International Journal of Applied Earth Observation and Geoinformation 38 (2015) 242–250

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Integrating optical satellite data and airborne laser scanning in habitat classification for wildlife management

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ARTICLE INFO

Article history:
Received 10 October 2014
Received in revised form
10 December 2014
Accepted 15 December 2014
Available online 7 February 2015

Keywords:
Lidar
Grizzly bear
Habitat
Landcover
Classification
Landsat

ABSTRACT

Wildlife habitat selection is determined by a wide range of factors including food availability, shelter, security and landscape heterogeneity all of which are closely related to the more readily mapped landcover types and disturbance regimes. Regional wildlife habitat studies often used moderate resolution multispectral satellite imagery for wall to wall mapping, because it offers a favourable mix of availability, cost and resolution. However, certain habitat characteristics such as canopy structure and topographic factors are not well discriminated with these passive, optical datasets. Airborne laser scanning (ALS) provides highly accurate three dimensional data on canopy structure and the underlying terrain, thereby offers significant enhancements to wildlife habitat mapping. In this paper, we introduce an approach to integrate ALS data and multispectral images to develop a new heuristic wildlife habitat classifier for western Alberta. Our method combines ALS direct measures of canopy height, and cover with optical estimates of species (conifer vs. deciduous) composition into a decision tree classifier for habitat – or landcover types. We believe this new approach is highly versatile and transferable, because class rules can be easily adapted for other species or functional groups. We discuss the implications of increased ALS availability for habitat mapping and wildlife management and provide recommendations for integrating multispectral and ALS data into wildlife management.

Introduction

Wildlife respond to a large number of factors when selecting habitat, involving complex behavioral decisions which are made at multiple spatial scales (Ciarniello et al., 2007; Herfindal et al., 2009; Johnson et al., 2002). Broad scale spatial variation in biodiversity is thought to respond to three major drivers; climatic stability, productivity, and habitat structure (MacArthur, 1972) – with empirical evidence demonstrating the importance of each of these variables (Coops et al., 2008). Bioclimatic models are often applied to estimate broad-scale distribution of species (Guisan and Zimmermann, 2000; Rahbek and Graves, 2001; Willis and Whittaker, 2002). However, at finer spatial scales land cover, disturbance, and habitat heterogeneity are more important factors affecting local distribution and habitat selection of species (Iverson and Prasad, 1998; Thuiller, 2004).

The vertical and horizontal structure of vegetation plays a critical role in defining suitable wildlife habitat and can do so in a variety of ways. For certain species, vegetation structure drives food quality, diversity, and availability (Hamer and Herrero, 1987; Johnson et al., 2002; Månsson et al., 2007). Access to high quality forage in early successional stage forest stands, deciduous overstorey stands, or open areas with grass, forb, herb and berry species (Allen et al., 1987; Dussault et al., 2005; Munro et al., 2006) decrease energy required for foraging and digestion in Grizzly bear *(Ursus arctos)*, and thus, maximise energy intake (White, 1983). Vegetation structure also provides protection and/or cover which provides security against predation and can protect species from heat stress when ambient temperature exceeds optimal levels (Schwab and Pitt, 1991), or deep snow during winter; with snow accumulation often adversely impacting species mobility and food intake, and thus, the survival and reproductive rates (Cederlund et al., 1991; Mech and McRoberts, 1987; Post and Stenseth, 1998). Vegetation structure is also inextricably linked to disturbances; especially fire, harvesting, and insect defoliation. As a result, disturbances potentially increase future habitat suitability for bears (Nielsen et al., 2008, 2004b; Rempel et al., 1997; Stewart et al., 2012). Heterogeneity in

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http://dx.doi.org/10.1016/j.jag.2014.12.004
0303-2434/

vegetation structure also provides access to forest edges, where forage and protection are amplified (i.e., the cover-food edge concept) which is a key habitat type selected by many species (Courtois et al., 2002; Dussault et al., 2005; Stewart et al., 2013), although edges can also represent attractive sinks where survival is low (Nielsen et al., 2006, 2004a).

Grizzly bears have diverse seasonal habitat requirements with three distinct foraging seasons, hypophagia, early hyperphagia, and later hyperphagia (Nielsen et al., 2006). In hypophagia they forage on roots (such as alpine sweetvetch), early herbaceous material and ungulate kills, in early hyperphagia their main diet is green herbaceous material (such as cow parsnip, sedges, and horsetails) with some insect matter, whereas in late hyperphagia berries make up a the majority of their diet (Hamer and Herrero, 1987; Munro et al., 2006). The optimal habitat for Grizzly bears, therefore, changes significantly throughout the season and contains herbaceous areas, wetlands, and open forest, as well as proximity to forest stands for other habitat requirements including bedding and hiding cover. Over the past 40 years, since the launch of the first Earth observation satellites, satellite-based image classification techniques have been used to map species habitat and has become an important tool in large area mapping and management of wildlife habitat (McDermid et al., 2005; Wang et al., 2009). The Landsat series of sensors in particular have set the standard for regional classification projects because of their combination of spatial and spectral resolution, consistent long term record, and excellent data availability (Cohen and Goward, 2004; Franklin and Wulder, 2002; Leimgruber et al., 2005). However, considerable limitations exist in the application of optical satellite imagery specifically involving the detection of detailed forest structural characteristics beyond initial canopy closure (Franklin et al., 2003; Wang et al., 2009). The issue of signal saturation on optical remote sensing imagery with increasing leaf area is well known. Studies have shown both theoretically and practically that estimation of canopy parameters can be difficult beyond a leaf area index of 3–5 (Baret and Guyot, 1991; Song, 2012; Turner et al., 1999) and that canopy parameter estimation also varies between conifer and deciduous canopy types (Song, 2012). As a result while classification schemes often recognize the importance of forest structure in the class definition (Franklin and Wulder, 2002; McDermid et al., 2009; Wulder et al., 2008b), they are often generalized or have considerable uncertainty in forest density classes caused by the inherent limitations of the optical sensor system.

