The characterization of stream and riparian features of importance for fish habitat using laser scanning

by

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Abstract

Understanding changes in salmonid populations and their habitat is a critical issue given changing climate, their importance as a keystone species, and their cultural significance. Further, there is an increasing need to provide up to date, accurate, and spatially explicit information to forest managers to make informed decisions within a sustainable forest management context. The increasing availability of Airborne Laser Scanning (ALS) data for forest applications offers an opportunity to utilize these data for assessing the quality and quantity of habitat, which is often costly and difficult to characterize at broad scales. ALS data provides detailed and accurate Digital Elevation Models (DEMs) under forest canopies, which in turn enable the characterization of detailed stream networks, as well as stream and terrain attributes important to salmonids. The primary objective of this thesis is to examine the potential of ALS to characterize stream habitat features important for salmonids. To accomplish this a systematic review examining how remote sensing technologies have been used to characterize stream habitat features was completed. Next, workflows and models were developed to extract stream width and individual morphological features classified as pools, riffles, runs, and cascades using ALS data. Additionally, the ability of ALS to extract instream wood features was assessed, examining which ALS and environment attributes influenced the detection rate. Lastly, a broader perspective was used and a framework was developed to integrate ALS derived indicators of watershed condition and pressure into existing watershed status evaluations procedures. Ultimately, the research presented in this thesis describes a series of value-added approaches to better understand how ALS data can be used to characterize stream and riparian vegetation features important to salmonids in a forested environment.

Lay Summary

There is a need for spatially explicit and accurate information regarding fish habitat in forested watersheds. Remote sensing technologies, specifically laser scanning have a strong history in providing accurate information on vegetation and terrain due to their ability to provide three-dimensional characterization of the environment. This thesis examines the ability of airborne laser scanning data (ALS) to characterize stream habitat features important to salmonids in a forested environment and presents a framework to assess the quality of these habitat indicators. Methods to use this technology to map stream width, habitat, and instream wood features were developed and assessed for accuracy.

Preface

The dissertation's research goals were established in consultation with my supervisory committee. The content featured in Chapters 2, 4, and 5 of this dissertation has already been published in peer-reviewed journals. A paper based on the content of Chapter 6 has been submitted to a peer reviewed journal, as indicated below. In these published works, I executed the methodologies in collaboration with co-authors and my supervisory committee. This involved conducting rigorous analyses, composing original manuscript drafts, and incorporating subsequent revisions. Throughout the manuscript preparation and peer-review process, co-authors contributed invaluable feedback, comments, and revisions to ensure the manuscript's quality and readiness for submission.

Chapter 2:

Dakin Kuiper, S., Coops, N. C., Hinch, S. G., & White, J. C. (2023). Advances in remote sensing of freshwater fish habitat: A systematic review to identify current approaches, strengths and challenges. *Fish and Fisheries*, *24*(5), 829–847. https://doi.org/10.1111/faf.12772

Chapter 4:

Dakin Kuiper, S., Coops, N. C., Tompalski, P., Hinch, S. G., Nonis, A., White, J. C., Hamilton, J., & Davis, D. J. (2022). Characterizing stream morphological features important for fish habitat using airborne laser scanning data. *Remote Sensing of Environment*, *272*, 112948. https://doi.org/10.1016/j.rse.2022.112948

Chapter 5:

Dakin Kuiper, S., Coops, N. C., Jarron, L. R., Tompalski, P., & White, J. C. (2023). An automated approach to detecting instream wood using airborne laser scanning in small coastal streams. *International Journal of Applied Earth Observation and Geoinformation*, *118*, 103272. https://doi.org/10.1016/j.jag.2023.103272

Chapter 6:

Dakin Kuiper, S., Coops, N.C., White, J.C., Hinch, S.G., Tompalski P., Stackhouse, L.A. (2023). Enhanced watershed status evaluation: towards an integrated framework to assess fish habitat in forested watersheds using laser scanning. In Review

In addition, I contributed to the following publications that are relevant to the scope of this dissertation:

Stackhouse, L. A., Coops, N. C., Kuiper, S. D., Hinch, S. G., White, J. C., Tompalski, P., Nonis, A., & Gergel, S. E. (2023). *Modelling Instream Temperature from Solar Insolation Under Varying Timber Harvesting Intensities Using RPAS Laser Scanning* (SSRN Scholarly Paper 4525540). https://doi.org/10.2139/ssrn.4525540

Nonis, A., Dakin Kuiper, S., Coops, N.C., Tompalski, P., Hinch, S. (2023). Assessing habitat associations of juvenile salmonids using stream metrics derived from Airborne Laser Scanning. In Review

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List of Abbreviations

ALS	Airborne Laser Scanning
AVRIS	Airborne Visible \ Infrared Imaging Spectrometer
CASI	Compact Airborne Spectrographic Imager
CHAMP	Columbia Habitat Monitoring Program
CHM	Canopy Height Model
CSF	Cloth Simulation Filter
CWH	Coastal Western Hemlock
CWHVM	Coastal Western Hemlock Very Moist
DEM	Digital Elevation Model
DSM	Digital Surface Model
EO-1	Earth Observation One
ETM	Enhance Thematic Mapper
FHAP	Fish Habitat Assessment Procedure
FREP	Forest and Range Evaluation Program
FRPA	Forest and Range Protection Act
GEE	Google Earth Engine
GIS	Geographic Information System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
InSAR	Interferometric Synthetic Aperture Radar
ISS	International Space Station
LIDAR	Light Detection and Ranging
MAD	Mean Absolute Deviation
MDA	Mean Decrease Accuracy
MSI	Multispectral Instrument
MSS	Multispectral Scanner
NIR	Near InfraRed
OLI	Operational Land Imager
PIBO	PacFish/InFish Biological Opinion Monitoring
RF	Random Forest
RMSD	Root Mean Squared Deviation
RPAS	Remotely Piloted Aerial System
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
UAV	Unmanned Aerial Vehicle
VRI	Vegetation Resource Inventory

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This dissertation and its successful completion would not have been possible without the encouragement and contributions of these individuals. I am deeply grateful for their support and guidance, and I look forward to carrying their wisdom and mentorship with me into my future endeavors.

To the forests and the fish, nature's timeless marvels.

An endless source of inspiration.

Chapter 1: Introduction

1.1 Introduction

Understanding changes in Pacific Salmon and trout (Salmonidae, *Oncorhyncus* spp; hereafter termed salmonids) populations and their habitat is a critical issue given changing climate, their importance as a keystone species, and their cultural significance (Atlas et al., 2021; Dey et al., 2021; Irvine & Fukuwaka, 2011). Within their freshwater stream habitats, salmonids require suitable food, shelter, spawning areas, water quality, and unimpeded migration access both upstream and downstream (Quinn, 2004). These habitat features are the products of interactions between climate, watershed hydrology, hillslope and erosional processes, management, and upland and riparian vegetation dynamics (Pike, 2010).

Riparian ecotones are the component of the terrestrial environment that exert influence on a stream and (or) that is influenced by the waterbody (Naiman & Décamps, 1997). These influences include thermoregulation of streams through channel shading, addition of nutrients to stream systems through leaf shedding, bank stabilization, and creation of habitat features through supply of instream wood (Tschaplinski & Pike, 2010). Riparian areas are hotspots for terrestrial and aquatic biodiversity including both plants and animals (Domer et al., 2019; Semmens & Ancona, 2019). Compared to upland forests, riparian vegetation is more dense, has greater biodiversity, and has a more complex vertical canopy structure (Naiman & Décamps, 1997). Yet, riparian habitat loss driven by climate change, forest harvesting and associated road construction, development, and other anthropogenic disturbances, is increasing and as a result it is important for forest managers to actively protect riparian areas to ensure that these areas continue to provide a wide variety of ecosystem services.

The degree to which the riparian ecotone, climate change, and anthropogenic disturbances influence a stream is dependent on stream size, as many smaller streams have less predictable flows (Pike, 2010), or are less protected under current management practices (Ministry of Forests, 2019). Generally, headwater streams are considered order one or order two and include tributaries with permanent, intermittent and ephemeral flows (Colvin et al., 2019; Strahler, 1957). Small headwater streams account for over 70% of stream networks across the world (Colvin et al., 2019; Datry et al., 2014). These streams strongly influence ecological function within both headwater and downstream areas, including lakes and coastal estuaries by transporting water, sediments and organic material, while enhancing water quality and nutrient cycling (Colvin et al., 2019).

Headwater streams provide critical habitat conditions for fish, specifically salmonids in British Columbia, Canada (Gregory & Bisson, 1997). The aquatic habitat of these species is influenced by, in addition to riparian vegetation, a variety of terrain characteristics which act as key drivers of hydrologic and geomorphic processes (Hogan & Luzi, 2010). Stream geomorphic processes, such as flow rate, sediment transport, and channel shape, create complexity in stream structures, which have been directly linked with quality and quantity of salmonid habitat and by association the distribution of salmonids (Bjornn & Reiser, 1991).

Within a watershed, the distribution of salmonids is broadly influenced by stream features such as bankfull width and gradient (McMillan et al., 2013; Ptolemy, 2013). However, within a single stream reach, salmonid distribution becomes increasingly correlated to microhabitat features such as morphological units (e.g. pools and riffles), instream wood, and depth (Dolloff & Warren Jr, 2003; Fausch, 1993; Fausch & Northcote, 1992). The importance of morphological units, specifically pools and riffles is well recognized with many salmonids relying on pools during seasonal low flow periods and using riffles during the spawning season (Bjornn & Reiser, 1991; Gonzalez et al., 2017; MacIsaac, 2010). Further, instream wood not only contributes to stream structural complexity by influencing pool availability but also provides nutrients and influences sediment distribution and has also been corelated with salmonid abundance (Bilby, 2003; Boss & Richardson, 2002; Montgomery et al., 2003; Rosenfeld et al., 2000). Thus, understanding the distribution of habitat features across fine and broad scales is important for assessing the distribution of salmonids species and quality habitat within headwater streams and throughout an entire watershed.

As watershed and forest processes that influence salmonid habitat shift, salmonids are facing increasing pressures through climate change and anthropogenic disturbances (Dey et al., 2021; Peacock et al., 2023). There is a growing need to characterize salmonid habitat and quantify the stressors and pressures facing watersheds (Dey et al., 2021). Conventional methods to characterize stream habitat are conducted by small teams *in situ* and generally target single stream reaches ranging in length from 50 – 500 m. The goal of these approaches is to quantify habitat features and draw inferences about habitat quantity and quality throughout a watershed. However, these approaches seek to characterize representative stream reaches and then make extrapolations rather than completing a comprehensive watershed census, leading to missing information on the hierarchical and heterogeneous nature of freshwater habitat features (Fausch et al., 2002). Indeed, monitoring and measuring salmonid habitat is costly, time consuming and can be extremely difficult to achieve at a broad spatial scale using conventional *in situ* measurements, thereby resulting in a need to develop tools and approaches to characterize habitat features across a variety of different spatial scales.

Over two decades ago, Fausch et al. (2002) called for increases in research and applications across longer time scales and over larger geographic areas to better understand the natural and anthropogenic processes affecting fish habitat and ultimately to better manage fish and prevent habitat and population declines. Remote sensing systems generate new opportunities to observe both the condition of salmonid habitat and the pressures (i.e., climate change, habitat loss) that they are facing. Specifically, conventional passive optical earth observation satellites, such as Landsat systems, have well developed research histories in riverine applications (Piégay et al., 2020). Passive optical sensors record the amount of electromagnetic radiation reflected off the earth's surface in the visible, near infrared (NIR), and shortwave infrared portions of the electromagnetic spectrum (Chuvieco, 2016). One strength of these sensors is the ability to examine phenomena outside of the visible region of the electromagnetic spectrum. For example, differences in the reflection and absorption properties of water can be used to differentiate between amounts of suspended sediment, changes in depth and flood extent, submerged aquatic vegetation levels, and instream habitat units (Marcus et al., 2012). A second strength of these systems is the temporal resolution, with the Landsat series of satellites having collected over 50 years of open source, analysis ready data (Wulder et al., 2022). The large temporal span of these systems allows for the ability to explore previous watershed condition and examine changes in watershed processes through time (Pekel et al., 2016). However, these systems are generally limited to larger river systems due to their moderate spatial resolutions, 30 m for Landsat, and their inability to see into and below the forest canopy to detect three dimensional ground topography. These limitations become particularly problematic in headwater streams where a single Landsat pixel could contain portions of the wetted stream, some dry stream bed, bankside riparian vegetation and upland vegetation leading to more noise than signal in the data. Further, in some regions, like the Pacific Northwest of North America, headwater streams can have high canopy cover leading to total occlusion when viewed from above using passive sensors (Johansen, et al., 2010).

The use of light detection and ranging (lidar), has a demonstrated capacity to penetrate forest canopies to generate fine scale digital elevation models (DEM) and point clouds from which a variety of stream structures, physical terrain information, and vegetation characteristics can be derived (Johansen et al., 2010; O'Callaghan & Mark, 1984; Tompalski et al., 2017). Lidar systems typically consist of three components; a laser scanner, a Global Positioning System (GPS), an Inertial Measurement Unit (IMU) all mounted on a platform such as a tripod often termed terrestrial laser scanning (TLS), an airplane or airborne laser scanning (ALS) or a satellite system (Lefsky et al., 2002). Working in unison, these components derive information on the three-dimensional location of reflected objects, be it vegetation or terrain, very accurately based on the amount of time it takes for a laser pulse to reflect off a surface and return to the laser scanner (Lefsky et al., 2002). Processing of the reflected laser pulses provides a three-dimensional point cloud used to extract detailed terrain and vegetation characteristics (Reutebuch et al., 2003; Wasser et al., 2013).

Studies using ALS data to characterize riparian and stream attributes are becoming increasingly common. For example, ALS has been used to map riparian zone extent and stream width of large Australian rivers with some success (Johansen et al., 2011). In France, ALS systems were used to extract indicators of ecological integrity of riparian zones finding a decrease of riparian forest integrity in built up areas and lower flooding frequency with more intact riparian forests (Michez et al., 2013). Further, in a Canadian context, Tompalski et al (2017) used ALS to characterize riparian vegetation and stream networks based on riparian management area guidelines (Forest and Range Practices Act, 2002). As demonstrated above, ALS and remote sensing have been used to examine riparian and stream ecosystems. However, there has been limited development of methodologies to characterize small headwater streams, specifically deriving morphological units important to salmonids. With the increased acquisition of ALS data across larger areas, there is increasing opportunities to create value-added information products that take advantage of the data to support other forest management objectives.

Key to this research is evaluating the capacity of ALS data to charactertize the freshwater aquatic environments important to salmonids across multiples scales. By doing so, this research will support the information needs of forest and fisheries managers by providing approaches to better understand the streams and aquatic environments in their management areas, enabling operational planning that aligns with sustainable forest management philosophies. Further, this research aims to create tools and aproaches to leverage ALS data to provide a more robust characterization of the entire forest ecosytems beyond the vegetation attributes routinely derived (Eitel et al., 2016). The capability of ALS to characterize stream structures important to fish habitat needs to be quantified, as there has been limited research on characterizing small streams less than 10 m wide, classifying individual morphologic units, and detecting instream wood, which could prove invaluable in assessing habitat quality and abundance of salmonids. Furthermore, few remote sensing studies have looked at how ALS data can be integrated into current fish habitat and watershed health status assessments. Therefore, the goal of this research is to further the application of ALS data for the characterization of riparian and aquatic environments.

1.2 Research questions

To address the above, this PhD aims to answer the following research question:

What stream and riparian features of importance for fish habitat can be accurately characterized using airborne laser scanning?

This question will be divided into four sub questions:

1. How have remote sensing technologies been used to characterize freshwater fish habitat?
2. To what extent can individual fish habitat units be characterized in small streams using ALS data?
3. How can ALS data be used to characterize instream wood and what physical and environmental properties effect detection rate?
4. How can ALS derived indicators of habitat condition and pressure integrate into existing landscape scale habitat monitoring protocols?

1.3 Dissertation overview

The remainder of this dissertation aims to address the research questions outlined above in 6 chapters (chapters 2 -7; Figure 1-1):

How have remote sensing technologies been used to characterize freshwater fish habitat?

Chapter 2 provides a systematic review on the ability of remote sensing technologies to characterize fresh water fish habitat. I describe the trends, challenges, and opportunities in the research field and provide background information for the dissertation.

To what extent can individual fish habitat units be characterized in small streams using ALS data?

Chapter 3 describes the two study watersheds and gives an overview of the ALS and field data collected.

In chapter 4 I describe the process of extracting stream width, and reach level instream wood counts from an ALS point cloud. Further, in this chapter I train and test a random forest model for predicting four classes of stream morphological units in the study stream reaches.

How can ALS data be used to characterize instream wood and what physical and environmental properties effect detection rate?

Chapter 5 describes a methodology to extract individual instream wood features from a point cloud and examines which environmental and ALS data properties impact detection rate.

How can ALS derived indicators of habitat condition and pressure integrate into existing landscape scale habitat monitoring protocols?

Chapter 6 builds off the previous chapters and presents a framework for using ALS data and the methods developed in this dissertation, to provide a description of the condition and pressures facing salmonid habitat at the watershed scale.

Lastly, chapter 7 offers conclusions and synthesis of the dissertation providing an overview, highlighting innovations, and detailing limitations and future directions of the work.

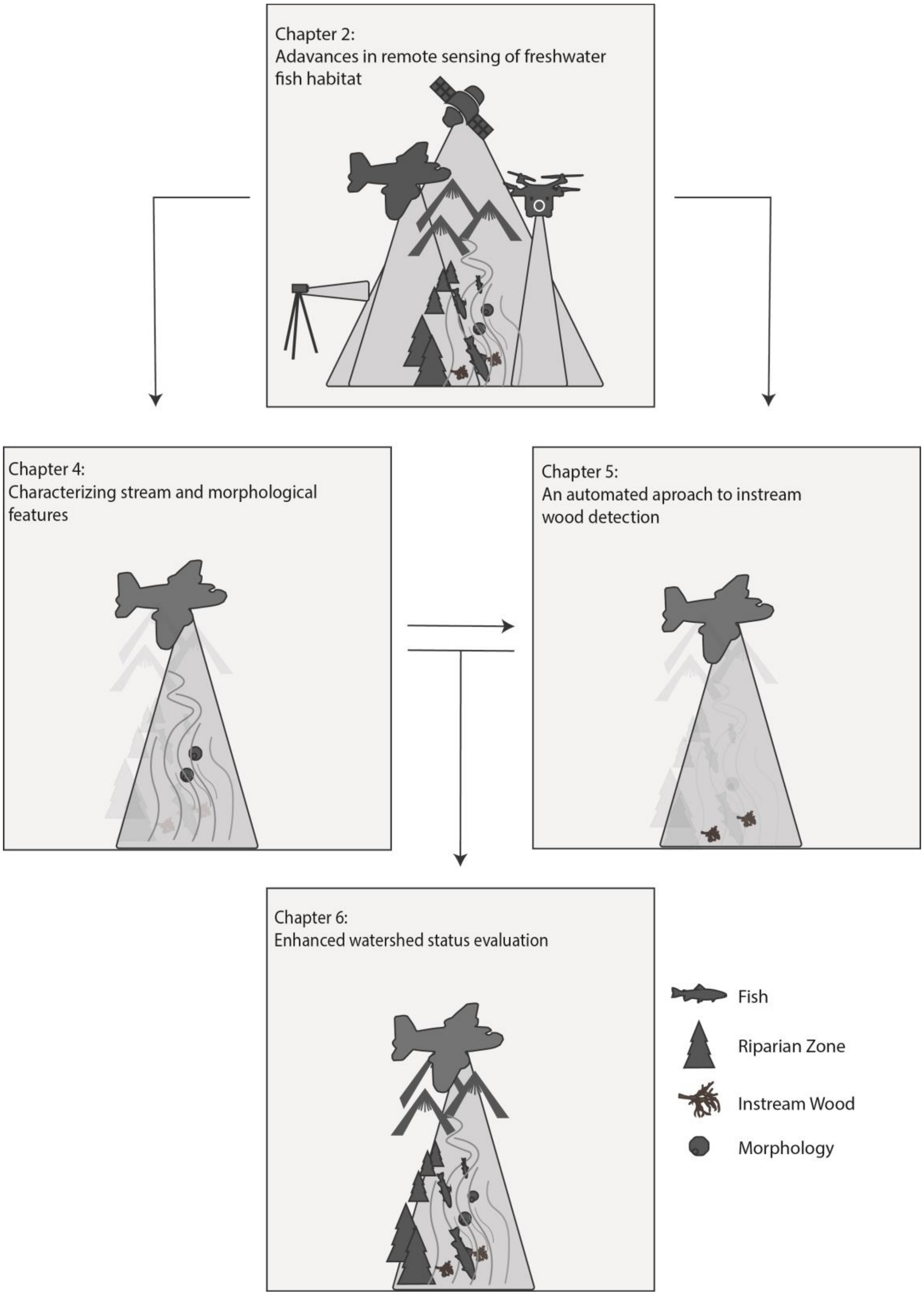

Figure 1-1. Conceptual diagram demonstrating the general structure of this dissertation.

Chapter 2: Background - Advances in remote sensing of freshwater fish habitat: A systematic review to identify current approaches, strengths and challenges

Recent advances in the use of remote sensing have revolutionized many fields of ecology and environmental management in terrestrial and aquatic ecosystems (Cavender-Bares et al., 2022; Iskin & Wohl, 2023; Lines et al., 2022). Monitoring to support management decisions typically relies on ground sampling across time and space, which is associated with high labour costs and safety issues, as well as logistical challenges in inaccessible areas. The diversity of remote sensing technologies and platforms has expanded greatly in the past few decades. Technological advances have resulted in remotely sensed data with greater spatial, temporal, and spectral resolutions (Chuvieco, 2016). This, accompanied by trends toward free and open data policies, analysis ready data products, and the increasing availability of cloud computing resources, has made these data more widely available (Wulder et al., 2022). These innovations and trends are resulting in the development of powerful new tools and data sources that can be applied to regions and to map and monitor environmental phenomena historically not possible.

The identification and protection of habitat is of critical importance to the management and conservation of freshwater fish species. Indeed, habitat availability is often seen as the limiting factor for species recovery in degraded ecosystems and thus habitat features are often targeted during the restoration of aquatic ecosystems (Bond & Lake, 2003). Additionally, freshwater habitat is an important determinant of fish population health and has therefore been included in a variety of different environmental protection legislation globally (Dey et al., 2021). Given the scale and pace of habitat degradation that is occurring as a result of a changing climate, land-use practices, and resource extraction industries, methods are needed to rapidly assess, delineate, identify, and monitor the quantity and quality of important components of freshwater fish habitat (Dey et al., 2021).

Assessments of freshwater habitat are most often obtained using field sampling, wherein crews spend time in streams and lakes measuring attributes and installing/retrieving *in situ* data loggers. These methods are costly, time consuming, and in many circumstances, impossible to scale-up geographically and temporally (Diggins et al., 2016; Papa et al., 2020). Remote sensing allows for continuous data collection across large geographic areas, often with repeat sampling, and increasingly finer spatial, temporal, radiometric, and spectral resolutions. There has also been an increase in the availability of consumer-level Unmanned Aerial Vehicles (UAV) (also known as Remotely Piloted Aerial Systems (RPAS) or colloquially as drones), which has allowed an exponential increase in the number of habitat details observed (Coops et al., 2019). Additionally, there has been a revolution in the acquisition of 3D landscape information principally through developments in Light Detection and Ranging (lidar) and the ability of these technologies to be mounted on a range of platforms, from hand-held to spacecraft (Lines et al. 2022). Coupled with the rise of open access computing resources and image archives such as the Landsat archive and Google Earth Engine (GEE), we are now able to undertake unprecedented image analysis at broad scales (Gorelick et al., 2017; Wulder et al., 2012).

Despite these advances, the use of remote sensing for studies of freshwater fish habitat is a relatively nascent field of study and one that comes with a number of specific challenges. While there is a rich history of remote sensing of rivers and lakes, limited work has been done connecting these derived metrics and attributes with fish-specific data (Dörnhöfer & Oppelt, 2016; Piégay et al., 2020). Likewise, while some focus has been placed on remote sensing of riparian vegetation, a critical component of freshwater habitat, this work is often not explicitly linked to fish or fish habitat information (Huylenbroeck et al., 2020).

To better understand the natural and anthropogenic process affecting fish habitats and thus better manage fish, and prevent habitat and population declines, research and applications across longer time scales and over larger geographic areas are needed (Fausch et al., 2002). To help address this, the review examined recent developments in remote sensing of freshwater fish habitat. I briefly reviewed available remote sensing platforms and sensors, and then undertook a systematic review of peer-reviewed studies that have utilized remote sensing technologies to characterize freshwater fish habitat. I classified studies based on when they were published (year), where they were conducted (geographic region), the type of habitat characteristics and species that were mapped or monitored, and concluded with a discussion of future research directions and the important considerations fisheries scientists and managers need to make if they are thinking about utilizing remote sensing in fish habitat monitoring or research.

2.1 Remote sensing technologies

In this section I introduce the various remote sensing technologies available (Table 2-1). I characterize the technologies by platforms and sensors. Some sensors may be mounted on several different platforms, whereas other sensors are less versatile. Specific data characteristics and capabilities often relate to specific platform and sensor combinations.

Table 2-1. Overview of remote sensing technologies, their strengths and weaknesses and applications for fresh water habitat characterization.

Technology		**Strength**	**Weakness**	**Example Freshwater Habitat Application**	**Citations**
Platform	Ground based	Very high spatial resolution (cm), easy to pair with field data	Very small geographic coverage	Single reach	(Grantham, 2013; Resop et al., 2012)
	UAV	High spatial resolution (cm-m), decreased cost in recent years	Small geographic coverage	Multiple reach, single stream	(Cheek et al., 2016; Harrison et al., 2020; O'Sullivan et al., 2022)
	Aerial	High spatial resolution (cm-m), moderate geographic coverage	Costly, generally a one-off collection	Single watershed/ multiple watersheds	(Dauwalter et al., 2015; Duffin et al., 2021a; Hedger et al., 2006)
	Satellite	Moderate to high spatial resolution (m-km), Large geographic coverage, repeated data acquisition on a regular cycle	Spatial resolution may not be sufficient depending on application	Multiple watersheds/ continental	(Carter et al., 2021; Liu et al., 2021; Luck et al., 2010)
Sensor	Optical imagery	Most common sensor type, broad range of available information, many open access data, archives and long-term calibration enable time series applications	Difficult to get vegetation structural information, passive sensor relies on suitable illumination conditions, obscured by clouds and haze	Habitat type and complexity, landcover, spawning	(Grimm et al., 2016; J. E. Hall et al., 2018)
	Thermal	Best for temperature information	Only useful for temperature information	Stream and lake surface temperature	(Frechette et al., 2018; Tonolla et al., 2012;

					Wilbur et al., 2020)
	Lidar	High spatial resolution 3D information on terrain and vegetation structural, active sensor	Lack of spectral information, costly (although price varies)	Habitat type and complexity, hydrological features, spawning	(Dakin Kuiper et al., 2022; Hedger et al., 2020; Tompalski et al., 2017)
	Radar	Active sensor, able to penetrate cloud, can provide some information on vegetation structure	Limited data availability for longer wavelength radar, difficult to process	Ice cover, hydrological features	(Brown et al., 2010; Marcaccio et al., 2022; Wissmar et al., 2010)
	Digital Photogrammetry	High spatial resolution information on forest structure that is similar to that provided by lidar (but not the same), can have some limited spectral information	Limited geographic coverage, most often UAV based, lack of penetration through vegetation and cloud	Habitat type and complexity, hydrological features, spawning	(Kalacska et al., 2018; Pichon et al., 2006; Tamminga et al., 2015)

2.2 Platforms

Across the globe, there has been a marked increase in the variety of platforms available on which to mount remote sensing instruments. These range from ground-based sensors, typically used in the field to acquire optical or lidar data, to aerial platforms including aircraft and the recent proliferation of UAV's. Space-based platforms can include stand-alone satellite platforms as well, as more recent developments that allow infrastructure to be mounted on existing space based infrastructures such as the International Space Station (ISS) (Dubayah et al., 2020).

The choice of platform for data acquisition fundamentally involves trade-offs in spatial and temporal resolution and the required spatial extent of the data (Chuvieco, 2016). Space-based platforms offer the advantage of regular data acquisition, dictated by orbit overpass time, and conventionally cover larger spatial extents (100–1000's of square kilometers) at spatial resolutions ranging from sub-metre to < 2000 m (Belward & Skøien, 2015) or have larger spatial footprints in the case of spaceborne lidar. The temporal resolution of the data acquired is dependent on the spatial resolution of the sensor and as a result the spatial extent, but can vary from daily coverage for coarse spatial resolutions, for example, 1 km x 1 km, to 16 days for Landsat (or currently 8 days with both Landsats 8 and 9 in operation). In contrast, imagery acquired from airborne platforms—either aircraft or UAV's— is acquired with a much finer spatial resolutions, in some cases 0.1 m, however these images are often collected on a one-off basis over relatively small spatial extents.

Recently the operational use of satellite constellations has overcome some of these inherent trade-offs between spatial resolution and revisit time. Acquisition utilizing multiple, identical satellite platforms, allows increased temporal resolutions. For example, Cubesat constellations such as from the Planet constellation, allow imagery to be collected at fine spatial resolutions (3 m) similar to that acquired by aircraft but on a daily temporal revisit, due to the fact there are over 200 identical Cubesat satellites in orbit acquiring data (Francini et al., 2020; Leach et al., 2019). However, it must be noted that data from Cubesat constellations are not radiometrically corrected or calibrated across sensors making time series analyses or model transferability difficult. Virtual constellations (Wulder et al., 2015), which integrate data from multiple existing satellites into a fused, standardized data stream, for example the Harmonized Landsat and Sentinel-2 (HLS) datasets (Bolton et al., 2020; Claverie et al., 2018), are also producing increased temporal revisit times while maintaining the 30 m spatial resolution and global coverage.

Recently, there has been a large increase in off-the-shelf UAV's that come ready to use out of the box to create detailed and geospatially accurate data sets (Ivosevic et al., 2015; Zhang et al., 2016). Similar to other platforms, there are trade-offs between spatial resolution and image extent, with some sensors onboard UAVs being able to obtain sub-centimeter resolution but only over very restricted spatial extents limited by battery life of the UAV system itself (Coops et al., 2019). Off-the-shelf rotary UAVs can generally fly for up to 1 hour, covering < 5 km^2 per day, and can hold a variety of different sensors. The ability to acquire repeat imagery using these airborne or drone platforms essentially becomes user-defined although in practice acquiring multiple images overtime using these platforms can become cost prohibitive.

2.3 Sensors

In addition to platform considerations, remote sensing technologies are able to provide data from a broad range of spectral wavelengths and modalities that can provide unique insights into fish habitat and conditions.

2.3.1 Passive optical imagery

Passive optical imagery is the most well-known of the remote sensing datasets and includes imagery acquired from the visible, near infrared (NIR) and shortwave infrared regions of the electromagnetic spectrum, typically covering between 400 - 3000 nm. This imagery can be acquired from a single (panchromatic) band, a small number of discrete bands (multispectral), or hundreds of narrow spectral bands (hyperspectral). The strength of multispectral and hyperspectral sensors is the ability to examine phenomena outside of the visible region of the electromagnetic spectrum. For example, unhealthy vegetation reflects less in the NIR region of the electromagnetic spectrum compared to healthy vegetation (Chuvieco, 2016). In an aquatic environment the ability to observe a waterbody with increased spectral resolution allows for the characterization of aquatic vegetation, turbidity, water quality, and even chlorophyl (Marcus et al., 2012). Further, taking advantage of the relationship between different band combinations allows for the development of spectral indices (the most common being the normalized difference vegetation index (NDVI)) which has even been used to quantify the effect of spawning pacific salmon on bankside vegetation (Brown et al., 2020). Historically, panchromatic and multispectral sensors have been mounted on a variety of platforms from ground-based to satellites, with common instruments including conventional aerial cameras (which make use of the visible and / or near infrared regions of the spectrum) and satellite sensors such as the Landsat series of sensors (Multi Spectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM) and the Operational Land Imagery (OLI) (Masek et al., 2020; Wulder et al., 2019), and Sentinel-2 (Multi-spectral imager (MSI);(Drusch et al., 2012)) which acquire data in 7–13 bands covering this entire region. Hyperspectral image acquisition to date has been restricted principally to airborne-based sensors such as the Airborne Visible / Infrared Imaging

Spectrometer (AVIRIS, Vane et al., 1993) from NASA JPL or the Compact Aerial Spectrographic Imager (CASI, Babey & Anger, 1989) from Canada. There have been a small number of space-based hyperspectral missions, most recently the Italian PRISMA (Cogliati et al., 2021), German EnMAP systems (Guanter et al., 2015) and the American Earth Observing One (EO-1) – Hyperion (Ungar et al., 2003), and increased miniaturization is also allowing hyperspectral imagery acquisition from UAVs (Adão et al., 2017).

2.3.2 Thermal

At longer wavelengths, beyond the shortwave infrared regions of the spectrum, is thermal infrared radiation, which is emitted from both the atmosphere and surface objects on the Earth. Thermal imaging sensors are designed to detect this emitted radiation, which can provide key insights into surface temperature (Neinavaz et al., 2021). Typically, the relatively low energy associated with these thermal emissions requires spatial resolutions to be coarser than those acquired from optical sensors, resulting in satellite thermal images typically having resolutions ranging from 100 to 1000 m (Neinavaz et al., 2021). Again, miniaturization of these sensors is allowing thermal data collection from drones, thereby increasing spatial resolution to centimeters and allowing a wide range of fine scale applications of thermal data to be more comprehensively examined. For example, temperature heterogeneity within urban areas as well as habitats including surface temperatures of water, rocks and vegetation (Kuenzer & Dech, 2013). Surface temperature itself however, is often inadequate to fully describe the thermal conditions of the particular environment given that these detectors do not directly measure air temperature and as a result only provide a partial insight into the thermal regime of a habitat or environment. In addition, they also detect the instantaneous thermal conditions at one point in time and if the overall thermal conditions of a habitat or environment needs to be assessed, then multiple thermal images would need to be acquired more frequently and subsequently linked into with some type of heat transfer model in order to understand the full thermal heterogeneity both temporally and spatially over the landscape over time.

