Identifying permafrost slope disturbance using multi-temporal optical satellite images and change detection techniques

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A B S T R A C T

Active layer detachments (ALDs) are a common form of permafrost slope disturbance that pose a serious risk for infrastructure and can impact environmental and ecological stability in Arctic regions. Effective recognition and detection of slope disturbances are critical for future hazard analysis. Historically, this has primarily been done through manual image interpretation and field mapping, both of which are cost-intensive. Semi-automatic detection techniques have been successfully applied in more temperate regions to identify slope failures, however, little work has been done to map permafrost disturbances. In this paper we present a methodology to detect and map ALDs using multi-temporal IKONOS satellite imagery in combination with vegetation index differencing and object-based image analysis, to semiautomatically identify landscape change associated with ALDs. A normalized difference vegetation index (NDVI) was computed for each of the two dates (2004 and 2010) and then subtracted generating a NDVI difference surface. Using areas where vegetation was removed as a proxy for the presence of ALDs, a multi-resolution segmentation algorithm was used to threshold the NDVI difference map into objects to demarcate regions of similarity (i.e., potential ALDs). To discriminate between disturbed and undisturbed zones a NDVI threshold was applied removing false positives. The thresholded image was then verified with a disturbance inventory collected from the field. These methods were successfully applied to the study area achieving 43% detection accuracy when identifying all ALDs. Morphometric characteristics were used to separate ALDs into two forms, elongate and compact, with accuracies assessed for each. Elongate ALDs, with a detection accuracy of 67%, are typically more destructive, moving substantially more material downslope over longer distances and posing a greater risk for infrastructure. By contrast, compact ALDs are associated with minimal downslope sliding distances (<1 m to several meters) and result in little to no extension in the scar zone and thus limited downslope material movement. The method used in this study detected only 7% of compact disturbances indicating that morphology and size are important variables when detecting ALDs. These results collectively show promise for the semi-automated detection of slope disturbances (i.e., elongate ALDs) in permafrost settings and a cost-effective method to delineate areas for more detailed hazard assessment methods.

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1. Introduction

Permafrost related hazards are of growing concern in Arctic regions where the effects of climate change are rapidly resulting in unstable landscapes (ACIA, 2005; Nelson et al., 2002). Thawing of near surface ground ice on slopes can lead to instabilities in the substrate, resulting in exposures of ice bodies and/or ice-rich sediments that generate rapid mass movements such as active layer detachments (ALDs) (Lewkowicz, 1992). Permafrost slope disturbances have been documented across the Arctic (Lamoureux and Lafrenière, 2009; Lantz and Kokeij, 2008; Lewkowicz and Harris, 2005) and constitute a hazard for infrastructure and a source of environmental degradation. Knowledge of landslide distribution and geological associations are an important first step in hazard and risk assessment. Mapping permafrost-related hazards is labor and cost intensive due to the vast size and remoteness of many Arctic regions. Visual interpretation of remote sensing data is time consuming and thus not an optimal method, and while automatic and semi-automatic detection techniques have been applied in more temperate regions to identify landslides (Barlow et al., 2006; Lu et al., 2011; Martha et al., 2010; Nichol and Wong, 2005), little work has been done in cold regions to automatically map permafrost disturbances.

When dealing with any form of mass movement, effective hazard and risk management begins with comprehensive detection and mapping, providing insight into their spatial and temporal occurrence (Carrara and Merenda, 1976; Guzzetti et al., 2000). Until recently, most hazard inventory mapping was completed manually by combining field investigations with visual interpretation of aerial photographs or satellite imagery (Kaab, 2008; vanWesten and Getahun, 2003). Many researchers have used satellite imagery and various detection strategies with mixed success. Pixel based change detection methods using digital number (DN) values (McDermid and Franklin, 1994; Nichol and Wong, 2005) have been moderately successful but are limited in that DN alone
will not characterize the entirety of the landslide. Contextual analysis techniques applied by Barlow et al. (2006) achieved good detection accuracy but only considered very large landslides (>10,000 m²). Martha et al. (2012) increased the accuracy of these detection techniques through the utilization of expert knowledge and object-oriented analysis; however, the methods have not been applied to permafrost-related settings.

