Journal of Environmental Management 234 (2019) 297–310

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

# EcoAnthromes of Alberta: An example of disturbance-informed ecological regionalization using remote sensing

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ARTICLE INFO

Keywords:
Ecological regionalization
Multivariate clustering
EcoAnthrome
Anthropogenic disturbance
Habitat
Ecological classification

ABSTRACT

Humans influence ecosystems on magnitudes that often exceed that of natural forces such as climate and geology; however, frameworks rarely include anthropogenic disturbance when delineating unique ecological regions. A critical step toward understanding, managing and monitoring human-altered ecosystems is to incorporate disturbance into ecological regionalizations. Furthermore, quantitative regionalization approaches are desirable to provide cost-effective, repeatable and statistically sound stratification for environmental monitoring. We applied a two-stage multivariate clustering technique to identify 'EcoAnthromes' across a large area – the province of Alberta, Canada – at 30 m spatial resolution, and using primarily remotely sensed inputs. The EcoAnthrome clusters represent regions with unique ecological characteristics based on a combination of natural ecological potential (e.g., climatic and edaphic factors) and disturbance, both natural and anthropogenic. Compared to existing expert-derived Natural Subregions in Alberta, the model-based EcoAnthromes showed greater class separation and explained more variance for an assortment of variables related to land cover, disturbance and species intactness. The EcoAnthromes successfully separated important ecological regions that are defined by complex assemblages of topography, climate and disturbance, such as gravel-bed river valleys, boreal forests, grasslands, post-fire recovery areas and highly disturbed agricultural, industrial and urban landscapes. In addition to presenting a flexible method for EcoAnthrome regionalization, we group and describe the EcoAnthromes created for Alberta and discuss how they can complement expert-derived regionalizations to aid in environmental management efforts, such as species recovery planning and monitoring for threatened species.

## 1. Introduction

The extent and magnitude of human impact on ecosystems has increased exponentially in response to rapid industrialization – as much as three quarters of Earth's ice-free surface may be human dominated and the majority of wild lands are limited to the coldest and driest biomes (Ellis et al., 2010; though see Sayre et al., 2017 for a critique of this supposition). Humans shape ecosystems at such a scale as to be called a 'force of nature', rivalling the impacts of climate and geology and warranting the proposition of a new geological epoch: the Anthropocene (Ellis and Ramankutty, 2008; Steffen et al., 2011). Maintaining ecosystem integrity to support wildlife and provide environmental goods and services requires consideration of both natural and human ecological forcing (Foley et al., 2005; Martin et al., 2014). Long-term monitoring plans and conservation efforts need to account for interactions between anthropogenic disturbances and natural drivers of ecological processes (Martin et al., 2014); however, ecological regionalization frameworks (e.g., ecoregions) rarely include anthropogenic activities and influences in their delineation of unique environments.

Ecological regionalization maps are heavily utilized tools in environmental management and monitoring because they provide a useful context for understanding ecological patterns and processes by separating broad environments into smaller regions that each have distinct biotic and abiotic capacities to support ecosystem health and function (McMahon et al., 2001). Ecoregions are often used as stratifying classes during sampling, as covariates for modeling or to summarize and compare results of data analysis, and they are fundamental to a wide range of environmental management applications, such as conservation and biodiversity monitoring (Guo et al., 2017; Leathwick et al., 2003; Powers et al., 2013) and understanding fire dynamics (Amiro et al., 2000). Historically, qualitative weight-of-evidence approaches have

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https://doi.org/10.1016/j.jenvman.2018.12.076
Received 6 April 2018; Received in revised form 10 December 2018; Accepted 20 December 2018
Available online 08 January 2019

been the primary method used to map ecoregions, for example the Canadian Ecological Framework (Ecological Stratification Working Group, 1995), the ecoregions of the conterminous United States (Omernik and Griffith, 2014) and the terrestrial ecoregions of the world (Olson et al., 2001).

Given the rapid change occurring globally, ecoregion mapping has become more important than ever, and recent work emphasizes the potential to use remotely sensed data for quantitative mapping of ecoregions to enable timely, accurate and repeatable monitoring programs (Fitterer et al., 2012; Hargrove and Hoffman, 2005; Metzger et al., 2013; Snelder et al., 2010; Thompson et al., 2016). To date, most quantitative regionalization approaches have limited their data inputs to environmental variables representing climatic, topographic and edaphic factors (Andrew et al., 2013; Fitterer et al., 2012; Hargrove and Hoffman, 2005; Leathwick et al., 2003; Mackey et al., 2008; Metzger et al., 2013, 2005; Thompson et al., 2016; Trakhtenbrot and Kadmon, 2005).

