Remote Sensing of Environment 143 (2014) 73–84

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

# A decision-tree classification for low-lying complex land cover types within the zone of discontinuous permafrost

L. Chasmer [a,c,*], C. Hopkinson [c], T. Veness [b], W. Quinton [b], J. Baltzer [d]

[a] Department of Geography and Environmental Management, University of Waterloo, Waterloo, ON N2L 3G1, Canada
[b] Cold Regions Research Centre, Wilfrid Laurier University, Waterloo, ON N2L 3C1, Canada
[c] Department of Geography, University of Lethbridge, Lethbridge, AB T1K 3M4, Canada
[d] Deptartment of Biology, Wilfrid Laurier University, Waterloo, ON N2L 3C1, Canada

ARTICLE INFO

*Article history:*
Received 8 August 2013
Received in revised form 20 December 2013
Accepted 23 December 2013
Available online 19 January 2014

*Keywords:*
Discontinuous permafrost
Peatland
Classification
Airborne LiDAR
WorldView 2
Discharge
Permafrost thaw
Hydrological model

ABSTRACT

This study presents a decision-tree (DT) approach to classifying heterogeneous land cover types within a northern watershed located in the zone of discontinuous permafrost using airborne LiDAR and high resolution spectral datasets. Results are compared with a more typically applied supervised classification. Increasing errors in discharge resulting from an inaccurate classification are quantified using a distributed hydrological model.

The hierarchical classification was accurate between 88% and 97% of the validation sub-area, whereas the parallelepiped classification was accurate between 38% and 74% of the same area (despite overall accuracy of ~91%, kappa = 0.91). Topographical derivatives were best able to explain variations in land cover types (82% to 96%), whilst spectral and vegetation structural derivatives were less accurate. When compared with field measurements, the hierarchical classification of plateau edges (adjacent to a fen) was within 2 m of measured, 60% of the time, whilst this occurred only 40% of the time when using a spectral classification. When examining the impacts of land cover classification accuracy on modelled discharge, we find that the length of the Hydrological Response Unit defined by the classification (and subject to varying levels of errors) was linearly related to discharge ($m^3$) such that an increase in permafrost plateau area would increase discharge by 26% of the total. The methodology presented in this paper clarifies previous classification and modelling studies using Landsat and IKONOS data for the same basin. This study greatly improves upon past classifications in the same area, furthers our understanding of the distribution of connected bogs and fens (as conveyors of water to the basin outlet) within the watershed, and current spatial extents of rapidly thawing permafrost plateaus, which are critical for better understanding the impacts of climate change on these northern environments.



## 1. Introduction

The zone of discontinuous permafrost has undergone significant climate warming and permafrost loss over the past number of decades (e.g. Anisimov & Reneva, 2006; Beilman, Vitt, & Halsey, 2001; Chasmer, Hopkinson, & Quinton, 2010; Quinton, Hayashi, & Chasmer, 2010; Shur & Jorgenson, 2007). This is especially evident in colder permafrost areas, which are subject to rapid permafrost warming (Romanovsky, Smith, & Christiansen, 2010) and the existence of thermal inertia within warm, thin perennially frozen ground (Lewkowicz, Etzelmüller, & Smith, 2011). Permafrost underlies approximately 25% of the total land area within the Northern Hemisphere and therefore small shifts in ground heating and vegetation succession and the associated changes in permafrost distribution and extent can have globally relevant implications (e.g. Jorgenson, Racine, Walters, & Osterkamp, 2001). In the discontinuous permafrost zone, rates of permafrost thaw are expected to accelerate (Anisimov & Reneva, 2006) as plateaus become increasingly fragmented (Baltzer, Veness, Chasmer, & Quinton, in press; Chasmer et al., 2010). This can have significant impacts on both human and environmental systems, including greenhouse gas fluxes (Chasmer, Kenward, Quinton, & Petrone, 2012; Myers-Smith, McGuire, Harden, & Chapin, 2007), forest fires (Camill & Clark, 2000); changes to surface hydrology and flooding (Guan, Westbrook, & Spence, 2010; Wright, Hayashi, & Quinton, 2009); and northern infrastructure and economy (Prowse et al., 2009).

