Assessing the utility of Airborne Laser Scanning for Terrestrial Ecosystem Mapping

by

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Abstract

Observing landscape patterns at various temporal and spatial scales is central to mapping ecosystems. Traditionally, ecosystem mapping uses a combination of fieldwork and aerial photography interpretation. These methods, however, are time-consuming, prone to subjectivity, and difficult to update. Airborne Laser Scanning (ALS) is an advanced remote sensing technology that has increased in application in the past decade and has the potential to significantly increase and refine information content of ecosystem mapping, especially in the vertical dimension. ALS technology provides detailed information on topography and vegetation structure and has considerable potential to be used for terrestrial ecosystem classification and mapping. In this thesis, the potential to use ALS data to advance ecosystem mapping is examined. The current state of the science for using ALS data to classify and map key ecosystem attributes within an existing ecosystem mapping scheme is discussed by focusing on British Columbia's Terrestrial Ecosystem Mapping (TEM) and its associated Predictive Ecosystem Mapping (PEM).

Based on a detailed literature review, a site-specific case study was also developed with the goal of mapping TEM polygons for a forested landscape on Vancouver Island, British Columbia. To do so an object-based image analysis approach was used. The analysis examined which were the best suite of ALS-based terrain and vegetation metrics to define and distinguish individual site series. It established a workflow for the classification of site series within the study site and examined the capacity to map site series based on ALS derived values. Best segmentation parameters were first established and then the study area was classified for slope position-wetness and finally into the specific site series. In the classification of site series two approaches were used. One approach used only terrain metrics and the other incorporated vegetation metrics. Overall accuracies were 59% and

56% respectively. While this workflow requires refinement, it shows potential for improved accuracies by applying suggestions discussed.

The thesis concludes with a discussion summarizing the findings of this research and highlighting future refinement to the methods applied in the case study, while also providing recommendations for the current application of ALS technology to TEM.

Lay Summary

The primary goals of this research was to establish if it was possible to use the remote sensing technology, Airborne Laser Scanning (ALS) to map ecosystems at the site level scale. British Columbia's Terrestrial Ecosystem Mapping (TEM) scheme was used as the basis for determining key ecosystem attributes and outcomes. A literature review was conducted to establish the current state of science for using ALS to classify the ecosystem attributes that are used in the TEM process. From this, best methods were established for the next steps, which would be a case study. The case study used an area on Vancouver Island. It attempted to map the TEM ecosystem units by using ALS data in a computer program that grouped similar pixels together to create objects, and then classified these objects based on statistic information that related to the various ecosystem attributes.

Preface

This thesis is the combination of two scientific papers written for peer-review of which I am the lead author. I was responsible for defining research objectives, developing methodology and analyzing data, in addition to writing and editing both manuscripts. The conceptual idea for this research began as a partnership with British Columbia's Ministry of Forests, Lands and Natural Resource Operations Research Program. Primary conceptual development, project oversight and editorial assistance were provided by Dr. Nicholas Coops. Dr. Sari Saunders and Dr. Suzanne Simard were involved in project development and editorial assistance.

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A version of Chapter 3 is currently being reviewed by co-authors and is titled:

> Campbell, L. B., N. Coops, S. Saunders, S. Simard. 2017. Classifying and mapping site level ecosystems in coastal British Columbia using Airborne Laser Scanning.

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List of Acronyms

ALS	Airborne Laser Scanning
BEC	Biogeoclimatic Ecosystem Classification
CFS	Canadian Forest Service
CHM	Canopy height model
CWH	Coastal Western Hemlock
CV	Coefficient of Variation
DEM	Digital Elevation Model
DSM	Digital Surface Model
EPC	Elevation Percentile
OBIA	Object-Base Image Analysis
PEM	Predictive Ecosystem Mapping
SS	Site series
SP-W	Slope position-wetness
SD	Standard deviation
TEM	Terrestrial Ecosystem Mapping
TLS	Terrestrial Laser Scanning
TO	Topographic Openness
TPI	Topographic Position Index
TRASP	Topographic Radiation Aspect
TWI	Topographic Wetness Index

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The TEM classification of the 5 x 5 km subset area at the "Fluxnet Canada DF 49 site" was compiled by the Canadian Forest Service from source data provided by Timberwest and Weyerhauser in 2005. We gratefully acknowledge Timberwest for its provision of the data to the Fluxnet Canada project.

I am grateful to my supervisory committee, Dr. Sari Saunders and Dr. Suzanne Simard, for their involvement in this project. Their encouragement and insight was very much appreciated. The members of the Integrated Remote Sensing Studio provided support, which was very helpful along my journey. Finally, I would like to say a big thank you to Dr. Nicholas Coops, my supervisor, for taking me on as his student and for believing in me; his time, support and effort were integral to my success and I am extremely thankful for being a member of the IRSS and for this opportunity.

Chapter 1: Introduction

1.1 An introduction to ecosystems

Ecosystems are the result of complex interactions between biotic and abiotic dynamics, which manifest as wide-ranging spatial patterns across the landscape (Bailey 1985; Rowe 1996; Gustafson 1998; McMahon et al. 2004). Ecosystems are recognized as distinct, comparatively homogeneous units that have multiple connections and dependencies with adjoining units from which they have a relatively abrupt transition (Bailey 1985). Environmental attributes, primarily climate, physiography, soil, and vegetation (Barnes et al. 1982; Rowe 1996), are often defined as the most influential factors driving ecosystem formation across a range of scales. Variations in landscape ecosystems, assuming equal time and access to biota, result from landforms and their modification of local climates (Rowe 1996). These various landforms interact with climate and directly influence hydraulic and soil-forming processes (Bailey 1987). At the site scale, local moisture influences the type of vegetation present, with minor differences in slope and aspect markedly influencing vegetation patterns (Bailey 1987).

1.2 Mapping ecosystems

Classifying ecosystems and mapping their arrangements is central to understanding and observing ecological landscape patterns at various temporal and spatial scales (McMahon et al. 2004). The ability to observe ecosystems at varying scales and discern how their distribution varies across a landscape provides insight about why particular sites exist and how they are maintained. Improving the ability to understand ecosystem attributes spatially and monitor them temporally will facilitate our capacity to anticipate downstream effects and gain insight about why changes take place and how management might mitigate any harmful effects (McMahon et al. 2004). Classification and mapping ecosystems therefore, are critical preliminary steps for land management and biodiversity conservation, and are important components to evaluating how a landscape might respond to both direct and indirect influences (Bailey 1987).

Mapping ecosystems at the land management scale involves multi-level nested classification (Allen and Starr 1982; Bailey 1987). At the broadest scale, the primary influence on ecosystems is climate, followed by landform, which influences landscape level macroclimates (Bailey 1987). These various landforms interact with climate to directly influence hydraulic and soil-forming process (Bailey 1987). Finer still, at the site scale, local moisture and nutrient availability influence the type of vegetation present with minor differences in slope and aspect markedly influencing vegetation patterns (Bailey 1987). Ecological mapping requires reference to these scale-specific attributes to best assist managers in understanding how individual ecosystems interact with adjacent landscapes (Bailey 2009). Having access to practical tools that can be used for management purposes, such as high quality maps with the appropriate spatial and temporal scale, is critical to furthering our understanding of underlying connections and how these may alter ecosystem health. Yet the process of classifying and mapping ecosystems remains highly complex.

1.3 Mapping ecosystems in British Columbia

Conventionally, the task of mapping ecological units comprises fieldwork and aerial photography (Bailey et al. 1994; Rowe 1996; Wulder et al. 2012). While these processes have been effective, they are not without shortcomings. Installation of plots and their subsequent measurement can be time-consuming and expensive, and often can be neglected in difficult-to-access areas. Temporal monitoring is additionally challenging and costly (Lucas et al. 2008; Jones et al. 2012) because plots must be relocated and remeasured. Moreover, manual interpretation of aerial photography introduces biases and requires specialized interpreters (Morgan et al. 2010).

In British Columbia, Terrestrial Ecosystem Mapping (TEM) or Predictive Ecosystem Mapping (PEM) data provide ecosystem-based information, which is used for environmental/resource management and various mapping projects. Both the TEM/PEM approaches integrate biotic and abiotic attributes. The delineation of a landscape into ecosystem units is based on a combination of ecological features, primarily climate, physiography, surficial material, bedrock geology, soil, and vegetation (Ecosystems Working Group 1998). Both TEM and PEM employ a nested classification order: at the broadest scale, there are both ecoregion and biogeoclimatic classifications, which represent broad level regional and climatic landscape units, and through to the site level with more detail.

Within these units there are site units termed "ecosystem units", which describe terrestrial ecosystems at a more detailed level. Ecosystem units are generally derived from site series classification, site modifiers and structural stage and these are then mapped as relatively homogeneous polygons. Each polygon may encompass as many as three site series, annotated as "deciles" (Ecosystems Working Group 1998). Site series accounts for the variation in site conditions across a topographic sequences encountered within a biogeoclimatic unit; it describes all land areas capable of supporting specific late successional vegetation. Site modifiers encompass site-specific conditions that fall outside of typical conditions for a site series. Structural stage defines the current stand physiognomy for the ecosystem unit being described. Ecological units are interconnected and therefore polygons are delineated with consideration to the existing classifications for the area (ecoregion, biogeoclimatic and site). As a result, for each polygon, the various influences of topography, terrain, soil characteristics and developmental patterns on the landscape are taken into account.

Terrestrial Ecosystem Mapping

Terrestrial Ecosystem Mapping is the typical approach used for mapping when detailed ecological information is required. The TEM approach relies on using attributes (Table 1) that are distinguishable from aerial photography; units are delineated, classified, and pre-typed on photos by local experts from various ecological fields. A portion of units and polygons are subsequently checked in the field to refine understanding of the relationships between photo attributes and ground conditions; pre-typed attributes are then updated as necessary (Resources Inventory Committee 1998). Field sampling additionally provides the information required to confirm biogeoclimatic unit boundaries, describe the individual site series, classify new ecosystems and describe structural and vegetation characteristics of younger structural stages. For all mapped polygons, 'core attributes' are those that are primarily interpreted attributes. While some, such as structural stage and a few site modifiers, can be modeled or derived from other sources, the majority are directly interpreted from the base photography. While the ecological information provided by TEM is critical for planners and managers, the data and the interpretation process is principally subjective, cannot be easily updated and can lack sufficient detail for some of the desired applications.

Table 1 Criteria required to classify attributes in ecosystem mapping, using Terrestrial Ecosystem Mapping as an example.

Mapped attribute	Example of a feature type for the mapped attribute	Criteria for classification
Geomorphic process	Snow avalanches Gully erosion Permafrost process	Geomorphic process Topography[a]
Terrain attributes	Sandy gravelly (texture) Fluvial (surficial material) Terrace (surface expression)	Texture Parent material Surface expression Qualifiers
Soil drainage	Poorly drained Very rapidly drained Imperfectly drained	Topography[a] Soil depth Terrain attributes Drainage pattern
Site series	CWHvm1/HwBa –Blueberry[b] CWHvm1/HwPl – Cladina CWHvm1/BaCw – Salmonberry	Stand height Canopy characteristics Understory or non-forested vegetation composition Tree species composition Geomorphic process Topography[a] Soil depth Terrain attributes Drainage pattern Forest floor

[a] Includes landscape position and shape, aspect, slope, and drainage pattern.

[b] CWH = Coastal Western Hemlock biogeoclimatic zone; vm = Very Wet Maritime subzone; 1= submontane variant; Hw = western hemlock; Ba = amabilis fir; Pl = lodgepole pine; Cw = western redcedar.

Predictive Ecosystem Mapping

Alternatively, the Predictive Ecosystem Mapping approach is a newer inventory approach which automates the process using spatial data and ecosystem knowledge. As with TEM, the primary PEM mapping unit is the Biogeoclimatic Ecosystem Classification (BEC) site series. Rather than photo interpretation and field checking as in the TEM process, PEM uses computer modelling, which incorporates existing knowledge of ecosystem attributes and relationships, to predict ecosystem occurrence in the landscape. Information for polygon delineation is usually derived from data sources such as forest inventory, soils, or bioterrain mapping. Ecologists with local experience may still provide some interpretation. While in the TEM process, the rules of interpretation may be biased, in the PEM process the rules relating ecological characteristics to ecosystem classification are formally structured in the knowledge base. PEM has attempted to solve some of the weaknesses presented by the TEM process but particular case studies have shown it does not always provide the level of accuracy required (Walton & Meidinger 2006).

1.4 Current limitations and the potential of ALS

A hybrid TEM/PEM pilot project was conducted in the Draney Landscape Unit (LU) of the Central Coast Forest District, British Columbia (Ecora Resource Group Ltd. 2012). The project utilized PEM methods for mapping the matrix ecosystems of the landbase, where it performs with reliability and has advantages to the TEM system. TEM methods are applied for mapping ecological exceptions and extremes (which includes fluvial benches, alluvial fans, erosional gullies-which are necessary to natural resource management and the correct delineation of their boundaries is indispensable). Exception classes generally have distinctive photo signatures and the TEM method is able to map this portion of the landbase with acceptable accuracy and requiring limited field sampling. Overall, across the landbase, 11% was mapped as ecological exceptions, totaling 5,005 ha. Depending on the terrain being mapped, ecological exceptions and extremes typically account for up to 10-20% of a given landscape. Results of the analysis highlight that the nature of a particular landscape and limited availability and low spatial resolution of existing input data make it difficult for predictions to be made with consistency and a high level of accuracy with the PEM process.

While the TEM and PEM approaches have become an important component of ecological mapping in the Province, because of the limitations already discussed, opportunities exist to assess the capacity of new technologies to be used in the derivation process. Advanced remote sensing tools are a likely candidate. Remotely sensed data are becoming increasingly available, less expensive and the application of the data is becoming more diverse. Airborne Laser Scanning (ALS), particularly, is an example of a new technology whose use has rapidly increased in the last decade and is currently utilized globally to quantify forest structure, vegetation classes, tree or stand metrics, and topography metrics such as slope, elevation and aspect (Wulder et al. 2013). Due to its suitability for developing high spatial resolution Digital Elevation Models (DEMs), as well as providing detailed information on vegetation structure, its use as a data input into the TEM or PEM processes is worth investigating.

Many studies have used ALS data to classify various ecosystem attributes, but few have attempted to classify ecosystem units, such as site series, specifically. To examine this potential, British Columbia's TEM (with some consideration for PEM) criteria were used as the focus for this literature review to examine the current state of science for ALS and how it could be applied to advance ecological understanding and mapping.

1.5 Research objectives

The overall research objective of this thesis was to explore the feasibility to use ALS data for mapping ecosystems to site series scale. To achieve this, a literature review was conducted to assess the current state of science for using ALS data to delineate and classify key ecosystem attributes. To integrate and test selected methods from the literature, a case study was conducted for a 25-km^2 area on Vancouver Island (aka. Oyster River) for which both TEM and ALS data were available. The outcomes of this thesis were to propose state of the art approaches for using ALS data to map ecosystems according to TEM methods and the development of a workflow for mapping TEM based site series on a specific landscape.

To meet these goals the following sub-objectives are outlined:

1. By completing a literature review, summarise current research on the application of ALS data for mapping ecosystem attributes (using BC's TEM structure as a guide), highlighting the most promising methods which could be applied to a BC specific case study. For each attribute integral to the TEM process, suggest the feasibility (low, med, high) of using ALS data for its classification and mapping.
2. Using the Oyster River study site as a case study, determine the most appropriate ALS derived terrain and/or vegetation metrics to segment and classify site series using an Object Based Image Analysis process; and establish a validated workflow that could be applied to other BC locations.

The structure of the thesis is as followed. Chapter 2 focuses on the literature review, introducing ALS technology and its strengths for capturing vegetation and terrain information and describes how it might benefit ecosystem mapping. This chapter breaks down each attribute used in the TEM methods and provides the feasibility for mapping it using ALS data based on current research.

Chapter 3 contains the case study. It describes the methods used and the outcomes. It further expands on the feasibility for mapping ecosystems to site series and provides an example workflow.

Chapter 4 discusses key findings, conclusions and imitations of the research. Recommendations for future research are also discussed.

Chapter 2: ALS as an advanced remote sensing technology to augment ecosystem classification and mapping

2.1 ALS technology

Airborne Laser Scanning (ALS) is an active remote sensing technology that accurately measures the distance between the sensor and the target (Jelalian 1992); it does so by emitting intense, focused beams of light and measures the time it takes for the reflections to be detected by the sensor. ALS is a multi-sensor measurement system that identifies three-dimensional coordinates (latitude, longitude and elevation) of the target objects. An ALS systems typically consists of a laser scanner unit, a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU) from which the system records the time difference between the laser pulse being emitted and returned, the angle at which the pulse was sent and the precise location of the sensor on or above the surface of the Earth (Carter et al. 2012). In doing so, ALS instruments can quickly measure the height of the Earth's surface. Sampling rates can be as high as 240 kHz (Höfle & Rutzinger 2011) giving a densely spaced network of highly accurate georeferenced elevation points (point clouds). ALS data specifically are acquired by a system mounted on an aircraft and flying over targeted areas. Laser scanning can also be performed from ground-based stationary and mobile platforms or from satellites, but these methods are less common; this thesis will focuses on the applications of airborne laser scanning.

ALS elevation data are extremely accurate with absolute accuracies between 15 - 30 centimeters for older systems and 10 - 20 centimeters for more recent systems (Carter et al. 2012). The accuracy of ALS data is contingent on various influencing factors such as the system being used, flight conditions and characteristics of the area being scanned, such as slope or vegetation cover (Höfle & Rutzinger 2011). Even in forested areas however, ALS is able to detect the ground in enough locations to provide highly detailed information. ALS reflections are often referred to as "reflection", "return" or "pulse". In forested areas, an emitted laser pulse can result in a first return coming from the tree canopy and a last return from the ground surface beneath (Höfle & Rutzinger 2011) (Figure 1).

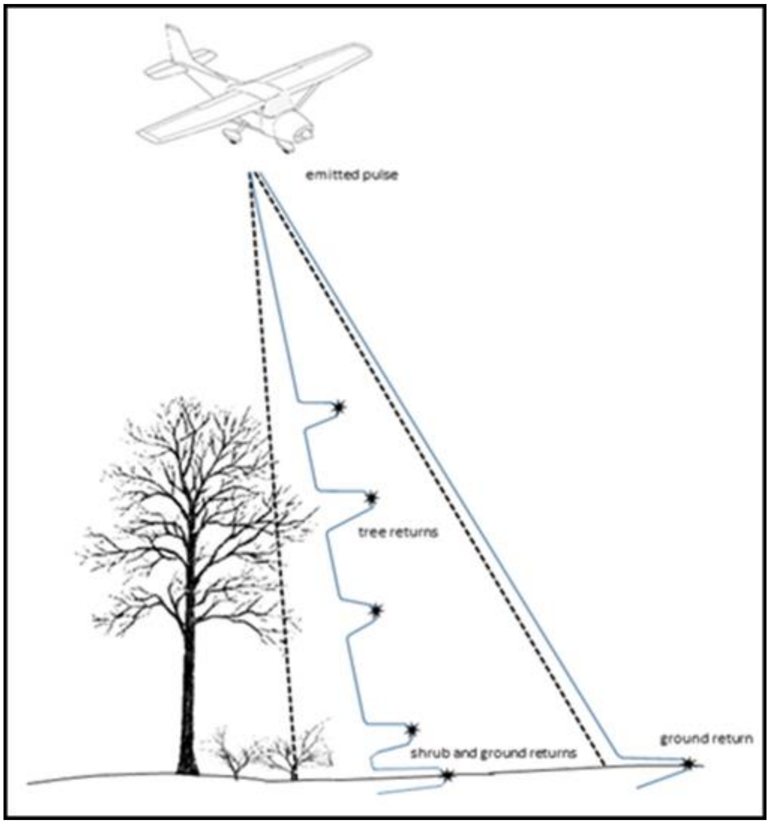

Figure 1 Airborne Laser Scanning and its emitted pulse and returns

The illuminated area from the ALS beam is known as the footprint; footprint size is directly related to flight height. The area of small-footprint ALS is typically 0.25 to 1 m in diameter (Höfle & Rutzinger 2011) and two types of ALS data are commonly acquired, discrete echo recording systems and more recently full waveform systems (Höfle & Rutzinger 2011). Discrete return systems record single or multiple returns from a given laser pulse. As the laser pulse is reflected back to the sensor, large peaks are recorded as clouds of points representing intercepted features (Wulder et al. 2012). Full waveform systems digitize the entire reflected energy from a return with point clouds providing complete vertical vegetation profiles (Wulder et al. 2012). Full waveform also has the added benefit that each laser pulse can provide additional qualities such as signal amplitude and reflection width (Höfle & Rutzinger 2011).