2.3.3 Lidar

Lidar is an active remote sensing technology, meaning it emits its own energy (in the form of laser pulses) and then measures the time it takes for that energy to return (i.e. be reflected back) to the sensor. The rapid uptake of lidar technologies on a variety of acquisition platforms has revolutionized the capture of vegetation structure information through the acquisition of highly detailed three-dimensional point clouds (Lefsky et al., 2002b; Lim et al., 2003). Lidar sensors can be mounted on ground (or terrestrial), drones, and aircraft- or satellite-based instruments, with all being successfully applied to extract a range of forest structural attributes (White et al., 2016). Small footprint airborne laser scanning (ALS) systems typically record between 1 – 5 returns per laser pulse in discrete mode, or a fully digitized vertical profile of the returned energy in full-waveform mode (Wulder et al., 2008) and produce footprint sizes of 0.1 – 2 m (Lim et al., 2003) and can achieve sub-meter accuracy of terrain surface heights (Lefsky et al., 2002b). Typically, lidar sensors utilise lasers tuned to the NIR region of the spectrum, maximising vegetation return energy, which limits however any water penetration due to the absorbance of the NIR signal by water (Höfle et al., 2009). Bathymetric lidar systems are available with lasers tuned to the green region of the spectrum, allowing water penetration and thus estimates of stream water depth however these systems are less common and can have more restrictions due to eye safety concerns (Bonisteel et al., 2009; McKean et al., 2008). Again, miniaturisation is allowing the development of drone-based lidar sensors, which allow extremely dense point clouds to be acquired up to 1000 points per m^2, however similar to optical systems, areal coverage is limited with only a few km^2 be acquired in one day.

Satellite laser sensors onboard the Ice, Cloud and land Elevation Satellite (ICESat-2, Neuenschwander & Pitts, 2019) provide global lidar data from 2018 and the full-waveform Global Ecosystem Dynamics Investigation (GEDI, Dubayah et al., 2020) on the International Space Station (ISS) provides large footprint lidar data with a 25 m footprint for environmental assessments, but are limited by the orbit extent of the ISS (between 51° north to south).

2.3.4 Radar

Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR) are examples of active remote technologies that sense in the microwave/radiowave region of the spectrum. SAR data can be acquired in a range of wavelengths from the shortest (X band) through to the longest, P band (Sinha et al., 2015). Radar satellites such as the European Sentinel-1 (Torres et al., 2012), Canadian RadarSat (Morena et al., 2004) and RadarSat Constellation Mission (Thompson, 2015) acquire data with C band and provide global coverage, unimpeded by cloud cover. Longer wavelengths (L band) have been shown to be more sensitive to changes in terrestrial biomass, especially at higher amounts of biomass, than the shorter radar wavelengths, but are only available on very limited satellite or airborne platforms (Lu et al., 2016). X band radar, acquired from the Tandem-X mission, has also been used to acquire elevation information as well as provide insights into the amount (and height) of forest vegetation when compared to conventionally derived digital elevation models (Hyde et al., 2006).

2.3.5 Digital photogrammetry

The advent of high spatial resolution optical image acquisition, be it from UAVs, aircraft, or even satellites, is allowing digital photogrammetric algorithms to be applied to map three-dimensional surface features from images (Remondino et al., 2014). To do so, imagery needs to be acquired with extremely high lateral and side overall to facilitate automatic processing to derive sub-centimeter point clouds (Leberl et al., 2010). These point clouds in some respect are similar to lidar point clouds, as they represent three dimensional structures; however, as they are derived from imagery they are unable to provide three-dimensional information over areas obscured by dense vegetation or in dark shadows (Baltsavias, 1999). However, the derived point clouds can also provide spectral information if the images are colour. The low cost of image acquisition from drones or aircraft is an additional advantage allowing for example ongoing monitoring using these photogrammetric tools after initial surveys are completed with lidar systems to accurately capture the terrain surface under canopy (Goodbody et al., 2019).

2.4 Characterizing freshwater fish habitat using remote sensing: literature review

2.4.1 Methods

2.4.1.1 Data Collection

To find relevant publications on the use of remote sensing for freshwater fish habitat characterization, I conducted a systematic literature search within the Web of Science core collection. I searched the abstracts, titles, and main text of journal articles published in the last 50 years (1973–2023; based on the beginning of the Landsat program) for keywords relating to fish habitat and remote sensing. Our keywords were categorized as follows and each paper was required to have at least one word from of the first three lists with a fourth list including keywords that should not be included:

1. Remote sensing keywords: “remote sensing” OR “LiDAR” OR “RADAR” OR “satellite” OR “DEM” OR “UAV” OR “UAS” OR “drone”
2. Fish and fish species keywords: “fish” OR “salmon” OR “trout” OR “whitefish” OR “gar” OR “catfish” OR “pike” OR “muskie” OR “bass” OR “lamprey” OR “grayling” OR “carp” OR “sturgeon”
3. Habitat Keywords: “habitat” OR “freshwater” OR “fluvial”
4. Keywords NOT included: “bird” OR “marine” OR “Ocean” OR “Estuary”

Further, additional literature was added manually by scanning the reference section of the identified literature for relevant papers that were not captured with our query.

The initial search yielded 868 records which were then manually assessed to meet our criteria. The scope of this review was limited to studies that explicitly used remote sensing technology to characterize freshwater fish habitat. Studies that did not explicitly mention the remote sensing technology that was used to create habitat indicators were removed. Further, I did not include studies that used a field-based approach for terrain generation (i.e. using surveying tools to measure elevations). Studies that used remote sensing approaches to characterize stream features but did not link either the approaches or features, directly or indirectly, to fish or fish habitat were also excluded. The majority of articles I identified through our aforementioned search criteria were removed because they focused on birds, mammal or other species, were in saltwater environments, did not use a remote sensing technology, or did not relate a back to fish. Further, I opted not to include, government reports, dissertations, and other forms of gray literature. Ultimately, 96 published studies were identified that met all of our search criteria.

2.4.1.2 Data organization and analysis

To examine general trends, the identified studies were organized by remote sensing technology and further subdivided into type of indicator used, fish species of concern, geographic region, and year published (Table 2-2). Due to the wide variety of remote sensing technology found in this review, I grouped studies into six classes: multispectral, hyperspectral, thermal, lidar, radar, and digital photogrammetry with the possibility of multiple remote sensing technologies being assigned to a study. Next, studies were categorized based on type of indicator, which included: temperature, habitat type and complexity, hydrological features, landcover (forested, urban, etc.) and ice cover, passage, and the identification of spawning locations. There was some overlap between these indicators, for example, spawning locations and habitat type. However, studies assigned into the spawning category specifically used remote sensing to characterize and/or find nest locations. Further, I assigned studies into categories based on how the studies framed their research questions. Additionally, I examined which fish species were studied (grouped by genus), the study location and identified the habitat type (lentic, lotic). Lastly, I identified if studies collected their own fish data or utilized existing information from the literature.

Table 2-2. Indicators used to examine trends for using remote sensing to examine freshwater fish habitat features.

Indicator group	Indicator	Description
General information		
	Year	Study publication year
	Location	Location of the study area
	Water body type	Type of waterbody studied (river, lake, lagoon, reservoir)
Remote sensing technology		
Passive Optical	Multispectral	Small number of discrete bands, including true colour images (visible wavelengths red, green, blue)
	Hyperspectral	Hundreds of narrow bands
Thermal		Imagery acquired from the thermal regions of the electromagnetic spectrum
Lidar		Data collected via the active remote sensing technology; light detection and ranging
Radar		Data collected with the active remote sensing technology radar
Digital photogrammetry		Use of photogrammetry data on any platform
Fish		
	Genus	Genus of fish species examined
	Collection method	Method used to collect fish data
Habitat metrics		
	Temperature	Temperature of waterbodies
	Habitat units and complexity	Mapping of physical river or lake complexity and habitat units (pools, riffles, etc)
	Hydrological features	Using hydraulic modeling or other techniques to extract depth, flow rate, and gradient
	Landcover and Ice cover	Classification of land cover types near rivers and lakes, classification of ice on rivers and lakes.
	Spawning	Mapping and analyzing suitable spawning sites
	Passage	Characterizing stream features related to fish migration and passage (Dams, culverts, steepness)

2.5 General trends

Our review found that the majority of studies occurred in the northern hemisphere (87%) with 80% in North America alone (Figure 2-1). Riverine habitats dominated the studies (85%) while 15% and 1% examined lakes and lagoons, respectively. Only three studies were undertaken in Asia and a single study was published describing research undertaken in Africa. Two-thirds of the studies examined were published since 2015, with the greatest number of studies published in 2022 (Figure 2-2).

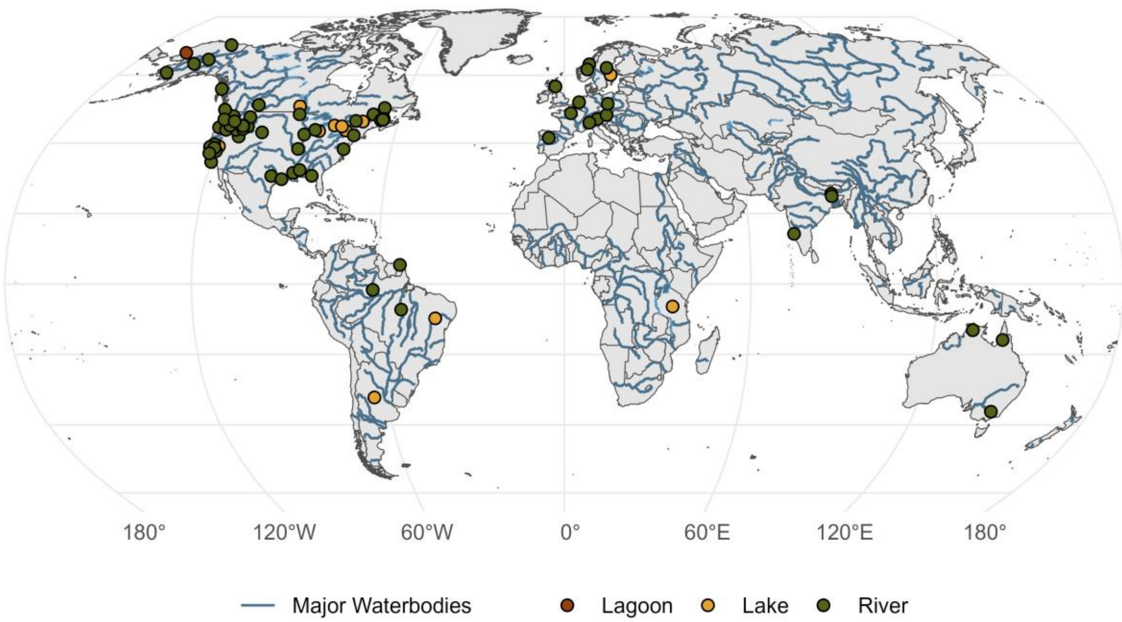

Figure 2-1. Location and waterbody type of studies found in this review that used remote sensing data to characterize freshwater fish habitat.

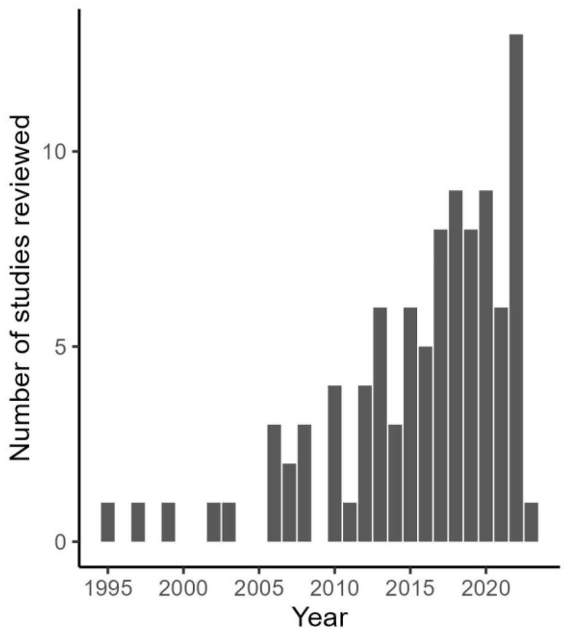

Figure 2-2. Number of studies reviewed that use remotely sensed data to characterize freshwater fish habitat, by year published.

With respect to sensor types, the most common remote sensing technology used for characterizing freshwater fish habitat was multispectral data, with a focus on moderate resolution optical satellite imagery (> 10 m spatial resolution), principally acquired from the Landsat series of satellites (Figure 2-3). The second most common applied technology was lidar. In general, studies that used lidar focused on characterizing terrain/ morphological features of streams (Dakin Kuiper et al., 2022; Duffin et al., 2021a). In contrast, the studies that utilized satellite imagery examined broader habitat features such as landscape structural complexity (i.e. channel sinuosity, % of vegetated land, % water, floodplain width, channel length) or specific land cover information (Bellido-Leiva et al., 2022; Whited et al., 2013).

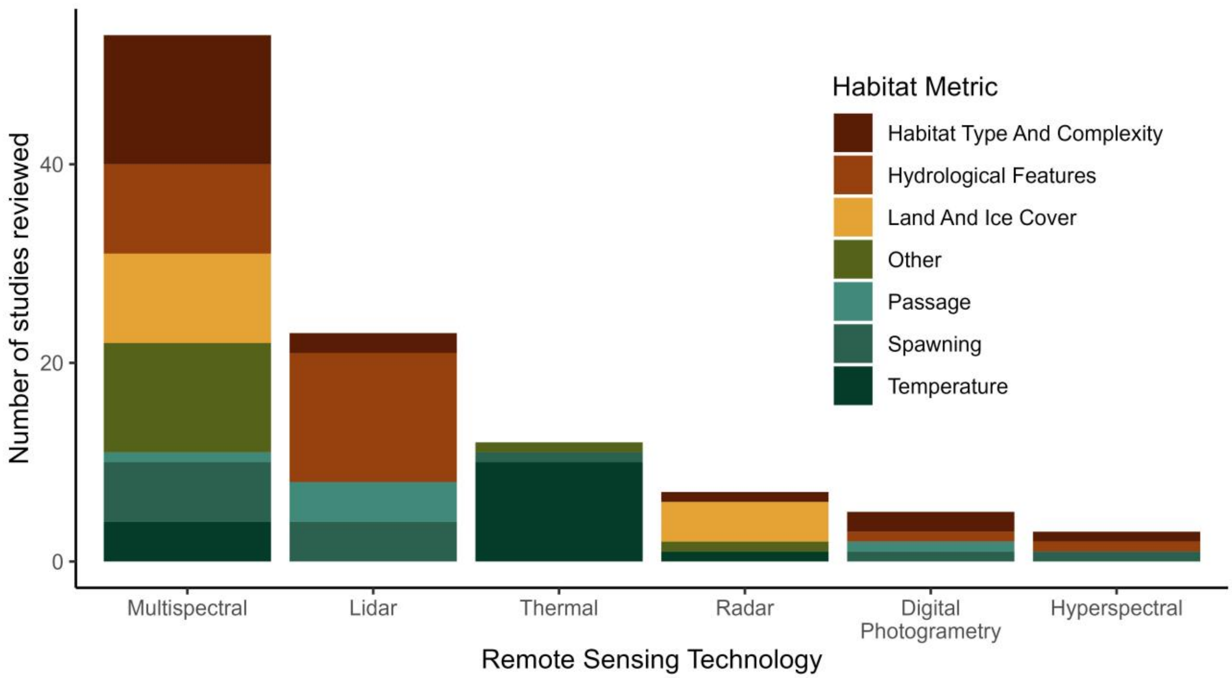

Figure 2-3. Number of studies reviewed using different remote sensing technology coloured by habitat metric. If multiple technologies are used in a study then both appear in the graph.

The three most prevalent fish genera studied were *Oncorhynchus* (38%), *Salmo* (17%), and *Salvelinus* (4%), all of which are within the family Salmonidae (Figure 2-4). 22% of studies did not focus on a single species but rather examined assemblages of fish species often including more than four species or species groups and not limited to those listed in Figure 4. In order to be included in this review, the study must have indicated how the remotely sensed habitat metric was important for a specific fish species or group of fish species.

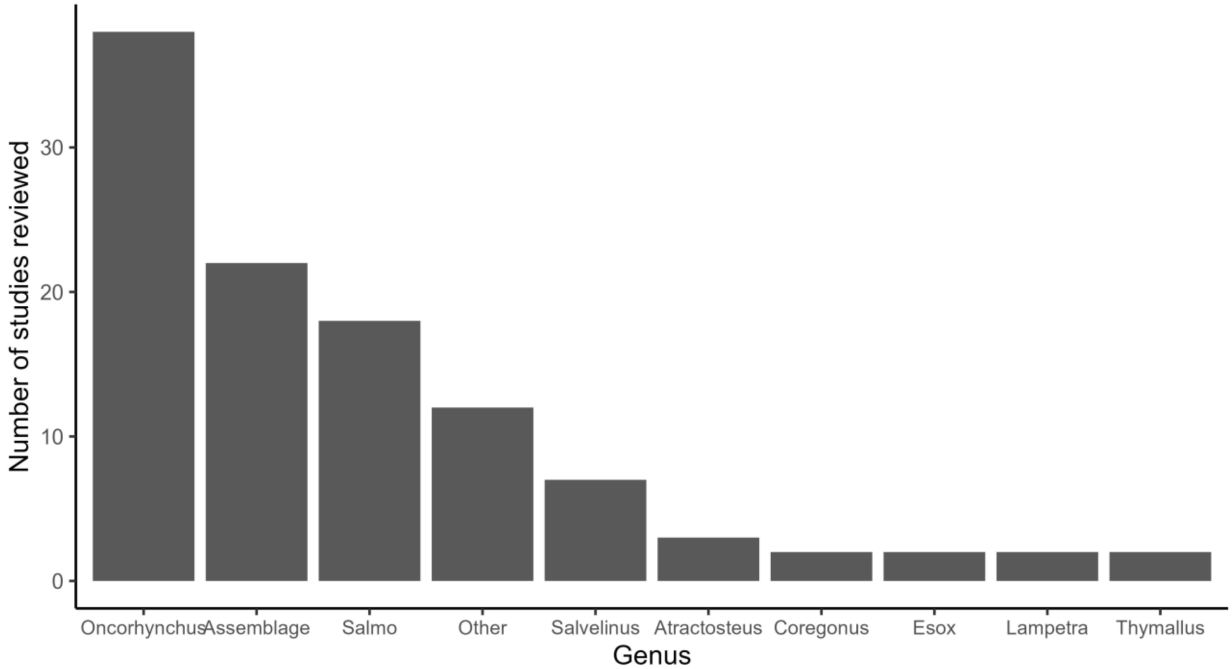

Figure 2-4. Number of studies reviewed that examined different genera. At least two studies were required to receive a unique column; other genera are included in the "Other" column.

Of the habitat features examined, the most common were hydrological features, habitat type and complexity, followed by temperature, land cover/ and ice cover, spawning and passage (Figure 2-5).

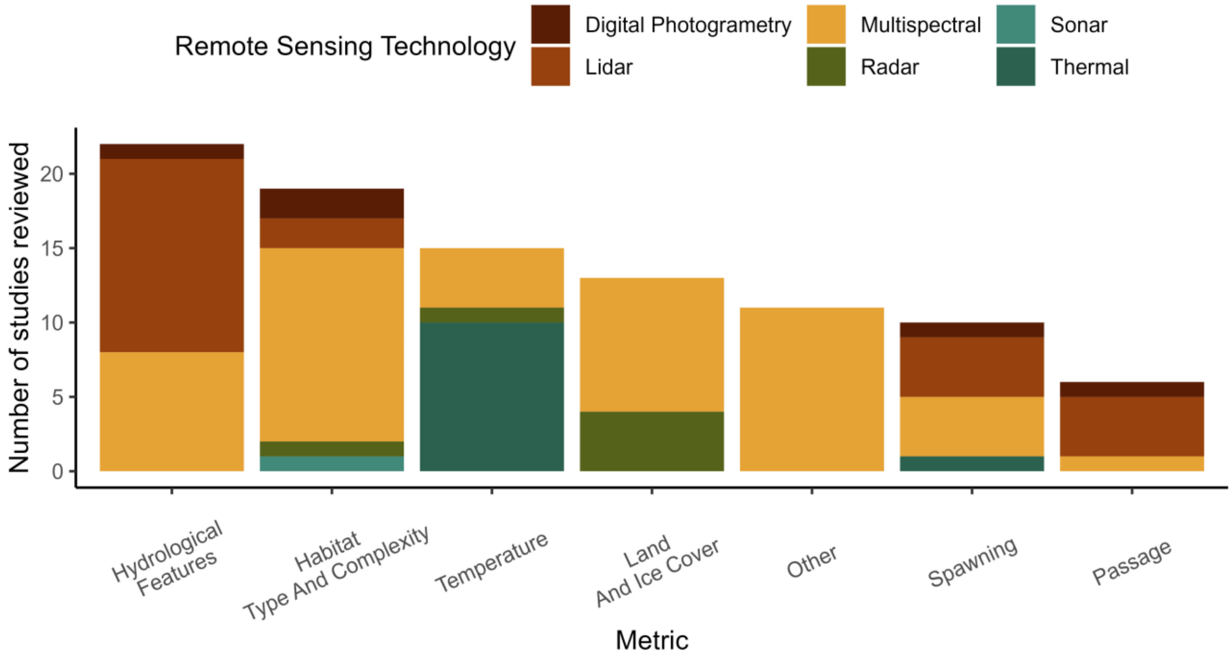

Figure 2-5. Number of studies reviewed that examined different habitat metrics coloured based on the remote sensing technology used. The other column includes habitat metrics that were only examined in a single study.

Less than half of the studies collected their fish data at the same time as habitat was being assessed using remote sensing technologies. The majority used individual fish or population data from existing literature, either from the same sites or from laboratory-based studies (Figure 2-6). Of those studies that collected fish data, telemetry was the most common collection method followed by electrofishing and gillnetting.

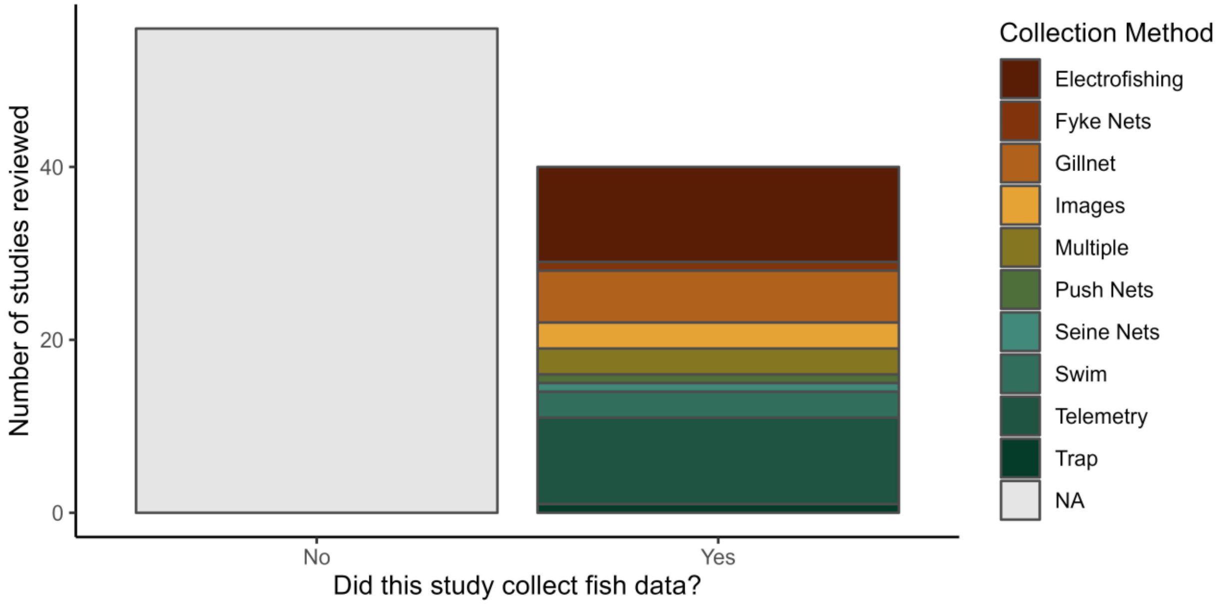

Figure 2-6. Number of studies reviewed that collected fish data and the method used for collection.

Multispectral and lidar sensors were used to examine the broadest range of habitat metrics (Figure 2-7). In contrast thermal sensors were used almost exclusively to analyze stream and lake temperatures. The characterization of habitat type and complexity were undertaken with broadest variety of remote sensing technologies while ice and land cover were exclusively examined with radar and multispectral technologies.

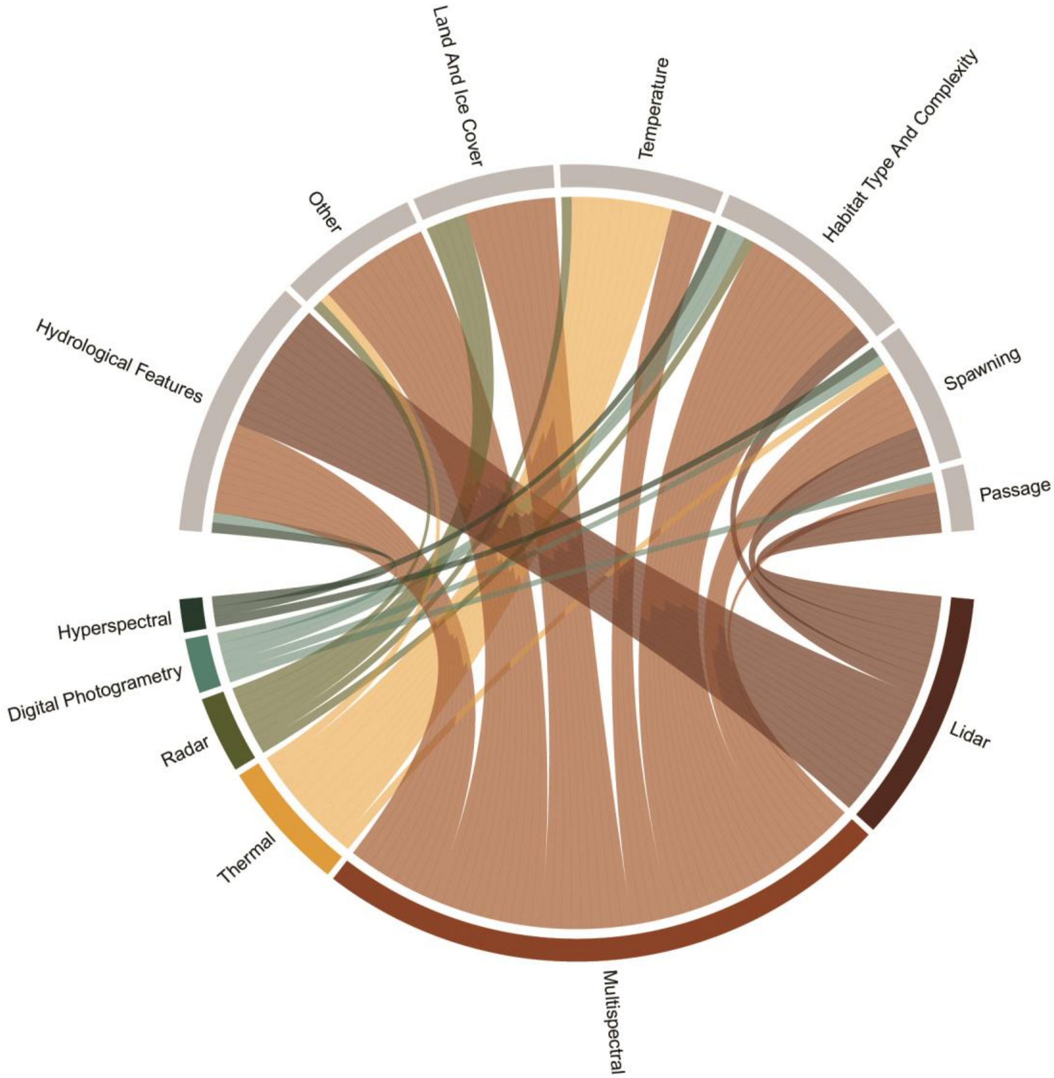

Figure 2-7. Chord diagram showing the remote sensing technologies that were used to examine habitat metrics in the studies reviewed. The width of each line represents the number of papers reviewed.

2.6 Remote sensing of habitat features

2.6.1 Hydrological features: depth, velocity, gradient

Depth and velocity are primary drivers of habitat availability in streams. There is a long history of examining these properties using hydrological modeling approaches. Underpinning the generation of these hydrological models is high resolution Digital Elevation Models (DEM), derived from lidar, photogrammetry, or in some cases radar. However, it must be noted that additional information on flow rate is required for these techniques. For example Tamminga et al. (2015) used a true colour camera mounted on a UAV to acquire 5 cm resolution imagery from which they produced a very fine scale terrain model to derive depth and velocity. The depth and velocity layers used in combination with manually extracted cover features (instream wood, vegetation overhang) were then used to create a habitat suitability index of the 1 km long study reach. The ability to measure elevation across a broad spatial scale allows for an examination of mesoscale habitat characteristics. Sundt et al, (2022) used bathymetric lidar and aerial images to examine the relationship between depth and velocity and European grayling (*Thymallus thymallus*, Salmonidae*)* and brown trout (*Salmo trutta,* Salmonidae) occurrence. The authors found that during spawning seasons river sections with a high occurrence of European grayling had shallower depths and slower velocities, a similar trend was found with brown trout, however brown trout occurrence levels were less related.

Stream gradient is often an important metric when modeling fish occurrence and abundance. Remote sensing of stream gradient can be highly accurate across watersheds but becomes increasingly difficult at finer resolutions due to differences between detecting water surface gradient and terrain gradient. However, lidar and radar derived gradient measurements have been used to model fish presence absence and fish density throughout a watershed. Tompalski et al (2017), used breakpoint detection on lidar derived stream profiles to find stream reaches longer than 100 m with a continuous gradient greater than 20%, which can act as barriers to fish passage. Radar-derived stream gradients were used to predict juvenile coho salmon (*Oncorhynchus kisutch)* and Dolly Varden (*Salmo malma)* densities in a northern temperate rainforest on the Prince of Wales Island in south eastern Alaska (Wissmar et al., 2010). Wissmar et al, (2010) found that the radar derived predictions were comparable to density predictions based off of a field-measured gradient.

2.6.2 Habitat type and complexity

Habitat complexity can be defined by the variation in scale, diversity, spatial patterning, size, and abundance of habitat features. Fish habitat complexity is often described by examining the variation in the physical characteristics of a stream or alternatively by examining areas of homogenous characteristics known as habitat units (i.e. pools and riffles). Habitat type and complexity is a primary driver of productivity and diversity in stream ecosystems (Kovalenko et al., 2012). These changes in productivity and diversity are influenced by stream size, gradient, structure, and slow water habitat units such as pools (Calderon & An, 2016; Naman et al., 2017; Rosenfeld et al., 2000). A variety of remote sensing data and techniques have been successful at identifying and analyzing habitat units and complexity at a variety of different spatial scales. Multispectral satellite imagery has allowed for broad scale, repeated observations of lakes and rivers (Pekel et al., 2016). For example, Carter et al (2021) used MODIS and Landsat derived ecological indicators to model habitat suitability and occurrence predictions of invasive rainbow trout (*Oncorhynchus mykiss*, Salmonidae) with 87% accuracy using 30-fold cross validation in the upper Flathead River system. Further, Liu et al (2021) used Sentinel-2 imagery to separate lotic and lentic habitat and examined the abundance pattern, shape pattern and spatial distribution pattern of lentic habitats in the Mobile River basin. The authors found that the majority of habitat objects are small oblong lakes and fish ponds densely distributed throughout the basin, which greatly increase the availability of habitat for the catfish aquaculture industry of this region. Perhaps the greatest strength of satellite imagery is at the capacity to examine very large geographic areas. Luck et al. (2010) used Landsat imagery and a terrain model to examine the relationship between salmon productivity and river physical complexity, measured as a ranked index, across 1509 catchments or 3,000,000 km^2 area across the North Pacific rim. The authors found that the most complex rivers were located in the western Kamchatka Peninsula and in western Alaska, and that as physical complexity increased, so too did salmon productivity. McPhee et al (2014), further compared Landsat derived physical complexity, measured using the riverscape analysis tool (RAP) (Whited et al., 2012), with anadromy and genetic diversity of steelhead or rainbow trout in the Pacific rim. While the proportion of anadromy was correlated with riverine complexity in their study, they stipulated that this was largely driven by a confounding negative relationship between drainage area and anadromy. The authors hypothesized that anadromy may be less frequent in larger drainages because of the higher energy requirements of migration and reported that genetic diversity decreased with latitude and in drainages with a larger ratio of floodplain area to total drainage area.

Airborne lidar has also been used to examine habitat complexity, at the habitat unit scale and to examine at migration hindrances. For example, Hedger et al. (2020) used lidar to determine the location and effect of migration hinderances (stream crossings and culverts), on brown trout in a stream network in the Trondheim Region in Norway. The authors found that sea trout prevalence was inversely related to the number of downstream crossing or culverts identified from the lidar data. Further, lidar has been used to delineate different habitat units (pools, riffles, glides, cascades), instream wood features, and stream width on Vancouver Island, British Columbia, Canada (Dakin Kuiper et al., 2022).