Human caused disturbance histories (e.g., fires, forest harvesting, industrial and agricultural transformations, etc.) have significant impacts on spatial-temporal patterns of ecological change (Pickell et al., 2014), which in turn can be regionalized to inform management objectives – for example wildlife conservation in a landscape with active resource extraction and recreation. However, examples of regionalizations utilizing data representing natural and anthropogenic disturbances are scant and limited. The few existing examples have generally been at coarse spatial resolution ($\geq 1$ km) and have relied primarily on proxies for disturbance such as population, land use and land cover classes (e.g., Coops et al., 2009; Ellis and Ramankutty, 2008), or have focused solely on forest-change metrics (e.g., Bourbonnais et al., 2017; Powers et al., 2013). The use of discreet proxies and population as disturbance proxies is problematic. For example, in the widely cited publication by Ellis and Ramankutty (2008), anthromes were classified as anthropogenic either as a definition of their land use (e.g., settlements, cropland, rangeland) or based on population density (e.g., populated forests). In some cases, such as the large swaths of remote rangelands where human influence may be inconsequential or non-existent, this approach may result in a substantial overestimation of anthropogenic influence (Sayre et al., 2017). In other areas, human activity is increasing far from population centers (e.g., recreation, hunting, oil and gas exploration, forest harvesting and replanting), and thus anthropogenic influence may be underestimated.

Advances in remote sensing technology and data access now allow for the measurement of both naturally occurring and human generated ecosystem constraints across large areas, over decadal time scales and at fine spatial resolution (Bourbonnais et al., 2017; Pickell et al., 2014; Powers et al., 2013). For example, the NASA Shuttle Radar Topography Mission (SRTM) has provided a void-filled digital elevation model (DEM) at 30 m spatial resolution, critical for derivation of detailed topographic and climate variables. Likewise, the opening of the Landsat satellite archive has enabled mapping of vegetation, forest disturbance and other natural and anthropogenic variables over time and at fine spatial scales (Hermosilla et al., 2015a; White et al., 2017), and satellite imagery of nighttime light emittance can effectively capture the extent of urban (e.g., Zhang et al., 2013) and industrial activity (e.g., Elvidge et al., 2009) with unprecedented precision.

With data available, there is a new opportunity to create regionalization frameworks that integrate massive and complex datasets representing both natural and anthropogenic drivers of ecological conditions, especially at finer spatial scales ($< 1$ km). We present a quantitative, 30 m spatial resolution regionalization for the province of Alberta, Canada as a case study, utilizing primarily remotely sensed inputs that are freely available and account for both environmental and anthropogenic influences and disturbances occurring over time. We use the term ‘EcoAnthromes’ to define this regionalization, integrating the anthrome concept first proposed by Ellis and Ramankutty (2008) with quantitative fine-scale ecological regionalization methods.

We focus our approach on Alberta for several reasons. First, Alberta is biogeographically diverse, with widespread and complex disturbance patterns of both natural and anthropogenic origins. Human alteration of many ecosystems is well documented (e.g., ABMI, 2017) and Alberta is home to 33 endangered or threatened species, with another 17 species of special concern (Government of Alberta, 2014). Second, the province is relatively data rich. The provincial government and the Alberta Biodiversity Monitoring Institute (ABMI) manage large databases of publicly available spatial data related to anthropogenic activities, species distribution and biodiversity. Additionally, annual gap-filled Landsat reflectance mosaics developed for Canada provide a time series of land cover and disturbance-related variables covering the entire province (Hermosilla et al., 2015b).

We applied a two-stage multivariate clustering technique to map EcoAnthromes across the province, representative of the period 2006–2015. EcoAnthromes were compared with the existing Natural Subregions (NSRs) of Alberta for spatial overlap and statistical stratification of important environmental variables (e.g., fire intensity, overall species intactness) and anthropogenic activities (e.g., forest harvesting intensity, nighttime lights). We then group and describe the final EcoAnthromes and discuss the strengths and limitations of our regionalization approach, as well as highlight specific applications, such as species recovery monitoring and range planning.

