.62	<0.001	18.36
Biomass	$-31.3 - 98.0 * skewness + 24.84 * p20$	0.84	<0.001	19.44
Volume	$-300.14 - 61.92 * stddev + 47.68 * p95$	0.83	<0.001	19.10

*Stem Count was transformed with a logarithmic transformation as it was the only value that was not normally distributed.

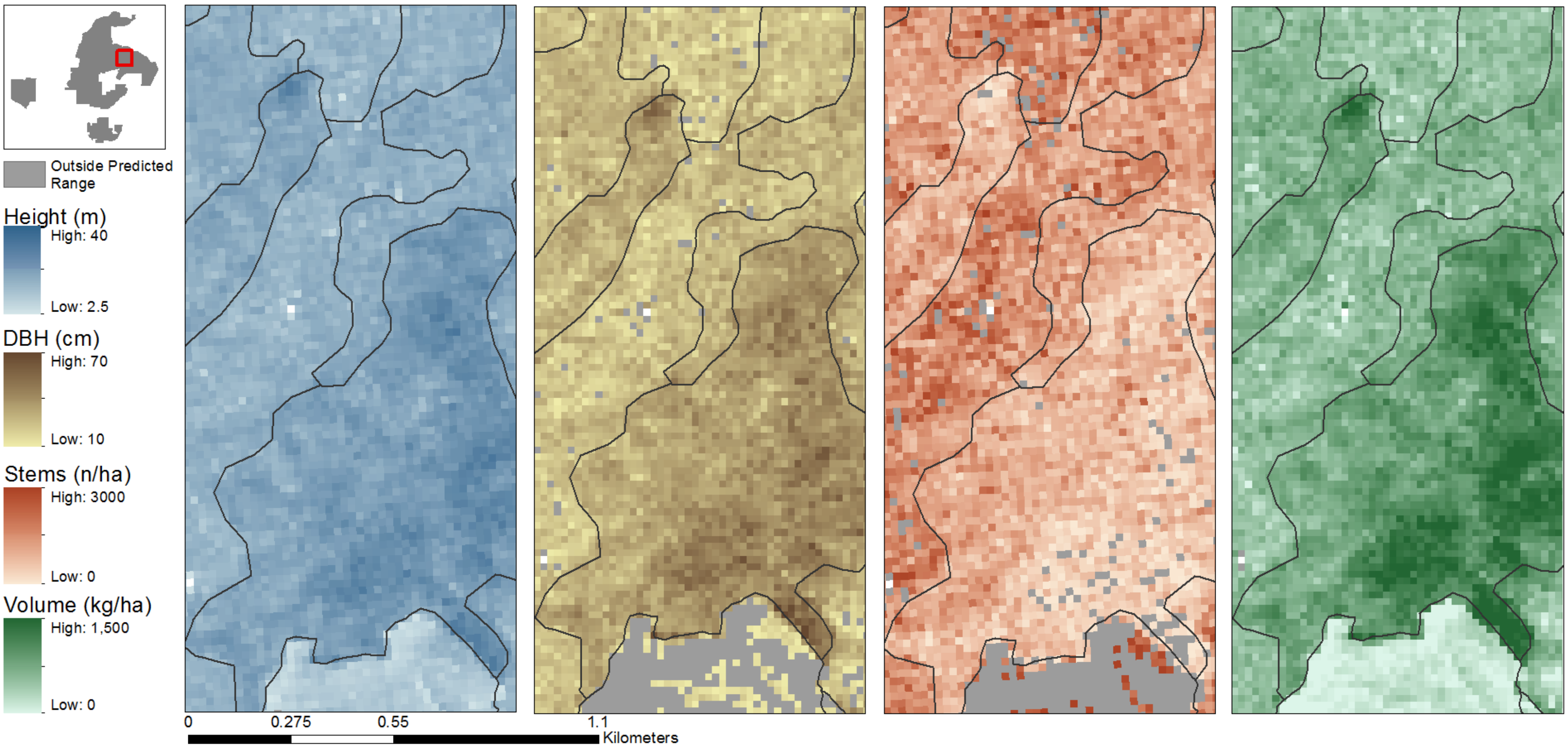

Figure 7: Exemplary results for a section of the SCCF tenure for height DBH, number of trees per hectare and volume, respectively. Grey areas indicate that estimations were outside the acceptable predicted range determined by field measurements. VRI polygons are overlaid the model predictions.

A variety of ALS metrics were used for predicting the Weibull distribution parameters (*k* and λ) as seen in Table 5. The 20th height percentile and skewness were used to predict *k*, representing the shape parameter. Kurtosis and standard deviation were used to predict the λ, representing that scale parameters. The R^2 value for *k* (0.43) was lower than the λ (0.65), percent bias and percent RMSE was larger for λ. The agreement between reference and predicted Weibull parameters varied across plots of different stand characteristics. For example, Figure 9, Plot 27 and Plot 14 showed a closer agreement between reference and predicted parameters compared to Plot 3 and Plot 18.

Table 5: Predictive models for Weibull shape (k) and scale (λ) parameters. Adjusted R^2 value and p-value indicating the significance of the models along with relative bias (%) and RMSE (%)

Secondary Attribute					
Dependent Variable	Predictive Model	R^2 (Adjusted)	p-Value	Bias (%)	RMSE (%)
k	$e^{12.8-4.97*skewness-0.61*p20}$	0.43	<0.001	3.59	28.61
λ	$e^{-6.28+1.44*stdev+0.67*kurtosis}$	0.65	<0.001	5.69	44.75

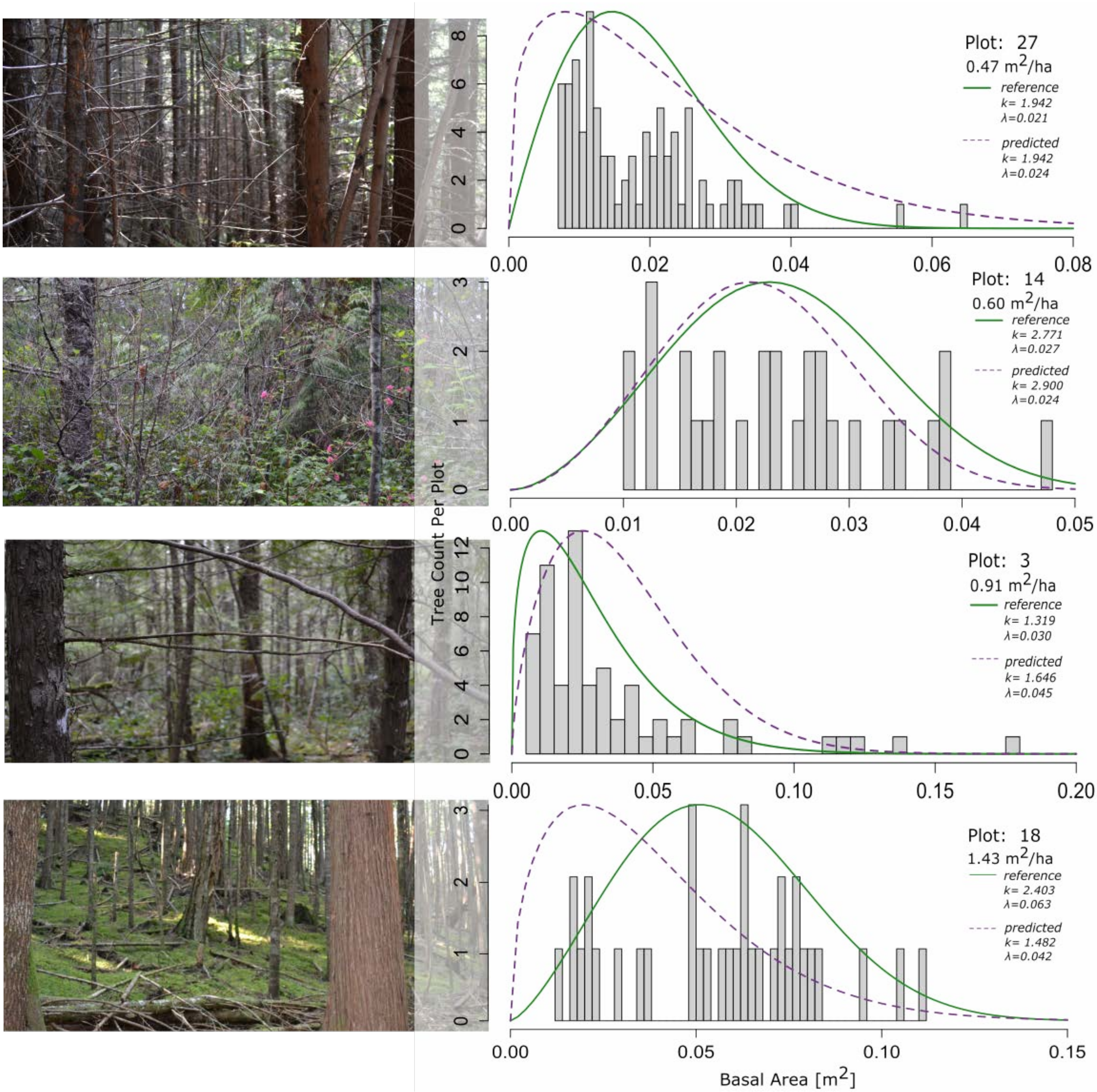

Figure 8: Individual tree basal area (grey bars) overlaid with Weibull PDF curves shown for four of the 32 plots. Parameters for the reference curves were derived using field measured basal area. Predicted parameters were modeled using ALS data. Basal area shown on the x-axis, frequency of tree shown on the y-axis.