Many have tried to bridge the gap between the need for structural information and the inability of direct optical classification to provide this information. Solutions may include the use of ancillary data, texture information, object based analysis, post classification procedures, or other remotely sensed data like radar (Lu and Weng, 2007; Roberts et al., 2007). The most common source of ancillary data is elevation models (Franklin et al., 2002; Johnson et al., 2003; McDermid et al., 2009) and topographic derivatives like slope and aspect. Texture information is used in the form of gray-level co-occurrence matrices (Franklin et al., 2002), spatial autocorrelation (Magnussen et al., 2004), or variogram functions (Zhang et al., 2004), based on homogeneity assumptions within the forest stand and the information content of shaded vs. sunlit parts in the canopy. In post classification methods the fine scale patterning of simple land-cover types (e.g., treed, herb, bare) or vegetation indices can be used to define habitat classes (Sluiter et al., 2004). Radar in particular is able to partially penetrate vegetation canopies, but the efficacy in detecting structure is highly dependent on the microwave wavelength, vegetation height and moisture content (Imhoff et al., 1997). All of these potential solutions can improve classification results in certain cases, but can be laborious, costly and require extensive training data or manual steps which may lead to interpreter-related differences and locally optimised but regionally less applicable results.

Airborne laser scanning (ALS) uses discrete return small footprint airborne lidar to map the elevation of the ground surface and canopy elements. ALS provides high accuracy measurement of canopy heights and density through the separation of the terrain model from canopy returns. Terrain height and landforms are used to model hydrological and soil processes (White et al., 2012) and are shown to be key drivers of plant species distribution (Nijland et al., 2014). The potential of ALS to detect structural forest characteristics has been shown in many studies, and it has quickly become an operational technology for estimation of forest height, cover and structure around the world (Lim et al., 2008; Wulder et al., 2008a). ALS data can provide specific information on forest structure, such as understory and midstory cover assessment, topographic morphological variables, such as slope and aspect, as well as the presence of old, tall trees or snags. As a result, the use of ALS technology has increased for assessments of wildlife habitat. Hyde et al. (2005) utilized ALS data to characterize montane forest canopy structure in the Sierra National Forest for large-area habitat mapping. They found that the accurate prediction of canopy height, canopy cover, and biomass was an important prerequisite predicting wildlife habitat showing significant promise in its use. Vierling et al. (2008) provide a review of the current status of ALS remote sensing and habitat characterization and conclude that, although a growing number of studies highlight interest in ALS advances, few studies have actually used the data to quantitatively address these relationships.

Western Alberta, Canada is a highly dynamic region where widespread resources extraction from the forestry and fossil fuels industries occurs on important habitat for species at risk (Roever et al., 2008). Coal, oil, gas, and timber extraction, in addition to related population growth, urban development and expanding demands for outdoor recreation impact biodiversity through habitat alteration and fragmentation (Schneider et al., 2003). Western Alberta represents the eastern limit of Grizzly bear habitat in Southern Canada (Nielsen et al., 2009) and has an important population of woodland caribou (*Tarandus rangifer)* (Bradshaw and Hebert, 1996; Festa-Bianchet et al., 2011). Effective management of wildlife habitat is of paramount importance for sustainable support of both ecological values and resource extraction in the region. To support wildlife and habitat management, we need a detailed account of habitat status and a thorough understanding of the habitat requirements of different key species. The availability of accurate habitat maps is crucial for both objectives.

In this research, we introduce an approach to integrate ALS and multispectral satellite images to develop a new heuristic wildlife habitat classifier for western Alberta. The classifier uses vegetation structure, species composition, and terrain characteristics derived from available ALS and multispectral data directly in a decision tree. We evaluate the accuracy of the habitat layers and discuss the added value of the created products for the classification. Based on our results, we look at implications of increased ALS availability for habitat mapping and wildlife management, and make recommendations on the application of ALS in regional habitat mapping efforts.

Methods

Study area

Our focus areas encompasses the western Rocky Mountains in Alberta, Canada constrained by the Upper and Lower foothills Natural subregions, with the higher elevations in the Alpine natural subregion (Downing and Pettapiece, 2006) (Fig. 1). Elevations range