## 2. Methods

### 2.1. Study area

The province of Alberta encompasses approximately 662,000 $km^2$ in western Canada (Fig. 1). Elevations range from 210 to 3747 m, with high alpine and subalpine areas found in the Rocky Mountains along the southwestern border with British Columbia, giving way to forested foothills and agricultural prairies moving east, and a complex mosaic of mixedwood boreal forest, shrublands and wetlands moving north (Natural Regions Committee, 2006). Alberta is home to an array of National Parks, Provincial Parks and other protected areas, which together cover about 14% of the province. Meanwhile, a legacy of forestry, mining and oil and gas exploration has a led to a dense network of roads, pipelines and seismic lines. When these activities are combined with agricultural and urban development, the ‘footprint’ of direct human land use covers nearly a third of the province (ABMI, 2017). The cumulative impact of these activities, combined with frequent and large forest fires, have resulted in a fragmented mosaic of forest ages and types, benefitting some wildlife species (e.g., coyotes), while also raising concerns about the survival of others (e.g., grizzly bears and woodland caribou) and the general loss of habitat integrity and timber resources (Boulanger et al., 2014; Schneider et al., 2003). The heterogeneous mix of wild- and anthropogenic-dominated landscapes, combined with complex conservation and natural resource extraction goals, make Alberta a fitting study area for applying moderately-high spatial resolution EcoAnthrome mapping techniques.

### 2.2. Data acquisition

For EcoAnthrome-regionalization, 19 variables representing climate, terrain, vegetation, disturbance and human activity were used as inputs for the two-stage clustering process (Table 1). Ten of these variables represent environmental influences on ecosystems, separated into climate and terrain variables. The other nine represent land cover and vegetation, natural and anthropogenic disturbances, and human activities related to access (e.g., roads) and residential/industrial development. Major water bodies and permanent ice were masked prior to all analysis.

#### 2.2.1. Climate

Climate is an important broad-scale stratification variable directly

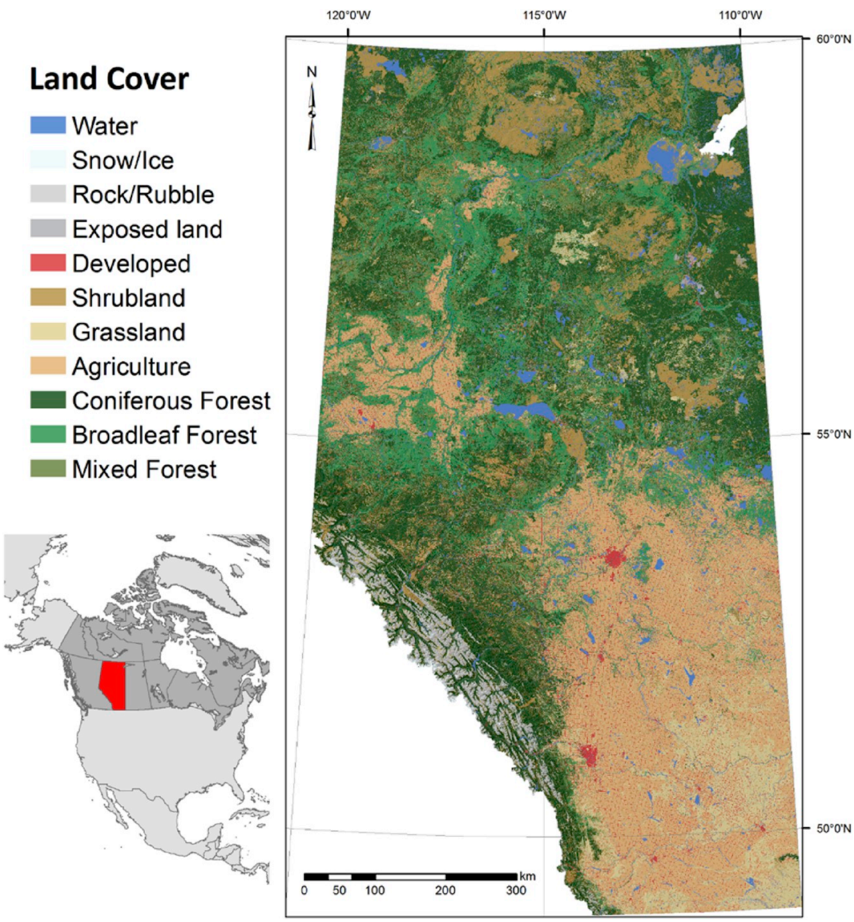


**Fig. 1. Map of the study area**. Land cover map of Alberta, Canada for the year 2010 (ABMI, 2013). Percent of total area by land cover class: Water = 4.5%, Snow/Ice = 0.2%, Rock/Rubble = 1.9%; Exposed land = 0.4%; Developed = 3.9%; Shrubland = 13.1%; Grassland = 9.8%, Agriculture = 19.7%, Coniferous forest = 26.2%, Broadleaf forest = 15.7%, Mixed forest = 4.8%.

related to primary productivity, and is often the principal discriminating input for ecological regionalization (Metzger et al., 2013; Snelder et al., 2010). We created six climate variables using the *ClimateAB* software, which interpolates from weather stations and elevation to create spatially contiguous climate maps (Mbogga et al., 2010). We used a void-filled 30 m DEM (SRTM; downloaded from https://earthexplorer.usgs.gov/) to predict 1971–2000 climate averages for mean annual precipitation (MAP), mean annual temperature (MAT), the temperature difference from mean warmest and coldest months (TD), a summer heat/moisture index (SHM), growing degree days over 5 °C (DD > 5) and chilling degree days below 0 °C (DD < 0).