3.3.2 Tertiary Attribute

The overall comparison of SI calculations for 946 forest covered VRI polygons indicates a relatively small difference between SI_{ALS} and SI_{VRI} (RMSE=35.1%). The range of SI from the VRI was between 4-45m. Relative to the VIR low productivity sites were overestimated with ALS data. There is a greater level of agreement between SI_{VRI} and SI_{ALS} with stands that have a “medium” level of productivity between 20-30m. Finally, there is an underestimation of VRI outliers by ALS data. However, overall SI_{ALS} increased the estimate of site productivity across the landscape (Figure 9). SI estimations were questionable for certain polygons with the age of stands being far younger than one would expect with maximum height calculations from ALS. Table 6 notes the outliers between ALS maximum stand height (H_{ALS}) and VRI_{AGE}.

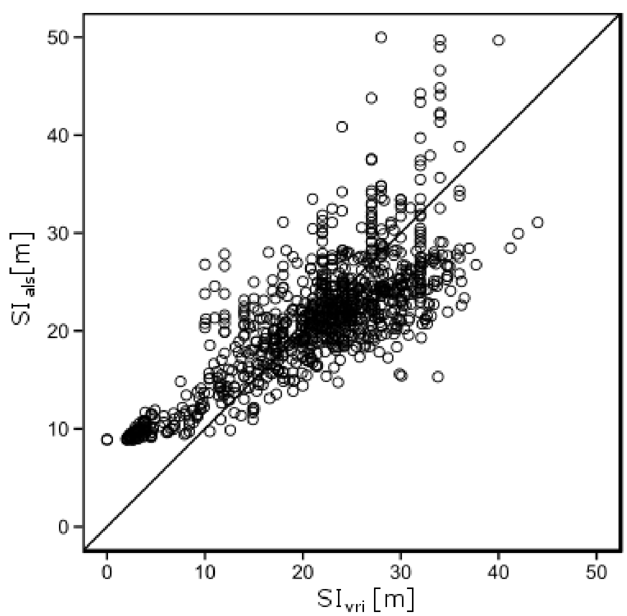

Figure 9: Scatterplot of ALS derived site index and VRI site index values (RMSE=7.47/RMSE%=35.09), outliers are not shown on figure image.

Table 6: Table of extreme Site Index outliers 13 out of 948 polygons

Species	**Projected Age (VRI)**	**SI_{VRI}**	**SI_{ALS}**	**H_{VRI}**	**H_{ALS}**
Douglas-fir	18	27	73.3	7.4	31.3
	19	32	75.4	8.8	35.5
	4	40	189.2	0.3	25.1
	4	28	216.5	0.4	30.8
	4	34	151.1	0.5	17.9
	4	34	192.4	0.5	25.7
	7	34	73.1	1.1	11.2
	7	34	75.4	1.1	14.2
	8	34	91.1	1.7	20.9
	2	34	386.3	0.2	26.8
	2	34	411.7	0.5	30.0
Western Hemlock	8	32	72.7	3.1	16.3
	9	32	90.3	0.5	25.7

3.3.3 Timber Supply Analysis

The landscape units developed within S1 and S3 based on a classification of SI to SQ resulted in a higher proportion of the landscape being classified as GOOD (SQ_{ALS}=1,665ha; SQ_{VRI}=178ha) as seen in Table 7 and Figure 10. A slight decrease in the sum of GOOD stand types defined by ALS data was noted with the inclusion of RMA. There was no decrease in GOOD stand types defined by the VRI data with the inclusion of RMA. There was a substantial decrease in both ALS and VRI data when stands were defined as POOR.

Table 7: Total hectares of site quality classification for scenario 1 (VRI) and scenario 3 (ALS) from site index values derived from VRI and ALS with the inclusion of non-harvestable riparian management areas.

SITE QUALITY	VRI (HA)	VRI RMA (HA)	ALS (HA)	ALS RMA (HA)
GOOD	178	178	1,665	1,572
MEDIUM	5,852	5,375	5,687	5,216
POOR	4,471	3,847	3,150	2,604

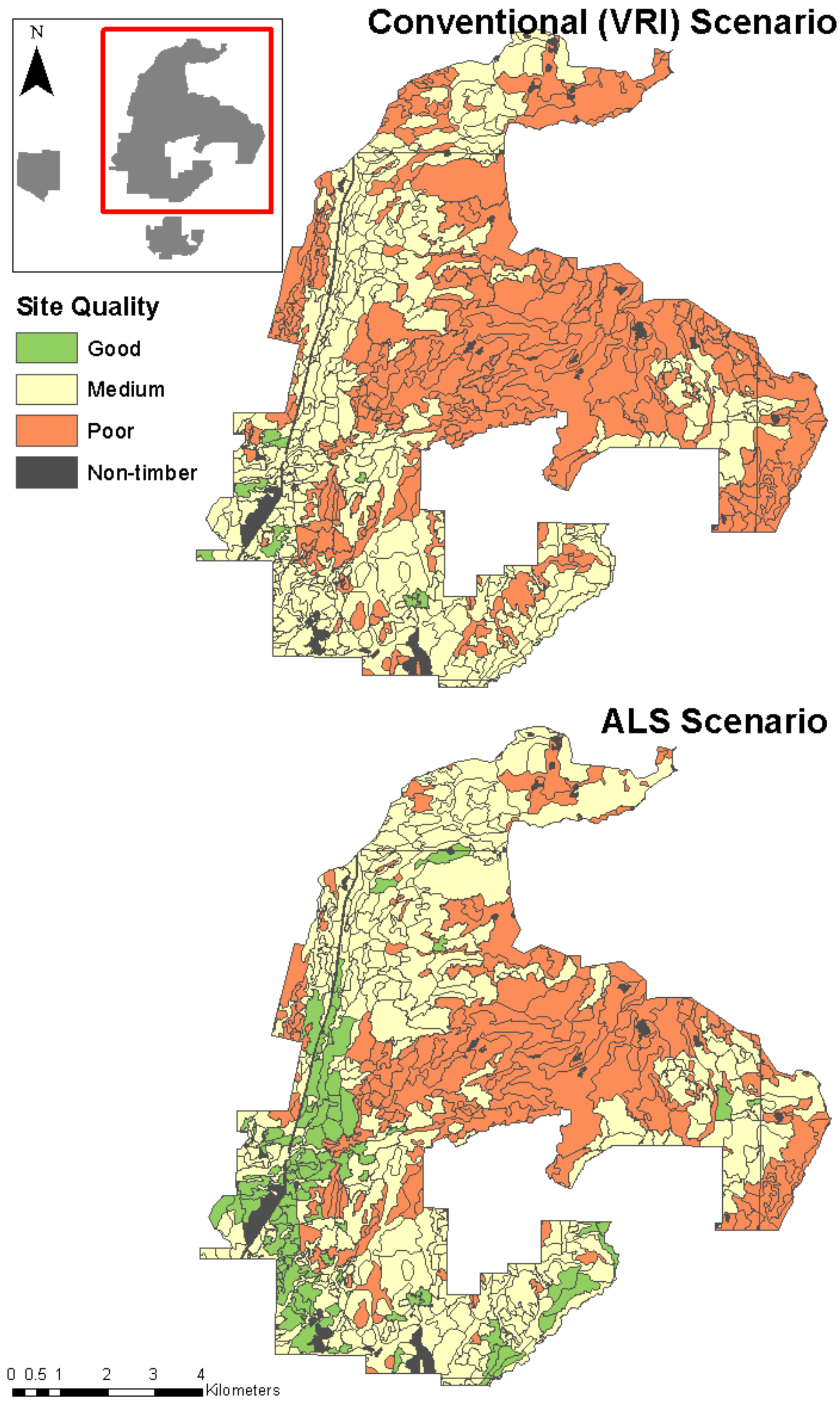

Figure 10: Site index derived from the VRI and ALS data grouped into site quality values (Good: SI > 35m, Medium: 20m < SI < 35m and Poor: SI > 35m)

WOODSTOCK estimates of the available timber supply varied between S1 and S3 with and without the inclusion of RMA (Figure 11). The maximum harvesting rate was always larger when using ALS derived SI (harvest rate$_{ALS}$=98,532 m^3/5years, harvest rate$_{Conventional}$= 45,140m^3/5years; RMA harvest rate$_{ALS}$ RMA=63,965m^3/5years, RMA harvest rate$_{Conventional}$=38,541m^3/5years). S3 had an initial standing inventory (period 0) of 1,536,717m^3 whereas S1 (Conventional (VIR)) had an initial standing inventory of 1,231,915m^3. The maximum standing inventory in all scenarios occurred during the final period (Standing Inventory$_{ALS}$=6,517,633m^3, Standing Inventory$_{Conventional}$=6,332,931m^3; RMA Standing Inventory$_{ALS}$=7,321,558m^3; RMA Standing Inventory$_{Conventional}$=6,513,077m^3).