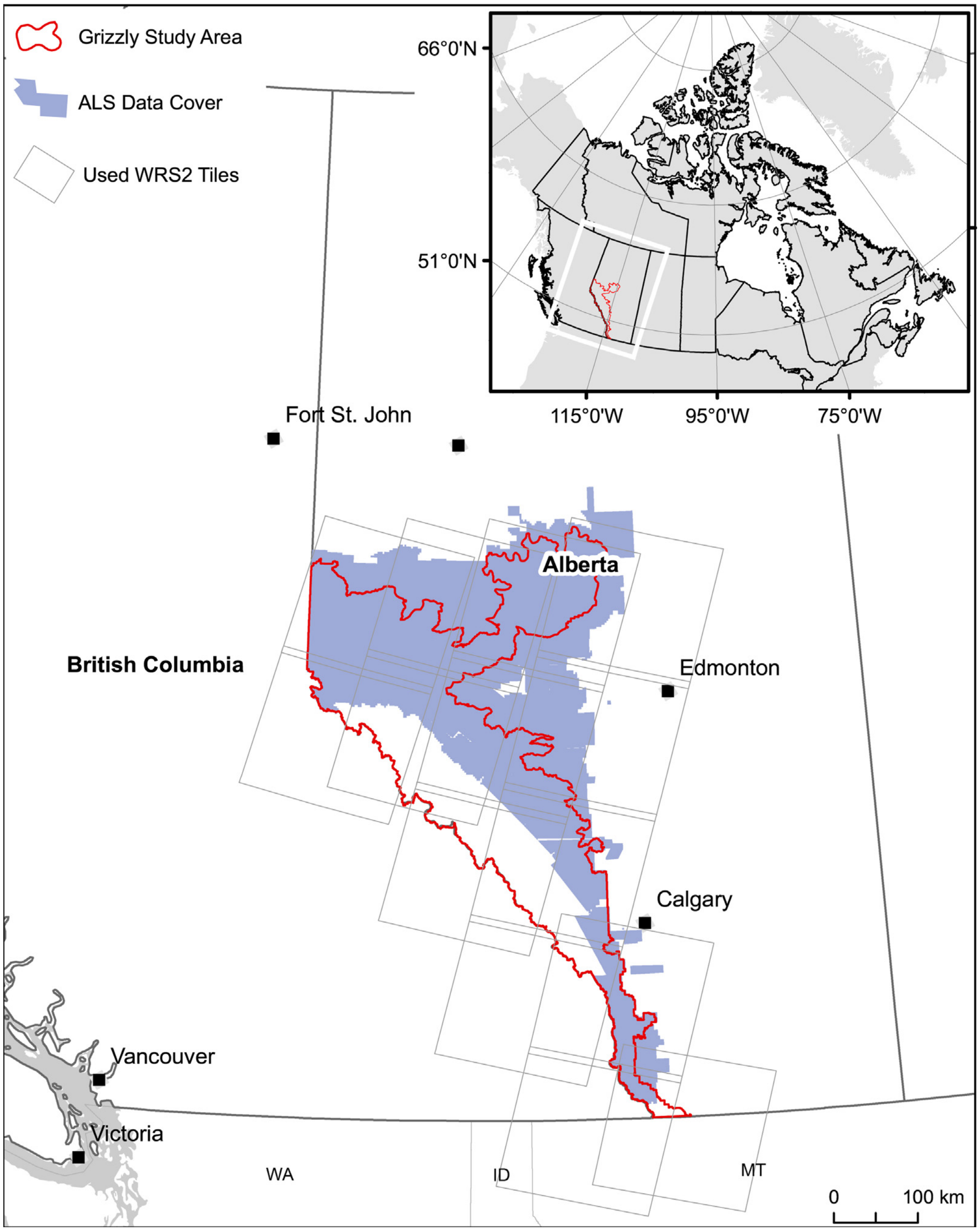

Fig. 1. Overview of the Study area (~867000 km^2) with indication of the area of interest, ALS data coverage and used Landsat image tiles.

from 700 to 3000 m ASL with steep montane topography in the west, transitioning to a gently rolling landscape in the eastern parts of the area. The natural vegetation in the sub-alpine areas is forested with Lodgepole Pine (*Pinus contorta*), White Spruce (*Picea glauca*), and Trembling Aspen (*Populus tremuloides*) as the dominant tree species. The area has extensive resource extraction of underground resources (coal, oil, and natural gas) and forest harvesting. This results in a mosaic of mature forest, regrowth forest and barren or recovering areas.

Our focus species for the habitat assessment is the Grizzly bear which was designated as a threatened species within Alberta with considerable pressures on the population from human caused mortality, and habitat changes associated with forest management, resource extraction, and natural disturbances (Festa-Bianchet, 2010). The provincial government has a provincial Grizzly bear recovery plan underway for this species.

Classification scheme

The habitat classification scheme developed is based on a merging of a standardised landcover classification based on the Alberta Vegetation Inventory (AVI) (Nesby, 1997) combined with a Landsat-based Grizzly bear habitat classifier presented by McDermid et al. (2005, 2009). Cut-off values of percent canopy cover were taken from the existing classification as they are currently well understood and used by the management community. The classes are well proven and used in other related models, such as habitat selection functions which makes it desirable to build upon these existing classes (Table 1). The AVI is an interpreter-derived delineation of vegetation units based on aerial photography and field sampling of forest characteristics, including timber productivity, tree species composition, height, and crown closure. The scheme closely matches the Canada wide forest classification by Wulder et al.

Table 1
Class definitions.