### 2.2.2. Terrain

Topographic terrain features are an important driver of ecosystems at scales finer than climatic influences. We developed four terrain variables, also from the SRTM-DEM: solar insolation, topographic wetness, topographic position and sediment thickness. Solar insolation provides an estimate of the amount of primary energy received from the sun, accounting for variation in elevation, slope, aspect and shadows. Topographic wetness represents surface water flows and accumulation, and a topographic wetness index (TWI) was calculated as:

$$\mathrm{TWI} = \ln\left(\frac{f}{\tan s}\right) \tag{1}$$

where $f$ is the upslope contributing area in meters and $s$ is slope in radians of a given pixel. Topographic position refers to the location of an area relative to the broader landscape (e.g., ridge-top, valley bottom, plain, etc.). A topographic position index (TPI) was calculated to create a continuous variable representing the difference between the elevation of a given cell and the mean elevation of the surrounding area. The TPI was calculated for an annulus (doughnut-shaped) neighbourhood of pixels at least 4 km and no more than 6 km from the center cell to capture broad-scale physical geomorphic patterns (Weiss, 2001). Sediment thickness was also included as a continuous variable representing parent material and underlying geology. We calculated sediment thickness as the difference between bedrock elevation, as modeled by the Alberta Geological Survey (MacCormack et al., 2015), and surface elevation derived from the SRTM-DEM.

### 2.2.3. Land cover and vegetation

Land cover and vegetation reflect primary productivity potential (e.g., climate and terrain), the impacts of recent and legacy disturbances (e.g., fire, forest harvesting), and feedbacks between the two. Therefore, these variables are critical inputs to account for the current state of ecosystems. To represent land cover and vegetation as continuous variables, several transformations were derived for the 2006–2015 period from best-available-pixel (BAP) proxy composites of surface reflectance from annual Landsat images (TM, ETM+ and OLI sensors) acquired August 1, ± 30 days (Hermosilla et al., 2015b). The BAP proxies were created by analyzing the entire available Landsat time series (1984–2016) choosing the best pixel available based on data quality criteria, flagging data gaps and anomalies (e.g., haze or cloud) and infilling with temporally smoothed proxy values where required to create a gap-free annual surface reflectance composite. We refer readers to Hermosilla et al. (2015b) for a complete description of how BAP proxies were developed.

Tasseled cap transformations of spectral brightness, greenness and wetness were created from the Landsat proxies to account for land cover, vegetation productivity and moisture. These transformations have been shown to outperform common vegetation indices (e.g., NDVI) when analyzing forest disturbance and changes in vegetation structure (Liu et al., 2016). A single set of coefficients was used in the

**Table 1**
Input variables for EcoAnthrome regionalization. List of variables (n = 19) used for EcoAnthrome regionalization (using two-stage clustering), including a description with units (where applicable) and an interpretation of what each variable represents. Information on how variables were developed and relevant references (where applicable) are included in the ‘Comments’.

