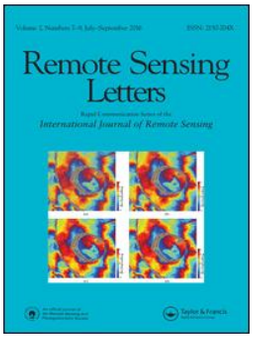

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Detection accuracy of new well sites using Landsat time series data: a case study in the Alberta Oil Sands Region

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ABSTRACT

Forest change features related to resource exploration and extraction are important in the Alberta Oil Sands Region (AOSR), where, for example, 2486 oil and gas well sites were established in a 5000 km^2 area on three leases in the period 1984–2011. A newly established well site is typically readily identified visually in Landsat multispectral and high spatial resolution imagery, but poses an automated detection and mapping challenge over larger areas and long time periods relative to other major disturbance features. In this study, Landsat time series image composites from the national Composite-2-Change (C2C) change detection protocol were used in a comparison to randomly sampled, independently-generated well site reference data. The highest accuracy reported was approximately 83%, with relatively low errors of omission (13%) and high errors of commission (up to 37%). Future research will incorporate well site disturbance object characteristics in this type of regionally-sensitive forest change analysis.

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1. Introduction

The Composite-2-Change (C2C) standardized Landsat time series protocol is the de-facto standard in Canada to support monitoring and reporting of forest change over large areas (White et al. 2014; Hermosilla et al. 2015a; 2015b; 2016). The C2C protocol, designed to support national carbon budget analysis, is based on the production of annual Landsat-based change composites, spectral trend analysis and breakpoint thresholds, change object segmentation and machine learning attribution using a variety of spectral and geometrical indicators. Stand-replacing changes, such as fire and harvesting patterns, and non-stand-replacing changes, such as forest insect damage and hydrological changes, have been detected and classified with high accuracies with the C2C protocol in several diverse forest environments in Canada. Detection accuracy is a first order measure (e.g., change or no change) of the proportion of changes that have been detected by the change detection protocol. In one northern Ontario environment, for example, approximately 75–90% detection accuracy was reported for forest disturbances later then attributed to – or classified as – wildfire, harvesting, roads, ephemeral wetland variability, and two types of insect defoliation (Ahmed et al. 2017). Recently, Zhu (2017) highlighted the availability of Landsat time series

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data, which has 'revolutionized' change detection applications, and usefully identified 'change-target' and 'change-agent' time series approaches. Additional case studies, and consideration of the effect of certain time series analysis decisions, such as breakpoint threshold selection, were recommended (see also Cohen et al. 2017).

Of particular interest in Canada are applications of Landsat-based time series analysis in regional environments in which locally-significant change-agent disturbance processes associated with the oil and gas industry occur (Bourbonnais et al. 2017). More than 400,000 natural gas, conventional oil and in situ oil sands wells have been established in a wide range of environments in Alberta in the past 100 years. With proven conventional and oil sands reserves in the Alberta boreal forest region now estimated at more than 166×10^9 barrels (CAPP 2014), many more such disturbances are considered likely in future. Spatially, well sites are important eco-hydrologically and in wildlife management in the boreal forest (Bayne, Habib, and Boutin 2008; Pickell et al. 2014). Individual well sites have a typical area between 0.5–1.0 ha (Salehi et al. 2014), although sites containing multiple well heads may be up to 2.0 ha in size (Pasher, Seed, and Duffe 2013). Thus, most well sites are represented by fewer than 20–25 pixels in a Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) or Operational Land Imager (OLI) satellite image. Initial well site establishment includes removal of surface vegetation and exposure of substrate; such fine scale change, which could nominally be considered 'forest stand-replacing', is of a smaller spatial extent and may be expressed with lower magnitude and less persistent spectral changes than larger stand-replacing disturbance processes, such as wildfires, forest harvesting, industrial mining and road-building activities (Powers et al. 2015; Pickell et al. 2015). Recently established well sites often display near-continuous herbaceous cover and may also be reclaimed naturally or through planting/seeding, with regrowth beginning as early as two to three years following well site decommissioning (Zhang et al. 2014). Such features are not considered in the current C2C national protocol (Hermosilla et al. 2016), however, available time series reflectance composites provide an opportunity to determine potential time series forest change detection accuracy of this regionally-important feature.

