LiDAR as an Advanced Remote Sensing Technology to Augment Ecosystem Classification and Mapping

Discussion Paper

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Abstract

Observing landscape patterns at various temporal and spatial scales is central to classifying and mapping ecosystems. Traditionally, ecosystem mapping is undertaken through a combination of fieldwork and aerial photography interpretation. These methods, however, are time-consuming, prone to subjectivity, and difficult to update. Light Detection and Ranging (LiDAR) is an advanced remote sensing technology that has rapidly 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. LiDAR technology is therefore well-suited to providing detailed information on topography and vegetation structure and has considerable potential to be used for ecosystem classification and mapping. In this article, the potential to use LiDAR data to advance ecosystem mapping is examined. The current state of the science for using LiDAR data to classify and map key ecosystem attributes within an existing ecosystem mapping scheme is discussed by focusing on British Columbia Terrestrial Ecosystem Mapping and its associated Predictive Ecosystem Mapping. The article concludes by summarizing which components of ecosystem mapping and classification are best suited to the application of LiDAR data, followed by a discussion of the feasibility and future directions for mapping ecosystems with LiDAR technology.

KEYWORDS: ALS-based ecosystem mapping; ecosystem classification; ecosystem mapping; ecosystem site unit; LiDAR-based ecosystem mapping; Predictive Ecosystem Mapping; Terrestrial Ecosystem Mapping

Introduction

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). 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 availability dictates the type of vegetation present, with minor differences in slope and aspect markedly influencing vegetation patterns (Bailey 1987). The ability to observe ecosystems at varying scales and discern how their distribution changes across a landscape provides

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insight about why particular sites exist and how they are maintained, which improves the capacity to anticipate downstream effects and gain insight about why changes take place or how harmful effects might be mitigated (McMahon et al. 2004).

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).

Digital, remotely sensed data are increasingly being applied to ecosystem mapping because, in general, they are becoming more diverse, readily available, and inexpensive (Lefsky et al. 2002). Digital data allow for automated or semi-automated mapping methods to be used, thereby reducing bias and increasing cost-efficiency and the 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 increase the 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 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. Light Detection and Ranging (LiDAR) is an example of a recent 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 digital elevation models (DEMs), and can provide detailed information on vegetation structure.

The objective of this article is to examine the potential to use LiDAR data to advance ecosystem mapping by:

1) presenting a brief overview of LiDAR technology and its general applications for classifying and mapping various abiotic and biotic ecosystem attributes;
2) examining more specifically LiDAR's potential to classify key ecosystem attributes within an existing ecosystem mapping scheme—British Columbia's Terrestrial Ecosystem Mapping (Resources Inventory Committee 1998); and
3) discussing the feasibility and future directions for using LIDAR data to map ecosystems.

LiDAR and its application for classifying abiotic and biotic features

LiDAR is an active remote sensing technology that can provide simultaneous measurements of Earth's surfaces, both above ground (e.g., vegetation) and the terrain surface itself (i.e., topography) (Harpold et al. 2015). To accomplish this, the distance between the LiDAR sensor and the target is calculated (Jelalian 1980) by emitting beams of light and measuring the time it takes for the reflections to be returned to the sensor (Figure 1). In addition to the laser scanner unit, there is a Global Positioning System and an Inertial Measurement Unit that track the orientation and location of the scanner (Harpold et al.

2015). There are various LiDAR platforms, each operating on the same principle. Airborne laser scanning (ALS) data are acquired by a system mounted on an aircraft, while terrestrial laser scanning systems collect data from ground-based stationary and mobile platforms. Less common is spaceborne laser scanning, which uses a system mounted on an orbiting spacecraft. Overall, ALS is the most common application and is likely the predominant platform for ecosystem-based classification research; it is the major focus of this discussion.

There are two types of systems for acquiring ALS data: discrete return 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 that represent 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 and consequently more detail and information than that of discrete ALS (Mallet & Bretar 2009; Höfle & Rutzinger 2011; Wulder et al. 2012). Discrete return LiDAR is currently more common and less expensive to obtain, which makes it the most likely candidate for ecosystem classification and mapping.