| | Variable | Description | Interpretation | Comments |
|---|---|---|---|---|
| ENVIRONMENTAL | *Climate* | | | |
| | MAP | Mean Annual Precipitation (mm) | Rainfall | Standard outputs from ClimateAB, 1971–2000 normals (see Mbogga et al., 2010) |
| | MAT | Mean Annual Temperature (°C) | Temperature | |
| | TD | Temperature Difference of warmest and coldest months | Seasonality and ‘continentality’ | |
| | SHM | Summer Heat:Moisture Index | Productivity potential | |
| | DD > 5 | Growing Degree Days (> 5 °C) | Length of growing season | |
| | DD < 0 | Chilling Degree Days (< 0 °C) | Chilling impact | |
| | *Terrain* | | | |
| | INSOL | Solar Insolation | Micro-climate and productivity potential | Output of the *Solar Radiation* tool (ESRI, 2017) |
| | TWI | Topographic Wetness Index | Soil moisture | see Methods section |
| | TPI | Topographic Position Index | Physical geomorphic attributes | Based on Weiss (2001) |
| | SED | Sediment thickness (m) | Parent material and geologic attributes | Difference between surface and bedrock elevation |
| LAND COVER & DISTURBANCE | *Land Cover and Vegetation* | | | |
| | BRT | Average spectral Brightness | Land cover | Tasseled cap indices from Landsat 2006–2015 average proxies (Hermosilla et al., 2015b) |
| | GRN | Average spectral Greenness | Land cover and productivity | |
| | WET | Average spectral Wetness | Land cover and surface moisture | |
| | NBR | Average of Normalized Burn Ratio | Current vegetation structure | NBR calculated as (NIR - SWIR2)/(NIR + SWIR2) from Landsat 2006–2015 proxies (Hermosilla et al., 2015b) |
| | FOR | Forest Connectivity | Forest intactness and fragmentation | Index calculated as density × connectivity of treed pixels (see Riitters et al., 2000) |
| | *Disturbance* | | | |
| | GRN-sd | Standard deviation of spectral Greenness | Recent disturbance of land cover and productivity | Standard deviation from 2006 to 2015 of spectral greenness (see above) |
| | NBR-sd | Standard deviation of Normalized Burn Ratio | Recent disturbance(s) to vegetation structure | Standard deviation from 2006 to 2015 of NBR (see above) |
| | *Human activity* | | | |
| | NTL | Nighttime lights disturbance index | Built infrastructure, night time activity | Index calculated from 2006 to 2013* average nighttime lights (NTL) satellite data |
| | ACC | Access disturbance index | Human accessibility and activity | Index calculated from weighted access features (see Table 2 for weights) |

**Table 2**
Percent area of each Natural Subregion and protected area within each EcoAnthrome. Columns indicate the percent of each EcoAnthrome (cut at 21 clusters) with protected status (first row), and the breakdown of the percent area of each EcoAnthrome by Natural Subregion (NSR). Note that breakdown by NSR may not total 100 percent due to rounding.

| | EcoAnthromes | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* | *13* | *14* | *15* | *16* | *17* | *18* | *19* | *20* | *21* |
| ***Protected area*** | 2 | 5 | 3 | 48 | 0 | 0 | 3 | 0 | 41 | 16 | 3 | 2 | 79 | 83 | 0 | 49 | 1 | 56 | 80 | 2 | 22 |
| ***Natural Subregions*** | | | | | | | | | | | | | | | | | | | | | |
| Northern Mixedwood | | 4 | 4 | 19 | | | | | 17 | 16 | | | | | | | | 11 | | 13 | 5 |
| Kazan Uplands | | | | 9 | | | | | 5 | 1 | | | | | | | | 13 | | | 5 |
| Boreal Subarctic | | | 2 | 11 | | | | | 7 | 3 | | | | | | | | 2 | | 6 | 2 |
| Lower Boreal Highlands | 1 | 23 | 22 | 10 | 2 | 1 | | | 18 | 18 | | 3 | | | | | | 2 | | 28 | 3 |
| Central Mixedwood | 14 | 55 | 56 | 28 | 9 | 6 | | 1 | 36 | 35 | 9 | 50 | | | | | 4 | 18 | | 39 | 20 |
| Peace-Athabasca Delta | | 1 | | 4 | | | | | 1 | | | | | | | | | 1 | | | 4 |
| Athabasca Plain | | 1 | | 6 | | | | | 4 | 1 | | | | | | | | 49 | | | 2 |
| Dry Mixedwood | 24 | 11 | 14 | 6 | 41 | 21 | 3 | 18 | 4 | 4 | 2 | 20 | | | | | 10 | | | 11 | 9 |
| Upper Boreal Highlands | | 4 | 1 | 6 | | | | | 8 | 4 | | | | | | | | 4 | | | 1 |
| Peace River Parkland | 1 | | | | 2 | 2 | | 1 | | | | | | | | | 3 | | | 1 | 1 |
| Lower Foothills | 15 | 2 | | | 4 | 5 | | | | 10 | 43 | 25 | | 1 | | 1 | 2 | | | | 1 |
| Upper Foothills | 6 | | | | 1 | 5 | | | | 7 | 29 | 1 | | 6 | | 10 | 1 | | | | |
| Subalpine | 2 | | | | | 1 | | | | 1 | 11 | | 17 | 71 | | 76 | | | 34 | | |
| Alpine | | | | | | | | | | | | | 83 | 7 | | 10 | | | 65 | | |
| Montane | 5 | | | | | | 1 | | | | 5 | | | 16 | | 3 | 1 | | 1 | | 1 |
| Central Parkland | 21 | | | | 29 | 15 | 5 | 40 | | | | | | | | | 20 | | | 1 | 19 |
| Northern Fescue | 4 | | | | 5 | 17 | 6 | 4 | | | | | | | 2 | | 4 | | | | 8 |
| Dry Mixedgrass | 1 | | | | | 22 | 61 | 8 | | | | | | | 59 | | 29 | | | | 9 |
| Foothills Fescue | 3 | | | | 3 | 2 | 6 | 14 | | | | | | | 6 | | 9 | | | | 4 |
| Foothills Parkland | 3 | | | | 1 | | | 1 | | | | | | | | | 4 | | | | 1 |
| Mixedgrass | 1 | | | | 2 | 2 | 17 | 12 | | | | | | | 33 | | 13 | | | | 5 |