Cheek et al. (2016), used UAV true colour imagery to manually delineate mesohabitat types and a variety of micro habitat characteristics including distance to nearest eroded upstream bank, sinuosity and distance to nearest barrier. Further, Cheek et al. (2016), used UAV imagery at the reach scale to characterize the proportion of pools and riffles, and the perimeter area ratio of these habitat units. When paired with electrofishing and sonar data, this study found that very fine scaled microhabitat variables and the channel unit variables had the highest explanatory power on fish assemblage structure in their study area explaining 35% and 29% of variance respectively.

2.6.3 Temperature

Temperature influences all aspects of the aquatic environment from primary producers (e.g. algae and plants) to aquatic predators (such as fish) (Moore, 2006). Changes in water temperature can affect physical habitat features, and behaviour and physiological processes of fish (Quinn, 2004). Certain fish species such as salmonids are disproportionally affected by changing temperature regimes due to a narrow thermal tolerance. In a freshwater aquatic environment, stream temperature is driven primarily by environmental factors such as snow melt, air temperature, and shading through riparian vegetation (Poole & Berman, 2001).

Remote sensing has transformed our ability to detect changes in surface temperature at a variety of different resolutions and this information can be applied to examine multiple habitat characteristics. For example, O'Sullivan et al. (2022) used a thermal sensor mounted on a UAV to compare habitat use by juvenile Atlantic salmon (*Salmo salar,* Salmonidae) during warm >19˚C and cool <19˚C stream temperature events in Atlantic Canada. During warm events the authors observed a grouping behaviour by the fish and found increased use of cooler regions of the stream. Wilbur et al. (2020) used aerial thermal infrared imagery to map cold water anomalies and found that brook trout (*Salmo fontinalis,* Salmonidae) and Atlantic salmon parr density and use increased near cold water anomalies across a 53 km reach of the Cains River in New Brunswick, Canada. Aerial thermal imagery has been used to characterize thermal heterogeneity and fish assemblages across 350 ha of lowland river floodplain in the Oder River in Germany, with distinct species assemblages found based on spatial and seasonal thermal signatures (Tonolla et al., 2012). These aforementioned studies demonstrate the ability of thermal imagery as a non-invasive method for characterizing spatial heterogeneity and changes in temperature across complex and large study areas.

Lidar data have also been used been used to examine factors influencing stream temperatures. Tompalski et al. (2017) used lidar data to determine the total hours of shade received by stream reaches on northern Vancouver Island, Canada. The authors found that 25% of fish bearing streams had at least 11.3 hours of shade, while only 7% of fish bearing streams had less than 10 hours of shade. However, they found that small streams were less shaded than large streams in the study area. Loicq et al.(2018) used lidar-derived shading information in a regional stream temperature model and found that the cooling effects of vegetation ranged from -3.0 ˚C to -1.3 ˚C. The accuracy of the stream temperature model was improved with the use of lidar shading information compared to more simple shade models. These studies demonstrate that lidar is capable of accurately measuring the vertical structure of stream side vegetation making it very useful for shade modeling. However, lidar derived shading and stream temperature variations have not, to our knowledge, been explicitly linked to fisheries data but represent an area for future research.

2.6.4 Land cover and ice cover

There are well known relationships between landscape level metrics and the availability and quality of fish habitats in stream reaches. Significant research has taken place using multispectral satellite data for detailed characterizations of land cover. However, few studies have looked at the relationships between terrestrial land cover and available fish habitat use. Walther et al

(2021) used landscape level terrestrial metrics derived from remote sensing data such as drainage area, elevation, geology type, wetland presence, and precipitation data to explain species-specific differences in population neighbourhoods of coho salmon, steelhead trout and chum salmon (*Oncorhynchus keta,* Salmonidae*)* across habitats. The authors found that that drainage area, elevation and geology where important variables for predicting upper limit of occurrence across all three species with 78 – 89% accuracy. High spatial resolution aerial photographs have been used to map landcover classes across large spatial areas. Dauwalter et at al (2015) used supervised classification aerial RGB imagery and found that the woody vegetation class was strongly positively associated with redband trout (*Oncorhynchus mykiss gairderi,* Salmonidae*)* occurrence and density. Further they found that together with stream temperature, the percent woody vegetation class was a stronger predictor of trout occurrence compared to instream and riparian field measured variables.

Variations on the duration and extent in ice cover on lakes and rivers can affect primary productivity, as well as growth and survival of most freshwater fish species. Suitable data sets to examine the relationships between ice cover and fish species can be acquired via remote sensing. Recently, Sentinel-1 data has been used to classify ice cover in the Canadian great lakes region (Marcaccio et al., 2022). The authors found decreased movement in overwintering Walleye (*Sander vitreus,* Percidae) when habitat areas were covered in ice. In a riverine environment, Wirth et al, (2012) used data from the RADARSAT -1 to locate persistent ice-free areas on an Alaskan river and found that these areas served as core spawning areas for fall run chum salmon. Persistent ice-free features such as those found with radar would not be captured with a traditional in-situ field survey but rather are captured extremely well by the repeated survey nature of this particular remote sensing dataset.

2.6.5 Spawning

While habitat features associated with spawning may be comprised or described by of some of the general attributes that were reviewed (i.e. hydrological or temperature features), this particular life-history focused suite of habitat features was frequently the focus of remote sensing research so it was examined separately. A variety of remote sensing techniques have been used to map spawning habitat, such as lidar, hyperspectral and thermal sensors. For example, a study by Harrison et al. (2020), used true colour and hyperspectral sensors mounted on a UAV to accurately (76% and 90%, respectfully) map Chinook salmon (*Oncorhynchus tshawytscha,* Salmonidae*)* redd locations using machine learning and object based image analysis techniques. Further, UAV thermal sensors were used by Clawson et al, (2022) to identify warm thermal refugia in a subarctic river, finding increased use by spawning chum salmon in these areas. Duffin et al. (2021) used continuous wavelet analysis on lidar-derived DEMs to examine topographic variability on three rivers in the Salmon River basin in Idaho. They found that higher small-scale wavelet power related to pool-riffle topography and that wavelet power was an important factor in Chinook salmon spawning site selection. A habitat suitability index for alligator gar (*Atractosteus spatula,* Lepisosteidae*)* was developed by van der Most & Hudson (2018) using lidar and the authors found that 19% of the overall floodplain is available spawning habitat along the Lower Mississippi River.

2.6.6 Passage

The majority of freshwater fish species require unimpeded movement between spawning, rearing, and in some cases marine habitats. Impediments to movement include natural barriers such as waterfalls, landslides, and steep gradients, or anthropogenic barriers such as dams, and culverts, all of which can block access to quality habitat. Remote sensing technologies including lidar and digital photogrammetry have been used to characterize barriers to fish passage. For example NIR lidar was used to quantify migration hindrances across the Trondheim Region in Norway (Hedger et al., 2020). This study found that that seatrout (*Salmo Trutta*, Salmonidae*)* prevalence was negatively related to the number of downstream crossings and culverts. Another study by May et al. (2017) used NIR lidar to characterize salmonid habitat above and below natural barriers in two watersheds along the Oregon coast. They found and increase in habitat quality and quantity above the waterfall due to the reduction in overall gradient above the barrier.

2.7 Strengths, challenges, and opportunities for future research

The reviewed studies highlighted key successes in characterizing freshwater fish habitat, however challenges remain for the adoption of remote sensing at several operational scales (Table 2-3).

Table 2-3 Observations, challenges, strengths and opportunities for adopting the use of remote sensing technologies in freshwater habitat assessments.

Observation	Challenges	Strengths	Future Research and Development Opportunities
Limited linkage between predicted habitat charicteristics and existing fisheries data	Data availability. Matching temporal and spatial scales, domain knowledge.	Landsat series of satelites has > 50yr of global coverage.	Use historical fisheries data and archival remote sensing data together.
Minimal development of novel remote sensing metrics specific to fish habitat characterizations	Research area is nascent. Difficult without common domain knowledge between fishery experts and remote sensing analysts.	Increase colaboration between remote sensing and fisheries scientists.	Basic science required to examine new spectral indices to detect for example, salmon redd sites, oxygen concentrations in stream water.
Lack of automated workflows and models for existing methods	Time consuming to develop, not scalable, lack of transferability studies between sites and species.	Many remote sensing techniques can be automated in stand alone software or with code.	Transferability studies, to examine if methods and models are applicable for other sites and species. Open access of code, and algorithms for refinement and application.
Studies have a limited number of fish species or were undertaken in a limited number of regions or over a limited spatial extent	Cost and data. Lack of awareness of the power of these remote senisng technologies.	Coverage of remote sensing data is increasing annually with new satelite options and abilty to aquire own data with consumer level UAV systems.	Test the applicability for these methods in different regions. Some habitat features might be simple or straightforward to obatin with some senors, but not applicable to certain species.
Lack of reasearch using remote sensing data fusion	Most studies limited to one platform or sensor type. Not analyzing all dimensions of the acquatic system. Lack of	Many fusion techniques exist in remote sensing literature, especially	More fusion between remote sensing technologies. Increase instrument payloads to allow simultaneous collection of

	ground based remote sensing.	between ground and aerial platforms.	LiDAR and thermal data, for example.
Lack of multitemporal studies	Large datasets, lack of multitemporal fisheries data.	Key benefit of remote sensing, specifically, satelite imagery, is repeated data acquisitions.	Examine remote sensing datasets over time, to estimate habitat change and impacts on fisheries.

Our review identified that over half of the remote sensing studies that examine fish habitat metrics did not explicitly use fish data (e.g. presence/absence, abundance, density, etc.) that were collected at the same time and locations as the remote sensing data. This is a major limitation in many current studies as much can change between years and seasons in fish populations and in the physical environment. To use remote sensing to its full potential in freshwater habitat studies it is important to further develop linkages between remote sensing metrics and *in situ* fisheries data. For future research I suggest pairing the collection of fish data with remote sensing data acquired at the same time. If fish data are not available, focus should be placed on developing novel remote sensing methodologies specifically for freshwater habitat monitoring that focuses on supporting existing monitoring protocols such as the fish habitat assessment procedures in British Columbia Canada (Johnston & Slaney, 1996), the Columbia Habitat Monitoring Program (CHAMP) in the Columbia river basin (Nortwest Fisheries Science Centre, 2023) and the PacFish InFish Biological Opinion (PIBO) Monitoring Program from the US forest service (Saunders et al., 2019). Developing linkages between remote sensing technologies and existing monitoring protocols will help to increase the accessibility of remote sensing data and methods to practitioners who are not well acquainted with remote sensing.

Of the studies reviewed, 80% occurred in North America with a specific focus in the Pacific Northwest and salmonid species. This focus on North American study sites was also identified by Huylenbroeck at al. (2020) in their review on remote sensing of riparian vegetation.

Salmonids are an important group of species in this part of the world for their cultural, ecological and economic benefits, which could be a factor in their prevalence in the literature reviewed. Indeed, salmonids are umbrella species and the ability to characterize their habitat should be applicable to other species in similar ranges. However, by focusing on salmonids of the Pacific Northwest, a stenothermal group of fishes with specific habitat associations and requirements, a gap in knowledge has occurred in how the remote sensing techniques described above can be used to characterize freshwater habitat in different environments specifically for warm tropical waters. Therefore, an avenue for future research could focus on the less prevalent species and regions, for example anabas (Genus *Anabas)* in the Mekong River (South East Asia), carp (Family *Cyprinidae)* in Yangtze River (China) or tilapia (Genus *Oreochromus)* in Lake Victoria (Kenya, Tanzania and Uganda) which are all managed species that have different habitat requirements compared to salmonids of the Pacific Northwest.

Interestingly, spawning locations were the only habitat type related to a life history stage consistently identified in this review. I believe this is because spawning locations for salmonid species are generally in shallow, gravel bed, stream reaches with slow flow and can often be directly seen in the remote sensing data (i.e. Harrison et al. 2020). Future research could focus on developing relationships between other life history stages (rearing, migration) and remote sensing data. This would be especially important when using remote sensing-based habitat indicators in fisheries management and in conservation and restoration decision making.

One of the major strengths of remote sensing is the ability to characterize large spatial areas across broad time periods (Pekel et al., 2016). I found a lack of studies that harnessed the full temporal power of remote sensing and believe more emphasis should be placed on using remote sensing technology for multitemporal analysis. For example, having over 50 years of coverage with the Landsat missions highlights the potential for retrospective analysis pairing historical fisheries data with historical remote sensing data (Wulder et al. 2022). Pairing existing fisheries data sets with previously collected remote sensing data could greatly aid restoration and management practices in important habitat areas by identifying areas most effected by landscape change. Further, many of the studies identified in this review were one-off studies conducted over small areas. In order to gain operational capacity of remote sensing technologies emphasis should be placed on the replication of existing methods across different aquatic environments and over broader spatial extents.

Often the remote sensing methods and approaches reviewed were relatively simple, for example image classification, simple spectral index derivation or the manual extraction of features from the imagery by interpreters, rather than automatic classification of the imagery. To fully harness the information capabilities of remote sensing data, focus should be placed on increasing automation and automatic extraction of habitat indicators. When the scale of studies shift from single reach to continental or even global scales, the ability to automate metric extraction becomes important. Further, remote sensing allows for the ability to uniquely characterize the environment and extract information that is difficult or even impossible to measure manually. The development of specific remote sensing indices and metrics directly related to fish habitat features is an important area of future research.

The key remote sensing technologies and platforms for fish habitat characterization identified in this review were lidar, moderate resolution satellite imagery and UAV. I posit that airborne lidar has the most to offer because it provides detailed information on terrain and vegetation across large geographic areas, and currently is used operationally in the forest industry (White et al., 2016). Moderate resolution satellite imagery such as the Landsat and sentinel series of satellites have frequent and repeated coverage allowing for detailed time series analysis of freshwater fish habitat. Further, the global coverage of these data sets gives the ability to test methodologies across different watersheds and with a variety of species. Additionally, I recognize the role that consumer level UAV’s will have in advancing the linkages between *in situ* fisheries data and remote sensing data due to their relatively low cost and ease of use. The ability to acquire aerial imagery, photogrammetry data, or thermal data at the same time as fisheries data are crucial for advancing this science. Support should be given to develop these technologies and their linkages to *in situ* fisheries data as well as their synergies when combined.

2.8 Operational considerations for use of remote sensing for fish habitat characterization

In the final component of this paper, I offer some guidance to fish and habitat biologists and other related practitioners, with limited exposure to remote sensing technologies, who may be interested in utilizing remote sensing technology for freshwater fish habitat characterization, but who may lack knowledge of the appropriate platform, sensor and processing approach to use. In general, these three decisions are related to sensors, scales and standards.

As I have demonstrated herein, there are a wide variety of information outputs that can be produced using remotely sensed data. As a result, fish and habitat biologists should consider their information needs: which aspects of fish habitat do they need to characterize and monitor, over what spatial extent and with how much spatial detail? If temperature is the primary habitat feature to be mapped, then thermal sensors are the required technology. Mapping of habitat type and complexity can be undertaken using either multispectral imagery (allowing classification of land cover) or active remote sensing imagery, such as lidar, in order to map the structural characteristics of the stream bank and surrounding vegetation. In the case of hydrological features, the underlying terrain model is of paramount importance, which therefore suggests that lidar data, which enables a detailed high spatial resolution characterization of the terrain surface underneath the vegetation canopy, is needed in order to extract these hydrological characteristics.

Imagery can be acquired at a variety of spatial scales. Given that many of the questions posed by fish biologists occur at local stream reach scales or lake nearshore scales, it is likely that most applications will be driven from either aircraft, UAV or using field-based instrumentation. The decision around which of these platforms to use in order to acquire the data is fundamentally a question of spatial scale. Fish biologists should consider the spatial extent of their area of interest, as well as the spatial resolution at which they require that information. Airborne sensors are able to provide very high-density remote sensing data such as lidar as well as fine spatial resolution optical or thermal imagery. There are significant cost savings with aircraft on a per km^2 basis, compared to UAV's, which makes them a more cost-effective instrument at the watershed scale. If individual stream reaches are of interest, as well as integrating multiple flights in order to understand the dynamics of the system, then a UAV platform producing very fine scale imagery offers unique opportunities to consider. Beyond working at the finer scale, there are a variety of other trade-offs that need to be considered. Data with a higher spatial resolution equates to larger file sizes, larger storage requirements, and longer processing times. Therefore, additional considerations around data processing and storage need to be considered when dealing with these very fine scale aircraft and UAV based technologies.

Lastly, standards refer to the protocols followed for both remote sensing data collection and the subsequent data processing to drive the key habitat characteristics. Satellite remote sensing data acquisition is managed by large government or private companies from which the data is purchased or is available for download. In contrast, UAV data collection may be undertaken by end users themselves with a number of best practice guidelines around acquisition and processing needed to ensure high data quality (Goodbody et al., 2017). Lidar data collection often falls between the two, by contracting private companies for airborne lidar acquisition, or with researchers collecting data themselves with UAV or mobile mounted lidar sensors (White et al., 2013). Further, many governments are beginning to provide open access to their lidar data catalogues, providing tiles of either raw point clouds or pre-processing gridded data products.

In terms of data processing standards remote sensing data often requires specific, often proprietary, software. In recent years there has been an increase in open-source tools used to process remote sensing data. Specifically, both the R and Python languages have a variety of free and open source libraries for processing remotely sensed data (Gillies, 2021; Hijmans et al., 2022; Roussel, Auty, Coops, et al., 2020) while free and open source geospatial data processing software with large user bases are also available (QGIS Development Team, 2022).

2.9 Conclusions

This review highlighted a growing body of literature that uses remotely sensed data to map, monitor, and characterize freshwater fish habitat. In recent years, there have been rapid advancements in computational capacity and remote sensing technologies, resulting in reduced acquisition costs and processing requirements and thus an increased number of studies using these technologies. Further, I identified three key technologies/platforms: lidar, UAV, and moderate resolution satellite imagery that have been well studied and are positioned to transform approaches to freshwater fish habitat studies. Currently, the majority of research in this field focuses on three genera of fish and is predominantly being undertaken in western North America. This review provides the context and background for fish and habitat biologists to better understand the remote sensing technologies used for freshwater habitat characterization. I hope that this review will serve as an introduction, allowing for the increased use of remote sensing in fish habitat research and foster interdisciplinary collaboration between fish biologists and remote sensing scientists.

Chapter 3: Study area and data

3.1 Study area

The focus of this research is two watersheds; the Artlish River and Nahmint River, located on northern and central Vancouver Island, British Columbia, Canada, respectively (Figure 3-1). Both watersheds are within the coastal western hemlock biogeoclimatic zone, specifically the very wet maritime sub zone (CWHvm) across the lower elevations and the moist maritime biogeoclimatic subzone at higher elevations. The CWHvm ecosystem is dominated by a canopy of western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), and amabilis fir (*Abies amabilis*). The understory is composed of salal (*Gaultheria shallon*), deer fern (*Blechnum spicant*), and Alaskan blueberry (*Vaccinium alaskanense*) with a diverse array of mosses on the forest floor (Meidinger & Pojar, 1991). These ecosystems are characterized by moderate winter temperatures, cool summers, and high annual precipitation (approximately 5000 mm), with a majority of the rainfall occurring between October and April (Meidinger & Pojar, 1991). Elevation in these areas ranges from sea level to 365 m for the Nahmint and sea level to 426 m for the Artlish.

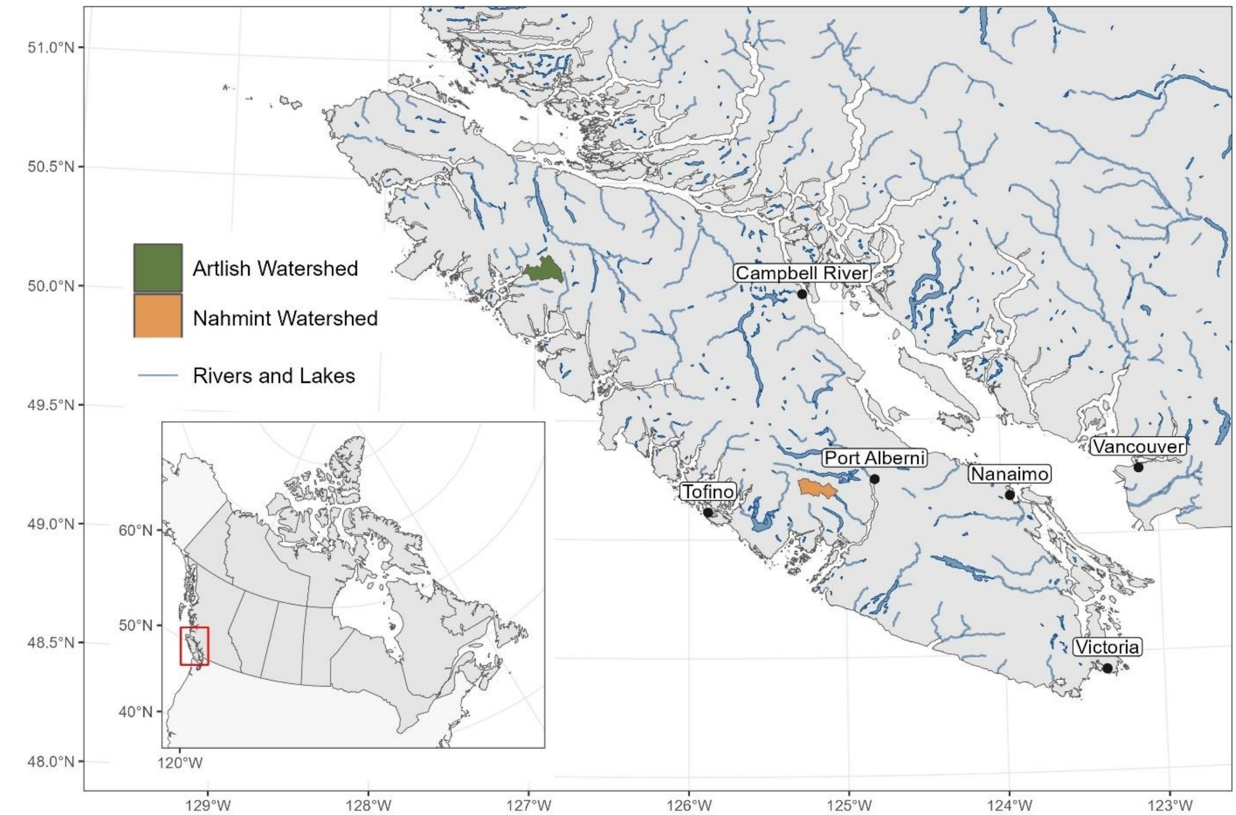

Figure 3-1. Study area map showing the location of the two study watersheds relative to major Canadian cities and rivers.

The Nahmint watershed is 192 km^2 and is bisected into an upper and lower region by a large lake. The reaches in this study were all located in the upper Fisheries Sensitive Watershed portion of the catchment. There has been continuous logging since the early 1920s in the area with over 20% of the watershed having been harvested (Brayshaw, 2018b). Currently there is a well-established 60–75 year old second growth coniferous forest throughout the area (Brayshaw, 2018b). In both watersheds, the primary inputs of large wood to stream channels are windthrow and mass wasting events. Historically, riparian harvesting and cross-stream yarding also contributed wood to stream systems. Resident salmonid species can be found in the upper watershed including, rainbow trout (*Oncohrynchus mykiss*), kokanee (*Oncorhynchus nerka*), and Dolly Varden char (*Salvelinus malma*) (Narver, 1974) . A 4 m tall waterfall, located 4.8 km up the Nahmint river from the estuary, limits the distribution of anadromous salmonids including chum (*Oncorhynchus keta*), chinook (*Oncorhynchus tshawytscha*), coho (*Oncorhynchus kisutch*), sockeye (*Oncorhynchus nerka)*, and pink salmon (*Oncorhynchus gorbuscha*) (Brydges et al., 1999). Summer and winter run steelhead trout (*Onycorhynchis mykiss)* can be found throughout the system, as they are able to pass through the falls and into the lake (Narver, 1974). The Artlish is a 125 km^2 catchment that is also designated as a Fisheries Sensitive Watershed. The main river channel runs through a cave and eventually flows into the Tahsish Inlet on the west coast of Vancouver Island. The watershed supports runs of salmonids (Pink, Chum, Coho, Sockeye, Chinook, and steelhead) throughout its reaches from its mouth to the caves upstream in the provincial park. There are no barriers to fish passage downstream of the caves and fish have been recorded in the North Artlish sub basin but not upstream of the caves (Brayshaw, 2018a). Harvesting began in the late 1960s in this watershed but was not heavily established until the mid-1970s (Brayshaw, 2018a). Early forest harvesting including riparian harvesting and cross stream yarding have resulted in changes to instream wood and channel morphology in the watershed (Brayshaw, 2018a).

In total, eleven focus stream reaches, three in the Artlish and eight in the Nahmint watershed were located and measured using the fish habitat assessment procedure (Johnston & Slaney, 1996, section 3.1.2)(Table 3-1).

Table 3-1. Summary of study streams. Asterix in stream name indicates whether or not a stream was fish bearing. All values are based on field measurements of the listed stream attributes.

Stream (* indicates a non-fish bearing stream)	**Length (m)**	**Average stream surface gradient (degrees)**	**Average bankful width (m)**	**Average depth (cm)**	**Dominant Substrate**
Nahmint Watershed					
Bug Creek*	196	1	3	55	Boulder/Cobble
Elk Creek	196	1	7	59	Cobble/Gravel
Gray Creek*	214	5	5	93	Boulder/Cobble
Head Water Creek	255	2	5	79	Cobble/Gravel
Headache Creek	254	1	11	98	Boulder/Cobble
Rainbow Creek	128	2	5	73	Bedrock/Cobble
Steep Creek *	103	11	3	55	Bedrock
View Creek	249	1	9	81	Boulder/Cobble
Artlish Watershed					
Bun Creek	263	1	8	69	Cobble/Gravel
Lunch Creek*	212	1	13	104	Boulder
Trickle Creek*	120	1	10	89	Boulder

3.1.1 Instream wood field data

In the summer of 2022 field data was collected at eight roughly 200 m long stream reaches in the Nahmint watershed and three 200 m long reaches in the Artlish watershed (Table 3-2). The location of individual pieces of instream wood were collected with a Trimble Geo7X GNSS unit with differential corrections obtained from BC Active Control System base stations, resulting in 75% of positional accuracies falling between 30 and 200 cm and 14% above 200 cm. This range of error can be attributed to the rugged topography, dense vegetation and distance between the nearest base station and the study reaches. Additionally, I cannot attribute any directionality to this error and it should therefore be considered a radius of error around the points.

For inclusion, pieces of instream wood needed to meet the following criteria: greater than 10 cm width at log center, dead, and at least partially contained within the bankfull width of the stream channel. These criteria are based on previous studies detecting forest floor wood and the definitions of functional instream wood (Hassan, Hogan, et al., 2005; Jarron, Coops, MacKenzie, et al., 2021; Joyce et al., 2019).

Table 3-2. Average recorded characteristics of field measured instream wood.

Stream	Count	Length (cm)	Diameter (cm)	Submerged Depth (cm)
Bun Creek	27	608	90	3.78
Elk Creek	15	620	62	0.80
Head Water Creek	34	531	70	0.45
Headache Creek	10	734	121	1.70
Lunch Creek	6	521	86	0.00
Rainbow Creek	5	480	78	1.00
Steep Creek	9	509	85	0.11
Trickle Creek	4	693	115	1.50
View Creek	15	830	118	0.27

Instream wood was separated into two classes, logjam (>3 pieces of wood) or individual pieces (Figure 3-2). For individual pieces the length, diameter, submerged depth, position relative to the stream (parallel versus across), and azimuth were measured and any additional notes of interest were recorded. Only the location of each logjam was recorded.

Figure 3-2. Examples of field measured (A) individual wood pieces and (B) a logjam.

3.1.2 Field based stream characterization

I selected six stream reaches, roughly 200 m in length each, within the upper Nahmint watershed based on the accessibility from logging roads to represent a variety of streams sizes. In the summer of 2019, the Fish Habitat Assessment Procedure (FHAP), developed by the British Columbia Ministry of the Environment, Lands, and Parks as a method to determine the quality of salmonid habitat instream reaches (Johnston & Slaney, 1996), was used to assess the stream reaches based on a number of physical characteristics. Starting at their downstream end, streams were classified into four geomorphic habitat units; pools, glides, riffles and cascades based on the classification system developed by Hawkins et al. (1993) (Figure 3-3). Pools are deep slow moving units with a water surface gradient near 0% (Johnston & Slaney, 1996). Glides are non-turbulent fast flowing units with relatively flat bottoms (Johnston & Slaney, 1996). Similarly, riffles are turbulent areas of fast flowing water with gravel or cobble bed material often projecting above the water surface (Johnston & Slaney, 1996). Lastly, cascades are steep stepped areas with emergent boulders in channels with surface gradients greater than 4% (Johnston &

Slaney, 1996). Once categorized, the length, gradient, mean bankfull width, mean wetted width and mean bankfull, wetted depth and gradient (using a Suunto clinometer) of each individual unit is measured. Instream wood is also counted in each habitat unit and split into three categories based on diameter, small (10-20 cm), medium (20-50 cm), large (>50 cm) (Johnston & Slaney, 1996) (Table 3-3).

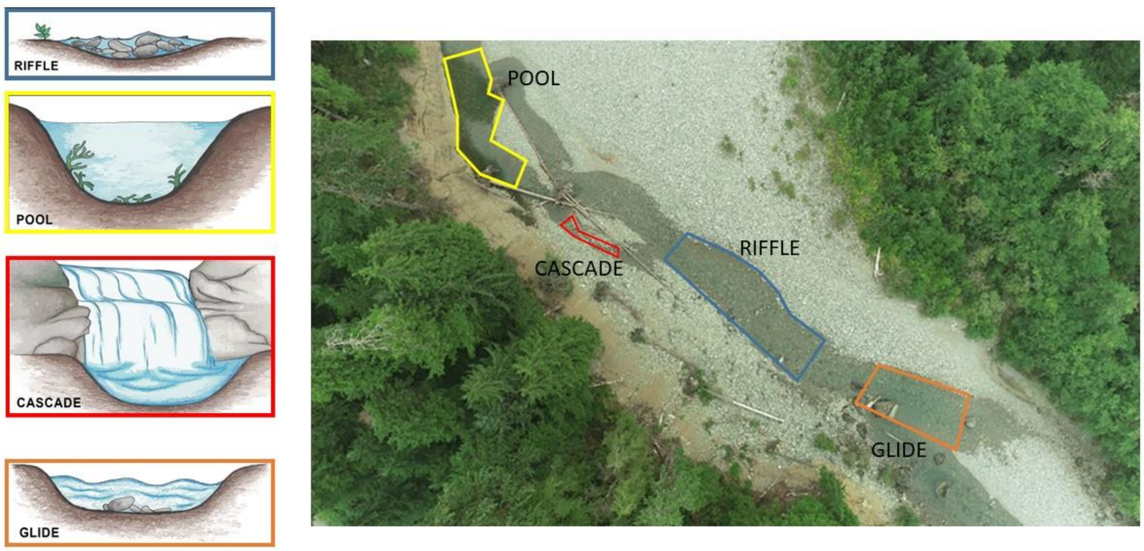

Figure 3-3. Examples of stream morphological units identified in our study area.

Table 3-3. A summary of field measured stream attributes

	# of recorded Instream wood (medium and large)	Mean Bankfull Width (m)	Length (m)	Gradient (%)	# of Cascade	# of Glide	# of Pool	# of Riffle
Elk Creek	18	6.89	185.3	1.66	2	4	5	5
Gray Creek	17	5.1	172.8	4.96	13	2	16	2
Head Water Creek	44	5.26	202.7	2.68	1	8	21	10
Headache Creek	15	10.57	231.1	1	0	7	11	11

Rainbow Creek	7	5.3	116.2	2.5	5	4	7	7
View Creek	19	9.86	179.9	1.34	5	5	10	5

Location of the start and end of each habitat unit was determined using a Trimble Geo7X GNSS unit, with differential corrections obtained from BC Active Control System base stations resulting in an estimated accuracy between 5 - 50 cm. Individual points were then connected into stream segments and joined with the field data to be used in validation of the models described below.

3.1.3 ALS data

ALS data were acquired over the two watersheds using a Riegl Q1560 sensor (Table 3-4).

Table 3-4. Details of ALS data collection.

Watershed	Artlish	Nahmint
Sensor	Riegl Q1560 Dual-Channel	Riegl Q1560 Dual- Channel
Point Density	25–35 points/m^2	25–35 points/m^2
Date Flown	July 28th, 2016	September 12th, 2015
Total Area	232 km^2	154 km^2
Intensity (5 bytes)	2097–65535	6651–65535
Scan Angle	±29°	± 29°
Acquisition Altitude (above ground level)	1600 m	1600 m
Flight Speed	115 knots nominal	115 knots nominal
Number of returns recorded	436337984	660910337
Number of ground returns	12941164	257126231

Chapter 4: Characterizing stream morphological features important for fish habitat using airborne laser scanning data

4.1 Introduction

Habitat loss driven by climate change, forest harvesting and associated road construction, development, and other anthropogenic disturbances, are major threats to populations of Pacific salmon and trout (Salmonidae, *Oncorhyncus* spp; hereafter termed salmonids; Gregory and Bisson, 1997). The freshwater aquatic habitat of these species is influenced by a variety of terrain characteristics, which act as key drivers of hydrologic and geomorphic processes (Hogan & Luzi, 2010). Stream geomorphic processes, such as flow rate, sediment transport, and channel shape, create complex instream structures, which have been directly linked with quality and quantity of salmonid habitat (Bjornn & Reiser, 1991). These stream processes are determined by topographic features such as elevation, slope, and aspect and therefore have been widely adopted for use in both hydrologic and geomorphic models as well as stream classification systems (Jenson, 1991; Lidberg et al., 2017;Lindsay & Dhun, 2015; Strahler, 1957).