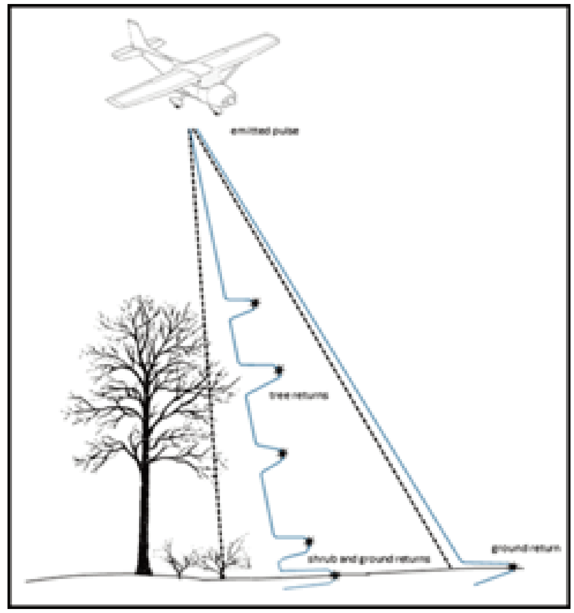

Figure 1. Airborne LiDAR emitted pulse and its returns

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). LiDAR-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 (Luscombe et al. 2014; 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).

LiDAR 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).

Ecosystem mapping in British Columbia: Terrestrial and predictive ecosystem mapping

Many studies have used LiDAR data to classify various ecosystem attributes, but few have combined terrain and vegetation metrics to classify ecosystem units specifically. To examine this potential, British Columbia's Terrestrial Ecosystem Mapping (TEM) and its associated Predictive Ecosystem Mapping (PEM) methods were used in this study to examine the current state of science for LIDAR and how it could be applied to advance ecological understanding and mapping. Terrestrial Ecosystem Mapping/Predictive Ecosystem Mapping are part of a provincially mandated program that includes standards for inventory and mapping, which was established by the British Columbia Resource Information Standards Committee. Due to the extensive area of the province and the complexity, lengthy time required, and expense of the program, much of British Columbia remains unmapped to the site level. With refined methods that use remotely sensed data, it is possible that large areas could be mapped, which would improve the ability to manage these landscapes.

Both the TEM/PEM approaches integrate biotic and abiotic attributes. Terrestrial Ecosystem Mapping is the typical approach used for mapping at larger scales when detailed ecological information is required. The TEM approach relies on using attributes (Table 1) that are distinguishable from aerial photography; units are classified, delineated, and pre-typed on photos by local ecologists. 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 (RIC 1998). Alternatively, the PEM approach is often used when less detail is required and smaller scale maps are appropriate. Predictive Ecosystem Mapping uses computer modelling, which incorporates existing knowledge of ecosystem attributes and relationships, to predict ecosystem representation in the landscape. Predictive Ecosystem Mapping uses spatial data and local knowledge within an automated modelling process for map generation. In the PEM process, information for polygon delineation is usually derived from data sources such as forest inventory, soils, or terrain mapping. Ecologists with local experience may still provide some interpretation.

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; vm1 = Submontane Very Wet Maritime subzone; Hw = western hemlock; Ba = amabilis fir; Pl = lodgepole pine; Cw = western redcedar

The topographic detail and precision that LiDAR data afford can improve the efficiency and accuracy of most terrain attributes used within TEM/PEM (e.g., geomorphic process, terrain attributes, and soil drainage). Improved classification models could increase the ability to identify features that may otherwise be difficult to predict. In British Columbia, for example, complex mountainous terrain often makes mapping features such as alluvial fans, incised channels, and talus slopes difficult when using predictive methods, and as a result requires manual classification methods. LiDAR 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; Möller & Dowling. 2015; Sarala et al. 2015). Many metrics for topology (e.g., elevation, slope gradient, slope aspect, curvature, and topographic openness) can be obtained from high-quality DEMs and can be used to improve models (Anders et al. 2011a; Greve et al. 2012; Maynard & Johnson 2014; Akumu et al. 2015; Thompson et al. 2016).