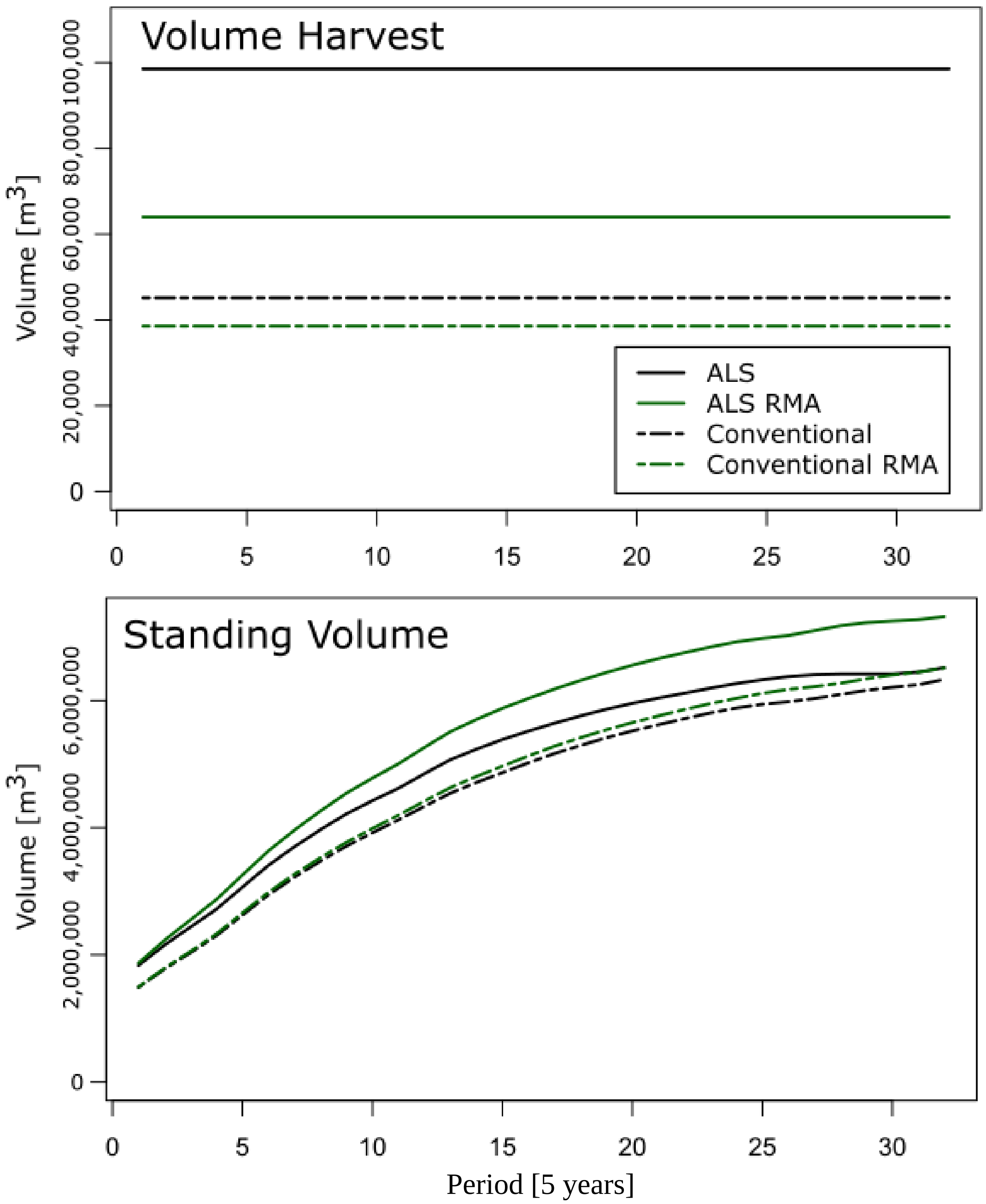

Figure 11: Timber supply results using WOODSTOCK with inputs from ALS and Conventional formats for defined timber harvesting landscape and for the entire defined timber harvesting landscape with the inclusion of riparian management areas.

The landscape themes developed for S2 and S4 based on SI_{VRI} and SI_{ALS} showed a higher variability in SI derived from ALS data relative to that of the VRI data as seen in Figure 12. This is a result of SI_{ALS} predicting site indices.

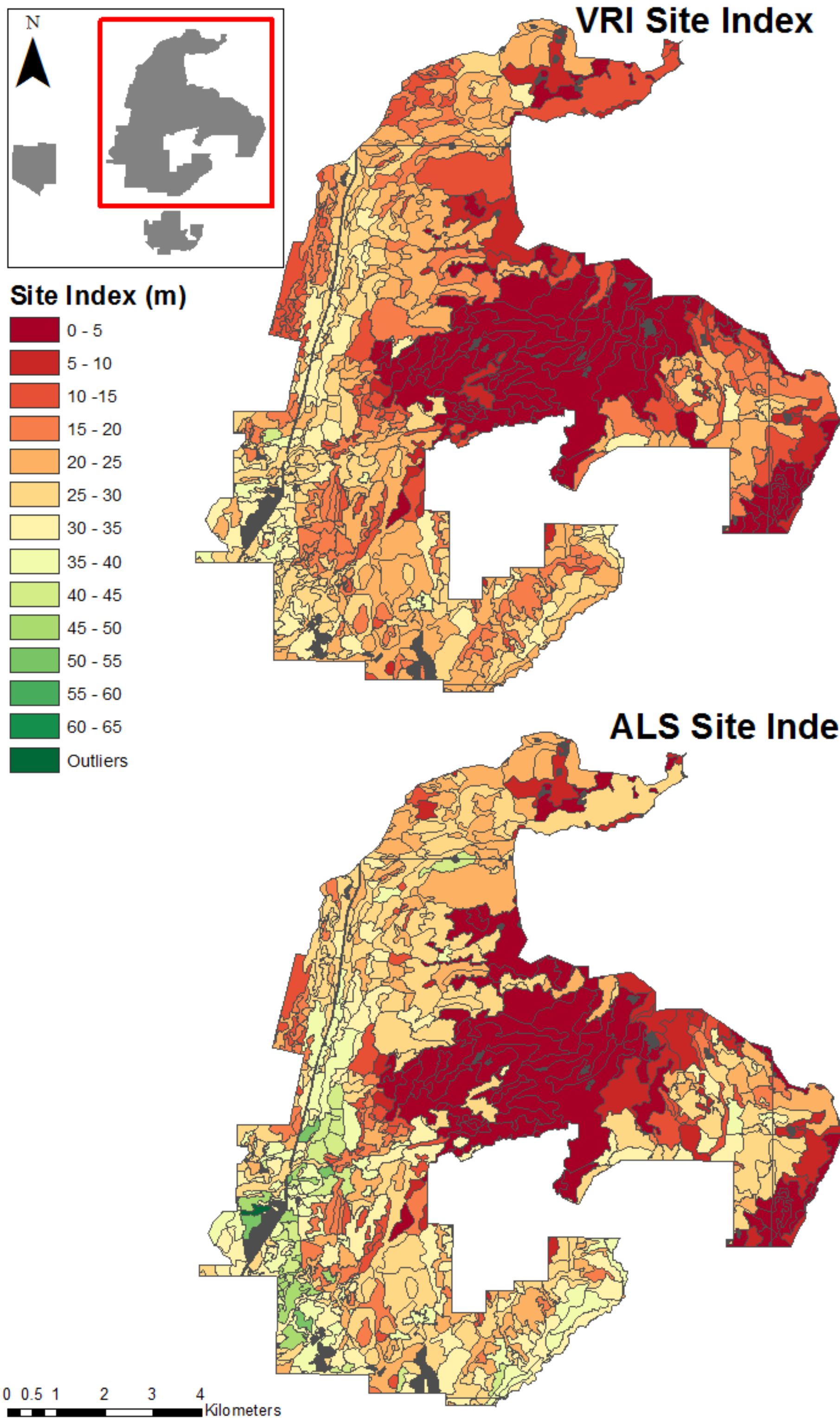

Figure 12: Site index derived from the VRI and ALS data

WOODSTOCK estimates of the available timber supply varied between S2 and S4, with and without the inclusion of RMA (Figure 13). The maximum harvesting rate was always larger when using ALS derived SI (harvest $rate_{ALS}$=691,305 m^3/5years, harvest $rate_{Conventional}$=481,863m^3/5years; RMA harvest $rate_{ALS}$ RMA=463,718m^3/5years, RMA harvest $rate_{Conventional}$=346,592m^3/5years). S4 had an initial standing inventory (period 0) of 7,166,259m^3 whereas S2 (Conventional (VIR)) had an initial standing inventory of 5,637,816m^3. The maximum standing inventory in all scenarios occurred during the final period (Standing $Inventory_{ALS}$=8,382,380m^3; Standing $Inventory_{Conventional}$=5,687,433m^3; RMA Standing $Inventory_{ALS}$=11,247,792m^3; RMA Standing $Inventory_{Conventional}$=7,950,187m^3).