While the importance of stream structure on salmonids habitat is well recognized, the existing methods for classifying stream structure and morphology are not standardized (Bisson et al., 2017). Older stream classification systems are biologically founded, splitting streams into zones marked by shifts in dominant aquatic species (Huet, 1959). More recent classification systems have been developed based on a hierarchical scale, classifying stream systems into individual stream units to entire watersheds (Belletti et al., 2017). Physical factors including the structure of the stream network, morphology of the channels, size and mobility of the channel, and the ability of stream units to transport sediment have also been used in classification systems (Buffington &

Montgomery, 2013). These factors can in turn inform on changes in the physical properties of a stream and the instream channel morphology over time (Bizzi et al., 2019; Norman et al., 2017). Hawkins et al (1993) developed a stream classification system using a hierarchical framework of individual channel units, starting with fast and slow moving units (pools and riffles), further subdividing based on turbidity, slope, and formation process (riffles, falls, damned pools). With an accurate classification of these physical factors and channel units, a description of the microhabitat requirements of aquatic organisms, such as salmonids can then be developed (Belletti et al., 2017; Bisson et al., 1988).

Subsequent studies have linked a selection of the stream units characterized by Hawkins et al (1993), specifically pools (Bisson et al., 1988; Gonzalez et al., 2017; Rosenfeld et al., 2000) and riffles (Buffington et al., 2004; MacIsaac, 2010) to habitat and subsequently the quality and quantity of salmonids. Further stream structural attributes have been identified as important indicators of quality salmonid habitat. In small streams, wood inputs contribute to structural complexity by influencing the formation of channel units (predominantly pools) and influence the distribution of sediment size throughout a reach (Beechie & Sibley, 1997; Bjornn & Reiser, 1991). Many previous studies have found positive relationships between density of instream wood and salmonid abundance in small coastal streams indicating that instream wood is an important habitat feature (Boss & Richardson, 2002; Gonzalez et al., 2017; Rosenfeld et al., 2000). Stream bankfull width is another key predictor of salmonid abundance in small coastal streams (Rosenfeld et al., 2000). These small streams have a high bankfull width to depth ratios, which increases the availability of habitat and ultimately the abundance of salmonids (Gomi et al., 2002).

In addition, these stream structural attributes and classification systems are important for a variety of other aquatic ecosystem services. Naman et al (2017), found that stream channel structure, specifically riffles and pools, has a direct influence on both the size and abundance of aquatic invertebrates. Furthermore, Calderon and An (2016) found that pool units had greater amounts of nutrients and higher levels of sestonic algae compared to riffle units.

While these stream features are important to habitat classification ,watershed management and water quality, field surveys of stream structure, salmonid habitat, and salmonid abundance are expensive, time consuming and constrained to small geographic areas (Alho et al., 2009; Hummel et al., 2011). Field surveys typically involve multi-person teams, walking in and along streams for extensive periods, which can be both costly and dangerous especially in remote or mountainous areas.

A complement to these extensive field based approaches, is the use of remote sensing systems, which have been used to examine the physical characteristics of streams and employed by forest and fisheries managers to reduce the costs of *in situ* surveys (Piégay et al., 2019). Spaceborne remote sensing platforms, such as the Landsat series of satellites, have allowed for attributes of large streams to be assessed at the watershed scale, however are generally limited to the main river system due to the 30 m spatial resolution of these satellites (Pekel et al., 2016). High spatial resolution imagery acquired from WorldView, Quickbird, or SPOT allow for the examination of smaller stream segments with some additional success (Johansenet al., 2010). However, overall these multispectral instruments are not ideal for characterizing salmonid habitat in small streams because of the inability to detect the three dimensional structures of terrain, and the inability to penetrate over-stream structures such as forest canopies, making it difficult to detect fine scale stream characteristics in dense forests (Doxaran et al., 2002; Johansenet al., 2010).

The use of Light Detection and Ranging (lidar), also known as airborne laser scanning (ALS), has a demonstrated capacity to penetrate forest canopies to generate fine scale digital elevation models (DEM) from which a variety of stream structure and physical terrain information can be derived (Johansen, Phinn, et al., 2010; O'Callaghan & Mark, 1984; Tompalski et al., 2017). ALS systems typically consist of three components, a laser scanner, a Global Positioning System (GPS), an Inertial Measurement Unit (IMU) all mounted on an airplane (Lefsky et al., 2002a). Working in unison, these components derive information on the 3-dimensional location of reflected objects, be it vegetation or terrain very accurately (Lefsky et al., 2002a). As ALS becomes increasingly popular for forestry applications (Coops et al., 2021), there are increasing amounts of Near-Infrared (NIR) ALS being flown. In contrast, bathymetric or green wavelength ALS, which has been specifically designed for aquatic applications is much less available and is rarely flown across large areas limiting its use in an operational management context (McKean et al., 2009). Therefore, the use of "ALS" and "LiDAR" in this study refers to the more common NIR version.

Methodologies to delineate stream networks from a DEM, be it conventionally derived from topographic maps, or from ALS, are well documented and act as the base for additional research (Jenson, 1991; Jenson & Domingue, 1988; O'Callaghan & Mark, 1984). Subsequent studies have demonstrated that ALS-derived terrain models can successfully be used to characterize a variety of stream attributes in higher order wider streams. James et al. (2007) used ALS derived DEMs to measure the order and magnitude of head water streams in South Carolina, USA under dense forest canopies. They found that errors in mapping channel location and topological connectivity increased with smaller streams (James et al., 2007). Using a DEM-derived stream gradient estimate, Cavalli et al. (2008) found that ALS data were able to differentiate between step-pools and riffle-pools reaches. Stream width has also been measured using ALS data with some success in European and Australian ecosystems (Biron et al., 2013; Johansen, Arroyo, et al., 2010; Johansen et al., 2011; Michez et al., 2013). Johansen et al. (2010) used object-based image analysis to measure the width of larger streams ($R^2 = 0.99$, $n = 11$) using DEM and slope layers derived from ALS. A study by Tompalski et al. (2017) developed a full characterization of riparian ecosystems on Vancouver Island, Canada, using stream gradient as a proxy for fish bearing potential with 82.9 % accuracy, and used ALS-derived vegetation metrics combined with solar insulation to predict total daily hours of stream shade.

ALS has also been used in conjunction with high-resolution orthophotos to quantify recruitable and instream large wood (LW) (Kasprak et al., 2012;Richardson & Moskal, 2016). Recently, Joyce et al. (2019) and Jarron et al., (2021) utilized ALS data to count and estimate the volume of forest floor coarse wood using a point cloud segmentation algorithm that also has potential to be adopted within stream environments. Key to this extraction is the use of ALS intensity information, which provides an indication of the returned energy in each pulse. Due to absorption characteristics of water for the ALS near-infrared laser pulses (Höfle et al., 2009), variations in intensity within the stream may be indicative of coarse wood.

While previous research has shown the successful application of ALS to derive both terrain and stream physical features, there has been limited research on characterizing smaller streams (defined in this research as <10 m wide), or the classification of specific individual channel units, which is needed to comprehensively assess salmonid habitat conditions over the landscape. The objective of this paper is therefore to apply state of the art techniques to examine how ALS point clouds can be used to develop a novel framework to characterize stream morphology important to salmonid habitat in small streams in Coastal British Columbia, Canada. To do so, I first utilized ALS to delineate small stream reaches. I then examined local terrain characteristics to estimate stream bankfull width and developed a novel methodology to detect instream wood through point cloud processing. I generated a series of point cloud metrics from the ALS data for input into a Random Forest model to classify individual habitat units. Lastly, I compared the derived stream attributes to field data and assessed the accuracy of the approach. Through this work I hope to provide forest and fisheries managers with tools to better characterize stream features important in assessing the quality of salmonid habitat to be used as a framework for conserving critical aquatic ecosystems (Bjornn & Reiser, 1991; Mellina & Hinch, 2009a; Rosenfeld et al., 2000).

4.2 Methodological approach

The general approach for processing the ALS data consisted of three key steps: 1) producing a DEM and a set of standard ALS metrics, 2) delineating the study streams, 3) generating stream attributes from ALS metrics (Figure 4-1).

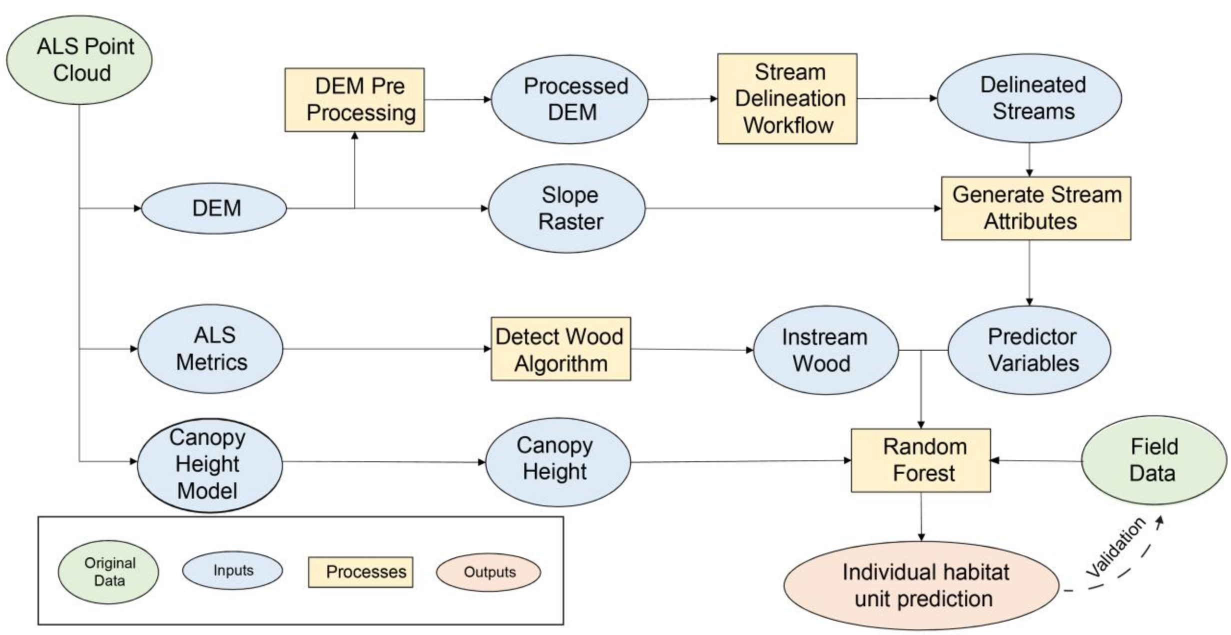

Figure 4-1. Full methodological flowchart.

4.2.1 DEM and ALS metrics

First, ALS ground returns were used to create two Digital Elevation Models (DEM) with a 1 m and 10 m spatial resolution. The 1 m DEM raster layer was then used to normalize point cloud heights above ground level. A suite of standard ALS-derived metrics were calculated for 1 x 1 m cells along the study reaches including maximum height of returns to create a canopy height model (CHM; Roussel et al., 2020), the proportion of first returns above 2 m divided by the total number of first returns representing canopy cover (Wulder et al., 2008), 15th percentile of height returns (p15) to characterize understory and midstory vegetation (Roussel et al., 2020), and the mean value of the raw intensity, classified into five equal classes, as a proxy for water depth/occurrence (Hofle et al., 2009). Three topographic layers were then derived from the 1 m DEM including terrain slope, normalized elevation (Cavilli et al., 2008), and a terrain roughness index (edge density; Lindsay, 2016). Normalized elevation was calculated, based on the methods of Cavilli et al. (2008), by taking a moving window standard deviation of a cell-by-cell subtraction between the ALS derived DEM and a 5 x 5 moving window mean DEM. I used the edge density algorithm from Whitebox Tools (Lindsay, 2016) to quantify breaks in slope between DEM pixels, creating the terrain roughness index.

4.2.2 Delineating streams

Figure 4-2 shows the workflow for the second step of ALS processing, delineating the full stream network.

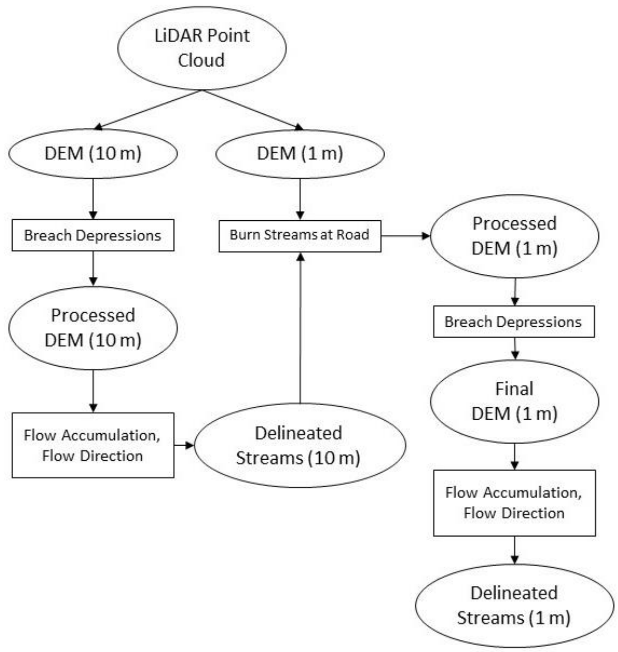

Figure 4-2. Stream delineation workflow.

Due to the topographic complexity of the study area and size of the study streams, I initially delineated a stream network using the 10 m DEM for the process of "stream burning", which allowed streams to flow freely through road embankments and enforcing flow paths (J. Lindsay, 2015). The 1 m DEM was pre-processed using stream burning and a breach depression algorithm instead of a traditional sink filling algorithm to limit the amount of change to the DEM and had been shown previously to better match field measured points (Lindsay, 2016). After pre-processing of the DEM, I followed the workflow of Tompalski et al (2017), who delineated streams in a similar Vancouver Island watershed, calculating flow direction, accumulation, and stream extraction using a stream initiation area of two ha. Lastly, I clipped the delineated ALS streams to the field measured stream line to allow comparison with field data (Figure 4-3).

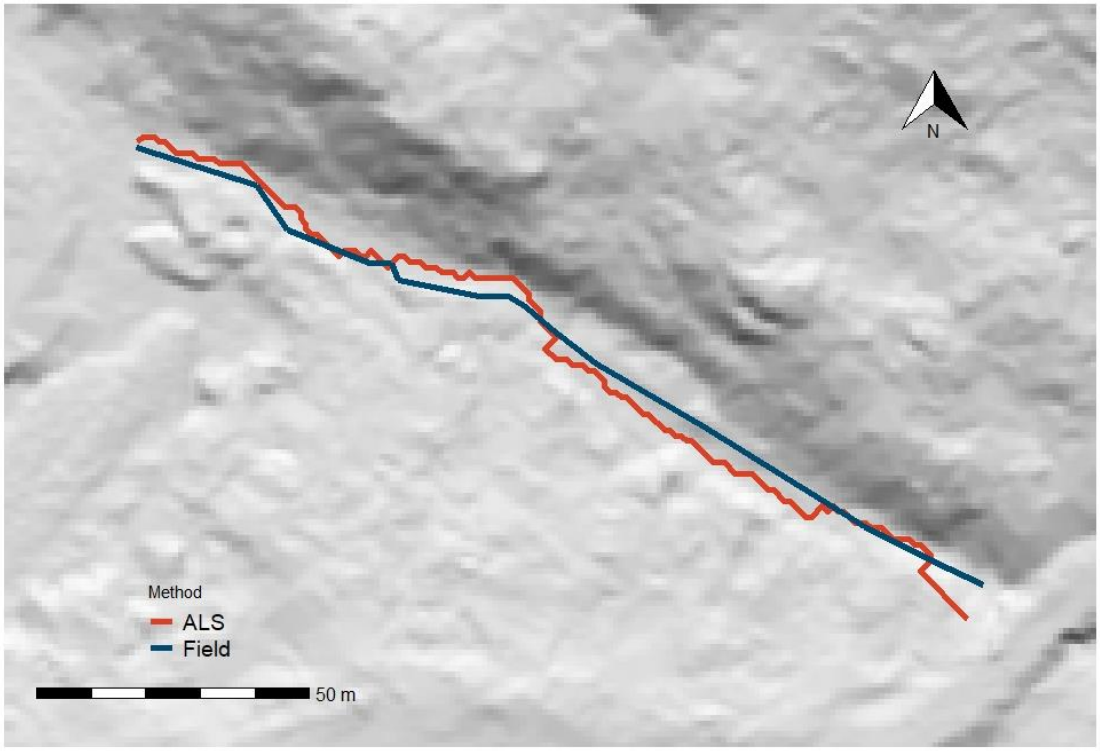

Figure 4-3. Elk Creek as measured in the field and as delineated from ALS.

4.2.3 Stream attributes

In the third step I determined a series of stream attributes from the derived ALS layers specifically: bankfull width, instream large and medium wood, percent canopy cover, gradient and stream morphological unit.

4.2.3.1 Bankfull width

Stream bankfull width was estimated based on the methods of Johansen et al (2011) who expanded stream width from a centerline using terrain slope and elevation thresholds (Figure 4-4).

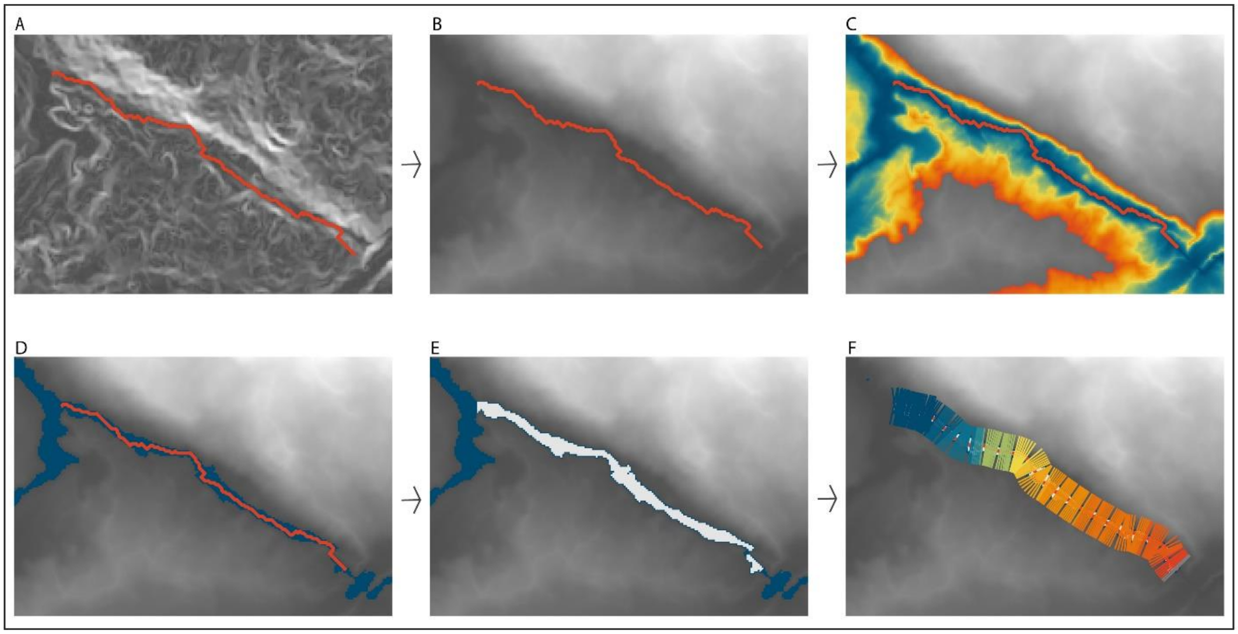

Figure 4-4. A workflow for deriving stream width: A) terrain slope layer with the overlaid stream centerline (red); B) terrain slope layer after cost accumulation to nearest stream source; C) thresholds between 0 and 200 applied to the cost accumulation layer (low threshold – dark blue, high threshold - red);D) threshold set to 18; E) threshold layer converted to a polygon; F) stream width derived for a set of perpendicular lines established along stream centerline.

I first calculated the accumulated cost of moving from each terrain slope cell to the nearest stream source (Figure 5 A, B, C). A "wetness threshold" (<=18) was applied to the accumulated cost raster representing pixels which had marked water accumulation (Figure 5 D). To measure stream width, a series of perpendicular lines were generated at 1 m intervals across a smoothed version of the ALS derived stream line (Figure 5 E, F). The number of DEM grid cells along the perpendicular line that exceeded the wetness threshold were used as the stream width. In areas where streams became too wide, or where two streams converged and stream width exceeded reasonable stream width estimates for the region (based on mean width), only stream widths within ± 1 SD of the overall mean stream width were compared. The relationship between the ALS estimated stream width and the field-measured stream width was assessed using Pearson's correlation coefficient, root mean square deviation (RMSD), mean absolute deviation (MAD) and bias. Bias is the average difference between the ALS measured width and the field measured width and was calculated using the equation:

(1) $$Bias = \frac{\sum(predicted - observed)}{n}$$

4.2.3.2 Instream large wood

Instream wood detection was adapted from the methods of Jarron et al. (2021) and Joyce et al. (2019) to both count and measure coarse wood on the forest floor. The methodology consists of two main workflows; beginning with point cloud filtering, followed by the skeletonization process (Figure 4-7).

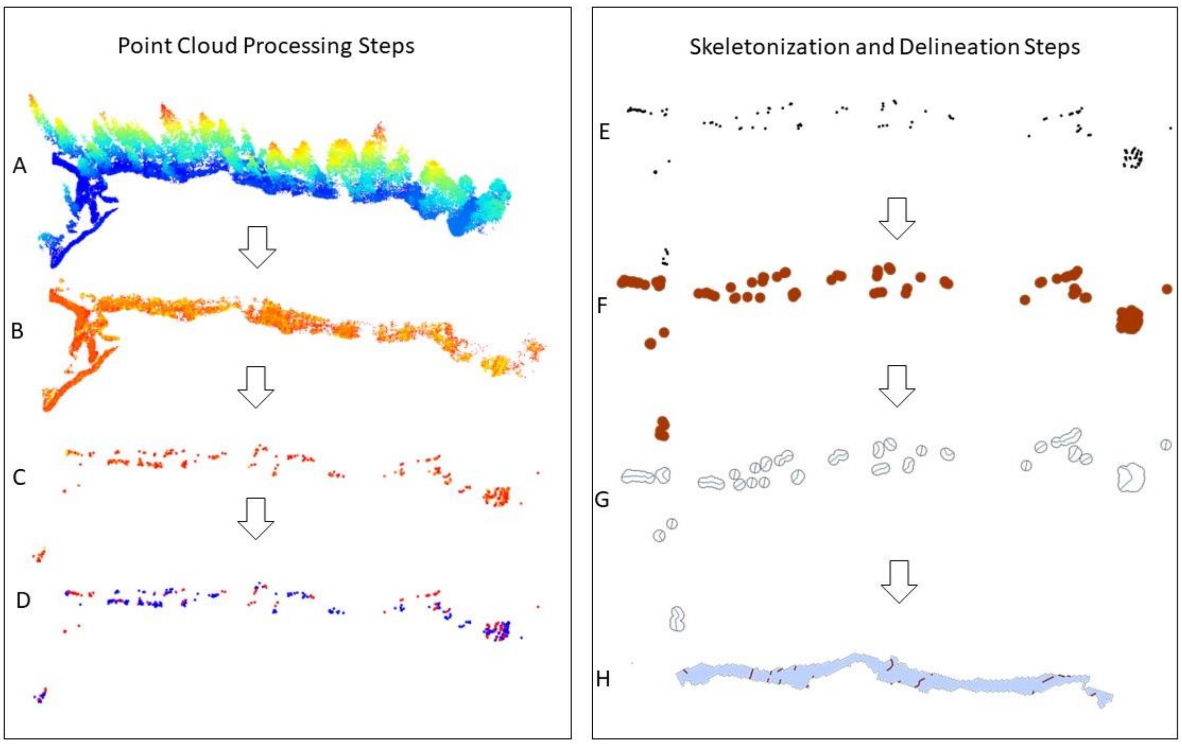

Figure 4-5. Instream large wood detection methodology: A) isometric view of a point cloud corresponding to one of the streams, colored by height (low elevations – dark blue, high elevations – yellow to red); B) normalized point cloud cropped to below 2 m above ground level; C) returns with highest 30% of intensity values; D) linear feature detection (linear features – red, non-linear feature – blue); E) points corresponding to linear features; F) a 1 m buffer applied to all points classified as linear features; G) centerlines through buffered points; H) centerlines clipped to stream width.

First, the ALS point clouds were limited to encompass the entire stream width and stream bank (Figure 45- A). Next, point clouds were classified into ground and non-ground returns using a cloth simulation filter (Zhang et al., 2016;). The derived ground surface was then used to normalize point elevations filtered to only include returns less than 2 m above ground level before further processing (Figure 4-5 B). An intensity threshold was applied to include only returns with the highest 30% of intensity values to remove returns reflecting off water (Höfle et al., 2009; Figure 4-5 C). In order to differentiate instream wood from low lying shrubs and branches, only pulses with one return under the 2 m threshold were selected (Jarron et al 2021). ALS pulses with multiple returns under 2 m are unlikely to represent instream wood as denser objects such as wood generally allow for only single pulse returns. Lastly, a linear feature detection algorithm was used to classify each return as a linear or nonlinear relative to neighboring returns (Jarron et al., 2021; Figure 4-5 D). Filtered points were buffered by 1 m and then converted to linear features by generating centerlines through each buffered point (Figure 4-5 F, G). All resulting vectors representing linear piece of coarse instream wood were clipped to within the stream width boundary and lines with < 1 m in length were discarded (Figure 4-5 H). Two comparisons were then made, first I compared the total number of medium and large pieces (>20 cm) of wood per stream to the numbers detected by the ALS and second, I split the stream reaches in half and compared the field and ALS detected instream wood using Pearson's correlation coefficient.

4.2.3.3 Channel morphology and habitat units

A Random Forest (RF) (Breiman, 2001) modelling approach was used to classify individual geomorphic habitat units within our study streams (Table 4-1). To do so, the predictor variables were extracted every metre along the delineated stream line. For instream wood a total count of all detected segments within five metres of each measurement point along the delineated stream line was used as a predictor. Prior to model development predictor variables were assessed for covariance with no significant inter-correlations found. To account for uneven class distribution, riffles (n = 375) were randomly under-sampled to n = 300, while pools (n = 167), cascades (n = 295) and glides (n = 257) were randomly oversampled ensuring that each class had an equal sample size (n = 300). Data was split 75-25% for training and testing, respectively, with the final model applied to the testing dataset being reported in section 3.3. Additionally, predictor variable importance is assessed within the Random Forest algorithm by calculating the Mean Decrease in Accuracy (MDA). For final mapping purposes the most frequently predicted habitat type, meter by meter, along each unit was used.

Table 4-1. Predictor variables used in the Random Forest model.

Predictor	Unit	Description	Category
Width	m	Bankfull width of the stream channel	Stream Structure
Instream wood	Count	A count of instream large and medium wood	Stream Structure
Canopy Height	m	The maximum height of returns per pixel	Vegetation Structure
15^{th} percentile of height	m	Height of the 15^{th} percentile of returns	Vegetation Structure
Normalized Elevation	Index between 0-1	Mean focal filter followed by a standard deviation filter of elevation	Topography
Edge Density/ roughness	Index between 0-1	Surface roughness index	Topography
Intensity Class	Very Low, Low, Med, High, Very High	Equally distributed quantile classes of intensity from ALS ground returns	Stream Structure

All statistical analyses were conducted using the R programing language (R Core Team, 2022). ALS processing was done using the lidR package (Roussel, Auty, Coops, et al., 2020; Roussel, Auty, de Boissieu, et al., 2020). Stream delineation was done using the Whitebox tools R package (Lindsay, 2016; Wu, 2019). Stream width was calculated in ArcGIS and R (ESRI, 2020). Stream morphological units were classified using the RandomForest package in the R programing environment (Liaw & Wiener, 2018).

4.3 Results

4.3.1 Stream attributes

Canopy cover was highest at Gray Creek with 87% cover and the lowest at Elk Creek with 48% cover (Table 4-2). Overall, the mean canopy cover was 72% across all of the study streams.

Table 4-2 ALS derived stream level canopy cover.

Stream	Canopy Cover
Elk Creek	48%
Gray Creek	87%
Headwater Creek	76%
Headache Creek	78%
Rainbow Creek	76%
View Creek	80%

The mean difference between field and ALS delineated stream reaches was 0.72 m. A strong linear relationship ($r = 0.80$, $p < 0.01$) was found between the ALS estimated and field-measured stream widths (Figure 4-6). A bias of -1 m signifies that this approach generally under predicts bankfull width with a mean absolute deviation (MAD) of 1.89 m and an RMSD of 2.05 m. The approach was accurate at estimating width across a wide range of field measured widths. Certain streams, in particular Elk Creek, had a wide range of field measured widths, which were captured accurately by the ALS approach. When applied to narrower streams with less variability in width (e.g. Head Water and Gray Creek), the predicted width was overestimated.

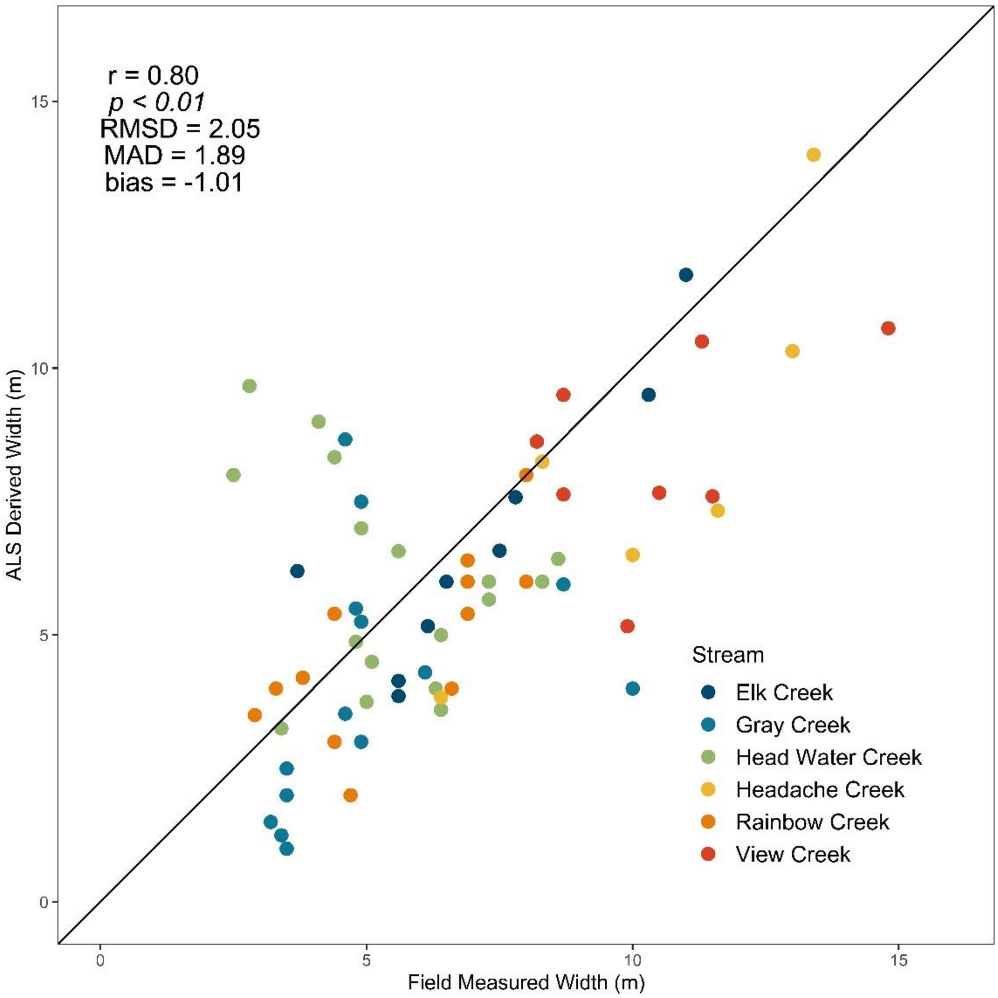

Figure 4-6. Field measured stream width versus ALS derived width coloured by stream reach.

Superimposing the predicted stream width over ALS derived terrain and vegetation attributes, allows for an initial analysis of stream morphology (Figure 4-7). Normalised elevation shows the residual topography of an area, with higher values (shown in red) representing areas with a greater change in local elevation. Roughness represents a finer scale of variation in topography and shows breaks in slope derived from a DEM ranging from 0 to 1. Generally, higher roughness values represent more variability in local terrain surrounding and within streams, such as boulders emerging above water level and is likely indicative of more turbid channel units. The intensity shows the near infrared return energy of the pulses divided into five classes (Table 4-1). Canopy height varies along the stream section ranging from 0 - 40 m with the height of understory cover (p15) ranging from 0 - 25 m along the stream reach with the vast majority being less than 5 m tall. Lastly, instream wood shows an overlay of ALS estimated locations of wood.

