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Remote sensing and object-based techniques for mapping fine-scale industrial disturbances

Ryan P. Powers[a,*], Txomin Hermosilla[a], Nicholas C. Coops[a], Gang Chen[b]

[a] Integrated Remote Sensing Studio, Department of Forest Resources Management, University of British Columbia, 2424 Main Mall, Vancouver, BC, Canada V6T 1Z4

[b] Department of Geography and Earth Sciences, University of North Carolina at Charlotte, 9201 University City Boulevard, Charlotte, NC 28223, USA

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ABSTRACT

Remote sensing provides an important data source for the detection and monitoring of disturbances; however, using this data to recognize fine-spatial resolution industrial disturbances dispersed across extensive areas presents unique challenges (e.g., accurate delineation and identification) and deserves further investigation. In this study, we present and assess a geographic object-based image analysis (GEOBIA) approach with high-spatial resolution imagery (SPOT 5) to map industrial disturbances using the oil sands region of Alberta's northeastern boreal forest as a case study. Key components of this study were (*i*) the development of additional spectral, texture, and geometrical descriptors for characterizing image-objects (groups of alike pixels) and their contextual properties, and (*ii*) the introduction of decision trees with boosting to perform the object-based land cover classification. Results indicate that the approach achieved an overall accuracy of 88%, and that all descriptor groups provided relevant information for the classification. Despite challenges remaining (e.g., distinguishing between spectrally similar classes, or placing discrete boundaries), the approach was able to effectively delineate and classify fine-spatial resolution industrial disturbances.

Introduction

Successful forest ecosystem management and large area planning requires spatially explicit data on natural resources to inform on forest condition, composition and extent (Desclée et al., 2006). In this regard, the detection and monitoring of disturbances is an integral component to effective forest management, especially in locations like Alberta's boreal forest, where anthropogenic activities greatly contribute to contemporary change (Schneider and Dyer, 2009). While forests do have a natural capacity to re-establish after a disturbance event, the degree of ecological effects (Zager et al., 1983; Archibald et al., 1987; Mace et al., 1996) and rate of regeneration can differ greatly between disturbance types. In the Canadian boreal forest, recovery from periodic natural disturbances such as fire is relatively rapid, with signs of advanced recovery usually taking place within 10 years (Schneider, 2002). In contrast, industrial disturbances associated with the creation of seismic lines can take decades to regenerate (Osko and MacFarlane, 2001), and the establishment of access roads, well sites (i.e., core holes) and pipelines represent a more permanent change. Seismic exploration, for example, is the process of mapping subsurface geology to locate and assess oil and gas reserves by creating seismic lines and recording shock waves. Such industry activities (e.g., forest cutlines, roads, clearings and the operation of large equipment) fragment the landscape and can compact the soil or damage the vegetative mat (Severson-Baker, 2004). The cumulative impacts associated with repeated and/or intensification of seismic surveys (i.e., greater density) by the same or competing companies can also increase environmental damage to affected areas and, subsequently, lead to a longer recovery period (Severson-Baker, 2004).

Given the magnitude and diffuse nature of industrial disturbances across Alberta's boreal forest and the anticipated slow recovery, it is apparent that these human activities have the potential to radically alter the forest ecosystem structure and condition (Schneider and Dyer, 2009); thus, warrant additional monitoring to ensure proper management of the region. Typically, broad, long-term patterns associated with disturbances are identified, detected

* Corresponding author. Tel.: +1 778 997 3646.
E-mail address: rppowers@alumni.ubc.ca (R.P. Powers).

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and mapped using satellite data. To date, the focus of most anthropogenic disturbance studies in boreal areas has been on quantifying the impact of fragmentation (e.g., Hobson and Bayne, 2000; Meddens et al., 2008; Linke et al., 2005) or land cover variation (e.g., Gillanders et al., 2008; Potapov et al., 2011; Schroeder et al., 2011) using Landsat (TM and ETM+) imagery. While these moderate resolution (30 m) analyses are well suited for detecting fragmentation and land cover changes at a patch dimension (~1 ha), they may not be sufficient for detecting finer-scale fragmentation or fine-pattern landscape change. For example, seismic lines, which typically vary between 6 and 8 m in width (GOA, 1998), are much smaller than the 30 m Landsat pixel. On the other hand, high spatial resolution data (<5 m) provides the opportunity to identify fine-spatial resolution elements and patterns (Wulder et al., 2004), but the sensors used to derive the imagery typically compensate the number of spectral bands for increased spatial resolution. With fewer spectral channels, it becomes increasingly challenging to differentiate subtle differences amongst similar land cover types. Given the limitations of both the moderate and fine-spatial resolution imagery, it appears that (*i*) finer spatial resolution imagery (<5 m) are required to isolate physically smaller industrial disturbances, and (*ii*) that additional characterization (e.g., structural and statistical) is needed to more effectively differentiate spectrally similar elements within a scene.

