Terrain controls and landscape-scale susceptibility modelling of active layer detachments, Sabine Peninsula, Melville Island, Nunavut

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ABSTRACT

Modelling the susceptibility of permafrost slopes to disturbance can identify areas at risk to future disturbance and result in safer infrastructure and resource development in the Arctic. In this study we use terrain attributes derived from a digital elevation model, an inventory of permafrost slope disturbances known as active-layer detachments (ALDs), and generalized additive modelling (GAM) to produce a map of permafrost slope disturbance susceptibility for an area on northern Melville Island, in the Canadian High Arctic. By examining terrain variables and their relative importance we identified factors important for initiating slope disturbance. The model was calibrated and validated using 70 and 30 % of a dataset of 760 mapped ALDs, including disturbed and randomized undisturbed samples. The GAM calibrated and validated very well, with areas under the receiving operating characteristic curve of 0.89 and 0.81, respectively, demonstrating its effectiveness at predicting disturbed and undisturbed samples. ALDs were most likely to occur below marine limit on slope angles between 3 and 10° and in areas with low values of potential incoming solar radiation (north-facing slopes).

KEYWORDS

Active-layer detachment, permafrost disturbance susceptibility, generalized additive model, geomorphology

INTRODUCTION

Permafrost temperatures in Arctic regions have risen by up to 2 °C in the last two to three decades, particularly in cold permafrost (AMAP, 2011). Changes to the thermal regime of the permafrost play an important role in landscape stability, which is reflected by increasing amounts of permafrost slope disturbance observed across the Arctic (Jorgenson *et al.*, 2006; Lantz and Kokelj, 2008; AMAP, 2011). An important type of permafrost slope disturbance is known as an active-layer detachment (ALD), a localized mass movement restricted to the active layer and typically occurring on ice-rich unconsolidated sediments (French, 2007). ALDs are caused when high pore-water pressures reduce the effective shear strength at the base of the active layer from thaw of ice-rich sediment (Lewkowicz and Harris, 2005). ALDs have been of increasing concern in Arctic regions, pose a substantial risk to infrastructure and may alter environmental conditions (Nelson *et al.*, 2002). In order to effectively assess and mitigate permafrost slope disturbance risk, disturbance-prone areas can be predicted by applying susceptibility models to quantitatively assess the relation between the distribution of past permafrost slope disturbances and influencing terrain attributes (Glade *et al.*, 2005). Permafrost slope disturbance susceptibility maps may be useful for land planners, decision makers and geotechnical engineers.

Landslide susceptibility modelling has provided useful information on the spatial probability of landslide occurrence in temperate regions (Varnes, 1984; Glade *et al.*, 2005; Petschko *et al.*, 2014). The principles used for landslide susceptibility modelling can also be

applied to slope disturbance in permafrost regions. The premise behind susceptibility modelling is that conditions that led to slope failures in the past will also result in unstable conditions in the present-day and future (Varnes, 1984). Susceptibility modelling does not specify a time frame or recurrence interval because it does not include information on the frequency of disturbance (JTCl, 2004). Statistical models are developed to represent the susceptibility of an area given the current distribution of climate, topographic and material conditions, with an understanding that these conditions likely influence past disturbance. This contrasts with a physically-based model, which is based on specific mechanisms controlling slope failure (Regmi *et al.*, 2010). As physically-based models typically require local data on slope geometry, shear strength and pore-water pressure, obtaining such data for large areas is not practical.

We performed susceptibility modelling on Melville Island, Nunavut, Canada. To our knowledge, this is the first study of modelling permafrost slope disturbance susceptibility in the High Arctic, although several statistical methods have been used to model landslide susceptibility elsewhere. The most common are: (i) logistic regression (e.g., Ayalew and Yamagishi, 2005); (ii) bivariate models such as weights of evidence (e.g., Sterlacchini *et al.*, 2011); (iii) machine learning techniques such as artificial neural networks (ANNs) (e.g., Pradhan and Lee, 2009); and (iv) support vector machines (e.g., Marjanovic *et al.*, 2011). Comparisons of these modelling techniques have found that machine learning algorithms are flexible but tend to over-fit the data, and linear models may not portray non-linear relations between slope failure occurrence and predictor variables (Goetz *et al.*, 2011). To account for non-linearities, landslide susceptibility studies have recently used non-linear generalized additive models (GAM) (Goetz *et al.*, 2011; Petschko *et al.*, 2014). A GAM is an extension of a generalized linear model (GLM) that incorporates non-linear relations between the response (disturbance) and the predictor (terrain) variables. GAMs are less prone to

overfitting in geomorphological modelling than more flexible models such as ANNs (Hastie and Tibshirani, 1990; Brenning, 2005).