This case study was designed to determine Alberta Oil Sands Region (AOSR) well site detection accuracy using the C2C time series composite data and breakpoint thresholds selected to test well site detectability. Initially, a lower breakpoint threshold was expected to yield higher well site detection accuracy, with fewer errors of omission, but higher errors of commission, relative to a higher breakpoint threshold. Detection tests were conducted to provide insight into the use of Landsat time series data for users in this regional application of the C2C protocol. The rationale was influenced by the expectation that different applications of the time series may be designed to provide different levels of accuracy for specific change-agent features of interest. In the particular instance of oil and gas well sites, for example, users may express different tolerance for the relatively high commission errors that typically will accompany the use of low breakpoint thresholds in time series analysis.

2. Study area and data

A 5000 km^2 study area in the Alberta Oil Sands Region encompassing three industrial leases near Conklin, south of Fort McMurray, was selected (Figure 1). The majority of the study area is comprised of mixedwood and pure aspen (*Populus tremuloides*), white

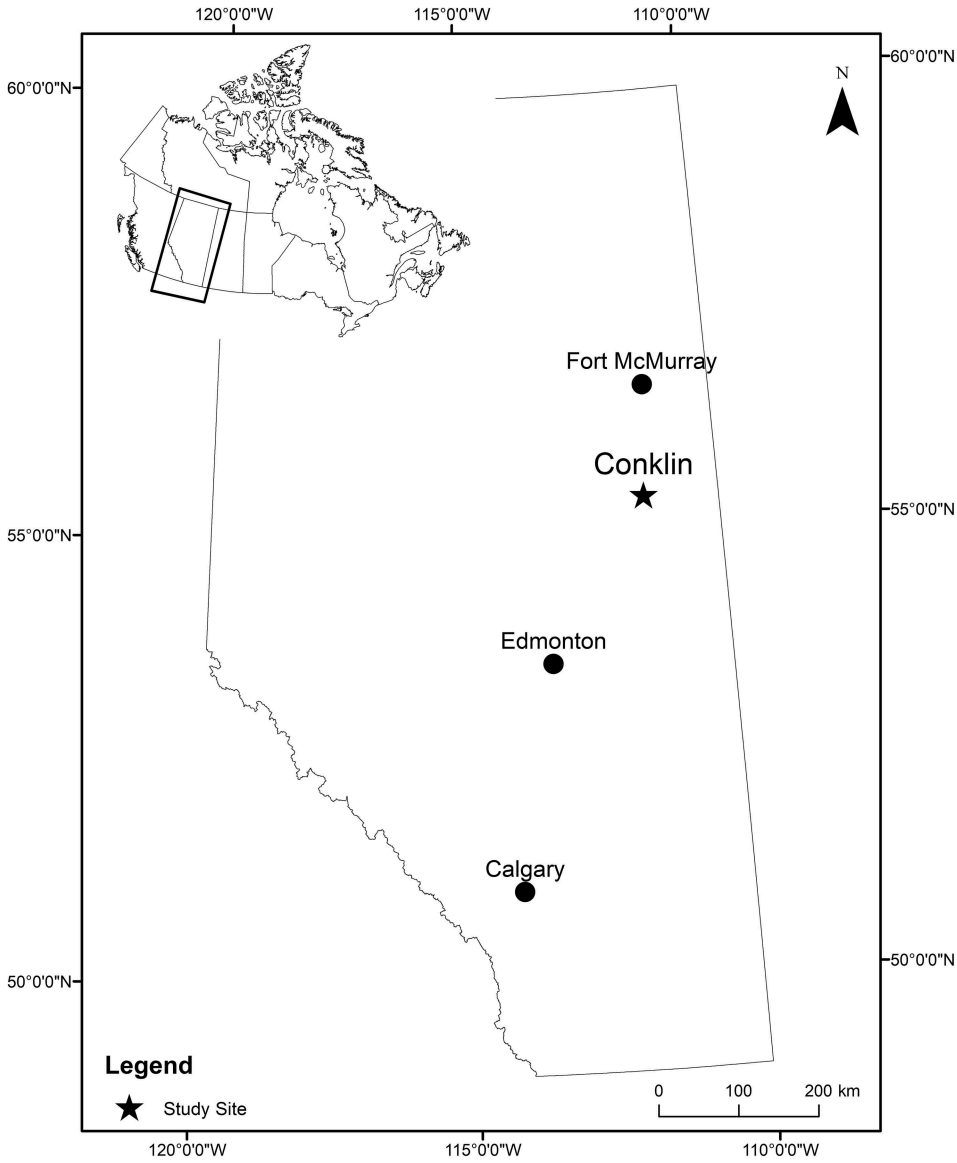

Figure 1. Location of the study area near Conklin in northeastern Alberta (Alberta Oil Sands Region).