tasseled cap transformation to maintain consistency across Landsat sensors (Liu et al., 2016; Table A1). The normalized burn ratio (NBR; Key and Benson, 2006) was also calculated to represent disturbance, recovery and structure of vegetation. NBR has been shown to be better related to structural complexity and long-term forest recovery following disturbance compared to other vegetation indices (Pickell et al., 2016). Finally, an index representing forest connectivity and fragmentation was calculated as the product of the density and connectivity of treed cells within a 33 × 33 cell window (~100 ha), following methods described by Riitters et al. (2002). Treed cells were identified as cells within treed classes based on Landsat-derived land cover for the 2006–2015 period (Hermosilla et al., 2018).

### 2.2.4. Disturbance

We analyzed the year-on-year changes in vegetation from the Landsat time series to account for historical disturbances that influence ecosystem function. To do this, we calculated the standard deviation of tasseled cap greenness and NBR over the 2006–2015 period. In this manner, we account for the frequency and magnitude of changes within herbaceous and forest-dominated vegetative land covers, which can include year-on-year variation (e.g., annual cropping), vegetation losses (e.g., forest harvesting) and new growth (e.g., reforestation, fire recovery).

### 2.2.5. Human activity

The land cover, vegetation and general disturbance variables capture detailed variation in land cover over space and time, however they do not distinguish between anthropogenic and natural influences. Therefore, two indices were developed to characterize anthropogenic activity beyond the disturbance and alteration of vegetation.

The first index utilized nighttime lights (NTL) data captured by the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS), and represents urban, built-up and electrified infrastructure and associated activity. NTL data was first calibrated, resampled to 30 m resolution and corrected for vegetation and bare ground using Landsat-derived tasseled cap greenness and the normalized bare lands index (Li et al., 2017), respectively, following methods similar to those proposed by Zhang et al. (2013). The NTL disturbance index was then calculated based on the proximity, density and intensity of corrected NTL values surrounding a given cell. Proximity was calculated as the nearest cost-weighted distance (m) to a cell with a positive NTL value, with change in elevation and aspect included as 'cost' variables. A maximum distance of 12,616 m was imposed to roughly delineate the maximum distance at which an urban area would directly influence wildlife and habitat. This distance was chosen to correspond with the home range of an average adult female grizzly bear (Alberta Environment and Parks, 2016), representing a threatened species in Alberta with a large home range. An exponential decay function was then applied to the proximity value to reflect findings that proximity impacts of roads and other human features on wildlife tend to decline nonlinearly as distance to the feature increases (e.g., Eigenbrod et al., 2009; Rogala et al., 2011). Density was calculated as the sum total of pixels, weighted by their intensity (NTL value) within a 7440 m search window, the approximate distance an adult female grizzly travels in a day. The proximity and weighted density values were each rescaled from 0 to 500 according to their respective minimum and maximum values and added together, producing a final index scaled from 0 to 1000.

The second disturbance index represents ease of access to and utilization of the landscape by people. This index was calculated based on the proximity, density and intensity of select access features surrounding a given cell. Access features were mapped by the Government of Alberta (2017a), and we used the same method to calculate the access disturbance index as that described for the NTL disturbance index, except that weights were assigned based on feature type and their relative expected facilitation of access. Feature types and their weights are given in Table A2. Of the 19 input variables, the access index is the only variable that was not based solely on remotely sensed data, as it also relies on GPS data, hand delineation and digitization.

## 2.3. EcoAnthrome regionalization

We used two-stage multivariate clustering to perform the regionalization, with the first step generating pre-clusters using a one-pass '*k*-means + +' algorithm, followed by agglomerative hierarchical clustering on the centroids produced by the *k*-means pre-clustering step (Tamura et al., 2014). Multivariate agglomerative clustering is one of the most common quantitative ecological regionalization procedures (Snelder et al., 2010) and the two-stage approach has been successfully applied for ecosystem-related classification in Canada (Coops et al., 2009; Fitterer et al., 2012; Guo et al., 2017; Thompson et al., 2016) and elsewhere (Leathwick et al., 2003).

