Monitoring anthropogenic disturbance trends in an industrialized boreal forest with Landsat time series

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## Abstract

Human transformation of the terrestrial biosphere via resource utilization is a critical impetus for monitoring and characterizing anthropogenic change to vegetation condition. The primary objective of this research was to detect anthropogenic forest disturbance for a recent Landsat time series. A novel combination of an autonomous change detection procedure and spectral classification scheme was applied and tested in a landscape that has undergone significant resource development over the last 30 years. Anthropogenic disturbances were correctly classified to within ±1 year. The signal of anthropogenic disturbance was significant in the landscape, accounting for more than 91% of all disturbances and 86% of total disturbed area during the 23-year study period. The study demonstrated a robust approach for examining historical disturbance trends related to human-modification of the environment.

#### 1. Introduction

Humans now appropriate a greater fraction of the terrestrial surface of Earth than ever before (Imhoff et al. 2004), in particular of forested ecosystems, which contain the highest density of biomass of all ecosystems and provide a wide variety of ecosystem goods and services to humanity (Millenium Ecosystem Assessment 2003). Mapping anthropogenic changes to forest cover is essential to monitoring landscape condition. Forested landscapes in North America have undergone significant changes in forest cover due to the extraction of energy and mineral resources (Pickell et al. 2014) as well as extraction of timber resources and long-term conversion to other land uses. Such activities have altered ecosystem structure and function (Simmons et al. 2008) and significantly reduced biodiversity (Butt et al. 2013).

The extent of human modification of forest cover in North America remains relatively unknown. Pasher et al. (2010) estimate the footprint of anthropogenic disturbance in the Canadian boreal zone to be approximately 24 million hectares, most of which was attributed to forest harvesting. Their mapping efforts were undertaken using manual interpretation, which is both costly and time-consuming, especially for large areas such as the Boreal. Efficiently monitoring human modification of the environment requires robust automated methods and remote sensing is well-positioned to meet these mapping needs (Powers et al. 2014).

The Landsat satellite program has continually overflown the planet every 16 days for the last 42 years. The open release of the Landsat image archive to the public in 2008 (Woodcock et al. 2008) has spawned numerous advancements in image processing and automated change detection methods (Wulder et al. 2008a). As a result, every available Landsat image is potentially able to be integrated into forest cover change assessment at local to global scales (Hansen et al. 2013).

Spectral trend analysis approaches can be used to track changes in surface reflectance from time series of Landsat imagery. This approach takes advantage of three properties of energy exchange and forest dynamics when detecting changes through time: (1) disturbed vegetation is spectrally dissimilar from healthy vegetation, particularly in the mid- and near-infrared bands; (2) disturbed vegetation takes several years to recover; and (3) persistence of a trend through time can be used to attribute a class of disturbed, forest, or non-forest. Spectral trend analysis has been implemented in several automated algorithms such as LandTrendr (Kennedy et al. 2010) and the highly autonomous vegetation change tracker (VCT; Huang et al. 2010). The VCT was recently used to estimate recent forest disturbance trends in the United States and shows promise for detecting multiple types of disturbance (Masek et al. 2013).

In this letter, we present an examination of a spectral trend analysis approach in a western Canadian boreal forest that has undergone significant resource development and human modification. The western Canadian boreal forest is an ideal location to apply automated detection of anthropogenic disturbance due to the high severity and extent of resource development in the region. We applied the VCT algorithm to detect anthropogenic

disturbances with the objectives of (1) discriminating anthropogenic from wildfire disturbances over a 28-year period and (2) quantifying the contribution of anthropogenic disturbance to landscape dynamics where oil and gas development has increased significantly over the last two decades.

### 2. Study area and data

The study area was a single Landsat WRS-2 path-row (p45 r23) located in the Rocky Mountain foothills of Alberta, Canada. The terrain is gently undulating with elevation ranging from 500 m to 1500 m.a.s.l. Approximately two-thirds of the study area is forested (Wulder et al. 2008b), which is primarily evergreen forest comprised of *Picea*, and *Pinus* species. The forests in the area have been actively managed and harvested since 1955. Approximately half of the study area is reserved for protected areas while the remaining forest lands are actively managed. Large deposits of coal and natural gas underlay most of the forest cover in the region and recent advancements in recovery technologies have allowed for unprecedented rates of extraction since *ca*. 2000.