Geographic object based image analysis (GEOBIA) is a useful approach for addressing the two considerations outlined above. Specifically, GEOBIA builds upon the object-based paradigm to include spatial location and context as key components of its analysis (Hay and Castilla, 2008) and allows for more meaningful classification of the landscape than traditional pixel-based image processing methods, especially when high spatial resolution data is used (Blaschke and Strobl, 2001; Benz et al., 2004; Zhou and Troy, 2008). Segmentation, the initial step in GEOBIA, is the partitioning of the scene into a set of jointly exhaustive, discrete regions or objects that are more internally uniform than when compared to their neighbouring objects (Wulder et al., 2008). From these segments it is possible to obtain information about geometry and context, such as size, shape, and topology in addition to spectra, which allows for more accurate and useful classifications (Hay et al., 2005; Johansen et al., 2010; Blaschke et al., 2014). This approach is particularly useful in instances where spectral properties are similar, but the geometry and context are distinct. Seismic lines, for example, are narrow, linear features (i.e., cleared strips of land or cutlines) created in seismic surveys. Like most disturbances, such features can experience many possible successional trajectories based on their particular site conditions (e.g., soil, climate, topography, etc.). Since these trajectories and subsequent land covers are not unique to seismic lines, it is very challenging to consistently identify these features with just spectral information. That said, as long as the geometry of features (e.g., industrial disturbances) are maintained, it provides a distinct set of properties that can be used to identify them irrespective of its land cover appearance (Blaschke et al., 2014). In essence, by classifying the objects (groups of pixels) it is possible to define meaningful image objects based on its unique size, shape and spatial distribution (e.g., individual tree, forest, access road, well site, seismic line, etc.).

The main objective of this study is to assess the application of remote sensing for detecting and subsequently monitoring fine-scale industrial disturbances within the boreal forest of Alberta. To achieve this goal, we (*i*) applied a GEOBIA approach in conjunction with high spatial resolution imagery (2.5 m); (*ii*) incorporated contextual measures in the object-based classification using decision trees and boosting; and (*iii*) compared disturbance effects between ecologically varied study sites.

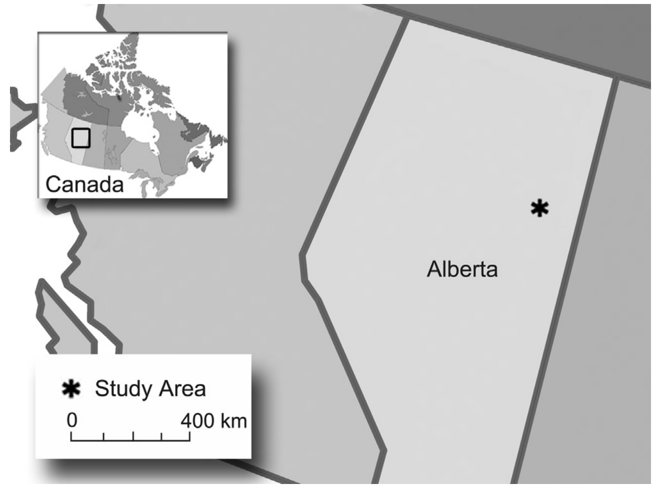

Fig. 1. Study area.

Methods

Study area and data

The study area (Fig. 1) is located in the oil sands region near Fort McMurray, Alberta, Canada, which is approximately 400 km northeast of Edmonton and west of the Saskatchewan border. The extent of the 60 km × 60 km study area is defined by a single SPOT 5 image at N 57°7′56″ to N 56°26′32″ and W 111°30′46″ to W 111°53′49″. Water features such as rivers (i.e., Athabasca River), lakes and wetlands (e.g., bogs, fens, marshes, and aquatic bed) are common. Forested areas include cold tolerant tree species such as Trembling Aspen [*Populus tremuloides* Michx.], Balsam Poplar [*Populus sect. tacamahaca*], White Spruce [*Picea glauca* (Moench) Voss.], White Birch [*Betula pubescens* Ehrh.], Black Spruce [*Picea mariana* (Mill.) Britton, Stems and Poggenburg] and Tamarack [*Larix laricina* (Du Roi) K. Koch], with the latter two species residing mostly in poorly drained wetland areas. This area is dominated by disturbances associated with anthropogenic activities (e.g., oil and gas exploration and extraction). The majority of the oil sands development is concentrated in the northwest; however, other industrial disturbances such as access roads, seismic lines, and well sites are present throughout.

We used a cloud-free SPOT 5 scene acquired on June 29, 2006. The image has an 8-bit radiometric resolution and was obtained at a low angle of incidence (6.8°). It consists of a 2.5 m panchromatic band (0.48–0.71 μm) and four multispectral bands with 10 m spatial resolution for the green (0.50–0.59 μm), red (0.61–0.68 μm), and near infrared bands (0.78–0.89 μm), and a short-wave infrared band (1.58–1.75 μm) with 20 m spatial resolution. The Gram–Schmidt Spectral Sharpening image fusion technique (Laben et al., 2000) combined with cubic convolution interpolation was applied to produce a 2.5 m fused image. Eight ecologically varied sites were selected for classification (Fig. 2).

The object-based classification, described in more detail in the following sections, used 1235 samples (i.e., polygons) for training and testing the classification of five broad classes, which consist of two wetland classes: *bog* (90 reference samples) and *fen* (260) and three upland classes: *forest* (170), *shrub* (218), and *industrial disturbance* (487). These five broad classes, which are functionally different, represent the dominant land covers within the eight ecologically varied study sites. Here the *fen* wetland class comprised of six subclasses (i.e., graminoid poor, shrubby poor, treed poor, graminoid rich, shrubby rich, and treed rich), whereas the *bog*