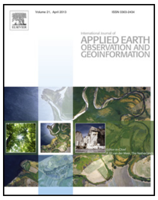
International Journal of Applied Earth Observation and Geoinformation 38 (2015) 242–250

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

W. Nijland[a,*], N.C. Coops[a], S.E. Nielsen[b], G. Stenhouse[c]

[a] *Department of Forest Resources Management, University of British Columbia, 2424 Main Mall, Vancouver, BC V6 T 1Z4, Canada*
[b] *Department of Renewable Resources, University of Alberta, 751 Generals Services Building, Edmonton, AB T6G 2H1, Canada*
[c] *Foothills Research Institute, Box 6330, Hinton, AB T7V 1X6, Canada*

ARTICLE INFO

Article history:
Received 10 October 2014
Received in revised form
10 December 2014
Accepted 15 December 2014

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 land-cover 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

---

[*] Corresponding author. Tel.: +1 6048274429.
E-mail address: irss.ubc@wiebenijland.nl (W. Nijland).

http://dx.doi.org/10.1016/j.jag.2014.12.004
0303-2434/© 2014 Elsevier B.V. All rights reserved.

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