Accurate classification of the spatial distribution of land cover types, especially in areas that are rapidly changing (e.g. Chasmer et al., 2012), is fundamentally important for quantifying how these changes are affecting ecosystems (Foody, 2002). Land cover change, often as a result of climatic or anthropogenic disturbance, is viewed as the single most important variable affecting ecosystem processes (e.g. Foody, 2002; Vitousek, 1994), whilst our ability to predict future global environmental

* Corresponding author at: Cold Regions Research Centre, Wilfrid Laurier University, Waterloo, ON N2L 3C1, Canada. Tel.: +1 519 998 5894.
*E-mail addresses:* laura.chasmer@gmail.com (L. Chasmer), c.hopkinson@uleth.ca (C. Hopkinson), vene7610@mylaurier.ca (T. Veness), wquinton@wlu.ca (W. Quinton), jbaltzer@wlu.ca (J. Baltzer).

0034-4257/$ – see front matter 
http://dx.doi.org/10.1016/j.rse.2013.12.016

scenarios as a result of climate change depends significantly on the accuracy of land cover classification (e.g. Feddema et al., 2005). Remote sensing data are most frequently used for the classification of land cover types (e.g. Heginbottom, 2002). Data are spatially continuous and provide a recognisable photographic appearance of the Earth's surface, thus facilitating the comparison of features of interest through space and/or time. Furthermore, datasets often have a lengthy history of acquisition, which can be used for the detection of land cover change or conditions through time (e.g. Heginbottom, 2002).

Remote sensing-based classification of permafrost extent and ice content over broad areas has had early and ongoing interest, especially where multiple layers of land surface characteristics (e.g. vegetation, topography, etc.) correlating to the existence of permafrost are used. Early studies attempted to classify ranges of active layer thickness using thermal imagery and visible layers of vegetation cover (Morrissey, Strong, & Card, 1986; Peddle & Franklin, 1993) and topographic derivatives (Peddle & Franklin, 1993), but were unable to quantify useful ranges relative to *in situ* spring-time measurements. Vitt, Halsey, and Zoltai (1994) visually assessed aerial photographs acquired in Alberta, Saskatchewan, and Manitoba between 1949 and 1953 and counted the numbers of bogs within each photograph, manually assigning rare to abundant classes to each. They found that permafrost areas containing bogs had rates of degradation that were greater than rates of aggradation. By the late 1990s, more sophisticated methods of automated classification (e.g. neural networks) were applied to correlating indicators of permafrost (e.g. Leverington & Duguay, 1997), and whilst less time intensive, these were not easily transferred between sites. The integration of remote sensing data within statistical models of mountain permafrost distribution (Gruber & Hoelzle, 2001) did not improve model accuracy of permafrost prediction, possibly due to complex non-linear feedbacks between energy inputs to the surface and permafrost losses in some areas but not others (e.g. Anisimov & Reneva, 2006). Early permafrost classification accuracies ranged from approximately 40% to 70%.

Spectral classifications of land cover types identified using remote sensing data within the zone of discontinuous permafrost are often problematic due to fragmented land cover boundaries, low spectral contrast between land cover types, and rapidly changing spectral characteristics at bog/fen and plateau edges as a result of soil moisture changes. Further, the extension of often living but unhealthy “remnant” trees beyond plateau boundaries makes it exceedingly difficult to accurately represent true plateau edges using spectral data alone (Chasmer et al., 2010). This is important as historical rates of permafrost and land cover changes become an indicator of the effects of climate change on northern environments. In some cases of permafrost change detection, the accuracy of the classification was not discussed. Classification and geometric errors may lead to substantial inaccuracies in permafrost extent, which will propagate uncertainties associated with the quantification of permafrost loss/land cover change as well as the use of land cover maps within land surface and hydrological models (e.g. Miller, Guertin, & Goodrich, 2007). Studies that combined digital elevation models with spectral image classification and multi-temporal data were better able to characterise permafrost by minimising misclassification errors. Nguyen, Burn, King, and Smith (2009) were able to map permafrost extent to approximately 90% accuracy using high resolution SPOT imagery of vegetation communities through the use of spectral vegetation indices, texture analysis, and principal components analysis (PCA). However greater than 90% of the land surface was underlain by permafrost, and the application of the methodology to more heterogeneous (discontinuous permafrost) regions was not assessed. Other methods, including object-based image analysis (e.g. Hay, Blaschke, Marceau, & Bouchard, 2003; Johansen, Coops, Gergel, & Stange, 2007) that use the pixel spectrum, spatial location, spectral homogeneity, and clustered shapes to identify objects can be highly accurate, but also require user intervention which may or may not be applicable to broad areas of discontinuous permafrost. New applications of Random Forest and machine learning classification methods have been applied with high accuracies to spectral remote sensing data (e.g. Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012) and LiDAR data (e.g. Im, Jensen, & Hodgson, 2008) but not in the zone of discontinuous permafrost.