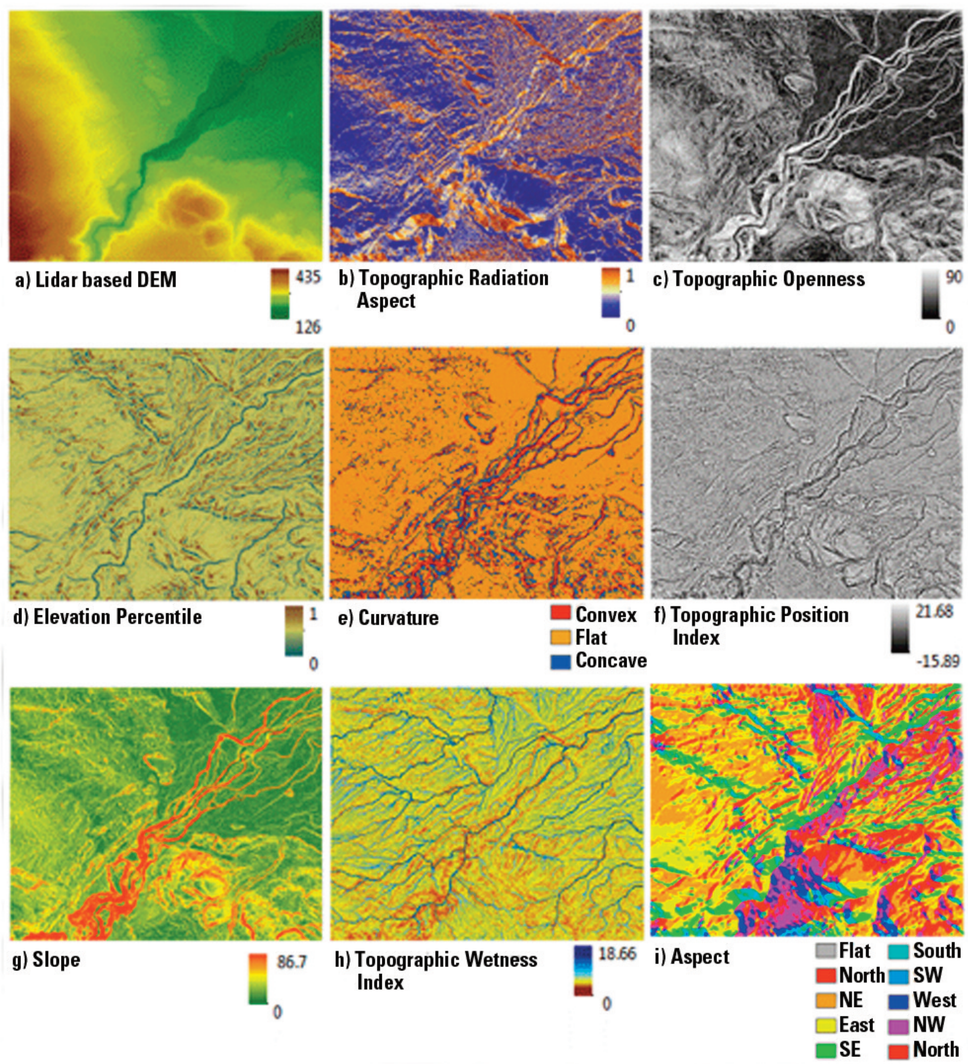

Figure 2. Example of layers created from a) a digital elevation model that could be used for ecosystem mapping: b) topographic radiation aspect; values closer to 0 are cool, and those near 1 are warm; c) topographic openness is the mean angle between a centre cell and its surrounding cells; d) elevation percentile is the percentage of cells that are lower than a centre cell in a given window; e) curvature; f) Topographic Position Index is the difference between a cell elevation value and the mean elevation of its surrounding cells; g) slope in degrees; h) Topographic Wetness Index is a measure of wetness based on flow direction and accumulation; higher values are increasingly wet; i) aspect.

