Canadian Journal of Remote Sensing
Journal canadien de télédétection

ISSN: 0703-8992 (Print) 1712-7971 (Online) Journal homepage: www.tandfonline.com/journals/ujrs20

Modeling Watershed-Scale Historic Change in the Alpine Treeline Ecotone Using Random Forest

David R. McCaffrey & Chris Hopkinson

To cite this article: David R. McCaffrey & Chris Hopkinson (2020) Modeling Watershed-Scale Historic Change in the Alpine Treeline Ecotone Using Random Forest, Canadian Journal of Remote Sensing, 46:6, 715-732, DOI: 10.1080/07038992.2020.1865792

To link to this article: https://doi.org/10.1080/07038992.2020.1865792

Published online: 06 Jan 2021.

CANADIAN JOURNAL OF REMOTE SENSING
2020, VOL. 46, NO. 6, 715–732
https://doi.org/10.1080/07038992.2020.1865792

Modeling Watershed-Scale Historic Change in the Alpine Treeline Ecotone Using Random Forest

Modélisation des changements historiques à l'échelle du bassin versant dans l'écotone alpin de la limite forestière à l'aide du modèle Forêt aléatoire

David R. McCaffrey and Chris Hopkinson

Department of Geography, Alberta Water & Environmental Science Building, University of Lethbridge, 4401 University Drive, Lethbridge, Alberta, T1K 3M4, Canada

ABSTRACT

Historic changes in Alpine Treeline Ecotone were modeled using 21 topographic, climatic, geologic, and disturbance variables in a random forest model. Airborne LiDAR and oblique historic repeat photography were used to identify changes in canopy cover in the West Castle Watershed (WCW), Alberta, Canada (49.3° N, 114.4° W). A Random Forest model was trained on ~30% of the watershed which was observable in oblique imagery, then used for a spatial extension to predict change classes in the unobserved regions of the watershed. Overall accuracy of the model was 77.3% and kappa showed moderate agreement at 0.56. The relative strength of each prediction variable was compared using permutation importance. Fire exposure, annual temperature, and annual solar radiation were the highest-ranking variables; canopy cover decreases on warm, fire-exposed aspects at high elevations, and increases on cool, non-fire-exposed aspects.

RÉSUMÉ

Les changements historiques dans l'écotone alpin de la limite forestière ont été modélisés à l'aide de 21 variables topographiques, climatiques, géologiques et de perturbation et du modèle Forêt aléatoire (*Random Forest*). Des données LiDAR et des photographies obliques aériennes historiques ont été utilisées pour identifier les changements dans la couverture de la canopée du bassin versant West Castle (WCW), Alberta, Canada (49,3° N, 114,4°W). Le modèle a été entraîné sur environ 30% du bassin hydrographique qui était observable dans l'imagerie oblique, puis utilisé pour une extension spatiale afin de prédire les classes de changement dans les régions non observées du bassin versant. La précision globale du modèle était de 77,3% et le kappa a montré un accord modéré à 0,56. La force relative de chaque variable de prédiction a été comparée en utilisant l'importance de la permutation. L'exposition aux incendies, la température annuelle et le rayonnement solaire annuel sont les variables les plus significatives; la couverture de la canopée diminue sur les versants chauds et exposés au feu en haute altitude, et augmente sur les versants frais et non exposés au feu.

ARTICLE HISTORY
Received 1 December 2019
Accepted 15 December 2020

Introduction

The alpine treeline ecotone (ATE) is a transition zone, below alpine tundra and above closed canopy forest, where tree height and density gradually decrease as elevation increases (Körner and Paulsen 2004). Heterogenous tree cover in the ATE is generally attributed to patterns of climate, topography, and response to disturbance (Butler et al. 2007; Holtmeier and Broll 2005; Weiss et al. 2015), but the absolute limit to tree growth at the upper boundary of ATE is thermal (Körner 1998). Increases in atmospheric temperature are expected over the 21st-century, and the effects of warming on mountain ecosystems may be amplified by elevation-dependent processes (Pepin et al. 2015). The potential for atmospheric warming to increase the elevation of ATE globally has been a matter of debate (Grace et al. 2002; Harsch et al. 2009). Some models predict a linear increase in the elevation of

CONTACT David R. McCaffrey david.mccaffrey@alumni.uleth.ca

ATE, correlating to increases in atmospheric temperature (Schwörer et al. 2014). Other models suggest that ATE elevation will remain static (Paulsen and Körner 2014), or that advance may be limited by geomorphic barriers (Macias-Fauria and Johnson 2013). To predict what effect future atmospheric warming may have on ATE position, improved methods of observing historic change are required, in order to model the environmental drivers of change.

Several observation methods are used to assess historic change in the ATE, such as dendrochronology (Bekker 2005; Elliott and Cowell 2015; Mamet and Kershaw 2012; Sakulich 2015), palynology (Tinner and Theurillat 2003), and remote sensing (Coops et al. 2013), but each of these has limits on spatial and temporal resolution (Danby 2011). Remote sensing has a distinct spatial advantage in monitoring ATE change, which is important given the increasing awareness of the multi-scale nature of factors affecting change in the ATE (Case and Duncan 2014; Weiss et al. 2015). High spatial resolution data, such as LiDAR, can provide information on microsite processes and canopy composition (Bolton et al. 2013; Coops et al. 2013), while optical satellite platforms, such as Landsat TM, offer insights at landscape and continental scales (Allen and Walsh 1996; Walsh et al. 1994; Weiss et al. 2015).

However, the spatial benefits of remote sensing are often offset by temporal limitations. Landsat data only extends to the 1970s, and orthorectified aerial imagery catalogs in Canada generally begin in the 1940s. This observation window is not adequate to directly observe patterns of change in the ATE, particularly when post-disturbance regrowth in the ATE may lag decades or centuries (Aplet et al. 1988; Romme and Knight 1981).

Several studies have extended the observation period of ATE change to a century or more using repeat photography (Butler and DeChano 2001; Kullman and Öberg 2009; Moiseev and Shiyatov 2003). A limitation of repeat photography is that oblique imagery is difficult to analyze quantitatively, as spatial scale varies with perspective in the image (Roush et al. 2007); pixels in the foreground cover a smaller area than pixels in the background, and oblique photographs cannot be orthorectified. However, this issue has been resolved using a fishnet monoplotting technique (McCaffrey and Hopkinson 2017; Stockdale et al. 2015), and software courtesy of the WSL (Bozzini et al. 2012) (Note: WSL is the German acronym for "Eidgenössische Forschungsanstalt für Wald, Schnee und Landschaft," the Swiss Federal Institute for Forest, Snow and Landscape Research). Using the WSL software, common tie points are identified between oblique imagery and high-resolution orthogonal imagery. The camera calibration is solved using a collinearity equation, and topography from a high-resolution (<2 m) DEM. This allows orthogonal grids, with a set spatial resolution, to be projected onto oblique views. The grids are "draped" over topography, providing a standardized spatial scale for land cover analysis in oblique imagery.

Recent studies of historic change in the ATE have made use of the Mountain Legacy Project (MLP – https://mountainlegacy.ca) (Trant et al. 2015), a collection of over 120,000 historic photographs of the Canadian Rockies, with over 8,000 repeat photograph pairs now available. Many of the repeat photographs were collected over a century after the historic photographs, providing an observation window sufficient to monitor ATE change.

Two of these studies examine land cover changes in the Canadian Rockies over the 20th century with MLP photography and the WSL monoplotting tool (McCaffrey and Hopkinson 2020; Stockdale et al. 2019). McCaffrey and Hopkinson (2020) use seven MLP photo pairs in a single watershed in Southern Alberta, Canada, classifying canopy cover over a 92-year period (1914–2006), and identifying a pattern of reduced canopy cover on south-facing aspects that experienced fire between observations. This mortality is in contrast to increased canopy cover on north-facing aspects in areas of the watershed that did not experience fire between observations. Stockdale et al. (2019) note changes in subalpine forests as part of a larger, regional study on vegetative succession over the 20th century. A set of 137 MLP photo pairs are used to observe a study area $>3{,}100\,\text{km}^2$, gridded at 100 m. While the study examines several natural subregions other than ATE, it does note that in high elevation subalpine forest there is a trend toward conversion of alpine meadows to closed canopy forest, which is more prominent on north-facing slopes receiving less solar radiation. The model also suggests that, across study regions, forward succession is related to elevation and time since last fire.

Trant et al. (2020) investigates ATE change across the Canadian Rockies, using a collection of 81 MLP photo pairs along a 5 degree latitudinal transect. Rather than employing the WSL monoplotting tool, their research uses the custom MLP Image Analysis Toolkit (Sanseverino et al. 2016) to estimate stand density and ATE advance on specific slopes. Trant et al. (2020) demonstrate that regionally, treeline advance is driven by latitude and elevation, with more northern latitudes and higher elevations experiencing greater advance. The model also provides some evidence of aspect control on ATE advance. However, in Trant et al. (2020) warm aspects (W, SW, S, SE) predicted treeline advance, unlike McCaffrey and Hopkinson (2020) and Stockdale et al. (2019).

The MLP provides an extremely useful resource to study mountain land cover change, yet occluded areas in the oblique imagery remain an obstacle. For example, McCaffrey and Hopkinson (2020) observed 37.7% of a study watershed. Stockdale et al. (2019) iteratively optimized observation coverage from multiple vantage points, and observed 59.5% of the subalpine region of their study area. Trant et al. (2020) notes that, even given the large MLP catalog, there were few images that met their image selection criteria. Discontinuous spatial sampling data in headwater regions undergoing disturbance-related or gradual changes in land cover can be problematic for analyses requiring continuous coverage or cumulative impacts at the watershed-scale. For example, long-term water resource assessments must decouple the relative historical impacts of vegetation cover and climatic changes on runoff if future shifts in water availability are to be quantified (e.g. Springer et al. 2015). Given the spatial sampling occlusions inherent within MLP imagery, we suggest a method of modeling canopy cover change in unobserved areas, based on data collected in observed areas.

Objectives

Our research focused on two main objectives. Our first objective was to test a spatial extension of an ATE canopy change model using random forest. A suite of topographic, climatic, geologic, and disturbance variables were developed to train a model based on regions of our study area that were observed in MLP repeat photographs. Model accuracy was tested using a reserved subset of observed features. Using that model, we predicted ATE canopy change classes for regions of our study area that were unobserved in the MLP photographs, and validated these predictions with LiDAR -derived estimates of canopy fractional cover.