Landsat surface reflectance (SR) data were acquired annually during the growing season (152 < day of year < 273) between 1984 and 2011. Scenes were preferentially selected to minimize cloud cover with acquisition dates later in the growing season. Landsat TM acquisitions were preferred over ETM+, and ETM+ SLC-off acquisitions were not included in the time series analysis. Forest inventory data were acquired for a forest management zone, which included anthropogenic forest changes such as roads, pipelines, well sites, and forest harvesting since 1955. The inventory data were derived from standard interpretation of aerial photographs that are collected on an on-going basis for forest management objectives (Alberta ESRD 2005). In addition, we used the Alberta Historical Wildfire Database (Alberta ESRD 2014) to identify the perimeters of fires that occurred in the study area during the study period. The wildfire polygons were collected from interpretation of post-fire aerial photographs.

All data were filtered to a common minimum mapping unit (mmu) to make the data compatible and minimize noise while still being able to detect small disturbances in the final disturbance map product. The forest inventory data were mapped to Alberta Vegetation Inventory standards (Alberta ESRD 2005) at a mmu of 1 ha for anthropogenic features; the fires were mapped at 0.01 ha mmu, but only fires larger than 1 ha were used; and changes from the Landsat time series were mapped to a 12-pixel (~1 ha) mmu. The Landsat scenes were used to detect changes in the time series while the forest inventory data and fire perimeters were used to train the classification and assess the quality of the change detection procedure.

# 3. Methods

## 3.1 Overview of methods

A combination of two methods were undertaken to quantify the contribution of anthropogenic land cover change in the study area. First, forest disturbance was detected from a Landsat time series. The outcome of this procedure was an estimated year of disturbance for pixels classified as disturbance. Second, disturbed pixels were filtered by a mmu, converted to objects, and classified as either anthropogenic or wildfire using a suite of descriptive attributes. Both processes are described in more detail below.

## 3.2 Change detection procedure

The VCT (Huang et al. 2010) was applied for mapping forest disturbances using the disturbance index (DI; Healey et al. 2005). The DI utilizes a linear combination of the Tasseled Cap Transformation (TCT) that normalizes each pixel value to a dense forest class (Masek et al. 2008). Significant and consistent deviations from the dense forest class are then classified as disturbance and the year of disturbance is recorded. Pixels that remain spectrally similar to the dense forest class throughout the time series are classified as persisting forest and pixels that are spectrally dissimilar are persisting non-forest.

A dense forest training mask was created annually for each Landsat scene by visually inspecting dense vegetation cover during the year 2000 from the version 5 MODIS vegetation continuous field (VCF) product collected in 2000 (DiMiceli et al. 2011), normalized differenced vegetation index (NDVI) values, and a true color composite. The NDVI and VCF values for dense forest identified in the true color image in 2000 were then used as thresholds for creating the dense forest mask for each image in the time series.

Once a forest mask was created, the DI was calculated at annual time steps for each Landsat image. In order for a pixel to be flagged as disturbed, the DI trend had to exceed an upper and lower threshold for a designated number of observations. A sensitivity analysis was performed from initial threshold values based on previous research with the VCT in western U.S. forests (Masek et al. 2013). Final threshold values were selected to reduce single pixels detected as disturbance and overall noise while preserving the spatial and temporal integrity of the mapped disturbance events. Pixels could be disturbed more than once during the time series, but only the most recent year of disturbance was recorded. Pixels that contained cloudy observations for more than half of the time series or more than five consecutive years were not classified. Cloudy values were interpolated linearly when good observations were available for previous and subsequent years. Finally, a water mask based on near-infrared reflectance was applied to the time series analysis to classify persistent water bodies.

## 3.3 Disturbance type classification

In the second step, we differentiated between resource extraction and wildfire disturbances. A subset of the forest inventory data and wildfire maps were randomly divided into two equal-number samples to be used to train and evaluate the classification. Approximately

50% of the objects were used to train the classification and 50% were used to evaluate the classification. The wildfire sample (19,022 ha) was randomly drawn from the entire Landsat path-row, while the resource extraction sample (94,588 ha) was randomly drawn only from the forest management zone.

Disturbances were classified using a set of object-based descriptive attributes derived using FETEX 2.0 software (Ruiz et al., 2011) describing the geometrical, spectral and textural properties of the disturbances. The geometry and shape was described using area, perimeter, compactness (Bogaert et al., 2000), shape index (McGarigal & Marks, 1995), and fractal dimension (Krummel et al., 1987). Spectral attributes were computed from the spectral bands and from common indices: DI; normalized burn ratio (NBR; Key and Benson, 2006); NDVI (Tucker, 1979); and greenness, wetness and brightness from the TCT (Crist, 1985). The mean and standard deviation of the indices and the differences of spectral means between the pre- and post-disturbance years were computed. The texture descriptors extracted were: edge density (Sutton and Hall, 1972); gray level (Haralick et al., 1973); skewness and kurtosis; and experimental semivariogram indices (Balaguer-Beser et al., 2013). These attributes were computed from the near-infrared band (band 4) during the disturbance year.