The main objective of this study was to identify permafrost disturbances, specifically ALDs, using IKONOS satellite imagery and a combination of semi-automatic change detection techniques including image differencing and object-oriented analysis. ALDs are a common form of permafrost disturbance that represent translational landslides of soil, vegetation, and other surface materials in the seasonally thawed or thawing active layer. This study is based on an area of recent and well-documented ALD activity in the Canadian High Arctic where ground-based field mapping of disturbances was conducted. During the summers of 2007/8, substantially higher than normal air temperatures and intense precipitation resulted in extensive slope failures throughout the study area at Cape Bounty, Melville Island, Nunavut (Lamoureux and Lafrenière, 2009). The ALDs that formed at Cape Bounty have a mean area of 2000 m² and varied considerably in morphology.

The removal of vegetation within disturbances results in spectrally different zones and is best represented in terms of spectral indices, specifically, the normalized difference vegetation index (NDVI). Using areas devoid of vegetation as a proxy for the presence of ALDs, NDVI differencing and object-based methods were used to detect change associated with ALDs. Further research objectives included examining the influence of disturbance size and morphology on the accuracy of automatic change detection analysis to represent the potential for applying this method to areas without prior ground-based mapping of disturbance.

2. Study area

This study was carried out at Cape Bounty, located on the south-central coast of Melville Island, Nunavut (74°55′ N, 109°35′ W) (Fig. 1). Cape Bounty is the location of multidisciplinary research focused on aquatic and terrestrial systems operating within paired High Arctic watersheds (East and West watersheds, unofficial names). Water, sediment, carbon, nutrient, and contaminant fluxes have been integrated with studies of soil biogeochemical, vegetation, and trace gas processes. Many of these processes have been monitored since 2003 as a part of the overall Cape Bounty Arctic Watershed Observatory (CBAWO).

Bedrock in this region is composed of upper Devonian sandstone and siltstone of the Weatherall, Griper Bay, and Hecla Bay formations (Hodgson et al., 1984). Glacial and early Holocene marine sediments drape the region resulting in a landscape characterized by incised low elevation plateaus and gentle hills (Hodgson et al., 1984). The region is underlain by continuous permafrost and forms an active layer that is 0.5–1 m deep by late summer. Vegetation cover is organized into three categories largely based on moisture regimes and includes: polar semi-desert, mesic tundra, and wet sedge (Gregory, 2011).

Extensive slope failures were observed at Cape Bounty during the summers of 2007/8. Substantially higher than normal air temperatures and intense precipitation resulted in a thickening of the active layer which destabilized slopes and resulted in ALDs (Lamoureux and Lafrenière, 2009). These ALDs were subsequently documented and mapped annually on foot using a handheld GPS.
system and account for approximately 1.2 and 2.1% of the East and West watersheds, respectively (July 31, 2010 mapping). The area chosen for this study is ~20 km² and includes 75 mapped ALDs (Fig. 2).

3. Material and methods

3.1. Data sources

The high-resolution (4 m) multispectral IKONOS images used for this study were acquired on July 23, 2004 and July 12, 2010. It is anticipated that the use of fine resolution satellite imagery will facilitate the identification of a range of disturbance sizes and morphologies. In addition to the IKONOS images, a digital elevation model (DEM) generated from a GeoEye stereo pair acquired on August 22, 2009 was used for orthorectification. The DEM was created using PCI Geomatica 2013 and has a vertical accuracy of 1 m. Details of the satellite acquisitions can be found in Table 1. Validation of the change detection map produced from the satellite data was completed using a disturbance inventory compiled on July 31, 2010 from field mapping. Perimeters for all disturbances within the study areas were collected using a Garmin 60Cx GPS unit (5 m typical ground uncertainty).

3.2. Satellite data pre-processing

3.2.1. Geometric rectification and image registration

Accurate geometric registration of satellite data is a key requirement for change detection analysis when using multiple image dates. In this study, a hybrid approach to image rectification/registration was used while maintaining a uniform projection (UTM) and datum (WGS 84). Using an orthorectified IKONOS image from 2009, the 2010 image was first orthorectified using the rational function optical satellite model in PCI Geomatica 10.3.2. The rational functions model builds a correlation between pixels and their corresponding ground locations using a DEM and ground control points. Twenty ground control points (GCPs) were collected throughout the image producing a root mean square (RMS) error of 0.19 pixels (0.7 m). The orthorectified 2010 IKONOS image was subsequently used to register the 2004 image using the polynomial model in PCI Geomatica 10.3.2. Fifteen GCPs were collected with an RMS error of 0.16 pixels (0.65 m). The maximum RMS error was substantially less than 1 pixel.