Understanding the relation between terrain variables and permafrost slope disturbance is important for predicting areas susceptible to future disturbance and can provide insight into the underlying geomorphological mechanisms of disturbance. Hence, the objectives of this research are to: 1) create an accurate permafrost slope disturbance susceptibility model for a location in the Canadian High Arctic using a GAM; and 2) use the model to explore the terrain variables that appear to control the locations of past disturbance.

STUDY AREA

The study covers an area of $\sim 240 \text{ km}^2$ located on the Sabine Peninsula, northeastern Melville Island, Nunavut ($\sim 77^\circ \text{N}$) (Figure 1). The area is characterized by undulating topography with surface materials composed of sedimentary bedrock draped with silty-clay Quaternary glacial and marine sediments (Stangl *et al.*, 1982; Hodgson *et al.*, 1984). Three bedrock units of the Mesozoic Sverdrup Basin underlie the study area: (i) the Kanguk Formation, represented by dark marine shale; (ii) the Hassel Formation, consisting of yellow sandstone; and (iii) the Christopher Formation, composed of grey marine silty shale (Barnett *et al.*, 1977). The majority of surficial sediments have developed through reworking and incorporation of weathered bedrock into marine and glacial sediments. As a result, each bedrock formation possesses relatively distinctive topography, drainage patterns, surficial sediments, soil types and ground-ice conditions (Stangl *et al.*, 1982).

The annual mean air temperature recorded at a temporary station (by Onset U23 logger, 1.5 m above ground, accuracy of $\pm 0.2^\circ \text{C}$, $76^\circ 32' \text{ N } 108^\circ 41' \text{ W}$) was -16.6°C for 2011-12, which is representative of regional temperatures. The permafrost is continuous and has a moderate to high ground-ice content (20-30 % or greater) and the active-layer thickness

(ALT) is typically $\sim 0.5 - 1$ m (Collingwood *et al.*, 2014). Localities below Holocene marine limit ($\sim 60 - 70$ m above sea level (asl)) are usually characterised by higher silt and ground-ice contents than areas above marine limit (Barnett *et al.*, 1977; Nixon *et al.*, 2014).

Figure 1 Sabine Peninsula study area with inset of location of Melville Island in the Canadian High Arctic. Bedrock units are mapped by Harrison (1995) and estimated Holocene marine limit (80 m asl) is indicated. Two parallel lines represent faults.

METHODS AND MATERIALS

Data Sources and Preparation

A high-resolution digital elevation model (DEM) (resolution 1 m horizontal and vertical) of the study area was derived from WorldView-2 image pairs collected on July 16,

2011 (processing by PhotoSat, Vancouver, Canada) using a proprietary stereo image matching process. In order to reduce processing time and minimize memory requirements the DEM was aggregated from 1 m to a resolution of 2 m using a mean aggregation strategy. Bedrock geology maps (Harrison, 1995) were georeferenced and rasterized with ArcGIS (ESRI, version 10.2.2).

Active-Layer Detachment inventory (Response Variable)

The ALD inventory used for this model was produced by combining field mapping in 2010/2011 and a visual inspection of the 2011 Worldview-2 panchromatic data. One hundred and fifty ALDs were mapped in pre-selected areas ($\sim 3 \text{ km}^2$) in each geological unit with a Garmin 60Cx GPS unit ($\pm 5 \text{ m}$ typical uncertainty). The remainder of the study area was mapped using a systematic visual inspection of the Worldview-2 image. The panchromatic data were divided into 2 km^2 tiles and 590 ALDs were mapped with a criteria-specific methodology that uses distinct morphologic and tonal characteristics, including: tone/contrast; the presence of a headscarp, scar zone or toe; and shape. The minimum size of an ALD detected through the visual inspection of the satellite imagery was $\sim 100 \text{ m}^2$ (Figure 2). The total inventory includes 760 ALDs.

To represent the conditions that make slopes sensitive to disturbance, we digitized initiation points immediately downslope of the ALD headscarps. Each initiation point represents a zone of 78 m^2 (average of raster cells within a 5 m buffer around the initiation point), a size selected to capture terrain characteristics associated with slope disturbance initiation and include disturbed areas only (Figure 2). A point inventory was chosen over a polygon inventory to equally represent large and small disturbances in the model (Petschko *et al.*, 2013; Heckmann *et al.*, 2014).

Figure 2 (A) Panchromatic Worldview-2 image (July 16, 2011) of the study area, Sabine Peninsula, Melville Island, NU with initiation points of all mapped disturbances. (B) Inset shows an example of mapped permafrost disturbances with disturbance initiation points.