Prior to the initial *k*-means stage, outliers were removed and all variables were re-scaled. To handle the very large dataset arising from 30 m spatial resolution across a large geographic extent and 19 input variables, we used a mini-batch process to read the dataset in chunks and perform clustering out of core. The dataset was first shuffled and batches selected randomly to avoid spatial bias. The initial number of *k*-means pre-clusters was set at 1001 to ensure an input of centroids to the hierarchical clustering stage that was much larger than the desired number of final clusters.

Hierarchical clustering was performed using the 'Ward' linkage algorithm (Murtagh and Legendre, 2014; Ward, 1963) and Euclidian distances between pre-cluster centroids. The resulting dendrogram was then cut at 21 clusters using dynamic tree cutting to prune branches based on their shape, rather than a fixed height (Langfelder et al., 2008). Pruning was undertaken by iteratively adjusting the maximum allowable proportional scatter of clustered objects until 21 clusters was achieved, and the final map was filtered to remove singletons and very small groupings (< 3 conterminous pixels). We chose to prune the dendrogram at 21 EcoAnthrome clusters (i.e., regions) to facilitate comparison against the 21 expert-derived NSRs of Alberta.

### 2.4. Comparison of EcoAnthromes and Natural Subregions

We compared spatial overlap and areal land cover distribution for the EcoAnthromes and NSRs to evaluate how they differ, and better understand the heterogeneity within NSRs. We expected that large NSRs in areas prone to frequent fire and industrial expansion would be comprised of a large number of EcoAnthromes and land cover classes, indicating that some NSRs are highly heterogeneous and may be less suitable for certain applications.

Overlap was evaluated in two ways: (1) a simple spatial overlap as the total area of each class (i.e., EcoAnthrome cluster or NSR) from one regionalization approach within each class of the other approach, and (2) the diversity of overlap as the diversity of classes from one regionalization within each class of the other. In the latter relationship, higher diversity indicates lower correspondence between maps (Thompson et al., 2016). Diversity was calculated as Simpson's Diversity Index:

$$D = 1 - \frac{\sum n(n-1)}{N(N-1)} \tag{2}$$

where $n$ is the number of classes from the comparative regionalization approach within an individual class of the approach being evaluated, and $N$ is the total number of classes in the evaluated approach.

We also compared NSR and EcoAnthrome distinctness across important environmental and anthropogenic variables (see Table 2 for a list of variables), as well as for the 2010 ABMI land cover map. Region distinctness was evaluated based on the variance of each variable explained by each map. We analyzed, in turn, all of the input variables used for the EcoAnthrome clustering, as well as three other metrics: two related to specific disturbance types and one related to wildlife integrity. The two specific disturbance metrics represent fire and forest harvesting events in the last 30 years. The fire and forest harvest variables were calculated as the intensity of change in NBR attributed to each type of disturbance, respectively, as identified using annual Landsat proxies (Hermosilla et al., 2015a). The two variables were rescaled from 0 to 1000 based on the minimum and maximum and take into account the entire time series going back to 1986, but weight more recent events more heavily. The third metric represents overall species intactness as mapped by ABMI (2014). Species intactness ranges from 0 to 100%, with 100% being the abundance expected in an area without anthropogenic disturbance. The overall value accounts for different responses to anthropogenic disturbance as modeled for different species.

To calculate indicators of explained variance of a given variable for each regionalization, linear regression analysis was performed on a stratified random sample of values of each variable taken for each EcoAnthrome cluster, NSR and land cover class. The sample size was set at approximately one percent of all grid cells within each cluster or NSR, with the condition that at least 10,000 cells, and no more than 1,000,000 cells be sampled. Each variable was used, in turn, as the response variable and the categorical regionalization set up as contrasts. The coefficient of determination ($R^2$) and residual standard error (RSE) were then evaluated as indicators of the variance of each variable explained by the EcoAnthrome clusters and NSRs, respectively. Boxplots were also created for each variable and compared to the overall mean value across all classes to visualize separation between classes.

Total area, stratified by 2010 land use (ABMI, 2013), was calculated for each NSR and each EcoAnthrome cluster to compare the sizes and composition of regions within and between the two regionalization approaches. The percentages of each EcoAnthrome within each NSR and with protected status, as mapped by Global Forest Watch Canada (2012), were also calculated.