spruce (*Picea glauca*), and jack pine (*Pinus banksiana*) forest stands with extensive herbaceous-, bryoid- and treed- bogs and fens. Low topographic relief, extensive wetlands and deranged drainage patterns are a result of Holocene deglaciation with consequently thin luvisol and brunisol veneers over Cretaceous shales (Natural Regions Subcommittee 2006). Forest fires are the dominant stand-replacing forest change-agent in the area, which has also experienced large area stand-replacing and non-stand-replacing anthropogenic disturbances associated with industrial forestry, mining and oil and gas operations. Such changes are expected to intensify as a result of ongoing resource management, exploration and extraction activities.

Annual individual Landsat TM and ETM+ multispectral images (bands 1 to 5 and 7) and best available pixel (BAP) composites produced following the methods described by White et al. (2014) were selected for 1984–2011 representing the study area on August 1 (± 30 days). These composites were used to compute normalized burn ratio (NBR) and annual change in NBR (denoted as ΔNBR) values. NBR values ranged from negative to positive one ($-1 \leq NBR \leq 1$), with positive values representing vegetation presence and negative values representing vegetation absence (e.g., healthy vegetation (+1) and exposed substrate (−1) occur at opposing extremes along this continuum). Annual change in NBR (ΔNBR) values ranged from negative to positive two ($-2 \leq NBR \leq 2$). As these layers are vegetation changes between years, positive values represent vegetation loss and negative values represent vegetation gain (Jin et al. 2013). Greater absolute ΔNBR values represent loss or gain of vegetation of a greater magnitude; however, the amount of vegetation loss or gain was not quantified in this study.

Well site reference data were obtained from the Alberta Biodiversity Monitoring Institute (ABMI) in annual data layers that were produced using a combination of interpretation of high spatial resolution imagery, historical aerial photography, other satellite or aerial data types, field assessments and a consolidation of other available data (Sólymos et al. 2015). The ABMI well site reference data for the three leases in the study area contained 2486 well sites established in the period 1984–2011.

3. Methods

Following generation of the C2C time series composites, changes were generated using different ΔNBR breakpoint thresholds for the time period 1984–2011. Visual assessment of ΔNBR raster file histograms revealed that C2C protocol change values were normally distributed, with the majority of ΔNBR values clustered near zero (ΔNBR of 0 = no change). Four breakpoint thresholds were implemented based on 0.5, 1.0, 1.5, and 2.0 standard deviations from the mean ΔNBR value (expressed as $\mu_{\Delta NBR} + 0.5\,\sigma_{\Delta NBR}$, $+ 1.0\,\sigma_{\Delta NBR}$, $+ 1.5\,\sigma_{\Delta NBR}$, and $+ 2.0\,\sigma_{\Delta NBR}$, respectively, where $\mu_{\Delta NBR}$ and $\sigma_{\Delta NBR}$ are the mean and standard deviation of NBR change). This approach represents an initial test of the detectability of new well sites at different time series breakpoint thresholds (after Franklin, Jagielko, and Lavigne 2005). More complex change thresholds and other trajectory-based change detection methods are reviewed by Banskota et al. (2014) and Zhu (2017).

The changes detected at each threshold were analyzed visually, using Landsat composite image data, and through interpretation of the NBR data and the ABMI well site reference dataset. In essence, different ΔNBR breakpoint thresholds detection results were compared to a temporally stratified random sample (Olofsson et al. 2014) of the 527 ABMI reference well sites representing the study area and 1984–2011 time period. Detection accuracy was computed with an estimate of omission error (i.e., the number of known well sites not detected at each threshold, or false negatives) and commission error (i.e, the number of changes detected that were not identified as well sites in the reference data, or false positives) by comparing the reference dataset against detected well sites in the year in which they occurred relative to the image date for that year, and vice versa. To assess commission error, the distinctive shape, size and context of well sites was used initially to identify visually the change pixels that may represent this feature. These locations were then compared to the reference dataset in a temporally stratified random sample design. In all

samples, a well site was considered detected when more than half of the detected change and the ABMI reference data were spatially coincident. A minimum spatial overlap of 50% between detected changes and reference data is consistent with previous studies (e.g., Jarron et al. 2016). Finally, a map of the spatial distribution of change objects at selected breakpoint thresholds was produced for visual analysis.