#	Class	Description
1	Water	>6% standing or flowing water
2	Snow & Ice	>6% permanent snow or ice cover
3	Barren	<6% vegetation cover
4	Alpine barren	<6% vegetation cover; alpine area
5	Herb	<25% shrub cover; <6% tree cover
6	Alpine herb	<25% shrub cover; <6% tree cover; alpine area
7	Shrub	>25% shrub cover; <6% tree cover
8	Open wetland	'wet' or 'aquatic' moisture regime; <10% crown closure
9	Treed wetland	'wet' or 'aquatic' moisture regime; >10% crown closure
10	Open conifer	>80% conifer cover; 6–40% crown closure
11	Moderate conifer	>80% conifer cover; 40–75% crown closure
12	Dense conifer	>80% conifer cover; >75% crown closure
13	Open mixed	25–80% broadleaf cover; 6–50% crown closure
14	Closed mixed	25–80% broadleaf cover; >50% crown closure
15	Open deciduous	>80% broadleaf cover; 6–50% crown closure
16	Closed deciduous	>80% broadleaf cover; >50% crown closure

(2008b,c) and Wulder et al. (2006) – the Earth Observation for Sustainable Development of Forests (EOSD) – with exclusion of classes irrelevant to the study area (like bryoid tundra). In accordance with McDermid et al. (2005) and Nielsen et al. (2009), additional habitat classes for alpine barren areas, alpine meadows, and dense coniferous forests based on their relevance for Grizzly bear were included. Alpine meadows have specific food resources like Alpine Sweetvetch (*Hedisarum alpinum)* (Coogan et al., 2012; Nijland et al., 2012), plus both alpine meadows and alpine barren areas are expected to be stable, while meadow and barren landcover types in lowlands are often the result of disturbances and may quickly develop more vegetation cover. Dense coniferous forest is separated as a distinct class because of their relevance for denning sites (Ciarniello et al., 2005; Pigeon et al., 2014), but usually lower yield of fruiting species (Nielsen et al., 2004b). These classes were not separated previously, because they were not reliably detected in previously used multispectral classifiers. They are more likely however to be successfully separated using topographical and canopy structure information from ALS. We chose to split them from existing classes to allow for a backwards compatible generalization of the newly created habitat types with existing maps.

Data sources

The province of Alberta, Canada together with industry partners has created a near wall to wall coverage of ALS data over the forested area of the provincially managed lands. With these data, we can fully integrate ALS information into a habitat classification for wildlife management. ALS data over the region were acquired between 2003 and 2009, with the majority collected in 2007 and 2008. Data from different acquisitions were acquired, thinned, and distributed as 1×1 m gridded products including a bare earth layer, and a full feature (top of canopy) layer. Fig. 1 shows the extent of ALS coverage in the study area, cover is near complete for the core Grizzly range with the exception of the Rocky Mountain national park lands managed by the Federal government. Prior to classification, the 1 m products were generalized to 25×25 m grid metrics in FUSION (McGaughey, 2014), with metrics including maximum canopy height, and returns above 2 m. The bare earth product was used to create a 25 m digital terrain model (DTM) and slope layers. In addition to these ALS products, a depth to groundwater layer was also developed from the bare earth model using a hydrological modelling process described in White et al. (2012).

A Landsat Thematic Mapper mosaic based on data acquired in the summers of 2008–2010 was also developed. All scenes were processed to surface reflectance by the USGS using their standard image preprocessing procedures (Masek et al., 2006; USGS, 2013). In addition to summer images, a leaf-off mosaic was created using snow free images acquired in October and November, for this mosaic less cloud-free images were available which was compensated for by including Landsat 7 ETM + (SLC-off) images and a wider range of years (2007–2011). The leaf-off mosaic was used only to improve the conifer model; all other classes were derived from the ALS and the Summer mosaic.

Reference data

Field reference data were collected during a field campaign in 2013. During the campaign, 102 variable radius plots were established using a structurally guided sampling scheme based on species composition and vegetation height. The centre point located using GPS. At each plot, habitat class, vegetation height (using a vertex III hypsometer (Haglof Sweden AB)), vegetated cover (using a spherical densitometer), soil wetness (dry|mesic|wet), and canopy species composition were recorded. Reference data were used to evaluate the ALS based models of canopy structure, and to build the regression model for percent conifer cover for use in the classification.

Classification models

The overall classification approach is shown in Fig. 2, integrating a spectral classifier to separate water and bare ground from the vegetated classes, which are further divided based on height, density and species composition measures. Conifer cover is modeled using a linear model based on leaf-on—leaf-of NDVI (Tucker, 1979) difference, and tasseled-cap (Kauth and Thomas, 1976) brightness. Vegetation structure is directly derived from ALS metrics without regression models. In all forest structure models, areas with a vegetation height less than 4 m were excluded as they are not considered as forest in our classification. The hydrologic model for depth-to-water-table is described in White et al. (2012) and uses topographic routing of water over the terrain surface together with fixed area for flow initiation to derive the water table height. The parts of the study area that have no ALS data present are in-filled using a standard maximum likelihood classifier on the Landsat visible, near infrared and short wave infrared spectral bands, DTM, and Percent Conifer layers. We evaluate the agreement between our integrated classification with the classification without ALS data using an equalized random sample of 1000 points per class taken from the area where both classifications area available. While this cannot be interpreted as a validation of our results, the comparison reflects on the improvement our integrated classification provides over a more traditional classifier.