The increased use and development of airborne ALS systems has led to increased automation for many of the steps involved to use and apply ALS, from data acquisition through to DEM generation (Höfle & Rutzinger 2011). The analysis of ALS data begins with the 3D point cloud. For most ALS applications the separation of terrain returns (i.e. bare earth/DEM) and returns from objects (i.e. buildings and trees) needs to take place. This process is called filtering and is accomplished by either working directly on the point cloud or on an already rasterized Digital Surface Model (DSM). Canopy height models (CHMs) are produced from the difference between the DEM and DSM. Elevation models (terrain) and canopy models (vegetation) can be used for greater ecological understanding and interpretation. However, interpretation is often scale dependent making the classification a multi-resolution problem (Höfle & Rutzinger 2011).

2.2 ALS application in ecosystem mapping

Digital, remotely sensed data are increasingly being applied to ecosystem mapping because, in general, they are becoming more diverse, readily available, and inexpensive (Dube et al. 2016; Gilvear & Bryant 2016; Reif & Theel 2016). Digital data allow for automated or semi-automated mapping methods to be used, thereby reducing bias and ideally increasing cost-efficiency, in part through the increased ability for map updating and data collection for expansive or difficult-to-access locations (van Asselen & Seijmonsbergen 2006; Thompson et al. 2016). Multispectral imagery is used to measure tree structure, differentiate among tree age classes, and distinguish tree species (Li et al. 2013; Yang et al. 2014). Indices such as the Normalized Difference Vegetation Index (NDVI) increase our ability to monitor net primary production, and have been used for wetland delineation, land cover classification, and identification of various ecological responses (e.g., green-up timing, treeline change, fire recovery).

Conventional passive airborne and satellite sensors, however, are limited in their capacity to discriminate and map ecosystems, primarily because they lack the ability to denote spatial patterns in three-dimensions; thus, they produce only two-dimensional images (Lefsky et al. 2002). As a result, fine-scale topographic and vegetation structural observations are neglected or simply inferred. ALS is an example of a recent active remote sensing technology that has rapidly advanced and increased in application and use over the last decade. It can extend spatial analysis into the third dimension, is well-suited to developing high spatial resolution DEMs, and can provide detailed information on vegetation structure.

Ecosystems are influenced by abiotic attributes, such as geomorphology, drainage patterns, and soil, which in turn, largely determine the vegetative community in a location (Barnes et al. 1982). ALS-based DEMs provide a strong basis from which predictive physiographic classifications can be performed. They have helped improve the identification of drainage patterns (including within peatlands), stream channel delineation, and floodplain mapping (Demarchi et al. 2016; Gaspa et al. 2016; Hamada et al. 20016). By applying filters to DEMs, anomalous pits and peaks can be removed, which provides a smoothed surface that allows discontinuities in the data (drainages) to be extracted and classified (Heung et al. 2014; Luscombe et al. 2014).

ALS data are also used successfully to accurately describe a variety of vegetation metrics such as height, crown cover, volume, and diameter (Leiterer et al. 2012; Wulder et al. 2012). The data are capable of providing detailed information to describe three-dimensional texture, foliage-clustering characteristics, and gap distribution in an individual tree crown (Jones et al. 2012; Li et al. 2013). Additionally, there has been marked success in classifying forest structural classes (Jones et al. 2012; Reese et al. 2014; Valbuena et al. 2016), differentiating between coniferous and deciduous trees (Leiterer et al. 2012; Tiede et al. 2012; Alberti et al. 2013), and estimating the position of alpine treelines (Coops et al. 2013).

2.3 Mapping TEM specific attributes

Discrete-return Airborne Laser Scanning (ALS) is the most likely form of laser scanning data to be used for ecosystem mapping due to its availability and practicality for gathering data on large and hard to reach locations. The following review will address research using ALS data specifically. Additionally, to best assess the feasibility for applying ALS data to ecosystem mapping, it is helpful to use an already existing system as a baseline. As explained in the introduction, the provincially mandated mapping system for British Columbia is TEM, with some areas mapped using the PEM methods. There are four principal sets of ecosystem attributes (geomorphic process, terrain attributes, soil drainage and site series) used in the classification and subsequent mapping of ecosystem units (Table 1).

Below, each attribute is defined and the current state of science for mapping the attribute is discussed; additionally this is summarized in Table 2. The feasibility for using ALS data for classifying and incorporating each attribute into a process for mapping is highlighted and ranked.

Geomorphic Process

Geomorphological processes are the natural mechanisms of weathering, erosion and deposition that result in the modification of the surficial materials and landforms at the earth's surface (Ecosystems Working Group 1998). These processes can be erosional, fluvial, or glacial based; they can be mass movements that happen slowly or very quickly (landslide). Geomorphological process play an important role in influencing the type of vegetative community found at a particular location. Classifying the type of geomorphological process affecting a particular location is not directly identifiable from ALS data but requires some interpretation. However, as geomorphological processes are largely a result of topography, high-resolution ALS-based DEMs can increase the capacity for reliable predictive geomorphological mapping.

The topographic detail and accuracy ALS data affords can improve classification models and has the potential to increase the ability to identify features that may be otherwise difficult to predict. In BC for example, complex mountainous terrain often makes mapping features such as alluvial fans, incised channels and talus slopes difficult using predictive methods and as a result requires manual classification methods. ALS data can enhance the interpretive capabilities of geomorphic classification given the recent work in this field, which has produced reasonably high accuracies (Anders et al. 2011a, 2011b, 2013; van Asselen & Seijmonsbergen 2006). Research by Greve et al. (2012). Many metrics for topology can be obtained from high-quality DEMs and can be used to improve models (e.g., elevation, slope gradient, slope aspect, curvature, and topographic openness) (Anders et al. 2011a; Greve et al. 2012; Maynard & Johnson 2014; Akumu et al. 2015; Thompson et al. 2016).

Ecosystems are subject to dynamics, disturbance, and change (Huston 1979; Gustafson 1998). Terrestrial Ecosystem Mapping classifies geological processes as active or inactive. Mapping active processes temporally would allow dynamic landscape change to be detected, quantified, and reclassified where applicable. Anders et al. (2013) compared delineation results for two years of data and showed that identifying geomorphological change is possible by quantifying volumetric change for each landform class. Compared to current change detection methods that primarily subtract multi-temporal DEMs from each other to detect change, the Anders et al. (2013) methods allow changes in landforms due to geomorphological processes to be determined. The authors believe that their methods provide a reproducible framework to repeat landform classifications and analyze change detection.

Terrain

Terrain attributes are characteristics relating to terrain, whether it is surficial material or bedrock (Ecosystems Working Group 1998). TEM includes several categories of terrain attributes, (terrain texture, parent material, surface expression and qualifiers); the characteristics of these categories are used as criteria for delineating ecosystems with experts being able to use them for photo interpretation purposes. Like geomorphological process, terrain attributes cannot be directly attained from ALS data and indirect, interpretive methods must be applied. Research specifically addressing the use of ALS to map terrain attributes, as defined by TEM, is sparse. The following terrain attributes all contribute to the ecology of a location and are therefore an integral part of the TEM process:

1. **Terrain Texture** describes the size, roundness and sorting of particles in unconsolidated clastic sediments (i.e. boulders, pebbles, mud, shells, sand, silt, and clay), and the proportion and degree of decomposition of plant fibre in unconsolidated organic sediments (i.e. fibric, mesic, or humic).
2. **Parent material** is the non-lithified, unconsolidated sediment occurring on the earth's surface. They are materials produced by weathering, biological accumulation, human, and volcanic activity. They weathered from rock *in situ* or transported materials deposited by water, wind, ice, gravity, or any combination of these agents.
3. **Surface expression** is the form and patterns of forms expressed by surficial material at the land surface. The three-dimensional shape of the material is equivalent to "landform" used in a non-genetic sense (e.g., ridges, plain). Surface expression also describes the manner in which unconsolidated surficial materials relate to the underlying unit (e.g., veneer, blanket, hummock and terrace).
4. **Qualifiers** provide additional information about the mode of geologic formation and/or the depositional environment of surficial materials and about the status of activity of geological processes (i.e. glacial qualifying descriptors and activity-qualifying descriptors).

The terrain attributes described are somewhat specific to TEM in their categorization and/or definition. However, the basis for describing terrain is in part, linked with defining slope gradient and slope position. As well, the process for mapping geomorphology is very much associated with processes required for classifying terrain attributes. Terrain texture was the only criterion for which research incorporating ALS data for classification purposes was not found. Terrestrial Laser Scanning (TLS) was used to identify terrain texture in several studies; for example, Brasington et al. (2012) were able to map the spatial pattern of particle size, grain roughness, and sedimentary facies at the reach scale for streambeds. However, applying TLS on a large scale (i.e. provincially) is not practically feasible. There is, however, sufficient research indicating that ALS based data could be very useful for describing the remaining terrain criteria.

The high accuracy of ALS based DEMs provide an excellent platform from which terrain attribute classification can take place as demonstrated above for geomorphological mapping. High quality, detailed DEMs help quantify the relationships between topography and a specific criterion that changes with topography such as geomorphology and surface expression, which are both influenced by slope angle and position.

The classification of parent material (i.e., genetic material) is particularly difficult because ALS cannot penetrate the ground to provide below-surface metrics; therefore, its classification process completely relies on predictive methods. However, using a Random Forest classifier, Heung et al. (2014) predicted relationships between soil parent material and topography. They were successful at delineating major parent material classes but less so for minority classes. They used single-component soil polygons from conventional soil survey maps to generate randomized training points for nine parent material classes. Each point was intersected with values from 27 topographic and hydrologic indices derived from a 100 m DEM. Predictions made by a non-optimized Random Forest classifier resulted in a kappa index of 89.6% when validated with legacy soil survey data from single-component polygons and a kappa index of 79.5% when validated with field data.

Soil Drainage

How water moves through the landscape has a profound effect on ecosystem characteristics of a particular area. Soil drainage is defined as how quickly and how much water passes through the soil relative to additional inputs (Ecosystems Working Group 1998). Drainage can be either surface runoff or water infiltrating through the soil. It is important that the contextual catchment that an area is situated within must be considered when evaluating soil drainage since water inputs, as rain or snow, can vary significantly between topographic and climatic regions. For example, high elevation bogs on steep slopes are common within coastal areas of BC and being able to identify them accurately is an important part of TEM ecosystem delineation. The criteria used for TEM air photo interpretation for classifying soil drainages are landscape position and shape, slope, drainage pattern, soil drainage and soil depth.

The incorporation of high-quality DEMs is integral to mapping topographic depressions and drainages, and it enhances the delineation of slope classes by providing detailed differentiation, even in areas with only subtle local relief changes (Aspinall & Sweeny 2012; Luscombe et al. 2014). Such detailed metrics allowed Luscombe et al. (2014) to highlight drainage patterns across a peatland and identify sinks as drainage features or flushes. They identified microtopographic sinks in the landscape by selecting pixels with a height threshold of 0.11 m from the DSM data. Their results showed that ALS classification had similar results to maps created from aerial photography. Drainage scale however, is much finer than ALS captures and the microtopographic depressions were not captured consistently. Luscombe et al. (2014) also found that ALS data were able to identify drainage ditches but unable to quantify if they were continuous features.

Aspinall & Sweeny (2012) renewed existing soil maps using high-resolution ALS-based DEMs and were able to differentiate drainage patterns in subtle relief areas that had previously gone undetected. High-resolution DEMs also provide soil landscape feature definition that allows for subtle differentiation of morphometric elements to be used as diagnostic elements (Aspinall & Sweeny 2012). Soil depth is a criterion used in the TEM process to help map drainages; however, because ALS does not penetrate the ground, using it as a tool for measuring soil depth is not possible, and no studies were found that used ALS topography metrics to predict soil depth.

Site Series

Site series is one of the most important attributes in the British Columbia ecosystem mapping approach. It accounts for the variation in site conditions encountered within a biogeoclimatic unit (Ecological Data Committee 2000). Site series describe all land areas within a biogeoclimatic subzone or variant that are capable of supporting mature communities of the same plant association or subassociation (Pojar et al. 1987). This can usually be related to a specified range of soil moisture and nutrient regimes, but sometimes other factors, such as aspect, air flow (e.g., cold air ponding), or disturbance regime (e.g., flooding), are also important determinants. The criteria used for TEM air photo interpretation for classifying site series includes all of the terrain attributes discussed in the above sections and also the vegetation attributes of stand height, canopy characteristics, understory or non-forested vegetation composition or characteristics, tree species composition and forest floor, which will be discussed here.

Stand height and forest canopy characteristics offer insight about the particular site series, and ALS is a well-demonstrated tool used to gather height metrics and canopy variables, such as canopy closure, stem count, and tree diameter and volume (Næsset & Økland 2002; Lim et al. 2003). ALS estimates of individual tree height have been shown to be more consistent than manual, field-based measurements (Næsset & Økland 2002). Canopy height descriptors, height percentiles, and canopy volume profiles are some of the most widely used metrics for determining structural or seral stages (Jones et al. 2012). Canopy structure is necessary for differentiating coniferous and deciduous trees (Alberti et al. 2013; Kumar et al. 2015), detecting residual trees (García-Feced et al. 2011), and quantifying canopy height ranges (Latifi et al. 2015; Lopatin et al. 2015).

Describing the vegetative community of a specific location is integral to site series classification. However, it is not always crucial for grasses and shrubs to be identified to the species level; rather, defining the structural class (i.e., herb, grassland, shrub) could be sufficient for classifying site series when combined with other biotic and abiotic attributes (e.g., differentiating between bog woodland and bog forest). In British Columbia's southern Gulf Islands, Jones et al. (2012) were able to differentiate among TEM-defined structural classes using three common metrics derived from ALS data. All ALS variables significantly distinguished among certain TEM structural classes. The importance of each metric used varied with the stage differentiation under consideration. All structural classes were differentiable, however the number and types of ALS metrics that were able to distinguish among particular combinations decreased with stand age and structural complexity (Jones et al. 2012).

Spectral data, particularly hyperspectral data, can provide important information about ecological conditions (Lawley et al. 2016), tree health (Michez et al. 2016), above-ground biomass (Greaves et al. 2016), and tree species classification (Dalponte et al. 2012, Zhang et al. 2016). Site series define the potential vegetation for a site. The most promising advances in determining tree species using ALS occur when other optical remote sensing imagery are incorporated. The dense sampling and narrow band measures of the tree species' spectral signatures allow each portion of the spectrum to be related to specific characteristics of the trees, which can then be interpreted for classification purposes (Dalponte et al. 2012). As a result, a number of studies have mapped species using a combination of spectral- and ALS-derived structural information (Colgan et al. 2012; Dalponte et al. 2012). Yang et al. (2014) combined satellite multispectral imagery (RapidEye) and ALS data for species identification within the Canadian boreal forest. Their best result combined ALS and RapidEye using the Random Forest classifier. Yang et al. (2014) concluded that the most significant ALS metrics and RapidEye bands for tree species mapping were DEM, slope, canopy height, red-edge NDVI, and red-edge and near-infrared spectroscopy bands. Without the fusion of spectral and ALS data, full waveform data provide the most likely candidate for species classification. Li et al. (2013) were able to classify four species, sugar maple (*Acer saccharum*), trembling aspen (*Populus tremuloides*), jack pine (*Pinus banksiana*), and eastern white pine (*Pinus strobus*), with an overall accuracy of 77.5% using only full waveform data.

Finally, characterizing the forest floor is used to help classify site series. The forest floor is made up of organic matter that has fallen from the vegetation above (i.e., leaves, twigs, bark); it exists in various decompositional states, and organic matter can be macro sized (upper litter layers) or indistinguishable (lower humic layers). No studies were found that used ALS to specifically describe these characteristics. The primary studies that use ALS to measure or describe a forest floor characteristic are associated with forest fuel loads and are not directly applicable to TEM classification methods.

Table 2 Primary papers used in the literature review to assess the capability of ALS to classify TEM based attributes. DTM=digital terrain model; DEM=digital elevation model; NDVI=normalized difference vegetation index; SD=standard deviation; CHM=canopy height model

Authors	Remote Sensing Technology	Primary Metrics	Classes
Akumu et al. 2015	ALS	Elevation, slope, surface curvature, wetness index, slope position	Soil texture: clay, coarse loamy, coarse sand, fine sand, organic, silt
Alberti et al. 2013	ALS	Stem density, tree height, crown depth	Deciduous/coniferous classes; forest structural class (scrubland, regeneration phase, thicket, pole wood, adult forest, mature forest, multilayer forest)
Anders et al. 2011a	ALS	Elevation percentile, slope angle, topographic openness, hydrologically conditioned DEM, Upstream area	Glacially eroded bedrock, ablation till, fluvial incision, river terrace or recent streambed, deep-seated mass movement, shallow mass movement, fall deposits, flow and/or slide deposits and gypsum karst
Anders et al. 2011b	ALS	Slope angle, topographical openness, elevation percentile, hydrologically conditioned DTM, upstream area,	River terrace, gypsum sink holes and fluvial incision
Anders et al. 2013	ALS	Slope angle, shaded relief, and two relative elevation and topographic openness layers, upstream area	Glacially eroded bedrock, fluvial incisions, recent fluvial deposits, fluvial terraces, alluvial fans, slopes subject to shallow mass movement processes, and flow/slide deposits
Aspinall & Sweeney 2012	ALS	Slope, hydrologically conditioned DEM, hillsheds, peaksheds and pitsheds	Soil series/slope classes
Brasington et al. 2012	TLS	Rugosity, local slope, surface relief, elevation	NA-spatial pattern of particle size, grain roughness, and sedimentary facies
Colgan et al. 2012	Hyperspectral ALS	NDVI, various crown and height metrics	15 tree species
Dalponte et al. 2012	Hyperspectral ALS	Max height, interquartile range of all heights, 50th, 75th, 90th and 95th percentiles	Macro-classes (forest/non forest, coniferous/broadleaf); Forest types Maple-Ash, Fir-Beech, Pine, Spruce replacement, Mugo Pine shrubbery; Seven tree species