3.2.2. Radiometric normalization

To ensure that detected change was a direct result of disturbance and not due to atmospheric variations, radiometric corrections were applied. As both images were acquired at approximately the same anniversary date a relative radiometric correction was applied to normalize the intensities for the various bands within each image. Dark object subtraction (DOS), a form of radiometric standardization was selected for this study. The primary principle behind DOS is based on the fact that infrared data (>0.7 μm) are largely free of atmospheric scattering whereas the visible region (0.4–0.7 μm) is strongly influenced by various forms of scattering (Jensen, 2005). As a result there are pixels that have very low or no reflectance on the ground yet there is a measured difference between the brightness values of these pixels and zero, a difference is attributed to atmospheric scattering (Chavez, 1988). This simple algorithm models the first-order effects of atmospheric scattering from haze and is based on a subtractive bias established for each spectral band. The atmospheric effects correction algorithm (i.e., dark object subtraction) is defined as (Jensen, 2005):

\[
\text{Output } BV_{ijk} = \text{input } BV_{ijk} - \text{bias}_{ijk}
\]

where:

- \( BV_{ijk} \) input value at line \( i \) and column \( j \) of band \( k \)
- \( BV_{ijk} \) the adjusted pixel at the same location
- \( \text{bias}_{ijk} \) atmospheric reflectance for band \( k \).

The effects of atmospheric scattering are minimized with the removal of within-band bias. It is assumed that ‘dark objects’ exist

![Image 1](image1.png)

![Image 2](image2.png)

**Fig. 2.** IKONOS image with change detection study area outlined, image acquired July 12, 2012.
within the image when applying DOS. In the case of the 2010 and 2004 images the deep ocean water served as a good proxy for a dark object.

3.2.3. Detection approach

The morphology of a typical ALD can be broken into different geomorphic and spectral zones: 1) the scarp; 2) the scar or extension zone; and 3) the toe or compression zone (Fig. 3). The scarp is the initiation point of the disturbance and is typically evident as a vertical to near-vertical headwall. The scar zone, located at the upper initiation point of the slide, is characterized by bare ground, giving it a bright appearance. Extension fractures and isolated vegetated blocks from the upslope portion of the sliding mass can give this zone a mottled spectral signature due to the resulting patterns of these vegetated and non-vegetated areas (Lewkowicz, 1990). Material moving downslope accumulates in the compression zone and is composed of vegetated, irregular transverse ridges that are spectrally similar to adjacent undisturbed surfaces. The only zone that is substantially different from the surrounding area in regards to spectral signature is the scar zone, which is well captured by the remotely sensed data and can be used for the identification of these disturbances. This change in land cover from vegetated to un-vegetated is best represented using NDVI. Although NDVI has been successful in separating landslides from vegetated features (Barlow et al., 2006; Martha et al., 2010; Schneevoigt et al., 2008), it has not been used to identify permafrost slope disturbances. The methods designed for this detection analysis are outlined in Fig. 4.

Field mapped ALDs were separated based on length to width (L/W) ratios into elongate and compact types. Elongate forms are characterized by a larger scar zone where the extent of the disturbance can span the length of the slope and results in a highly deformed toe zone. Of the ALDs observed in the field, those with elongate morphometry were typically constrained by L/W ratios \( \geq 2 \). ALDs classified as compact disturbances had L/W ratios \(< 2\), tended to be smaller, and displayed curved headwalls with sliding distances of only a few meters; this morphometry results in minimal internal deformation of the displaced mass, making compact disturbances nearly indistinguishable from surrounding vegetated areas. By contrast, elongate forms, with their larger scar zones, are more readily identifiable.

3.2.4. NDVI derivation and differencing

NDVI is used to measure vegetation cover and biomass production using multispectral satellite data. The principle behind NDVI takes advantage of the different absorption and reflectance characteristics of vegetation in the red and near infrared regions (Eq. (2)) (Tucker, 1979). Chlorophyll in the vegetation absorbs considerable amounts of radiation in the 600–700 nm wavelength range (i.e., red wavelengths) while the vegetation’s internal structure causes high reflectance in the near infrared region of the electromagnetic spectrum (Jensen, 2007). NDVI is a dimensionless radiometric measure that ranges from −1 to +1 where healthy productive vegetation has NDVI values close to +1 and non-vegetated surfaces (rock, soil), water, snow, ice and clouds have near zero or negative NDVI values.

\[
\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})}
\]  

(2)

NDVI differencing is a commonly applied technique when identifying differences in vegetation between multiple dates (Fraser et al., 2000; Lunetta and Elvidge, 1998). Areas of change can be detected through the subtraction of the NDVI image from two dates. Using these methods, NDVI images were produced for both IKONOS images and subsequently subtracted from one another (\(\text{NDVI}_{2010} - \text{NDVI}_{2004}\)). In the NDVI difference map, pixel values centered at approximately zero represent no-change areas while pixels with positive and negative values identify change.