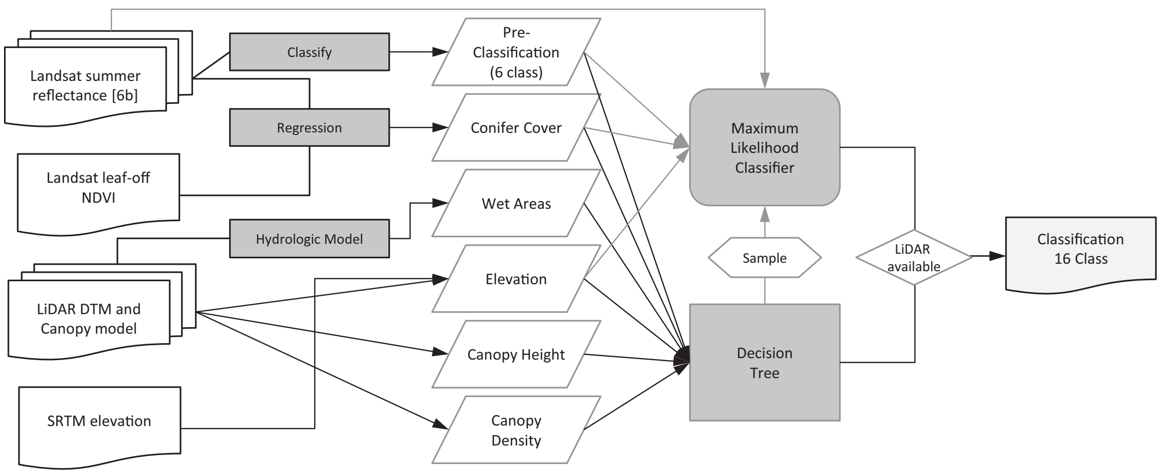

Fig. 2. Classification flow chart.

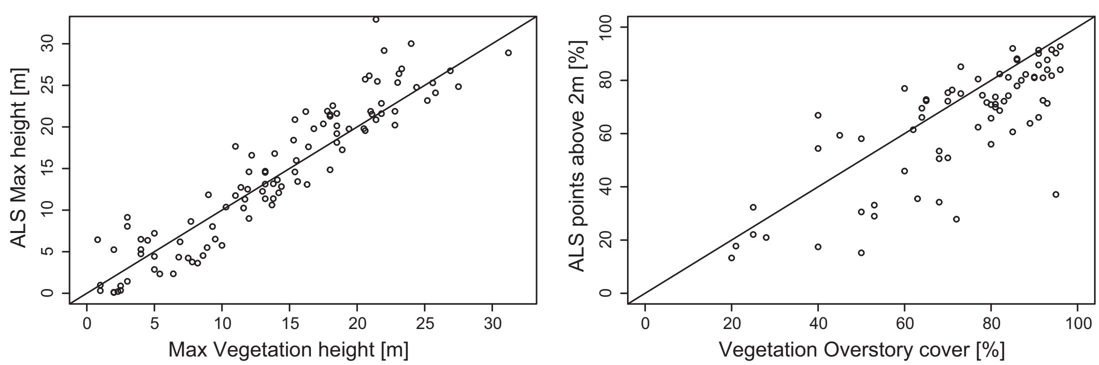

Fig. 3. Scatterplot of field and LiDAR derived data for plot locations of vegetation height (r^2 = 0.87, RMSE = 3.08 m), and vegetation cover (r^2 = 0.60, RMSE = 16.2%).

Results

Pre classification models

ALS derived maximum canopy height and points above 2 m were selected to represent canopy height and cover directly without using any models. The relations between the selected variables and field based measurements of canopy structure were strong (R^2 vegetation height: 0.87, vegetation cover over 2 m: 0.60) and visual evaluation of the relations reveal no bias in the estimators (Fig. 3). The accuracy of using direct ALS variables (RMSE canopy height: 3.08 m, canopy cover: 16.2%) is acceptable for our classification scheme.

Conifer cover was modeled using a linear model based on leaf-on—leaf-of NDVI difference, and tasseled-cap brightness (R^2: 0.60, RMSE: 0.18). The linear model was then thresholded into three classes, conifer, mixed, and deciduous based on maximum likelihood showing acceptable class separation (Fig. 4).

Classification

Fig. 5 shows the decision tree classification showing the input data and the subsequent class decisions. Of the total study area 63% was classified as forested, 12% as herb and shrub, 5% as wetland and 20% as barren land. Table 2 shows an overview of the cover for individual classes. The proportion of land cover classes over the

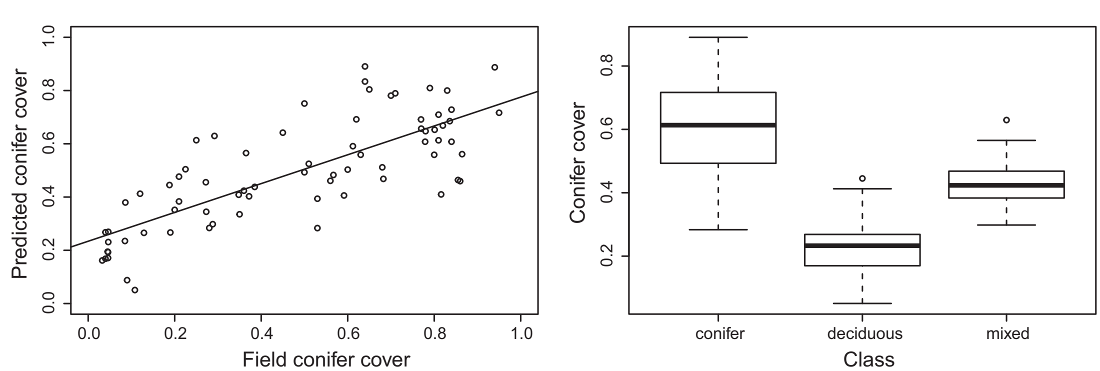

Fig. 4. Scatterplot of Percent Conifer model (r^2 = 0.60, RMSE = 0.18), and boxplots for the three classes.