Authors	Remote Sensing Technology	Primary Metrics	Classes
Farrell et al. 2013	ALS Aerial photographs	Tree height, canopy density	NA-used to improve bird species distribution models
Garcia-Feced et al. 2011	ALS	Crown radius, tree height	NA-detecting residual trees for owl habitat
Greaves et al. 2016	ALS, multispectral	Canopy volume, veg density, max height, SD max height, topographic position index, hillshade, wetness index, openness, NDVI, 2GRBi (excess greenness)	NA-shrub biomass
Greve et al. 2016	ALS	Elevation, slope gradient, slope aspect, plan curvature, profile curvature, flow direction, flow accumulation, topographic wetness index	Clay, silt, fine sand, coarse sand
Heung et al. 2014	ALS	Elevation, slope, aspect, and curvature, wetness index, convergence index, relative hydrologic slope position, normalized height, slope height, sky view, terrain view, distance to nearest stream and river	Parent material: colluvial, eolian, fluvial, glaciofluvial, lacustrine, glaciolacustrine, morainal, marine, glaciomarine
Jones et al. 2012	ALS	Height percentiles (10, 20, 30, 40, 50, 60, 70, 90, 95 and 99th), mean standard deviation, variance, coefficient of variation, max height, kurtosis, skewness, harmonic mean, closed gap, oligophotic, euphotic, open gap, total cover	Structural stages (sparse/bryoid, herbaceous, shrub/herbaceous, pole/sapling, young forest, mature forest and old forest)
Kumar et al. 2015	ALS	NA: Point cloud used-horizontal and vertical cluster patterns analyzed	30 different canopy structure classes
Latifi et al. 2015	Full waveform ALS	Various height and density metrics	NA-density described for 5 canopy layers
Leiterer et al. 2012	Full waveform ALS	Amplitude, width and intensity of vegetation echos, height metrics	Understory 0.5 – 3 m, < 0.5 m, litter, non-vegetated

Authors	**Remote Sensing Technology**	**Primary Metrics**	**Classes**
Li et al. 2013	ALS	Angular second moment, contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measure of correlation 1, information measure of correlation 2, and maximal correlation coefficient	Trembling aspen, sugar maple, jack pine, and white pine trees
Lopatin et al. 2015	ALS	CHM split into height ranges: >16 m, 8-16 m, 2-8 m, 0-2 m	NA-species richness
Luscombe et al. 2014	TLS, ALS	Hillshade, pixel density, canopy height metrics, aspect	ALS classes: surface-drainage networks (natural or artificial and rush dominated); stream order
Maynard & Johnson 2014	ALS	Elevation, slope gradient, aspect, profile curvature, plan curvature, longitudinal curvature, cross-sectional curvature, minimum curvature, and maximum curvature	Clay, sum of bases, and total carbon
Reese et al. 2014	ALS, optical satellite data (SPOT)	Elevation, slope, aspect, wetness index, 95th and 99th height percentiles, vertical canopy density metrics, mean and SD of height, veg ratio, SD of veg ratios, NDVI and NDII (normalized difference infrared index)	9 vegetation classes
Simonson et al. 2014	ALS	95th quantile height, standard deviation, skew, foliage projected cover, veg permeability, mean veg height, mean understory height, foliage height diversity	6 vegetation communities
Thompson et al. 2016	ALS Multispectral	Elevation, mean height, max height, coefficient of variation, NDVI, Slope, topographic position index, topographic radiation aspect, topographic wetness index	18 ecosystem clusters, river, pond

Authors	Remote Sensing Technology	Primary Metrics	Classes
Tiede et al. 2012	ALS	Pixel statistics: min, max, median, SD, sum etc. of the intensity value, point height value and number of points per object	Tree crown objects. Deciduous/coniferous
Van Aardt et al. 2011	ALS	Height metrics	NA: Coarse woody debris modelling
Van Asselen and Seijmonsbergen 2006	ALS	Elevation, slope angle	Fluvial terrace, Alluvial Fan, Slope with mass movement, Talus slope, Rock cliff, Glacial landform, Shallow incised channel and Deep incised channel
Yang et al. 2014	Rapideye, ALS	canopy height, percentile heights (50, 75, 80 and 95), percentage of returns above a pre-defined set of height break values ranging from 1.4 to 21.4 m using a 2-m step, average intensity, slope, aspect, NDVI	Species: trembling aspen, Balsam popular, white spruce, black spruce, tamarack, and jack pine
Zhang et al. 2016	ALS, hyperspectral	CHM, NDVI, 118 spectral bands	Seven tree species

2.4 The road to mapping ecosystems with ALS data

Considerations

The most practical form of ALS for ecosystem mapping is likely to be discrete return ALS because it is more available than full waveform and it can cover areas that are not practical for terrestrial laser scanning. Point densities can vary between 1 and 15 points/m^2. Increasing point density will likely improve feature identification, classification, and subsequent ecosystem mapping. For example, Wu et al. (2016) compared five data sets of varying point densities from 0.5 to 8.0 points/m^2 and found that for aboveground biomass, estimate errors decreased alongside increasing point density. With regard to terrain features, Anders et al. (2013) classified geomorphic features using data sets with point densities of 0.8 and 7.5 points/m^2; these produced an average accuracy of 0.66 and 0.79, respectively. Increased point density has subsequently larger storage and increased processing time and power requirements. Depending on the application or even the terrain features, lower point densities could be sufficient. Coarse landforms or open forests do not require the same detail to identify features or understory shrubs. Subtle, micro-terrain or closed canopies may require higher point densities for accurate interpretation of features.

The quality of ALS data collected directly relates to the quality of classification output (Anders et al. 2013). Vegetation (leaf-off versus leaf-on) and ground (snow cover) conditions during data acquisition can affect data quality. However, White et al. (2015) found no significant difference ($p < 0.05$) between most leaf-on and leaf-off ALS metrics used in area-based models. Canopy density metrics for deciduous trees and the fifth height percentile for coniferous trees were significantly different based on leaf conditions. ALS has contributed to the advancement of cryospheric research on features such as snow cover, glaciers, ice sheets, and permafrost (Bhardwaj et al. 2016). It does not however, penetrate snow, and to obtain the most accurate terrain metrics, data acquisition must occur while the ground is snow-free.

Ranking feasibility

Criteria used to classify ecosystem attributes that are highly feasible to attain using ALS data and which can be used in additional research are canopy characteristics, stand height, and topography (Table 3). While not stand-alone criteria for ecosystems, these attributes do provide a reliable and essential base for predictive modelling. Conversely, attributes that are currently not feasible to classify with ALS data are soil depth and forest floor (Table 3). Inferring soil depth, and to a lesser extent, soil order, based on terrain attributes and geomorphologic process is possible. However, depth classifications would likely be very broad and the resolution too coarse for reliable accuracies to be reached (e.g., valleys have deep soil; steep slopes have shallow soil). Additionally, using ALS data to describe the forest floor is currently not likely given that they provide minimal information that can contribute toward ecosystem classification.

Table 3 Feasibility of using ALS data to describe criteria for attribute classification.

	High Feasibility	Moderate Feasibility (requires more research)	Low Feasibility
Criteria for classification	Canopy characteristics Stand height Topography[a]	Geomorphological process Drainage pattern Terrain attributes[b] Soil drainage Tree species composition Understory or non-forested vegetation composition	Soil depth Forest floor

[a] Includes landscape position and shape, aspect, slope, and drainage pattern.

[b] Includes texture, parent material, surface expression, and qualifiers.

The important next step is to use the well-established ALS-based metrics and integrate them with the classification of the less established ecosystem attributes: geomorphic process, drainage pattern, terrain attributes, soil drainage, tree species composition, and understory or non-forested vegetation composition (Table 3). The use of ALS data to classify these attributes independently is increasing. The integration of this knowledge into a workflow alongside the well-established metrics has yet to be used to test the feasibility of ALS-based ecosystem mapping.

Next steps

Terrain attribute criteria that are most plausible to successfully classify using ALS are surface expression (e.g., blanket veneer, terrace, hummock) and surficial material (i.e., parent material). Drainage patterns can be discerned from hydrologically conditioned DEM and can form a critical component for classification of soil drainage (e.g., poorly drained, well drained). Geomorphological classification from ALS data has had marked success through the work of Anders et al. (2011a, 2011b, 2013) and van Asselen & Seijmonsbergen (2006). The most appropriate layers to use for the delineation and classification of terrain attributes, drainage pattern, and geomorphic process will need to be tested. However, topographic openness (Yokoyama et al. 2002 in Anders et al. 2011a), elevation percentile (Gallant & Wilson 2000 in Anders et al. 2011a), surface curvature (Akumu et al. 2015), Topographic Position Index (TPI), (Jenness 2006 in Akumu et al. 2015), and slope angle (Burrough & McDonnell 1998 in Anders et al. 2011a) have all been shown to be useful (Figure 2).

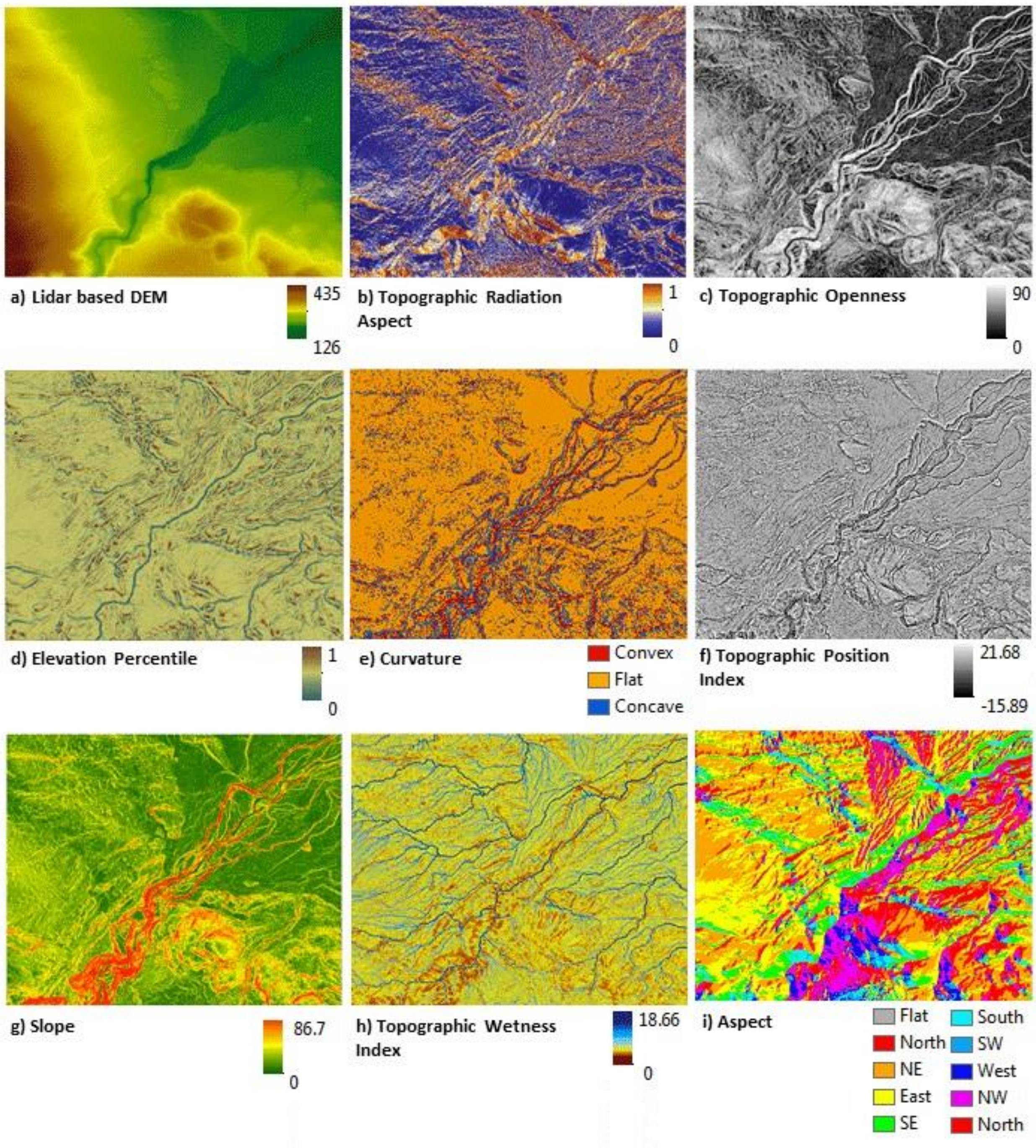

Figure 2 Example of various terrain metrics that can be calculated from an ALS based DEM and used for mapping ecosystems

For vegetation layers, delineation and classification could be improved by using the ALS point cloud rather than just using ALS-based DEMs (Tiede et al. 2012). It is expected that coniferous and deciduous trees can be distinguished and the structural stage (e.g., herbaceous, shrub, mature forest) identified with ALS data. For species classification, it is anticipated that spectral data will be an important addition to ALS data, as will indicators of the local environment, including terrain attributes such as Topographic Wetness Index (Figure 2) (Tarboton 1997 in Thompson et al. 2016), Topographic Radiation Aspect (Figure 2) (Roberts & Cooper 1989 in Thompson et al. 2016), gap fraction (Thompson et al. 2016), Normalized Difference Vegetation Index, height percentiles (Jones et al. 2012), canopy height descriptors, and volume profiles (Jones et al. 2012).

Suggested methods

Within the current science, a wide variety of techniques for attribute classification exists, the most plausible being Object-based Image Analysis. Object-based approaches are applied directly to the point cloud or to rasterized canopy or terrain models and/or images (Höfle & Rutzinger 2011). Generally, these approaches first spatially segment (i.e. delineate) the surface into homogeneous areas to define patches of points or pixels, which represent a part of an object. Segments are then merged to create an object of interest by applying a classification on statistical features. Features that describe segments can be either related to the statistical distribution of the point or pixel values within them or to their geometrical and topological characteristics, such as segment shape, size, and neighborhood relations.

It is likely that the best method will be to use a stratified approach that first segments and classifies individual ecosystem attributes (e.g., geomorphic process) to feature type (e.g., snow avalanches, gully erosion) and then applies all of these layers to segment and classify ecosystem type. For Object-based Image Analysis methods, objects can be created from ALS-derived DEM data but also from almost every other continuous data set of an area, like optical imagery, or already existing classifications (e.g., cadastral maps, soil maps, land use/land cover maps, forest inventory maps) (Tiede et al. 2012). However, at a provincial level, many of these data are not available, so it will be important that attributes can be classified without these data or that areas that do have multiple data sets (such as many Tree Farm Licenses) are mapped first. Implementation of automated methods will be important to ecosystem classification and mapping. By using automated methods, analysis becomes easier to replicate and update.

Chapter 3: Classifying and mapping site series in coastal British Columbia using Airborne Laser Scanning

3.1 Introduction

Landforms and their modification of climate, influence the structure and composition of vegetation for a given area (Rowe 1996). Boundaries between relatively homogeneous sites are typically gradual, and species composition overlaps and changes across various aspects and slope positions (Bailey 1985). There are often many interactions and dependencies, such as energy and water movements, that link sites (Bailey 1987), and mapping ecosystems at the site level can strengthen our ability to understand and manage landscapes. As discussed in the earlier chapters, the Terrestrial Ecosystem Mapping (TEM) approach used in British Columbia primarily uses aerial photography and fieldwork to identify and delineate ecosystem patterns and define classes. In the TEM system, site series is the finest scale used to classify ecosystem type at the site level and describes the potential climax community for a site, as indicated by the soil nutrients and moisture in a location.

The current practice for mapping site series through TEM in BC can be labour intensive, requiring the input of expert ecologists, who preferably are familiar with the location being mapped, and additional field verification. Due to the level of detail required and often, difficult terrain (limited accessibility) of the landscapes, this is a time consuming and expensive process. Field observations in hard to access areas are often limited, and thus, interpretations of data may be subject to bias. With the continued advancement and application for ecosystem attribute mapping using remote sensing, testing the capacity of these technologies to map site series is the next logical step.

Mapping Site Series

A site series is the suite of sites within a BEC subzone or variant (i.e., subregional climatic envelope) that support the same (potential) mature plant community (Pojar et al. 1987). Site condition (and potential vegetation) is determined by attributes such as warmth (e.g. south slopes are warm, or a depression may experience cold air ponding), moisture, which is influenced by soil texture and slope position (e.g. sandy soils drain quickly, depressions hold water longer), slope position (e.g. ridge crests have fewer nutrients and more exposure to sun and wind), and slope angle (e.g. steep slopes may have shallower soils and drain water relatively rapidly). All of these attributes are connected and sometimes attributes compensate for each other. An attribute that tends to increase moisture may compensate for an attribute that tends to decrease moisture or nutrient availability nutrients (e.g., coarse-textured soil in a lower slope position) (Green and Klinka 1994). Thus, site series can be difficult to predict, especially if soil type is unknown. One outcome, regardless of the factors at play, is the composition and structure of a site's vegetation (Swanson et al. 1988).

Mapping site series has largely depended on using vegetation as the indicator of site level moisture and soil nutrients. However, this has limitations. With climate change affecting tree line positions and species migration (Aitken et al. 2008; Potter et al. 2017), late successional species are changing, and the full dynamics of this transition are not fully understood (Aitken et al. 2008, Prasad et al. 2016; Wang et al. 2016). Defining ecosystems based on climax vegetation potential could be difficult in this changing environment, especially for an area that is in post disturbance and early successional stages. What the late successional vegetation for a site will look like in 100 years is no longer something that can be easily predicted.

Additionally, mapping site series based on vegetation can be difficult in areas that have been heavily harvested or have experienced widespread natural disturbances (e.g. fire, insect) and for which no seral classification currently exists. It can be difficult for the human interpreter to segment or classify site series from aerial photography in this scenario. Fieldwork to verify site conditions and /or knowledge of the specific location will be required. Since species composition is, in part, a result of topography, it is reasonable to assume that using topographic information for mapping site series would confer advantages. Even as species composition changes in future decades, being able to segment a site based on attributes that are typically slower to change (e.g. drainage, aspect, and slope position), allows room for refining definitions and predictions surrounding ecosystem ecology for a given location. The goal of this study was to use the inventory of ALS-based approaches compiled in the previous chapter to guide site series classification of a test landscape with an existing Terrestrial Ecosystem Map, using ALS derived vegetation and terrain metrics both in isolation and in combination.

3.2 Study Site

The study site is approximately 25-km^2, near Campbell River, BC located within the very dry-maritime Coastal Western Hemlock Biogeoclimatic subzone (CWHxm) (Pojar et al. 1987) (Figure 3) The CWH zone has 10 subzones (Figure 4), which vary in precipitation and continentality. The study site spans the east (CWHxm1) and west (CWHxm2) variants of the subzone with annual precipitation averaging 1500 mm and temperature averaging 9.1°C (Pojar et al. 1991). This subzone has a maritime climate with typically cool summers and mild winters, though some years dry conditions dominate summer. The study area has an elevation ranging from 120 - 460 m, and is within 10 -15 km from the coast. Douglas-fir (*Pseudotsuga menziesii*) is the dominant tree species on dry to mesic site series, though wetter site series will contain (relatively more) western redcedar (*Thuja plicata*) and western hemlock (*Tsuga heterophylla*) (Green and Klinka 1994). The study site has a history of harvesting. When the ALS data was acquired (2004) much of the overall area had been harvested within the past several decades. Soils within the area range from very gravelly textured Duric Humo-Ferric Podzols of fluvial origin at low elevations, to gravelly sandy loam textured Duric Humo-Ferric and Ferro-Humic Podzols of morainal origin at intermediate elevations to shallow stony Ortho Humo-Ferric Podzols on colluvium on higher elevation hilltops (Jungen 1985).