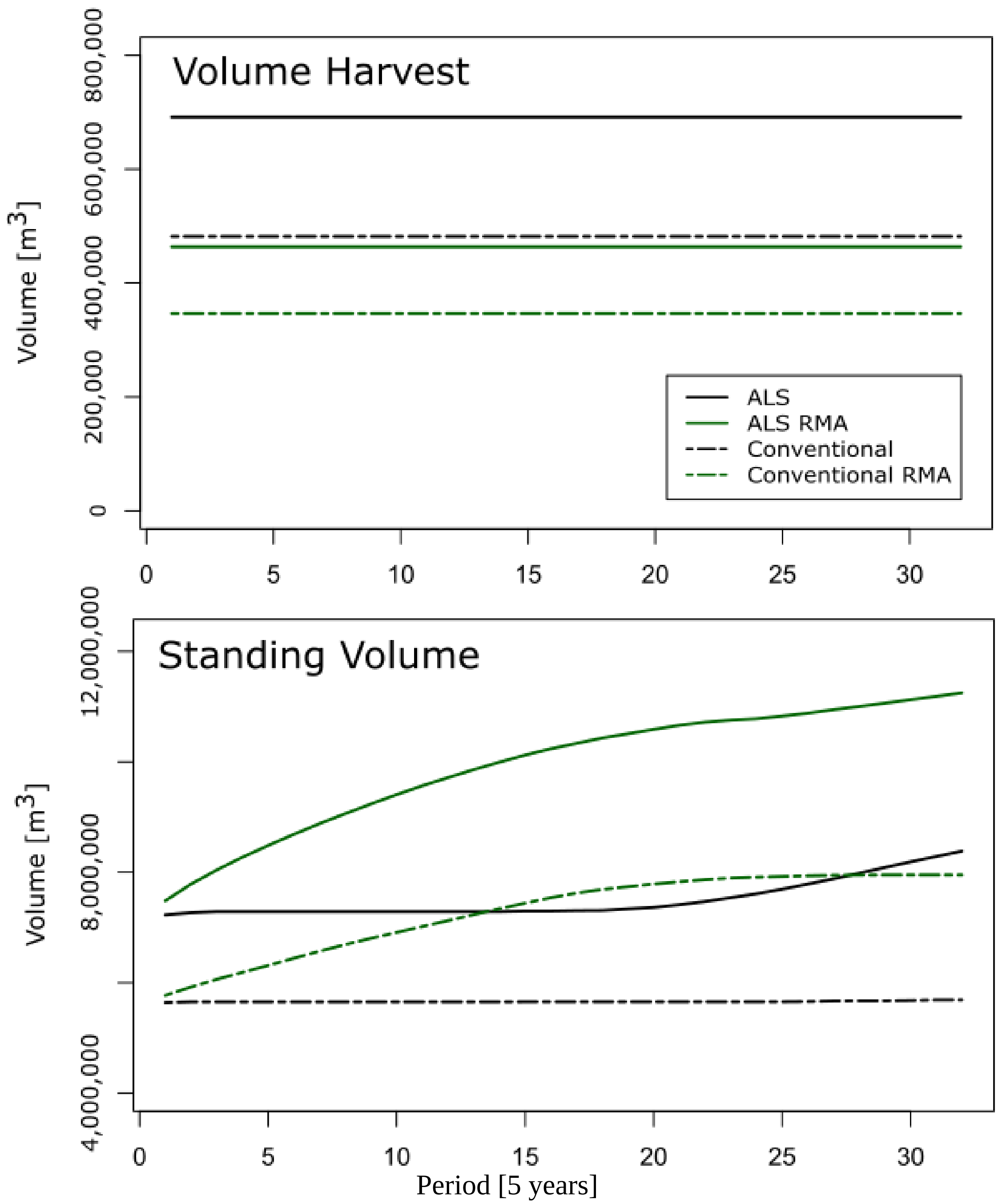

Figure 13: Timber supply results using WOODSTOCK with inputs from ALS and Conventional formats for defined timber harvesting landscape and for the entire defined timber harvesting landscape with the inclusion of riparian management areas. These results use individual SI estimations for each stand type.

3.4 Discussion

3.4.1 Primary and Secondary Attributes

The ALS ABA approach allowed for a range of forest inventory attributes to be calculated, with accuracies similar to those found in other studies. Næsset et al., (2004) found that the accuracy of mean height could range from R^2=0.77-0.95, mean diameter and stem number could range from R^2 =0.50-0.68, basal area could range from R^2=0.69-0.89, and volume could range from R^2=0.78-0.97. The usefulness of height percentiles for the estimation of plot level forest inventory attributes is well known (Holmgren, 2004; Næsset et al., 2004). Skewness describing the characteristics of the distribution in relation to vegetation structure was an important metric for all models, except for Lorey's height. The negative coefficient for skewness indicates that a higher number of returns occurred in the upper canopy (Montealerge et al., 2014). This could be attributed to the increased density of stems in certain plots relative to others.

ALS does not directly measure DBH, however, it is one of the most frequent measurements carried out by foresters (Popescu et al., 2004; Zhao et al., 2009). This attribute will have lower model confidence as will stem number, and QMD. Low model accuracy can be related to the difficulty of directly linking ALS metrics to measurements under the forest canopy (Popescu et al., 2004). Stand dynamics, such as competition can influence the relationship between DBH and height. QMD performed better than DBH as it used the weighted mean of all DBH measurements per plot compared to that of the average DBH (Popescu et al., 2004). QMD is useful for characterizing groups of trees which have been measured, it can be used to approximate other stand attributes and provide exact relationships compared to that of the arithmetic mean (Curtis and Marshall, 2000).

However, care should be taken when estimating QMD from ALS data, as QMD gives a greater weight to larger trees and ALS data does not directly distinguish the DBH of tree, as a result QMD might be overestimated for certain forest stands.

Diameter distribution of basal area per plots within various stand types was estimated from ALS data assuming that they followed the two-parameter, shape and scale Weibull PDF. The estimated Weibull λ (scale parameter) was more accurate than the k (shape parameter), similar to the findings of Tompalski et al., (2015b) and Saad et al., (2014). The difficulty in model performance for the k parameter is a result of the difficulty in determining the number of trees within a plot due to stand complexity and multistoried canopies, this results in uncertainty with the k parameter representing the range of the distribution (Tomplaski et al., 2015b). The error in k would result in the number of trees per plot being over or under-predicted for the most frequent BA. Whereas the error in λ could increase or decrease the distribution of BA resulting in a narrow or larger range of BA being estimated, potentially affecting the classification of stand type. A key limitation in using the unimodal-Weibull distribution is the difficulty in capturing data with more than one mode. Stands with multiple modes proved to be problematic when using the unimodal-Weibull PDF to predict BA. In stands with a wide range distribution of BA the Weibull distribution often missed capturing larger outliers. This is problematic as larger trees contribute to higher estimates of volume and biomass. Stands with increased complexity would be underestimated which would underestimate volume and biomass. Other modeling approaches such as finite mixture modelling (Thomas et al., 2008) and non-parametric k-most similar neighbor (Maltamo et al., 2007) have been explored to try and predict stem size distribution. Finite mixture modelling was found to be more effective for modeling irregularly shaped diameter distributions in low-density coniferous plots than unimodal 2-parameter Weibull PDF (Thomas et al., 2008).

3.4.2 Tertiary Attributes

Determining appropriate site indices is a key element for choosing the right growth and yield curves for the use in subsequent TSA. SI was predicted for stand dominant heights using height-age curves derived from ALS data and ground based forest inventory data (Tompalski et al., 2015b). A comparison of predicted SI_{ALS} and SI_{VRI} found that SI_{VRI} was generally lower than SI_{ALS}, supporting research by Tompalski et al., (2015b), who observed a mean difference of 3.5m and a relative mean difference of 25.6% between ALS estimated SI and forest inventory data SI. In this study we did not examine the variability of SI between leading stand species. This is a limitation of the work as the SI effects on stand volume is not constant across all species. Tompalski et al., (2015b) showed that there are larger difference in estimations of certain species dominant stands such as western red cedar and western hemlock (Tompalski et al., 2015b). Incorporating variability between species and SI estimations would present a more robust framework for analyzing SI. The assumption that all stands are pure stands is a restriction of this study, mixed species composition is likely to have effect on the estimation of SI.

It has been well documented that ALS data can predict height just as accurately as field estimates can, and more accurately than air photo-interpretation (Næsset and Økland, 2002; Næsset et al., 2004). Relating age from the VRI and height from ALS data was questionable for certain polygons, with the age of the actual stand being far younger than the maximum height calculated from ALS data. This could be due to high productivity or uncertainty within the VRI_{AGE} (questionable example: Age: 19, H_{ALS}: 35.5m, SI_{ALS}: 75.35m). Even though the VRI is considered to be up to date, errors in recording of recent logging activity or natural disasters may exist. Since ALS data alone cannot be used to estimate site productivity as age and species information are required, the VRI data is a necessity to estimating SI. Age has been estimated using ALS data but requires extremely complex and time intensive modeling of height-age relationships (Racine et al., 2014). Errors within the VRI may have led to an overestimation or underestimation of SI affecting the classification of SI across the landscape, resulting in inaccurate calculations of growth and yield and subsequent errors with the TSA. The ability to integrate ALS estimates of SI is very valuable especially when SI is estimated using aerial photography, doing so provides a level of certainty to stand height measurements when estimating volume yields on the landscape (Tompalski et al., 2015b). There is value in combining accurate measures of stand height from ALS data with existing inventory information to improve estimates of site index, volume, biomass and height as it allows for the remote and detailed estimation of SI with reasonable accuracy. However, age for each stand type should be assessed in detail and the reliability of stand history should be looked at in order to determine accuracy of stand age.

3.4.3 Timber Supply Analysis

The objective to achieve a maximum harvest with two constraints (NDY and an even flow harvest) were met by all four scenarios. The even flow and NDY constraint effected all four simulations. An even flow harvest allowed for economic stability by extracting the same amount of timber each year, this reduced the chance of economic boom and bust cycles. A NDY provided ecological stability preventing a decline of timber on the landscape from overharvesting. The results provide a theoretical simulation of a sustainable and economically viable TSA.

S1 and S3 used SQ classification and MFLNRO volume estimates to conduct a TSA. This method is similar to that of the TSA generated for the Sunshine Coast. The increase in overall SQ from ALS data compared to that of the VRI lead to an increase of estimated volume on the landscape. The increase in standing inventory in period 0 allowed WOODSTOCK to set a higher harvesting level for the entire simulation. As mentioned above, in tertiary attributes, the increase in SQ classification is influenced by potential errors related to age estimates. The inclusion of RMA within both scenarios resulted in a decreased amount of harvestable wood on the landscape, by reducing the area harvestable. There was a larger decrease in S3 (ALS scenario) relative to S1 (Conventional (VRI)) as the RMA reduced the availability of sites that had a higher volume of timber present within S3.

S2 and S4 had higher estimates of volume harvested and standing inventory compared to S1 and S3. This is a result of the volume estimates generated from TIPSY and VDYP compared to the volume estimates provided by the MFLNRO. One limitation of the TIPSY volume estimates is they did not incorporate any operational adjustment factors or treatment types, as a result, these TIPSY estimates are believed to be overestimated which would increase the amount of volume of wood on the landscape available for harvest. The increase in site variability across the landscape resulted in an increase of timber volume across the landscape as seen in S4 relative to that of S2. S2 and S4 are important in understanding how the differences between SI_{ALS} and SI_{VRI} could compound across the landscape when using individual SI values for estimated volumes. For example, the estimated harvestable volume derived from ALS data almost doubled compared to the Conventional data along with a substantial increase in the estimated standing inventory.