4. Results

A visual assessment of NBR and ΔNBR image values confirmed that the Landsat time series and NBR values interpreted by human visual analysis supported the notion that spectral response pattern changes occurred in areas that had experienced the establishment of a new well site (Figure 2). In addition, the size and pattern of well site changes could be visually confirmed for well sites and were less spatially-extensive when compared to changes associated with other disturbance processes, such as new wildfires or roads. New well sites were reasonably associated with distinctive spectral response patterns, low or negative NBR values and positive ΔNBR values. Well site changes had characteristic shapes (typically square or rectangular geometric change objects), size and context. The visual analysis suggested that NBR and ΔNBR values representing a new well site were highly variable. Many well sites were expressed as singularly bright spectral response patterns while others displayed less visible and less distinctive responses (see Figure 2). A human interpreter was able to associate such variability with a well site disturbance feature, a step that automated methods would likely find more challenging. Finally, this visual interpretation confirmed the expectation that these disturbance features were likely to be sensitive to breakpoint thresholds.

Table 1 contains the detection accuracy and estimated omission and commission errors for the random sample of 527 ABMI well sites. The best detection accuracy of well sites achieved was approximately 83% (±2%) using the lowest breakpoint threshold in the study. Lower detection accuracies were reported using higher breakpoint thresholds;

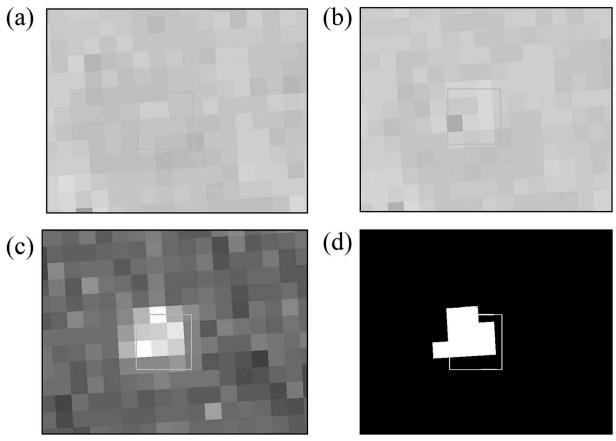

Figure 2. Well site change detection example: (a) Landsat NBR data for 1994; (b) Landsat NBR data for 1995; (c) ΔNBR data 1994–1995; and (d) threshold change object. Area shown approximately 25 ha; the outline of a 2.0 ha independently surveyed well site is shown for reference.

Table 1. Detection accuracy based on independent randomly sampled reference data for different ΔNBR breakpoint thresholds and estimated errors of commission and omission of oil and gas wells sites in three oil leases covering 5000 km^2 in the Alberta Oil Sands Region (1984–2011). $\mu_{\Delta NBR}$ and $\sigma_{\Delta NBR}$ are the mean and standard deviation of annual NBR change, respectively.

Change detection threshold	Overall detection accuracy (N = 527)	Omission error	Commission error
$\mu_{\Delta NBR} + 0.5\ \sigma_{\Delta NBR}$	0.83 ± 0.02	0.17	0.37
$\mu_{\Delta NBR} + 1.0\ \sigma_{\Delta NBR}$	0.77 ± 0.02	0.24	0.30
$\mu_{\Delta NBR} + 1.5\ \sigma_{\Delta NBR}$	0.70 ± 0.02	0.30	0.22
$\mu_{\Delta NBR} + 2.0\ \sigma_{\Delta NBR}$	0.63 ± 0.02	0.37	0.18

in other words, higher breakpoint thresholds were not as sensitive to the changes in spectral response produced by the introduction of a well site in the area. Estimated omission errors, i.e., the number of well sites in the reference data that were not detected as well sites in the C2C time series data, appeared reasonable, ranging from approximately 17–37% with gradually more restrictive breakpoint thresholds. Therefore, as expected, a relatively high breakpoint threshold generated correspondingly lower detection accuracy (63%) with higher errors of omission and lower errors of commission (18%). The highest commission error in these tests was 37%, reported when using the lowest breakpoint threshold. These patterns of detection accuracy and errors are illustrated graphically in Figure 3.