Our second objective was to determine ranked variable importance of topographic, climatic, geologic, and disturbance variables using a permutation importance test, and infer the role of these variables in ATE change at our study site. Random forest provides strong predictive capability, while also demonstrating the ability to rank the importance of classification variables in ecologically relevant ways (Cutler et al. 2007). Ranked variable importance has been used to study the environmental drivers of ATE in several studies, including the *Nothofagus* treeline in New Zealand (Case and Buckley 2015), and in Canadian Rockies (Macias-Fauria and Johnson 2013). Given the apparent discrepancy between the role of aspect in models of ATE change, we elected to use ranked variable importance in our model to attempt to understand interactions between elevation, aspect, and fire disturbance, and their respective influence on ATE change.

Methods

Study area

Located in the Southern Canadian Rockies of Alberta, the West Castle Watershed (WCW) is ∼103 km^2 in area, with elevation ranging from ∼1400–2600 m a.s.l. (Figure 1a). Lower elevations in the watershed are covered by closed canopy forest, dominated by lodgepole pine (*Pinus contorta)*. At higher elevation, in the ATE, the forest becomes less dense and the species mix transitions to dominance of subalpine fir (*Abies lasiocarpa*) and Engelmann spruce (*Picea engelmanii*), with small stands of subalpine larch (*Larix lyallii*) and lodgepole pine (*Pinus contorta*). The exact position of ATE varies, but generally it is found between 1700 and 2200 m a.s.l. (Figure 1b), with rocky alpine areas occurring above ATE. The western boundary of the WCW is also the continental divide, making it an important headwater region for southern Alberta. Moreover, snowpack melt from the mountains of the southern Canadian Rockies represents the dominant contribution to regional annual runoff (Byrne et al. 2006) and it is known that peak snowpack accumulation in this region coincides with the ATE (Hopkinson et al. 2012). Consequently, understanding long term variations in ATE has regional significance for water supply forecasts in the arid Prairie regions downstream.

The WCW has a history of logging in the 20th Century, but harvested areas were exclusively below ATE elevation. A small ski resort and village are located in the NW region of the WCW, comprising less the 2.9% of the area of the watershed. Both the harvested area and the ski resort were omitted from all analysis.

Repeat photography

We used a land cover change dataset that was generated with fractional cover estimates from repeat oblique photography (McCaffrey and Hopkinson 2017). The high-resolution images, provided by MLP, contain pairs of photographs from a 1914 survey of

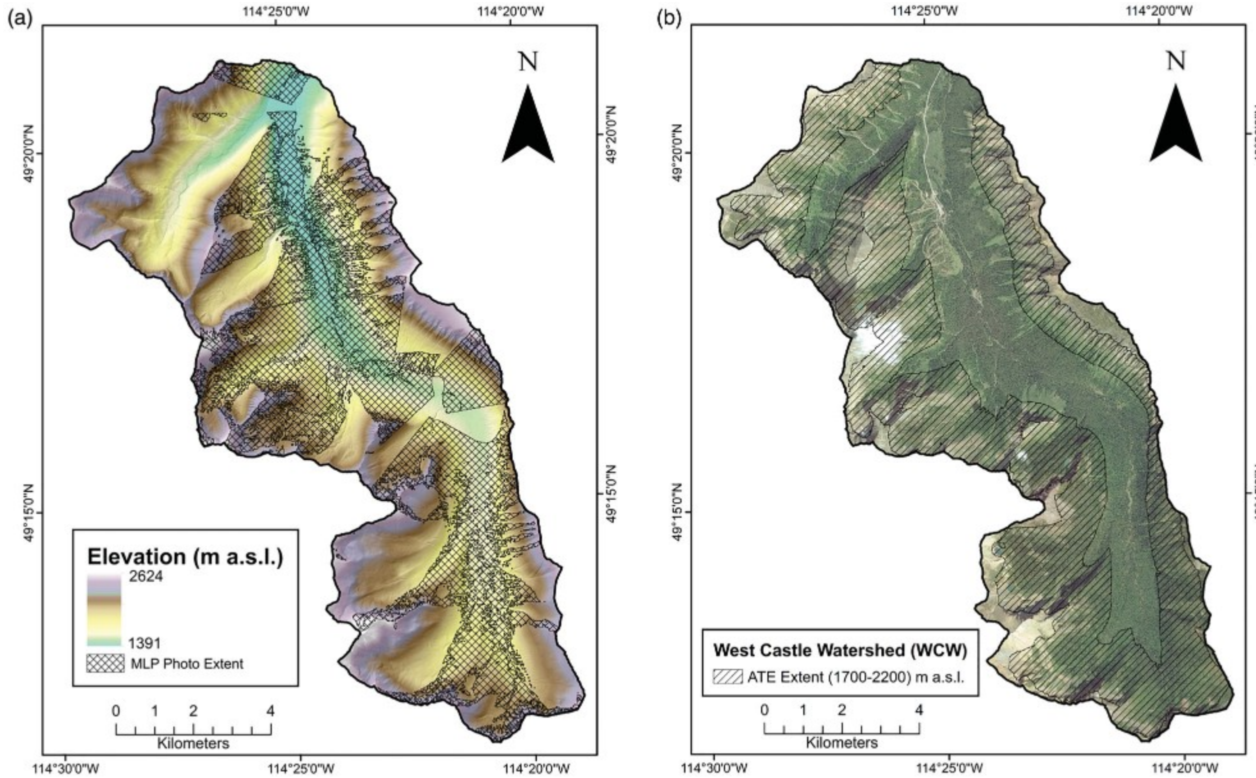

Figure 1. Observation extents in the West Castle Watershed (WCW); (a) elevation gradient in the WCW, with crosshatched shading showing areas that were visible in Mountain Legacy Project (MLP) imagery, (b) SPOT 6 RGB image of the WCW, 150 cm resolution, captured 31 July 2014, copyright 2014 CNES – shaded areas show the Alpine Treeline Ecotone (ATE) region of the watershed, 1700–2200 m a.s.l.

the Canadian Rockies by surveyor Morrison Parsons Bridgeland, and repeat photographs from 2006 (Trant et al. 2015). We explored the MLP catalog and selected 7 photo pairs with unobstructed views of the ATE in the WCW.

Once transformed in the monoplotting software, grid cells were manually classified into 4 ordinal classes of canopy cover (Figure 2). The 4 canopy cover classes were: (i) *no cover* – grid cells devoid of vegetation; (ii) *low vegetation* – grid cells appear vegetated, but context and texture suggest shrubs or krummholz, upright trees <2 m; (iii) *partial canopy* – upright trees >2 m are present, but ground is visible in >50% of the grid cell; (iv) *full canopy* – upright tress >2 m trees cover >50% of a grid cell. To assess historic change, we compared canopy cover class from 1914 with 2006. If the class increased (e.g. 1914 = partial canopy, 2006 = full canopy), then historic change was classified as *vegetation increase*, reflecting both forward succession from shrubs to trees and increases in stand density over time. If the class decreased (e.g. 1914 = partial canopy, 2006 = low vegetation), then historic change was classified as v*egetation decrease*. Grid cells where the canopy cover class did not change between 1914 and 2006 were classified as *no change*.

A total of 89,440 grid cells at a 20 m resolution were classified, representing ~36% of the total WCW area. Of this, a subset of data between 1700 and 2200 m a.s.l. was selected, so that the model would be trained on environmental features in the current and historic ATE, omitting alpine areas and subalpine valley floor. The unobscured ATE training data included 43,738 cells, representing 30.4% of the total ATE area in the watershed (Figure 3).

LiDAR

An airborne LiDAR survey of WCW was flown on 18 October 2014 with a Leica ALS70 and a minimal point spacing of 3 pts/m^2 at nominal altitude (1,300 m above the mean ground surface elevation). Data were classified into ground and non-ground using Terrascan (Terrasolid, Finland) and a 1 m DEM was interpolated from the ground-classified points.

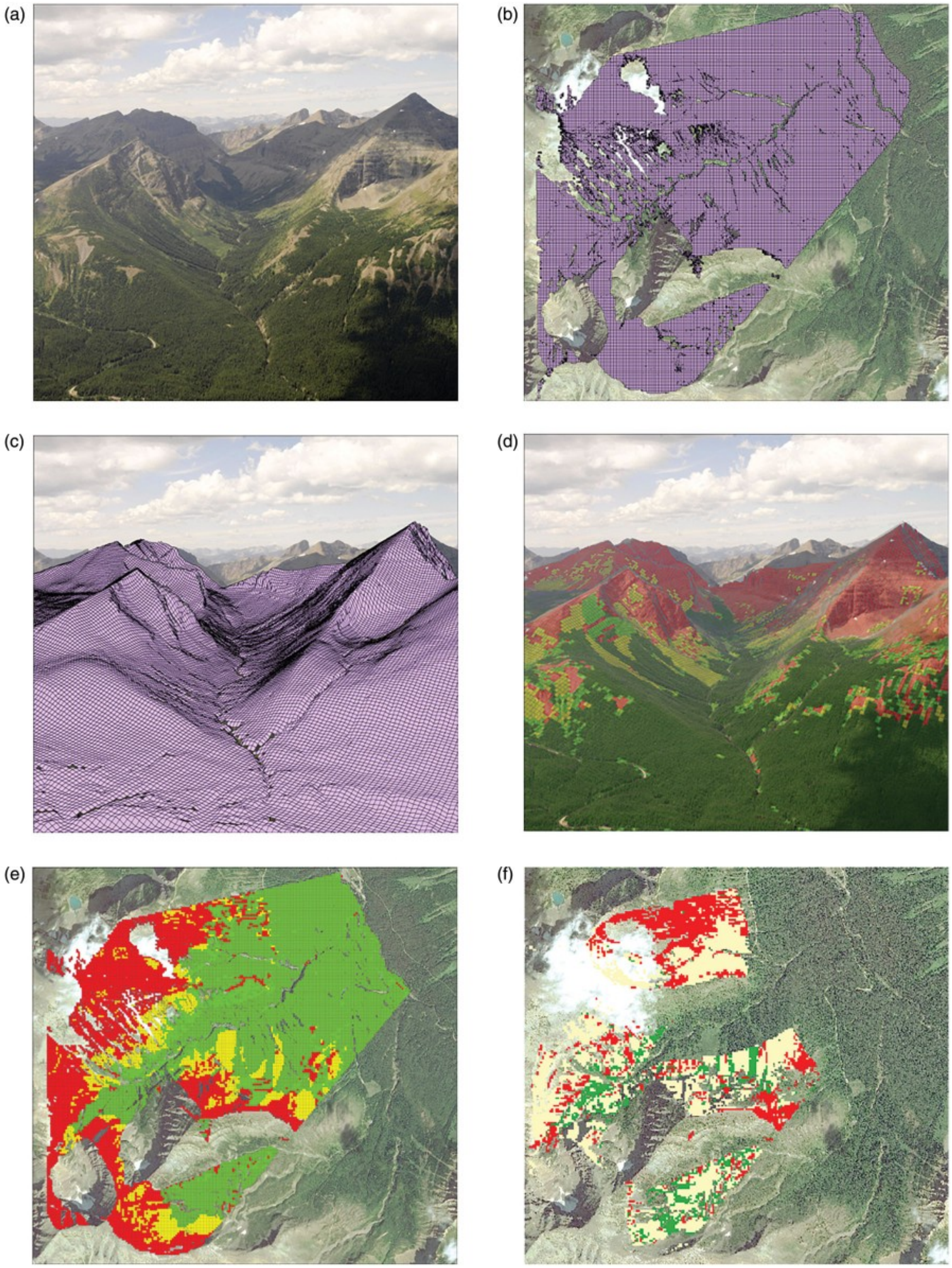

Figure 2. Image classification workflow, adapted from McCaffrey and Hopkinson (2017); (a) an oblique image of Mount Haig, in the West Castle Watershed (WCW); (b) a 20 m fishnet applied to the orthogonal Mount Haig view shed; (c) fish net grid projected back to oblique view using WSL monoplotting tool; (d) oblique image with ordinal canopy cover classification, red = *no cover*, yellow = *low vegetation*, light green = *partial canopy*, dark green = *full canopy*; (e) orthogonal image with canopy cover classification; (f) change class for Alpine Treeline Ecotone (ATE) elevation (1700–2200 m a.s.l.), red = *vegetation decrease*, beige = *no change*, green = *vegetation increase*. Background images in a, c, and d copyright Mountain Legacy Project 2016, and in b, e, f, copyright CNES 2014.