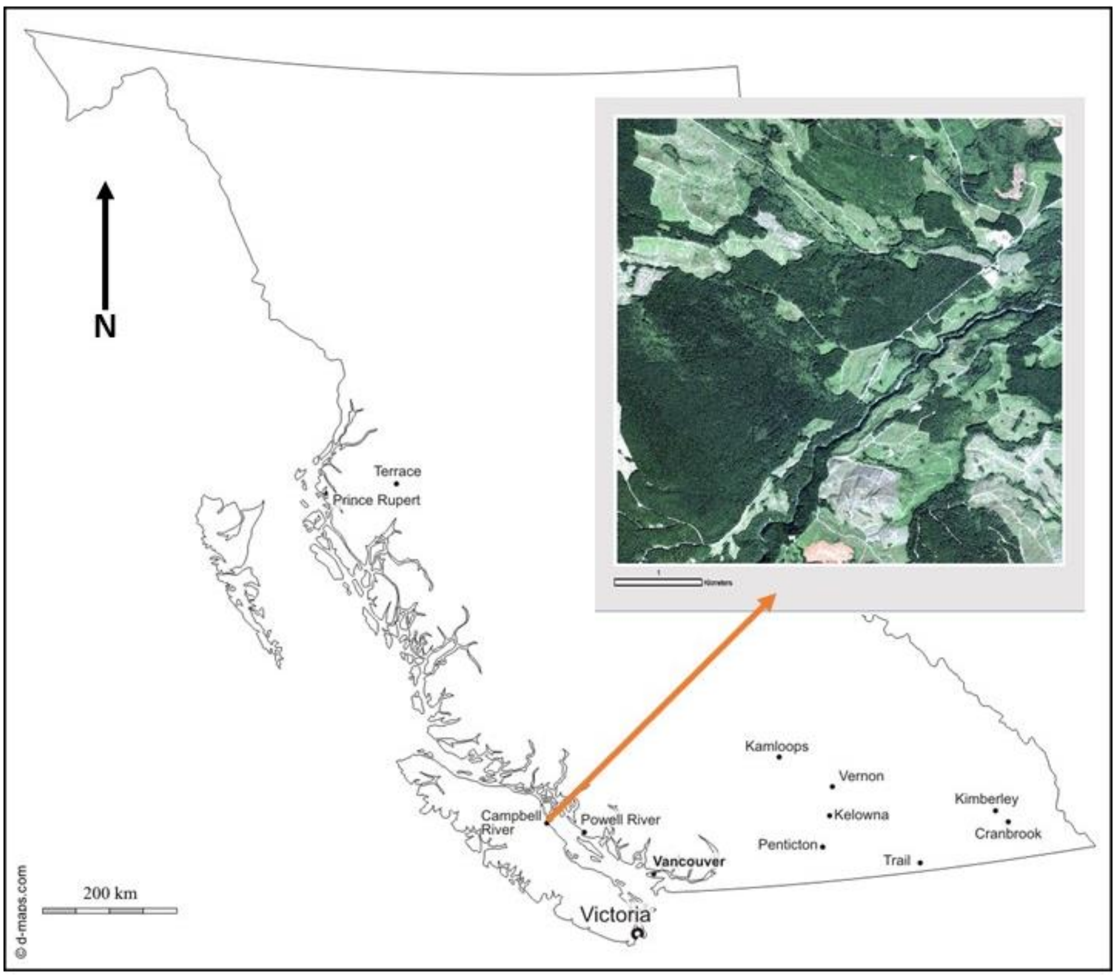

Figure 3 Approximate location of study site (Quickbird image), which is near Campbell River, British Columbia

Site Series

The TEM classification was provided by the Canadian Forest Service (CFS 2005). The CFS compiled source data provided by Timberwest and Weyerhauser in 2005, the two forest companies that were operating in the area. The CFS completed GIS operations to combine the two datasets along the boundary within the study area (CFS 2005). The study site contains nine site series and five non-vegetated/sparsely vegetated or anthropogenic units (14 total) according to the TEM map. The mapped area of each of nine of these 14 classes made up less than 1% of the total mapped area. For simplification, these minor classes, with the exception of the water bodies (river and pond), were grouped and not discriminated. As a result, the major TEM site series and non-vegetated units, which were the focus of this study, are show in Table 4.

Table 4 Site series and non-vegetated unit descriptions for the study area

Site Series Code	Site Unit Name	Dominant Tree Species	Primary Understory Species	Slope Position and Angle	Aspect	Drainage [1]
01	Western hemlock-Douglas fir-Oregon beaked moss	Western hemlock Douglas-fir	Feather mosses (e.g. Oregon beaked moss) Salal Dull Oregon Grape Red huckleberry	Varied	Varied	m-w
03	Douglas-fir western hemlock-salal	Douglas- fir Western redcedar Western hemlock	Salal	5-100% Upper slope or valley bottom	Varied	w-r
05	Western redcedar-sword fern	Western redcedar Western hemlock Grand fir Douglas-fir	Sword fern Salal Red huckleberry	10-100% Mid-slope	North facing (285-135°)	m-w

Site Series Code	Site Unit Name	Dominant Tree Species	Primary Understory Species	Slope Position and Angle	Aspect	Drainage [1]
07	Western redcedar-foam flower	Western redcedar Western hemlock Red alder Grand fir Bigleaf maple	Dull-Oregon grape Salmonberry Thimbleberry Herbs (e.g. foam flower; swordfern)	Toe slopes Level sites with poor drainage	Varied	i-m
12	Western redcedar-Sitka spruce-skunk cabbage	Western hemlock Sitka spruce Red alder Big leaf maple	Salmonberry Thimbleberry Skunk cabbage	0-10% Depressions	Varied	p
RI	River	NA	NA	Depression	NA	p
PD	Pond	NA	NA	Depression	NA	P

[1] r=rapidly drained; w=well drained; m=moderately well drained; i=imperfectly drained; p=poorly drained

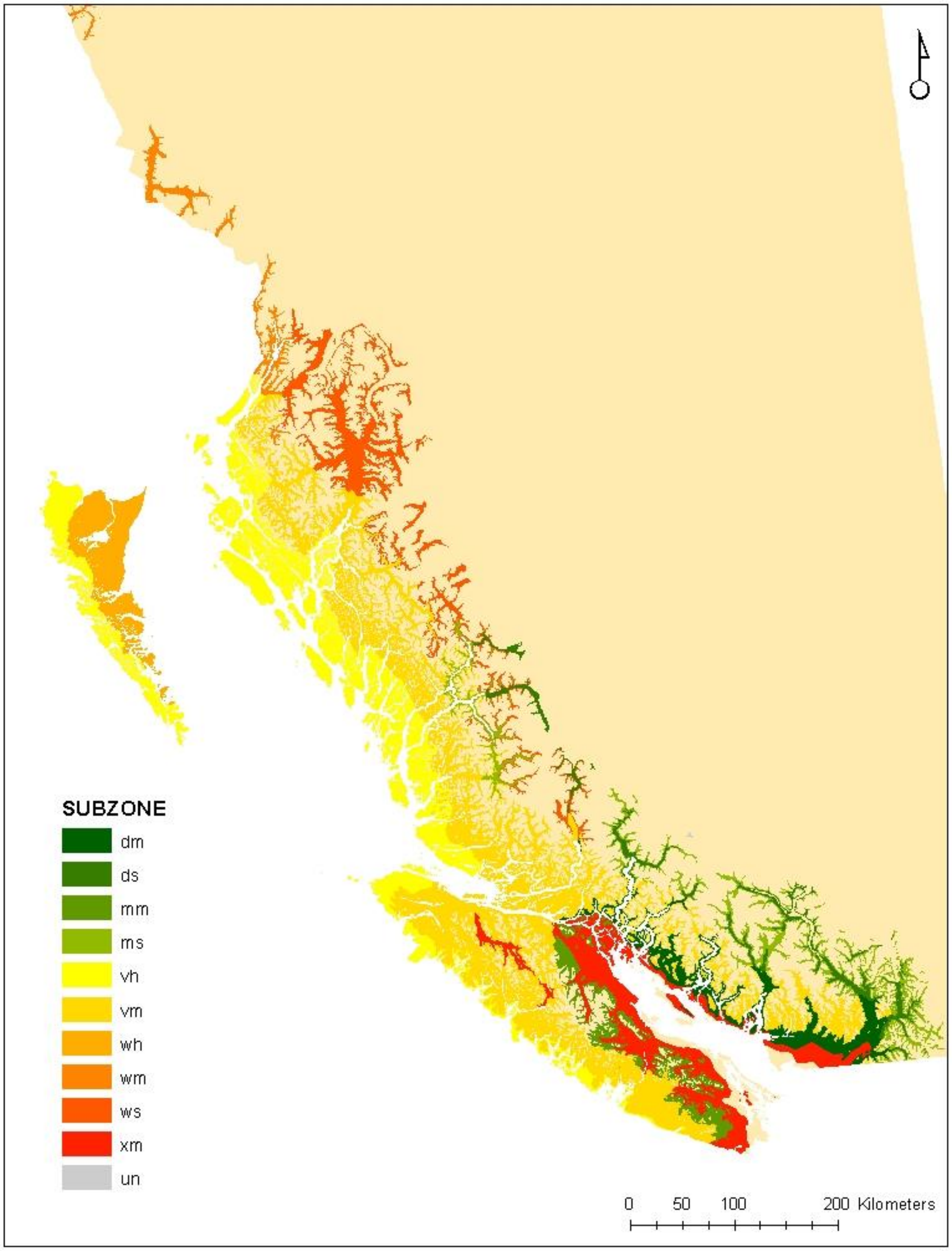

Figure 4 Subzones for the British Columbia's Coastal Western Hemlock Zone. The study site is located within the xm subzone. Name codes are: x = very dry; d = dry; m = moist; w = wet; v = very wet; h = hypermaritime; m = maritime; s = submaritime; un = undifferentiated.

3.3 Data acquisition

Airborne laser scanning data were acquired June 8, 2004, using the Terra Remote Sensing's (Sidney, British Columbia, Canada) ALS instrument on a Bell 206 Jet Ranger helicopter. Based on the pulse frequency, lowest sustainable flight speed and altitude, ground point sampling densities of 0.7 m–2 were achieved with a beam footprint (ground spot size) of 0.19 m diameter (Coops et al. 2007). Separation of ground versus non-ground (canopy) hits was conducted using Terrascan v4.006 (Terrasolid, Helsinki, Finland). Additionally, a 2-m gridded digital elevation model (DEM) was developed from all ALS ground hits using GIS-based DEM generation software (Arc/Info, TOPOGRID), based on the ANUDEM program (Hutchinson 1989). All ground classified ALS hits were used in the DEM development and all non-ground ALS hits were subtracted from the topographic surface to produce a canopy height model (CHM).

3.4 Methodology

Object Based Image Analysis

Object-Base Image Analysis (OBIA) approaches are increasingly being used as a tool for analyzing and classifying remotely sensed data. Object-based approaches can be applied either directly to an ALS point cloud or to rasterized canopy or terrain models (Höfle and Rutzinger 2011). Often OBIA uses a multiresolution segmentation algorithm to spatially segment the surface into homogeneous areas, which represent an image object. Objects are then classified using rules based on statistical features. Features describing objects can be either related to the statistical distribution of the point or pixel values within them, or to the features' geometrical and topological characteristics, such as segment shape, size, and neighborhood relations.

Object-Based-Image-Analysis allows for the integration of multiple data sets (thematic or raster) in both the segmentation and classification. The data used at each stage can be different. Multi-resolution segmentation approaches uses input layers as criteria for calculating the heterogeneity of pixels within a defined object size threshold. The size of the image objects created is controlled by the scale parameter. Larger objects contain more information and affect the scale at which classification can be performed. If objects are too small, there is not enough information for classification; on the contrary, too much information makes class-specific heterogeneity harder to define (Anders et al. 2011a). The goal is to have image objects similarly sized, or slightly smaller, than the features being classified (Anders et al. 2011a). Likewise, if too many layers are used as inputs, segmentations may lose meaning. Therefore, it is critical to determine both the scale and input layers most suitable for the features being mapped.

In the classification process, rules can either be pre-established based on existing information or manually applied using tools such as feature view (Cleve et al. 2008; Aksoy & Ercanoglu 2012). Feature view allows the values of a chosen metric to be represented on a colour gradient from blue to green, with green representing higher values. Value thresholds can then be tested to determine which objects would be classified in the given threshold. Object-Based-Image-Analysis is ultimately a trial-and-error approach, controlled by the interpreter (Yildiz et al. 2012; d'Oleire-Oltmanns 2013; Kolecka et al. 2014). The interpreter is typically an expert in the field for the feature being mapped and ideally, familiar with the landscape being mapped. If classification rules can be identified through successive classifications that have high validation accuracies, the segmentation parametrization and classification rule setting can become increasingly automated with a reduced trial-and-error approach (Anders et al. 2011a).

Workflow overview

Landform directly influences ecosystem patterns and processes. Elevation, aspect, and slope angle influence air and ground temperature and the quantities of moisture and nutrients available, which in turn, are expressed in the composition and structure of vegetation (Swanson et al. 1988). Vegetation patterns resulting from these influencers can been observed across landscapes at varying scales from a few to thousands of hectares (Billings 1973; Bailey 1987; Swanson et al. 1988). Based on this understanding, the workflow implemented here begins by using terrain indices to segment and create broad classes (slope position and wetness) that are then used to classify site series. Vegetation metrics are used to distinguish site series within the broader classes. ALS vegetation data for the study area were limited due to recent harvesting and could not adequately be used to test applicability of vegetation information to the segmentation and broader classification.

The workflow implemented for this study is highlighted in Figure 5. Both the segmentation and classification stages are stratified into multiple steps. The primary steps for the entire process include: (1) Data preparation; (2) Find the best segmentation parameters; (3) Segment and classify the river; (4) Segment for site series; (5) Classify moisture; (6) Classify slope position-wetness; (7) Classify site series (8) Accuracy Assessment

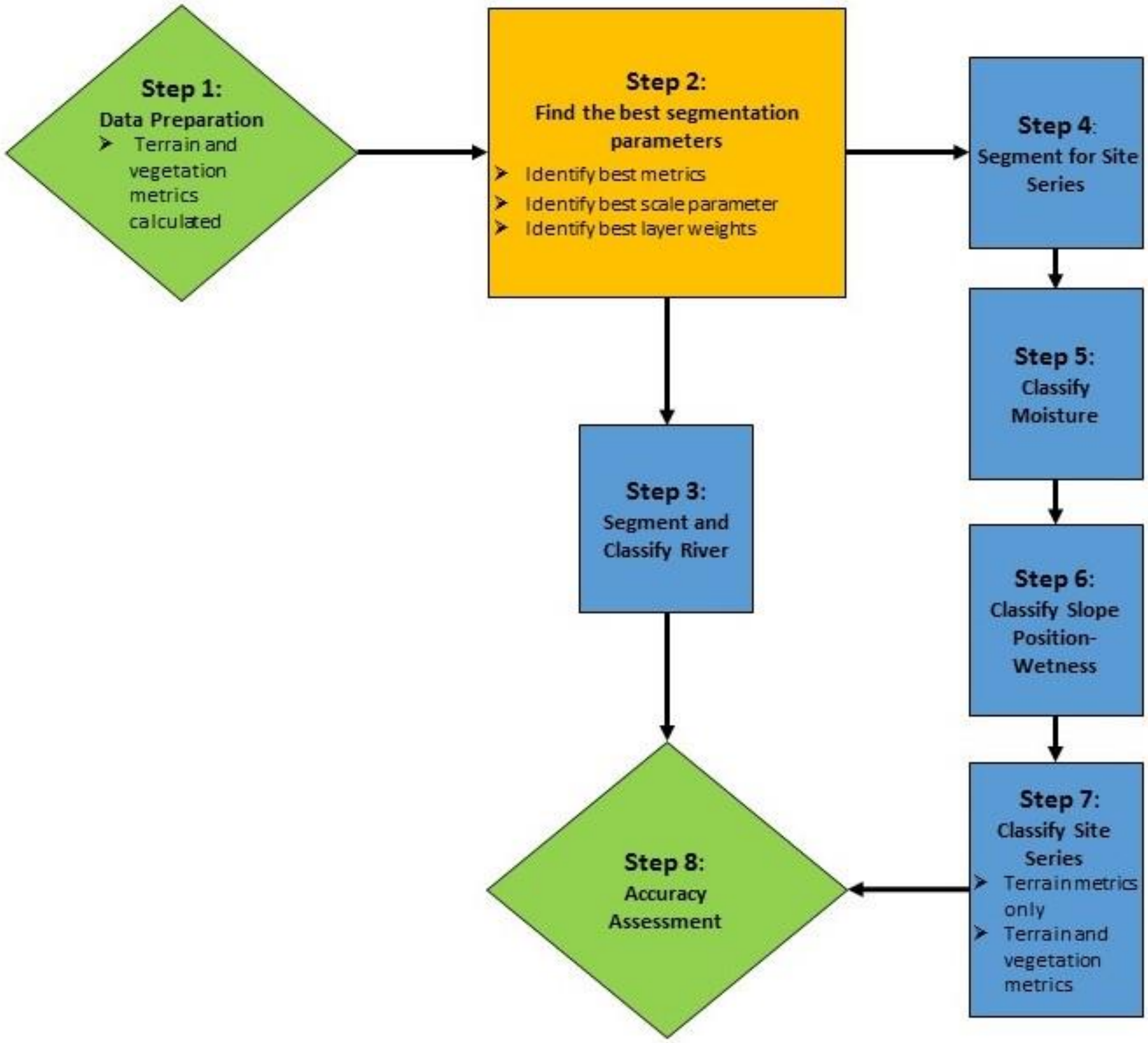

Figure 5 Overview of workflow used for this study. Segmentations are performed on individual pixels and classifications are performed on objects or existing classifications

Data Preparation and Derivation of ALS metrics

Various studies that have used ALS data to map ecosystem attributes have implemented a wide range of metrics for both terrain and vegetation classifications (Thompson et al. 2016; Campbell et al. 2017). Terrain metrics can describe the position of a given location on the landscape (e.g. slope, aspect, elevation or openness) and indicate how water flows through it. Vegetation metrics often relate to the structure and composition (e.g. tree heights or canopy density).

In step 1, a number of metrics were extracted from the ALS data based on the review in Chapter 2 and are described in Table 5. All terrain metrics were calculated from the ALS derived DEM in ArcGIS or in R-studio when an ArcGIS tool did not exist to perform the calculation. Vegetation metrics were calculated from the canopy height model (CHM) and processed using FUSION software (McGaughey 2014). A grid cell size of 20 was used for the vegetation metrics and a height break of 2 m was used (Magnussen & Boudewyn 1998; Næsset 2002).

Table 5 Terrain and vegetation metrics used for the segmentation and classification of site series

Metric	Derivation	Interpretation
Elevation	Height, in metres, above sea level. Derived directly from the 2 m DEM.	Study site elevations range from 126 m to 435 m.
Elevation Percentile (EPC)	The percentage of cells lower than a centre cell in a given neighbourhood. A neighbourhood of 25-m was used (Gallant & Wilson 2000).	Provides information about a specific location relative to its surrounding. Values closer to 0 are lower in their surrounding landscape (valleys), while values closer to 1 are higher (ridge).
Slope angle	The maximum rate of change between each cell and its neighbours.	Slope in the study site ranged from level (0°) to very steep (87°)
Topographic Openness (TO)	Calculated as the mean angle between a centre cell and its surrounding cells in 8 directions (Yokoyama et al. 2002). A neighbourhood of 25 m was used for this study.	The degree of enclosure of a particular location within a landscape
Topographic Position Index (TPI)	The difference between a cell elevation value and the mean elevation of its surrounding cells (Jenness 2006). Neighbourhoods of 10 m (TPI10) and 500 m (TPI500) were calculated.	Smaller neighbourhoods highlight detailed slope position; for example, a small depression on a ridge would likely be included as a ridge in a larger neighbourhood.
Topographic Wetness Index (TWI)	TWI = ln (flow accumulation)/tan(slope)) (Beven and Kirkby 1979) Flow accumulation calculated using the D8 algorithm.	Measure of wetness based on flow accumulation and slope. Higher values are increasingly wet and lower values are drier.
Topographic	TRASP = (1-cos (3.1416/180) (aspect-30)))/2,	Measure of slope warmth based on

Metric	Derivation	Interpretation
Radiation Aspect (TRASP)	where aspect is in degrees (Roberts and Cooper 1989).	aspect. Values closer to 0 are cooler (N, E, NE, NW) and values closer to 1 are warmer (S, W, SW, SE).
Drainage Network	Log^{10} of the flow accumulation value for each cell with a contributing area greater than 100 m^2	Not used directly in the OBIA process but used to identify the primary drainage pathways and visually confirm that classes are logical.
Gap Fraction	Ratio of total numbers of ALS points < 2 m to the total number of returns within a grid cell (Hopkinson & Chasmer, 2009).	Measure of how dense a canopy is. Higher values represent lower canopy cover.
Height max	Based on the CHM. It is the highest return value (m) per grid cell.	Height of the tallest tree (or shrub) in a grid cell
Height mean	Mean of return height values (m) ≥ 2 m per grid cell.	The average height of trees within a grid cell
Coefficient of Variation (CV)	Second central moment about the mean.	Describes vegetative vertical heterogeneity; higher values have greater heterogeneity.