The general relationship between breakpoint thresholds and errors of omission and commission in forest disturbance change detection, recently described by Cohen et al. (2017) in a comparison of Landsat-based time series change detection algorithms, was confirmed in this study (see also Wulder et al. 2009; Cohen, Yang, and Kennedy 2010; Li, Jiang, and Feng 2014; Chance et al. 2016; Gómez, White, and Wulder 2016; Jarron et al. 2016). Most studies have shown that high detection accuracy and low errors of omission are accompanied by relatively high errors of commission. Reducing these commission errors

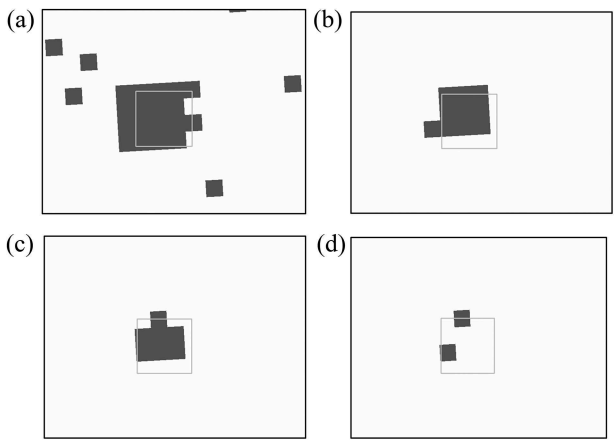

Figure 3. Well site change detection example with varying Landsat ΔNBR breakpoint thresholds: (a), (b), (c) and (d) show the results with breakpoint thresholds of $\mu_{\Delta NBR} + 0.5\ \sigma_{\Delta NBR}$, $+ 1.0\ \sigma_{\Delta NBR}$, $+ 1.5\ \sigma_{\Delta NBR}$, and $+ 2.0\ \sigma_{\Delta NBR}$, respectively, where $\mu_{\Delta NBR}$ and $\sigma_{\Delta NBR}$ are the mean and standard deviation of NBR change, resulting in different object shapes and sizes, and associated errors of commission and omission. Area shown approximately 25 ha with a 2.0 ha independently surveyed reference data shown for reference.

requires additional effort. For example, well sites are not typically isolated on the landscape but instead are connected via a network of seismic lines, roads and pipeline infrastructure (see also He et al. 2009; Powers et al. 2015). A classification analysis of such features with specific spatial-context-based object identifiers is a logical next step (Hermosilla et al. 2016; Zhu 2017). Others have noted that spatial filtering and pre-selection of change objects based on prior knowledge of 'change-agent' size, shape and other characteristics could be usefully applied (e.g., He et al. 2009).

Considerations of change detection accuracy and error patterns are application-specific. In this study a reasonable level of detection accuracy was possible with different thresholds, but there were consequential levels of omission and commission error that may or may not be considered appropriate for subsequent analysis by different users. In the Alberta Oil Sands Region, lower errors of commission may be preferred by many users since the impact of reporting change that has not occurred could be punitive in terms of cost for vegetation restoration/reclamation or natural regeneration management (Audet, Pinno, and Thiffault 2015). In addition, while well sites are recognized as numerous (Pasher, Seed, and Duffe 2013), the accuracy and spatial distribution of large-area change features, such as land cover change caused by forest harvesting, new infrastructure and industrial operations (e.g., open pit mining), may be prioritized. Wildlife managers, however, might favour lower errors of omission and may not be as concerned with relatively high commission error. Specifically, small area features that influence habitat and animal behaviour (perhaps through anthropogenic noise) could be considered a higher priority for the change detection analysis to be of value (Bayne, Habib, and Boutin 2008; Linke et al. 2009; Venier et al. 2014). In Alberta, for example, woodland caribou, an endangered species, are known to avoid well sites seasonally and during calving time periods (Dyer et al. 2001), and wolves (a key predator species) have been documented to use areas within close proximity of anthropogenic non-linear features, such as well sites (Ehlers, Johnson, and Seip 2016). In such applications, forest changes and change detection error patterns related to existing and new oil and gas well sites could have an important impact on subsequent analysis and management decisions.

5. Conclusion

Identifying and mapping the occurrence of small area forest change associated with resource extraction and development, such as new oil and gas wells, is an important management and monitoring requirement in the Alberta Oil Sands Region of northern Alberta. The national Composite-2-Change (C2C) protocol Landsat time series reflectance composites were employed in visual analysis and with simple NBR breakpoint thresholds to detect these fine scale and regionally important change features over the period 1984–2011. Lower breakpoint thresholds provided high detection accuracy (up to 83%), low omission error (approximately 13%) but high commission error (up to 37%) in comparison to a random sample of independent public reference well site data. This analysis of Landsat time series changes confirmed well site feature variability, and the importance of quantifying the spatial distribution and error patterns for different users of the resulting change detection maps.

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