Terrain conditions at mapped ALDs (i.e., slope disturbances) were used to calibrate the susceptibility model. To evaluate undisturbed areas within the model, we selected 760 randomized undisturbed sites to match the number of ALDs. Random points were produced in ArcGIS (Create Random Points Toolbox) with constraints for distance to a water source (>10 m away) and distance to a disturbed sample (>20 m away). The numbers of undisturbed points were also limited for areas above marine limit as there are a greater proportion of disturbances below marine limit.

GIS Derived Geomorphological Variables (Predictor Variables)

Predictor variables are selected based on the expectation that they have an effect on the occurrence of ALDs and hence can be used to predict future slope disturbances (van Westen *et al.*, 2008). Selected predictor variables represented easily derived hydrological and geomorphological terrain conditions important for ALD initiation. ArcGIS was used to calculate slope angle, distance to water, topographic position index (TPI) (Jenness, 2006), and potential incoming solar radiation (PISR) (Solar Analyst, Fu and Rich, 1999) from the DEM. Topographic wetness index (TWI) (Beven and Kirby, 1979) was calculated using Whitebox Geospatial Analysis Tools (Lindsey, 2012) and elevations were extracted from the DEM to represent the Holocene marine limit at each location. The shale and sandstone geological units were also included as predictor variables. All terrain variables were represented as rasters with spatial resolutions of 2 m.

Slope angle is an important factor in mass movements, and in permafrost regions ALDs can occur on low-gradient slopes (Niu *et al.*, 2014). Distance to water was calculated for all samples using the Euclidean Distance tool in ArcGIS and a vector hydrology layer. Thermal erosion as well as mechanical erosion from undercutting at stream banks may increase the susceptibility to disturbance (Dai *et al.*, 2001).

The TPI is produced by comparing the elevation of each cell in a DEM to the mean elevation of a specified neighbourhood around that cell. Positive TPI values indicate that the selected locations are higher than the average of their surroundings (i.e. ridge, hilltops), negative TPI values represent locations that are lower than their surroundings (i.e. concavities, valley bottoms) and TPI values close to zero represent flatter surfaces (Guisan *et al.*, 1999). TPI was derived using a 150 m diameter circular window, which is small enough to distinguish depressions and ridges throughout the landscape.

PISR represents differences in the intensity of solar radiation, which can contribute to variations in microclimate and affect local temperature and evaporation, patterns of snowmelt and soil moisture (van Westen *et al.*, 2008; Regmi *et al.*, 2010). Total PISR was calculated for the snow-free period (estimated to be from July 15 to September 15) using a mean cloud cover factor of 0.75 based on the Nav Canada Graphic Area Forecast (Hudson *et al.*, 2001). Calculations reflect changes in seasonal cloud cover, elevation, orientation of the slopes (slope aspect and angle), topographic shadowing and daily and seasonal solar angles (Regmi *et al.*, 2010).

The TWI uses the upslope contributing area draining through a cell as well as the local slope angle of the landscape to determine an index of wetness or surface saturation at each cell (Beven and Kirkby, 1979). The FD8 flow algorithm in Whitebox Geospatial Analysis Tools was applied to represent flow of water into multiple neighbouring cells based on slope concavity or convexity.

Surficial geology plays an important role in ALD initiation because it influences the permeability, thermal properties and ground-ice content of the substrate. In the study area, surficial geology can be linked to early Holocene marine limit through the likely presence of marine sediments, although detailed mapping is not available. Localities below marine limit are typically characterized by higher silt and ground-ice contents than those areas above it (Barnett *et al.*, 1977). Hence, the geological units (shale, sandstone and early Holocene marine sediments) serve as a proxy for a detailed surficial sediment map and provide insight into local frost susceptibility. While ground ice is an important variable for disturbance initiation, it was not used as a predictor variable for the model as ground-ice maps were unavailable and impractical to attain.

To test for multicollinearity amongst the variables, we used variance inflation factors (VIF) and Spearman's rank correlation coefficient. VIF is a measure of how much the

variance of the estimated regression coefficient is ‘inflated’ by the existence of correlation among the predictor variables in the model and Spearman’s coefficient is a measure of the statistical dependence between two variables (Goetz *et al.*, 2011; Heckmann *et al.*, 2014).

Generalized Additive Model (GAM)

Modelling was performed as a case-control study, with mapped ALD points as cases and randomly selected undisturbed points as controls. An equal number of undisturbed points were produced, resulting in a total of 1520 points (760 disturbed and 760 undisturbed). The dataset was then randomly subdivided into 70 % calibration and 30 % validation subsets.