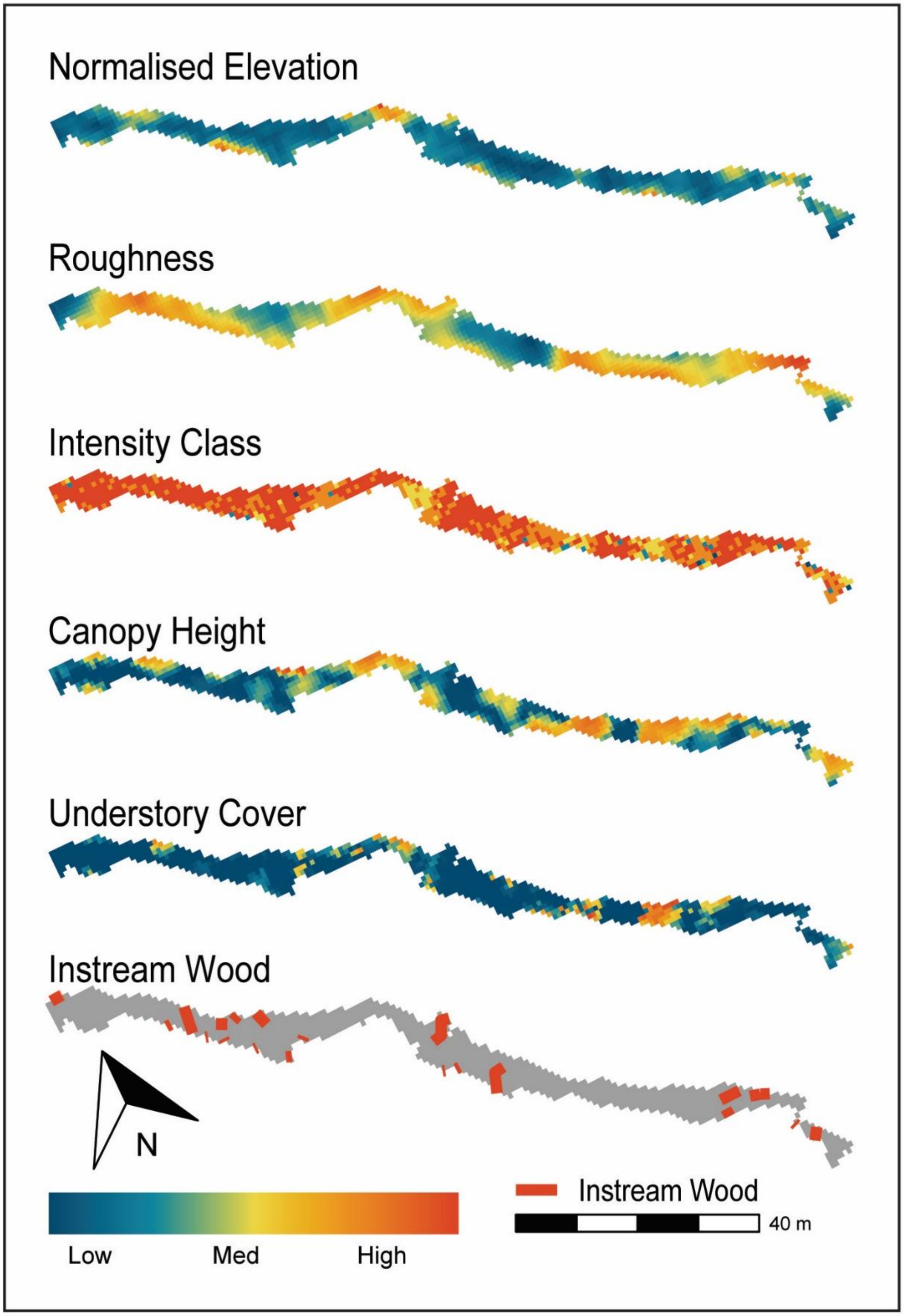

Figure 4-7. ALS derived predictor variables for Elk Creek.

4.3.2 Instream large wood

In total, 76 of 95 (80%) individual pieces of instream medium and large wood were detected across the streams in the study area (Figure 4-8). When dividing the stream into upstream and downstream sections, ALS derived wood versus field measured wood showed strong correlation (r = 0.81). In 4 out of 6 streams the method over predicted the number of pieces of stream wood, in Gray Creek the number was greatly underpredicted with only 1 out of 13, while in Head Water Creek the approach moderately underpredicted the number detecting 21 of 32 pieces.

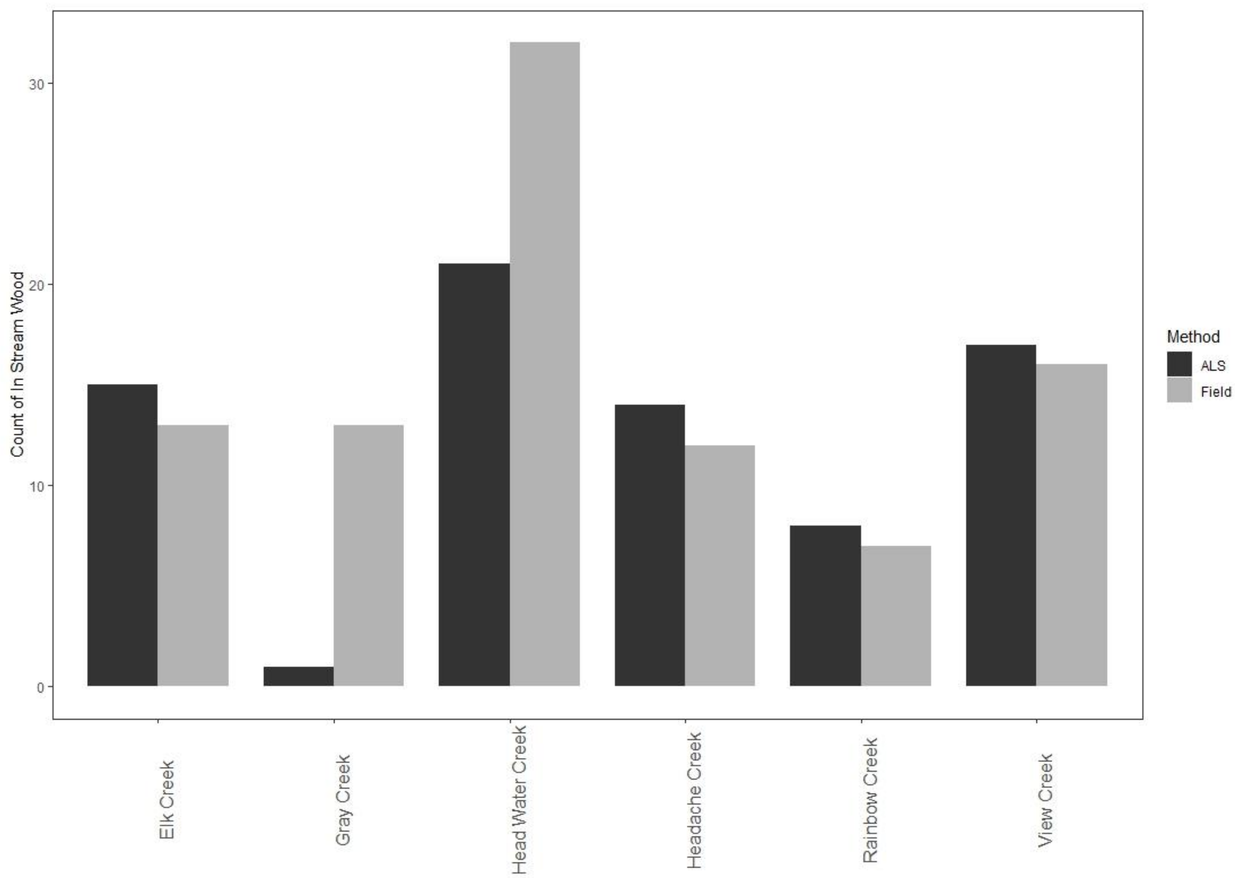

Figure 4-8. ALS predicted and field counted instream wood by stream.

4.3.3 Channel morphological units

The developed RF model to predict the four channel morphological units had a mean overall classification accuracy of 85% when applied to the testing data set (25% of features withheld for validation). Generally, the model had the greatest success predicting the "pool" morphological unit, with a user's accuracy 96% and producer's accuracy 83% (Table 4-3). Riffles had the most variation in model accuracy with a user's accuracy of 76% and a producer's accuracy of 93%. Riffles were most often confused with glides, and least often confused with the pool class. In contrast, pools were equally miss-classified across all classes although overall maintained the highest accuracies.

Table 4-3. Error matrix from Random Forest model.

	Cascade	**Glide**	**Pool**	**Riffle**	**Total**	**User's Accuracy**
Cascade	65	4	5	1	75	87%
Glide	3	65	5	2	75	87%
Pool	1	1	72	1	75	96%
Riffle	6	7	5	57	75	76%
Total	75	77	87	61	300	
Producer's Accuracy	87%	84%	83%	93%		Overall accuracy = 86%

Furthermore, overall model accuracy was compared across the 6 different study streams (Table 4-4). Elk creek had the highest overall accuracy at 96% while Headwater Creek had the lowest overall accuracy at 74%.

Table 4-4. Overall classification accuracy by study site.

Stream	**Accuracy**
Elk Creek	96%
Gray Creek	90%
Headwater Creek	74%
Headache Creek	92%
View Creek	84%
Rainbow Creek	81%

Spatial mapping of the ALS predicted habitat units and visually comparing them to the field measured habitat units shows good correspondence (Figure 4-9). For Elk Creek I see a misclassified riffle as a pool in the north west section of the stream with the remaining units classified correctly. In Gray Creek there were more discrepancies between ALS units and field units especially in the narrower southern section of the stream. Head Water Creek shows the most misclassifications between riffle and glide units similar to what is shown in Table 4-3 with riffles and glides showing the greatest confusion. Overall, Figure 4-9 demonstrates that feature size impacts classification accuracy: the most misclassification was within smaller habitat units and the highest accuracy in wider and longer units.

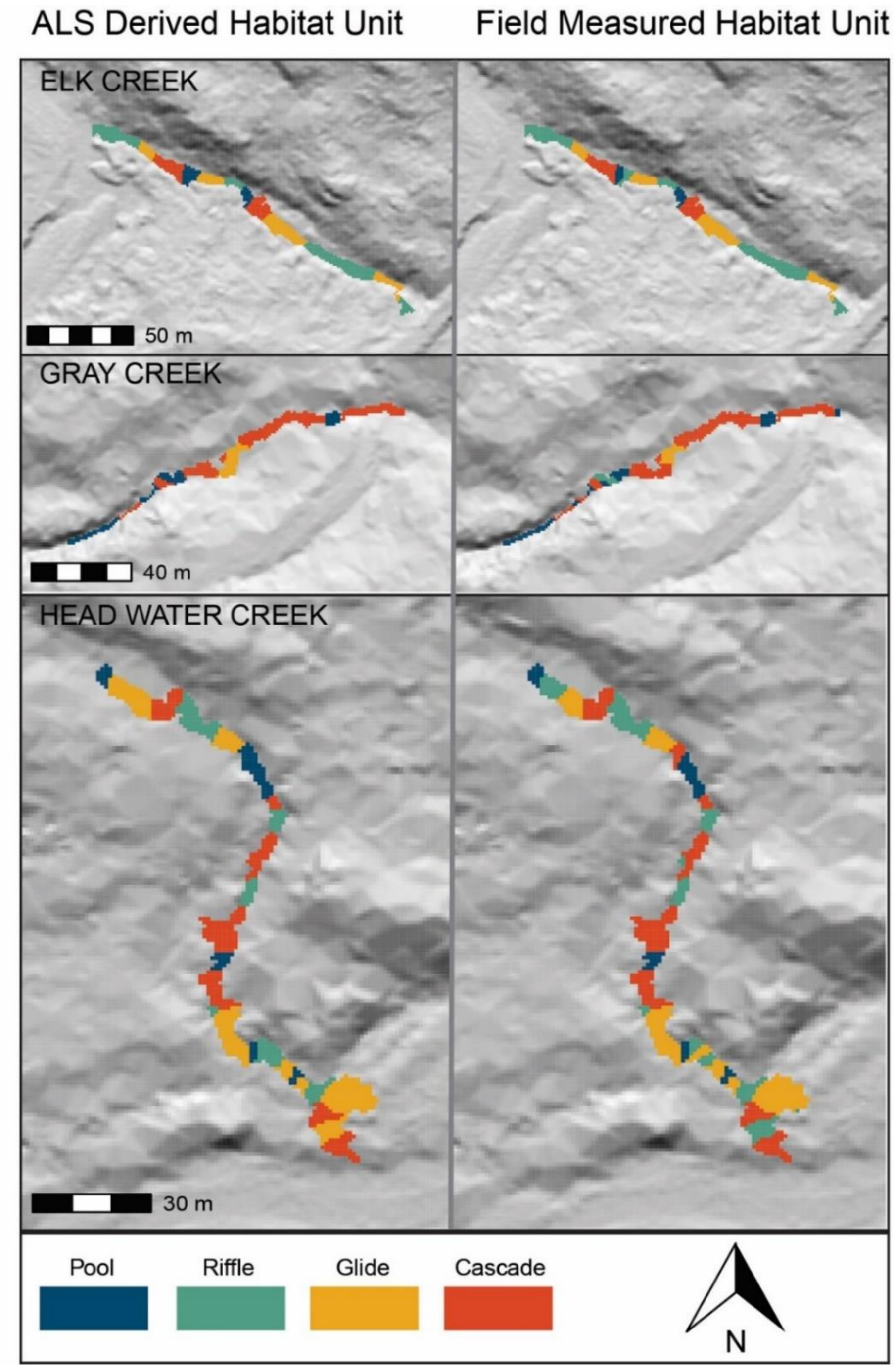

Figure 4-9. Map showing field measured channel habitat units and ALS derived channel habitat units expanded from stream centerline points.

The variable importance for the model indicates that all seven ALS derived predictor variables contributed to the model's predictive power (Figure 4-10). The top three predictors all had very similar Mean Decrease Accuracy (MDA) values, demonstrating the importance of topographic variables in morphological classification. MDA showed almost equal importance between intensity class (MDA = 73.9) and understory cover (P15; MDA = 73.5). Bankfull width and instream wood had lower MDA values, ranking them lowest in importance but still having a strong impact on overall model accuracy.

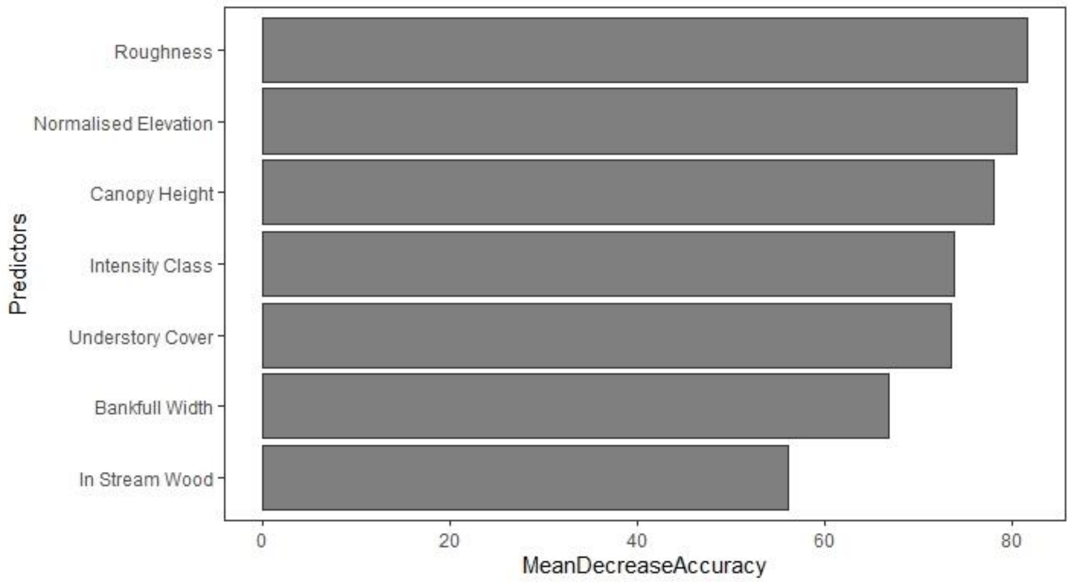

Figure 4-10. Variable importance for stream morphological unit random forest model.

4.4 Discussion

In this study I examined the capability of ALS to characterize the morphology and structure of small streams important for salmonid species in a coastal western hemlock zone on Vancouver Island, BC, Canada. To do so, I used state of the art point cloud processing techniques to extract stream attributes to use as predictor variables in a novel modeling framework to classify channel morphological units. Our results demonstrate that ALS data can successfully be applied to characterize stream width, instream wood, and discrete channel morphological units. With the growing popularity of ALS data acquisitions for forest inventories, fisheries and forest managers have the capacity to use these types of data to extract these relevant habitat components and use them for improved habitat assessments in forested ecosystem, maximizing the data value.

A critical stream characteristic that many management decisions and forestry practices are based on is stream width (Pike, 2010). After delineating our study streams from an ALS derived DEM, I used a slope thresholding algorithm to expand stream width into areas of homogenous elevation. Our methodology for estimating bankfull width showed a positive relationship ($r = 0.80$) between ALS derived width and field measured width. Streams with high canopy cover, steeper gradients, and less variable field measured widths, resulted in less accurate ALS width estimations. Other studies e.g., Johansen et al.,(2010a); $R^2 = 0.99$, $n = 11$ and Johansen et al., (2011); $R^2 = 0.93$ $n = 35$, have shown improved results for stream width models on larger rivers which generally have smaller gradients, consistent with our findings.

The ability of ALS to estimate instream large wood is a key finding of this research. Our approach, based on Jaron et al (2021), found 80% of medium and large wood in our study streams. While previous research has used high-resolution optical imaging (J. Richardson & Moskal, 2016) to count instream and recruitable wood, our results demonstrate that ALS alone is a viable option. Streams with <80% canopy cover had much higher, and more accurate counts of instream large wood, suggesting that in very closed canopies such as those present in Gray Creek estimation is more difficult. While further studies are needed, ALS should be able to more accurately measure instream wood under closed canopies, particularly full waveform data, when compared to optical imagery.

The classification of the channel morphological habitat units (pools, riffles, glides, and cascades) with 85% accuracy is a promising result, with the confusion matrix indicating that the model predicted well across the study area with the lowest user’s accuracy (76%) occurring in the riffle class, likely due to the similarities between riffles and glides (Hawkins et al., 1993). Pools had the highest user's accuracy (96%) which could be explained by their distinct topography and placement hierarchically within the Hawkins et al. (1993) classification scheme. Additionally, I examined model accuracy across the six study stream reaches. Elk Creek had the highest overall accuracy with 96% of units identified. A possible reason for the high accuracy at Elk Creek is the even distribution of habitat units across the classes and relatively low gradient, low canopy cover, and average bankfull width compared to the other stream reaches. In contrast, Headwater Creek had the lowest accuracy at 74% and the largest distribution of classes with 21 pools and only a single cascade. Interestingly, Gray Creek, the stream with the largest gradient and highest canopy cover had the second highest classification accuracy at 90%. Gray Creek had 13 cascade units and 16 pool units, the two units that were most accurately distinguished, highlighting the importance of topographic variability in model accuracy.

Importantly, spatial mapping of the stream reaches by habitat unit demonstrated a close spatial sequence correspondence between field measured and ALS derived morphological units. A key finding of the spatial mapping was that the most misclassification occurred within smaller habitat units and the highest accuracy in wider and longer units, confirming the difficulty of the approach when stream widths and unit lengths are commensurate with the spatial resolution of the derived lidar DEM. While all seven predictor variables contributed to the model's predictive power, the three most important, at this analysis scale, were terrain roughness, normalized elevation and canopy height. Since stream morphology is influenced primarily through local terrain characteristics, it was expected that the two topographic variables (terrain roughness and normalized elevation) would have the largest effects on model accuracy. The importance of canopy height could be attributed to the effect of stream side vegetation on bank stability (Krzeminska et al., 2019).

ALS return intensity proved an important attribute for both instream wood detection and channel morphological unit classification. The magnitude and range of ALS intensity values can vary across different ALS sensors and manufacturers and is often uncalibrated making the use of intensity values across different datasets challenging. It is however a very useful ALS attribute to utilize within a single flight source and as a result I used intensity information with success. To ensure transferability between locations and datasets further work regarding the transferability of an intensity-based model would be required. Our results demonstrate however an innovative use of ALS return intensity values and have shown a novel application of this understudied component of ALS data.

Interestingly, the results suggest that the presence of instream large wood, despite still contributing to the model's predictive accuracy, was among the least important predictors of channel morphology. In this study I was limited in the field description of instream large wood, as it was collected as part of standard fish surveys, which did not position these items along the stream reach, rather counted pieces within a channel unit. Additional data including the width, length, and geographic position of instream wood would allow for a more comprehensive examination of the approach (Jarron et al., 2021).

The rugged topography and complex forested environments of Vancouver Island result in a variety of stream structural attributes important for salmonids. For example, pool units have been shown to positively influence fish abundance and biodiversity in small coastal streams (Rosenfeld et al., 2000). Other studies have demonstrated an increase in juvenile salmonid abundance instreams with a high amount of instream wood (Boss & Richardson, 2002; Gonzalez et al., 2017). The ability of our model to differentiate between these morphological classes and detect instream wood, shows that these attributes could become key inputs for advanced salmonid habitat models. Protecting salmonid spawning and rearing fresh water habitats has been identified as a key measure to maintain declining populations (Gregory & Bisson, 1997). A landscape level analysis of these features would provide important information on the availability and quality of salmonid habitat and develop a holistic understanding of a watershed helping forest managers make decisions concerning the conservation of these keystone species. Whilst the focus of this paper was the classification of fish habitat units, partitioning an aquatic ecosystem into different units is useful for a wide variety of additional ecological applications. The classification model developed in this study could be applied to the study of aquatic invertebrates (do Amaral et al., 2015; Naman et al., 2017), sediment distribution (D. M. Thompson & Wohl, 2009), and aquatic vegetation (Kuhar et al., 2007). Furthermore, the stream attributes directly extracted from the ALS point clouds, both stream width and instream wood, provide additional information on aquatic biodiversity (Schmera et al., 2012; Wondzell & Bisson, 2003).

In a forestry context, these models can inform on forest management plans, influencing harvesting activity and riparian area management as these practices are commonly determined by stream size and fish occurrence (Richardson et al., 2012). ALS derived stream attributes used in conjunction with ALS derived riparian ecosystems assessments (e.g. Tompalski et al., 2017) provide forestry practitioners a powerful landscape level analysis tool to complement traditional field-based surveys. Additionally, the information on stream size, salmonid habitat quality and stream morphology that our methods provide could help guide road planning and culvert placement near streams. Globally, as ALS data acquisition becomes an increasingly common tool used to guide sustainable forest management, decision makers are looking for additional applications and ultimately more information from the data. Using the methodologies described in the study, riparian ecosystem and fish habitat assessments could become standard attributes routinely derived from ALS data.

While the approach developed in this paper was successful in predicting stream attributes, there are a number of areas where additional research would be warranted to ensure the methodology is more broadly applicable. These fall under two distinct categories: ALS data acquisitions and field data collection. With respect to the acquisition of ALS data, in a forestry context, ALS data are usually acquired in the near infrared wavelength. The near infrared wavelength allows for high reflectance of vegetation surfaces; however, it is restricted in its ability to penetrate the water column, limiting our ability to measure stream depth and streambed topography, which would be key indicators of channel morphology and ultimately salmonid habitat identification. Other types of ALS, such as green bathymetric LiDAR, would provide insights into the depth of the water, however they would be limited in their characterization of the vegetation and stream banks (J. McKean et al., 2009). Furthermore, these bathymetric systems are not frequently flown outside of marine coastal mapping applications, making their usable application in this context relatively weak. A second issue concerns the density of the ALS data. The data for this study were acquired at 25-35 points/m^2 , which is relatively high density for forestry applications. However, increased point density either from decreased flight elevation or scanner technology improvements, may allow for a finer demarcation of instream wood which may be limited based on the number of returns that penetrate the canopy due to the lower density. Additional research could focus on the acquisition of denser point clouds, from UAV LiDAR, for example, which might be able to provide up to 500 points/m^2 , thereby allowing for full characterization of these areas, in limited swaths due to increase in data size, for validation or calibration purposes.

A second limitation of this study is the accuracy of the field data. Accurately mapping a stream using GPS technology is hazardous and difficult when streams banks get wide and deep. As a result, the ground data with which to relate the stream to the ALS might not be, positionally, the most accurate, thereby hindering a fully independent verification of the accuracy of this technique. Alternatively, additional remotely sensed data, such as Mobile Laser Scanning (MLS) or under canopy drone-derived orthophotos have the potential to be incorporated into this methodology as a validation data set for both instream wood and stream width delineation. However, the density of the canopy and underlying vegetation in our study region would make this style of validation difficult in small headwater streams. Whilst there may be some error in the position of the field data, I am confident that they represent a good delineation of the streams and in many cases represent the best that can be achieved in real world situations.

Logical next steps, now that approaches for deriving habitat have been developed, would be to relate these ALS derived stream attributes to fish abundance, biomass, and fish presence / absence which is important for habitat modeling, riparian ecosystem management and salmonid conservation. In addition, extrapolation of this methodology to larger streams, with wider banks, deeper pools, and smaller gradients, is important for landscape level analysis and as a result, further research is required to see how our methodology could be applied in those situations.

4.5 Conclusion

Previous studies have demonstrated the ability of ALS to characterize basic stream attributes. In this research I used high resolution ALS point clouds and DEMs to extract stream characteristics associated with salmonid abundance and habitat quality from six small stream reaches located on

Vancouver Island, British Columbia, Canada. A series of stream characteristic models were compared to ground truthed data collected using the fish habitat assessment procedure. Estimates of stream width, instream large wood, and stream morphological units were tested against field data. This research demonstrates the capabilities of ALS data to model more complex attributes of stream morphology and structure that are important for salmonids and moves toward the application of identifying quality salmonid habitat for use in biological analysis.

Chapter 5: An automated approach to detecting instream wood using airborne laser scanning in small coastal streams

5.1 Introduction

Sustainable forest management requires holistic approaches to ensure that forests continue to offer social, environmental and economic benefits, while balancing forest resources, biodiversity and ecosystem function. An often overlooked component of sustainable forest management frameworks is the riparian ecotone, which acts as a transition zone between upland forests and aquatic ecosystems (Naiman & Décamps, 1997). The riparian forest influences thermoregulation of streams through channel shading, addition of nutrients to stream systems through leaf shedding, bank stabilization, and facilitates the input of large wood to aquatic ecosystems (Tschaplinski & Pike, 2010).

In forested watersheds, forest management can influence water quality, sediment supply, and wood inputs to stream channels, which in turn can significantly affect channel morphology, channel stability, and aquatic habitat (Chamberlin et al., 1991). Specifically, harvesting practices and road building in steeper areas can increase the possibility of mass wasting events leading to changes in the size and amount of sediment input and the characteristics and amount of wood supplied to a stream (Hassan, Church, et al., 2005). Improving road design and harvesting practices can help mitigate the effects of logging, specifically through the reduction of channel instability in low order streams, which consequently reduces the impacts of increased sediment and modified wood budget (Hassan, Hogan, et al., 2005).

Defined as pieces of dead wood of appropriate size to influence channel structure, not only does large instream wood influence stream structural complexity (Beechie & Sibley, 1997; Hassan, Church, et al., 2005), but also provides nutrients (Bilby, 2003), is a primary driver of sediment distribution (Montgomery et al., 2003), and acts as habitat for aquatic plants and animals (Benke & Wallace, 2003; Dolloff & Warren Jr, 2003). Instream wood is actively introduced to the channel through blowdown, mass wasting and bank erosion and, in some cases, forest management practices. Wood moves and is transported throughout a watershed via streams through some of the same processes, as those listed above, but can also be transported through flotation, which can move wood in large groups of pieces or individual pieces (Hassan, Hogan, et al., 2005). Wood leaves a watershed via decomposition or as fine particulate matter rather than as large wood pieces (Swanson, 2003). Large pieces of wood relative to the stream size have a larger geomorphic effect therefore small streams are disproportionately impacted by changing wood dynamics (Hassan, Hogan, et al., 2005). Previous research has reported a correlation between the amount of instream wood and the abundance of salmonids in small coastal streams. (Boss & Richardson, 2002; Gonzalez et al., 2017; Rosenfeld et al., 2000). Further, studies have demonstrated a negative response between instream large wood removal associated with riparian logging and juvenile salmonids (Mellina & Hinch, 2009).

Currently, collecting data on location, quality and quantity of instream wood within streams, requires extensive field work either by hiking or rafting, which is hindered by a lack of safe launch and landing sites. Additionally, field-based methods are often limited geographically to small study reaches, due to both budget and time constraints. Field-based methods are critical for quantifying the amount of wood stored in a watershed or stream reach at a set point in time, however it is difficult to use field-based methods to quantify long term changes in wood distribution (Hassan, Hogan, et al., 2005).

Remote sensing technologies offer an alternative for the monitoring of the presence and distribution of instream wood in a watershed and is an already well established research area for a variety of riverine applications (Piégay et al., 2020). Passive optical remote sensing systems such as the Worldview series of satellites that utilize both visible and near infrared spectral information have been used to map the location of large wood and logjams in streams (Atha, 2014; Helm et al., 2020; Marcus et al., 2003; Smikrud et al., 2008). For example, Atha (2014) used satellite imagery within Google Earth to manually delineate pieces of wood in the Queets River basin in Washington, USA, and determined that manual delineation was possible if wood pieces were less than 50% submerged in water during low flow periods. Helm et al (2020) used remotely piloted aircraft (RPAS) derived orthophotos and digital elevation models (DEMs) to manually extract instream wood location throughout Carnation Creek on Vancouver Island, British Columbia, Canada, and used this information to help survey small forested streams. However, as noted by a number of these authors, techniques that use optical remote sensing have limitations where canopy cover is dense and obscures the stream channel, which is often the case in small streams in heavily forested environments. Furthermore, these techniques all require varying degrees of manual interpretation and lack the ability to derive wood structure, a necessary measurement when assessing instream wood volume.

Airborne Laser Scanning (ALS), is an active remote sensing technology, which creates a 3D model of topography and vegetation based on the measured time between emitting a pulse of light and recording the return of the pulse. An ALS system generally consists of four key components; the sensor which sends and receives laser pulses, an inertial measurement unit to determine the pitch, roll and yaw of the sensor, a global position system to record the precise location information, and a platform, for example an airplane, for carrying the above components

(White et al., 2016). Airborne platforms offer a broad spatial scale compared to terrestrial platforms and are often used to characterized landscape level features (Harpold et al., 2015). Previous studies have demonstrated the ability of ALS to detect and characterize both functional (influencing channel processes) and recruitable (potential to become functional) instream wood in forested watersheds (Abalharth et al., 2015; Atha & Dietrich, 2016; Kasprak et al., 2012; J. Richardson & Moskal, 2016). To date, there have been two main methodologies for detecting wood features. The first, used primarily for forest floor coarse wood detection, involves DEM differencing wherein an ALS-derived high spatial resolution DEM is subtracted from a modified digital surface model (DSM) to highlight residual differences, which are then attributed to wood features (Nyström et al., 2014). The second approach is based on point cloud filtering, and consists of applying various filtering algorithms to a raw ALS point cloud to isolate the points located on wood pieces from those representing the ground or vegetation (Atha & Dietrich, 2016). Both methods require manual delineation of the detected objects, which is both time consuming and difficult to scale across entire watersheds. Moreover, studies that described these methods have focused on large river reaches with limited canopy cover. Recent advances in the detection of downed wood on the forest floor are based on an automated point cloud filtering approach (Joyce et al., 2019) and a skeletonization process (Jarron, Coops, MacKenzie, et al., 2021), which has the potential to be adopted within stream environments. The intensity information obtained from ALS serves as an indicator of the energy returned from each laser pulse. The absorption properties of water for ALS near-infrared laser pulses can result in variations in intensity within the stream, which may be indicative of the presence of coarse woody debris (Abalharth et al., 2015; Höfle et al., 2009).

The capacity to use ALS data for counting instream wood has been demonstrated at the reach scale (Dakin Kuiper et al., 2022) and for counting individual pieces and logjams in large rivers (Abalharth et al., 2015; Atha & Dietrich, 2016). However, further research is required to assess the capabilities of ALS to automatically detect instream wood and to generate an improved understanding of how the size and location of instream wood, as well as the characteristics of the stream and associated riparian forest impact the accuracy of instream wood detection. Given this context, our objectives were to 1) develop and test a new framework to automatically map functional instream wood in small (bankful width <= 10 m) coastal streams, and to determine 2) which ALS metrics, representing the riparian environment, and 3) which field-measured physical properties of the instream wood features, were important for the accurate detection of instream wood.

5.2 Materials and methods

5.3 Data processing

Our framework for instream wood detection consists of three key steps: 1) lidar point cloud filtering; 2) filtered point cloud skeletonization; and 3) validation of results (Figure 5-1).

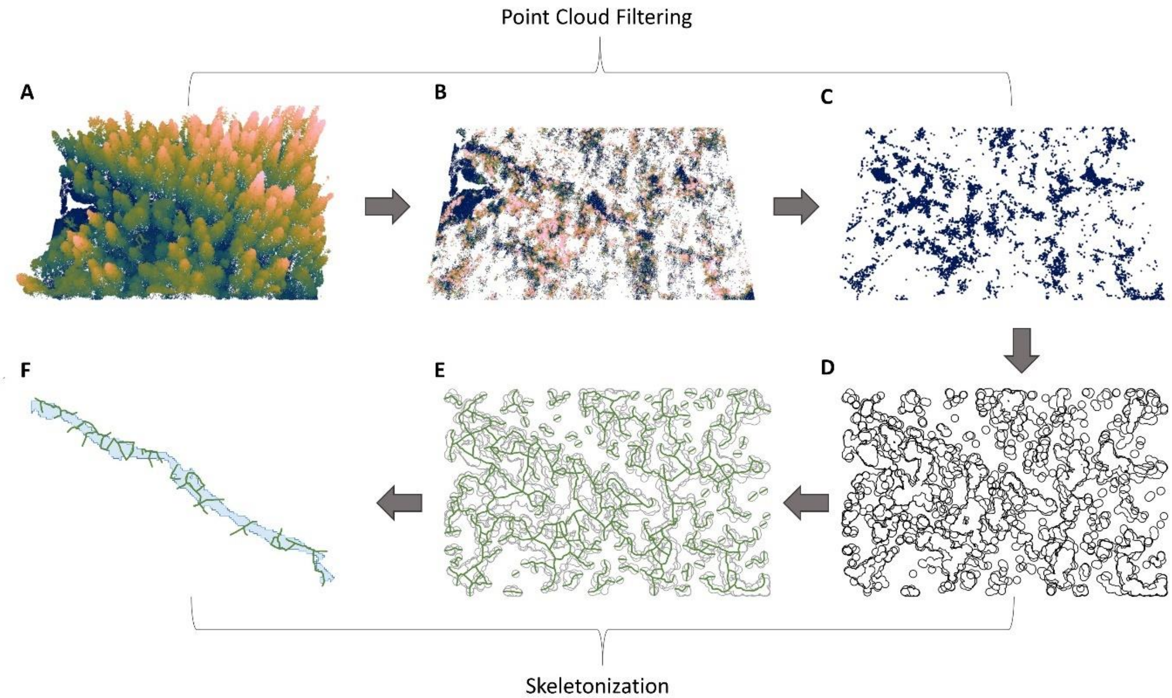

Figure 5-1. Workflow graphic demonstrating the process of point cloud filtering and skeletonization for the detection of instream wood features. A) Unfiltered ALS point cloud, coloured by height above ground; B) Normalized to height above ground and filtered to under 2 m point cloud coloured by height; C) Intensity filtered point cloud showing only points with linear relationships to neighbours; D) Polygons created by buffering points by one metre; E) Centerline of dissolved buffers shown in green; F) Green lines representing instream wood cropped to the ALS derived stream width

5.3.1 Point cloud filtering

First, watershed wide ALS ground returns were used to create a DEM from which a stream network and stream width were extracted. The stream network was delineated using a standard processing procedure beginning with DEM pre-processing, followed by calculating the flow accumulation and flow direction. Stream width was determined by expanding the delineated stream network centerlines into an area of homogenous slope and elevation (see Dakin Kuiper et al., 2022).