Areas where vegetation has decreased between dates appear gray to black whereas areas with increased amounts of vegetation are bright (Fig. 5). In this study only change associated with vegetation removal is of interest, as the removal of vegetation will be used as a proxy for the presence of disturbance. Upon initial inspection of the NDVI difference map (Fig. 5) there are distinct regions of black and dark gray pixels that are possible ALDs but in order to discriminate between disturbances and other areas of change additional analysis is required.

3.2.5. Image segmentation

Object-based image analysis (OBIA) based on image segmentation techniques is a form of change detection analysis not commonly applied

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**Fig. 3.** Geomorphic zones within a typical active layer detachment. *After Lewkowicz (1990).*

**Fig. 4.** Methodology for detection of permafrost disturbances using multi-temporal multispectral IKONOS images.

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to arctic settings. OBIA involves creating spectrally homogenous regions from an image and performing subsequent analysis and classification on those regions rather than on the individual image pixels (Mather, 1999). This method was used to identify regions of similar NDVI values that could then be optimized to classify areas of disturbance.

In this study the multi-resolution segmentation (MS) algorithm in eCognition was used to segment the NDVI difference image into objects based on shape, color and scale. Essentially, MS exemplifies a bottom-up approach; it identifies single image-objects of 1 pixel in size and merges them with neighbors based on homogeneity criteria, demarcating regions of similarity (eCognition, 2009; Martha et al., 2010). Homogeneity criteria are based on a combination of color, shape, and scale characteristics where shape is a function of compactness and smoothness and color is attributed to spectral properties. The shape and color parameters are intrinsically related, the ratio of the two determines the extent to which shape influences the segmentation process compared to color. Changing the scale parameter can modify these variables. The scale parameter is a function of the images’ initial resolution and is used to control the maximum allowed heterogeneity of the objects; a lower scale parameter will yield a larger number of segments and vice versa (eCognition User Guide, 2009). For this study, where the goal was to minimize operator intervention during identification, parameters for color, shape and scale were set at 0.9, 0.5 and 15, respectively.

3.2.6. Optimization of image segments — setting thresholds

Using NDVI as an indicator of disturbance requires that additional thresholds or rule sets be established to discriminate between disturbed and undisturbed areas. Based on the morphology of ALDs, bare soil within the scar zone distinguishes and sets it apart from the surrounding landscape. To separate these features, segments were optimized by applying additional rules to the NDVI image. These rules were set without prior knowledge of the field mapping to ensure automatic processing. When thresholding an image a priori, most studies set thresholds that are ±1 standard deviation from the mean (Cakir et al., 2006; Dobson et al., 1995). It is assumed that the difference image yields a pixel value distribution that is approximately Gaussian in nature and pixels associated with change fall within the tails of the distribution (Dobson et al., 1995). To separate possible areas of disturbance from areas of increased vegetation, a threshold was implemented in eCognition for the NDVI difference image. All objects with at least 10 connected pixels with NDVI difference values less than −0.1 were classified as potential ALDs removing all objects that did not fit these disturbance criteria. A threshold of −0.1 was chosen as it is one standard deviation from the mean displaying objects with decreased vegetation that fit the criteria delineating possible ALDs (Figs. 6 and 7).

Since a threshold was applied to the NDVI difference data, features with similar or lower NDVI difference values such as water, exposed channel beds and rocky outcrops may be detected and misclassified. It is essential to identify these false positives in order to reduce the error of commission. A blue band threshold was used to remove false positives associated with open water. The blue band has a short wavelength that penetrates water more than the other bands and exhibits maximum reflectance (Jensen, 2005). All objects classified as ALDs with mean values in the blue band greater than 85 were removed from the ALD classification. To account for false positives associated with differences in channel snow cover, a one-meter buffer was placed around a river vector layer. ALDs do not occur directly in river channels and as a result objects falling within the buffered zone were removed.