High-quality, detailed DEMs improve the ability to quantify the relationships between topography and a specific criterion that changes with topography, such as surface expression (e.g., hummock, terrace). The classification of parent material (i.e., genetic material) is particularly difficult because LiDAR 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) were successful at delineating major parent material classes but less so for minority classes.

Drainage is another terrain attribute that is affected by topology; it can occur via surface runoff or soil infiltration. It is important that the contextual catchment that an area is situated within be considered when evaluating soil drainage since water inputs such as rain or snow can vary significantly among topographic and climatic regions. For example, high-elevation bogs and fens on steep slopes are common within coastal areas of British Columbia (Banner et al. 2005), and successful identification of these wetlands is an important part of TEM ecosystem delineation. 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.

Aspinall & Sweeny (2012) renewed existing soil maps using high-resolution LiDAR-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 LiDAR does not penetrate the ground, using it as a tool for measuring soil depth is not possible, and no studies were found that used LiDAR topography metrics to predict soil depth.

Improving topographic information will also aid in the classification and mapping of vegetation attributes. 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.

Stand height and forest canopy characteristics offer insight about the particular site series, and LiDAR 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). Airborne laser scanning estimates of individual height have been shown to be more consistent than manual, field-based measurements; however, ALS estimates of plot mean tree height may be lower than field-measured height, and bias increases with stand height but is not evident in the ALS data for maximum tree heights (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) can 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, but the number and types of LiDAR metrics that were able to distinguish among particular combinations decreased with a stand's 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 LiDAR 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 LiDAR-derived structural information (Colgan et al. 2012; Dalponte et al. 2012). Yang et al. (2014) combined satellite multispectral imagery (RapidEye) and LiDAR data for species identification within the Canadian boreal forest. Their best result combined LiDAR and RapidEye using the Random Forest classifier. Yang et al. (2014) concluded that the most significant LiDAR metrics and RapidEye bands for tree species mapping were DEM, slope, canopy height, red-edge Normalized Difference Vegetation Index, and red-edge and near-infrared spectroscopy bands. Without the fusion of spectral and LiDAR 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 LiDAR to specifically describe these characteristics. The primary studies that use LiDAR to measure or describe a forest floor characteristic are associated with forest fuel loads and are not directly applicable to TEM classification methods.

Future directions and applications

The most practical form of LiDAR for ecosystem mapping will 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 above-ground 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 LiDAR 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. LiDAR 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.

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.

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 2). While not stand-alone criteria for ecosystems, they 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 2). 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

Table 2. Feasibility of using LiDAR data to describe criteria for attribute classification

	Feasible/well established	Feasible/requires more research	Not feasible
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

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.

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 2). 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.

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 segmentation 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).

For vegetation layers, segmentation 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) can be 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 (NDVI), height percentiles (Jones et al. 2012), canopy height descriptors, and volume profiles (Jones et al. 2012).

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 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 Licences) 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.

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References

Akumu, C., J. Johnson, D. Etheridge, P. Uhlig, M. Woods, D. Pitt, & 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, & 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.

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

___________. 2013. Geomorphological change detection using object-based feature extraction from multi-temporal LiDAR data. IEEE Geoscience and Remote Sensing Letters 10(6):1587–1591.

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

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.G. 1985. The factor of scale in ecosystem mapping. Environmental Management 9(4):271–275.

___________. 1987. Suggested hierarchy of criteria for multi-scale ecosystem mapping. Landscape and Urban Planning 14:313–319.

Bailey, R., M. Jensen, D. Cleland, & P. Bourgeron. 1994. Design and use of ecological mapping units. Ecosystem Management: Principles and Applications 1:95–106.

Banner, A., P. LePage, J. Moran, & A. de Groot. 2005. The HyP 3 Project: Pattern, process, and productivity in hypermaritime forests of coastal British Columbia–a synthesis of 7-year results. B.C. Ministry of Forests, Research Branch, Victoria, B.C. Special Report 10.

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.

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

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

Colgan, M.S., C.A. Baldeck, J. Féret, & 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., F. Morsdorf, M.E. Schaepman, & N.E. Zimmermann. 2013. Characterization of an alpine tree line using airborne LiDAR data and physiological modeling. Global Change Biology 19(12):3808–3821.