The addition of RMA added more complexity and met the minimum requirements of the FRPA. S1 approached a harvest level that as relatively close to the AAC set by the MFLNRO (AAC=20,000m^3/year, RMA harvest rate$_{Conventional}$=38,541m^3/5years). If additional management considerations such as old growth management areas, cut block proximity and variable retention were incorporated it would be expected that the harvestable volume for each scenario would decrease and become even closer to that of the AAC. It should be noted that the TSA generated is unlikely to reach the AAC set by the BC's MFLNRO as social, ecological and socio-economic considerations are not taken into consideration within WOODSTOCK simulations. The use of ALS data in S3 and the incorporation of RMA was almost twice that of the S1 (RMA harvest rate$_{ALS}$ RMA=63,965m^3/5years). Bringing into question if there is an overall underestimation of SI values from the VRI. The estimates derived from SI$_{ALS}$ do hold some validity due to the results achieved in the tertiary attributes but one should be careful relying solely on ALS data to derive SI estimates for a TSA.

Chapter 4: Using LiDAR to Map Ecosystem Services

4.1 Introduction

Ecosystems provide a variety of goods and services to society, who rely heavily upon these services for economic wealth, physical and emotional well-being (Ostrom, 1990; Fisher et al., 2009; de Groot et al., 2010; Andrew et al., 2014). Ecosystem services (ES) lack a consistent definition within the literature (Boyd, 2007; Barbier, 2007): Costanza et al. (1997) define ES as the benefits the human population derives directly or indirectly from ecosystem function, ecosystem function refers to various properties and abiotic and biotic processes of an ecosystem. Daily (1997) defines ES as the conditions and processes by which natural ecosystems and the species that make them up sustain and fulfill human life. The Millennium Ecosystem Assessment (MEA) (2005) provides a simpler definition of ES as the benefits people obtain from ecosystems. More recently Daniel et al., (2012) defined ES with respect to an ecosystem's natural capital and enhances social and human capital. Despite different definitions, common to each is an emphasis on the benefits ES provide to human life. Fisher et al. (2009) identified some of the most common terms used to describe ES, such as, goods, benefits, income, processes, capital and human life.

Many individuals do not fully understand the extent to which humans rely upon ES in terms of cultural, sociological or economic values (Bastain et al., 2013). We rely upon on ecosystems to provide, clean air, access to water, climate regulation and aesthetic and recreational values (Costanaza et al., 1997). Furthermore, the total benefit contributed by ES to human well-being is estimated to be more than twice the global gross domestic product (GDP) (Costanza et al., 2014). Within the last two decades it has been estimated that there is a global loss and diminishment of services largely due to human conversion of natural habitat, overuse of environmental goods and lack of knowledge of specific services (MEA, 2005; Costanza et al., 2014). In 2014 it was projected that the global loss of ES due to land use change was $US 4.3-20.2 trillion/year depending on the valuation process used (Costanza et al., 2014). In an attempt to provide a more comprehensive understanding of ES and their benefits, the Millennium Ecosystem Assessment (MA) developed a classification scheme that organizes ES under four main categories: provisioning, cultural, regulating and supporting (MEA, 2005; Fisher et al., 2009; Andrew et al., 2014). Table 8 provides specific examples and definitions of each class.

Table 8: Definition of ecosystem services their service capacity, examples of service capacity and received services.

	Provisioning	**Regulating**	**Cultural**	**Supporting**
Definition[a]	Products obtained from ecosystems	Benefits obtained from the regulation of ecosystems and their processes	Nonmaterial benefits obtained from ecosystems through spiritual enrichment, cognitive development, reflection, recreation and aesthetic experiences	Necessary for the production of all other ecosystem services
Service Capacity[b]	Feature-based measurements Usually measured directly through ecosystem properties	Process-based measurements Usually requires extensive knowledge and understanding of ecological processes and models. Development of detailed process–based models and extensive field data	Feature and process-based measurements Measurement depends on a mix of biophysical properties as well as anthropogenic conditions	Process-based measurements Detailed understanding of energy flow and process-based models
Example of Service Capacity[a]	Food Fresh water Wood and fiber Fuel (Energy)	Carbon regulation Flood regulation Disease regulation Water purification	Spiritual Education Aesthetic Recreation	Nutrient recycling Soil Formation Primary productivity
Received Service (Service Flow)[b]	Produces an end good/product	Lacks a clear end product that is manageable or commonly represented in markets. Environmental quality has been adopted as a metric of service flow and ecosystem state.	Received services is measured in terms of duration and quality of experience with nature	No end service received except all other ecosystem services

[a] MEA, 2005
[b] Villamagna et al., 2013

Spatially describing ES is necessary to comprehensively assess the alterations and diminishment of various services (Crossman, 2013). Spatial description of ES can assist policy makers to preserve ES supply and better manage ES demand (Troy and Wilson, 2006; MaKenzie et al., 2011). The spatial description of ES is dependent on assessing a particular service and the properties that influence the service; it is important to find testable connections between ecological patterns and/or processes and a measurable indicator (Andrew et al., 2014). However, many ES are conceptually linked to an ecological process rather than an actual good, for example climate regulation (regulating service), through carbon storage and sequestration (conceptual link) (MEA, 2005). A common approach to mapping ES is to assign proxy variables derived from land cover maps to represent ecosystem processes (Seppelt et al., 2011). Land use/land cover maps are extensively used in ES assessments as they are widely available, interpretable and are key to providing data on altered ES supply (Foley et al., 2005; MEA, 2005). The application of proxy variables to ES can abstract and conceptual or employ mechanistic models. The diversity of methods available makes direct assessments, valuation or description of ES proves to be challenging (Seppelt et al., 2011; Andrew et al., 2014).

Remote sensing (RS) has the ability to provide information over various spatial scales efficiently and cost effectively; the application of RS in relation to ES will assist in increasing the ES knowledge base (Feld et al., 2010; Tallis et al., 2012). The capacity to use RS data to assess ES has not yet been fully developed to date (Feld et al., 2010; Tallis et al., 2012). Andrew et al., (2014) conducted an extensive review that focused on a wide variety of RS products that have the potential and capability to describe ES spatially, while also providing examples of direct estimates of ecosystem properties and services. One RS technology with significant potential to assist with the quantification and spatial distribution of ES is LiDAR (Troy and Wilson, 2006; Andrew et al., 2014). LiDAR can provide information on both terrain and above ground structures (Figure 1, pg. 8). Terrain data can be used to describe stream morphology (Hohenthal et al., 2011) and geomorphology (Lloyd and Atkinson, 2006). Above ground structural information can be used to derive measure of forest volume, above-ground biomass (Nilsson 1996; Næsset et al., 2004; Wulder et al., 2008) and archeological information.

The purpose of this review is to examine the application of LiDAR for mapping, monitoring, identifying, quantifying and describing ES using both direct ES indicators and proxies. I explore the benefits and limitations of spatially describing ES using LiDAR alone and its integration with other RS products and ground based measurements.

4.2 Provisioning Services

Provisioning services are considered to be the easiest of the four services to conceptualize and quantify. Provisioning services are used to describe materials and/or energy outputs from an ecosystem, often equated to specific goods provided through various ecosystem processes. For example, clean drinking water is conceptualized to arise from water filtration, flood regulation and other regulating and supporting services (Crossman et al., 2013). Provisioning services tend to be grouped into products or goods provided: food, water, raw materials and genetic, medicinal and ornamental resources (Crossman et al., 2013). Each of these goods has the ability to be mapped using different methodologies, with services such as food, water and raw materials easier to map than others such as wind energy (Crossman et al., 2013). Water, food and raw materials have a wide variety of robust modelling approaches that are used to map volume, availability and flow of various goods. These easily mapped goods tend to be readily quantifiable and, when commoditized, are directly affected by the supply and demand of the global economy (Burkhard et al., 2012). The demand for a particular good is dependent on the induvial or community need for said good, with not all services being demanded equally. Examples of mapping provisioning services using LiDAR data is more readily available in the literature than that of regulating, cultural and supporting services.

All three forms of LiDAR have been used to quantify and spatially describe various provisioning services (Table 9). This is largely due to the ongoing research and integration of LiDAR data – and in particular ALS data – to achieve accurate descriptions of forest resource for the development of spatially explicit forest inventories (Corona, 2010; Brosofske et al., 2014). ALS data is being used for operational level forest management to summarize forested landscapes with the development of spatially continuous maps of forest inventory attributes at the individual plot, stand and landscape level (Lim et al., 2003; Wulder et al., 2008; Brosofske et al., 2014). Forest inventory measurements derived from ALS data include species, diameter, height, volume and biomass (Næsset et al., 2004).

Numerous studies have also looked at how LiDAR-derived data may assist with other provisioning services such as habitat mapping for the consumption of animals. A review conducted by Davies and Anser (2014), highlights LiDARs ability to measure the 3D structure of ecosystems and how habitat structure has a direct influences on species richness and abundance. Habitat mapping using vegetative structural attributes derived from ALS has primarily been developed for predicting habitat of various bird species, especially songbirds (Leask et al., 2011). However, habitat mapping is being increasingly used to map larger mammal species habitat such as Mule Deer (*Odocoileus* *hemionus*) (Coops et al., 2010). Mapping of habitat structure can assist with species preservation or help managers create habitat desirable for subsistence hunting.