Fig. 5. NDVI difference map. Areas that are bright portray changes associated with increased vegetation cover/vigor while areas that are dark gray to black are changes due to decreases in vegetation cover/vigor.
4. Results

4.1. ALD recognition and discrimination

Optimization of image objects is essential to separate potential ALDs from other forms of change. Potential ALDs are those that have developed between 2004 and 2010. An NDVI difference value of $-0.1$, a value that is one standard deviation from the mean was used to discriminate potential ALDs from areas with an increase in vegetation (Fig. 7). From the extracted ALD class, false positives were sequentially eliminated, ultimately retaining only ALDs (Fig. 8). False positives, represented by incorrectly identified ALDs, can be explained by meteorological differences between 2004 and 2010. The mean daily July temperature was 3.1 °C in 2004 compared to 7.6 °C in 2010 (Lamoureux unpublished data; Lamoureux et al., 2006). As a result, 2010 was a more productive year than 2004 and this is reflected by the mean NDVI across the images of 0.26 and 0.15, respectively. Additionally, due to warmer temperatures in 2010 there was a substantial decrease in residual July snow cover with 2004 having approximately 1.5 times the amount of snow cover at the time of image acquisition compared to 2010 (Table 2). Consequently, the removal of residual snow exposed non-vegetated ground in 2010 throughout the mapping area, particularly in deep channels.

False positives associated with water and snow banks were removed with the application of additional thresholds removing objects associated with the lake and multiple objects affiliated with melt water from perennial snow banks. In addition to differing phenological and snow cover conditions, river erosive processes and several localized anthropogenic surface impacts could account for the misclassification of ALDs. These misclassifications are attributed to the high degree of spectral similarity that exists between these classes.

4.2. Detection limitations

Given the natural variability in size and morphology of ALDs, there are limitations to the multi-resolution image segmentation technique. Identified objects were compared to the disturbance inventory to assess the accuracy of the change detection technique. Accurately classified objects intersected and fell within a mapped disturbance while inaccurate objects were not associated with any of the mapped ALDs. There are a number of ALDs mapped in the field that were not identified using the initial change detection methods. These unidentified ALDs were smaller and have a compact morphology with L/W ratios less than two (i.e., $L/W < 2$). In contrast, correctly identified ALDs have $L/W$ ratios $\geq 2$ and are elongate. Within correctly identified ALDs, it is typically the upper portion of the disturbance or the scar zone that is detected.

The minimum ALD detection size is related in part to the ground resolution of the satellite sensor. To account for this the area of the

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**Fig. 6.** (A) Objects created using the multi-resolution segmentation algorithm. (B) Classified objects once the NDVI threshold has been applied. All objects in red fit the disturbance criteria and represent possible ALDs.

**Fig. 7.** NDVI difference histogram; all objects with NDVI values less than the NDVI threshold of $-0.1$ are considered as potential ALDs. The red line denotes the NDVI threshold.
The smallest accurately detected ALD was used as an effective minimum size threshold. In this study, the smallest field mapped ALD accurately identified had an area of 290 m²; disturbances from the reference inventory that had an area smaller than this (i.e., 5 disturbances) were removed.

### 4.3. Accuracy assessment

Accuracies of classification results derived from remote sensing data are commonly expressed through error matrices (Congalton, 1991). Error matrices are effective when the purpose is to assess the classification accuracy of the entire image; however, they are not the appropriate method for this study as our goal is to assess the accuracy of correctly identified ALDs. To independently assess the accuracy of the automatic change detection analysis, ground-based ALD mapping was used as a reference. The quality of these methods was evaluated by comparing how often segmented thresholded objects were associated with a field mapped ALD track using the following quality measures: true positive (TP) — methods correctly classified the object as an ALD and change polygons fall within a field mapped ALD; false positive (FP) — objects were misclassified as an ALD, objects classified as change did not fall within a field mapped ALD; and false negative (FN) — tracked ALDs were not identified using the change detection methods. Accuracy associated with one type of classification is expressed in terms of branching factor, miss factor, detection percentage, and quality percentage (Lee et al., 2003; Martha et al., 2012):

- Branching factor \( (BF) = \frac{\text{False Positive}}{\text{True Positive}} \)  
- Miss factor \( (MF) = \frac{\text{False Negative}}{\text{True Positive}} \)  
- Detection percentage \( = 100 \times \left( \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \right) \)  
- Quality percentage \( = 100 \times \left( \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative} + \text{False Positive}} \right) \)

Branching and miss factors indicate two potential errors generated during the detection process. The branching factor, a measure of commission error, results in an over-classification of ALDs represented by false positives. A branching factor of zero results if the method never incorrectly classifies an object while a BF of 1 means that for every object correctly classified there is one object incorrectly classified. The miss factor relates to the under-classification of objects producing false negatives and is a measure of omission error (Lee et al., 2003; Shaker et al., 2010; Shufelt, 1999). The detection percentage measures the number of objects that were correctly referenced to a tracked disturbance and can be used as a measure of the object detection performance (Shufelt, 1999). Quality percentage indicates how likely a tracked disturbance identified by these detection methods is true (Lee et al. 2003). To obtain

### Table 2

Meteorological differences between 2010 and 2004 and its effect on NDVI and snow cover.