Dalponte, M., L. Bruzzone, & 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.

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

Ecological Data Committee. 2000. Standard for Terrestrial Ecosystem Mapping (TEM) – digital data capture in British Columbia: ecosystem technical standards and database manual. Victoria, B.C. Ecosystems Working Group, version 3.0.

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, & 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, & 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.

Greve, M.H., R.B. Kheir, M.B. Greve, & 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.

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, & 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.

Harpold, A.A., A. Harpold, J. Marshall, S. Lyon, & T. Barnhart. 2015. Laser vision: LiDAR as a transformative tool to advance critical zone science. Hydrology and Earth System Sciences 19(6):2881–2897.

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

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

Jelalian, A.V. 1980. *Laser radar systems,* pp. 546–554. EASCON’80, Electronics and Aerospace Systems Conference.

Jenness, J. 2006. Topographic Position Index (tpi_jen. avx) extension for ArcView 3. x, v. 1.3 a. Jenness Enterprises. http://www.jennessent.com/arcview/tpi.htm [Accessed September 2015]

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

Kumar, J., J. Weiner, W. Hargrove, S. Norman, F. Hoffman, & 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, & 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, & D.J. Harding. 2002. LiDAR remote sensing for ecosystem studies. Bioscience 52(1):19–30.

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

Li, J., B. Hu, & 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, & 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, & J. Hernández. 2015. Using a multistructural object-based LiDAR approach to estimate vascular plant richness in Mediterranean forests with complex structure. IEEE Geoscience and Remote Sensing Letters 12(5):1008–1012.

Lucas, R.M., A. Lee, & 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, & R.E. Brazier. 2014. What does airborne LiDAR really measure in upland ecosystems? Ecohydrology 8:582–592.

Mallet, C., & F. Bretar. 2009. Full-waveform topographic LiDAR: state-of-the-art. ISPRS Journal of Photogrammetry and Remote Sensing 64(1):1–16.

Maynard, J., & 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.

McMahon, G., E.B. Wiken, & D.A. Gauthier. 2004. Toward a scientifically rigorous basis for developing mapped ecological regions. Environmental Management 34(1):S111–S124.

Michez, A., H. Piégay, J. Lisein, H. Claessens, & 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.

Möller, P., & T.P. Dowling. 2015. The importance of thermal boundary transitions on glacial geomorphology; mapping of ribbed/hummocky moraine and streamlined terrain from LiDAR, over Småland, South Sweden. GFF 137(4):252–283.

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

Næsset, E., & 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, & D. Meidinger. 1987. Biogeoclimatic Ecosystem Classification in British Columbia. Forest Ecology and Management 22(1):119–154.

Reese, H., M. Nyström, K. Nordkvist, & 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.

Resources Inventory Committee (RIC). 1998. Standards for terrestrial ecosystem mapping in British Columbia. Government of British Columbia, Victoria, B.C.

Roberts, D.W., & 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.

Sarala, P., J. Räisänen, P. Johansson, & K. Eskola. 2015. Aerial LiDAR analysis in geomorphological mapping and geochronological determination of surficial deposits in the Sodankylä region, northern Finland. GFF 137(4):293-303.

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

Valbuena, R., M. Maltamo, & P. Packalen. 2016. Classification of multilayered forest development classes from low-density national airborne LiDAR datasets. Forestry 45:15–25.

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

White, J.C., J.T. Arnett, M.A. Wulder, P. Tompalski, & 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, & 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.A., J.C. White, R.F. Nelson, E. Næsset, H.O. Ørka, N.C. Coops, T. Hilker, C.W. Bater, & 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, & B. Purdy. 2014. Mapping tree species in a boreal forest area using RapidEye and LiDAR data, pp. 69–71. Geoscience and Remote Sensing Symposium (IGARSS), IEEE International.

Yokoyama, R., M. Shirasawa, & 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, Z., A. Kazakova, L.M. Moskal, & D.M. Styers. 2016. Object-based tree species classification in urban ecosystems using LiDAR and hyperspectral data. Forests 7(6):122.

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