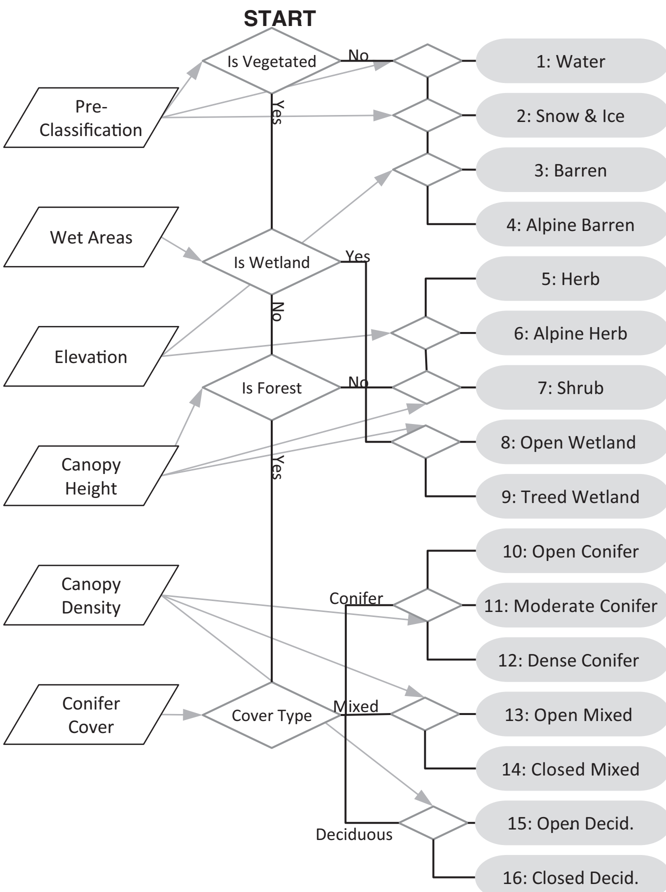

Fig. 5. Tree classifier structure, arrows indicate which data layers are involved in each class decision.

region corresponds well with existing landcover products: EOSD (Wulder et al., 2008b; Wulder et al., 2006) (forest:60%, wetlands:6%, herb and shrub:16%, barren:18%), and the classification made for the Grizzly bear project (McDermid et al., 2009) (forest:61%, wetland:4%, herb and shrub 14%, barren: 21%). The main difference is that the current classification contains less shrub cover due to the classification assigning all pixels with a canopy cover over 4 m to forested classes using the ALS whereas a conventional optical classifier may have classified these regenerating stands as shrub. The overall pattern of classes across the study area is shown in Fig. 6A (panels B–D present a more detailed view of the characteristics

Table 2
Cover statistics for the 16 classes in the Grizzly bear habitat classifier for the area of interest (Fig 1).

Class	Percent cover	km^2
Water	0.9	808
Snow & ice	1.4	1174
Barren	4.0	3487
Alpine barren	14.1	12212
Herb	2.5	2207
Alpine herb	3.0	2588
Shrub	6.3	5474
Open wetland	1.2	1056
Treed wetland	3.5	3029
Open conifer	4.1	3582
Moderate conifer	21.7	18793
Dense conifer	15.5	13415
Open mixed	3.7	3231
Closed mixed	5.8	5045
Open deciduous	5.2	4529
Closed deciduous	7.0	6064

of the final product). In Fig. 6B, the vegetation pattern in mountainous areas is clear and the high grounds are barren (albeit with some snow cover), then transitioning to alpine meadows, shrub, and coniferous forest cover in lower elevations. The southwest corner of the panel has a fire scar which is still partially barren and has open deciduous forest in recovering areas. Fig. 6C has an example of a mosaic of forest harvest areas in different stages of recovery with associated mixtures of forest types and canopy cover. The barren area in the southwest is a mining area with herbaceous vegetation around it on reclaimed lands. Fig. 6D shows a nearly continuous forested area, the dominant forest types are moderate and dense coniferous, but small pockets of treed and barren wetlands are present as well as areas with a deciduous cover and a mixed cover type in the transition zone.

Comparison of our integrated classification with a traditional Landsat based maximum likelihood classifier (Table 3) gives an indication of the gained by including ALS based terrain and structural information. Considerable disagreement exists between the herbaceous, shrub, wetland, and open forest classes. The shrub class has high levels of confusion with almost all vegetated classes except the moderate and dense conifer. Wetlands are confused among themselves for treed and open, and specifically treed wetlands are often confused with mixed and deciduous forest. Within each of the forest types the open and closed classes are often confused. The non-vegetated classes like water, snow, and barren have high levels of agreement between the two classifiers as do the forest types. The high agreement within these classed is as expected as separation between them in our integrated classifier is already made based on spectral information.

Discussion

Traditional spectral classifiers rely on training data (for supervised classifications), or the discretion of the interpreter (for labeling unsupervised clustering), and maximise class separability for classes that are spectrally different. By adding ancillary data sources such as terrain information, by stratifying datasets, or including the spatial domain into the classification it is possible to improve the classification accuracy.