<table>
<thead>
<tr>
<th>Image year</th>
<th>Mean daily temperature (°C)</th>
<th>Mean NDVI</th>
<th>Snow cover (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>3.1</td>
<td>0.15</td>
<td>223,360</td>
</tr>
<tr>
<td>2010</td>
<td>7.3</td>
<td>0.26</td>
<td>144,816</td>
</tr>
</tbody>
</table>

Fig. 8. Classified change map with NDVI, blue band and exposed channel bed thresholds. False positives associated with water are represented in teal and false positives associated with exposed river beds are represented by green objects. All remaining objects represent true positives in red and false positives in blue. Field mapped disturbance tracks are in yellow.
100% quality the methods must correctly identify every field mapped ALD (Shufelt, 1999).

Using the reference inventory and the change map, true positives, false positives and false negatives were calculated. Due to the complexity of scar zones it is possible that multiple objects may be identified from a single mapped ALD (Fig. 9A). In this study, a disturbance inventory is available and in order to compare how this method performed, objects were grouped and a direct comparison was made between the inventory and the detected objects (Fig. 9B). Accuracy statistics were calculated for all objects and subsequently for objects grouped by morphology into elongate and compact forms (Table 3).

The branching factor and the detection percentage for all objects are 0.78 and 67%, respectively. These values demonstrate that the change detection techniques perform moderately well. Elongate ALD detection was much better than compact ALD detection with detection percentages of 100% and 7%, respectively (Table 3). There was much less over-classification of the elongate ALDs with a BF of 0.04 while the opposite occurred with compact ALDs. When objects were grouped and compared to the reference inventory, the methods performed moderately well — accurately detecting 43% of all ALDs and 67% of elongate ALDs.

5. Discussion

Taking advantage of the spectral differences that occur with the formation of ALDs, NDVI differencing and object-based analysis achieved 43% detection accuracy when identifying all ALDs and 67% accuracy when identifying elongate ALDs. It is important to note that this methodology was not optimized with further field-based information but instead maintained a semi-automatic detection approach to maximize the applicability of this method where field verification is not possible or economical.

Elongate ALDs are typically larger and more destructive, moving substantially more material downslope over longer distances (Lewkowicz, 1990) and altering hydrologic connectivity; hence posing a greater risk for infrastructure and the surface environment. By contrast, the complexity of scar zones can result in multiple objects being detected within individual ALDs (Fig. 9B). Objects within individual ALDs were then grouped to allow for a direct comparison between the reference inventory and the detected objects produced from the change detection methods resulting with one object associated with each referenced ALD.

Table 3

<table>
<thead>
<tr>
<th>Object Type</th>
<th>TP</th>
<th>FP</th>
<th>FN</th>
<th>Total</th>
<th>Branching Factor (BF)</th>
<th>Miss Factor (MF)</th>
<th>Detection Percentage</th>
<th>Quality Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>50</td>
<td>39</td>
<td>25</td>
<td>75</td>
<td>0.78</td>
<td>0.5</td>
<td>67</td>
<td>44</td>
</tr>
<tr>
<td>Elongate</td>
<td>48</td>
<td>2</td>
<td>0</td>
<td>47</td>
<td>0.04</td>
<td>0.04</td>
<td>100</td>
<td>96</td>
</tr>
<tr>
<td>Compact</td>
<td>2</td>
<td>48</td>
<td>26</td>
<td>28</td>
<td>0.04</td>
<td>0.04</td>
<td>13</td>
<td>7</td>
</tr>
<tr>
<td>Grouped</td>
<td>32</td>
<td>39</td>
<td>75</td>
<td>47</td>
<td>1.2</td>
<td>1.2</td>
<td>43</td>
<td>28</td>
</tr>
<tr>
<td>Elongate</td>
<td>30</td>
<td>2</td>
<td>15</td>
<td>47</td>
<td>0.1</td>
<td>0.5</td>
<td>67</td>
<td>64</td>
</tr>
<tr>
<td>Compact</td>
<td>2</td>
<td>30</td>
<td>26</td>
<td>28</td>
<td>1.1</td>
<td>1.1</td>
<td>13</td>
<td>7</td>
</tr>
</tbody>
</table>

be noted that many of the compact disturbances are often subtle to identify during ground surveys, and mapping used for verification in this study likely represents a level of detail that is unlikely to be available elsewhere (cf. Lantuit et al., 2012).