A GAM is a semi-parametric extension of a GLM that combines the linear and nonlinear relation between predictor and response variables (Hastie and Tibshirani, 1990). GAMs replace the linear predictors used in GLMs with a smoothing function used to transform nonlinear predictor variables, potentially capturing, more accurately, the non-linear response of slope failure in a dynamic system (Goetz *et al.* 2011). As a result, a GAM is able to fit the data more closely as it is not constrained to predefined parametric shapes and provides a greater understanding of complex relationships between variables (Hastie and Tibshirani, 1990). Recently, GAMs have shown stronger predictive performance than GLMs for susceptibility modelling, specifically landslide susceptibility (Goetz *et al.*, 2011; Petschko *et al.*, 2014).

In our initial exploratory analysis we tested both GLMs and GAMs, and bivariate plots were used to examine the relationship between the predictor variables and ALD occurrence (Figure 3). With the addition of the smoothing (non-linear) parameter, the GAM is able to model the relationship between the predictor variable and ALDs more closely. While both models result in meaningful relationships between the predictor variables and

ALD occurrence, a GAM was ultimately selected to produce a model with the best predictive power.

Figure 3 Bivariate plots were used to examine the relationship between the predictor variables and ALD occurrence. GLMs (red line) and GAMS (blue line) were fit to each predictor variable with a confidence interval of 0.95 (grey bands). Number of disturbed and undisturbed samples is 760 each.

For model selection GAMs were fitted with all possible combinations of terms in the global model. All predictor variables with the exception of “geol” were fitted to the occurrence of slope disturbance using a spline smoother with four degrees of freedom (df), which allows for the detection of complex non-linear responses without the high risk of overfitting (Hastie and Tibshirani, 1990). Candidate models were ranked according to

Akaike's Information Criterion (AIC). We considered all models with ΔAIC values (the difference in AIC units from the highest-ranking model) ≤ 3 as possible models. To assess the relative variable importance in the model we computed cumulative AIC weights ($0 \leq \sum w_i \leq 1$) (Anderson and Burnham, 2002). The Akaike weight is an estimate of the probability of model i being the best model and model set. If a predictor appears in all of the top models, then its summed Akaike weight will tend towards 1, whereas if it is not included in many models its weight will tend towards 0. Models were also evaluated using explained deviance. Top models were checked for non-informative variables whose inclusion results in a slightly lower AIC, but do not improve the log-likelihood or the explained deviance. This approach allowed us to evaluate a wide range of possible models and ensure that each variable is informative and justified to avoid overfitting (Hosmer and Lemeshow, 2000; Petscho *et al.* 2014).

Model Performance Assessment

Two methods were used to assess model performance: area under the receiver operating curve (ROC) and a confusion matrix. The area under the ROC curve (AUC) measures the ability of the model to discriminate between two classes that are independent of a specific decision threshold on the model output, while a confusion matrix uses a pre-assigned probability threshold to assess various metrics.

AUC is a common unbiased metric of model performance for binary data (Guisan and Zimmermann, 2000; Wenger and Olden, 2012). The ROC curve graphically represents the trade-off between the sensitivity (Eq. 2) and the specificity (Eq. 3) for every possible cut-off value, and is independent of the spatial density of permafrost slope disturbance (Fawcett, 2006; Goetz *et al.*, 2011).

$$\text{Sensitivity (True Positive Rate, TPR)} = \frac{\text{Correctly classified positives}}{\text{Total positives}}$$

(Eq. 2)

$$\text{Specificity (1 – False Positive Rate, FPR)} = \frac{\text{True negatives}}{\text{False positives} + \text{True negatives}}$$

(Eq. 3)

AUC ranges from 0 to 1, where an AUC of 0.5 or less indicates random discrimination between classes and an AUC of 1 represents a model with perfect prediction (Brenning, 2005). The predictive accuracy of the model can be classified according to AUC as follows: 0.9-1, excellent; 0.8-0.9, very good; 0.7-0.8, good; 0.6-0.7, average; and 0.5-0.6, poor (Yesilnacar and Topal, 2005).

A confusion matrix was used to examine the agreement between predictions and observations. For a disturbance to be predicted as present or absent, the predicted probability will be higher or lower than a user-assigned probability threshold. For this study, a threshold was selected to maximize the sensitivity to specificity ratio. The confusion matrix represents the percentage of four possible outcomes: the correctly predicted slope disturbances (True Positive, TP); the correctly identified undisturbed samples (True Negative, TN); the falsely predicted slope disturbances (False Positives, FP); and the falsely predicted undisturbed samples (False Negatives, FN).

To assess the relative importance of each predictor variable in the selected model, seven models were produced, each missing one of the variables. A decrease in explained deviance suggests that the missing variable is an important contributor to explaining the variability in the full model. To assess the discriminatory power of individual variables, single variable models were produced and AUC and explained deviance were used to measure the accuracy of each single variable susceptibility model.