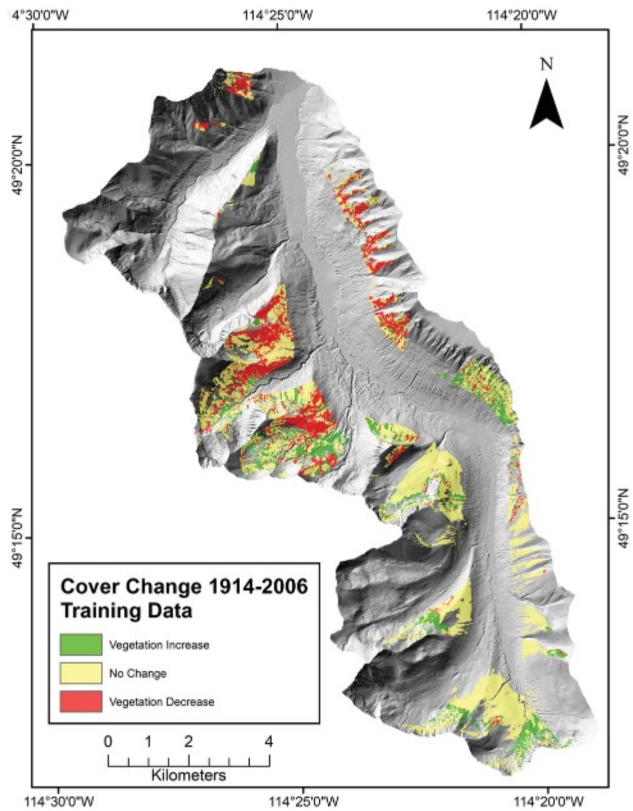

Figure 3. Canopy change classification for area observed in Mountain Legacy Project (MLP) imagery, at Alpine Treeline Ecotone (ATE) elevation. Areas of vegetation decrease, in red, occur predominantly on warm slopes, while areas of vegetation decrease, in green, occur on cool slopes.

Topographic variables

Five topographic variables were used to investigate potential correlations in ATE change: *elevation*, *slope*, *aspect*, *curvature*, and *compound topographic index* (CTI). All topographic variables were calculated using a 1 m DEM, aggregated to the 20 m resolution of the canopy cover change data using mean values. Topographic conditions in 2014 are an accurate representation of conditions in 2006, as there were no notable geomorphic disturbances (landslides, etc.) in the intervening period. For details on topographic variable construction, see Appendix A.

Climatic variables

Four climatic variables were used to model change: *annual precipitation*, *annual temperature*, *annual solar radiation*, and *summer potential evapotranspiration* (PET) (i.e. June, July, August—JJA). Given the geographic similarity in the research areas, this study largely followed the methods of Macias-Fauria and Johnson (2013) to develop precipitation, temperature, and PET model inputs.

In mountain environments, temperature and precipitation generally covary with elevation due to the influence of lapse rates. Spatial models of temperature and precipitation in the WCW were extrapolated from the DEM (for details on climatic variables construction, see Appendix B). Thus temperature, precipitation, and elevation variables were expected to be highly correlated, *a priori*. Our model of ATE change retains all three of these variables and uses an algorithm that determines variable importance, regardless of the degree of correlation among variables. Using this approach, we were able to examine which among temperature, precipitation, and elevation had the highest variable importance ranking in the ATE change model, while also determining how these elevation-driven processes ranked collectively, as a class, in relation to other environmental variables.

Surficial geology

It has been demonstrated that soil properties, bedrock type, and mountain architecture all have a significant effect on the position of ATE (Fagre et al. 2007; Macias-Fauria and Johnson 2013). We included surficial geology in the model to account for the potential impact on tree establishment. Areas of bedrock, colluvial deposits, fluvial deposits, glacio-fluvial deposits, and moraine were categorized using data from the Alberta Geological Survey (Fenton et al. 2013). Only three of the five surficial geology types intersected with ATE and were included in the model; *bedrock*, *colluvial deposits*, and *moraine*.

Wildfire disturbance

Two wildfires affected the WCW in the period between 1914 and 2006. The Pass Creek Fire of 1936 mainly affected the northern extent of the WCW, covering 45.2% of the area of the watershed. A smaller fire occurred in 1934 and was restricted to the southern-most slope, covering only 1.5% of the watershed. Fire extents were delineated using historic descriptions, and aerial imagery from 1949 where the remnant fire scars were still visible (Wildfire Management Branch - Alberta Agriculture and Forestry 2017). Gird cells that intersected with these fire extents were labeled *fire,* and those that did not were labeled *no fire.* A more detailed fire history of the WCW is available in Rogeau (2005) and Rogeau (2012).

Model execution

The topographic, climatic, geomorphic, and disturbance variables were taken as model inputs for classification of land cover change in a random forest model, using the random forest classifier from the *Scikit-learn* module (v 0.23.1) (Pedregosa et al. 2011) in

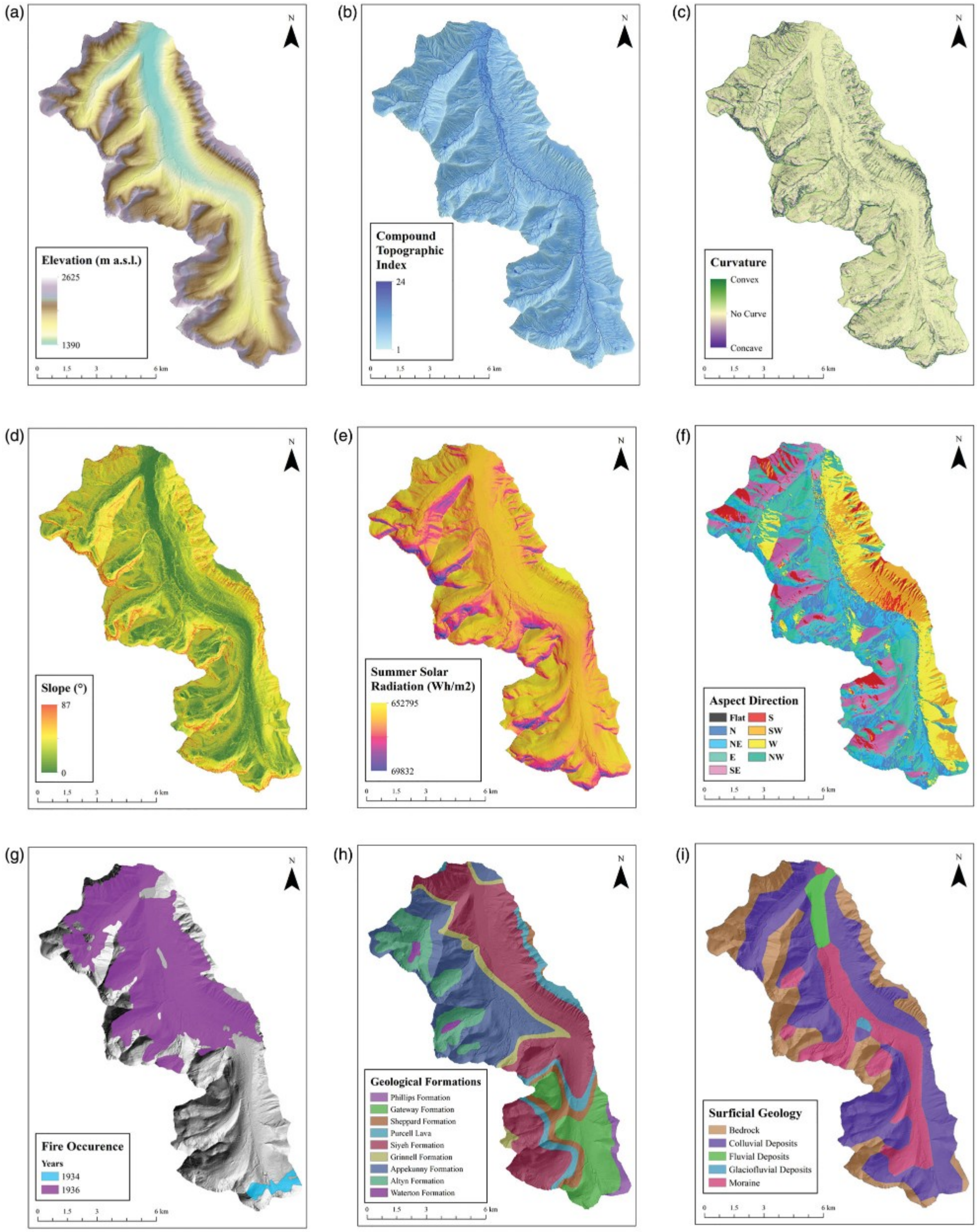

Figure 4. Variables used in random forest model training; (a) elevation, (b) compound topographic index (CTI), (c) curvature, (d) slope, (e) annual solar radiation, (f) aspect, (g) fire occurrence, (h) surficial geology; and model validation, (i) fractional cover.

Table 1. Summary of continuous variables used in random forest model.