5.1. Morphology and its effect on ALD detection

The contrast in detection accuracies is a result of both disturbance morphology and the use of NDVI differencing in this study. NDVI is widely used as a measure of plant productivity (Tucker, 1979) and has been used in this study to identify areas where disturbance has removed or significantly reduced the vegetation cover. In elongate ALDs there is typically substantial extension in the scar zone that removes vegetation entirely, or results in sparse residual and isolated vegetated blocks (Fig. 10A). The exposed soil material is spectrally different than the surrounding vegetated areas and results in negative NDVI values. In compact disturbances exposed bare soil is limited or at sub-resolution scales (<0.5 m) and consequently there is an insignificant change in NDVI values (Fig. 10B). These morphological characteristics are quite clearly depicted in the satellite imagery and derived maps (Fig. 11).

In the multispectral image of the elongate ALD (Fig. 11A) a light patch can be clearly seen just below the scarp and represents bare ground compared to the black and grayish hues where vegetation occurs. In the NDVI difference map, black and dark gray pixels, indicators of vegetation removal are found in the same location. This zone of vegetation removal is detected by our methods and is correctly identified in the change map illustrated by the black polygon. This typical example of an elongate ALD has an L/W ratio greater than two and a defined head scarp, scar zone and toe. By contrast, a compact disturbance does not have exposed soil material and there are no distinct zones indicating vegetation removal that were classified as changed (Fig. 11B). NDVI values extracted from the example elongate and compact ALDs strengthen this observation. Within the elongate ALD there is a greater frequency of pixel values below the threshold than there is in the compact ALD (Fig. 12). In this example, the area thresholds for the elongate and compact ALDs are 4576 m² and 272 m², respectively. Although an area of 272 m² is more than the amount needed to meet the threshold criteria of 160 m² (10 pixels at 4 m resolution) with NDVI difference values below —0.1 the criteria also require that these pixels be connected. In this case although there was change in the compact disturbance the degree of change was not detectable with the current detection thresholds. This was found to be the case for the majority of compact disturbances.

Detection difficulties arise when there is not a distinct spectral difference between the disturbed object being identified and the adjoining undisturbed zone. ALDs, while permafrost phenomena, are not dissimilar to other forms of mass movement found in temperate zones. The spectral similarities that result from the complex disturbance morphologies often result in a number of false positives and false negatives.
Although NDVI is widely used to represent changes in land cover, the NDVI values representative of disturbance are also similar to rock outcrops, water bodies, and river beds and hence, are subject to misclassification (Martha et al., 2010).

5.2. Implications of size and resolution for ALD detection

Additional complications concerning the detection of ALDs are directly related to their size. Elongate ALDs typically occur on slopes where material movement can span a large portion of the slope length and are much larger than compact ALDs. Improvements to the spatial resolution of satellite imagery have allowed finer scale landscape analyses, yet feature size remains a limiting factor (Barlow et al., 2006; Kaab, 2008). ALDs and other forms of disturbance are only detectable provided the surface change is much larger than the sensor’s spatial resolution (Kaab, 2008). In this study, compact disturbances ranged from 25 to 96 m in length and had a mean surface area of 2390 m², while elongate disturbances ranged from 39 to 684 m in length, and had a mean surface area of 8200 m². These dimensions are similar to those observed elsewhere in the Arctic (Leibman, 1995; Lewkowicz and Harris, 2005). The smallest ALD correctly identified by our method is 290 m²; while this is much larger than the spatial resolution of the IKONOS imagery (4 m pixels), only the bare soil of the scar zone of the ALD is actually being detected using our methods.

The complex morphology of ALDs results in varying degrees of bare soil within the scar zone. To more accurately compare detected ALDs to their ground-referenced counterparts, reference ALDs were visually remapped on the ground in 2012 to delineate areas of bare soil. When areas of bare soil within field mapped ALDs were compared with the total area of the field mapped ALD, results indicate that the area of bare soil is proportionate to the total ALD size and accounts for approximately 53% of the total area in detected ALDs (Fig. 13). In elongate ALDs the scar and track zone have been found to constitute ~60% of the disturbance area (Lewkowicz and Harris, 2005).

The disturbance criteria used in this study effectively imposed a minimum size threshold for image objects (10 connected pixels or 160 m²). When ALDs are separated based on morphology the role of the minimum size threshold is more clearly evident (Fig. 13 inset). Undetected compact disturbances have areas of bare soil less than the minimum threshold of 160 m². Elongate ALDs in general are all well detected with the exception of three cases that were above the size threshold but not identified. Upon closer inspection of these elongate ALDs, it was found that low lying clouds present in the 2004 imagery influenced the spectral signature and did not allow for accurate detection of these particular ALDs.