Classification was performed using linear discriminant analysis (LDA). LDA is a multivariate statistical technique where the dependent variable is categorical, whilst the independent variables are continuous and are used to determine the class to which the objects belong (Huberty 1994; Everitt and Dunn 2001). This technique maximizes the variability between groups based on the continuous variables, while minimizing variability within groups.

### 3.4 Disturbance classification accuracy assessment

The spatial accuracy of the disturbance classification was assessed using an error matrix (Congalton 1991). In addition to the overall accuracy, user's and producer's accuracies were calculated per class, which respectively measure the commission and omission errors. First, the reference data (mapped anthropogenic features and wildfires) were used to assess the area-based accuracy of the disturbed and non-disturbed classes generated from the time series analysis. Next, the temporal accuracy was assessed by inspecting a scatterplot of the reference data year and the VCT classified year. A final assessment was undertaken to scrutinize the accuracy of the disturbance type classification (i.e., anthropogenic vs. wildfire) using the reference wildfire database and forest inventory spatial dataset. The sample of objects that was used for training was excluded from the full set of objects that were used in the evaluation.

### 4. Results and discussion

The temporal quality of the disturbance classification was high, with the majority of errors within the range -1 to +1 year relative to the actual disturbance date (Figure 1). Most errors

in the temporal domain resulted from the VCT classifying disturbances 1 year after the known disturbance date. These temporal errors may have been related to errors in the inventory data. Harvesting occurs on an on-going basis in the study area and it may take multiple years before a harvest feature is considered complete. The harvest completion date was used to assess the temporal accuracy and thus some disturbances could have occurred before this date. Additionally, cloud, haze or shadow could cause the disturbance to be attributed the following cloud-free year in the time series.



Figure 1. Scatterplot of disturbance year attribution by the VCT. Values above the y=x line indicate that the VCT disturbance year is later than the inventory disturbance year.

An error matrix of the disturbance classification is presented in Table 1 and disturbance type classification is presented in Table 2. Overall accuracy for the area-based disturbance classification was about 93% and overall accuracy for the object-based disturbance type classification was approximately 94%. Errors of omission and commission were highest for the wildfire class (55% and 63% accuracy, respectively) which was also the class with the fewest samples (Table 2).

	Reference data (ha)				
VCT map (ha)	Disturbed	Non-disturbed	User's accuracy		
			(%)		
Disturbed	86,289	27,565	75.8		
Non-disturbed	15,357	474,267	96.8		
Producer's accuracy	84.9	94.5	92.9 (overall)		
(%)					

Table 1. Error matrix of disturbance classification.

Overall, the disturbance classification accuracy was within the range of previous classification accuracies reported for the VCT (Thomas et al. 2011). User's accuracy for the disturbed class was about 76%. The net committed errors (rate of false positives) and omitted errors (rate of false negatives) of the disturbed class were approximately 15% and 24%, respectively. These statistics suggest that the VCT was more likely to underestimate than overestimate the area of disturbance. The net committed and omitted errors for the wildfire class were 44% and 37%, respectively. The relatively low producer's accuracy of the wildfire class suggests that there are still some challenges associated with discriminating disturbance types which may be related to the structural characteristics of wildfires and typical anthropogenic disturbance. For example, shadowing and soil exposure vary between the classes, and also within wildfires, and the patchy nature of wildfires potentially affected the ability of the VCT to identify the heterogeneous canopy mortality of wildfires. The most important descriptive attributes for classifying disturbance type were mean NBR, change in NBR, band 5, band 2, DI, and greenness.