In order to differentiate the instream wood features from the stream bed, the ALS point clouds were cropped to the extent of each study stream and points were subjected to a second, more detailed ground classification routine. Points were classified into ground and non-ground returns using a cloth simulation filter (CSF) (W. Zhang et al., 2016). The CSF algorithm works by inverting the point cloud and draping a simulated cloth over the surface. If a return is touching the cloth the return is classified as ground, contrary if a return is too far from the cloth it is considered a non-ground return. Tuning the parameters of the algorithm adjusts the rigidness of the cloth and therefore is an important first step in determining which returns are the stream bed or the ground and which represent instream wood. The cloth simulation filter parameters were set to default, except slope_smooth (set to TRUE), and class_threshold (set to 0.1).

After using the CSF algorithm, point clouds were normalized and all returns under 0 m and returns over 2 m representing upper and middle canopy were removed. An intensity threshold was applied to include only returns with intensity values in the highest 40% of returned energy to differentiate potential wood returns and those interacting with wetted areas, that are known to have low intensity values or are absorbed by the waterbody (Abalharth et al., 2015; Höfle et al., 2009). It should be noted that the aforementioned filtering process uses the raw unnormalized intensity values. The point cloud was further thinned to only select pulses with one return under 2 m to differentiate instream wood from low lying bankside vegetation (Jarron, Coops, MacKenzie, et al., 2021). Denser objects such as wood often have only single return pulses. Therefore, ALS pulses with multiple returns under 2 m could represent understory vegetation instead of instream wood features. Lastly, linearity between neighbouring points was assessed using the “shp_line” function in the “lidR” package (Roussel, Auty, Coops, et al., 2020). This is an implementation of an algorithm developed by Limberger and Oliveira (2015) which classifies each return into linear or non linear classes based on a relationship between the angle (th1) and the number of neighbouring returns (k). Points without a linear relationship to at least 3 neighbours were removed before exporting the filtered point cloud into the skeletonization process (Roussel, Auty, Coops, et al., 2020).

5.3.2 Skeletonization

In the third step, skeletonization was used to connect the linear returns from the filtered point cloud. Skeletonization performs a series of spatial transformations to return line vector features, which in this case represent instream wood. The filtered points were buffered by 1 m with dissolved boundaries to create continuous polygon features. Next, polygon centerlines were computed along the longest axis through the greatest number of points. The vector centerlines were simplified to better match the topology of the field wood. The resulting vector line features were intersected with a stream width polygon to ensure that only linear features within the stream extent remained. Lines with a length < 2 m were discarded.

5.3.3 Validation of instream wood detection

Field data positions were transformed from points representing the end of a piece of wood or a logjam to polygons using the field measured azimuths, lengths, and widths. Validation protocol closely followed the logic presented in Nystrom et al (2014), if ALS delineated instream wood was within 5 m (representing the maximum error of the collected GNSS field data) and the azimuth was within 30° of the field measured azimuth, an individual piece of wood was classified as detected, when these criteria were not satisfied the individual piece of wood was classified as undetected.

5.3.4 Factors influencing detection

To examine the influence of the riparian vegetation and topography surrounding instream wood on instream wood detection, relevant point cloud metrics were calculated based on their importance for wood detection reported in previous studies (Abalharth et al., 2015; Jarron, Coops, MacKenzie, et al., 2021; Joyce et al., 2019; Wulder et al., 2008) and their ability to characterize riparian vegetation; point density, the point density under 2 m, mean intensity, percentage of ground returns, canopy cover, the number of multi return pulses under 5 m, and the absolute scan angle of returns and topographic slope (Table 5-1).

Table 5-1. Field-measured and ALS attributes used as independent variables in logistic regression models.

Attribute category	Metrics	Unit	Description
Field-measured	Length	cm	Length of field measured wood
	Width	cm	Diameter of field measured wood
	Logjam	yes or no	Classification of field measured wood, logjams have 3 or more pieces of wood touching
	Depth	cm	Submerged depth of field measured wood, 0 represents wood that is only partially submerged
	Azimuth	degrees	Azimuth determined between the two ends of the field measured wood
	Position	parallel or across	Position of instream wood relative to the stream
ALS	Point Density	pt/m^2	Density of ALS returns per unit area
	Point density under 2 m	pt/m^2	Density of ALS returns per unit area under a height threshold
	Mean intensity		Average intensity value of points within field measured wood polygon
	Proportion of points classified as ground	%	(# of returns classified as ground/ # of total returns) * 100
	Canopy cover	%	# of first returns above 2m/ # of total first returns
	Multi return pulses under 5 m	Count	Count of multi return pulses under 5 m
	Absolute scan angle	Degrees	Absolute scan angle value of points within field measured wood polygon
	Slope	Degrees	Gradient values of pixels within field measured wood based on neighbouring cells in a DEM

A suite of logistic regression models was developed with missed and detected instream wood as dependent variables and the ALS metrics and instream wood measurements as the independent variables. Influence of independent variables was assessed using p-values and the odds ratio calculated in the logistic regression.

The point cloud filtering, and statistical analysis was completed using R version 4.2.1 (R Core Team, 2022) and lidR version 4.0.1 (Roussel, Auty, Coops, et al., 2020), while point cloud skeletonization workflow was carried out in ArcGIS Pro version 2.9.3 (ESRI, 2022).

5.4 Results

Overall, the method presented herein detected 79 of 125 field-measured pieces of instream wood resulting in an overall detection accuracy of 63.0% (Table 5-2). View Creek had the highest accuracy at 86.7%, while Bun Creek had the lowest accuracy at 37.0% (Figure 5-2). The Artlish watershed had an overall accuracy of 56.8% while the Nahmint at an accuracy of 69.2% (Figure 5-2). Logjams had a much higher detection accuracy of 81.0% while individual pieces of instream wood had a detection accuracy of 49.0% (Figure 5-3). I detected instream wood positioned across the stream with 65.0% accuracy and instream wood positioned parallel to the stream with 53.0% accuracy (Figure 5-3).

Table 5-2. Results of detected vs missed instream wood pieces by stream and total.

Stream	Detected	Missed	Accuracy (%)
Elk Creek	11	4	73.3
Head Water Creek	24	10	70.6
Headache Creek	6	4	60.0
Rainbow Creek	4	1	80.0
Steep Creek	4	5	44.4
View Creek	13	2	86.7

Bun Creek	10	17	37.0
Lunch Creek	5	1	83.3
Trickle Creek	2	2	50.0
Total	79	46	63.0

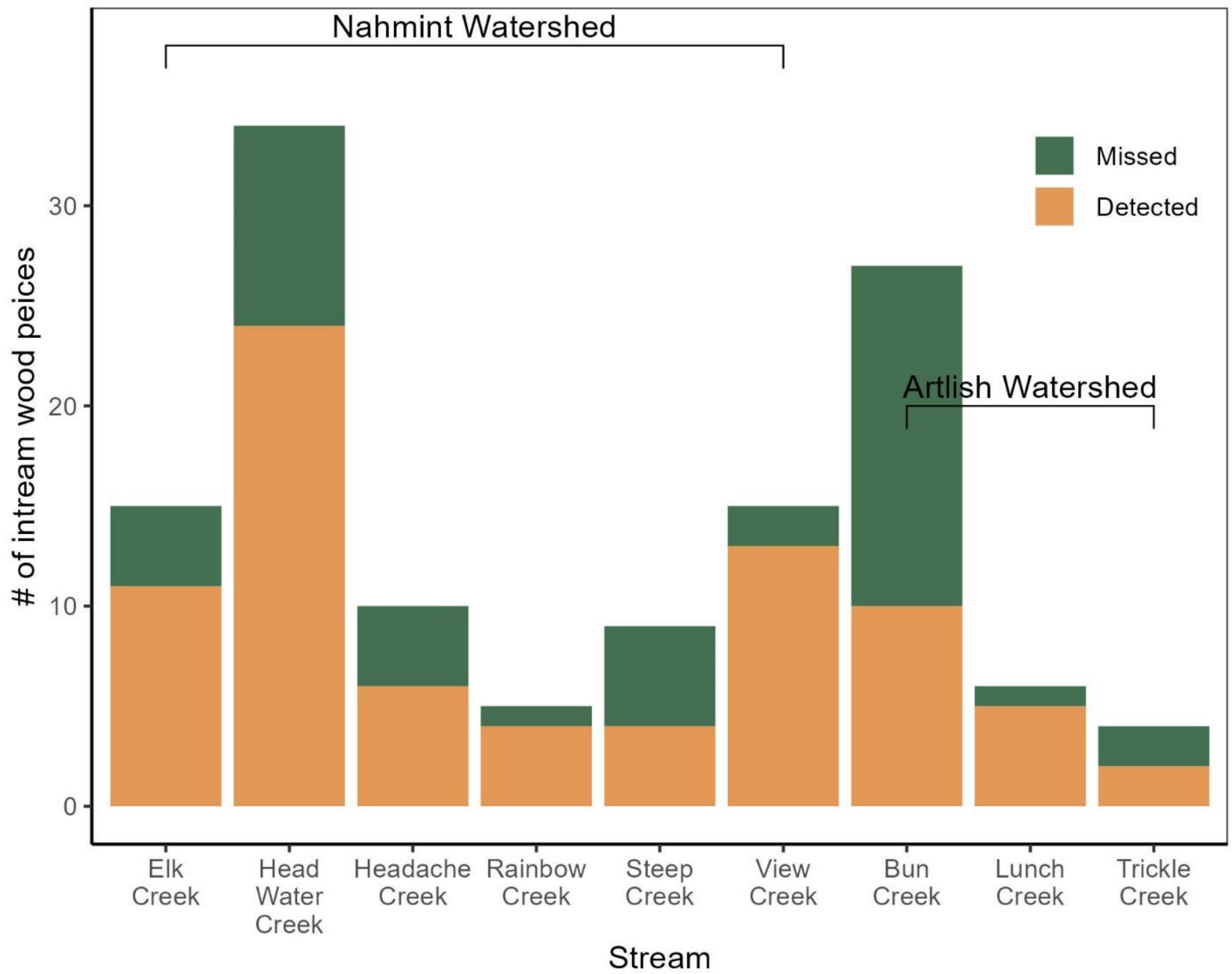

Figure 5-2. Count of detected and missed instream wood across study watersheds.

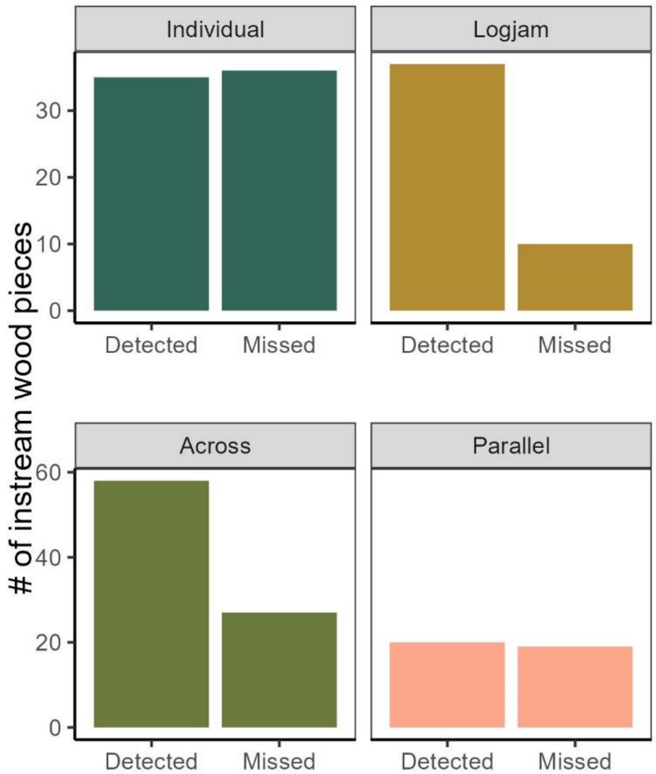

Figure 5-3. Comparison of logjam and individual instream wood and wood position relative to the stream to detection counts.

Table 5-3 shows the average of the computed ALS metrics used in the logistic regression analysis sorted by individual stream reach. Notably, Bun Creek had the lowest percentage of returns classified as ground and one of the highest canopy covers. View Creek had the lowest average intensity (28019), whereas Trickle Creek had the highest (29728) while all other stream reaches were quite similar with the largest difference being 2833 between Rainbow Creek and Head Water Creek.

Table 5-3. Average ALS metrics by stream.

Stream	Density under 2 m (pts/m^2)	Total density (pts/m^2)	Intensity	% of all returns classified as ground	Canopy Cover (%)	# of Multipulse Returns	Absolute Scan Angle	Slope
Elk Creek	8	23	28861	13	49	10	3	12
Head Water Creek	16	24	28019	3	30	5	3	10
Headache Creek	10	24	26366	2	53	9	1	8
Rainbow Creek	18	21	29199	9	10	2	1	13
Steep Creek	12	31	27054	8	46	14	4	30
View Creek	11	37	20404	6	62	22	2	9
Bun Creek	12	29	28432	1	57	15	5	7
Lunch Creek	12	21	27292	12	34	7	6	9
Trickle Creek	13	27	29728	1	45	10	3	15

Results of the logistic regression demonstrated that both instream wood width and length did not significantly influence detection accuracy (Table 5-4). However, submerged depth, azimuth and logjam classification did significantly influence detection frequency ($p < 0.05$). As submerged depth increased, the ability to detect pieces of instream wood decreased (Odds Ratio = 1.16). Additionally, logjams were much easier to detect than individual pieces of wood (Odds Ratio = 0.22). Of the tested ALS metrics, only the percentage of returns classified as ground and the absolute scan angle significantly impacted the detection rate. Density of returns under 2 m, and the number of multi return pulses had some influence on the detection rate but were not significant.

Table 5-4. Results of logistic regression for the influence of ALS and field-measured wood attributes on instream wood detections.

	Metric	Std- Error	P-Value	Odds Ratio
Field	Width	0.01	0.75	1.00
	Length	0.00	0.51	1.00
	Depth	**0.07**	**0.05**	**1.16**
	Logjam	**0.42**	**0.00**	**0.22**
	Azimuth	**0.00**	**0.04**	**1.00**
	Position	0.39	0.17	1.71
ALS	Slope	0.02	0.28	1.02
	Point Density	0.02	0.28	1.02
	Intensity	0.00	0.91	1.00
	% of points classified as ground returns	**0.04**	**0.02**	**0.91**
	Canopy Cover	0.01	0.36	1.01
	Multi-pulse returns under 5 m	0.02	0.19	1.02
	Point density under 2 m	0.03	0.51	0.98
	Absolute Scan Angle	**0.10**	**0.02**	**1.21**

Figure 5-4 shows how the detection rate changed with various ALS and field measured variables further demonstrating the relationships analyzed using the logistic regression. Only three instream wood objects were detected with a submerged depth over 5 cm, two of which were logjams. I characterized detection of instream wood by ALS metric (Figure 5-4). Of note, as the percentage of returns classified as ground increased, the ability to detect instream wood features also increased. If more than 10% of the returns are classified as ground the detection accuracy is 90%. Additionally, a higher detection rate is seen when the absolute scan angle is closer to 0˚. Detection accuracy was not significantly influenced by average ALS intensity or point density.

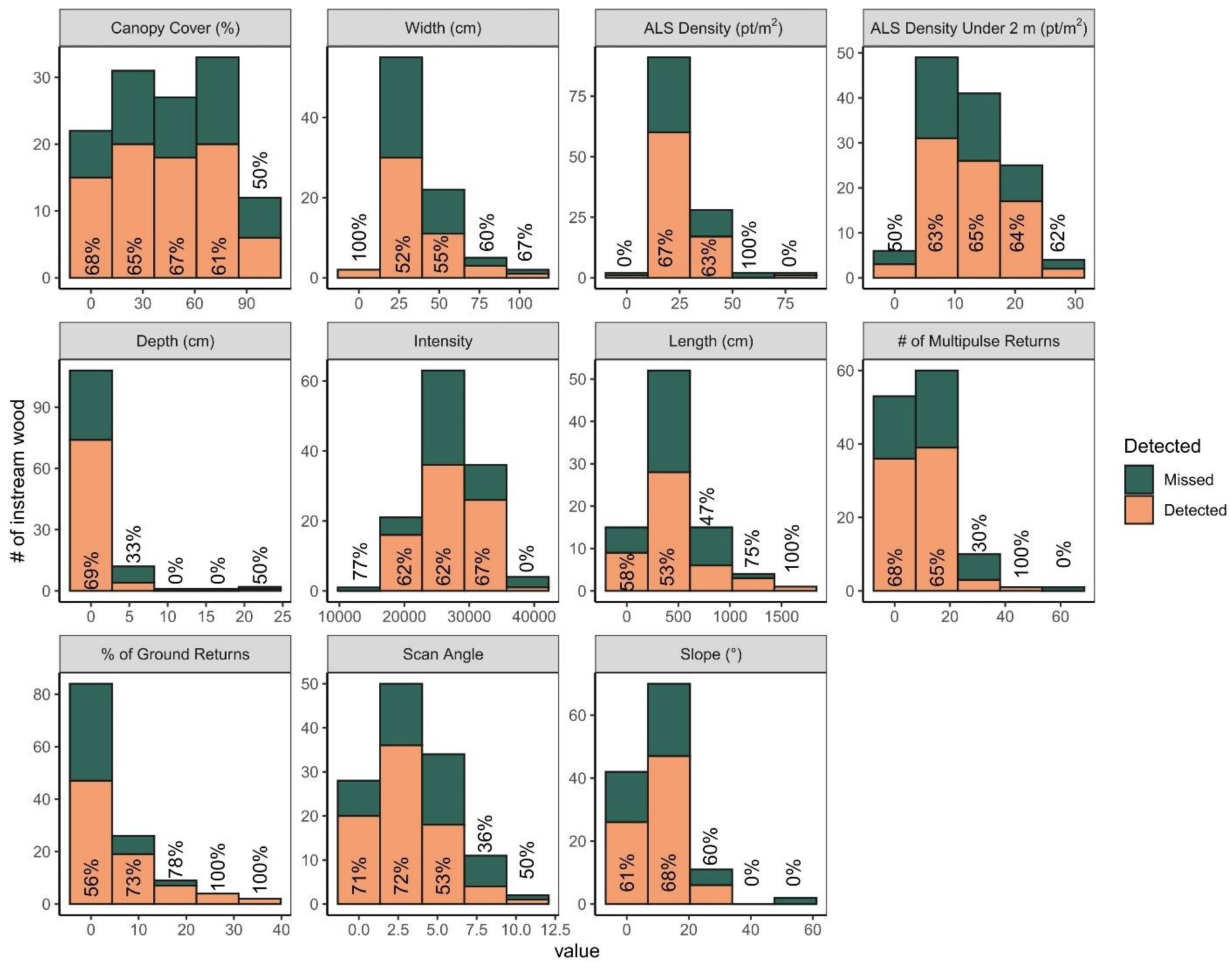

Figure 5-4. Number of detected and missed instream wood pieces and associated metrics and physical characteristics. Percentage of detected instream wood shown.

Figure 5-5 exemplifies the result of the workflow by highlighting the location of ALS detected instream wood relative to field measured wood in View Creek (See appendix for other stream reaches). Generally, there is good overlap between the ALS wood and the field wood points. Missed field wood points generally occur along the edges of the stream.

Figure 5-5. Map showing the field measured wood points and the lidar derived wood points along View Creek.

5.5 Discussion

In this study I developed an automated approach to detect both individual pieces of instream wood and logjams, in small (<10 m wide) stream reaches. I assessed the impact that both the physical properties of the instream wood and a series of ALS metrics have on wood detection in two watersheds on Vancouver Island, BC, Canada. Our results demonstrated that an automated approach to instream wood detection can successfully be applied to multiple watersheds and study reaches. Further, our results showed that certain wood characteristics, specifically submerged depth, azimuth and logjam classification significantly influenced the detection rate. The accuracy of instream wood detection was also significantly influenced by the absolute scan angle of ALS returns and the percentage of ALS returns classified as ground, which is indicative of the degree to which the emitted ALS pulses were able to penetrate the overstory and understory to reach the ground surface.

The highest stream level detection accuracy reported in this study was 86.7% at View Creek and the lowest was 37.0% at Bun Creek, with the average detection accuracy across all study reaches as 63.0%. Other studies have reported a range of accuracies for instream and forest floor wood detection. Most notably Joyce et al. (2019) who had an overall accuracy of 26.0% and Abalharth et al (2015) with a reported overall accuracy of 87.0%. However, Abalharth et al (2015) used a manual approach to detect only logjams and should therefore be compared to our fully automated logjam detection accuracy of 81.0%. Our results reported herein are comparable to other automated approaches such as that of Jarron et al (2021) who reported an overall accuracy of 64.0% for detecting forest floor woody debris. It is important to note that in contrast to these aforementioned studies, our methodology is completely automated, from instream wood detection to the comparison to the field data. Furthermore, the stream reaches used in our study are considerably smaller (with maximum bankful widths ranging from 5.05 m to 10.6 m) compared to the rivers surveyed by Abalharth et al (2015) and Atha and Dietrich (2016), which were wider than 50 m and 25 m, respectively. By comparison, our relatively narrow stream reaches likely have higher canopy cover leading to more occlusion and greater positional uncertainty.

The analysis of the influence of instream wood characteristics and ALS metrics on detection accuracy provided some unexpected results. Our expectation was that the length and width of instream wood pieces would have greater influence on the detection rate. Previous studies using ALS to detect forest floor coarse wood found that both width and length were significant attributes affecting the detection rate (Joyce et al., 2019; Nyström et al., 2014), although Jarron et al (2021) reported that size did not significantly influence detection accuracy. Our results indicated no significant effect of instream wood width or length. However, I found that logjams were more accurately detected, and as they represent larger clusters of 3 or more pieces of instream wood, this indicates that size may an effect on detectability.

While previous studies using ALS to detect instream wood did not specifically test the influence of different point cloud metrics on detection accuracy, Atha and Deitrich (2016) noted the effect of point density on detection rate and stated that a point density lower than 8 points/m^2 would make the manual detection of instream wood difficult. I found that average point density did have some, although insignificant, effect on detection rate. However, our ALS was much denser (>25 pts/m^2) than previous studies detecting instream wood. Our results showed that two ALS metrics, specifically the percentage of returns classified as ground and the absolute scan angle, had a significant effect on instream wood detection. Interestingly, I found no significant effect of mean intensity on instream wood detection accuracy. This result could be because of similar intensity values found across the study areas. In contrast, Abalharth et al (2015), noted intensity as an important factor in the manual delineation of instream wood. Additionally, Abalharth et al (2015) discussed the notable improvements to using a filtered point cloud compared to an unfiltered point cloud for manual instream wood detection, which I took into consideration during the development of our methodology. However, I found no significant relationship between the amount of canopy cover and detection rate.

I found similar detection accuracies between the Artlish and Nahmint watersheds, at 56.8% and 69.2% respectively. Bun Creek had the lowest detection accuracy (37.0%) and contained 27 out of 37 instream wood objects in the Artlish watershed. The low detection accuracy in Bun Creek could be explained by the low average percentage of returns classified as ground (1.0%) and relatively high average absolute scan angle (5°). In contrast, View Creek in the Nahmint Watershed had the highest detection accuracy (86.7%), a higher percentage of returns classified as ground (5.0%) and a lower mean absolute scan angle (1°). Both watersheds share similar climates and are within the coastal western hemlock biogeoclimatic zone. However, these watersheds and stream reaches have different management and disturbance histories causing the forests in each watershed and each stream reach to be at varying degrees of succession. Bun Creek is situated within a complex old growth forest, while View Creek is located in the portion of the Nahmint watershed that is now second growth forest. Previous studies have found that forest successional stage and management practices influence instream wood dynamics (Martens et al., 2020). Both stream reaches have similar average stream widths, substrate characteristics, gradients, and canopy covers. However, the instream wood pieces in Bun Creek are on average smaller (length = 608 cm, width = 90 cm) than those in View Creek (length = 830 cm, width = 118 cm) and are submerged at greater depths on average (3.8 cm) compared to those at View Creek (0.3 cm). Despite the differences between these two streams, I point to the similar overall detection accuracies between the two different watersheds and believe that the presented framework is robust and could be applied across a variety of watersheds in different regions.

A limitation and potential source of detection error for instream wood is the temporal difference between the ALS acquisitions in 2015–2016 and the field data collection in 2022. Previous work has demonstrated that marked changes in wood distribution are possible in small coastal streams after major flooding events (Hassan, Hogan, et al., 2005). This could be a contributing factor to the lower accuracies observed for detection of individual wood pieces, which are more likely to move during peak flow events, compared to logjams. I recommend that future research limit the amount of time between ALS acquisitions and field data acquisitions. This study focuses primarily on quantifying the number of true positive detections and identifying the ALS metrics, characteristics of the instream wood pieces and the local environment that influence the detection accuracy. I acknowledge that there are limitations to identifying if over segmentation of pieces of wood is occurring due to the complexity of the logjam features the difficulty in counting the number of individual wood pieces that make up a logjam feature in the field, and the time gap limitation discussed above. Additional inaccuracies could also arise from positional errors in the field data. Regardless, the field measures are important sources of validation information that have captured persistent instream wood features across a range of forest riparian conditions. Further, I believe that field validation is an important step in the framework and is helpful to assess the condition of instream wood based on decay rate, submerged depth, width and length. Whilst the focus of this paper was assessing the ability of a fully automated approach to detect instream wood and determine which factors influence its accuracy, mapping the distribution and presence of instream wood features is enormously useful for a variety of additional ecological applications. Indeed, instream wood presence and density have been positively corelated to salmonid abundance and biomass (Fausch & Northcote, 1992; Gonzalez et al., 2017; Rosenfeld et al., 2000). Further, the introduction of instream wood promoted invertebrate diversity in streams (Flores et al., 2017). Since instream wood acts as refuge for juvenile salmonids and invertebrates and is therefore an important habitat feature, I stipulate that the framework described herein could be used to generate important spatial layers to support watershed-level habitat modeling (Fausch et al., 2002).

In the context of sustainable forest management, understanding the distribution of instream wood could influence harvesting and retention practices, specifically in riparian areas. For example, identifying streams with high instream wood volume (high quality salmon habitat) highlights where additional riparian retention above the legal minimum would be most effective. Further, areas with a below average amount of instream wood, leading to degraded salmon habitat, could be located and identified for habitat improvement. The framework presented herein, when used in conjunction with other ALS-derived riparian and aquatic ecosystem assessments (Dakin Kuiper et al., 2022; Tompalski et al., 2017), becomes an increasingly useful and value added application for forest managers who are currently using ALS data for existing inventory and operational needs.

5.6 Conclusions

In this research I developed and demonstrated a fully automated approach to detecting instream wood features in nine study streams across two watersheds on Vancouver Island, British Columbia, Canada. Increased detection accuracy was observed when mapping logjams compared to individual pieces of instream wood. Further, the submerged depth, and percentage of lidar returns classified as ground significantly impacted detection accuracy. The ability to map important habitat and geomorphic features such as instream wood could be integrated into operational forest management and conservation practices on a routine basis and could be used to facilitate decision making where needed. This paper presents a framework to detect instream wood at a single point in time. As ALS acquisitions become more frequent, both spatially and temporally, the ability to describe changes in the amount of wood stored in a watershed over time and the changes occurring due to disturbance event or management practices is becoming more feasible. Future work could examine the effects that disturbance events such as fire or flood and different management activities such as road building and harvesting have on the distribution, function, and amount of instream wood in a watershed.

Chapter 6: Enhanced watershed status evaluation: towards an integrated framework to assess fish habitat in forested watersheds using laser scanning

6.1 Introduction

A key tenet to modern forestry practices is the concept of sustainable forest management. In brief, sustainable forest management supplements a concern with economic values with concerns of biodiversity, ecosystem function, and future resource availability (Franklin, 2001). In practice, sustainable forest management, when implemented, is designed to maintain and enhance the long-term health of forest ecosystems, while providing a variety of ecosystems services including ecological, social, economic, and cultural opportunities both in the present and the future (Canadian Council of Forest Ministers, 2003). Within a sustainable forest management framework, significant importance has been placed on aquatic resource protection and management, specifically riparian zone and watershed management, in order to facilitate a more resilient forest ecosystem (Tschaplinski & Pike, 2010). Indeed, it is important that forest management decisions are not made in isolation but with an integrated approach, considering multiple uses and resources including forest and watershed status in the decision-making process (Wang et al., 2016). Therefore, in addition to information on vegetation, forest practitioners need up-to-date landscape level information on riparian and stream ecosystems at the watershed scale in their management areas.

Watershed status refers to the interaction and combination of watershed elements, including upslope, riparian, and stream channel components (Pickard et al., 2014). Together, these components generate a range of hydrological, vegetation, soil, channel structure, thermal energy transfer, and system productivity processes, crucial for fostering conditions conducive to fish habitat and ecosystem function (Mehan, 1991; Quinn, 2004). A watershed is deemed to be in a 'good' state when all these attributes are able to sustain robust fish habitats, fostering a thriving diversity and abundance of aquatic and riparian-dependent species (Pickard et al., 2014).

Previous studies have demonstrated the impacts of harvesting in a watershed and specifically in the riparian zone adjacent to a stream on the quality of nearby, and downstream, aquatic habitats. The Alsea watershed study (Hall & Stednick, 2008) was one of the first long term studies to assess the effects of different harvesting practices on water quality, aquatic habitat, and salmonid resources. They found marked difference in streamflow, stream temperature, sediment levels, and salmonid populations across the different harvesting prescriptions (clear cut, riparian buffer, and no harvesting: Hall and Stednick, 2008). This study is often cited as the keystone paper on riparian management in the Pacific Northwest of North America, for example most jurisdictions require riparian buffers around streams to provide shade, large wood, and bank stability to increase habitat availability (Hall & Stednick, 2008; Ministry of Forests, 2019; Pike, 2010). Furthermore, other research streams like Carnation Creek in British Columbia, Canada have found similar results and have built upon the Alsea study (Bisson et al., 2008; Hogan et al., 1998), further demonstrating the need to examine the short and long-term effects of forest harvesting on watersheds.

Watershed evaluations programs assess the state of a watershed by examining and characterizing a series of indicators relating to both the pressures facing a watershed, such as urbanization, road construction, and forest operations (Tsai et al., 2021) and a watershed's current functioning condition. Specific examples of watershed indicators include the density of roads in a watershed, the number of stream and road crossings. Previous studies have identified how these processes can damage fish habitats effecting distribution, abundance, and survival of fish species (Mellina

& Hinch, 2009; Peacock et al., 2023). Indicators of watershed condition are used to characterize if a watershed remains in proper functioning condition, examples include, fish passage assessments, measurements of stream complexity, and riparian vegetation condition (Bjornn & Reiser, 1991; Rosenfeld et al., 2000).

Multiple jurisdictions across the Pacific Northwest have developed both field and GIS-based watershed assessments to provide practitioners with the information they require for sustainable forest management. For example, in British Columbia, the Forest and Range Evaluation Program (FREP) was established under the Forest and Range Practices Act (FRPA) (Forest and Range Practices Act, 2002). FREP supports the sustainable management of BC's forest resources by monitoring and evaluating the condition of BC's resources and the effectiveness of resources practices. For fish habitat and watershed monitoring there are two different assessments used by FREP: a Tier 1 GIS based assessment which examines the current pressures facing a watershed to facilitate and analyze of the risk of habitat degradation (Porter et al., 2019) and a Tier 2 field based watershed assessment (Pickard et al., 2014) based on a field assessment for evaluating the condition of streams and riparian management areas (Tripp et al., 2020). Other jurisdictions within the Pacific Northwest have also implemented watershed status monitoring programs including the Columbia Habitat Monitoring Program (CHAMP) in the Columbia river basin (Northwest Fisheries Science Centre, 2023) and the PacFish InFish Biological Opinion (PIBO) Monitoring Program from the US forest service (Saunders et al., 2019).

The majority of watershed status indicators are assessed through *in situ* measurements. However, these field-based programs are expensive, time consuming, and difficult to scale spatially and temporally. Remote sensing technologies allow for large scale characterization of these indicators. Whited et al. (2012) created the riverscape analysis tool using multispectral imagery from the Landsat series of satellites and the Shuttle Radar Topography Mission (SRTM) global digital elevation model (DEM) to derive a set of watershed, river and floodplain indicators that are important for salmon across the Pacific Northwest at a 30 m resolution. The riverscape analysis tool includes indicators relating to watershed condition for example, floodplain area, channel sinuosity, and watershed mean elevation. Additionally, watershed pressure indicators were also derived, including a human footprint index, urban area mapping, and road mapping. The Whited et al. (2012) study demonstrates the ability of remote sensing indicators to accurately assess the status of a watershed, however, at a 30 m spatial scale, this methodology and technology is limited to larger rivers and excludes smaller headwater streams under dense canopy cover that are important spawning and rearing habitat for fish (Dakin Kuiper, Coops, Hinch, et al., 2023).