Fig. 10. (A) A typical scarp of an elongate ALD — it is predominantly bare with some residual vegetated blocks. (B) An example of a compact ALD with minimal extension that results in the scarp remaining vegetated.
Comparisons between the area of bare soil classified in the ALDs to the mapped bare soil area indicate a strong correlation ($n = 48; \text{SE} = 0.02; P < 0.001$) (Fig. 14). Our detection method accurately detects the disturbed zone within detected ALDs; this method relies heavily on the presence (and contrast) of bare soil within the scar of the ALD. Results indicate that the methods used for this study are sufficient to accurately delineate the location and area of large elongate ALDs. However, the morphological characteristics of compact disturbances and their lack of exposed soil prevented accurate identification and represent a limitation to this approach.

Fig. 11. Morphological differences of elongate (A) and compact ALDs (B) are highlighted when compared in the 2004 and 2010 MS IKONOS image, NDVI difference map and change detection map. Elongate (A) and compact (B) ALDs are to scale.

Fig. 12. Histograms of NDVI differences from the example elongate and compact ALDs presented in Fig. 11. NDVI frequency histograms illustrate the differences between elongate and compact ALDs. The NDVI threshold of $-0.1$ is denoted by the red line.
5.3. Image classification and segmentation optimization

The approach for detection and identification of ALDs used in this study was designed to be applied to areas where field-based information was unavailable. Image segmentation optimization has been applied by previous researchers to detect different landslide types (e.g., Barlow et al., 2003; Lu et al., 2011; Martha et al., 2010). In these studies, image characteristics used for visual interpretation of landslides such as vegetation, drainage, and morphology, are used to classify landslide types through object-based analysis. With this expert knowledge, spectral, morphometric and contextual diagnostic features are quantified and integrated, making it possible to discriminate between landslide types.

With the application of expert knowledge, characteristics are specific to a landscape and may have to be adjusted when applied to other areas or when using other types of imagery. The goal of this study was to make this methodology applicable to any location in the High Arctic; as a result, only minimal image segmentation optimization was incorporated. Future work could incorporate additional expert knowledge and include other classification features beyond NDVI: i.e., length/width ratios, geometric asymmetry, surface texture, slope, terrain curvature, and flow direction, all possible elements that could help to distinguish between compact and elongate disturbances, thereby increasing their detection accuracies.

Another form of expert knowledge that can be used to drive image segmentation optimization is scale. Objects of interest are not always homogenous in size making it difficult to set a single scale parameter that does not over- or under-segment the image. With image segmentation, the scale used to detect the desired image objects must be significantly larger than the scale of image noise, represented by false positives (Baatz and Schäpe, 2000). The wide range of ALD sizes in this study complicates scale selection for successful discrimination of ALDs. Optimization of the scale parameter for large objects will decrease the number of false positives thereby resulting in reduced detection of small ALDs. The opposite is true with an optimization for smaller objects, where smaller ALDs will be detected, but with an increase in false positives. Ultimately, the scale parameter selected for this study was a default parameter to maintain a semi-automatic approach where no background knowledge of the area was required.

6. Conclusions

In this study, NDVI differencing and object-oriented image processing techniques were used to detect and identify ALDs in a High Arctic setting. NDVI differencing was used to detect zones where vegetation cover decreased and/or was completely removed as a direct result of ALD formation. These zones were then identified and separated from undisturbed zones using object based image analysis and a fixed NDVI threshold. Feature characteristics specific to ALDs known to the authors were not included in the analysis as the objective was to assess a semi-automated approach for future applications without prior ground-based mapping of ALDs.

The processing chain performed moderately well when identifying all ALDs and exceptionally well when identifying elongate ALDs. Meanwhile, ALDs with minimal vegetation removal were not consistently identified and generally had compact morphologies and small surface areas. Substantial extension in the scar zone is necessary to produce large areas of bare soil making detection possible; a characteristic typical of elongate morphologies. Both morphology and size were found to be
important variables when detecting ALDs. The size of the disturbance must be large enough to generate significant areas of bare soil which is a direct result of morphology. These results collectively show promise for the semi-automated detection of slope disturbances in permafrost settings. Mapping disturbances is an important primary task for assessing potential slope disturbance risk during the planning of infrastructure, and is also useful to determine potential changes to ecosystems and surface water.

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References


Fig. 14. Relationship between the areas of bare soil found within a disturbance and its corresponding image classified area. N=48 and includes all accurately detected elongate and compact ALDs (SE=0.02, P<0.001).