		Mean		Std dev.		Max		Min	
Variable	Unit	Training	Prediction	Training	Prediction	Training	Prediction	Training	Prediction
Elevation	m a.s.l.	1878.77	1957.35	134.24	136.75	2199.78	2199.99	1700.23	1700.02
Compound topographic index	Unitless	5.43	5.64	1.23	1.80	12.06	18.42	2.98	1.47
Curvature	Unitless	0.11	−0.11	1.10	2.51	9.42	69.99	−10.53	−62.62
Slope	°	29.87	30.04	8.80	12.55	67.76	87.38	2.43	0.01
Annual precipitation	mm	1518.98	1582.57	142.12	157.63	1858.28	1936.46	1211.33	1195.98
Annual solar radiation	Wh/m2	1,231,776.75	1,092,610.75	145,166.80	265,128.56	1,478,222.13	150,9141.88	709,934.25	171,480.11
Annual temperature	°C	1.87	1.51	0.59	0.60	2.84	2.95	0.30	−0.03
Summer PET	mm/day	1.33	1.22	0.09	0.23	1.51	1.52	0.95	0.17
Summer precipitation	mm	259.23	270.04	17.51	17.97	301.13	305.14	235.59	234.99
Summer solar radiation	Wh/m2	539,345.31	499,860.88	37,075.29	91,860.95	627,617.13	626,085.31	369,672.28	70,528.40
Summer temperature	°C	10.79	10.52	0.54	0.56	11.52	11.73	9.48	9.45

Training indicates values within observed ATE area of the WCW, prediction indicates values in unobserved ATE area.

Table 2. Summary of categorical variables used in random forest model.

	Observed		Predicted	
Variable	Count	Percent	Count	Percent
Aspect				
N	7018	16.0	8232	8.7
NE	7172	16.4	10460	11.1
E	8803	20.1	13870	14.7
SE	5916	13.5	19448	20.5
S	1943	4.4	7154	7.6
SW	4862	11.1	9598	10.1
W	3782	8.6	15253	16.1
NW	4241	9.7	10625	11.2
Fire exposure				
Fire	21158	48.4	59927	63.3
No fire	22580	51.6	34713	36.7
Surficial geography				
Colluvial deposit	26635	60.9	51737	54.7
Moraine	7522	17.2	10104	10.7
Bedrock	9581	21.9	32711	34.6

Percentages are among group, within observed and unobserved condition.

Python 3.8.1. After dummy-encoding of categorical data, a total of 21 predictive variables were used in the model (Figure 4, Tables 1 and 2). Random forest hyperparameters were optimized using the *RandomizedSearchCV* function in *Scikit-learn*, with 50 iterations and 3-fold cross validation.

Model accuracy was determined by reserving 20% of the training data as a test set, and calculating overall accuracy and Cohen's kappa value. Additionally, model accuracy for each class of the response variable (i.e. *vegetation decrease*, *no change*, and *vegetation increase*) was assessed using precision and recall. Precision is the number of true positive predictions of class, divided by the total number of predictions of that class and recall is the number of true positive predictions in a class, divided by the total number of actual occurrences of that class. Both precision and recall are measured as a ratio, between 0.0 and 1.0, with 1.0 being perfect class detection.

The model was then used to predict canopy cover change in the regions of ATE in the WCW that were not observed in repeat photography. Predicted change classes were validated by comparing fractional cover measurements from the 2014 LiDAR observation between *vegetation increase* and *vegetation decrease* classes. Fractional cover was assessed using the canopy-to-total returns method described in Hopkinson and Chasmer (2009) (Figure 4i), which has been shown to correspond to canopy cover classification derived from MLP imagery (McCaffrey and Hopkinson 2017). These measurements represent contemporary forest condition; to determine if differences in fractional cover between *vegetation increase* and *vegetation decrease* classes in the model prediction adequately represent historic change, we compared them to fractional cover differences in observed areas, where historical change condition was known. Mean fractional cover values were compared using a bootstrapped t-test, with 1000 random samples of 52 cells, the minimum sample required for adequate statistical power (0.8) given the effect size between samples.

One of the key reasons for using random forest to model change in the ATE was the ability to determine ranked variable importance, to better understand the environmental factors driving change in the ATE. In order to avoid the well-known bias toward high cardinality variables when determining importance from a combination of continuous and categorical data, we used permutation importance (Strobl et al. 2007). Instead of measuring variable importance by ranking splitting criteria, such as Gini Importance, the permutation importance method randomly permutes the values in a variable, one variable at a time, and measures the decrease in model accuracy when each variable is randomized. Each variable is permuted repeatedly, and the mean decreases in model accuracy among variables are ranked to determine permutation variable importance.

In our model, each of the 21 variables were permuted five times, for an initial total of 105 model runs. This initial run provides the permutation importance rankings for accuracy test and spatial extension of ATE change model in the WCW. But to infer physical processes from permutation importance ranking, we must account for correlated predictor variables. While highly correlated predictor variables may contribute to random forest model accuracy, they often introduce unexpected bias in permutation variable importance ranking (Strobl et al. 2008), which can disrupt the use of variable ranking to understand physical processes underlying a modeled phenomenon (Gregorutti et al. 2017). In order to remove the bias effect of correlated values on permutation importance, we used a recursive feature elimination (RFE) approach, as described in Gregorutti et al. (2017). Following the initial random forest training and permutation importance test, we removed all variables below a threshold of accuracy reduction. We then iteratively re-trained the model and recalculated permutation importance; after each round, we dropped the variable with the lowest permutation importance that was also highly correlated ($|r|>0.7$) to one of the remaining variables and repeated the process until none of the remaining variables were correlated. This method can reliably be used to improve feature selection based on permutation importance of correlated values, as demonstrated in a Landsat classification example (Gregorutti et al. 2017).

Finally, Strobl et al. (2007) note that bootstrapping of random forest models can also introduce importance bias; as such, none of our random forest models utilized bootstrapping.

Results

Model accuracy

Using the reserved 20% of the observed ATE area as a test dataset, the random forest model predicted canopy cover change classes with an accuracy of 77.3%. Cohen's kappa showed moderate agreement (0.56). Precision and recall values for each of the change classes are available in Table 3. In general, these values were highest in the no change class and lowest in the vegetation increase class. This order reflects the prevalence of the change classes in the training set. When change was detected, there was very little confusion between vegetation increase and vegetation decrease classes. The majority of model error came from low recall in the vegetation change classes, caused over-predicted of the *no change* class.

Change prediction in unobserved areas

Visual inspection of the predicted canopy change class in unobserved areas demonstrated distinct geographic patterns. Vegetation decreases were predicted in the northern area of the watershed, in fire-disturbed areas, while vegetation increases were predicted in northern-facing aspects in the southern area of the watershed, which was not fire-disturbed (Figure 5).

Fractional cover measurement demonstrated significant differences between canopy cover change classes. A bootstraped t-test showed signficantly higher fractional cover in vegetation increase class than in the vegetation decrease class in the unobserved, prediciton areas ($t = 75.5$, $p < 0.001$), which corresponds to the pattern of fractional cover in areas where historic change was observed (Figure 6). The dispropotionatly large sample size of the *no change* class caused the effect size to be too low for comparison using a bootstraped t-test, in both observed and predicted areas.

Variable importance

The initial permutation importance tests showed high importance for the continuous variables *annual temperature*, *annual precipitation*, *annual solar radiation*, and for the categorical variable *fire* (fire presence) (Figure 7). The lowest continuous variable ranking was in *elevation*, which might be seen as surprising considering that ATE distribution is clearly correlated to elevation. However, this result can be understood in context of the performance of highly correlated values in permutation importance tests of random forest models. If two variables are highly correlated, then when one of them is permuted, the predictive capacity of the other is retained, leading to a lesser decrease in accuracy of the model, and a lower permuted variable ranking. *Elevation* was highly correlated to both

Table 3. Confusion matrix for vegetation change classes, with overall accuracy, precision, recall, and Cohen's Kappa scores.

	Predicted				
Observed	Veg. decrease	No change	Veg. increase	Row total	Recall
Veg. decrease	1340	538	59	1937	0.69
No change	372	4716	281	5369	0.88
Veg. increase	90	649	703	1442	0.49
Column total	1802	5903	1043	Overall Accuracy = 0.77	
Precision	0.74	0.80	0.67	Cohen's Kappa = 0.56	

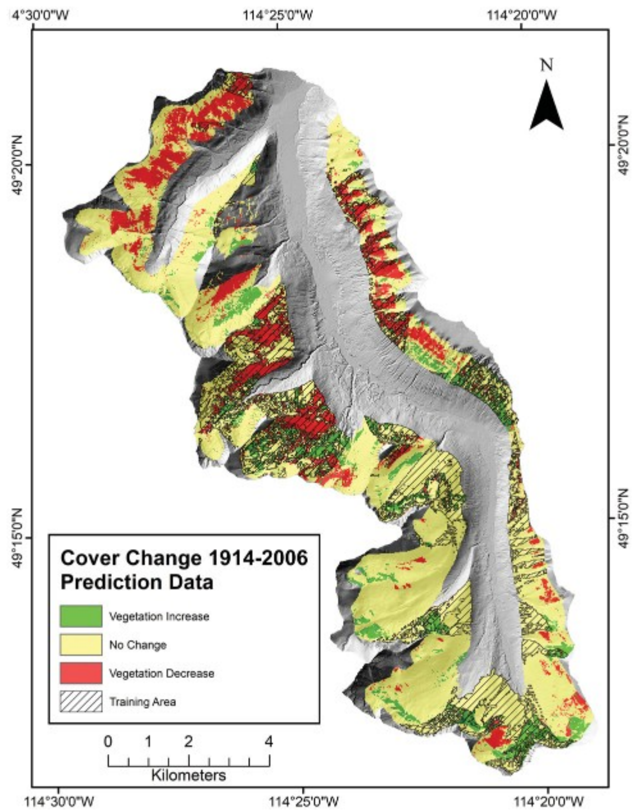

Figure 5. Predicted Alpine Treeline Ecotone (ATE) canopy change classification in areas of the West Castle Watershed (WCW) that were unobserved in Mountain Legacy Project (MLP) imagery. Predictions were also provided for observed areas, which are labeled as training areas (shaded). Vegetation decrease is generally predicted on warm, fire-exposed aspects, and vegetation increase is predicted on cool, non-fire exposed aspects.

annual temperature ($r = -0.94$) and *annual precipitation* ($r = 0.95$) (Figure 8), meaning the information in both temperature and precipitation variables was largely retrained when *elevation* was permuted, causing minimal decrease in model accuracy and resulting in a lower permuted variable ranking for *elevation*. *Annual temperature* and *annual precipitation* were also correlated ($r = -0.8$), as were *annual solar radiation* and *summer PET* ($r = 0.93$). Given that *fire* and *no fire* was a binary category, these variables have a perfect negative correlation ($r = -1.0$).