Airborne laser scanning (ALS) is an active remote sensing technology that uses laser beams to create accurate three-dimensional point clouds representing terrain and objects, including vegetation. The use of ALS is well-established in a forestry-context, providing information on forest attributes relevant for sustainable forest management (White et al., 2013; Wulder et al., 2008). As the collection and the availability of ALS data increases, there is an increasing interest to develop and assess the opportunities and limitations associated with the use of ALS systems to provide information on the health and quality of streams and aquatic ecosystems in forested environments.

Previous studies have demonstrated the ability of ALS to characterize riparian and stream characteristics that can be used as indicators of watershed status and watershed pressures. Michez et al. (2017) presented a methodology of using ALS for monitoring riparian buffer systems across a large (>12,000 ha) study area in southern Belgium using physical parameters of the stream (channel width and emerged depth) and riparian forest (height, longitudinal continuity and water accessibility). With this methodology Michez et al. (2017) were able to identify clear regional patterns in riparian vegetation across a large study area. Furthermore, Tompalski et al. (2017) developed a full characterization of riparian ecosystems for a 52,000 ha study area on Vancouver Island, Canada, using stream gradient as a proxy for fish bearing potential with 82.9 % accuracy, and used ALS derived vegetation metrics combined with solar insolation to predict total daily hours of stream shading. Stackhouse et al. (2023) used a random forest model to predict riparian forest class probability with roughly 70% accuracy across two Vancouver Island watersheds. However, these studies are focused primarily on riparian vegetation with only limited application for fish bearing potential and fish habitat quality.

ALS data have been used to characterize a variety of fine scale stream habitat features that can serve as indicators into the current conditions of a watershed and the pressures that a watershed is facing (Dakin Kuiper, Coops, Hinch, et al., 2023). For example, Duffin et al. (2021), used green bathymetric lidar to characterize stream morphology and related it to Chinook salmon (*Oncorhynchus tshawytscha*) spawning selection. Dakin Kuiper et al. (2022) used ALS derived predictor variables in a random forest model to classify stream morphology at the individual habitat unit scale. Additional stream habitat features have also been modeled with ALS including instream wood (Dakin Kuiper, Coops, Jarron, et al., 2023) and stream temperature based on solar insolation (Stackhouse et al., 2023). ALS can be used to characterize stream habitat features in forested watersheds across a variety of scales, however, it is rare that these studies combine the extracted or modeled attributes into one framework.

Given this context, the objective of this research is to examine the capacity of ALS data to integrate into existing watershed status evaluations. Using ALS data and advanced remote sensing techniques to extract stream and vegetation attributes that are important for fish, I present a framework to assess watershed status in forested watersheds. I develop and apply methods to extract and model stream and riparian vegetation features including stream complexity, riparian condition, and instream wood and stream morphology. By providing detailed and accurate information on stream features and watershed status, ALS data can help researchers and managers make informed decisions about the sustainable management of forests and by association, forested watersheds.

6.2 Methods

6.2.1 Methodological approach

In British Columbia, watershed status is evaluated using a two-Tier watershed status evaluation protocol. The Tier 1 protocol uses open source data layers to determine if a watershed is at risk of habitat degradation and at risk of losing proper functioning condition. If the Tier 1 assessment determines that a watershed is at a high-risk threshold then the Tier 2 protocol is initiated. The Tier 2 protocol assesses the condition of fish habitat in the watershed by conducting a series of in situ measurements.

The general methodological approach I applied consists of four steps. First, to demonstrate the potential of ALS to characterize indicators relating to the pressures facing a watershed I conducted a current Tier 1 watershed status evaluation using the existing BC open data and compare the results to an integrated Tier 1 watershed status evaluation that is supplemented with ALS data. Second, to demonstrate the ability of ALS to examine fine spatial scale indicators of watershed condition I use ALS data to characterize streams and bankside vegetation at the stream reach scale based on the Tier 2 watershed monitoring protocol. Third, to demonstrate how ALS can be used to as a tool to identify important areas for forest managers, I project the individual reach level indicators across the watershed and classify the values of each indicator into "Good", "Fair", and "Poor" categories, as per the classification system used in the existing assessment approach. Lastly, I combine all the indicators and present an overall ranking to assess habitat quality and watershed condition in the Nahmint and Artlish.

6.2.2 Watershed status evaluation

6.2.2.1 BC open data Tier 1 watershed status evaluation protocol

I calculated a subset of the Tier 1 watershed status evaluation indicators (Porter et al., 2019) for both watersheds. The Tier 1 assessment is intended to provide a broad watershed level assessment of risks to ecosystem health and proper functioning condition using readily available open source GIS layers (Porter et al., 2019). The evaluation protocol consists of deriving a series of indicators described in Table 6-1.

Table 6-1. Tier 1 Watershed Status evaluation Protocol Indicators (from Porter et al. 2019)

Indicators	Units	Description	Data Source
Peak Flow Index	Index 0-1	Peak flow index is a weighted measure of the proportion of the watershed that has been harvested.	DEM, Vegetation Resource Inventory (VRI)
Road Density for entire sub-basin	km/km^2	Calculated as the total length of roads in a watershed divided by the watershed area.	Digital Roads Atlas
Road density <100 m from a stream	km/km^2	Calculated as the total length of roads within 100m of a stream divided by the total watershed area.	Freshwater Atlas & Digital Road Atlas
Road density on erodible soils	km/km^2	Road density on slopes greater than 60 degrees divided by the total watershed area	VRI

Stream Crossing density	No./km^2	A count of stream road crossings divided by the total watershed area.	Freshwater Atlas
Portions of streams logged or otherwise disturbed	km/km	The length of streams intersecting a cutblock divided by the total length of streams in the watershed	VRI

6.2.2.2 ALS integrated Tier 1 watershed status evaluation protocol

The integrated ALS/BC open source data Tier 1 watershed status evaluation protocol developed herein consists of replacing the open-source BC government data, specifically the FWA streams, vegetation resource inventory (VRI) vegetation height, and the terrain model dataset with their ALS-derived equivalents.

Ground points were classified in the ALS data by the data provider. Once we obtained the data we generated a series of standard raster layers including a DEM, digital surface model (DSM), and a canopy height model (CHM) along with a suit of point cloud metrics at a 1 m pixel level. The metrics included measures of central tendency (mean, median, mode), measures of dispersion (variance, standard deviation, interquartile distance) and percentiles, and were generated with the lidR library for R (Roussel et al., 2020).

Streams were delineated based on the method described in Dakin Kuiper et al. (2022). The first step involves processing ALS ground returns into a 10 m and 1 m spatial resolution DEM. The 10 m DEM was subjected to a standard stream delineation methodology consisting of breaching depression (Lindsay, 2016a), flow accumulation (O'Callaghan & Mark, 1984) and flow direction calculations. The delineated stream layer derived from the 10 m DEM was used for the process of stream burning on the 1 m DEM to enforce flow patterns through road embankments (Lindsay, 2015). The stream burned 1 m DEM was then subjected to the same delineation methodology described above, with the final vector stream layers extracted using an initiation area of 2 ha. Each individual stream reach was then identified and assigned a Strahler stream order value used for subsequent analysis.

6.2.3 ALS derived Tier 2 enhanced habitat indicators

The ALS derived key indicators are based upon previous studies that identified habitat characteristics important for salmonids and British Columbia Tier 2 field assessment procedure (Pickard et al., 2014: Table 6-2).

Table 6-2. Tier 2 Watershed Status and Stream Condition Evaluation Protocol Indicators as per Pickard et al. 2014

Riparian/ Stream Indicators	
Question 1.	Is the channel bed undisturbed?
Question 2.	Are the channel banks intact?
Question 3.	Are channel LWD processes intact?
Question 4.	Is the channel morphology intact?
Question 5.	Are all aspects of the aquatic habitat sufficiently connected to allow for normal, unimpeded movements of fish, organic debris, and sediments?
Question 6.	Does the stream support a good diversity of fish cover attributes?
Question 7.	Does the amount of moss present on the substrates indicate a stable and productive system?
Question 8.	Has the introduction of fine inorganic sediments been minimized?
Question 9.	Does the stream support a diversity of aquatic invertebrates?
Question 10.	Has the vegetation retained in the RMA been sufficiently protected from windthrow?
Question 11.	Has the amount of bare erodible ground or soil disturbance in the riparian area been minimized?
Question 12.	Has sufficient vegetation been retained to maintain an adequate root network or LWD supply?
Question 13.	Has sufficient vegetation been retained to provide shade and reduce bank microclimate change?
Question 14.	Have the number of disturbance-increaser species, noxious weeds and/or invasive plant species present been limited to a satisfactory level?
Question 15.	Is the riparian vegetation within the first 10 m from the edge of the stream generally characteristic of what the healthy, unmanaged riparian plant community would normally be along the reach?

I then examined the ability of ALS to characterize the above indicators and selected six ALS indicators from existing literature that could help provide insight into the question listed in Table 4 and contribute to the enhanced watershed status evaluation (Table 6-3).

Table 6-3. ALS derived indicators of habitat quality. Q = question listed in Table 6-2

Indicator	Tier 2 indicator (see Table 4)	Source
Structural complexity	Passage indicator, Q.1,2,4	Johnston and Slaney, 1996
% Pool by area	Q. 1,2,4	Johnston and Slaney, 1996
Instream wood	Q. 3,6	Johnston and Slaney, 1996
Riparian condition	Q. 15	Stackhouse et al. 2023
Overhead Cover	Q. 6,9,12,15	Johnston and Slaney, 1996
Solar Radiation	Q. 13,15	Stackhouse et al. 2023

6.2.3.1 Stream complexity: width, sinuosity, and gradient

Stream complexity typically refers to the heterogeneity of physical stream characteristics. The greater the heterogeneity of such features the greater the complexity. In this study I use three stream characteristics to examine complexity, these include: stream width, sinuosity, and gradient. Stream width is extracted using the methods described in Dakin Kuiper et al. (2022), where the stream centerline is expanded into neighboring cells based on the accumulated cost of moving from each terrain slope cell to the nearest stream source. Stream sinuosity is calculated by dividing the length of the stream reach by the straight-line distance between start and end points of the reach. A stream flowing in a perfectly straight line will have a sinuosity value of one, meanwhile meandering stream reaches will have a value greater than 1. Stream gradient, also known as stream slope, is calculated by dividing the change in elevation between the start and end of a stream reach by the length of the stream reach. Stream sinuosity and gradient were combined to create a stream complexity index.

6.2.3.2 Morphological units: % pool by area

Stream morphological units were classified into pools, riffles, glides and cascades using the random forest algorithm developed by Dakin Kuiper et al. (2022). Seven predictor variables were extracted from the ALS data including: normalized elevation, terrain roughness, return intensity, canopy height, understory cover, instream wood, and stream width across the entire delineated stream layer. Predictor variables were then used to train a random forest model to predict morphological units, more information on this process can be found in Dakin Kuiper et al. (2022). To summarize the morphological units per stream reach I calculated the proportion of pool area per stream link.

6.2.3.3 Instream wood

Instream wood is extracted from the raw ALS data using the approach presented in Dakin Kuiper et al. (2023). The methodology contains two key steps beginning with point cloud filtering, then filtered point cloud skeletonization (Dakin Kuiper, Coops, Jarron, et al., 2023). Validation of results was previously presented in Dakin Kuiper et al. (2022) with 80% accuracy at the stream reach level and 63% accuracy at the individual instream wood feature level (Dakin Kuiper et al., 2023). For the purpose of this study I summarized the instream wood data by counting the number of instream wood pieces per stream segment.

6.2.3.4 Riparian condition and overhead cover

To examine the riparian extent and indirectly the health or function of the riparian environments, I used a riparian probability layer developed by Stackhouse et al. (2023). In short, a conditional random forest model was used to predict riparian and upland vegetation classes using 14 ALS derived predictor variables (Stackhouse et al., 2023). It should be noted that the probability of riparian class occurrence is only calculated in watershed areas where harvesting has not occurred. To characterize riparian condition, I summarized the average probability of riparian extent within 30 m of each stream reach to represent common riparian management buffers in the area (Ministry of Forests, 2019) .

Overhead cover was calculated using the proportion of returns above 2 m within the stream width layer. Previous studies have found that the relationship of returns below the canopy to total returns has strong correlation to canopy cover (Solberg et al., 2006). Overhead cover was then summarized by taking the mean across each stream reach.

6.2.3.5 Stream solar insolation

Previous studies have demonstrated a strong relationship between incoming solar radiation modeled from ALS data and stream temperature (Richardson et al., 2019; Stackhouse, Coops, Kuiper, et al., 2023). Solar insolation is the energy from the sun that reaches the earth's surface, and was calculated using the methods of Rich et al. (1994). A viewshed model was used in addition to a DSM to account for potential shading from surrounding topography and vegetation (Fu & Rich, 2002). I computed the solar insolation hourly for the 22nd day in September (fall equinox) using the 1 m Digital surfaceModel and then averaged the hourly values to get a daily insolation value using the *Area Solar Radiation* tool in ArcGIS Pro 3.0.1. Lastly, I summarized the amount of solar insolation per stream reach by calculating the average solar insolation within the stream width area.

6.2.4 Ranking criteria

Each stream attribute was then classified into one of three habitat quality or risk level categories: poor, fair, or good. The Tier 1 watershed status indicators were transformed into an index value based on the thresholds listed in the watershed status evaluation protocols Tier 1 guidebook (Porter et al., 2019: Table 6-4). Index values less than 0.2 are considered low risk, index values between 0.2 and 0.4 are moderate risk and index values above 0.4 were at high risk of habitat degradation and loss of proper functioning condition. The Tier 2 indicators of habitat condition (morphology, instream wood, and gradient) were classified based on the fish habitat assessment procedure guidebook (Johnston and Slaney, 1996: Table 6-5). Solar insolation and riparian condition were classified into high, medium, and low. Solar insolation was classified using the first and third quartile values. Riparian condition was classified based on the riparian class probability with class threshold values set at 80%, 60%, and 40%.

Table 6-4. BC open data and ALS integrated watershed status evaluation Tier 1 index value ranking criteria.

Index	**Peak Flow Index**	**Road Density** (km/km^2)	**Road Density on Erodible soil** (km/km^2)	**Road Density within 100 m of a stream** (km/km^2)	**Number of Stream Crossings** (no/km^2)	**Portion of Streams logged** (km/km)
0	0.00	0.00	0.00	0.00	0.00	0.00
0.1	0.06	0.30	0.05	0.04	0.20	0.03
0.2	0.12	0.60	0.10	0.08	0.40	0.06
0.3	0.18	0.90	0.15	0.12	0.60	0.09
0.4	0.24	1.20	0.20	0.16	0.80	0.12
0.5	0.30	1.50	0.25	0.20	1.00	0.15
0.6	0.36	1.80	0.35	0.25	1.20	0.18
0.7	0.42	2.10	0.45	0.30	1.40	0.21
0.8	0.48	2.40	0.55	0.35	1.60	0.24
0.9	0.54	2.70	0.65	0.40	1.80	0.27
1	0.60	3.00	0.75	0.45	2.00	0.30

Table 6-5. Tier 2 ALS derived habitat attributes ranking criteria.

Indicator	Poor	Fair	Good	Source
Instream Wood	<1	1 to 2	>2	Johnston and Slaney, 1996
% Pool Area	< 30 %	30 - 40 %	> 40 %	Johnston and Slaney, 1996
Overhead Cover	< 10 %	10 - 20 %	> 20 %	Johnston and Slaney, 1996
Solar Insolation	>1061 (kWh/m^2)	533 – 1061 (kWh/m^2)	<533 (kWh/m^2)	
Riparian Condition	<60%	60-80 %	>80%	Stackhouse et al. 2023
Structural Complexity	< 0.28	0.28-0.51	>0.51	

The overall rank for the Tier 2 enhanced watershed status evaluation was derived by assigning a numerical value to each rank of each individual indicator, where good, fair, poor, became 3,2,1 respectively. The numerical values were then averaged and assigned to good, fair, and poor categories with cut off values of greater than or equal to 2.5 for good habitat condition and less than or equal to 1.5 for poor habitat condition.

6.3 Results

6.3.1 Tier 1 watershed status evaluation

Across the suite of indicators, the ALS Tier 1 evaluation gave more indicators with a high risk ranking when compared to the conventional Tier 1 evaluation using open-source government data (Figure 6-1). All the attributes in the Artlish watershed exceeded the high-risk threshold using both methods. However, the ALS derived index values exceeded the standard values for the portion of logged streams, and for the number of stream road crossings. Interestingly, the roads on erodible soil had a higher index value for the conventional approach compared to the ALS derived index value. In contrast, the Nahmint watershed had indictors in the low risk, moderate risk, and high risk thresholds. The ALS integrated approach found three indicators in the high risk category (number of stream crossings, roads within 100 m of streams, and portion of streams logged) three indicators (road density, peak flow index, and roads on erodible soil) in the moderate risk category and no indicators in the low risk category. In contrast, the standard methodology, ranked three indicators in the high risk category (number of stream crossings and roads within 100 m of a stream), two indicators at moderate risk (peak flow index and road density), and two indicators at low risk (portion of stream logged and roads on erodible soil). Interestingly the portion of streams logged moved from the low risk category using the standard method to high risk when the indicator was assessed with the ALS integrated approach. In both watersheds the density of streams within 100 m of roads had an index value of 1 indicating that both watersheds a density exceeding 0.45 km/km^2.

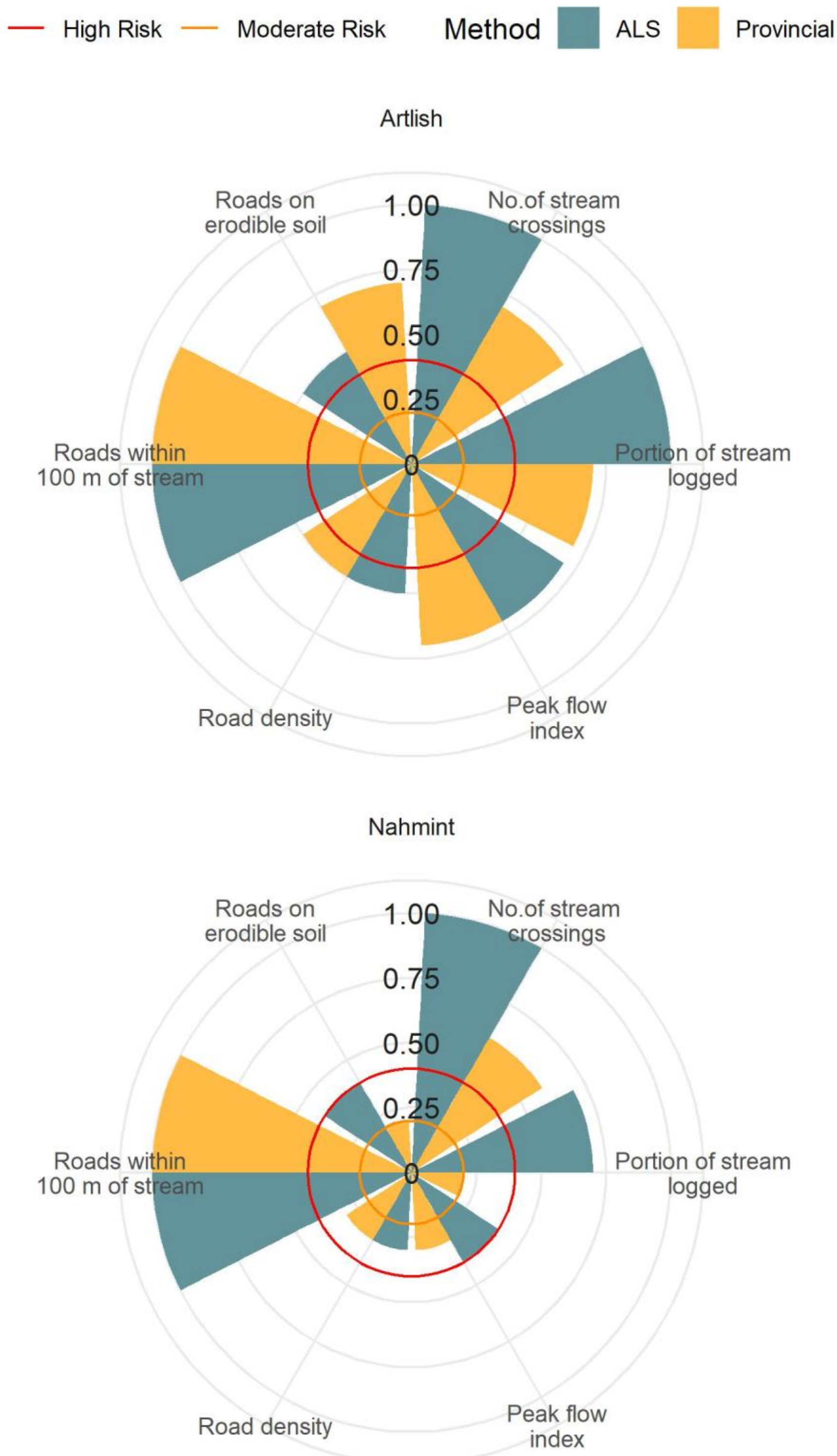

Figure 6-1. Results of the ALS and provincial Tier 1 watershed status evaluation protocol, by watershed.

6.3.2 ALS derived Tier 2 enhanced reach scale habitat condition

Based on the results presented above and keeping with the existing BC protocol the enhanced Tier 2 indicators were derived for only the Nahmint watershed to better highlight the driving factors between differences in the Tier 1 indicators.

6.3.2.1 Indicators

Table 6-6 shows the minimum, maximum and mean values across the entire Nahmint watershed. Two indicators, instream wood and overhead cover, exceeded the good ranking threshold. Three indicators, percent pool area, solar insolation, and structural complexity were within the fair ranking threshold. Riparian condition was the only indicator across the watershed to be within the poor ranking criteria.

Table 6-6. Minimum, maximum, mean and rankings for each Tier 2 indicators across the entire Nahmint watershed.

Metrics	Min	Max	Mean	Rank
Instream Wood	0.00	88.81	7.75	Good
Percent Pool Area	0.12%	97.53%	37.27%	Fair
Overhead Cover	0.00%	98.46%	45.94%	Good
Solar Insolation	23.13 (kWh/m^2)	3108.66 (kWh/m^2)	897.53 (kWh/m^2)	Fair
Riparian Condition	0.00%	100.00%	44.7%	Poor
Structural Complexity	0.03	1.06	0.42	Fair

Figure 6-2 shows the ALS derived indicators within a subset of the study area. In the top two panels the influence of vegetation on the stream is apparent with lower canopy cover and higher solar insolation present within stream areas. Both the instream wood and morphology panels are limited to the extent of the delineated stream network.

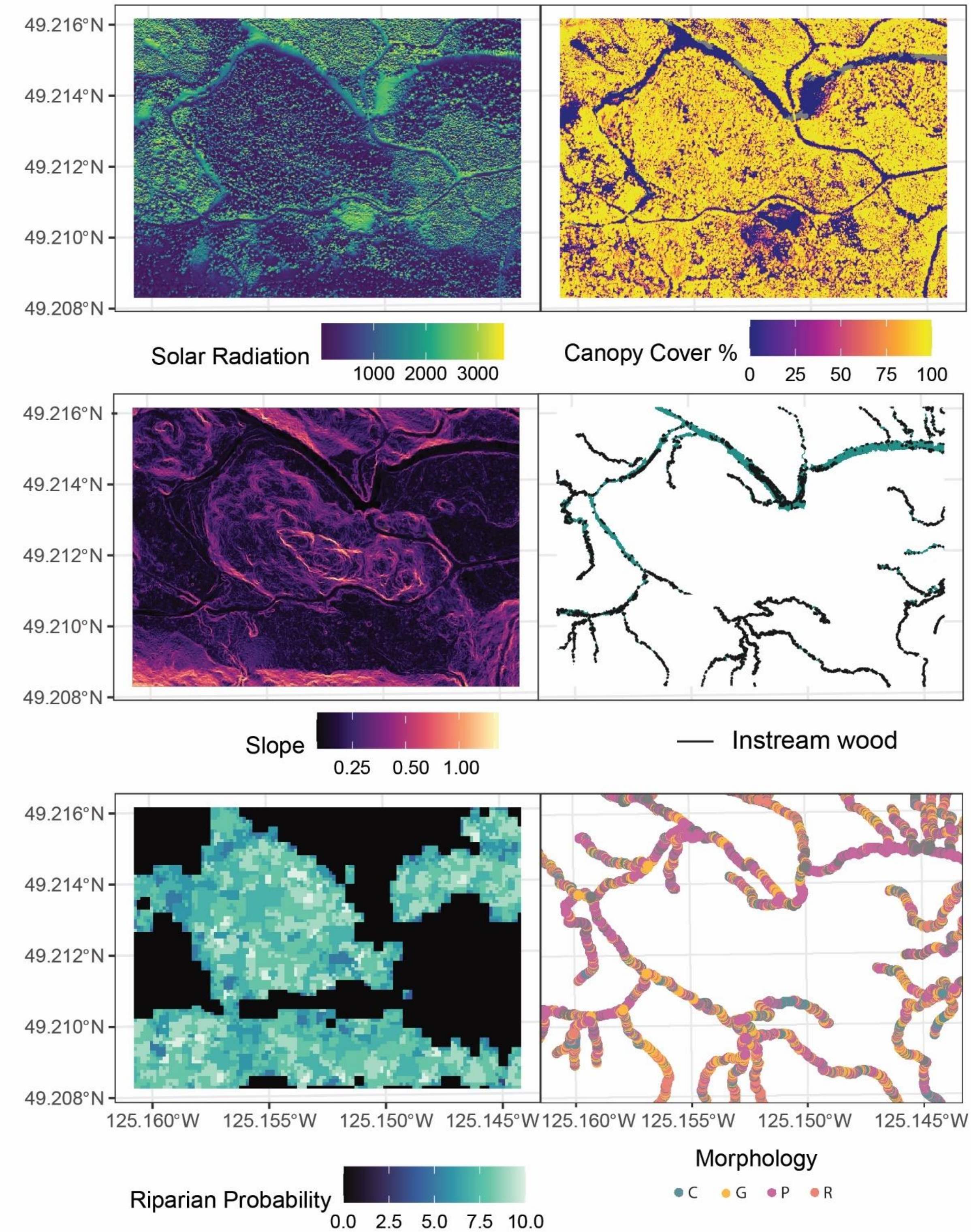

Figure 6-2. ALS derived indicators of watershed and habitat status for a subset of the Nahmint river watershed.

The overall ranking criteria of all stream reaches in the Nahmint watershed was 28%, 65% and 7% ranked as good, fair, and poor respectively (Table 6-7). The morphology indicator had the highest percentage of stream reaches with a poor ranking (45%: Table 6-7). Overhead cover had the highest percentage of stream reaches in the good category and the lowest percentage in the fair category (Table 6-7).

Table 6-7. Percentage of stream reaches in the watershed that meet the habitat condition thresholds for each condition indicator in the Nahmint river watershed.

	Good	Fair	Poor
Overall Rank	28%	65%	7%
Solar Radiation	33%	33%	34%
Riparian extent	33%	28%	39%
Complexity	34%	33%	33%
Morphology	38%	11%	45%
Wood	68%	12%	20%
Overhead Cover	81%	8%	11%

Figure 6-3 shows the proportion of stream reaches categorized by stream order that are within each habitat condition indicator ranking. It should be noted that of the 1,821 stream reaches delineated in the Nahmint watershed: 941, 455, 198, 148, 79 reaches were assigned a Strahler order of 1 to 5 respectively. The general trend is that as stream order increases so too does the percentage of stream reaches in the poor habitat condition. However, order 4 streams had the highest percentage in the good category for riparian extent. Solar radiation has the opposite trend, as stream order increases the percentage of stream reaches with poor habitat conditions decrease, with the exception of order 5 streams.

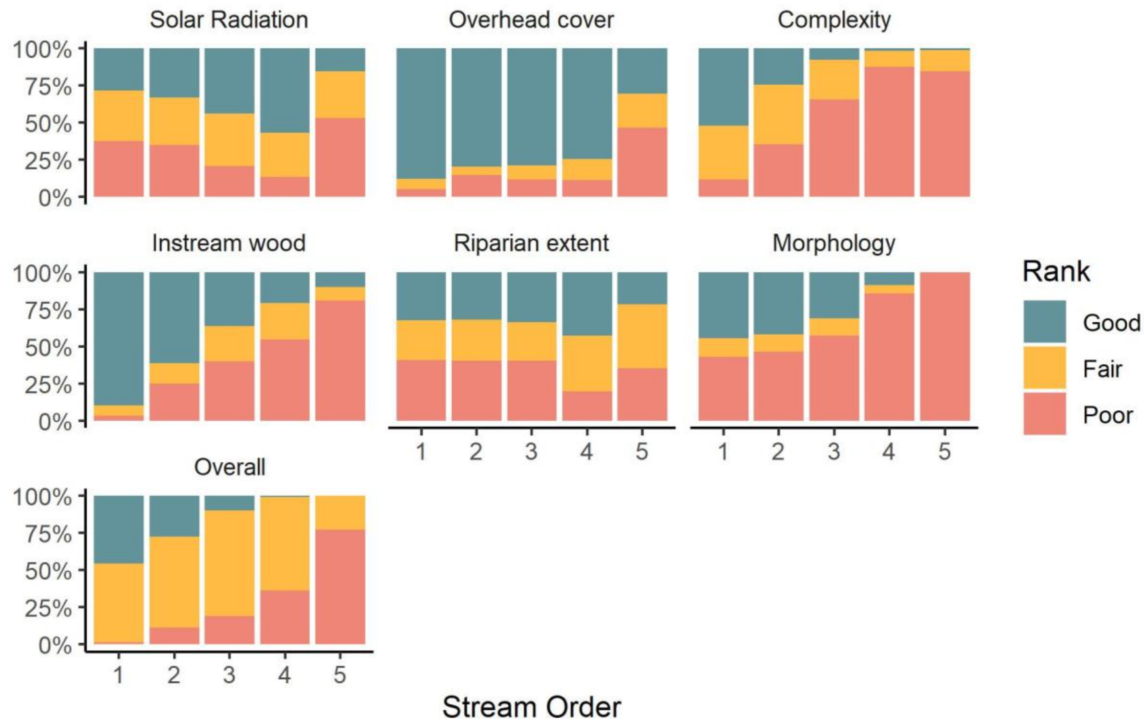

Figure 6-3. Ranking of ALS derived enhanced watershed status evaluation indicators stratified by Strahler stream order.

After each stream reach was given a ranking in each indicator they were mapped across the entire Nahmint watershed, however, a subset of the area is shown in figure 6-4 and figure 6-5 as an example to demonstrate the spatial detail provided by these indicators. Figure 6-5 shows the overall rank indicator cropped to the derived stream width overlayer on an ALS derived hillshade layer.

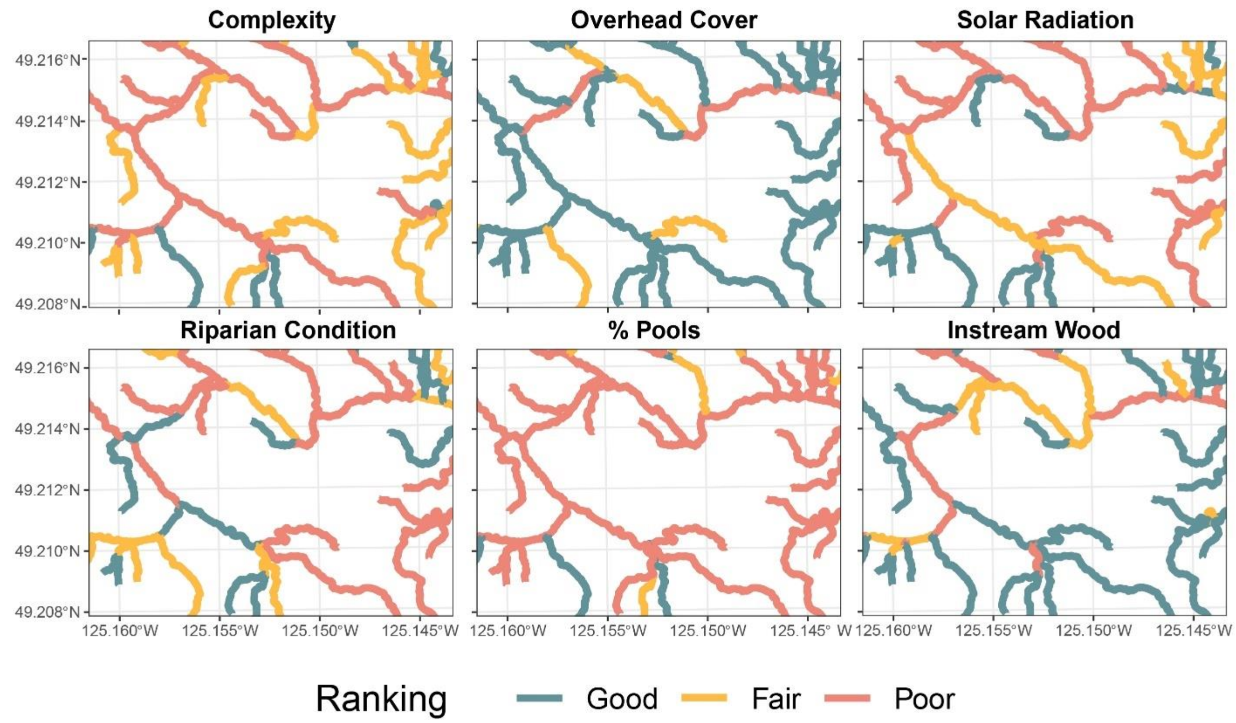

Figure 6-4. Individual ranking criteria mapped across a subset of the Nahmint watershed.