Statistical modeling and analysis was completed using R (version 3.0.0; R Development Core Team, 2013), with the packages ‘gam’ (Hastie, 2013), ‘MuMIn’ (Barton,

2013), ‘PresenceAbsence’ (Freeman, 2012), ‘raster’ (Hijmans *et al.*, 2015), and ‘rgdal’ (Bivand *et al.*, 2014)

Permafrost Disturbance Susceptibility Map

The GAM model was interpolated (and extrapolated) to the landscape, producing a probability map, which was classified into an ALD susceptibility map. The dominant method adopted in the literature for susceptibility mapping is to divide the probability distribution into different categories based on expert opinion (Dai and Lee, 2002; Ohlmacher and Davis, 2003). This subjective method is neither statistically tested nor fully automated. For this study we classified our map into susceptibility zones, using the 50, 75, 90, and 95 percentiles, representing “Very Low”, < 50 ; “Low”, $50 - 75$; “Moderate”, $75-90$; “High”, $90-95$; and “Very High”, >95 susceptibility to future disturbance (Chung and Fabbri, 2008; Goetz *et al.*, 2011). The permafrost susceptibility map was verified using the validation dataset and a user-specified threshold.

RESULTS

Model Fit and Predictive Performance

Two models had a $\Delta AIC < 3$ and were examined before selecting the best model (Table S1). Slope, PISR, elevation, wetness index, TPI and geology were included in the best two models, resulting in cumulative AIC weights of 1. Distance to water was not included in the second model and although there is only a slight decrease in AIC ($\Delta AIC = 2.07$), its explained deviance and log-likelihood decreases, indicating that it is not a non-informative variable and its presence leads to an improved model fit (Table S1). Ultimately, all of the variables were included as predictor variables to model ALD susceptibility.

The predictive performance of the model is very good, achieving an AUC of 0.89 and a sensitivity and specificity of 80 and 83%, respectively. These predictive metrics indicate that the GAM consistently identifies both disturbed and undisturbed points.

Importance of Predictor Variables

Spearman's rank correlation coefficient (ρ_{Sp}) and variance inflation factors (VIF) were used to examine correlations between predictor variables. Slope and wetness index had the strongest correlation ($\rho_{Sp} = -0.55$), and all other variables had weaker correlations ($|\rho_{Sp}| < 0.53$) (Table S2). All variables in this model had VIFs lower than 3, indicating that they are not inter-dependent and are acceptable for use in the model (Table S3) (Neter *et al.*, 1996). Some correlation among predictor variables is expected in real situations (Chung and Fabbri, 2008).

In terms of relative importance of each predictor variable in the model, the model lacking PISR (full model minus PISR) had the greatest decrease in explained deviance (32.9 % compared to 39.3 %, full model), followed by slope (34.5 % compared to 39.3 %, full model). The remaining variables all resulted in lower explained deviances but to a lesser degree (explained deviances > 37 %).

To assess the discriminatory power of individual variables outside of the full model, we used explained deviance and AUC of single variable models. PISR, as a single variable model, had the greatest explained deviance (29 %), followed by slope (15 %) (Table 1). The strongest predictors were PISR and slope ($AUC > 75$ %), followed by elevation and distance to water ($AUC > 60$ %). Although TWI and TPI were weakly related to disturbance occurrence ($AUC < 60$ %), their interactions with other variables led to an increase in the performance of the full model. In the single variable models, differences in values between

undisturbed and disturbed points were checked for significance using a Wilcoxon rank sum test (for continuous variables) and a Chi Square (X^2) test (for discrete geology classes). All continuous variables, except for TPI, are statistically significant at the 0.001 % level.

Table 1: Single variable model exploratory analysis. Variables are ranked by importance according to their explained deviance and AUC. Points refer to locations of estimated ALD initiation points for mapped ALDs and randomized undisturbed locations used for statistical comparison.

Predictor variable	Randomized undisturbed points: Mean	Mapped disturbed points: Mean	Explained Deviance (%)	AUC (%)
Potential Incoming Solar Radiation (MJ/m ²)*	1267.3	1242.9	29.1	84
Slope (°)*	3.0	5.5	14.8	75
Elevation (m)*	52.4	36.3	7.6	67
Distance to water (m)*	123.6	97.1	2.7	61
Topographic Wetness Index*	0.2	6.1	1.5	58
Topographic Position Index	0.2	0.1	1.4	58
Geology	Randomized undisturbed points (%)	Mapped disturbed points (%)		
1 (Shale)	71.5	90.8	4.5	60
0 (Sandstone)	28.5	9.2	4.5	60