Availability of ALS data into habitat classifications allows more direct estimates of vegetation structure in the classification scheme which has been shown to be of direct relevance to habitat evaluation and wildlife management (Vierling et al., 2008). By using ALS data in combination with optical data direct information on vegetation characteristics can be integrated using a heuristic-based classifier that directly employs the class definitions as set based on the management needs. Our results indicate that users can gain considerable accuracy improvements over solely Landsat-based classifications (Table 3).

Integrating ALS derived structural information into habitat classifications allows habitat classification to be tailored for specific species or functional groups. In this approach, we used continuous input layers for which the class rules can be adapted to create new products without the need of additional input data. ALS supports this system specifically by providing information difficult to obtain using passive optical sensing systems such as small scale topographical features and vertical vegetation structure. Improvements are also possible for classes which describe the understory which can be detected from ALS, but often have non-unique spectral signatures because of canopy cover. Key habitats where the fusion of ALS and optical data are likely to be beneficial include:

Wetland areas: moist soils and wetland areas are often not spectrally unique in the overstorey from drier forests or herbal vegetation as multispectral images are much more sensitive for vegetation density and vigor then individual species (Baker et al.,

Table 3
Confusion matrix (values as in percent) between our final classification product and the Landat based classification without ALS data with the same classes.

Landsat Only		Final Classification																commission agreement
Class	#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Water	1	90		1					1		1		1					94.1
Snow & ice	2	3	93															95.8
Barren	3	2		69	13	5	3	2	1	1	2			2	1	2	1	66.1
Alpine bare	4	1	6	9	76		2											80.5
Herb	5			9		28	9	10	5	1	1			2	1	8	3	37.2
Alpine herb	6			5	8	8	67	11						3	1	10	4	56.7
Shrub	7			1		6	4	7	1		1		1	1	1	7	3	20.6
Wetland open	8	2		3		24	6	16	44	7	1			3	1	13	3	36.1
Wetland treed	9	2				6	1	17	32	46	12	8	5	19	15	18	23	22.7
Conifer open	10	1		3	2	2	1	4	2	2	40	14	8	2	1			49.6
Conifer moderate	11					1		1	1	12	23	31	21					34.9
Conifer dense	12							1	1	15	16	44	62					44.4
Mixed open	13			1		3	2	8	4	3	1			32	13	1		46.6
Mixed closed	14					2		5	2	6	2	1	2	35	66	1	3	51.9
Deciduous open	15					11	4	9	2	1						14	9	27.9
Deciduous closed	16					4	1	8	2	5						27	51	52.0
Omission agreement		90.2	93.2	69.1	76.4	28.3	67.4	7.0	44.2	46.3	39.6	31.3	62.1	32.0	65.8	13.7	50.9	
																Total agreement		51.1%