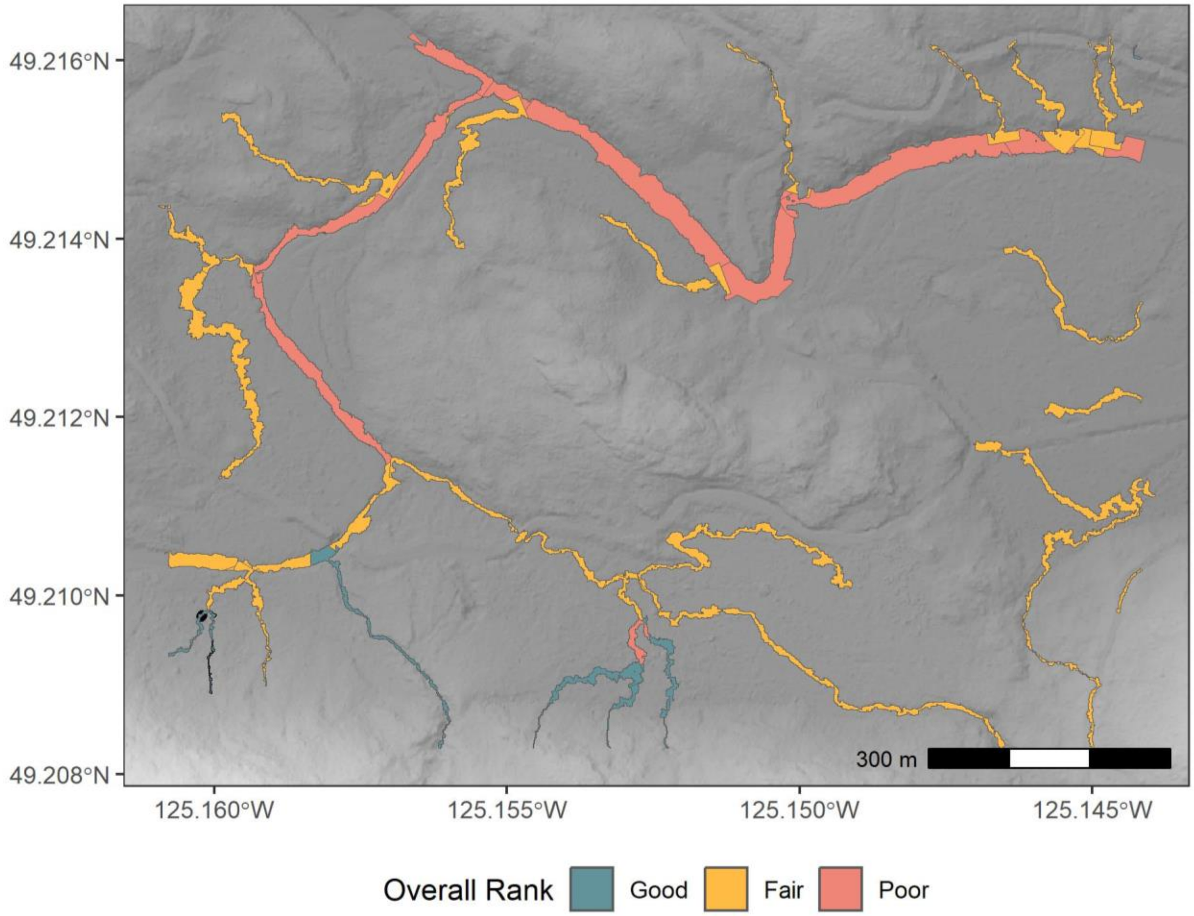

Figure 6-5. Overall habitat quality ranking for a small subset of the Nahmint river watershed overlayed on a hillshade raster layer.

6.4 Discussion

Understanding where quality salmonid habitat is distributed throughout a forested watershed is a critical piece of information that forest managers can use to make informed decisions within a sustainable forest management framework. The lack of spatial information provided by traditional watershed status assessments makes it difficult for forest managers to make decisions regarding the conservation of salmonids and the restoration of their habitat. Additionally, the majority of studies that use ALS to characterize salmonid habitat focus on only a single or limited number of stream features (Dakin Kuiper et al. 2023a). By combining these stream habitat condition indicators and riparian vegetation features into an assessment framework I can provide useful and spatially explicit information.

I presented a framework to assess the risk of habitat degradation within a forested watershed using ALS data and found that including ALS derived attributes generally ranked in the higher risk category compared to indicators derived from existing open government data. Indeed, the increased spatial detail contained in the ALS derived stream network and ALS derived terrain and vegetation variables reason for this discrepancy could be due to increased spatial detail found in the ALS data. Further, our results showed that the overall stream reach habitat quality varied by stream order with the lower order streams generally having a higher proportion of stream reach in the "good" category. Together, these results suggest that ALS data has a high capacity to be used by forest managers to make informed decisions regarding factors that influence the habitat conditions within watersheds.

6.4.1 ALS for watershed status evaluation

The research presented demonstrated the ability to integrate ALS data and more specifically ALS-derived stream and riparian characteristics into existing watershed status and habitat condition evaluation protocols. The conventional Tier 2 watershed status evaluation protocol involves answering a series of questions regarding the habitat conditions at specific reaches within a watershed using in situ data. Tier 2 evaluations are triggered by Tier 1 evaluations that indicate a high risk level and the reaches are selected and stratified based on a sampling protocol and then an assessment is made for the entire watershed (Tripp et al., 2020). The enhanced ALS-derived condition assessment uses similar indicators to the conventional approach but allows for an assessment of every stream reach in a watershed in a spatially explicit manner, rather than having to select a sample of reaches. The ability to assess habitat conditions within each stream reach throughout a forested watershed provides a level of insight not possible with traditional field sampling approaches. However, some aspects of the Tier 2 assessment are not currently possible or may never be possible to characterize with ALS data exclusively. For example, the capacity of ALS to characterize the amount of moss present on stream substrate is low. Additionally, answering questions regarding suspended sediment load will also be difficult. However, completing aspects of the fish passage assessment, specifically, examining culvert locations and characteristics is possible (Arsenault et al., 2023). Further, the ability of ALS to characterize insects and other invertebrates and their habitat is a developing field and could help to address question 9 of the Tier 2 protocol (Rhodes et al., 2022).

Understanding the strengths and limitations of our methods is important for interpreting the results of this study. Delineating the stream network is an essential early step in our proposed framework. Previous studies have found discrepancies between ALS stream networks and stream networks derived from interpreted imagery and other sources (James et al., 2007; Tompalski et al., 2017). Indeed, this is a major factor in the differing rankings between the ALS and open data watershed level status evaluation indicator values. Generally, due to the increased detail in the ALS-derived terrain models, differences occur in the length and locations of stream features (Tompalski et al., 2017). The number of stream reaches delineated is influenced from the accumulation threshold applied during the initial delineation workflow. Limited work has been accomplished to determine what threshold value to use as it is difficult to assess the accuracy of the different threshold values (Ozulu & Gökgöz, 2018). Further research on the most accurate method of flow accumulation thresholding is required, specifically for ephemeral streams.

Previous research using ALS data in a fish habitat context has generally focused on modeling or characterizing a specific habitat feature in a few stream reaches or across the network (Dakin Kuiper et al., 2022; Duffin et al., 2021; Stackhouse et al., 2023). This study derived a series of indicators from the literature and combined them to create a holistic understanding of habitat condition throughout the example watershed. A strength of this approach is the ability to only calculate a small subset of the indicator values depending on the project requirements and the availability field data. For example, the stream morphology is derived using a random forest model trained on a subset of the collected field data, additionally, thresholds in the extraction of stream width and instream wood counts were also tuned using field data (Dakin Kuiper et al., 2022). However, it is becoming more common that a forestry practitioner has access to only ALS data and limited field data. In this case, the watershed scale status evaluation can still be used, and ALS indicators such as canopy cover, gradient, structural complexity, and insolation could be calculated as part of a routine management protocol.

I chose to focus on ALS derived indicators in or adjacent to the stream. However other watershed indicators such as location and type of roads and presence and scale of landslides have been derived using ALS (Baldo et al., 2009; Roussel et al., 2022, 2023). Future research could add more ALS indicators to replace or supplement current open data sources derived from air photo interpretation. Further, additional remote sensing technologies could be integrated within this framework. For example, passive optical remote sensing technologies such as the Landsat or the Sentinel series of satellites have been used to quantify salmon habitat (Luck et al., 2010; Whited et al., 2012). Additionally, as the use of remotely piloted aerial vehicles (RPAS) and mobile laser scanning technologies increase, these technologies could be integrated into this framework potentially replacing field data.

6.4.2 Spatial distribution of condition indicators

The ALS derived enhanced indicators presented in this study varied spatially throughout the watershed. As I moved from the lower order streams in the upper portion of the watershed to the higher order larger rivers nearer to the outlet, the percentage of stream reaches in the "Good" category of the overall rank generally decreased. The opposite trend is seen in the solar radiation rank and the percentages are fairly even in the riparian extent indicator rankings. The even distribution seen in these two indicators could be driven by riparian management strategies such as fixed width buffers. The low percentage of "Good" reaches in the overall indicator category is influenced heavily by the complexity and morphology indicators with 1% and 0% of stream reaches ranked "Good" in these categories. The model for classifying stream morphology was trained and tested in small headwater streams and may not adequately capture the variations in larger river reaches. For example, in larger rivers, the predictor variables of intensity and zq15 (understory canopy) will be different than in headwater streams because of the absorption properties of deep water and limited bankside and overhanging vegetation.

Looking at how the indicators vary spatially throughout the watershed is important for interpreting the habitat indicators in a species-specific and life-stage-specific context. For example, using these indicators an approach could be tailored for different life stages. For spawning salmonids riffles, solar insolation and gradient become important indicators, whereas instream wood and percent of pools become less important (Quinn, 2004). For rearing fish that utilize cover to a greater degree, instream wood, complexity and canopy cover become more important indicators. At the species level, species like chum or pink salmon which spawn closer to the river outlet, I can stratify reaches by distance to the outlet and look at available habitat quality. For species that migrate further upstream like sockeye salmon or steelhead trout, gradient and road stream crossings become more important habitat indicators.

6.4.3 Management implications

ALS continues to be a valuable asset for sustainable forest management planning. Indeed, ALS has already reached a realized operational feasibility for applications such as timber resource assessment (Næsset, 2014; White et al., 2016), and is nearing an operational capacity for terrestrial habitat modeling (Merrick et al., 2013) and carbon and biomass assessments (Næsset, 2014). The operational readiness of the indicators presented in this research ranges from realized to developing. Delineating stream networks, calculating canopy cover, and stream complexity measurements require limited computational power and can be computed with limited or no available field data and are operationally realized in some areas (Dakin Kuiper et al., 2022; O'Callaghan & Mark, 1984; Tompalski et al., 2017). Instream wood, stream width, riparian condition, and solar radiation require limited field data for calibration; however, instream wood detection, and solar radiation are computationally intensive at the watershed scale. Further, riparian conditions require the development of a random forest model and the computation of a series of ALS derived predictor variables. Predicting stream morphological units at this scale requires field data to train a random forest model (Dakin Kuiper et al., 2022). However, methods at different scales (Cavalli et al., 2008), or using different remote sensing technologies including photogrammetry (Helm et al., 2020) and bathymetric lidar (Duffin et al., 2021b) are promising and could be adapted to ALS data.

As the availability of ALS data increases, there is growing incentive to extract more information from these datasets. It is the hopes of the authors that ALS applications for characterizing stream habitat indicators and watershed status indicators reach operational maturity alongside other ALS data products such as enhanced forest inventory. Further, as multi-temporal ALS acquisitions become more common, there will be an increased capacity to quantify the natural (fire, pest) and anthropogenic (harvesting, urbanization) pressures facing forested watersheds. By developing the capacity to characterize and quantify these cumulative effects, I can begin to formulate a more fulsome understanding of how management decisions could impact habitat condition and watershed pressures at a landscape level.

6.5 Conclusion

This study presents a framework to understand watershed status and riparian habitat quality in a forested watershed that builds upon and integrates existing assessment protocols. I found that integrating information derived from highly detailed ALS data into a watershed status evaluation protocol universally increased the risk of losing proper functioning condition to habitat degradation across the indicators. Further, the level of detail available in ALS dataset allows for a stream-reach scale habitat condition assessment. Within the Nahmint river watershed, two habitat condition indicators were good, three indicators were fair, and one was poor. Stratifying these habitat quality indicators by stream order provides valuable information on the spatial distribution of available quality salmonid habitat throughout the landscape. Specifically, I found that the overall condition of reach-level stream habitat features across the Nahmint watershed was 28% good, 65% fair and 7% poor. Value-added approaches that avail upon existing ALS datasets, such as the one presented in this study, are important for providing forestry practitioners and forest managers a full picture of forested ecosystems. Increasingly, provinces throughout Canada, including British Columbia, are committing to provincial wall-to-wall ALS acquisitions, creating enormous opportunity to leverage these datasets for applications to support forest management planning, such as those demonstrated herein.

Chapter 7: Conclusions

7.1 Dissertation objectives

The primary goal of this dissertation was to assess the ability of ALS data to characterize stream habitat features important to salmonids in forested watersheds. This objective was met by addressing the four research questions described below.

How have remote sensing technologies been used to characterize freshwater fish habitat?

Chapter 2 provides a systematic review on the ability of remote sensing technologies to characterize fresh water fish habitat examining the general trends in the literature and identifying strengths, challenges, and opportunities. Using a suite of keywords to search the Web of Science database, I identified 96 published studies that used remotely sensed data to map, monitor, or measure important fish habitat features. There was an increase in papers published through time, peaking in 2022, with multispectral sensors being the most common technology implemented (>50% published studies). I found minimal development of novel remote sensing metrics and automated methodologies specific to fish habitat characterizations. Key recommendations made in the review included, development of novel and automated remote sensing methodologies, examining the transferability of already developed models, and linking historical fisheries data to archival remotely sensed data.

To what extent can individual fish habitat units be characterized in small streams using ALS data?

Chapter 4 demonstrated the ability to accurately extract stream features such as stream width and to model individual habitat units using a series of ALS-derived predictor variables. Key to this chapter is the development of a methodology to derive stream width using ALS. Stream width was directly extracted from an ALS-derived digital terrain model by expanding the stream centerline into areas of homogenous slope and elevation. Next a workflow for extracting instream wood features was used to count the number of wood features in each study reach. Using the derived stream width as a spatial constraint, seven predictor variables were computed from the ALS data, specifically stream width, instream wood, normalized elevation, terrain roughness, intensity, understory vegetation, and canopy height. These predictor variables were then used in a random forest model to classify study reaches into four distinct morphological units (pools, riffles, glides, or cascades). ALS-derived stream bankfull width was positively corelated (r = 0.8, RMSD = 2.05 m) with field measurements. Individual stream morphological units modeled using the random forest algorithm had a mean overall accuracy of 85%, with pool morphological units having the highest accuracy (96%) and riffles the lowest (76%). Further, ALS predictors variables representing local terrain were most important for model predictions.

How can ALS data be used to characterize instream wood and what physical and environmental properties effect detection rate?

Chapter 5 built upon the results presented in chapter 4 by examining the accuracy of instream wood detection for individual wood pieces and for logjams. Further, this research identified the environmental features and ALS data attributes that significantly impacted detection rate. In this chapter, I presented a framework to detect instream wood features. The general workflow consisted of three steps 1) ALS point cloud filters: 2) filtered point cloud skeletonization and 3) automated validation of results. Point cloud filtering involved classifying ground points using a cloth simulation filter algorithm and removing returns above 2 m, with low intensity values and pulses with multiple sub 2 m returns. Skeletonization involved identifying points with a linear relationship to neighboring points and performing a series of spatial transformations to return a vector feature representing either a logjam or a single piece of instream wood. Then a suite of logistic regression models were developed using missed and detected instream wood as the dependent variable and ALS metrics and instream wood field measurements as independent variables.   Overall mean detection frequency for instream wood features was 63%. However, the accuracy varied by stream reach, and was higher for logjam features (81%) and lower for individual wood pieces (49%). Submerged depth, % of points classified as ground and absolute scan angle had a significant impact on detection rate ($p < 0.05$).

How can ALS derived indicators of habitat condition and pressure integrate into existing landscape scale habitat monitoring protocols?

Chapter 6 presented a framework to assess watershed risk status and condition using the stream attributes described in the previous two chapters and other indicators of watershed condition found in the literature. Further, this chapter demonstrated an integrated approach to using ALS data in existing watershed status assessment protocols and determined how ALS can supplement existing field-based evaluation protocols. In this chapter, I calculated six watershed-level risk status indicators including; the number of stream road crossings, the density of roads on erodible soils, the density of roads within 100 m of a stream, the portion of streams in logged areas, peak flow index, and the road density of a watershed, using provincial, open-source data, and then calculated the same six indicators using ALS derived streams, vegetation heights, and slope. Next, I computed six reach- level indicators of habitat condition, including incoming solar radiation, canopy cover, gradient, instream wood, riparian vegetation extent, and individual morphological units. When comparing provincial indicators of watershed pressure to ALS indicators of watershed pressure, the ALS derived indicators consistently ranked in the higher risk category. At the stream-reach scale, 28%, 65%, and 7% of stream reaches within the study watershed ranked as “good”, “fair”, and “poor” respectively for overall habitat condition. When stratified into stream orders, lower order streams generally had a higher percentage of "good" ranking habitat conditions compared to higher order streams. This chapter demonstrates the capacity of ALS to provide both fine stream reach scale and broad watershed scale information on habitat condition and habitat pressures within a watershed.

7.2 Innovations

This research has innovated and contributed to an enhanced understanding of the ability of ALS data to characterize stream habitat features:

- As highlighted in the introduction, limited research has been done on developing methods to characterize individual morphological units in small headwater streams. Chapter 4 developed a novel methodology to use ALS data to classify a stream reach into individual morphological units. To my knowledge it is the only study to do so at this scale with NIR ALS data.
- Chapter 5 presented an automated framework to extract instream wood features from an ALS point cloud and provided a detailed assessment of the environmental and ALS attributes that affected the detection rate. This provides one of the first studies that automatically extracted and validated instream wood features using ALS intensity information in the extraction process.
- Chapter 6 contributed to the development of an approach used to assess watershed status. It takes the methods described in the previous chapters and in the literature to develop a novel framework for watershed status assessment. This demonstrates the ability of ALS data to be integrated into existing watershed evaluation protocols and further, demonstrates the ability of ALS data to supplement field measured variables or habitat condition.

7.3 Limitations

7.3.1 Model Transferability

This dissertation focused on two study watersheds located on Vancouver Island British Columbia Canada. Both watersheds are within the Coastal Western Hemlock (CWH) bio geoclimatic zone and share similar disturbance mechanisms, specifically forest harvesting, however over different timescales and extents. The use of relatively similar study areas is a recognized limitation of this study. How these methods would work in other watersheds such as those in the interior of North America with less tree cover, and different topography (less mountainous), is unknown. The study stream reaches in this dissertation were primarily small (< 10 m wide) headwater streams. A limitation is the unknown ability of how these methods scale to wider, faster flowing stream reaches. Due to cost and data availability, testing the transferability of the methods developed in this dissertation were not undertaken.

7.3.2 Field Data

A recognized limitation of this dissertation and many other studies that use ALS data is the disconnect between the locational accuracy of field data and the ALS data. In this study, the known error of the GNSS acquired ranged from 30 cm – 300 cm. When extracting features such as stream width, or instream wood, from an ALS point cloud, the locational accuracy of the field data is a limitation in achieving high accuracy and has the possibility to create compounding errors throughout the developed methodologies.

Additionally, streams, watersheds and forests are dynamic environments in a constant state of change driven by natural and anthropogenic influences. It should be noted that there is a time-lag between the ALS acquisitions in 2016, and the field campaigns (2019,2020, 2022). This leads to the limitation that features measured during the field campaigns might not align with the same features found in the ALS or that features in the field data will not even exist in the ALS data. This temporal difference between the two data sets means that models could be under or over performing and could lead to incorrect predictions.

7.3.3 ALS Data

An objective of this dissertation was to determine what important habitat features can be characterized using ALS data. It should be noted that the majority of ALS systems use lasers in the near infrared (NIR) portion of the electromagnetic spectrum. These systems were developed primarily for terrain and vegetation monitoring. It is a known limitation that NIR photons are absorbed by a waterbody. As a result, NIR ALS pulses do not penetrate into the water and some interpolation is often required within the wetted channel area to determine elevation and other topographic variables. It should be noted that NIR ALS might not be the best data source for these applications and that bathymetric lidar, with laser scanners in the green portion of the electromagnetic spectrum, might be more suited for riverine applications. However, NIR ALS data is much more common than bathymetric data, especially in forested environments. Indeed, there are 10s of millions of ha of NIR lidar data over Canada's forests. Although limited by the capacity of NIR ALS, this dissertation presents a series of value-added approaches to extract more information from NIR ALS data, which facilitates a broader understanding of these ecosystems.

7.3.4 Methodological Constraints

The methods presented in this dissertation attempted to "stand on the shoulders of giants" when characterizing stream habitat features. This means that, when possible, I tried to use the best available algorithms for creating the initial data products, such as the delineated stream layers, DEMs and CHMs. In some cases, like delineating the stream network I had deviated from conventional routines in order to accurately match the collected field data (i.e., stream burning). Significant research has been dedicated to which stream delineation and DEM generation algorithms are best suited for the application of mapping habitat features. I acknowledge that a limitation in this study is a lack of testing how these initial preprocessing algorithms impact the final accuracy of the models and methods described in this thesis.

7.4 Future directions

7.4.1 Model transferability

More research is required to demonstrate the transferability of the models and methods developed in this dissertation to watersheds in different biogeoclimatic zones with different vegetation, soil, watershed dynamics, and harvesting histories. For example, watersheds in the interior of British Columbia could have less forest cover and morphology may not be influenced to the same extent by bankside vegetation. Further, examining how the models developed in this dissertation work on bigger streams is an important future direction to generate a comprehensive picture of a forested watershed. A major advantage of using ALS data is that it is becoming increasingly common across forested areas. In Canada, the government of British Columbia has already begun releasing current ALS acquisitions for free through an online open data portal and has recently announced an investment to acquire wall-to-wall ALS data for the entire province (BC Gov News, 2023). These readily available ALS data will greatly increase the capacity to evaluate the methods described in this dissertation across a range of study sites.

7.4.2 Other data sources and data fusion

Future work should examine the potential of other laser scanning data sources to characterize salmonid habitat. Specifically, single photon lidar (SPL, green wavelength) is increasingly available, with Ontario, Canada, acquiring wall-to-wall data coverage for the managed forest area. As these data become more available, methods to extract stream habitat characteristics important to fish should be tested. Mobile laser scanning, and remotely piloted aerial systems (RPAS) are promising new technologies. These systems create ultra-dense point clouds but generally have a less powerful sensor leading to a decreased capacity to penetrate dense upper canopy vegetation. These platforms are less expensive than conventional airplane based platforms and allow for a less costly multitemporal data acquisitions. Further, many of these platforms collect both the three dimensional data associated with laser scanning and multispectral RGB data concurrently. With that in mind, future work could use these new technologies to see how habitat features important to salmonids are changing through time and assess the value of fusing multispectral information with structural information to characterize habitat features.

7.4.3 Additional habitat features for freshwater fish

This dissertation only explored a subset of the habitat features important to freshwater fish species. Future work could explore the feasibility of modeling other habitat features with ALS data. For example, as off-channel habitats provide numerous benefits to salmonid species, methodologies to characterize off-channel habitat features should be developed. Specifically, assessing the potential of the methods described in this dissertation in braided channels. Other avenues of future research could include culvert or barrier assessment, linking ALS derived riparian structure to the thermal properties of streams, or characterizing sediment size within stream reaches. This thesis focused on characterizing habitat feature important to salmonid species. More work could be done to examine the capacity of ALS data to characterize habitat features important to other genera of fish.

7.5 Closing statement

Understanding changes in salmonid populations and their habitat is a critical issue given changing climate, their importance as a keystone species, and their cultural significance. With the increased use and collection of ALS data for forest management, there is an opportunity to develop value-added methodologies to further characterize salmonid habitat from these datasets. This dissertation presents a series of methodologies to harness ALS data to characterize important habitat features in forested watersheds. I hope the results and discourses presented in the dissertation facilitates the uptake of both ALS and other remote sensing approaches in the broader fish habitat research sphere and that the methodologies and products presented herein become a part of the standard outputs from ALS data when working in forested watersheds.

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Appendix

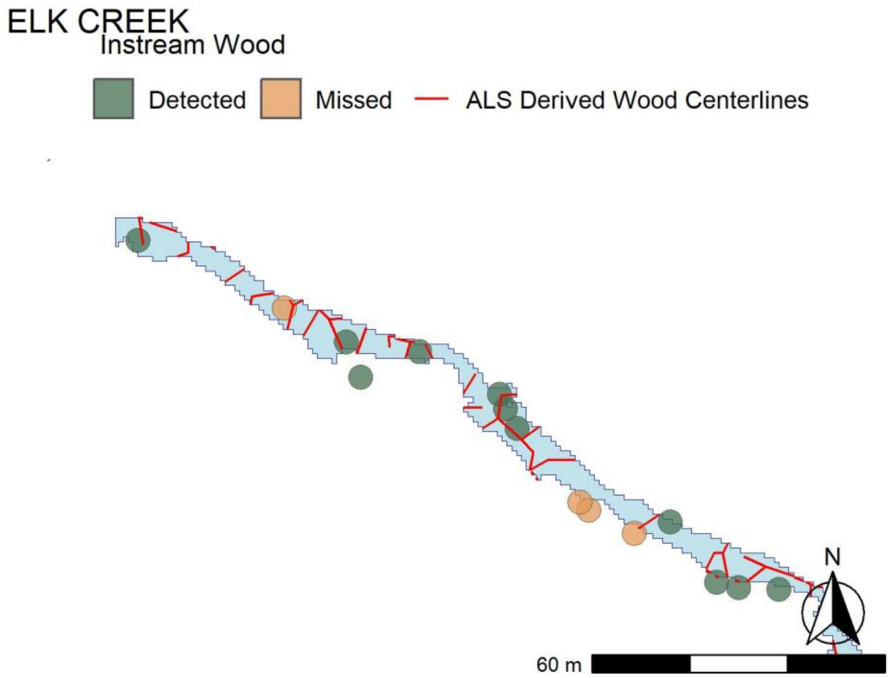

Figure A1: Map showing the field measured wood points and the lidar derived wood points along Elk Creek.

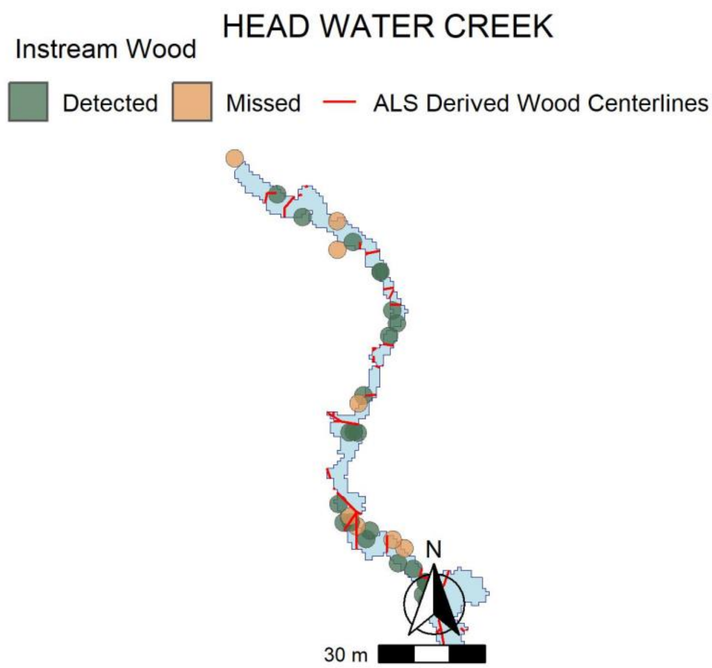

Figure A2: Map showing the field measured wood points and the lidar derived wood points along Head Water Creek.

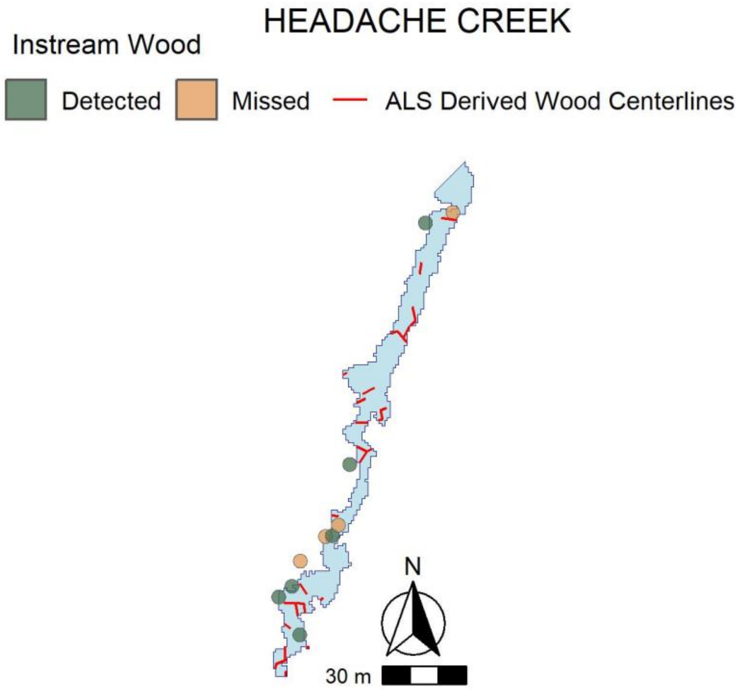

Figure A3: Map showing the field measured wood points and the lidar derived wood points along Headache Creek.

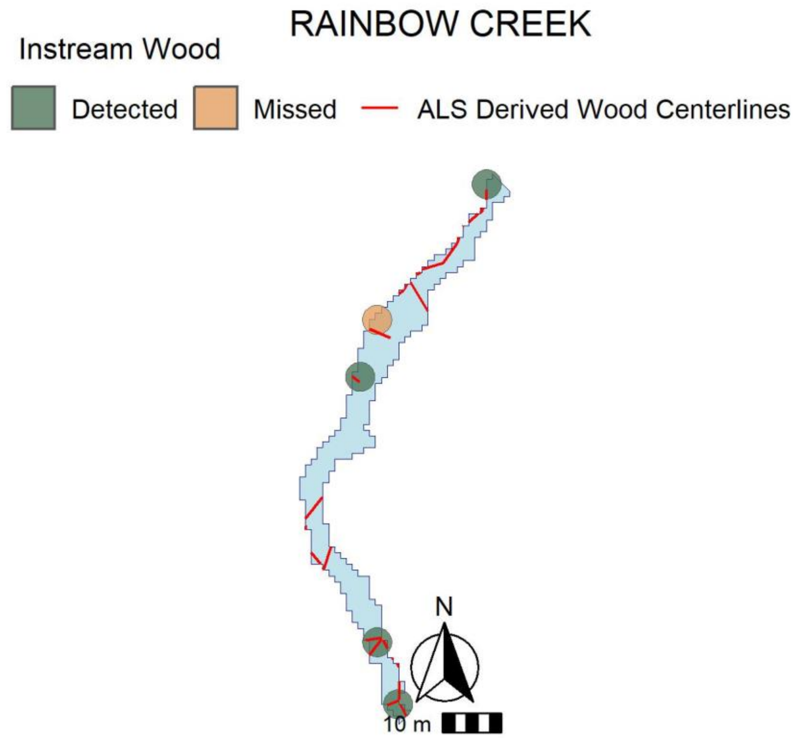

Figure A4: Map showing the field measured wood points and the lidar derived wood points along Rainbow Creek.

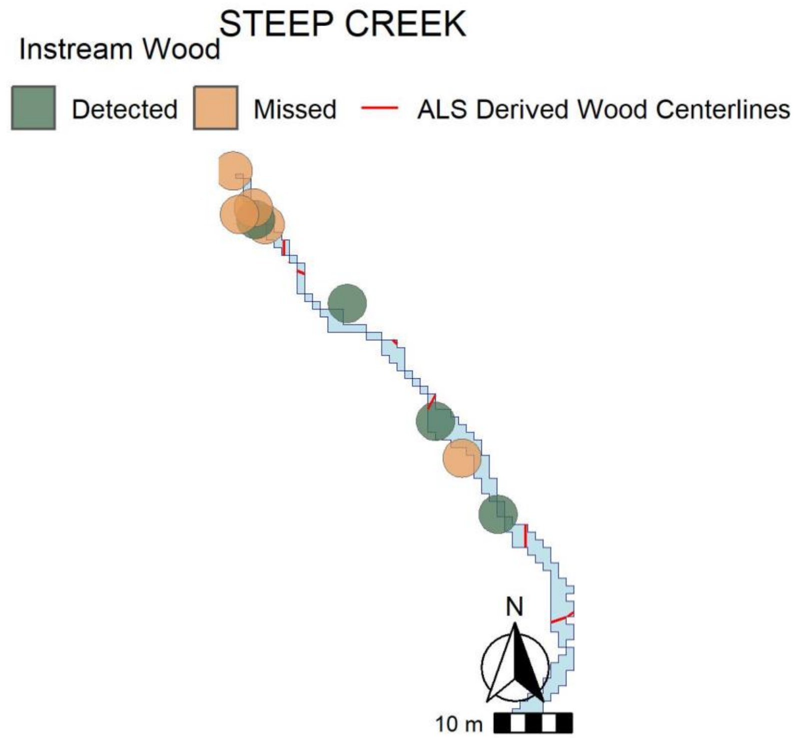

Figure A5: Map showing the field measured wood points and the lidar derived wood points along Steep Creek.