Land cover classifications integrating airborne LiDAR data with spectral remote sensing data for characterising vegetated environments are fewer in number than traditional spectral classifications, but are gaining popularity. Several studies have found marked improvements via the integration of textural, topographic and vegetation structure characteristics as well as spectral data in other regions (e.g. Goodale, Hopkinson, Colville, & Amirault-Langlais, 2007). Use of digital elevation models (DEMs) of underlying topography, LiDAR data products, and LiDAR/spectral data fusion classification methods have also become popular in mountainous permafrost areas (e.g. Kremer, Lewkowicz, Bonnaventure, & Sawada, 2011) where geomorphic changes due to permafrost thaw pose a considerable hazard. In the zone of discontinuous permafrost, use of LiDAR has been less popular, likely due to logistical expenses; however, there are a few notable studies. LiDAR data were used to map the existence of permafrost based on land cover characteristics (Panda, Prakash, Solie, Romanovsky, & Jorgenson, 2010) and wet areas from laser pulse intensity (Stevens & Wolfe, 2012). Research by Hubbard et al. (2012) integrated LiDAR data with geophysical data to characterise above- and below-ground linkages between permafrost, land surface properties, and sub-surface hydrology/energy balance. We have not yet found a study that integrates airborne LiDAR and spectral data fusion methods for characterising land cover classes within the zone of discontinuous permafrost. This is currently a highly relevant and topical area of research required for better understanding the sensitivity of these northern ecosystems to development, resources extraction, and (natural/anthropogenic) disturbance.

In this study we present a decision-tree land cover classification methodology for permafrost plateaus, bogs, fens, uplands and water (ponds, lakes). The classification combines multiple-resolution spectral, textural, and three-dimensional sub-tree classification layers within the global decision hierarchy. Sensitivity analysis is used to determine the greatest contributors to identification of land cover types, with comparisons to a supervised land cover classification of spectral WorldView 2 data. Classification accuracies are evaluated against field measurements, and implications of the classification accuracy are illustrated using a hydrological runoff model.

## 2. Study area

The Scotty Creek watershed (61.44°N, 121.25°W) is located ~50 km south of Fort Simpson within the zone of sporadic discontinuous permafrost (Hegginbottom, Dubreil, & Harker, 1995), Northwest Territories, Canada (Fig. 1). The ~150 km$^2$ watershed is comprised of a highly heterogeneous mosaic of small permafrost mounds <100 m$^2$ (palsas, Beilman et al., 2001) and larger plateaus (up to 20,000 m$^2$), ombrotrophic flat bogs, channel fens, upland moraine deposits with a dense cover of deciduous and/or spruce trees, and small lakes and ponds. Permafrost thickness varies with ground cover and ranges from a few metres to over 20 m (Smith, Burgess, & Riseborough, 2008), but in general, is very thin and warm (Smith et al., 2008). Plateau coverage has been estimated at ~22% for the year 2000 with a predicted reduction to ~17% by 2055 (Duchesne, Wright, & Ednie, 2008), whilst Beilman and Robinson (2003) have shown losses of 22% on average over the past 50 years in this area. Permafrost is typically found in organic terrain and was likely formed during the Little Ice Age and therefore, it is not in equilibrium with the current climate (Shur & Jorgenson, 2007). Further, permafrost plateaus and palsas, which rise slightly above peatlands, are surrounded by unfrozen and often very wet ground. This is some thermal influence on the degradation of permafrost at plateau edges (e.g. Quinton et al., 2010). Well drained upland moraine deposits covered with shallow