We used an RFE algorithm to eliminate the effect of these variable correlations on permutation importance. First, we eliminated all variables with mean accuracy reduction less than 0.02 (i.e. from CTI down in Figure 7); this segmentation point was not determined *a priori*, but rather was the result of a two-class Jenks Natural Breaks classification. Using the iterative approach of model training, permutation importance ranking, and removal of the variable with the lowest importance that was also correlated to a remaining variable, the order of variable removal was *elevation*, *no fire*, *summer PET*, and *annual precipitation*. The RFE variable selection algorithm left five remaining features (in order of importance): *fire*, *annual temperature*, *annual solar radiation*, *surficial colluvial deposit*, and *slope* (Figure 9).

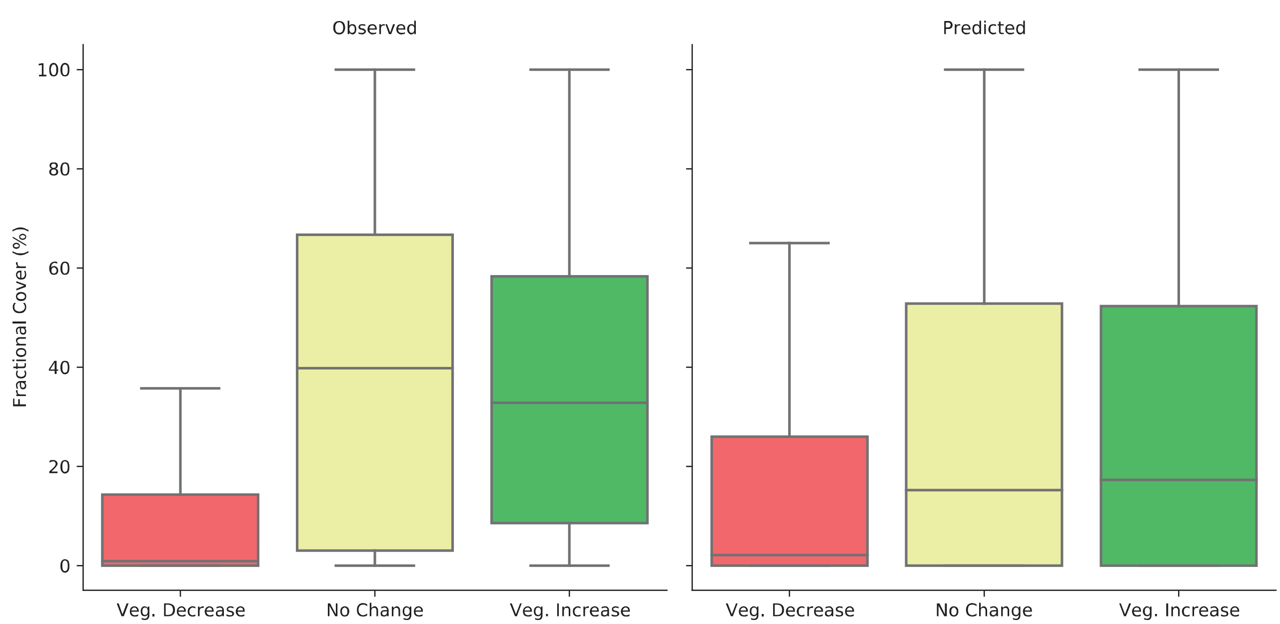

Figure 6. Boxplots of LiDAR-derived fractional cover measurements, comparing Alpine Treeline Ecotone (ATE) canopy cover change classifications. On the left, observed change classes, and on the right, change classes predicted in the random forest model. In both conditions, fractional cover in the vegetation increase class is significantly higher than the in the vegetation decrease class.

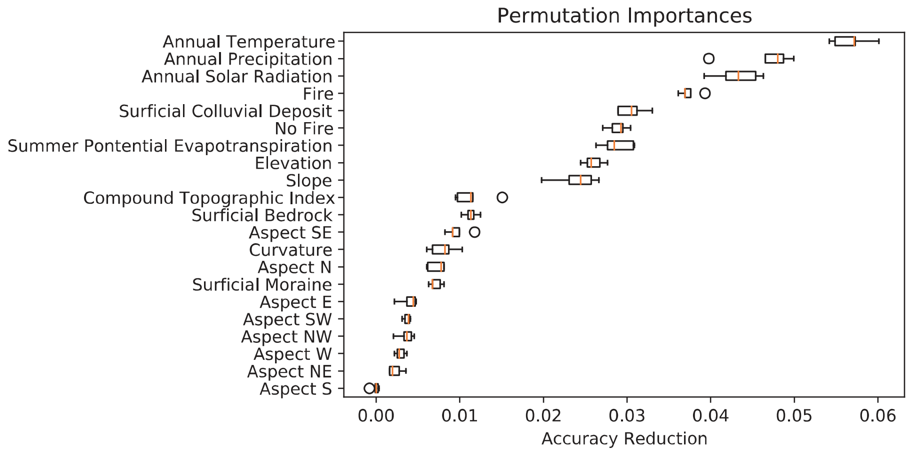

Figure 7. Boxplot showing permutation importance for the 21 variables used in the initial model accuracy assessment. Great accuracy reduction is associated with higher importance, as the model loses more accuracy when these variables are permuted. PET: Potential Evapotranspiration; CTI: Compound Topographic Index.

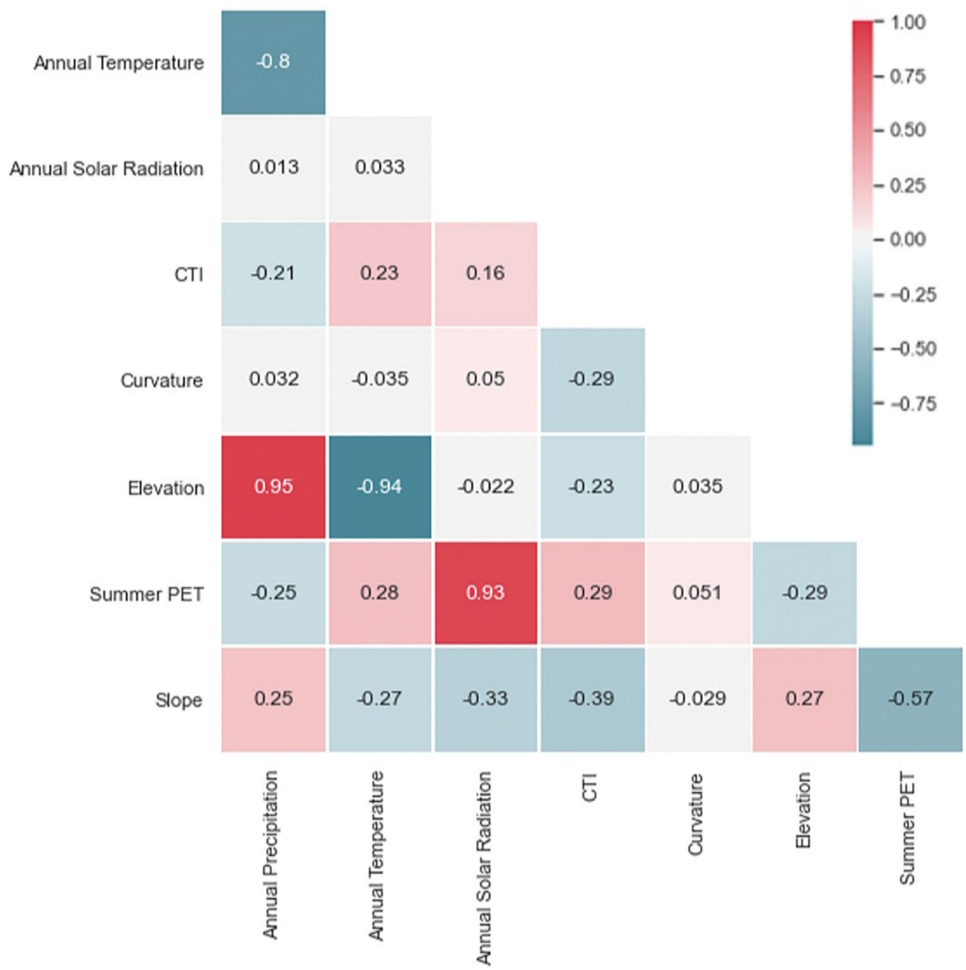

Figure 8. Pearson correlation matrix for the continuous model variables. PET: Potential Evapotranspiration; CTI: Compound Topographic Index.

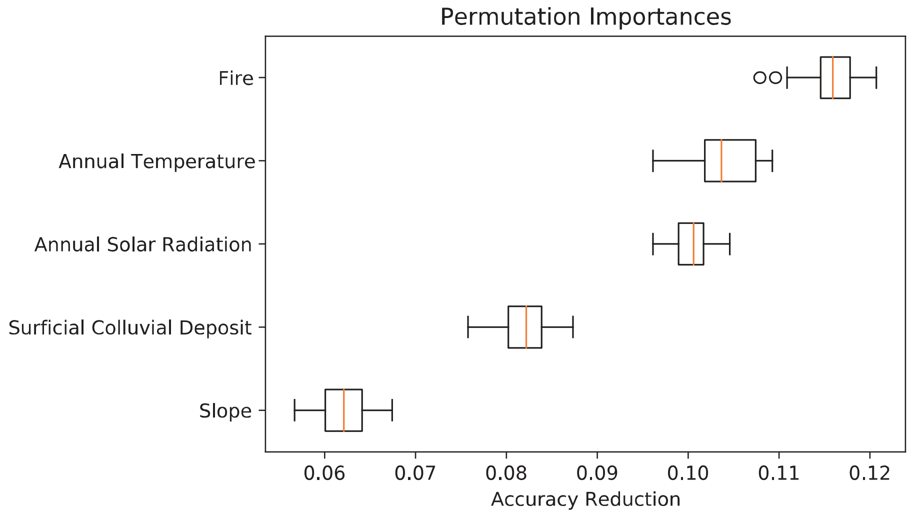

Figure 9. Boxplot showing permutation importance for the five model variables selected by the recursive feature elimination algorithm.

Discussion

Accuracy

Random forest proved to be an effective means of modeling unobserved or occluded areas of MLP repeat photography, extending the utility of this expansive dataset. Within the areas observed in MLP imagery, the measured accuracy of canopy cover change classification over the 92-year observation period suggested that the model was able to discern regions of the ATE that experienced increases in canopy cover from regions that experienced decreases in canopy cover, while also identifying unchanged areas. Further research using this method may benefit from using a more varied training dataset, as it appears that the large sample size of unchanged areas in the ATE, relative to areas that experienced change, may have been a source of classification uncertainty.