Through ALS data to it is possible to build spatial relationships between provisioning, regulating and supporting services through the function and productivity of a forest. In particular, ALS data can directly measure (e.g. canopy height), model (e.g. above-ground biomass) or be fused with other sensors (e.g. species diversity) to assess the structure, composition, health and productivity of a forest providing a link to various ES (Dubayah and Drake, 2000). This information can assist with the restoration of ES by analyzing biodiversity and structural function of forested ecosystems (Brosofske et al., 2014). Describing and extracting stream morphological features, discussed in regulating services, can be used to manage and maintain fresh and clean water supply. Many of the methodologies mentioned in obtaining information on regulating services can be adapted to map provisioning services, however, the end service has changed to a tangible product.

Table 9: The capabilities of LiDAR to map **provisioning services** are categorized into 3 categories demonstrating, potential and no capacity. LiDAR measurements that clearly exhibit LIDAR ability to map the service are classified as demonstrating. LIDAR growing capacity through fusion and additional methodologies are classified as potential. No capacity indicates that there is no current work that demonstrates LiDAR ability to map a service. White et al., (2013), Hudak et al., (2002) and Nijland et al, (2014) provides methodological information on how to derive direct and indirect measurements of forest attributes from LiDAR metrics and modelling. Holmgren et al., (2008), McMaster (2002) and Murphey et al., (2008) highlight how LIDAR-derived data may be applied to map and quantify a specific provisioning service.

PROVISIONING SERVICES	**Service**	**Measurements with LiDAR**	**LiDAR Source**	**Examples**
Demonstrating	Timber	Vegetation characteristics - Volume - Height - Basal Area - Tree size distribution Species Identification	ICESat ALS TLS	Næsset et al., 2004 Packalen and Maltamo, 2007 Orka et al., 2010 White et al., 2013
	Freshwater	Hydrological Mapping - Fresh water	ALS TLS	McMaster 2002 Murphy et al., 2009
	Subsistence Hunting	Vegetation characteristics - Habitat Mapping - Aquatic habitat structure	ALS	Vierling et al., 2008 and 2013 Martinuzzi et al., 2009 Nijland et al., 2013 Jones 2006 - Aquatic Kuffner et al., 2007 - Aquatic
	Biomass	Vegetation characteristics - Biomass	ICESat ALS	Hudak et al., (2002) Patenaude et al., (2004) Lefsky et al., (2005b) Popescu and Hauglin (2014)
Potential	Food	Vegetation characteristics - Species Identification	ALS	Holmgren et al., 2008
No Capacity	Medicinal needs	-	-	-

4.3 Regulating Services

Regulating services are defined as the benefits obtained from the regulation of ecosystem processes as a result of ecosystem structure and function (MEA, 2005). Regulating services prevent or mitigate processes that may be harmful to humans and human capital and provide other often essential services (Nedkov and Burhard, 2012) such as climate regulation, natural hazard regulation, water purification, waste management and pest control (MEA, 2005). Regulating ES are influenced by the spatial patterns of landscapes and the adjacent interactions between ecosystems (Nedkov and Burkhard, 2012). When trying to assess a regulating service, it is important to take into consideration how changes to a landscape act in concert to enhance regulating services. Conversely, it is also important to consider how significant manipulation of landscape characteristics could undermine a regulating service, potentially increasing the flow of disservices from a landscape (Nedkov and Burkhard, 2012). For example, forests and other landscape characteristics (e.g. topography, geomorphology) together play an integral role in the mitigation of flooding from runoff, snow melt and significant rainfall events (Nedkov and Burhard, 2012). Manipulation of landscape characteristics can affect the ability of a regulating service, for example, vegetation removal without considering the role of vegetation on the landscape could lead to an increase chance of a flood events. Mapping regulating services has become increasing important with the current discussion around climate change and with natural disasters becoming more frequent and extreme (Daniel et al., 2012).

Landscape characteristics are often described through digital elevation models (DEM), which are 3D terrain surface models. Recently LiDAR, in particular ALS data, has been used to derive DEM by classifying points as ground/non-ground using specialized software packages. A surface line is fitted through the classified ground returns through various techniques and an even surface representing the terrain is modeled (Gatziolis and Anderson, 2008; Bater et al., 2009). DEM generated from LiDAR have been shown to yield improved spatial information when compared to ground-based measurements and aerial photography (Baltsavias, 1999). LiDAR has had numerous benefits for mapping DEM by providing information in remote areas and describing terrain under thick forest canopies. The difference between DEM generated from terrain beneath open and closed canopies is small and does little to affect the overall DEM quality (Reutebuch et al., 2003). The accuracy of a terrain model is dependent on terrain complexity, sampling density and interpolation (Aguilar et al., 2010). The quality of a DEM generated from LiDAR alone might be sufficient to justify the often high price tag of obtaining LiDAR data (Reutebuch et al., 2003). ALS systems are the most cost-effective and efficient method of capturing the information needed for DEM (Baltsavias, 1999).

Some examples of using a DEM produced with ALS data to spatially describe regulating ES are provided in Table 10. Using a DEM, it is possible to analyze and map the distribution of various services, such as flood regulation, water quality and soil erosion. DEM created from ALS data can provide maps that quantify multiple hydrological characteristics and metrics: hydrological networks (James et al., 2007; Murphy et al., 2009); topographic wetness index and compound topographic index; and drainage characteristics (Straumann and Purves, 2007; Amatya et al., 2013). DEM also provide an opportunity to study slope morphology, slope aspect, drainage and ditch morphology (Luscombe et al., 2014). Combining various data products such as slope grade data from ALS and soil types derived from other remote sensing products or field surveys it is possible to predict areas susceptible to high levels of soil erosion (Bastain et al., 2013). Many of the measurements obtained from DEM are used indirectly to assess hydrological processes that can then be applied to regulating ES. From DEM it is possible to derive information on flow paths for surface run off, in-channel flow, elevation gradients, land use and location of channel cross sections and their elevation profile. These various data layers can then be used in hydrology and hydraulic models to determine water surface elevations and the potential of flood regulation capacity of a landscape (Nedkov and Burhard, 2012).

LiDAR derived forest attributes are used to assess, quantify and map regulating services though descriptive variables such as biomass and vegetation structure. For example, climate regulation through carbon sequestration and carbon storage can be mapped from snapshot and time series biomass estimates of forested and vegetated areas. LiDAR data has been widely used to predict biomass in various biomes (e.g. Andersen et al., 2011; Kankare et al., 2013; Yu et al., 2013), with two common methods of mapping biomass: area based approach (ABA); individual tree detection (ITD) approach. Both rely upon modeling a direct relationship between LiDAR derived metrics and field measurements through linear regression models or non-parametric regression models (Popescu and Hauglin, 2014).

LiDAR derived vegetation structure metrics can also be used to assist with fire management. Traditional fuel assessments have been criticized for their inability to capture the spatial distribution of fuels at the stand and landscape level (Erdody and Moskal, 2010). Using LiDAR – in particular ALS – data it is possible to characterize fuel metrics by measuring various biophysical properties of fuel: size, quantity, arrangement, crown bulk density, foliage biomass, vertical continuity, ladder fuels, and size of fuel elements (Riaño et al., 2003; Morsdorf et al., 2004; Erdody and Moskal, 2010). ALS data has also been used to assess the relative proportions of surface fuels, ladder fuels and canopy fuels by looking at various height percentiles (Skowronski et al., 2007). However, there are restrictions, especially in very dense forests, as it might not be possible to measure the full extent of surface fuels and ladder fuels using ALS alone (Riaño et al., 2003). Fuel metrics generated using ALS data can lead to the improvement of fuel maps, compared to data generated from more traditional remote sensing techniques allowing for enhanced prioritization and evaluation of fuel management (Skowronski et al., 2007; Mutlu et al., 2008). The creation of fuel maps allows for individuals to understand the capacity of an ecosystem to maintain a natural fire frequency and intensity. Natural process, like fire regimes, are affected by human development and the growth of public and private welfare, minimizing an ecosystems ability to use fire to regulate its interactions (de Guenni et al., 2005).

Table 10: The capabilities of LiDAR to map **regulating services** are categorized into 3 categories demonstrating, potential and no capacity. LiDAR measurements that clearly exhibit LIDAR ability to map the service are classified as demonstrating. LIDAR growing capacity through fusion and additional methodologies are classified as potential. No capacity indicates that there is no current work that demonstrates LiDAR ability to map a service. Næsset et al., (2004) and Murphy et al., (2008) provide methodological information on how to derive direct, and indirect measurements of forest attributes from LiDAR metrics and modelling. Straumann and Purves (2007), James et al., (2007) and Thoma et al., (2005) highlight how LIDAR-derived data may be applied to map and quantify a specific regulating services service.

REGULATING SERIVCES	Service	LiDAR Measurement	LiDAR Source	Examples
Demonstrating	Carbon Sequestration Carbon Storage	Vegetation characteristics - Biomass estimation	ALS	Næsset et al., 2004 Patenadue et al., 2004
	Water Flow Regulation	Digital Elevation Model - Hydrological modeling	ALS	Murphy et al., 2008 Lang et al., 2012
	Flood Regulation	Digital Elevation Model - Compound terrain index	ALS	Straumann and Purves, 2007
	Erosion	Digital Elevation Model - Slope and hydrological modelling	ALS TLS	Martínez-Casasnovas et al., 2004 James et al., 2007
	Fire Management	Vegetation characteristics - Canopy measurements	ICESat ALS TLS	Andersen et al., 2005 Mutlu et al., 2008
Potential	Soil retention/Soil erosion regulation	Vegetation characteristics	ALS TLS	Thoma et al., 2005
No Capacity	Water Quality	-	-	-

4.4 Cultural Services

Cultural services build a link between the social realm and the biophysical environment of an ecosystem (Daniel et al., 2012). They tend to be non-material benefits that individuals can gain from an ecosystem, such as spiritual and religious values, educational values, inspiration, aesthetic values, social relations, cultural heritage values, recreation and ecotourism (MEA, 2005). Because of their emotional appeal, cultural services are often used to help raise awareness and public support for the maintenance of ecosystems and ecosystem processes (MEA, 2005). The potential to use LiDAR data to map and measure cultural services is somewhat limited. This is because they are often characterized as being intangible, subjective and difficult to quantify both biologically and monetarily due to their intrinsic value to individuals, stakeholders and organizations (MEA, 2005). Nevertheless, it is possible for LiDAR data to be a unique and useful tool to discover, monitor and maintain cultural services. Some examples are viewshed modelling, cultural heritage, recreation and tourism. Table 11 highlights examples of LiDAR's ability to map cultural services.