Step 2: Find the best segmentation parameters

Segmentation was performed using eCognition software. In step 2 (Figure 5), the optimum segmentation parameters were determined through a multistage process. To determine the most appropriate terrain indicators and the optimum combination of input metrics for the study site, each possible combination of three, four, and five metrics was produced from the seven terrain metrics (91 total combinations) and segmentation was performed using a set scale parameter of 100. All segmentation objects were exported as shapefiles into ArcGIS and were overlaid with the TEM map, and a visual comparison of boundaries of the segmentation objects and the TEM polygons boundaries was performed (Zhang et al. 2008; Albrecht et al. 2010; Johnson and Xie 2011). The 10 combinations of metrics that produced units that best (visually) coincided with the TEM polygons were then applied using eCognition software to test for the best scale parameter.

To determine the most appropriate scale parameter, a second test was performed where each of the 10 different combinations of input metrics were segmented with scale parameters varying from 40 - 90 at intervals of 10. This produced a new set of 60 segmentation outcomes (10 input combinations of metrics at 6 different scale parameters each). Again, the segmentation outcomes were imported to ArcGIS and visually assessed relative to the TEM map..

Lastly, using eCognition, the best six combinations of metrics (with their associated scale parameters), were segmented again, but with varying image layer weights. Outcomes were visually assessed and image layer weights adjusted accordingly.

Step 3: Segment and classifying the Oyster River

Segmenting objects that identified the primary river (i.e. Oyster River) through the study area was performed in step 3. Once objects were created that included the river by following the process described in Step 2, classification rules were applied and the objects classified as 'river' were then merged.

Step 4: Segment for site series

In step 4, once the river segments were identified, segmenting for site series was then performed. The best parameters, established in step 2, were used to segment the landscape. The segmented objects created in this step were then used in three subsequent steps to assign site series. First each polygon was assigned a moisture class, then a topographic position and finally classified into one of the existing site series classes. These are described below as steps 5, 6 and 7.

Step 5: Assign moisture classes to each delineated site series

In step 5, classification rules were applied to the site series based image objects. Moisture was classified using the ALS derived TWI, which is a steady-state wetness index that takes into account upslope catchment area (flow accumulation) and slope angle (Beven & Kirkby 1979). Ponds (there are no lakes within the study site) were also classified in this step. Wetness thresholds were based on the range of TWI values within the TEM based site series and were allocated as:

Pond: TWI $\geq$ 8.7
Wet: 6.4 $\leq$ TWI < 8.7
Moderate: 5.5 $\leq$ TWI < 6.4
Dry: 4.2 $\leq$ TWI < 5.5
Very Dry: TWI < 4.2

Step 6: Assigning slope position-wetness classes

In step 6, slope position-wetness (SP-W) classes were established. Topographic Position Index (TPI) was used to calculate slope position as defined by Jenness (2006). Threshold TPI values are established according to standard deviations from the elevation, which accounts for elevation variability within that neighborhood (Jenness 2006). Values near zero are either flat or mid-slope so slope angle is used to differentiate them. A neighbourhood of 500 m was used (Weiss 2001; Jenness 2006). The classification rules combined slope position with the wetness classes to create the SP-W class (e.g. If "Wet" had a -1 SD < TPI500 $\leq$ -0.5 SD than it was classified as "Toe Slope-Wet"; if "Dry" had a TPI500>1 SD than it was classified as "Crest-Dry" etc.). The slope position thresholds used to establish slope position were:

Depression: TPI500 ≤ -1 SD

Toe Slope: -1 SD < TPI500 ≤ -0.5 SD

Flat Slope: -0.5 SD < TPI500 < 0.5 SD and Slope ≤ 5°

Middle Slope: -0.5 SD < TPI500 < 0.5 SD

Upper Slope: 0.5SD < TPI500 ≤ 1 SD

Crest: TPI500 > 1 SD

Where TPI500 = Topographic Position Index with a 500 m cell window and SD=Standard Deviation

Step 7: Classify site series

In step 7, the final step was to assign TEM classes to each of the moisture and topographic position ranked polygons. Rules for site series classification were both semi-automated and manual. Rules for site series classification were first set according to Table 6. This table is based on information from several reports and manuals (Klinka & Demarchi 1991; Madrone Environmental Services Ltd. 2008) (initially summarized in Table 4) and inferences the average slope position and wetness for each site series as found throughout the CWHxm. The table was referenced in such a way, that if a single site series (e.g. SS 03) fell under a particular slope position-wetness class (e.g. Crest-Very Dry) then class would be re-classified as the associated site series. Classes are then manually refined based on applicable metrics (e.g. max height, TRASP) in an effort to differentiate between classes with homogeneous data. Manual refinement was aided by using the feature view tool in eCognition. Step 7 was performed twice, once using both vegetation and terrain metrics and another time using only terrain metrics.

Table 6 Site series (01, 03, 05, 07, and 12) and their primary associated wetness and slope positions within the CWHxm subzone. Multiple site series can exist in one slope position and share similar wetness thresholds. Thus further refinement is required for classification.

Slope Position	Wetness (moisture class)			
	Very Dry	Dry	Moderate	Wet
Crest	03	03, 01	-	-
Upper	03	03, 01	01	-
Mid	-	01, 05	01, 05	-
Flat	-	01	01, 07	-
Toe	-	01	01, 07	-
Depression	-	-	01	12

Step 8: Accuracy Assessment

Lastly, the site series classifications were validated using the TEM map as the reference. Following the methodology identified in Wulder et al. (2007), a stratified random sampling approach was used to identify samples for validation. An overall sample size of 1128 was selected using Equation 1 (Cochran & William 1997) where n is the total sample size, z is the percentile of the standard normal (1.96 for 95% confidence interval), m is the margin of error (0.02) and p is the assumed population proportion (0.85).

$$n = \left\{\left(\frac{z}{m}\right)^2\right\} X\ p\ x\ (1 - p)$$

Equation 1

Sample points were allocated to site series classes using Equation 2 (Czaplewski and Patterson, 2003). Where n_i is the sample size allocated to class i, p_i is the proportion of the total area mapped as i, n is the total sample size, and k is the number of classes (7).

$$n_i = \left\{ p_i \, X \, \left(\frac{n}{2}\right) + \left(\frac{1}{k}\right) + \left(\frac{n}{2}\right) \right\}$$

Equation 2

ArcGIS was used to produce the random samples with a buffer applied between class samples at a minimum of 10 m (Table 7). The accuracy assessment was carried out in R-Studio.

Table 7 Sample allocation for accuracy assessment of site series classification

Class	% of Total Area	Target Number of Samples
1	67.87	482
3	9.90	134
5	9.62	134
12	8.58	126
7	3.43	96
RI	0.55	78
PD	0.05	78

3.5 Results

Find the best segmentation parameters

Table 8 displays the optimal parameters found for segmenting both the river and site series by comparing the TEM polygons to the derived image objects. Overall, the comparison of the segmentation indicated that the optimal image object size, for capturing the site series boundaries, was smaller than the average TEM polygon size. Objects were later merged to create polygons more similarly sized to the TEM polygons. Figure 6 demonstrates these size differences between the TEM polygons and the segmentation results for the river and site series. The TEM polygons are generally larger than those segmented in the OBIA process are; however, their size range is much larger (note the small SS 05 connected to the SS 12 lower centre in the TEM image). A larger scale parameter results in larger image objects as seen in the river and site series segmentations (Figure 6). The larger image objects produced in the river segmentation often included multiple site series and did not align to the TEM polygon boundaries. Additionally, the shape of the image objects differed according to the metrics and the associated layer weights used (Table 8). The river segmentation included TWI, which was weighted more heavily than EPC or TO (1.5) and as a result, generally included drainage patterns in the image object boundaries more distinctly than the site series segmentation. Elevation was found to improve site series segmentation but it required a lower weighting (0.25) otherwise the image objects were narrow and distinctly shaped according to the elevation contours.

Table 8 Optimum segmentation parameters used for the river and site series

	Metric	Image Layer Weight	Scale Parameter
River	EPC	1	90
	TO	1	
	TWI	1.5	
Site Series	Elevation	0.25	45
	Slope	1	
	TPI10	1	

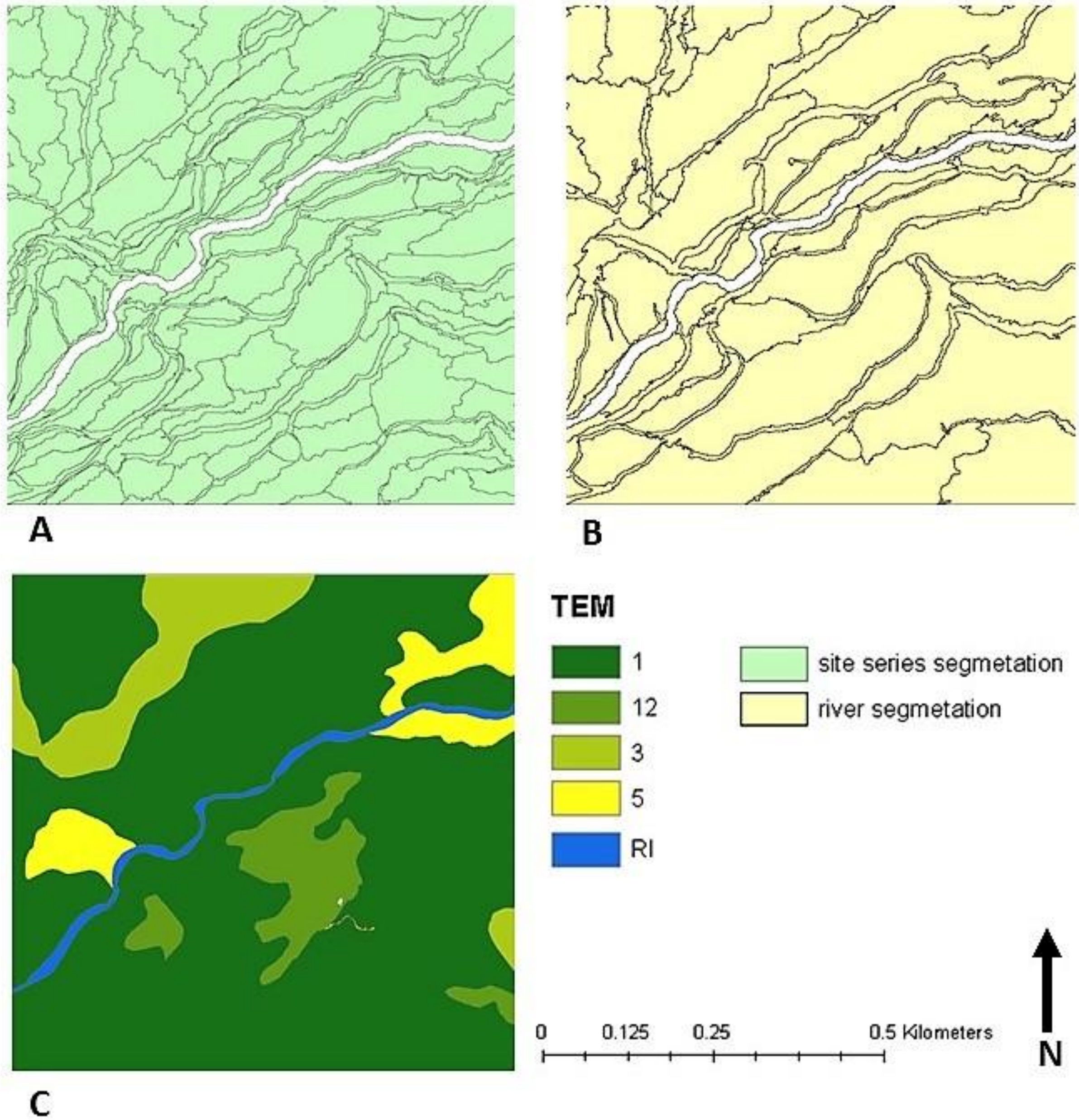

Figure 6 Enlarged section of study area segmentation results for site series and the Oyster River compared to TEM polygons. A shows the segmentation for site series; B shows the segmentation for the river and C is the reference TEM (classified for site series within the CWHxm).

Classification of Wetness and Slope Position

The results for the wetness and SP-W classes using the thresholds derived in Steps 5 and 6 are displayed in the classification maps (Figures 7 and 8) and tables of area by class (Tables 9 and 10).

The ‘moderate’ wetness class covered the most area (1148 Ha) and, with the exception of the pond (0.85 Ha), the ‘very dry’ class covered the least (45 Ha). Among slope positions, the dry upper slope position (Upper-Dry) covered the most area (361 Ha), while very dry mid-slopes (Mid-Very Dry) and wet upper slopes (Upper-Wet) covered the smallest area at 2.9 Ha and 17.5 respectively.

Table 9 Area (Ha) of each wetness class derived for the study area

Wetness Class	Area (Ha)
Very Dry	45.08
Dry	533.27
Moderate	1148.17
Wet	728.93
PD	0.85

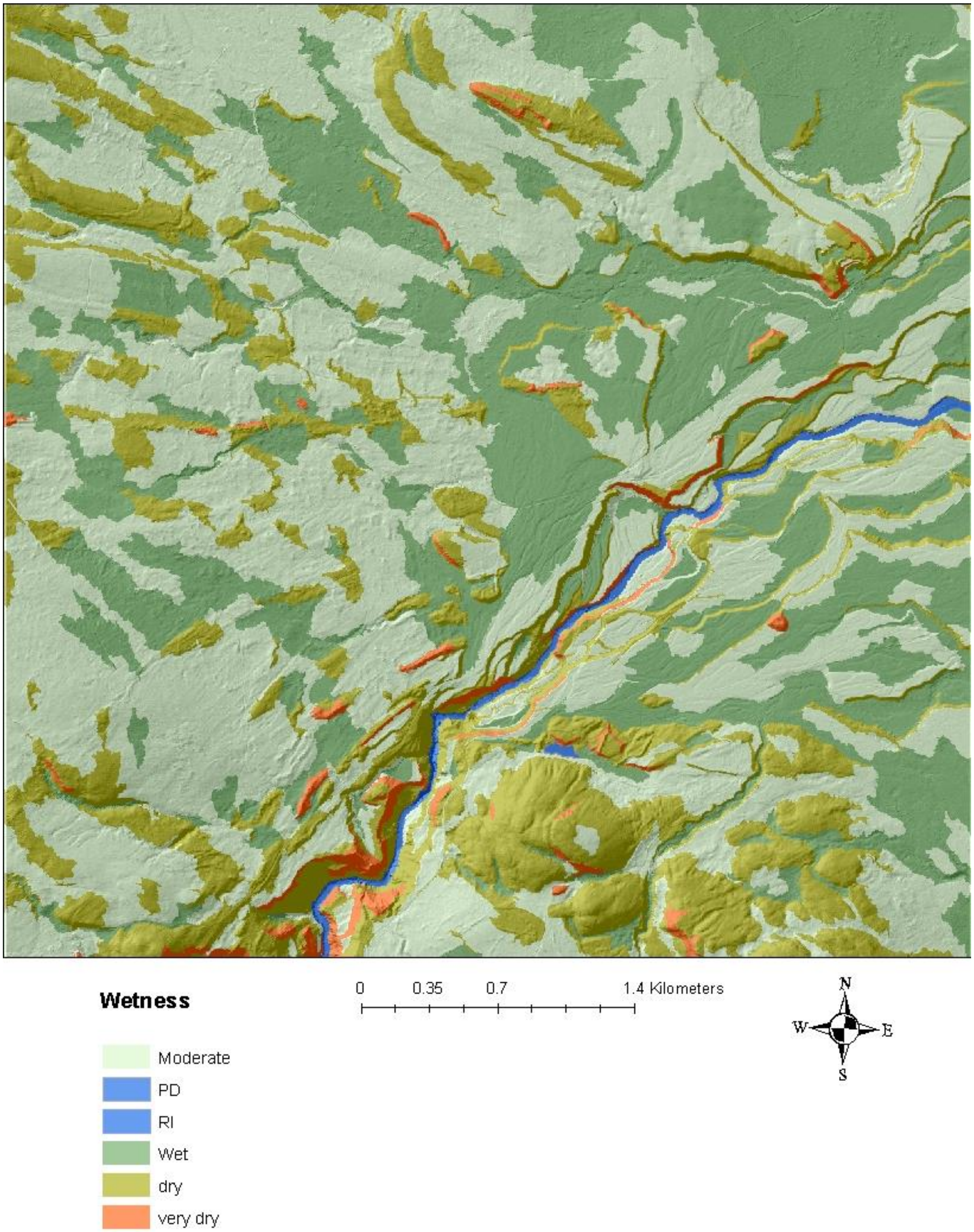

Figure 7 Wetness classes created using OBIA methods. Topographic Wetness Index was used to set class thresholds

Table 10 Area (ha) of each Slope Position - Wetness (SP-W) class derived for the study area

SP-W Class	Area (Ha)	SP-W Class	Area (Ha)
Depression - Moderate	156.10	Mid - Dry	66.68
Depression - Wet	215.62	Mid - Moderate	325.46
Flat - Dry	89.44	Mid – Very Dry	2.86
Flat - Moderate	171.08	Mid - Wet	32.24
Flat - Wet	341.17	Upper-Dry	361.25
Toe - Dry	23.95	Upper-Mod	338.32
Toe - Moderate	157.22	Upper – Very Dry	34.17
Toe - Wet	122.41	Upper - Wet	17.48