The spatial extension of the random forest model successfully predicted canopy cover change classification in areas of the watershed that were unobserved in MLP repeat photographs. Patterns of change that were clearly visible in the observed data, such as a decrease canopy cover on south-facing, fire-exposed aspects and an increase in canopy cover on north-facing aspects without fire, were also clearly visible in the predicted data. A more exhaustive method, such as a stand age reconstruction using dendrochronology, would be required to definitively validate these change classifications, but observed differences in LiDAR-derived fractional cover between change classes did corroborate the model predictions. This finding increases the potential utility of the MLP database by demonstrating that random forest prediction can serve as the basis for estimates of the potential extent of change phenomena observed in MLP image pairs.

Permutation importance tests in the random forest model provided insight into the environmental factors driving change in the ATE.

Fire ranked highest in final permutation importance, suggesting that exposure to fire in the 1934 and 1936 fires in WCW had the single highest capacity to predict ATE canopy cover change between 1914 and 2006. Considering that previous models of the environmental drivers of ATE change either combine fire with other disturbances (Trant et al. 2020), or omit fire entirely (Case and Buckley 2015; Macias-Fauria and Johnson 2013; Weiss et al. 2015), the primacy of fire as an agent of change in our study might be considered unexpected. Many of these studies cite the low frequency of fire at ATE elevation as justification for not modeling fire effects, and reduced fire frequency with elevation has indeed been observed in the Canadian Rockies (Rogeau and Armstrong 2017). Fire is sometimes considered a regional effect, not having biological explanatory value for the global phenomenon of treeline; Körner (2012) writes that there is, "… overwhelming ecological significance of fire for forest dynamics and likely interactions with tree regeneration in climatically harsh environments, but the impact is local or regional, and it is random and not specific to high elevation." However, while the effects of fire on ATE change in the WCW can certainly be described as regional in scale, there is evidence that regeneration from fire is nonrandom, and related to topo-climatic conditions that are exacerbated at high elevations (McCaffrey and Hopkinson 2020). Fire may also shape the forest-tundra ecotone at greater scale; in subarctic forest-tundra ecotone, minor forest gain in northern tundra was offset by significant forest loss in southern tundra, associated with increases in temperature and wildfire burn extent (Timoney and Mamet 2020; Timoney et al. 2019). We do not suggest here that, globally, fire is a primary modifier of ATE, on par with elevation-driven temperature deficits, but we do suggest that the accuracy of ATE models (both future and historic) will benefit from the inclusion of fire regime data.

Annual temperature and *annual precipitation* were the highest ranked variables in the initial permutation test, with both having a substantially higher ranking than *elevation*. Among these correlated variables, *annual temperature* had the greatest predictive capacity, ranking second in the final permutation importance. This finding supports the general orthodoxy that ATE occurs primarily in response to thermal deficits (Körner 1998; Körner and Paulsen 2004). But the fact that *annual precipitation* was omitted due to correlation does not necessarily diminish the role of precipitation in ATE change. The relative impact of thermal and moisture deficits on tree establishment at high elevations has been a recent topic of study (Elliott and Cowell 2015; Kueppers et al. 2017; Weiss et al. 2015). These findings suggest that precipitation, or moisture provided through accumulated snow, could be essential for treeline advance to result from increases in atmospheric temperature, which may explain observed ATE advance on some northern slopes in the Rockies. Our data support the consensus that these largely elevation-driven processes are major factors contributing to differences in ATE change.

Annual solar radiation was the third highest ranking variable in final permutation importance, with warm aspects experiencing considerably greater decrease in canopy cover, and cool aspects experiencing a greater increase. The large influence of solar radiation, and by proxy, aspect, agrees with findings by other studies of ATE in the Canadian Rockies using MLP imagery (McCaffrey and Hopkinson 2020; Stockdale et al. 2019; Trant et al. 2020). McCaffrey and Hopkinson (2020) and Stockdale et al. (2019) found a negative correlation between aspect/solar radiation and increase canopy cover/succession in the ATE, but Trant et al. (2020) found an association between warm aspects and treeline advance, which they suggested may be due to lengthened growing seasons and reduced permafrost on southern aspects. While treeline advance on warm aspects has been related to permafrost in the sub-arctic ranges (Danby and Hik 2007), and to isolated post-disturbance areas of the Rockies (Luckman and Kavanagh 2000), it is not immediately clear that a bias toward warm aspect treeline advance is the norm. One potential explanation for the discrepancy in the direction of the aspect effect in these studies is that both the WCW and the study region in Stockdale et al. (2019) are at the southern end of the latitudinal transect described in Trant et al. (2020), where treeline advance was generally suppressed compared to the northern end of the transect. A latitudinal axis of variation in the direction of aspect effect, possibly related to annual solar radiation budget or precipitation patterns, would create a scenario where increases in ATE density and elevation were biased toward northern aspects at lower latitudes, and southern aspects at higher latitudes.

Another explanation for the aspect discrepancy could be through interactions with fire. In both McCaffrey and Hopkinson (2020) and Stockdale et al. (2019), the negative relationships between aspect/solar radiation and canopy cover/succession are associated with a post-fire disturbance condition. McCaffrey and Hopkinson (2020) observed an asymmetric response to fire-exposure, with fire causing higher mortality on south-facing slopes than on north-facing slopes. One interpretation of this finding is that fire may interact with other topo-climatic variables at ATE elevations in a way that it does not at lower elevations. For example, a stand-clearing fire in the 1930s which occurred at low elevation would have ample resources (soil moisture, insolation, adequate growing season temperature) to replace the stand before the 2006 observation, thus recording *no change*. At ATE elevation, where these resources are limited, soil moisture and growing season temperatures which may have been adequate for a mature tree stand pre-fire may have posed limits to tree establishment post-fire.

Evidence of this high-elevation resource limitation effect can be seen in a study of post-fire tree establishment in the ATE (Stine and Butler 2015). This study reported significant soil erosion by wind and water following the removal of vegetation and duff layers by fire. A study 30 km north of the WCW showed a similar effect of high elevation erosion, post-fire (Silins et al. 2009). While effective soil depth did not significantly vary between burned and unburned sites in Stine and Butler (2015), seedling establishment was significantly higher in burned areas with deeper soil and more rock shelter. This finding was curious, as previous studies had shown these variables did not affect seedling establishment in unburned areas (Malanson et al. 2002). Thus, variables related to topography and climate that do not appear to affect tree establishment in normal ATE conditions can become critically important to tree establishment following disturbance by fire. Future research should investigate patterns of post-fire tree establishment using a method that controls for the effect of aspect on climatic variables.

Surficial colluvial deposits had the fourth highest permutation importance. Surficial geology variables were included in the model in order to account for the finding of Macias-Fauria and Johnson (2013), that upslope ATE advance under climate warming projections would be limited by geologic constraints such as bedrock. Specifically, that study found that colluvium had the highest probability of tree presence when compared to other geomorphology types, bedrock had the lowest probability of tree presence, and very little of the area above the present ATE was colluvium. Macias-Fauria and Johnson (2013) provided a model of future change in the ATE, but it is intriguing that our model of historic canopy cover change also appears to have identified the colluvium/bedrock boundary as an obstacle to ATE advance, corroborating their model.

Slope was the fifth and final variable to be selected through permutation importance. Slope has been shown to affect ATE through mechanical disturbance, with many treeline regions regulated by rockslide and avalanche (Butler and Walsh 1994; Walsh and Butler 1997; Walsh et al. 1994). The WCW has numerous chutes where ATE appears to be suppressed, potentially by avalanche, and previous research indicated that the high mortality class had significantly steeper slope than other change classes (McCaffrey and Hopkinson 2020). But this steep slope mortality is not associated with specific avalanche chutes. More likely, the hypsometry of the watershed causes larger slopes to be found at higher elevation, where greater mortality was observed. This hypothesis is supported by research in Glacier National Park, Montana, where an avalanche-regulated treeline was found to be stable over an observation period of >70 years in repeat photography (Butler et al. 1994). It is conceivable that in specific circumstances, the effect of slope on ATE position might outweigh the effects of variables correlated to elevation and aspect, but if this were broadly the case then slope would have had higher predictive value in the model. Aggregation of the 1 m DEM to 20 m is a potential source of error for topographic variables in our model, given that lower resolution DEMs are known to underestimate certain topographic metrics, like slope (Kienzle 2004).

Conclusion

We trained a random forest model of the WCW to classify historic changes in forest canopy cover, based on a set of topographic, climatic, geologic, and disturbance variables, at a resolution of 20 m. Changes in canopy cover were identified in repeat photography from the MLP, spatialized using the WSL monoplotting method, and modeled with 77.3% accuracy. The predictive capability of random forest allowed us to spatially extend our ATE change model, using environmental variables to estimate the direction of ATE change in areas of our study watershed that were not visible in the MLP repeat photograph pairs. The MLP dataset is an exceedingly useful resource to study historic change in the mountains of western Canada, but due to the nature of the terrain in the oblique repeat photographs, large portions of research areas can have occluded views. By demonstrating that observed change phenomena can be modeled and applied to produce estimates of change in unobserved areas, we aim to expand the utility of this resource to regional assessment and simulation needs where spatially continuous land cover change data are required.

Fire, annual temperature, and *annual solar radiation* were the highest ranked variables. These findings corroborated other studies of ATE in the region which suggest interactions among fire history, climatic variables correlated to elevation, and insolation aspect are strong predictors of ATE change. The potentially limiting effect of fire on upslope treeline advance should remain an area of focus. Future research could investigate how climatic variables which correlate to aspect (i.e. insolation, wind exposure, PET, soil moisture, soil temperature) alter patterns of post-fire tree establishment. Recent wildfires in southern Alberta, such as the Lost Creek Fire of 2003 and the Kenow Fire of 2017, could be useful for observing post-fire tree establishment in the ATE in a variety of aspects and growth stages. It is our hope that this work will add to the growing body of research investigating fire at high elevations.

Acknowledgments

Repeat photography was graciously provided by the Mountain Legacy Project. Dr. Claudio Bozzini is thanked for developing the WSL monoplotting tool and instructing our team on its use. Dr. Marie-Pierre Rogeau was instrumental in accessing the fire history data of the West Castle area. Dr. Craig Mahoney graciously provided tutorials on random forest modelling. The anonymous reviewers are thanked for their helpful input.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

McCaffrey acknowledges funding from the NSERC AMYTHEST program and the University of Lethbridge Graduate Students' Association. Hopkinson acknowledges funding from the Alberta Innovates Energy and Environment Solutions Water Innovation Program, the NSERC Discovery Grant Program, and Campus Alberta Innovates Program.

References

Allen, T.R., and Walsh, S.J. 1996. "Spatial and compositional pattern of alpine treeline." *Glacier National Park, Montana" Photogrammetric Engineering and Remote Sensing*, Vol. 62(No. 11): pp. 1261–1268.