* = stat. significant var at the 0.001 % level

Permafrost disturbance susceptibility map

The spatial predictions of the GAM (Figure 4) indicate that hillslopes with gentle to steep gradients and relatively low values of PISR are more susceptible to ALDs. These areas of high susceptibility are located adjacent to river channels and on moderate to steep upland slopes. Areas of low susceptibility are found on uplands and plateaus, far from surface water and receive greater PISR. This same relation is observed in the bivariate plots of the predictor

variable and ALD occurrence (Figure 3). Disturbances were 10 times more likely to occur in the shale bedrock units than in the sandstone unit (Table 1). Although high susceptibility zones account for a small portion of the landscape, the density of ALDs in these areas is much greater, with 32 ALDs per km² compared to a density of 1 ALD per km² in very low susceptibility zones (Table 2).

Figure 4 Susceptibility map produced from GAM model and inset illustrating an example of the locations of disturbance (polygons) and their initiation points (circles), as well as undisturbed points (triangles) used in the model development and verification. Percentiles used to distinguish between susceptibility classes are represented by <50th, >50th, >75th, >90th and >95th (see text).

Table 2: Susceptibility zones and disturbance density extracted from the susceptibility map. Disturbance density represents the number of disturbances per unit area.

Susceptibility Zone (probability range)	Area (km ²)	Disturbance Density (# / km ²)
Very low (0 – 0.51)	186	1
Low (0.51 – 0.84)	37	5
Moderate (0.84 – 0.98)	13	11
High (0.98 – 0.99)	2	22
Very high (0.99 – 1)	2	32

Verification of Permafrost Disturbance Susceptibility Map

To verify the susceptibility map, we extracted the predicted probabilities for the points in the independent validation dataset. A probability threshold of 0.50 was selected to maximize the sensitivity and specificity, and used to distinguish between predicted disturbed and undisturbed points, where probability values > 0.50 indicate slope disturbance and values < 0.50 indicate undisturbed points. The model verified well, with a sensitivity and specificity of 72 and 73 % respectively (Table 3). Additionally, the model was verified without a user-defined threshold, resulting in an AUC of 0.81, indicating very good discrimination between disturbed and undisturbed points (Table 3).

Table 3: Predictive metrics of the GAM calibration and validation data.

Model	Number of Samples	Sensitivity (%)	Specificity (%)	AUC
Calibration	1064	81	83	0.89
Validation	456	77	72	0.81

DISCUSSION

Predictive Map Interpretation

The permafrost disturbance susceptibility map produced in this site-specific study accurately characterized the susceptibility of the landscape to ALDs using terrain variables that can be derived from remote sensing data. The GAM model was effective at predicting

disturbed and undisturbed sites resulting in an AUC of 0.89, which is considered very good for this type of model and comparable to a number of other landslide susceptibility studies using the same methods (Guzzetti *et al.*, 2006, Goetz *et al.*, 2011). The model results provide a quantitative assessment of the relationship between the distribution of past permafrost disturbances and a set of physically informed terrain variables that may contribute to slope instability. ALDs commonly occurred on slopes ranging from 3 to 10° that were below marine limit and in areas with low values of PISR.

Overall the model performed well, except for a few disturbances classified as undisturbed (false negatives, ~10%). PISR was found to be a dominant variable in the model and may play a key role in disturbance prediction, which is demonstrated by the increased numbers of ALDs in areas with low values of PISR. At landscape scales, slope angle and aspect are the main determinants of PISR. To examine the influence of PISR on disturbance classification in more detail, we plotted disturbances identified correctly and incorrectly as a function of slope angle and aspect (Figure 5). In general, across the landscape there is a higher frequency of cells with low slope angles of all aspects and a slightly greater frequency of cells with higher slope angles on north- and northwest-facing slopes (azimuth: 292.5 – 22.5°); 92% of the high susceptibility zone is represented by north-facing slopes (Figure 5). This indicates that disturbances located in very high susceptibility zones are found primarily on steeper slopes and on north- and northwest-facing slopes (Figure 6). This is also the trend for both high and moderate susceptibility zones. Disturbances in low and very low susceptibility zones are primarily found on slopes ranging from 0 to 5°, with no discrimination between aspect classes.

Figure 5 True positives and false negatives are plotted with respect to slope and aspect as circles and triangles respectively. Disturbance colours denote the susceptibility zone into which each disturbance was classified. Isolines represent PISR in MJ/m^2 and the raster surface indicates pixel frequency of the landscape with respect to aspect and slope. North = 0 and 360° .

Figure 6 Percentage of susceptibility zones represented by aspect classes in the study area.