Disturbance rates varied temporally and spatially across the region. The rate of disturbance increased between 1986 and 2000, and declined since. Disturbance was mostly clustered in the north within the primary forest management zone (Figure 2). Taken across the entire time series, the average annual rate of disturbance was approximately 6,555 ha year<sup>-1</sup> ( $\sigma = 6,148$  ha). The large standard deviation was primarily a result of two outlying years (2003 and 2004) with much higher levels of disturbance (Figure 3). With those years removed, the average annual rate of disturbance declined to approximately 4,780 ha year<sup>-1</sup> ( $\sigma = 1,865$  ha), which is likely more representative of the landscape and region in general. The sharp increase in disturbance during 2003 was primarily attributed to the Syncline Ridge wildfire that burned nearly 28,000 ha in Jasper National Park. The sharp increase in resource extraction disturbance the following year (2004) was likely a result of misclassification of post-fire mortality of the Syncline Ridge wildfire and other wildfires as resource extraction disturbance and poor disturbance year attribution by the VCT due to extensive cloud cover.



Figure 2. Forest harvesting, roads and well sites in the north of Landsat tile p45 r23 within an intensive forest management zone.

Table 2. Error matrix of disturbance type classification.				
	Reference	e data (n objects)		
VCT map (n objects)	Wildfire	Resource	User's accuracy	
		extraction	(%)	
Wildfire	228	135	62.8	
<b>Resource extraction</b>	183	4592	96.2	
Producer's accuracy	55.5	97.1	93.8 (overall)	
(%)				

Table 2. Error matrix of disturbance ty	yp	e classification.
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Resource extraction disturbance rates were relatively stable across the time series and accounted for the majority of disturbance in any given year (Figure 3). The average annual rate of resource extraction disturbance was approximately 5,640 ha year<sup>-1</sup> ( $\sigma = 4,362$  ha) across the entire time series and 4,630 ha year<sup>-1</sup> ( $\sigma = 1,844$  ha) with 2003 and 2004 excluded. Approximately 91% of all disturbances was resource extraction and approximately 86% of total disturbed area was resource extraction.



Figure 3. Forest disturbance trends for the study area: resource extraction disturbance (grey), and wildfire (black).

The region underwent significant development of oil and gas resources beginning in the early 2000's. The year 2004 showed the greatest levels of anthropogenic disturbance and a large portion of the landscape was impacted by road and well site construction (Figure 2). However, the majority of resource extraction disturbance during that year was driven primarily by forest harvesting and subsequent annual resource extraction disturbance rates did not increase. While the method demonstrated good success with detecting and classifying disturbances larger than 1 ha, there are many finer-scale disturbances in the study area that do not contribute greatly to disturbance area, but have large impacts on the Boreal forest. For example, the density of seismic lines in the region is among the highest in the province of Alberta, but these features are below the spatial resolution of the Landsat imagery that we used (Powers et al. 2015). A classification of other disturbance types like roads and seismic lines would require finer spatial resolution imagery, but there is an inherent trade-off between detecting smaller features (spatial resolution) and sampling large areas for disturbance (extent). The results show that resource extraction disturbed more forested area than wildfire for the study area. Wildfire is believed to be the primary driver of landscape structure and forest change in the boreal zone as a whole (Weber and Flannigan 1997), however the study area, in the south-west of the boreal, was settled in the 1950's and fire suppression has been effective at reducing area burned in the region during the study period (Cumming 2005). The objective of contemporary forest management in the study area has been to replace the wildfire disturbance regime with forest harvesting while keeping the combined rates of disturbance similar to pre-settlement levels (Bergeron et al. 2002). Other non-anthropogenic disturbances such as wind throw and insect attack were not included in the classification due to the lack of available spatial reference data for these disturbances in the study area. However, given the levels of disturbance observed for the study area, these disturbance types were not likely to significantly alter the contribution of anthropogenic land cover change. In addition, the VCT algorithm is not designed to detect slow degradation or subtle disturbance events that only affect a small fraction of the forest canopy.

## 5. Conclusion

The demonstrated methodology was able to identify both wildfires and resource extraction disturbances in a southwestern Boreal forest in Canada and assign a year of disturbance with low and quantifiable error. The classification of the VCT disturbance map allowed for the analysis of disturbance rates by source, which determined that resource development was the primary driver of vegetation cover change in the study area. We foresee the VCT being utilized to map historical forest disturbances and track the trends of human appropriation of forested ecosystems. Such information may help predict rates of change in forested landscapes that may undergo significant resource development in the future. Knowledge of historical anthropogenic disturbance trends could significantly improve landscape planning and forest management, particularly where biodiversity and habitat are rapidly declining due to anthropogenic land cover changes. Specifically, the disturbance year attribution by the VCT may improve or validate stand origin estimation in standard forest inventory attribution. Additionally, the combination of the change detection procedure and the disturbance type classification could be used to automate feature extraction of roads or well sites. This study demonstrated a robust approach for examining historical disturbance trends related to human-modification of the environment.

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