Aplet, G.H., Laven, R.D., and Smith, F.W. 1988. "Patterns of community dynamics in Colorado Engelmann spruce-subalpine fir forests." *Ecology*, Vol. 69(No. 2): pp. 312–319.

Bekker, M.F. 2005. "Positive feedback between tree establishment and patterns of subalpine forest." *Arctic, Antarctic, and Alpine Research*, Vol. 37(No. 1): pp. 97–107.

Beven, K.J., and Kirkby, M.J. 1979. "A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant." *Hydrological Sciences Bulletin*, Vol. 24(No. 1): pp. 43–69.

Bolton, D.K., Coops, N.C., and Wulder, M.A. 2013. "Measuring forest structure along productivity gradients in the Canadian boreal with small-footprint LiDAR." *Environmental Monitoring and Assessment*, Vol. 185(No. 8): pp. 6617–6634.

Bozzini, C., Conedera, M., and Krebs, P. 2012. "A new monoplotting tool to extract georeferenced vector data and orthorectified raster data from oblique non-metric photographs." *International Journal of Heritage in the Digital Era*, Vol. 1(No. 3): pp. 499–518.

Butler, D.R., and DeChano, L.M. 2001. "Environmental change in Glacier National Park, Montana: An assessment through repeat photography from fire outlooks." *Physical Geography*, Vol. 22(No. 4): pp. 291–304.

Butler, D.R., Malanson, G.P., and Cairns, D.M. 1994. "Stability of alpine treeline in Northern Montana." *Phytocoenologia*, Vol. 22(No. 4): pp. 485–500.

Butler, D.R., Malanson, G.P., Walsh, S.J., and Fagre, D.B. 2007. "Influences of geomorphology and geology on alpine treeline in the American West—more important than climatic influences?" *Physical Geography*, Vol. 28(No. 5): pp. 434–450.

Butler, D.R., and Walsh, S.J. 1994. "Site characteristics of debris flows and their relationship to alpine treeline." *Physical Geography*, Vol. 15(No. 2): pp. 181–199.

Byrne, J., Kienzle, S., Johnson, D., Duke, G., Gannon, V., Selinger, B., and Thomas, J. 2006. "Current and future water issues in the Oldman River Basin of Alberta, Canada." *Water Science and Technology : A Journal of the International Association on Water Pollution Research*, Vol. 53(No. 10): pp. 327–334.

Case, B.S., and Buckley, H.L. 2015. "Local-scale topoclimate effects on treeline elevations: A country-wide investigation of New Zealand's southern beech treelines." *PeerJ.*, Vol. 3 pp. e1334.

Case, B.S., and Duncan, R.P. 2014. "A novel framework for disentangling the scale-dependent influences of abiotic factors on alpine treeline position." *Ecography*, Vol. 37(No. 9): pp. 838–851.

Coops, N.C., Morsdorf, F., Schaepman, M.E., and Zimmermann, N.E. 2013. "Characterization of an alpine tree line using airborne LiDAR data and physiological modeling." *Global Change Biology*, Vol. 19(No. 12): pp. 3808–3821.

Cullen, R.M., and Marshall, S.J. 2011. "Mesoscale temperature patterns in the rocky mountains and foothills region of Southern Alberta." *Atmosphere-Ocean*, Vol. 49(No. 3): pp. 189–205.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., and Lawler, J.J. 2007. "Random forests for classification in ecology." *Ecology*, Vol. 88(No. 11): pp. 2783–2792.

Danby, R.K. 2011. "Monitoring forest-Tundra ecotones at multiple scales." *Geography Compass*, Vol. 5(No. 9): pp. 623–640.

Danby, R.K., and Hik, D.S. 2007. "Variability, contingency and rapid change in recent subarctic alpine tree line dynamics." *Journal of Ecology*, Vol. 95(No. 2): pp. 352–363.

Elliott, G.P., and Cowell, C.M. 2015. "Slope aspect mediates fine-scale tree establishment patterns at upper treeline during wet and dry periods of the 20th century." *Arctic, Antarctic, and Alpine Research*, Vol. 47(No. 4): pp. 681–692.

Esri 2014. *ArcGIS 10.3 for desktop*. Redlands, CA USA: Environmental Systems Research Institute.

Fenton, M. M., Waters, E. J., Pawley, S. M., Atkinson, N., Utting, D. J., & Mckay, K. 2013. "Surficial geology of Alberta." *Alberta Energy Regulator, AER/AGS Map 601*, scale 1: 1 000 000.

Grace, J., Berninger, F., and Nagy, L. 2002. "Impacts of climate change on the tree line." *Annals of Botany*, Vol. 90(No. 4): pp. 537–544.

Gregorutti, B., Michel, B., and Saint-Pierre, P. 2017. "Correlation and variable importance in random forests." *Statistics and Computing*, Vol. 27(No. 3): pp. 659–678.

Harsch, M.A., Hulme, P.E., McGlone, M.S., and Duncan, R.P. 2009. "Are treelines advancing? A global meta-analysis of treeline response to climate warming." *Ecology Letters*, Vol. 12(No. 10): pp. 1040–1049.

Holtmeier, F.K., and Broll, G. 2005. "Sensitivity and response of northern hemisphere altitudinal and polar treelines to environmental change at landscape and local scales." *Global Ecology and Biogeography*, Vol. 14 (No. 5): pp. 395–410.

Hopkinson, C., and Chasmer, L. 2009. "Testing LiDAR models of fractional cover across multiple forest ecozones." *Remote Sensing of Environment*, Vol. 113(No. 1): pp. 275–288.

Hopkinson, C., Collins, T., Anderson, A., Pomeroy, J., and Spooner, I. 2012. "Spatial snow depth assessment using LiDAR transect samples and public GIS data layers in the Elbow River watershed." *Revue Canadienne Des Ressources Hydriques* [Canadian Water Resources Journal], Vol. 37(No. 2): pp. 69–87.

Jensen, M.E., and Haise, H.R. 1963. "'Estimating evapotranspiration from solar radiation.' Proceedings of the American Society of Civil Engineers." *Journal of the Irrigation and Drainage Division*, Vol. 89: pp. 15–41.

Kienzle, S. 2004. "The effect of DEM raster resolution on first order, second order and compound terrain derivatives." *Transactions in GIS*, Vol. 8(No. 1): pp. 83–111.

Körner, C. 1998. "A re-assessment of high elevation treeline positions and their explanation." *Oecologia*, Vol. 115(No. 4): pp. 445–459.

Körner, C. 2012. *Alpine treelines: functional ecology of the global high elevation tree limits*. New York, NY, USA: Springer Science & Business Media.

Körner, C., and Paulsen, J. 2004. "A world-wide study of high altitude treeline temperatures." *Journal of Biogeography*, Vol. 31(No. 5): pp. 713–732.

Kueppers, L.M., Conlisk, E., Castanha, C., Moyes, A.B., Germino, M.J., de Valpine, P., Torn, M.S., and Mitton, J.B. 2017. "Warming and provenance limit tree recruitment across and beyond the elevation range of subalpine forest." *Global Change Biology*, Vol. 23(No. 6): pp. 2383–2395.

Kullman, L., and Öberg, L. 2009. "Post-Little Ice Age tree line rise and climate warming in the Swedish Scandes: A landscape ecological perspective." *Journal of Ecology*, Vol. 97(No. 3): pp. 415–429.

Luckman, B., and Kavanagh, T. 2000. "Impact of climate fluctuations on mountain environments in the Canadian Rockies." *Ambio: A Journal of the Human Environment*, Vol. 29(No. 7): pp. 371–380.

Macias-Fauria, M., and Johnson, E.A. 2013. "Warming-induced upslope advance of subalpine forest is severely limited by geomorphic processes." *Proceedings of the National Academy of Sciences*, Vol. 110(No. 20): pp. 8117–8122.

Malanson, G.P., Butler, D.R., Cairns, D.M., Welsh, T.E., and Resler, L.M. 2002. "Variability in an edaphic indicator in alpine tundra." *CATENA*, Vol. 49(No. 3): pp. 203–215.

Mamet, S.D., and Kershaw, G.P. 2012. "Subarctic and alpine tree line dynamics during the last 400 years in north-western and central Canada." *Journal of Biogeography*, Vol. 39(No. 5): pp. 855–868.

McCaffrey, D.R., and Hopkinson, C. 2017. "Assessing fractional cover in the alpine treeline ecotone using the WSL monoplotting tool and airborne LiDAR." *Canadian Journal of Remote Sensing*, Vol. 43(No. 5): pp. 504–512.

McCaffrey, D., and Hopkinson, C. 2020. "Repeat oblique photography shows terrain and fire-exposure controls on century-scale canopy cover change in the alpine treeline ecotone." *Remote Sensing*, Vol. 12(No. 10): pp. 1569.

McGuinness, J. L., and Bordne, E. F. 1972. *A comparison of lysimeter-derived potential evapotranspiration with computed values*. Washington, DC: US Dept. of Agriculture.

Moiseev, P. A., and Shiyatov, S. G. 2003. *"Vegetation Dynamics at the Tree-Line Ecotone in the Ural Highlands, Russia" Alpine Biodiversity in Europe*. Berlin, Germany: Springer Science and Business Media.

Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andréassian, V., Anctil, F., and Loumagne, C. 2005. "Which potential evapotranspiration input for a lumped rainfall–runoff model?" *Journal of Hydrology*, Vol. 303 (No. 1-4): pp. 290–306.

Paulsen, J., and Körner, C. 2014. "A climate-based model to predict potential treeline position around the globe." *Alpine Botany*, Vol. 124(No. 1): pp. 1–12.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., and Dubourg, V. 2011. "Scikit-learn: Machine learning in Python." *The Journal of Machine Learning Research*, Vol. 12: pp. 2825–2830.

Pepin, N., Bradley, R.S., Diaz, H.F., Baraer, M., Caceres, E.B., Forsythe, N., Fowler, H., *et al.* 2015. "Elevation-dependent warming in mountain regions of the world." *Nature Climate Change*, Vol. 5(No. 5): pp. 424–430.

Randin, C.F., Engler, R., Normand, S., Zappa, M., Zimmermann, N.E., Pearman, P.B., Vittoz, P., Thuiller, W., and Guisan, A. 2009. "Climate change and plant distribution: Local models predict high-elevation persistence." *Global Change Biology*, Vol. 15(No. 6): pp. 1557–1569.

Rogeau, M. 2005. *Fire regime study C5 FMU*. Contract Report Prepared for Alberta Sustainable Resource Development, Alberta.

Rogeau, M. 2012. *Fire History Study Castle River Watershed*. Technical report prepared for Alberta Environment and Sustainable Resource Development. Calgary, Alberta, Canada: Forest Protection Branch, Southern Rockies Wildfire Management Area.