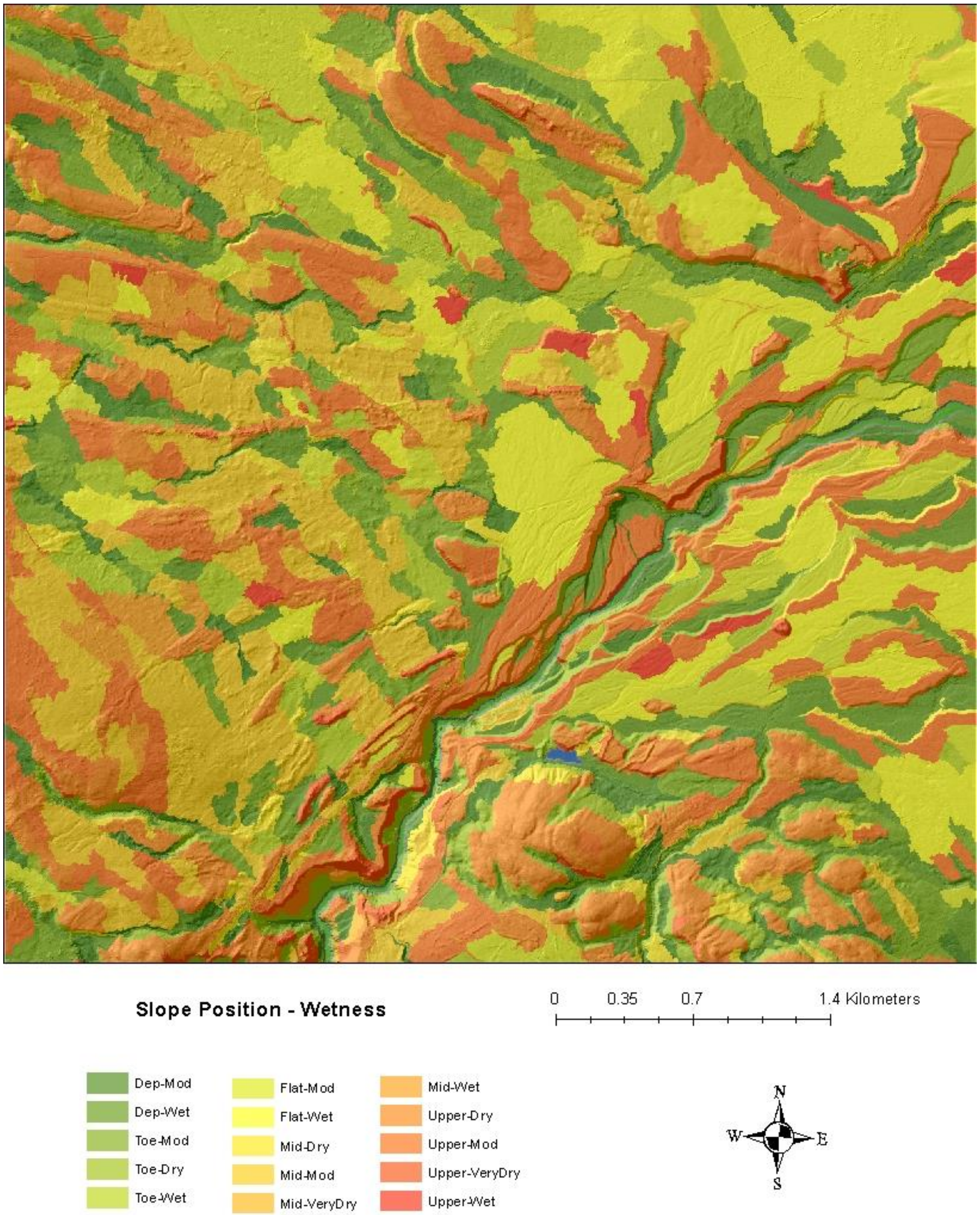

Figure 8 Slope Position - Wetness classes. Topographic Position Index and Topographic Wetness Index were used in conjunction to set classification thresholds

Classification of Site Series

Once slope position and wetness were established for each image object segmented for the study area, site series was classified (Figure 9). The areas each site series covers for both classifications (only using terrain metrics and using both terrain and vegetation metrics) and for the TEM polygons are summarized in Table 11. For all classifications, SS 01 covered the most area. Site series 07 covered the least (not including PD and RI) area for the TEM and terrain only classification but in the classification that included vegetation metrics SS 05 had the least coverage (112 Ha). The use of terrain only vs. joint vegetation and terrain metrics resulted in distinctly different relative proportions of site series classified. For example, using only terrain metrics classified a similar amount of the landscape as SS 01 relative to the TEM (0.43% decrease); whereas the addition of vegetation metrics resulted in mapping with 20% less total area in SS 01 than the TEM. Conversely, using only terrain metrics classified approximately 50% less area in SS 05 than the TEM, whereas the addition of vegetation metrics resulted in mapping with close to 50% more area in SS 05 than the TEM. Both approaches classified substantially more of the landscape in site series 07 than did the TEM. The classification that used only terrain metrics had an increase of 88%, while the inclusion of vegetation metrics resulted in the largest difference from the TEM at 165% increase of area covered by SS 07.

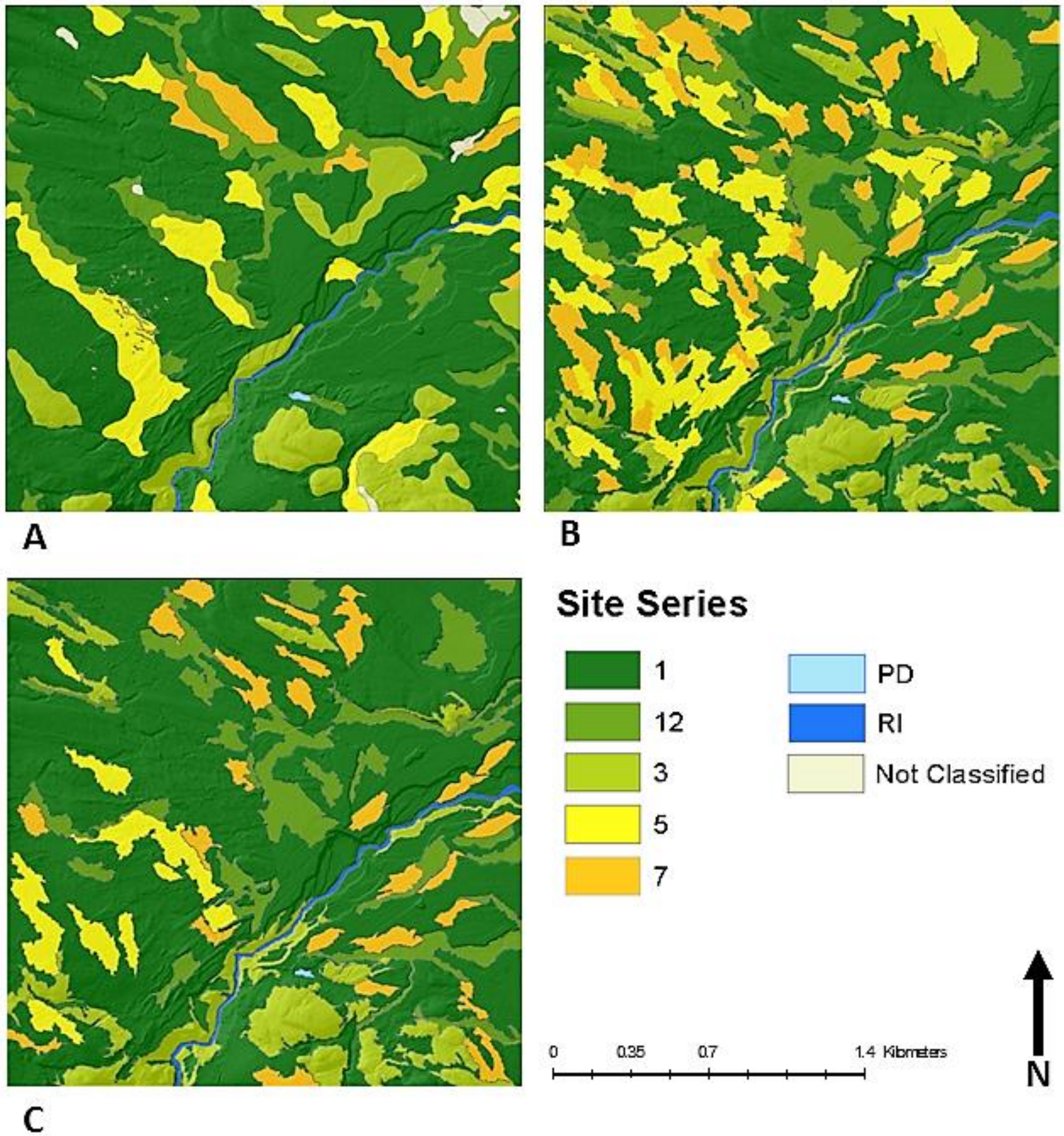

Figure 9 Classified maps produced using OBIA methods. A is the reference TEM map. B is when both terrain and vegetation metrics were used for classification and C is when only terrain metrics were used.

Table 11 Area (Ha) of each site series class for the reference TEM classification and for the ALS based (veg and terrain and terrain only) classifications. Percent increase or decrease from the base TEM map is also shown.

		Area			
Class	**TEM**	**Terrain**	**% Difference from TEM**	**Veg and Terrain**	**% Difference from TEM**
1	1678.41	1671.11	-0.43	1331.05	-20.70
3	244.73	248.29	1.45	269.89	10.28
5	237.45	112.32	-52.70	348.32	46.69
7	84.71	159.68	88.50	224.09	164.54
12	212.23	264.05	24.42	282.10	32.92
PD	1.24	0.85	-31.45	0.85	-31.45
RI	13.65	18.75	37.36	18.75	37.36

The specific parameters and their associated criteria used to classify site series were different for each process (terrain metrics only or terrain and vegetation) and are summarized in Table 12. For both processes, mean slope, mean TWI and mean TRASP were necessary for differentiating between site series. TWI was especially helpful for isolating the drier and wetter site series (3 and 12 respectively). Site series 05 is typically on cooler slopes; therefore, TRASP was used to help identify its boundaries. For the vegetation metrics, only CV and max height were found to help. Max height was used to differentiate SS 03 and SS 01 from each other (drier sites are typically less productive (i.e. shorter trees)). Mean CV had the most heterogeneity within SS 05, SS 07 and SS 12 for the vegetation metrics (SS 05 had the lowest CV and SS 07 had the highest). The capacity to use vegetation metrics for distinguishing classes was limited because many of the locations did not have data due to recent harvesting, also making it impossible to directly compare the classification results.

Table 12 Simplified overview of the process used for two classifications using eCognition software (terrain-only and veg and terrain). TRASP=Topographic Radiation Aspect; TWI= Topographic Wetness Index; CV=coefficient of variation (Veg height); height max refers to tree height >2m; VD=very dry; D=dry; Mod=moderately dry; W=wet; Up=upper slope; Mid=middle slope; Dep=depression; SS=site series.

	Class	Parameter	Criteria/Classified as
Terrain Only	SS 03	Classified as	Crest and Up-VD
		Mean slope	Threshold and Up-D
		Area, Relative Border	Thresholds and SS 01
		Merge	SS 03
	SS 05	Mean TRASP	Mid-Mod, Mid-D
		Merge	SS 05
	SS 07	Minimum TWI	Threshold and Toe-Mod, Flat-Mod
		Merge	SS 07
	SS 12	Classified as	Dep-Wet
		Mean TWI	Threshold and Toe-W, Flat-W
		Mean TWI	Threshold and SS 01
		Merge	SS 12
	SS 01	Classified as	Dep-Mod, Flat-D, Mid-VD, Mid-W, Toe-D, Up-Mod, Up-W
		Mean slope	Threshold and Up-D
		Mean TRASP	Threshold and Mid-Mod, Mid-D
		Minimum TWI	Threshold and Toe-Mod, Flat-Mod
		Mean TWI	Toe-W and Flat-W
		Area	Threshold and SS 12
		Shape Index and Relative Border	Thresholds and SS 03
		Area	Threshold and SS 03
		Shape Index and Relative Border	Thresholds and SS 05
		Area	Threshold and SS 05
		Shape Index and Relative Border	Threshold and SS 07
		Area	Threshold and SS 07
		Merge	SS 01
Terrain and Vegetation	SS 03	Classified as	Crest and Up-VD
		Mean Slope and Mean height-max	Threshold and Up-D
		Relative Border	Thresholds and Toe-D
		Area and Relative Border	Thresholds and SS 01
		Merge	SS 03
	SS 05	Mean TWI, Mean CV, Mean TRASP	Thresholds and Mid-Mod
		Mean TWI and Mean CV	Thresholds and Toe-Mod, Flat-Mod
		Mean TWI, Mean TRASP, Mean CV	Thresholds and Toe-Wet, Flat-Wet
		Merge	SS 05
	SS 07	Mean TWI, Mean CV, Mean TRASP	Thresholds and Mid-Mod
		Mean TWI and Mean CV	Thresholds and Toe-Mod, Flat-Mod
		Mean TWI, Mean TRASP, Mean CV	Thresholds and Toe-Wet, Flat-Wet

Class		Parameter	Criteria/Classified as
Terrain and Vegetation	SS 12	Mean TWI	Threshold and Dep-Wet
		Mean TWI and Mean CV	Thresholds and Toe-Mod, Flat-Mod
		Mean TWI, Mean TRASP, Mean CV	Thresholds and Toe-Wet, Flat-Wet
			Threshold and SS 01
		Mean TWI	SS 12
		Merge	
	SS 01	Mean TWI	Threshold and Dep-Wet
		Classified as	Dep-Mod, Flat-D, Mid-D, Mid-VD, Mid-W, Up-Mod, Up-W
		Mean Slope and Mean height-max	Threshold and Up-D
		Mean TWI, Mean CV, Mean TRASP	Thresholds and Mid-Mod
		Mean TWI and Mean CV	Thresholds and Toe-Mod, Flat-Mod
		Mean TWI, Mean TRASP, Mean CV	Thresholds and Toe-Wet, Flat-Wet
			Threshold and SS 12
		Area	Thresholds and SS 03
		Shape Index and Relative Border	Threshold and SS 03
		Area	Thresholds and SS 05
		Shape Index and Relative Border	Threshold and SS 05
		Area	Thresholds and SS 07
		Shape Index and Relative Border Area	Threshold and SS 07

Accuracy Assessment

The accuracy assessments are presented in confusion matrices (Table 13 and Table 14). The terrain-only classification and the terrain/vegetation classifications were evaluated with overall accuracies of 59% and 56% respectively. The producer and user accuracies for both comparisons show that some site series are easier to classify than others are. Site series 12 and SS 03 were the easiest to distinguish and had their highest accuracies in the terrain-only classification (user accuracies were 58% and 67% respectively). The best SS 05 classification (producer and user accuracy of 22%) was when vegetation metrics were included in the classification. Site series 07 was never classified accurately (producer and user accuracies of zero in both comparisons). Waterbodies (i.e. river and pond) had high classification accuracies for both user and producer accuracies (99% and 100%) for both classifications (terrain-only and terrain/veg).

Table 13 Comparison between the classification using only terrain metrics and the point-based reference data (TEM map)

Reference Data	Classification RI	PD	7	5	3	12	1	Total	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)
RI	78	0	0	0	0	0	0	78	99	100	59
PD	0	54	0	0	0	0	24	78	100	69	
7	0	0	0	0	0	0	0	0	0	0	
5	0	0	13	2	0	11	108	134	6	1	
3	1	0	2	4	65	3	59	134	67	49	
12	0	0	3	1	0	61	60	125	58	48	
1	0	0	40	28	32	31	350	481	58	73	
Total	79	54	58	35	97	106	601				

Table 14 Comparison between the classification using both terrain and vegetation metrics and the point-based reference data (TEM map)

Reference Data	Classification RI	PD	7	5	3	12	1	Total	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)
RI	78	0	0	0	0	0	0	78	99	100	56
PD	0	54	0	0	0	0	24	78	100	69	
7	0	0	0	0	0	0	0	0	0	0	
5	0	0	16	30	2	14	72	134	22	22	
3	1	0	5	17	64	4	43	134	61	48	
12	0	0	5	18	1	65	36	125	57	52	
1	0	0	52	70	38	32	289	481	62	60	
Total	79	54	78	135	105	115	464				

3.6 Discussion

Workflow overview

Ecosystems are highly complex with many interactions influencing their composition and structure; applying a stratified approach to the segmentation and classification is common practice for addressing similar complexities (Anders et al. 2011a; d'Oleire-Oltmanns 2013). While the overall accuracies for both classifications were not high (56% with vegetation metrics and 59% without), the workflow itself has potential. The workflow funnels information from broad to narrow, aiming to hone in on the attributes known to influence site series the most (nutrients and moisture) (Green and Klinka 1994). Upper slopes shed water more quickly and thus, are drier; lower slopes are water receiving and subsequently wetter (Figure 10). Additionally, dissolved nutrients make their way downhill with the water, and lower slopes are consequently often more productive. Middle slopes often shed and receive water equally and zonal sites often dominate here (Green and Klinka 1994). Therefore, classifying the study site using surrogates of slope position and wetness, helped build the classification rules for the more fuzzy boundaries of site series.

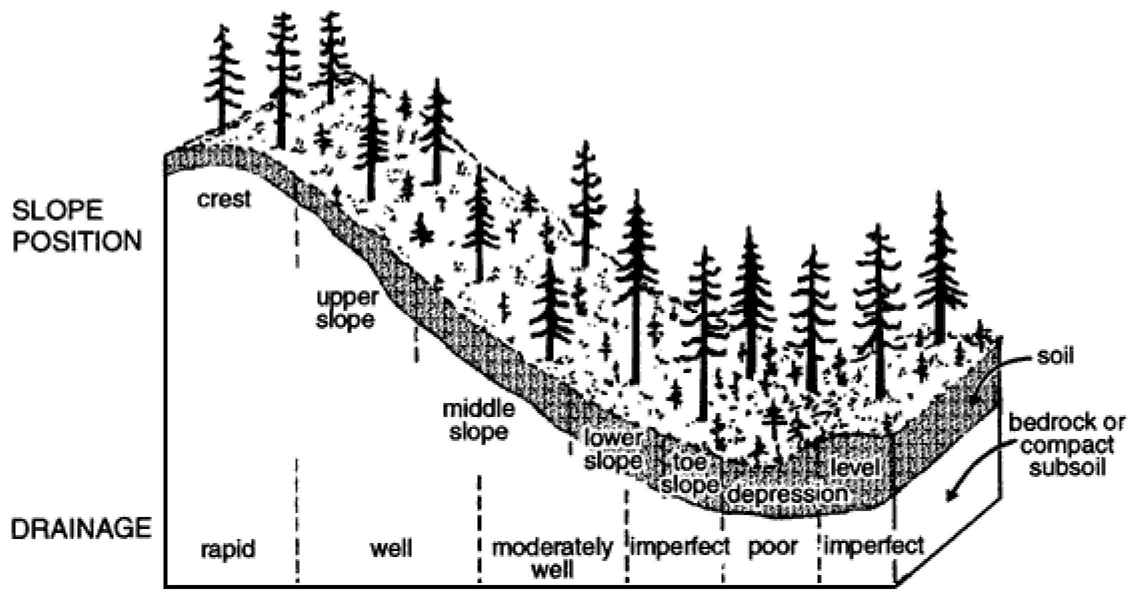

Figure 10 Typical relationship between slope position and drainage on a hillslope (Green and Klinka 1994)

This method of processing from distinct to indistinct is similar to those used in traditional mapping methods where obvious features are mapped first (De Graaff et al. 1987). If there were very specific thresholds to distinguish classes from one another (e.g. trees=forest and no trees=field) then such a process would not be necessary.

Considering Metrics

Determining the best metrics to use in OBIA is another important element. On a landscape such as the one used in this study where there are no extreme terrain features; the influences of terrain are not always notable between site series (Green and Klink, 1994). Microsites exist but these are not captured in the scale typically used in TEM. Soil moisture and nutrients are key determinants of site series, however ALS cannot measure them directly, therefore choosing metrics that can function as a proxy for them is ideal. Site moisture and nutrients are influenced by soil properties and drainage pattern (Swanson et al. 1988; Green and Klinka 1994). TWI has been found to correlate strongly with several soil properties such as horizon depth (r=0.55), silt percentage (r=0.61), organic matter content (r=0.57), and phosphorus levels (r=0.53) (Moore et al. 1993). Slope and flow accumulation are used to calculate TWI. Therefore, TWI, like slope position, is an excellent indicator of where water will move quickly through an area (steep slope) or where it will settle (depression). Unlike slope position, TWI also indicates where flow paths congregate or where there are only a few.

The TWI was the most important metric used for classification. TWI was the only metric used to classify PD, which had a user accuracy of 100%, but a much lower 69% producer's accuracy, which is likely due to inaccuracies in its segmentation. While helpful for segmenting the river in the initial stages and for classifying wetness, TWI was also important for the classification of every site series. Within the rule sets established for site series, TWI was used to distinguish the most homogeneous classes affected by wetness. Site series 12 and 3 had TWI values at either end of the spectrum, (i.e. wet and dry respectively) and their classification accuracies were some of the highest user and producer accuracies (for either the terrain only or terrain and veg classification). TWI was also used to refine the classification of lower slopes (toe, flat and depressions). Within these classes, it was found that SS 12, SS 07, SS 05 and SS 01existed. Site series 07 is wetter than SS 05, therefore mean TWI helped to isolate them. Teasing out SS 01was difficult because it encompassed such a large range of slope positions and wetness. It is possible that if the scale is increased to allow more detail, this range could be narrowed and increase the distinguishability of each site series. Field-testing would be needed to confirm this refinement. It is likely that having vegetation metrics for the entire study area could also help distinguish SS 01 more easily.