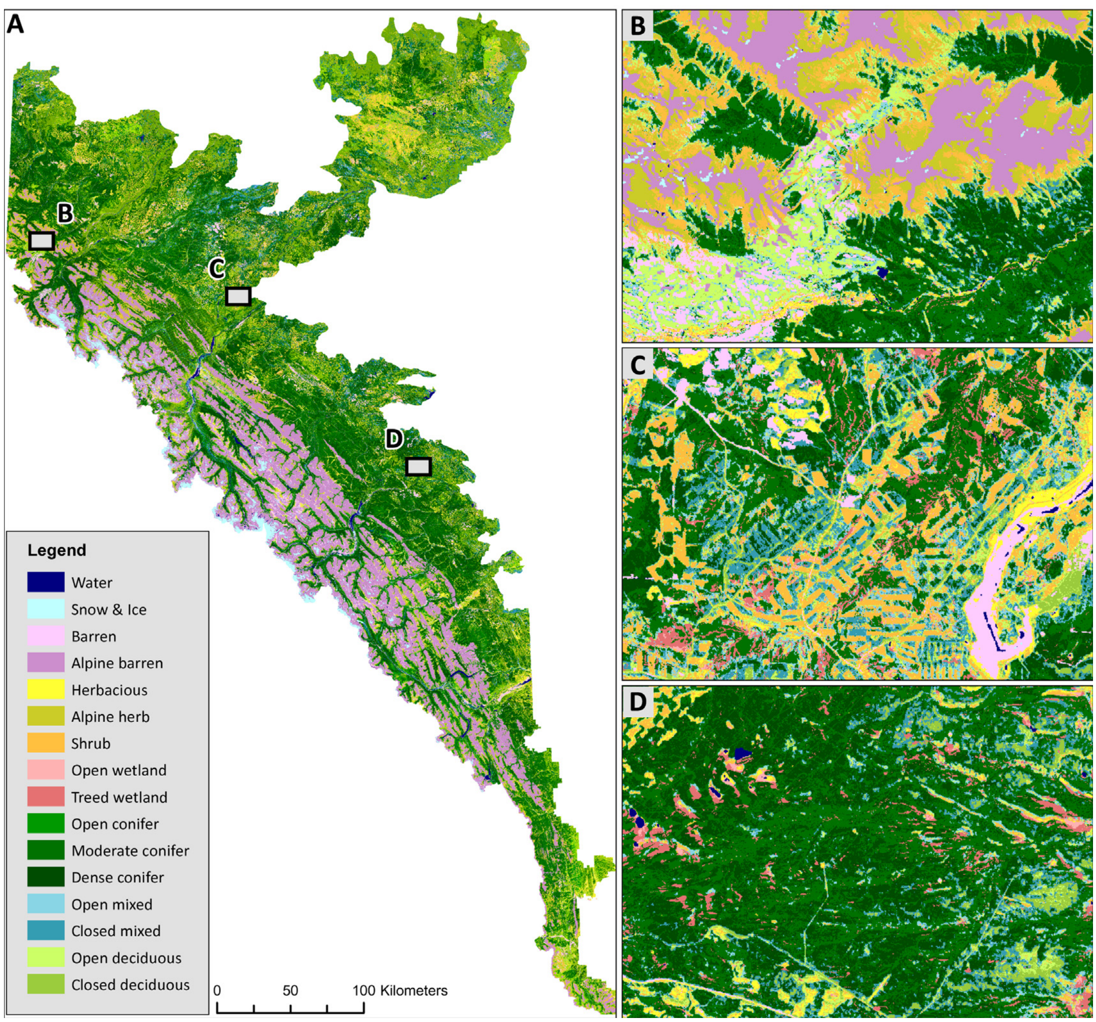

Fig. 6. Overview map of the classification results for the whole study area (A) and three detail sites as indicated in the first panel. (B) mountainous area with a recovering fire scar in the SW corner, (C) mosaic of regenerating forest harvests with a coal mine site in the east, (D) mostly continuous conifer forest interspersed with wetlands and mixed\deciduous patches.

2006; Johnston and Barson, 1993). However, understory cover and associated resources for animals are fundamentally different. The terrain detail ALS data provide enables accurate mapping of topographically wet areas (White et al., 2012) and separates them from other habitat types.

Alpine areas: Alpine meadows and barren terrain are spectrally similar to lower barren or herbal areas but provide different functions and resources to wildlife (Munro et al., 2006). Lowland areas with no forest cover are usually transient and result from disturbances, while alpine areas have more stable vegetation cover. The ALS-derived elevation model can be used to separate alpine areas by elevation threshold, or using an automated alpine tree-line detection algorithm as employed in Coops et al. (2013).

Forest-cover density: Canopy closure is a crucial habitat driver as it relates to understory composition, fruit productivity (Hamer, 1996; Nielsen et al., 2010, 2004b), and providing cover from adverse climate and snowfall (Mech and McRoberts, 1987; Schwab and Pitt, 1991). Optical methods saturate beyond LAI > 3–5 m^2/m^2 and may have ambiguous results depending on different species compositions. ALS cover measures are consistent over both deciduous and coniferous species and do not saturate at densities found in temperate or boreal forests. ALS, therefore, allows for the more detailed and consistent separation of canopy density classes.

Species composition: ALS has limited potential for the classification of specific species or the separation of coniferous vs. deciduous vegetation cover (Wulder et al., 2008a). Neither do commonly used height metrics separate low herbaceous vegetation and barren areas. We are fortunate that these classes are already reliably separated using multispectral images similarly to separating water bodies from terrestrial habitats. To maximise the separation of deciduous vs. coniferous vegetation cover, we use a combination of leaf-on and leaf-off images which leads to reliable separation of these forest types. Integrating both ALS and optical data sources, we demonstrate the possibility of a complete heuristic habitat classification scheme for wildlife habitat that can be easily adapted for the needs of specific species.

We recognise ALS is not ubiquitously available over all jurisdictions; however, this is quickly changing. Through the combined effort of industry and provincial government an almost wall to wall ALS coverage of the forested areas in Alberta has been acquired. This paper demonstrates how valuable these types of data are, not only in engineering and resource management, but also for improving wildlife management and supporting ecological values and other benefits of forests. The current map product is created for regional applications and uses a raster resolution of 25 m for summarizing the ALS derived canopy metrics. The generalization of data to this 25 m grid size facilitated integration with multispectral images and minimised the impact of different survey configurations of the merged large area ALS dataset. The approach of using naïve estimators from ALS to represent vegetation structure does produce relatively high RMSE values, but the relationship is highly transferable and has minimal bias. Loss in detail compared to the state of the art in laser scanning is in exchange for the gain in integration of ALS and multispectral satellite data for large area applications supporting more effective habitat and wildlife management.

Conclusions

In this paper, we present a new habitat classification for Grizzly bear management in Alberta, Canada. We combine optical satellite images and ALS into a heuristic, decision tree based habitat classifier. Based on the integrated use of optical and ALS data we are able to describe the major axes of landscape variability including species composition and vegetation structure and to use these data directly in the landcover classifier. The classifier allows for more detailed habitat classes in alpine areas, wetlands and overstory density and structure and represents a step forward from currently available products. This proposed system is versatile in the sense that the class rules can be easily adapted for other species or functional groups without the need of additional inputs or training data. Integration of multispectral satellite images and ALS enables an adaptable classification system that supports informed decision making for wildlife management.

Acknowledgements

Funding for this research was generously provided by the Grizzly bear program of the Foothills Research Institute located in Hinton, Alberta, Canada, with additional information available at: www.foothillsri.ca. Additional funds were provided by an NSERC Discovery grants to Dr. Nicholas Coops and Dr. Scott Nielsen. Lidar data was made available by the Government of Alberta. The authors thank Adam Erickson and Ilia Parshakov for their help with the field program, and Dr. Txomin Hermosilla for his assistance Landsat data compositing. The two anonymous reviewers are acknowledged for their constructive contribution to the manuscript.

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