Rogeau, M.-P., and Armstrong, G.W. 2017. "Quantifying the effect of elevation and aspect on fire return intervals in the Canadian Rocky Mountains." *Forest Ecology and Management*, Vol. 384: pp. 248–261.

Romme, W.H., and Knight, D.H. 1981. "Fire frequency and subalpine forest succession along a topographic gradient in Wyoming." *Ecology*, Vol. 62(No. 2): pp. 319–326.

Roush, W., Munroe, J.S., and Fagre, D.B. 2007. "Development of a spatial analysis metho using ground-based repeat photography to detect changes in the alpine treeline ecotone." *Glacier National Park, Montana, USA" Arctic, Antarctic, and Alpine Research*, Vol. 39(No. 2): pp. 297–308.

Sakulich, J. 2015. "Reconstruction and spatial analysis of alpine treeline in the Elk Mountains." *Physical Geography*, Vol. 36(No. 6): pp. 471–488.

Sanseverino, M.E., Whitney, M.J., and Higgs, E.S. 2016. "Exploring landscape change in mountain environments with the mountain legacy online image analysis toolkit." *Mountain Research and Development*, Vol. 36(No. 4): pp. 407–416.

Schwörer, C., Henne, P.D., and Tinner, W. 2014. "A model-data comparison of Holocene timberline changes in the Swiss Alps reveals past and future drivers of mountain forest t dynamics." *Global Change Biology*, Vol. 20(No. 5): pp. 1512–1526.

Silins, U., Stone, M., Emelko, M.B., and Bladon, K.D. 2009. "Sediment production following severe wildfire and post-fire salvage logging in the Rocky Mountain headwaters of the Oldman River Basin." *CATENA*, Vol. 79(No. 3): pp. 189–197.

Springer, J., Ludwig, R., and Kienzle, S.W. 2015. "Impacts of forest fires and climate variability on the hydrology of an alpine medium sized catchment in the Canadian Rocky Mountains." *Hydrology*, Vol. 2(No. 1): pp. 23–47.

Stine, M.B., and Butler, D.R. 2015. "Effects of fire on geomorphic factors and seedling site conditions within the alpine treeline ecotone." *Glacier National Park, MT" Catena*, Vol. 132: pp. 37–44.

Stockdale, C.A., Bozzini, C., Macdonald, S.E., and Higgs, E. 2015. "Extracting ecological information from oblique angle terrestrial landscape photographs: Performance evaluation of the WSL Monoplotting Tool." *Applied Geography*, Vol. 63 pp. 315–325.

Stockdale, C.A., Macdonald, S.E., and Higgs, E. 2019. "Forest closure and encroachment at the grassland interface: a century-scale analysis using oblique repeat photography." *Ecosphere*, Vol. 10 (No. 6): pp. e02774. doi:10.1002/ecs2.2774.

Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T., and Zeileis, A. 2008. "Conditional variable importance for random forests." *BMC Bioinformatics*, Vol. 9(No. 1): pp. 307.

Strobl, C., Boulesteix, A.-L., Zeileis, A., and Hothorn, T. 2007. "Bias in random forest variable importance measures: Illustrations, sources and a solution." *BMC Bioinformatics*, Vol. 8(No. 1): pp. 25.

Timoney, K.P., and Mamet, S. 2020. "No treeline advance over the last 50 years in subarctic western and central Canada and the problem of vegetation misclassification in remotely sensed data." *Écoscience*, Vol. 27(No. 2): pp. 93–106.

Timoney, K.P., Mamet, S.D., Cheng, R., Lee, P., Robinson, A.L., Downing, D., and Wein, R.W. 2019. "Tree cover response to climate change in the forest-Tundra of north-central Canada: Fire-driven decline, not northward advance." *Écoscience*, Vol. 26(No. 2): pp. 133–148.

Tinner, W., and Theurillat, J.-P. 2003. "Uppermost limit, extent, and fluctuations of the timberline and treeline ecocline in the Swiss Central Alps during the past 11,500 years." *Arctic, Antarctic, and Alpine Research*, Vol. 35(No. 2): pp. 158–169.

Trant, A., Higgs, E., and Starzomski, B.M. 2020. "A century of high elevation ecosystem change in the Canadian Rocky Mountains." *Scientific Reports*, Vol. 10(No. 1): pp. 1–10.

Trant, A.J., Starzomski, B.M., and Higgs, E. 2015. "A publically available database for studying ecological change in mountain ecosystems." *Frontiers in Ecology and the Environment*, Vol. 13(No. 4): pp. 187–187.

Walsh, S.J., and Butler, D.R. 1997. "Morphometric and multispectral image analysis of debris flows for natural hazard assessment." *Geocarto International*, Vol. 12(No. 1): pp. 59–70.

Walsh, S.J., Butler, D.R., Allen, T.R., and Malanson, G.P. 1994. "Influence of snow patterns and snow avalanches on the alpine treeline ecotone." *Journal of Vegetation Science*, Vol. 5(No. 5): pp. 657–672.

Weiss, D.J., Malanson, G.P., and Walsh, S.J. 2015. "Multiscale relationships between Alpine treeline elevation and hypothesized environmental controls in the Western United States." *Annals of the*

Association of American Geographers, Vol. 105(No. 3): pp. 437–453.

Wildfire Management Branch - Alberta Agriculture and Forestry. 2017. *Fire history polygons C5 FMU*. https://wildfire.alberta.ca/resources/historical-data/spatial-wildfire-data.aspx.

Zevenbergen, L.W., and Thorne, C.R. 1987. "Quantitative analysis of land surface topography." *Earth Surface Processes and Landforms*, Vol. 12(No. 1): pp. 47–56.

Appendix A.

Topographic variables

The DEM was aggregated to match the 20 m land cover change dataset, using mean value of the 1 m DEM within each 20 m pixel.

Slope values were calculated on the 1 m DEM using the *slope* function in ArcGIS 10.3 (Esri 2014), then aggregated to 20 m resolution, again using mean values. The 1 m DEM is expected to produce greater estimations of slope, compared to slopes calculated on the 20 m, aggregated DEM (Kienzle 2004).

Aspect was calculated on the 20 m grid and classified into nine categorical values, based on 45° bins, eight for the intercardinal directions (N = 337.5–22.5°, NE = 22.5–67.5°, E = 67.5–112.5°, SE = 112.5–157.5°, S = 157.5–202.5°, SW = 202.5–247.5°, W = 247.5–292.5°, NW = 292.5–337.5°) and one for flat surfaces without slope, which was omitted due to small sample.

Curvature refers to the convexity or concavity of a DEM grid cell, in relation to neighboring cells. It was calculated by fitting a fourth order polynomial to the 3×3 window around a DEM grid cell; positive values indicate convexity and negative values represent concavity (Zevenbergen and Thorne 1987). Curvature was calculated on the 20 m DEM, using the *curvature* function in ArcGIS 10.3. This function calculates standard curvature, which combines both profile and plan curvature.

Compound topographic index (CTI), is an index of the ratio of upstream area to slope (Beven and Kirkby 1979). In ATE research, CTI has been used as a proxy for both cold air pooling (Case and Duncan 2014) and soil accumulation (Schwörer et al. 2014). CTI is measured using the formula:

$$\mathrm{CTI} = \ln(A/\tan\beta) \tag{1}$$

Where A is the contributing upslope area and β is the slope in degrees. These variables were calculated in ArcGIS 10.3, using the *flow direction* and *flow accumulation* functions for A, the *slope* function for β.

Appendix B.

Climatic variables

Lapse rates were simulated using a method from Randin et al. (2009): (1) historic normal values (30-year) for temperature and precipitation were collected from three meteorological stations, within 32 km of their study site in the Canadian Rockies; (2) using locally observed temperature and precipitation enhancement rates (Cullen and Marshall 2011), monthly averages were normalized to sea-level (i.e. the residual if elevation is equal to 0), (3) residual temperature and precipitation values were interpolated, at 'sea-level', using inverse distance weighting (IDW), (4) using a DEM of the study area and the definition of the linear regression of lapse rate, temperature and precipitation values were calculated for each grid cell according to elevation, then adjusted by either adding or subtracting the value from the interpolated residual surface.

One issue with the Randin et al. (2009) method used by Macias-Fauria and Johnson (2013) is that the lapse rates described by Cullen and Marshall (2011) were from observations made between 2005 and 2009. Macias-Fauria and Johnson (2013) applied these to climate records for a period between 1971 and 2000. Given that the present study seeks to identify climatic variables associated with historic change in the ATE, a longer observation period was required (1914–2006). We acquired data from 7 weather stations within a 50 km radius of the WCW, with an observation period ranging from 1893 to 2007, and elevations ranging from 1154–1920 m a.s.l.

Using this method, our estimates of lapse rates for both annual and JJA temperature were −4.0 °C per 1 km of elevation, and were comparable to regional values reported in Cullen and Marshall (2011) (i.e. −4.2 and −5.0 °C, respectively).

Solar radiation was calculated in ArcGIS 10.3 using the *area solar radiation* tool on the 20 m DEM. Solar radiation was modeled at 30-minute simulated intervals, with all monthly totals summed for an estimate of annual insolation, and JJA totals summed for summer insolation.

Potential evapotranspiration (PET) values were modeled using the method of Oudin et al. (2005), which gives comparable results to Penman-Monteith calculations in rainfall-runoff models, but can be implemented when values for wind speed and humidity are unreliable. This method of PET calculation was based on the models of Jensen and Haise (1963) and McGuinness and Bordne (1972), which use the general form:

$$\begin{aligned} PE &= \frac{R_e}{\lambda\rho}\frac{T_a + K_2}{K_1} \quad if\ T_a + K_2 > 0 \\ PE &= 0 \quad otherwise \end{aligned} \tag{2}$$

where PE is the rate of potential evapotranspiration (mm day $^{-1}$), R_e is extraterrestrial solar radiation (MJ m^{-2}day^{-1}), λ is latent heat flux (2.45 MJ kg^{-1}), ρ is the density of water (1000 kg m^{-3}), and T_a is the mean daily air temperature (°C). The fixed parameters K_1 (°C) and K_2 (°C) scale the importance of $T_{a,}$ and set a threshold at which $PE = 0$. Oudin et al. (2005) empirically determined 100 and 5 to be the optimal values for K_1 and K_2, which are the values used in this study. Average summer potential evapotranspiration values were modeled by calculating average daily JJA solar radiation (total JJA solar radiation in Wh/m^{-2}, divided by number of days in summer, converted to MJ m^{-2}day^{-1}) for R_e, and using the average JJA temperatures (calculated from the previously described lapse rate analysis) for T_a.