Considering scale

Throughout the entire OBIA process, scale is an important consideration. The same ALS metric can highlight and define attributes very differently depending on the scale used. In this study, TPI10 (calculated with a small neighbourhood of 10 m) was useful for segmenting. In the segmentation, it was found that creating objects smaller than the average TEM polygon was the most appropriate for representing TEM polygons. The finer detail afforded by TPI10 helped identify the subtle boundaries between site series. For setting slope position classes, TPI500 worked well because the relatively large neighbourhood of 500 m provided an appropriate level of detail relative to the scale used in TEM. However, it is possible that a coarser scale could have helped for the classification of site series. For example, the primary determinant of SS 12 was the SP-W class Depression-VeryWet, but TPI500 was used to separate SS 12 from other classes within the broader SP-W class. SS 12 had an approximate 43% commission error, which could indicate that an even larger neighbourhood for TPI could have been used.

The appropriate scale to use for metrics within the OBIA process will change depending on the size and shape (i.e. flat terrain vs. undulating) of the features being mapped but also on the size of the area being mapped. In TEM, slope position is determined on a mesoscale, which is defined as having a vertical scale between 3 - 300 m for each class (Luttmerding et al. 1990). Therefore, in steeper, more undulating terrain, a TPI neighbourhood of 500 m would likely be to large and encompass greater vertical distances than 300 m. Scale is something that should regularly be evaluated throughout the process and next steps will involve several test locations (with field validation) with varying topography to determine the best scale-metric combinations.

Classification difficulties

Site series 07 was never classified correctly. This was likely due to three reasons. First, this site series only covered 3% of the total study site area, which makes it more difficult to isolate in both the segmentation and especially in the classification phase. Secondly, for most of the metrics used to distinguish site series, SS 07 was usually in the middle of the value range. This made detecting its locations using threshold rules difficult, as it was often associated with other classes. The few small objects containing SS 07 were indistinct from other objects not containing SS07. However, SS 07 is a wetter site, (drier than SS 12), but not so wet that productivity is limited. The use of vegetation metrics (e.g. gap fraction and height) could have helped distinguish it. Unfortunately, and the third reason it was so difficult to classify it, is that for the majority of locations where SS 07 was, there had been recent harvesting and vegetation data was absent.

In general, classification of site series in this area was difficult because the dominance of the zonal site (SS 01), which has an area greater than all other site series combined. Site series 01 made up 68% of the study area, with the next largest site series belonging to SS 03 at only 10 %. Notably, SS 03 was mostly classified with higher accuracies than SS 01, which had six times the coverage, because the typically high slope position and dryness of SS03 made it distinguishable. Likewise, the river and pond were the smallest classes in the site (0.05% of the area each) but were classified with high accuracies because their shape (river) and wetness made them distinct. Zonal site (i.e. SS 01) by definition is the mesic site for the Biogeoclimatic subzone and therefore has median levels of moisture and nutrients. When 68% of segmented objects are of average values, it becomes difficult to distinguish site series covering smaller areas, especially if their descriptive attributes do not vary distinctly from the central (zonal) concepts.

Classification with or without vegetation metrics

The overall accuracies for both the terrain-only classification and the combined terrain and vegetation metrics, are not very strong. They do suggest however, that terrain metrics alone may be suitable to classify site series for an altered landscape (e.g. harvested). Most of the accuracies were very similar regardless of the classification process used, but because much of the study area was absent of vegetation data a direct comparison between the two approaches cannot be made. However, for several site series specifically, vegetation metrics improved classification.

The one site series that particularly stands out is SS 05. Its accuracy was improved (still low at 22% user and producer) when vegetation metrics were included. Initially, it was presumed that isolating cool aspects (TRASP) would distinguish SS 05, since it is usually found on cooler slopes, however this was not the case. Given the moderate wetness and midslope position of SS 05 and that aspect overall did not seem to be a determinant of site series, (e.g. SS 03 was not only on south slopes, it was on many steep north aspects as well), it was a difficult site series to classify. However, mean CV helped distinguish it from site SS 07 and SS 12. Site series 05 had the lowest CV, likely because it is the driest and coolest site series of the three. Relative to SS 12 and SS 07, the tree heights on a SS 05 site likely have more variance because they receive less nutrients and water and have less access to sunlight (northward facing), all factors that influence tree height (Kosh et al. 2004).

3.7 Conclusion

This study has demonstrated the potential and difficulties of mapping TEM based site series using only ALS data. These methods are transparent, utilize the key influences on ecosystems, and indicate that site series could be mapped without the implementation of vegetation metrics. The process as it currently stands requires refinement. However, developing modifications based on the issues discussed and applying them to new strategies would likely increase accuracies. Using these refined methods applied to a larger study site, with more diverse terrain or a higher number/coverage of a zonal site series would allow the methods to be tested more thoroughly. The classifications with the highest accuracies highlight the importance of wetness and slope position for some site series. However, the low accuracies overall indicate that either homogeneity can only be found between classes if polygon size of site series is smaller (this would not replicate current TEM) or if there are other untested attributes that could distinguish classes.

As discussed at the start of this chapter and throughout the previous ones, there are many valuable reasons why mapping ecosystems with ALS data, or with only terrain metrics, is important. Aside from the classification of site series, this study demonstrated some of the ways that ALS data can be applied to relate ecosystem attributes with landscape. Wetness and slope position classes (and their combined classification), along with a flow network are all excellent attributes to be mapped and that can be helpful to ecologists, land managers and even TEM mappers. They can assist in the current map-making processes, whether they are used as references in the field or when interpreting aerial photographs.

If ALS data can be incorporated successfully into a reliable OBIA process it would become increasingly automated, increasing the cost:benefit ratio. The spatial resolution of the ALS data allows more boundaries to be segmented (Figure 6), likely picking up on more information than possible from aerial photographs or field work. To confirm the usefulness and true accuracy of the ALS based classifications, field validation will be necessary. It is possible that the ALS-based maps produced are a better representation the ecosystems in the study area.

Chapter 4: Conclusion

4.1 Overview

The aim of this thesis was to establish the feasibility of using ALS data to classify and map ecosystems. To accomplish this task: (1) a literature review was completed and (2) A case study was performed.

Literature Review

The review concluded there has been limited research into the application of ALS data to classify ecosystem units across a landscape. In order to determine if it is possible to achieve such a task a review of current research (within the last 5 years) was performed. To refine the process, British Columbia's Terrestrial Ecosystem Mapping (TEM) standards were used as a template. The feasibility for implementing the mapping of the various attributes and applying the methods to classify and map ecosystems was then evaluated.

Case Study

Applying what was learned through the literature review to a site specific case study was the next step. The goal was to map an area to site series (TEM ecosystem unit). A study site was required that had both ALS and TEM data. A 25 km^2 area near Campbell River, BC was selected. Object Based Image Analysis was chosen as the approach for segmenting and classify site series. The site series and non-vegetated units classified for this site and used in the study are as follows: 01, 03, 05, 07, 12, RI (river) and PD (pond). This study used a workflow that focused on two key factors that influence ecosystem variability, wetness and slope position. At the site level, slope position and wetness are strongly correlated and influence soil moisture and nutrients, which in turn influence the potential vegetation on a site (Bailey 1987; Swanson et al. 1988).

The workflow segmented the study area first for the river and a second time for site series. Finding the best parameters for segmentation was a critical part of this study; the metrics used and the scale parameter will strongly affect the ability to classify accurately. The study area was classified for slope position-wetness and then into the specific site series. In the classification of site series two approaches were used. One approach used only terrain metrics; the other incorporated both terrain and vegetation metrics. A confusion matrix was used to compare the classifications with the reference TEM polygons.

4.2 Key findings

Literature review conclusions

The following details the feasibility for each attribute to be used for the mapping of ecosystems at site level.

High Feasibility: Canopy characteristics, stand height and topography are attributes that can reliably be classified using ALS data; doing so is well established. The capacity for providing accurate and detailed DEMs with slope, aspect, elevation and curvature and the proven ability to quantify stand height and canopy metrics, place ALS in a strong position for use in ecosystem mapping. While vegetation metrics and detailed DEMs are likely not stand-alone criteria for ecosystem mapping, they do provide a reliable and essential base from which predictive modelling can be structured.

Moderate Feasibility: Geomorphic process, drainage pattern, terrain attributes, soil drainage, soil depth, tree species composition, and understory or non-forested vegetation composition or characteristics are TEM criteria that may require some additional research to demonstrate their applicability or accuracy. The classification of some of these criteria, however, has been well demonstrated elsewhere, but warrant further research. Species composition is an important criterion in determining site series, yet remains the criterion classified with the most variable success. The inclusion of spectral data into the classification methodology will likely be necessary. Hyperspectral and multispectral data would also serve to improve all vegetation mapping (i.e. site series, seral stage, and structural stage).

Low Feasibility: Soil depth and forest floor are the criteria that currently have not been successfully classified using ALS data. Soil depth can be somewhat inferred based on terrain attributes and geomorphologic process and to a lesser extent soil order. However, depth classifications would likely be very broad and the resolution too coarse (i.e. valleys have deep soil; steep slopes have shallow soil) to contribute effectively to ecosystem unit delineation. Additionally, using ALS data to describe forest floor is currently not likely given the minimal information the ALS data provides that can contribute towards ecosystem classification. The limited research being done has focused on fuel loads and fire management rather than relating forest floor composition to ecosystem type.

Case Study Findings

In the segmentation process, finding the appropriate scale parameter was crucial. If it was too high, heterogeneity among image objects was difficult to detect because multiple distinguishing features of various site series become enclosed. If the scale parameter was too small however, there is not enough information within image objects and they are not distinct. For this study segmentation worked best when image objects were slightly smaller than the average TEM polygon size.

Scale (both resolution and extent over which a metric is calculated) is also important to consider within the OBIA process. The same metric can highlight and define attributes very differently depending on the extent of the neighbourhood used for its calculation. For example, Topographic position index (TPI) was a metric that was used with varying scales in both the segmentation and classification stages. It was found that a smaller neighbourhood (10 m) for calculating TPI was better for segmenting the finer boundaries within the terrain but a larger neighbourhood (500 m) was better for classifying slope position and site series.

The topographic wetness index (TWI) was found to be one of the most important metrics used. It was applied at every stage in the workflow, from the segmentation of the river and site series and throughout all classification stages. The classifications with the highest accuracies highlight the influence of wetness on site series. Slope position was also necessary for classifying most site series. Vegetation metrics were limited in their usefulness for this study because of recent harvesting and a lack of data, especially in areas where difficult to segment site series exist; determining the extent to which vegetation metrics could improve classification accuracies could not be fully tested. However, the terrain-only classification and the terrain-vegetation classifications were evaluated with overall accuracies of 59% and 56% respectively, suggesting that they both have similar potential to classify site series in relatively modified landscape.

Overall, accuracies were low, but with workflow refinement it is likely these could be improved. The difficulty to classify site series could indicate that site series polygons need to be smaller so that homogeneity between classes is distinguishable; however, this would not replicate current TEM polygon sizes. With the scale currently used in TEM, the zonal site (SS 01) takes up considerably more space on the landscape than any of the other site series (68% of the study area), with the next largest site series belonging to SS 03 at only 10%. Zonal sites typically have average levels of warmth, wetness and slope for the particular biogeoclimatic zone. This makes it difficult to distinguish other site series with much smaller coverages, especially if their determining attributes do not vary far from the mean. It is also possible that terrain or vegetation metrics not used in this study could distinguish classes more easily.

4.3 Implications for refining site series mapping

There are many ways to approach classifying ecosystems using ALS data. The literature review highlights ways to measure and classify individual ecosystem attributes. Incorporating these into a succinct workflow for the classification of site series could take many forms and the case study results highlight some of the difficulties for integrating these various methods to map something as complex as ecosystems. While the classification had limited success, several implications can be made for refinement to the workflow used that would likely improve future accuracies.

Many of the biotic studies discussed in the literature review use multispectral data for classifying tree species and other vegetation related attributes. TEM uses vegetation species to indicate soil moisture and nutrients, and the site series classification defines the climax vegetation for a particular site based on the influences of terrain. Mapping site series using ALS data alone is a novel idea and the specificities of this study have not been done prior to this. Multispectral data were not used in the case study and the ALS vegetation data was limited because much of the study area harvested at the time the data was acquired. It is likely that if vegetation data could have been integrated more thoroughly, accuracies would have been higher.

The segmentation approach used in this study relied on visual assessment for comparing image objects created in the OBIA with the TEM polygons to determine the best segmentation parameters. This method is commonly used (Zhang 2008; Johnson & Xie 2011) and can be extremely effective but its limitations are worth considering. Visual assessment can be time consuming and labour intensive and can be prone to subjectivity (Johnson & Xie 2011). Segmentation quality affects image classification accuracy (Kim et al. 2008; Anders et al. 2011a), and while it is likely that the main limitations to classification accuracy in this study was a lack of heterogeneity between classes, a more rigorous approach with statistical validation could be advantageous (Drǎguţ et al. 2010; Anders et al. 2011; Johnson & Xie 2011). It is worth noting that while an unsupervised approach could improve objectivity in the segmentation process, visual assessment is required for many multi-scale approaches, especially to assess over and under-segmentation (Grybas et al. 2017).

Identifying the best metrics to input for both the segmentation and classification is also important. In the methods used for this case study, seven terrain and four vegetation metrics were initially chosen. All of the seven terrain metrics were used within the workflow, but only two of the vegetation metrics were required. The metrics EPC and TO, which were the inputs for the river segmentation, were not used again. Elevation percentile provides information about a locations relative position within a landscape and TO defines the degree of enclosure for a location. While these metrics easily identified the river as an object, it is likely that similar metrics could as well. Topographic Position Index could likely replace EPC and TO. All three metrics ultimately describe the position of a given location within the context of its surroundings (i.e. whether a location is lower (e.g. valley) or higher (e.g. ridge) than a specified neighbourhood around it). However, each of these metrics have their own nuances and should be considered within the context of a study's location and goals. Regardless of metrics used, eliminating metrics with overlapping qualities, should serve to streamline the process.

The classification steps of the workflow classified broader ecosystem influencers (wetness and slope position) first, and then attempted to segregate site series according to these broader classes and lastly applied increasingly specific rules based on distinguishers such as tree height, coefficient of variation, slope or aspect. An alternate approach could stratify according to site series. This would segment for a specific site series, followed by classifying it. Then a new segmentation for the next site series would be performed on the unclassified area. This approach would allow the segmentation parameters and objects produced to be more specific to each site series. However, polygon variance for site series can be high and changing the scale parameter might not adequately address this.

4.4 Limitations

This study was limited in its ability to test how the incorporation of ALS vegetation metrics could improve classification and distinguish site series where terrain information alone cannot. The ability to classify with and without vegetation metrics could not be directly compared because of the absent data for much of the study area. As well, the forest within the Oyster River study area was mostly young forest, adding further limitations to fully the capacity for using ALS data. The study area was small, but likely, its size was not the limitation, but rather the diversity of the landscape it contained. There were only five main site series to be mapped and the zonal site dominated this site. There are many landscapes like this and the goal of ecosystem mapping would ultimately be to map homogeneous or disturbed areas using ALS data. However, as a starting point for determining best methods and classification rules, a study site with more heterogeneity or more represented by other site series besides the zonal site would allow trends and thresholds to be identified and established more easily. With a diverse and complete vegetation dataset (i.e. no harvesting or stand level disturbance) more vegetation metrics could be tested and outcomes based on the incorporation of vegetation data or not could be directly compared.

Another limitation is that the accuracy of the TEM maps is not known. The boundaries of the polygons are not intended to be exact but rather representative and highlighting the dominant potential of an area. As the ALS mapping process becomes more efficient and accuracies are improved it would be beneficial to incorporate field validation. The detail of the ALS has potential to identify site series with greater accuracy than the TEM map being used as a reference. It is plausible that the ALS based maps could have much higher accuracies if validation was made using field data.

4.5 Future directions

Next steps should include some of the suggestions discussed above (statistically evaluate segmentations, test new metrics or simplify the number of metrics used, use a larger (more diverse) study area, field validate, have a more complete vegetation dataset, directly compare classification with and without vegetation data, try various stratification approaches etc.). The overall, future potential for using ALS data is continuing to expand and become more proficient. Access to ALS data is increasingly affordable and the diversity of its application is growing. Drones mounted with ALS sensors are one example of this increased accessibility and potential for new application. Improving the ability to map ecosystems using ALS data has vast implications and will likely play an important role in the future management of lands and resources.

The classification of site series requires more research but the case study produced many maps that have application independently. Maps of wetness, slope position and flow networks (stream network and drainage) all can be applied within a framework for managing and understanding ecosystems. They can also be useful for a mapper using more traditional mapping methods. The detailed terrain and vegetation metrics produced with the ALS data can provide more information about a specific location than simply observing an aerial photograph; they can even provide information that is difficult to measure in the field.

Additionally, the image objects created in the segmentation could help refine current TEM mapping methods even before classifying site series using ALS data attains higher accuracies. The OBIA image objects produced polygons that shared similar boundaries to many of the site series. This is because the process segments an area into relatively homogenous regions based on the information of the metrics used (e.g. influencers of ecosystems). Thus, image objects themselves are meaningful and a TEM ecologist could use these to aid their current mapping methods. Segmented boundaries might provide more detail than could be identified from aerial photos, especially in heavily forested landscapes where identifying ecosystem boundaries at a site scale is difficult. An expert TEM mapper could perhaps use the detail afforded by these segmented boundaries to map site series with greater accuracies than without the ALS data.

The ultimate goal of course is to use ALS data to map site series and this thesis provides important information for attaining that. The literature review includes methods not tested in the case study and information that can be applied to new, refined approaches. The case study identifies many of the difficulties using ALS data for mapping ecosystems and it also presents a novel method that, with further refinement, will likely see higher accuracies.

Bibliography

Aitken, S. N., S. Yeaman, J. A. Holliday, T. Wang, and S. Curtis-McLane. 2008. Adaptation, migration or extirpation: climate change outcomes for tree populations. Evolutionary Applications 1(1):95-111.

Aksoy, B., and M. Ercanoglu. 2012. Landslide identification and classification by object-based image analysis and fuzzy logic: An example from the Azdavay region (Kastamonu, Turkey). Computers & Geosciences 38(1):87-98.

Akumu, C., J. Johnson, D. Etheridge, P. Uhlig, M. Woods, D. Pitt, and S. McMurray. 2015. GIS-fuzzy logic based approach in modeling soil texture: Using parts of the Clay Belt and Hornepayne region in Ontario Canada as a case study. Geoderma 239:13-24.

Alberti, G., F. Boscutti, F. Pirotti, C. Bertacco, G. De Simon, M. Sigura, F. Cazorzi, and P. Bonfanti. 2013. A LiDAR-based approach for a multi-purpose characterization of Alpine forests: an Italian case study. iForest-Biogeosciences and Forestry 6(3):156.

Albrecht, F., S. Lang, and D. Hölbling. 2010. Spatial accuracy assessment of object boundaries for object-based image analysis. Proceedings of GEOBIA.

Allen, T. F., and T. B. Starr. 1982. Hierarchy perspectives for ecological complexity. University of Chicago Press, Chicago.

Anders, N. S., A. C. Seijmonsbergen, and W. Bouten. 2011. Segmentation optimization and stratified object-based analysis for semi-automated geomorphological mapping. Remote Sensing of Environment 115(12):2976-2985.

Anders, N., M. Smith, A. Seijmonsbergen, and W. Bouten. 2011. Optimizing object-based image analysis for semi-automated geomorphological mapping. Geomorphometry: 117-120.