GAM model variable selection

During the variable selection process PISR emerged as a primary variable. The modeled predictions of the PISR and full GAM model were evaluated using AUC and had values of 0.84 and 0.89, respectively. This suggests that the prediction of disturbances with the full GAM model can be achieved with slightly higher certainty than with the PISR model. While the two models yielded similar patterns of disturbance susceptibilities there are some discrepancies that can be explained using slope angle, aspect and PISR (Figure 7).

The full GAM model accurately identified 411 of the 532 disturbance points, whereas the PISR model only identified 371 accurately. Of the disturbances predicted incorrectly by the PISR model, 53% occur on south-facing slopes (135-270°), and 34 and 13 % on east-

facing (45-135°) and northwest-facing (315-337.5°) slopes, respectively (Figure 7). In the full GAM model, interactions between the terrain variables account for an increase in explained deviance and predictive power, leading to a more accurate ALD susceptibility map, while the PISR model is unable to accurately identify disturbances on all aspects, specifically south-facing slopes. While few studies have included PISR as a variable, those that did found it to be important for landslide initiation (Mossa *et al.*, 2005; Regmi *et al.*, 2013). Significantly, this is a site-specific model and the relative importance of terrain variables may vary in different landscapes. It is likely that a changing combination of terrain variables drives ALD initiation. The terrain at this location (predominantly west-east drainage pattern) may have inflated the importance of PISR and may not be representative elsewhere. Although no other permafrost disturbance susceptibility models have applied similar variables (and methods) as described in this study, our prediction accuracies are similar to those from landslide susceptibility models of other regions (Goetz *et al.*, 2011; Xiao *et al.*, 2013; Petschko *et al.*, 2014; Heckmann *et al.*, 2014).

Figure 7 True positives (TP) and false negatives (FN) are plotted in the context of slope and aspect. TP and FN correctly identified by both models are represented in black and white while TP associated with only one model are shown in teal and orange. Contour lines represent PISR in MJ/m² and the raster surface is a frequency plot of the landscape on a pixel-by-pixel scale with respect to aspect and slope. North = 0 and 360 °.

Geomorphic implications

In addition to predicting disturbance-prone areas, the model can be used to determine the effect of terrain variables on the spatial pattern of slope disturbance. The relation between the spatial distribution of ALDs and terrain variables that emerges from the model for this location also provides insights into geomorphic and climatic controls over slope disturbance. We found that PISR, slope and elevation were key predictor variables in the susceptibility model.

In the model we see an increasing frequency of ALDs as PISR decreases. Areas of reduced PISR are found on north-facing steeper slopes and river channel banks. In continuous permafrost zones, changes in radiation balance can impact snowmelt and radiation regimes (Woo, 2012). Uneven melt patterns resulting, in part, from differential melting and uneven snow accumulation due to drifting, can result in a higher water table, leading to wetter near-surface conditions on north-facing slopes (Benson *et al.*, 1975, Flugel, 1983). North-facing slopes have also been found to accumulate transient layer ice during extended cold periods, resulting in shallower active layer development and increased ice content (Shur *et al.*, 2005; Leibman *et al.*, 2014). The combination of these processes provides a basis for explaining why north-facing slopes appear to be more susceptible to slope disturbance than south-facing slopes, particularly in relation to seasonal thaw depth and active-layer ice content. These differences are highlighted in very high and high susceptibility zones, where 56 % of ALDs are found on north-facing slopes, while only 21 % of ALDs are found on south-facing slopes. Disturbances on northern slopes have also been observed in the southern Yukon Territory (Huscroft *et al.*, 2004); Yamal Peninsula, Russia (Leibman, 1995); and the Qinghai-Tibet Plateau, China (Niu *et al.*, 2014). While this relation is not consistently found in ALD studies (Lewkowicz and Harris, 2005), we identify a possible link between PISR and slope disturbance occurrence that warrants further examination through process-based research.

Only 10 % of the accurately identified ALDs on the Sabine Peninsula occurred on slopes $> 10^\circ$, and half of these ALDs were found in very high susceptibility zones. The majority of ALDs occurred on moderate slope angles (3 to 10°), a relation observed in numerous studies of permafrost slope disturbance (Leibman, 1995, Niu *et al.*, 2014; Lacelle *et al.*, 2015). The majority of thaw-induced slope failures (88%) along the Qinghai-Tibet Corridor in China occurred on slopes with gradients between 6 and 10° (Niu *et al.*, 2014). Similarly, disturbances on the Peel Plateau, in Canada, were two to three times more likely to

occur on slopes between 8 and 12 ° than on steeper or gentler slopes (Lacelle *et al.*, 2015). Steeper slopes tend to be shorter in length and more prone to erosion, whereas longer and gentler slopes can lead to larger more intensive disturbances due to the longer run-out distance and the reduced drainage, thereby increasing pore-water pressures (McRoberts and Morgenstern, 1974; Leibman *et al.*, 2014). Additionally, steeper slopes typically have thinner soil layers, reducing their susceptibility to ALD initiation (Vorpahl *et al.*, 2012).