Landscape characteristics and aesthetics best represent the cultural ES concept as they provide an opportunity to link underlying ecosystem processes and conditions (Daniel et al., 2012). For example, LiDAR has the ability to assist with the selection and valuation of housing property by quantifying the aesthetic value. In a study done by Hindsley et al., (2013) on the Gulf of Mexico, ALS data was used to create viewshed models analyzing the view each house had of the ocean and the fiscal amount each view added to the value of a give piece of real estate. Viewshed models based on ALS topographic features and data-intensive point clouds can determine where and what will skew an individual's view from a property. Computer visualization techniques can incorporate changes in landscape features, such as tree removal, and how those changes might effect viewsheds

(Hamilton and Morgan, 2010). It is then possible to create financial evaluations for various properties or landscapes that may have aesthetically desirable views (Hamilton and Morgan, 2010). Viewshed analysis can also be used to determine vegetative and structural view impairment: at fine scales, research on “near-views” within forest landscapes has shown that densities of different species, sizes of trees, amounts of vegetative understory, and volumes of downed wood have the strongest effect on aesthetic judgements (Brown and Daniel, 1986). Fine scale viewshed analysis using TLS data can derive single tree positions and diameters (Aschoff et al., 2004), single tree information would then be used at localized scales to derive potential views and valuation of views.

Cultural heritage ES are natural or semi-natural features that are important to the identities of individuals, communities or societies (Daniel et al., 2012). Cultural heritage ES incorporate a recognition that long-term interactions have occurred between humans and ecosystems and are used to identify legacies shared among biophysical features, physical artifacts and intangible attributes of a group or a society (MEA, 2005; Daniel et al., 2012). There are various types of attributes within ecosystems that can be identified to possess cultural significance, from an entire ecosystem type, to a feature on the landscape, or a specific species.

A prominent example of using LiDAR to identify cultural heritage ES, is the use of ALS data to identify sites of archeological significance. Chase et al., (2012) used ALS data to map detailed structures, residential groups, causeways, terrain, resource sinks and caves in the Maya, Mexico. There is also potential to augment knowledge of known archeological sites. For example, in 2001 the Stonehenge World Heritage Site was mapped using ALS data, revealing extensions to known field systems, insight into the military railway that had been previously unknown, as well as other historical landscape features not visible to the naked eye such as remnant ploughing networks (Bewley et al., 2005). TLS data has also been used for finer scale mapping of cultural heritage sites. A study done by Lerma et al., (2010) combined TLS data and photogrammetry to create 3D models of Palaeolithic engravings in the interior of the Cave of Parpalló situated on the Iberian Peninsula (Spain). In another instance TLS was used for the preservation of a historic town in Pitigliano, Tuscany (Central Italy) by analyzing the instability of the cliff edges where the buildings of the town were located (Fanti et al., 2011). Despite the limitations of LiDAR for mapping and monitoring cultural services, LiDAR data still has a role in the identification and preservation of cultural services. The monitoring and mapping of cultural services is limited by the extent that LiDAR data can be connected to how humans value and view our heritage.

Table 11: The capabilities of LiDAR to map **cultural services** are categorized into 3 categories demonstrating, potential and no capacity. LiDAR measurements that clearly exhibit LIDAR ability to map the service are classified as demonstrating. LIDAR growing capacity through fusion and additional methodologies are classified as potential. No capacity indicates that there is no current work that demonstrates LiDAR ability to map a service. Simonson et al., (2014) and Lerma et al., (2010) provide methodological information on how to derive direct and indirect measurements of forest attributes from LiDAR metrics and modelling. Hamilton and Morgan (2010), Hindsley et al., (2011) and Raimondi et al., (2013) highlight how LIDAR-derived data may be applied to map and quantify a specific cultural services service.

CULTURAL SERVICES	Service	LiDAR Measurements	LiDAR Source	Paper Examples
Demonstrating	Aesthetic value Aesthetic proximity	Digital Elevation Model - Viewshed modeling - Stucutral attributes	ALS TLS	Hamilton and Morgan, 2010 Hindsley et al., 2013
	Recreation	Digital Elevation Model - Viewshed mapping - Structural attributes	ALS	Kincey and Challis, 2010 Marion et al., 2011
	Species mapping (Existence value)	Vegetation characteristics - Habitat measurements - Vegetation monitoring	ICESat ALS TLS	Nelson et al., 2005 Anser et al., 2008 Simonson et al., 2014
Potential	Cultural Heritage	Digital Elevation Model - Landscape feature identification - Archeological exploration	ALS TLS	Bewley et al., 2005 Lerma et al., 2010
	Spiritual and Religious Encounters	Digital Elevation Model Structural characteristics - Restoration and conservation of cultural heritage assets	ALS TLS	Raimondi et al., 2013
No Capacity	Tourism	-	-	-

4.5 Supporting Services

Supporting services are fundamental and necessary for the production of all other services (MEA, 2005). They make it possible for ecosystems to provide services such as food supply, flood regulation and water purification. Examples of supporting services are nutrient cycling, soil formation and primary production (MEA, 2005). The relationship between supporting services and human needs can be indirect and complex, especially when trying to identify a supporting service (Daniel et al., 2012). Many of the products produced by RS are connected to other ecological processes that have an effect on the supply of supporting services; for example, nutrient, carbon and water cycles are supporting services that contribute too many regulating and provisioning services, including climate regulation, air/water purification, food and water provisioning (MEA, 2005). By spatially describing some of these services one is also identifying their underlying supporting service. Although, there is some research using LiDAR and other remote sensing sources to map regulating services to derive ES from forest productivity (Lefsky et al., 2005b) and landuse maps (Zhou, 2013), many of the mapped ES use proxies to describe the underlying supporting service (Table 12).

Table 12: The capabilities of LiDAR to map **supporting services** are categorized into 3 categories demonstrating, potential and no capacity. LiDAR measurements that clearly exhibit LIDAR's ability to map the service are classified as demonstrating. LIDAR growing capacity through fusion and additional methodologies are classified as potential. No capacity indicates that there is no current work that demonstrates LiDAR ability to map said service. Tompalski et al., (2015a) provides methodological information on how to derive direct and indirect measurement of a forest attribute from LiDAR metrics and modelling. Greve et al., (2012), Popescu and Hauglin (2014) and Nijland et al., (2015) highlight how LIDAR-derived data may be applied to map and quantify a specific supporting services.

SUPPORTING SERVICES	**Service**	**LiDAR Measurements**	**LiDAR Source**	**Paper Examples**
Demonstrating	Above-ground net primary productivity	Vegetation Characteristics - Biomass	ICESat ALS TLS	Lefsky et al., 2005b Popescu and Hauglin, 2014
	Site Productivity	Vegetation Characteristics - Tree height	ALS	Tompalski et al., 2015a
Potential	Land Use/Land Cover	Digital Elevation Model Vegetation Characteristics Structural Characteristics	ALS	Antonarakis et al., 2008 Zhou, 2013 Nijland et al., 2015
	Soil Formation/Soil Properties	Digital Elevation Model - Geomorphology - Compound topographic index	ALS	Aspinall and Sweeney, 2011 Greve et al., 2012
No Capacity	Nutrient cycling	-	-	-

4.6 Discussion

There are many challenges to the implementation of ES frameworks with respects to planning and monitoring: some of these challenges are due to the lack of spatially explicit assessments at regional, national and continental scales (Daily and Matson, 2008); the quantification and implementation of ES (Wallace, 2007); or the lack of ability to map ES and incorporate them into decision making process (Daily and Matson, 2008). With the advancement of remote sensing technology it has become possible to map and monitor a wide range of ES. However, the mapping of ES is considered to be in its infancy, and remains difficult due to the immense complexity of ecosystems and the numerous services they provide (Nedkov and Burkhard, 2012; Andrew et al., 2014). Throughout this review LiDAR has shown the potential to be a useful tool in the development of mapping, quantification and identification of ES.

LiDAR data (ALS, TLS and Spaceborne) can be exceptionally costly, with the cost dependent on the size of the area and the sensor used. Acquiring LiDAR information for the sole purpose of ES mapping may not be justifiable or feasible for many organizations as the value of the ES in some locations may be less than LiDAR data itself. However, many companies use LiDAR data for engineering purposes, and the application of previously acquired data to map ES can provide unique opportunities to develop methods for creating sustainable management decisions and EBM. Although LiDAR data does provide the ability to explore ES mapping, it does have its limitations. The data alone may not be suitable to provide enough detail, requiring fusion with other spatial datasets. Westcott and Andrew (2015) highlight that mapping cultural services, such as, recreation requires additional information in the form of user surveys or participatory research creating more robust maps of recreation activity and user preferences (Westcott and Andrew, 2015).