Anders, N., A. Seijmonsbergen, and W. Bouten. 2013. Geomorphological change detection using object-based feature extraction from multi-temporal lidar data. Geoscience and Remote Sensing Letters, IEEE 10(6):1587-1591.

Aspinall, J., & S. Sweeney. 2012. Digital soil mapping in Ontario, Canada: an example using high resolution LiDAR. In: Digital soil assessments and beyond. Minasny, Malone & McBratney (editors). pp. 307-312. Taylor and Francis, UK.

Bailey, R., M. Jensen, D. Cleland, and P. Bourgeron. 1994. Design and use of ecological mapping units. Ecosystem management: principles and applications 1:95-106.

Bailey, R. G. 1985. The factor of scale in ecosystem mapping. Environmental management 9(4):271-275.

Bailey, R. G. 1987. Suggested hierarchy of criteria for multi-scale ecosystem mapping. Landscape and Urban Planning 14:313-319.

Bailey, R. G. 2009. Ecosystem geography: from ecoregions to sites. Springer Science & Business Media. New York.

Barnes, B. V., K. S. Pregitzer, T. A. Spies, and V. H. Spooner. 1982. Ecological forest site classification. Journal of Forestry 80(8):493-498.

Beven, K., and M. J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. Hydrological Sciences Journal 24(1):43-69.

Bhardwaj, A., L. Sam, A. Bhardwaj, and F. J. Martín-Torres. 2016. LiDAR remote sensing of the cryosphere: Present applications and future prospects. Remote Sensing of Environment 177:125-143.

Billings, W. 1973. Arctic and alpine vegetations: similarities, differences, and susceptibility to disturbance. Bioscience 23(12):697-704.

Brasington, J., D. Vericat, and I. Rychkov. 2012. Modeling river bed morphology, roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resources Research 48(11).

Burrough, P.A., & R.A. McDonell. 1998. Principles of geographical information systems. Oxford University Press, UK.

Campbell, L., N. C. Coops, and S. C. Saunders. 2017. LiDAR as an Advanced Remote Sensing Technology to Augment Ecosystem Classification and Mapping. Journal of Ecosystems and Management 17(1).

Canadian Forest Service (CFS). 2005. Area_or_TEM-meta. Metadata document. Fluxnet Canada.

Carter, J., K. Schmid, K. Waters, L. Betzhold, B. Hadley, R. Mataosky, and J. Halleran. 2012. Lidar 101: An introduction to lidar technology, data, and applications. National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center.Charleston, SC.

Cleve, C., M. Kelly, F. R. Kearns, and M. Moritz. 2008. Classification of the wildland–urban interface: A comparison of pixel-and object-based classifications using high-resolution aerial photography. Computers, Environment and Urban Systems 32(4):317-326.

Cochran, W., and G. William. 1977. Sampling Techniques. John Wiley& Sons, New York

Colgan, M. S., C. A. Baldeck, J. Féret, and G. P. Asner. 2012. Mapping savanna tree species at ecosystem scales using support vector machine classification and BRDF correction on airborne hyperspectral and LiDAR data. Remote Sensing 4(11):3462-3480.

Coops, N. C., T. Hilker, M. A. Wulder, B. St-Onge, G. Newnham, A. Siggins, and J. T. Trofymow. 2007. Estimating canopy structure of Douglas-fir forest stands from discrete-return LiDAR. Trees 21(3):295-310.

Coops, N. C., F. Morsdorf, M. E. Schaepman, and N. E. Zimmermann. 2013. Characterization of an alpine tree line using airborne LiDAR data and physiological modeling. Global Change Biology 19(12):3808-3821.

Czaplewski, R. L., and P. L. Patterson. 2003. Classification accuracy for stratification with remotely sensed data. Forest Science 49(3):402-408.

Dalponte, M., L. Bruzzone, and D. Gianelle. 2012. Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data. Remote Sensing of Environment 123:258-270.

Degraaff, L., M. Dejong, J. Rupke, and J. Verhofstad. 1987. A GEOMORPHOLOGICAL MAPPING SYSTEM AT SCALE 110,000 FOR MOUNTAINOUS AREAS. Zeitschrift fur Geomorphologie 31(2):229-242.

Demarchi, L., S. Bizzi, and H. Piégay. 2016. Hierarchical object-based mapping of riverscape units and in-stream mesohabitats using LiDAR and VHR imagery. Remote Sensing 8(2):97.

d'Oleire-Oltmanns, S., C. Eisank, L. Drăgut, and T. Blaschke. 2013. An object-based workflow to extract landforms at multiple scales from two distinct data types. IEEE Geoscience and Remote Sensing Letters 10(4):947-951.

Drăguţ, L., D. Tiede, and S. R. Levick. 2010. ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. International Journal of Geographical Information Science 24(6):859-871.

ECOLOGICAL DATA COMMITTE. 2000. Standard for Terrestrial Ecosystem Mapping (TEM) – Digital Data Capture in British Columbia: Ecosystem Technical Standards and Database Manual. Victoria, BC: Ecosystems Working Group version 3.0(Terrestrial Ecosystem Task Force).

Ecora Resource Group Ltd. 2012. Investigating the feasibility of using a TEM/PEM hybrid method for ecosystem mapping in the Central Coast of British Columbia. Prepared for: Ministry of Forests, Lands, and Natural Resource Operations, Nanaimo, B.C.

Ecosystems Working Group. 1998. Standards for terrestrial ecosystem mapping in British Columbia. Resources Inventory Committee, Government of British Columbia.Victoria, BC.

Gallant, J.C., & J.P. Wilson. 2000. Primary topographic attributes. In: Terrain analysis, principles and applications. Wilson, J. P., & J. C. Gallant (editors). pp. 51-85. John Wiley & Sons, USA.

García-Feced, C., D. J. Tempel, and M. Kelly. 2011. LiDAR as a tool to characterize wildlife habitat: California spotted owl nesting habitat as an example. Journal of Forestry 109(8):436-443.

Gaspa, M., R. De La Cruz, N. Olfindo, N. Borlongan, & A. Perez. 2016. Integration of manual channel initiation and flow path tracing in extracting stream features from LiDAR-derived DTM. PIE Remote Sensing. International Society for Optics and Photonics.

Greaves, H. E., L. A. Vierling, J. U. Eitel, N. T. Boelman, T. S. Magney, C. M. Prager, and K. L. Griffin. 2016. High-resolution mapping of aboveground shrub biomass in Arctic tundra using airborne lidar and imagery. Remote Sensing of Environment 184:361-373.

Green, R. N., and K. Klinka. 1994. A field guide to site identification and interpretation for the Vancouver Forest Region. Ministry of Forests, Research Program. Victoria, BC.

Greve, M. H., R. B. Kheir, M. B. Greve, and P. K. Bøcher. 2012. Quantifying the ability of environmental parameters to predict soil texture fractions using regression-tree model with GIS and LIDAR data: The case study of Denmark. Ecological Indicators 18:1-10.

Grybas, H., L. Melendy, and R. G. Congalton. 2017. A comparison of unsupervised segmentation parameter optimization approaches using moderate-and high-resolution imagery. GIScience & Remote Sensing 54:1-19.

Gustafson, E. J. 1998. Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1(2):143-156.

Hamada, Y., B. L. O'Connor, A. B. Orr, and K. K. Wuthrich. 2016. Mapping ephemeral stream networks in desert environments using very-high-spatial-resolution multispectral remote sensing. Journal of Arid Environments 130:40-48.

Heung, B., C. E. Bulmer, and M. G. Schmidt. 2014. Predictive soil parent material mapping at a regional-scale: a random forest approach. Geoderma 214:141-154.

Höfle, B., and M. Rutzinger. 2011. Topographic airborne LiDAR in geomorphology: A technological perspective. Zeitschrift für Geomorphologie, Supplementary Issues 55(2):1-29.

Hopkinson, C., and L. Chasmer. 2009. Testing LiDAR models of fractional cover across multiple forest ecozones. Remote Sensing of Environment 113(1):275-288.

Huston, M. 1979. A general hypothesis of species diversity. American Naturalist 113:81-101.

Hutchinson, M. 1989. A new procedure for gridding elevation and stream line data with automatic removal of spurious pits. Journal of Hydrology 106(3-4):211-232.

Jelalian, A. V. 1992. Laser radar systems. Artech House, Boston.

Jenness, J. 2006. Topographic Position Index (tpi_jen. avx) extension for ArcView 3. x, v. 1.3 a. Jenness Enterprises. Accessed June 20, 2016. URL: http://www.jennessent.com/arcview/tpi.htm.

Johnson, B., and Z. Xie. 2011. Unsupervised image segmentation evaluation and refinement using a multi-scale approach. ISPRS Journal of Photogrammetry and Remote Sensing 66(4):473-483.

Jones, T. G., N. C. Coops, and T. Sharma. 2012. Assessing the utility of LiDAR to differentiate among vegetation structural classes. Remote Sensing Letters 3(3):231-238.

Jungen, J. 1986. Soils of the South Vancouver Island, British Columbia. Soil Survey Report 44. MoE Technical Report 17. Surveys and Resources Mapping Branch, Ministry of Environment, Province of BC, Victoria, BC.

Kim, M., M. Madden, and T. Warner. 2008. Estimation of optimal image object size for the segmentation of forest stands with multispectral IKONOS imagery. Pages 291-307 Object-based image analysis. Springer, New York.

Koch, G. W., S. C. Sillett, G. M. Jennings, and S. D. Davis. 2004. The limits to tree height. Nature 428(6985):851-854.

Kolecka, N., J. Kozak, M. Dobosz, and A. Psomas. 2014. Land abandonment mapping in the Polish Carpathians. South-Eastern Europe Journal of Earth Observation and Geomatics 3:103-108.

Kumar, J., J. Weiner, W. Hargrove, S. Norman, F. Hoffman, and D. Newcomb. 2015. LiDAR-derived Vegetation Canopy Structure, Great Smoky Mountains National Park, 2011.ORNL DAAC, Oak Ridge, Tennessee, USA.

Latifi, H., M. Heurich, F. Hartig, J. Müller, P. Krzystek, H. Jehl, and S. Dech. 2015. Estimating over- and understorey canopy density of temperate mixed stands by airborne LiDAR data. Forestry 89(1): 69-81.

Lawley, V., M. Lewis, K. Clarke, and B. Ostendorf. 2016. Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. Ecological Indicators 60:1273-1283.

Lefsky, M. A., W. B. Cohen, G. G. Parker, and D. J. Harding. 2002. Lidar Remote Sensing for Ecosystem Studies Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. Bioscience 52(1):19-30.

Leiterer, R., F. Morsdorf, M. Schaepman, W. Mücke, N. Pfeifer, and M. Hollaus. 2012. Robust characterization of forest canopy structure types using full-waveform airborne laser scanning. Proceedings of the SilviLaser.

Li, J., B. Hu, and T. L. Noland. 2013. Classification of tree species based on structural features derived from high density LiDAR data. Agricultural and Forest Meteorology 171:104-114.

Lim, K., P. Treitz, M. Wulder, B. St-Onge, and M. Flood. 2003. LiDAR remote sensing of forest structure. Progress in Physical Geography 27(1):88-106.

Lopatin, J., M. Galleguillos, F. E. Fassnacht, A. Ceballos, and J. Hernández. 2015. Using a Multistructural Object-Based LiDAR Approach to Estimate Vascular Plant Richness in

Mediterranean Forests with Complex Structure. Geoscience and Remote Sensing Letters, IEEE 12(5):1008-1012.

Lucas, R. M., A. Lee, and P. J. Bunting. 2008. Retrieving forest biomass through integration of CASI and LiDAR data. International Journal of Remote Sensing 29(5):1553-1577.

Luscombe, D. J., K. Anderson, N. Gatis, A. Wetherelt, E. Grand-Clement, and R. E. Brazier. 2014. What does airborne LiDAR really measure in upland ecosystems? Ecohydrology 8(4):584–594.

Luttmerding, H.A., D.A. Demarchi, E.C. Lea, D.V. Meidinger, and T. Vold (editors). 1990. Describing ecosystems in the field. 2nd ed. B.C. Min. Environ., Lands and Parks and B.C. Min. For., MOE Manual 11. Victoria, B.C.

Madrone Environmental Services Ltd. 2008. TEM Expanded Legend - Part 6 in Terrestrial Ecosystem Mapping of the Coastal Douglas-Fir Biogeoclimatic Zone. 15273. Ministry of Environment, Government of British Columbia, Victoria, BC.

Magnussen, S., and P. Boudewyn. 1998. Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. Canadian journal of forest research 28(7):1016-1031.

Maynard, J., and M. Johnson. 2014. Scale-dependency of LiDAR derived terrain attributes in quantitative soil-landscape modeling: Effects of grid resolution vs. neighborhood extent. Geoderma 230:29-40.

McGaughey, R. J. 2009. FUSION/LDV: Software for LIDAR data analysis and visualization. US Department of Agriculture, Forest Service, Pacific Northwest Research Station: Seattle, WA.

McMahon, G., E. B. Wiken, and D. A. Gauthier. 2004. Toward a scientifically rigorous basis for developing mapped ecological regions. Environmental management 34(1):111-124.

Michez, A., H. Piégay, J. Lisein, H. Claessens, and P. Lejeune. 2016. Classification of riparian forest species and health condition using multi-temporal and hyperspatial imagery from unmanned aerial system. Environmental monitoring and assessment 188(3):1-19.

Moore, I. D., P. Gessler, G. Nielsen, and G. Peterson. 1993. Soil attribute prediction using terrain analysis. Soil Science Society of America Journal 57(2):443-452.

Morgan, J. L., S. E. Gergel, and N. C. Coops. 2010. Aerial photography: a rapidly evolving tool for ecological management. Bioscience 60(1):47-59.

Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment 80(1):88-99.

Næsset, E., and T. Økland. 2002. Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. Remote Sensing of Environment 79(1):105-115.

Pojar, J., K. Klinka, and D. Meidinger. 1987. Biogeoclimatic ecosystem classification in British Columbia. Forest Ecology and Management 22(1):119-154.

Pojar, J., K. Klinka, and D. Demarchi. 1991. Coastal western hemlock zone. In D. Meidinger, & J. Pojar (Eds.), Ecosystems of British Columbia (Chapter 6, p. 330). Special Report Series No. 6. British Columbia Ministry of Forests, Victoria, B.C.

Potter, K. M., B. S. Crane, and W. W. Hargrove. 2017. A United States national prioritization framework for tree species vulnerability to climate change. New Forests 48(2):275-300.

Prasad, A. M., L. R. Iverson, S. N. Matthews, and M. P. Peters. 2016. A multistage decision support framework to guide tree species management under climate change via habitat suitability and colonization models, and a knowledge-based scoring system. Landscape Ecology 31(9):2187-2204.

Reese, H., M. Nyström, K. Nordkvist, and H. Olsson. 2014. Combining airborne laser scanning data and optical satellite data for classification of alpine vegetation. International Journal of Applied Earth Observation and Geoinformation 27:81-90.

Reif, M. K., and H. J. Theel. 2016. Remote sensing for restoration ecology: Application for restoring degraded, damaged, transformed, or destroyed ecosystems. Integrated Environmental Assessment and Management 13 (4):614–630.

Resources Inventory Committee. 1998. Standards for terrestrial ecosystem mapping in British Columbia. Government of British Columbia, Victoria, BC.

Roberts, D. W., and S. V. Cooper. 1989. Concepts and techniques of vegetation mapping. General Technical Report INT-US Department of Agriculture, Forest Service, Intermountain Research Station,USA.

Rowe, J. S. 1996. Land classification and ecosystem classification. Environmental monitoring and assessment 39(1-3):11-20.

Swanson, F., T. Kratz, N. Caine, and R. Woodmansee. 1988. Landform effects on ecosystem patterns and processes. Bioscience 38(2):92-98.

Tarboton, D. G. 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. Water Resources Research 33(2):309-319.

Thompson, S. D., T. A. Nelson, I. Giesbrecht, G. Frazer, and S. C. Saunders. 2016. Data-driven regionalization of forested and non-forested ecosystems in coastal British Columbia with LiDAR and RapidEye imagery. Applied Geography 69:35-50.

Tiede, D., C. Hoffmann, and G. Willhauck. 2012. Fully integrated workflow for combining object-based image analysis and LiDAR point cloud metrics for feature extraction and classification improvement. Pages 6 ILMF International LiDAR Mapping Forum.

Timothy, D., M. Onisimo, and I. Riyad. 2016. Quantifying aboveground biomass in African environments: A review of the trade-offs between sensor estimation accuracy and costs. Tropical Ecology 57(3):393-405.

Valbuena, R., M. Maltamo, and P. Packalen. 2016. Classification of multilayered forest development classes from low-density national airborne lidar datasets. Forestry 89(4):392-401.

van Asselen, S., and A. Seijmonsbergen. 2006. Expert-driven semi-automated geomorphological mapping for a mountainous area using a laser DTM. Geomorphology 78(3):309-320.

Walton, A., and D. Meidinger. 2006. Capturing expert knowledge for ecosystem mapping using Bayesian networks. Canadian journal of forest research 36(12):3087-3103.

Wang, T., G. Wang, J. Innes, C. Nitschke, and H. Kang. 2016. Climatic niche models and their consensus projections for future climates for four major forest tree species in the Asia–Pacific region. Forest Ecology and Management 360:357-366.

Weiss, A. 2001. Topographic position and landforms analysis. Poster presentation, ESRI user conference, San Diego, CA.

White, J. C., J. T. Arnett, M. A. Wulder, P. Tompalski, and N. C. Coops. 2015. Evaluating the impact of leaf-on and leaf-off airborne laser scanning data on the estimation of forest inventory attributes with the area-based approach. Canadian Journal of Forest Research 45(11):1498-1513.

Wu, Z., D. Dye, J. Stoker, J. Vogel, M. Velasco, and B. Middleton. 2016. Evaluating Lidar Point Densities for Effective Estimation of Aboveground Biomass. International Journal of Advanced Remote Sensing and GIS 5:1483-1499.

Wulder, M., N. Coops, A. Hudak, F. Morsdorf, R. Nelson, G. Newnham, and M. Vastaranta. 2013. Status and prospects for LiDAR remote sensing of forested ecosystems. Canadian Journal of Remote Sensing 39(sup1):S1-S5.

Wulder, M., J. White, S. Magnussen, and S. McDonald. 2007. Validation of a large area land cover product using purpose-acquired airborne video. Remote Sensing of Environment 106(4):480-491.

Wulder, M. A., J. C. White, R. F. Nelson, E. Næsset, H. O. Ørka, N. C. Coops, T. Hilker, C. W. Bater, and T. Gobakken. 2012. Lidar sampling for large-area forest characterization: A review. Remote Sensing of Environment 121:196-209.

Yang, X., N. Rochdi, J. Zhang, J. Banting, D. Rolfson, C. King, K. Staenz, S. Patterson, and B. Purdy. 2014. Mapping tree species in a boreal forest area using RapidEye and LiDAR data. Pages 69-71 Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International. IEEE.

Yildiz, M., T. Kavzoglu, I. Colkesen, and E. K. Sahin. 2012. An Assessment of the Effectiveness of Segmentation Methods on Classification Performance. Pages 133-138 10th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences.

Yokoyama, R., M. Shirasawa, and R. J. Pike. 2002. Visualizing topography by openness: a new application of image processing to digital elevation models. Photogrammetric Engineering and Remote Sensing 68(3):257-266.

Zhang, H., J. E. Fritts, and S. A. Goldman. 2008. Image segmentation evaluation: A survey of unsupervised methods. Computer Vision and Image Understanding 110(2):260-280.

Zhang, Z., A. Kazakova, L. M. Moskal, and D. M. Styers. 2016. Object-Based Tree Species Classification in Urban Ecosystems Using LiDAR and Hyperspectral Data. Forests 7(6):122.