Ice content can be controlled by surficial geology, particularly as fine-grained material has greater pore space than coarse-grained material and results in potentially increased ice content (Andersland and Ladanyi, 2004). Thawing of ice-rich fine-grained sediment causes thaw consolidation, increased pore-water pressures and reduced shear stresses, resulting in an overall decrease in soil shear strength and possible slope failure (Morgenstern and Nixon, 1971; Harris *et al.*, 2009). Due to limited mapping of surficial geology in this area elevation was used to delimit marine limit as a proxy for low elevation fine-grained sediments (Barnett *et al.*, 1977). The presence of marine clay is an important control over disturbance occurrence, with 91 % of disturbances occurring below marine limit (~ 60-70 m asl) (Nixon *et al.*, 2014).

This model is limited inasmuch as it is not possible to include dynamic data as predictor variables (i.e. temperature, precipitation), or to design scenarios of future permafrost slope disturbance susceptibility incorporating climate change. Furthermore, while the model predictor variables do not directly reflect mechanistic controls on ALDs, the selected variables act as proxies for the process or conditions they represent through their nonlinear relationships. This approach implies that the predisposing factors of disturbance or terrain characteristics do not change with time, providing an important understanding of processes controlling permafrost slope disturbance.

CONCLUSIONS

The ALD susceptibility model and map we developed are a first-order assessment of the susceptibility of the terrain to potential slope disturbance. The model accurately identified areas with varying degrees of susceptibility to permafrost slope disturbance using derived terrain attributes that may be applied to larger areas with limited field data. While only static terrain attributes were analysed, they were relevant for ALD initiation. PISR showed a particularly strong relationship with the occurrence of ALDs, as did slope angle and elevation. ALD susceptibility is highest on moderate slopes (3-10°) below marine limit and in areas with low values of PISR. In our study area, these terrain attributes commonly occur on north-facing slopes and can be associated with shallow thaw and increased ground-ice contents.

This modelling approach is promising for land-management and decision making in remote permafrost areas where detailed information on the location of slope disturbance is often unavailable. Without temporal data, the frequency of slope disturbances cannot be measured. However, we assume that the disturbances in this inventory likely record decades of change in the climate system, and their relative frequency and magnitude indicate past and present climate fluctuations. By using static variables in this model, we suggest that permafrost slope disturbance susceptibility maps indicate that terrain and fixed climate controls (e.g., solar radiation) can provide a long-term assessment of the disturbance potential of an area and facilitate further process-based research.

ACKNOWLEDGEMENTS

Funding was provided by ArcticNet NCE, NSERC Strategic, NSERC Frontiers ADAPT and the Northern Scientific Training Program (NSTP). Polar Continental Shelf Programme (PCSP), Natural Resources Canada, provided exceptional logistical support.

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SUPPORTING INFORMATION:

Table S1 Top three candidate GAM models. Models with $\Delta AIC \leq 3$ were considered in model selection. Relative variable importance in the model is portrayed through the cumulative AIC weights ($0 \leq \sum w_i \leq 1$). For complete description, see text.

	Candidate Models	df	logLik	AIC	ΔAIC	w_i
1	geol + s(elev) + s(pisr) + s(sl) + s(wi) + s(tpi) + s(mwat)	20	-432.883	906.2	0.00	0.738
2	geol + s(elev) + s(pisr) + s(sl) + s(wi) + s(tpi)	18	-435.668	908.3	2.07	0.262
3	geol + s(elev) + s(pisr) + s(sl) + s(wi)	14	-446.703	921.9	15.69	0.000

Table S2 Correlation of predictor variables represented by Spearman rank correlation coefficients.

	wi	tpi	sl	pisr	mwat	geol	elev
wi	1						
tpi	-0.38	1					
sl	-0.55	0.07	1				
pisr	0.28	0.07	-0.53	1			
mwat	0.05	0.2	-0.10	0.26	1		
geol	-0.12	0.04	0.1	-0.22	-0.06	1	
elev	-0.03	0.07	0.11	0.46	0.27	-0.24	1

Table S3 Calculated variance inflation factors used to assess the multicollinearity of the predictor variables.

Predictor Variable	Variance Inflation Factor (VIF)
sl	2.9
pisr	2.7
wi	1.7
elev	1.6
tpi	1.2
mwat	1.1
geol	1.1