Currently much of our knowledge about ES is static, in part because the concept of ES is relatively new (Nedkov and Burhard, 2012). LiDAR, like other RS products, is an extraordinarily powerful tool as it can deliver repeatable, synoptic observations allowing for the monitoring of ES over time. This is especially important with regards to the conservation and preservation of ES, a mission that requires comprehensive, detailed assessments of ES through time. Not only can LiDAR assist with the assessment of one particular service, but by obtaining data over different time periods provides insights into how the modification of one service may alter another can be gleaned. Many ES are interrelated, with the product or good provided by one ES possibly the result of two or more ecosystem functions that produce other ES (Costanza et al., 1997). The modification of one service has the potential to influence the functioning of another (Bastin et al. 2013), such as, timber harvesting resulting in a change of forest structure over time suitable for some wildlife species and not others.

The complexity of ES presents a challenge for all remote sensing efforts to map, quantify, and assign value (Andrew et al., 2014). Certain services are easier to spatially describe than others, for example, provisioning services tend to provide discrete, material products rather than processes. The difficulty with using RS products for regulating, cultural and supporting services is not only that they can be subjective but the connection between the data and the end ES is a proxy variable and not a direct indicator.

LiDAR, like other RS approaches can be a descriptive tool; for example, when using LiDAR data to investigate an area that may hold unique tourist opportunities (cultural services), or using the maximum height of a stand as a proxy for site quality (supporting services). Regardless, any additional positive effect of using a RS technology like LiDAR data for the preservation of biodiversity, improvement of landscape appearances, recreational values, improvement of water quality, and so on, would constitute a much higher net gain for society. Additional knowledge gained from mapping ES provides a further source of information that has the potential to increase the value of many of our ES. The literature and research done by various individuals is starting to focus on how RS products can be used to provide spatial information in a somewhat lacking field.

Chapter 5: Conclusions

5.1 Overview

Harvesting plays a vital role in many CFA, providing a source of revenue that financially supports local values through community projects and outreach programs. In particular, the community forest of Sechelt prioritizes the maintenance of the community's watershed while maintaining a sustainable and economically viable rate of harvest. As such ALS data was acquired to assist the manager of SCCF, providing detailed, timely, and accurate information about the forested land base compared to the classification of satellite imagery, aerial photo-interpretation and extensive field collection. Time intensive collection of forest inventory can lead to poor timing of management actions causing economic losses and mismanagement of environmental priorities (Saad et al., 2014). The use of ALS data for the compilation of forest inventory datasets is becoming more common place, numerous forestry organizations are using it for the assessment of harvesting, road engineering, and silvicultural practices. This thesis explored how ALS data may be used to derive various levels of forest inventory information within a community forest tenure. There were two key research questions posed within this thesis:

1) Is it possible to accurately predict AAC and other advanced inventory forest attributes, such as, stem size distribution using ALS data?

Chapter 3 addressed a wide array of forest inventory attributes derived from ALS data, providing information about the forested land base to assist community forest managers with decision making. Primary attributes developed were height, Lorey's height, DBH, QMD, stem number, biomass, and volume. Primary attributes developed could then be summarized for each stand type, describing landscape characteristics at the stand level or pixel level. A secondary attribute was developed to describe stem size distribution across the landscape using a relatively new technique, called a Weibull PDF. A two-parameter Weibull PDF function using shape and scale predicted the stem size distribution across the landscape. The distributions developed depended on plot level assessments, and models developed performed relatively well across all plots. Finally, a tertiary attribute, SI, was estimated and compared to that of the SI provided by the VRI. Overall, there was a general increase in SI values generated from ALS data. The direct application of primary, secondary and tertiary ALS attributes provides forest managers with estimations that are considered vital in the assessment of forest stands (Racine et al., 2014). These attributes potentially reduce socio-economic and environmental losses from poor decision making (Saad et al., 2014).

Lastly, Chapter 3 provided a case study of how a TSA could be generated using ALS data. The results of the TSA indicated that a greater level of harvest is achievable and sustainable overtime when using ALS data compared to VRI data. The various scenarios provided some insight into how a TSA could assist with determining an AAC, but did not predict the AAC. The results of the TSA using VRI data (S1) were relatively close to the AAC. With the increased estimate in SQ predicted by ALS data (S3) questions were raised if the TSA generated from S1 is an underestimate of the possible potential harvest levels.

2) Is it possible to identify and map ecosystem service indicators using ALS data?

Chapter 4 provides a comprehensive review of the various LiDAR platforms used to assess numerous ES. The results of the review suggest that ALS in particular was used far more frequently used to map, quantify and describe various ES.

Chapter 4 divides ES into 4 categories based upon their function; 1) regulating services 2) cultural services 3) provisioning services and 4) supporting services. Certain ES had far more examples of LiDAR being used than others. For example, provisioning services were by far the easiest ES to map and examples of supporting services difficult to find. Many applications of ALS data describe a growing development in modelling to map ES, indicating that this area of research is still in its infancy.

5.2 Practical Applications of Results for SCCF

The capacity of ALS data to directly measure forest structure is a significant advantage compared to other approaches, such as, conventional passive optical satellite imagery or aerial photo-interpretation (Racine et al., 2014). ALS data has the potential to reduce losses from poor decision making, since the accuracy of the derived information is high (Saad et al., 2014). The work within this thesis highlights the various approaches of directly applying ALS data to operational-level forestry and EBM within SCCF.

The primary attributes (height, DBH, Lorey's height, QMD, stem count, volume and biomass) developed provides detailed information about the CFA forested landbase. They were developed at a 20 x 20 m pixel scale which can be used to meet locally determined objectives and interests. The primary attributes developed can be linked to existing datasets used by the SCCF to assist with the stratification of the landscape. These spatial layers can facilitate the development of detailed forest harvest plans with accurate estimations of the volume of timber being extracted.

The secondary attribute developed within this thesis can enrich the ABA-derived forest stand attributes (primary attributes). The estimates of stem size distribution provide improved detail of stand structure. This level of detail offers an opportunity to classify the stand into successional stages, predict the number of trees within a stand and assist with silvicultural decisions for sustainable forest management.

Finally, the TSA generated in Chapter 3 can assist with managing Sechelt's community forest over time. The integration of ALS data within a TSA provides an opportunity for managers of CFA to develop models that predict future harvest rates. Predicting future harvest levels can be used to inform how SCCF is currently managing their landscape and how to make informed decisions regarding the potential revenue generated from harvesting timber. SCCF can take the models developed in WOODSTOCK and adapt them to take into account various management options. The ALS data obtained by SCCF has the potential to be used not only for forest harvest predictions but for mapping ES, describing a broad range of benefits derived from the community forest (Andrews et al., 2014).

CFA have emerged as a means to move beyond output-based resource management and focus on ecosystems as a whole. Encouraging adaptive and innovative approaches to management decisions (Gray et al., 2008). Many CFA like SCCF integrate a full array of values within their management decisions, including both environmental and socioeconomic sustainability. Understanding the various ES present within the landscape can assist with expanding the management practices and addressing community values. Chapter 4 provides various ideas and methodology to use ALS data to map ES. ALS data can be utilized to map a variety of ES that are beneficial to SCCF, including:

- Carbon sequestration and carbon storage, providing insight for acquiring and trading carbon credits. (**Regulating Service**).

- Hydrological mapping to assist with water flow regulation, flood regulation and water quality, especially if harvesting activities are taking place near streams (**Regulating and Provisioning Service**).
- Modelling of visually sensitive areas through the inclusion of visual quality objectives, for example, obscuring clear cuts from view (**Cultural Services**).
- Analyzing terrain characteristics to create and maintain bike routes within Sechelt (**Cultural Services**).
- Detailed models of volume, height, DBH and more to assess the supply of timber (**Provisioning Service**).
- Analyzing site productivity **(Supporting Service).**

5.3 Limitations and Future Work

A number of limitations should be highlighted when considering the results of this thesis. These limitations create a possibility for future work within the SCCF and for future CFA.

1) Additional plot data would be beneficial with new plot data assisting in capturing forest types not represented or under-represented. If access was not a limitation, the collection of plots in the northern regions of the tenure would assist in characterization of higher elevation stand types.
2) The VRI spatially describes stands that were delineated using predominantly photography. Some of these areas are exceptionally large and could possibly be far too generalized with respects to species age and stand type. The delineation of stand types could also be based upon the model results developed from primary attributes and secondary attributes. The

development of primary attributes for 2015 could be used to create an up-to-date entry into the VRI on stand height, volume, biomass and DBH for the spatial extents of the VRI.

3) The research conducted within this thesis provides a case study of how community forest managers can use ALS data to develop a TSA. Introducing additional management constraints would increase model complexity and lead to volume estimates closer to that of reality.

4) The research conducted in Chapter 4 provides a foundation for how ALS data can be used to map and identify a variety of ES, providing an opportunity for research into how ALS data to be used to map a variety of ES within a CFA. Deriving hydrological networks, subsequent riparian areas, habitat suitability and old growth management areas using ALS data would provide a perfect example of using ALS data for EBM.

5.4 Research Innovations

The research undertaken in this thesis is innovative in a number of key ways.

This thesis provides results for SCCF for decision making on a wide array of attribute data. It also provides a robust methodology of how to apply ALS data to describe forests resources for SCCF and other CFA interested in acquiring ALS data.

The second innovation is deriving SI from ALS data, a recently developed technique in itself. Building upon this work, this thesis provided an approach to creating a TSA within WOODSTOK based upon ALS SI. The four scenarios created within WOODSTOCK provided insight into the various ways SI could be used to derive a TSA.

Thirdly the creation of yield curves within TIPSY and VDYP based upon SI classification and the incorporation of these estimates within WOODSTOCK provides additional insight into how ALS data can be used to derive various volume and harvesting estimates over time.

Lastly, in Chapter 4, discusses the potential uses for ALS data for mapping and quantifying ES that have not been readily acknowledged in the existing literature.

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