### 2.5. Multivariate analysis of EcoAnthromes

In order to characterize the conditions represented by EcoAnthromes, we assessed land use by cluster and used multivariate analyses to visualize how clusters differed by climate, terrain, vegetation and disturbance. A heatmap of scaled input variables was aligned with the dendrogram from the hierarchical clustering step to visualize the relative values of each input variable by cluster and understand the hierarchical structure of the clustering. Lastly, principal component analysis (PCA) was performed to assess how the input variables are related to each other, and to three additional metrics (fire, harvest and species intactness), across the final EcoAnthrome clusters.

### 2.6. Software

Data pre-processing and k-means pre-clustering were performed using *ArcPy* (Esri, 2014) and the *scikit-learn* package (Pedregosa et al., 2012) in Python v2.7. Hierarchical clustering, regression and PCA were performed using the *stats* packages in R v3.4.1 (R Core Team, 2016). Dynamic branch pruning of the dendrogram to arrive at the final 21 clusters was performed using the R package *dynamicTreeCut* (Langfelder et al., 2008).

## 3. Results

### 3.1. EcoAnthrome regionalization

The dendrogram of the initial 1001 pre-clusters is shown in Fig. 2, split into 21 clusters (numbers are randomly assigned), where each cluster represents a unique EcoAnthrome. Three broad groups are evident based on the branching structure and the input variable heatmap (Fig. 2). These three broadest branching groups, highlighted in red, roughly correspond to: Group 1 – areas in colder, extreme climates with low levels of disturbance; Group 2 – areas with higher forest connectivity and varying levels of disturbance, and; Group 3 – areas in warmer climates with very low forest connectivity and high disturbance. Group 2 is the largest, comprising about 44.6% of Alberta's land area, while Groups 1 and 3 made up 16.8% and 38.6% of land

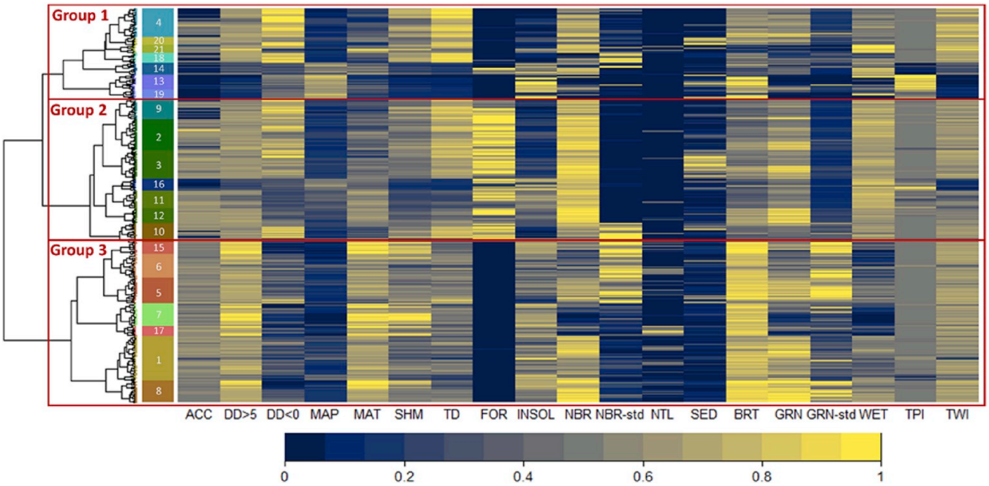


**Fig. 2. Final dendrogram cut at 21 clusters and heatmap of scaled input variables.** The dendrogram is the output of hierarchical clustering on 1001 k-means pre-clusters. Three broad groupings are highlighted by red rectangles and the final EcoAnthrome cluster assignment (n = 21) shown in colored bars, labeled by cluster number. Cluster colors correspond to the map in Fig. 3 and are relative to the most disturbed (red), most vegetated (green) and coldest/wettest (blue) clusters. Color value (i.e., brightness) is adjusted such that darker areas indicated increasing forest connectivity. The heatmap grid shows the rescaled value (0–1) of each input variable (columns) for each pre-cluster (rows). The codes for the input variable are given in Table 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

area, respectively. The final 21-cluster EcoAnthromes (Fig. 3) resulted in spatial patterns reflecting both land cover (Fig. 1) and the expert-derived NSRs (Fig. A1).

EcoAnthrome clusters 13, 14, 18 and 19 are mostly within protected areas (> 50%), while clusters 4, 9, 10 and 21 include some protected areas and the remaining clusters are mostly outside of protected areas (Table 2). Most protected areas (61%) correspond to Group 1, with roughly a third in Group 2 and less than 5% in Group 3. In general, EcoAnthrome clusters with greater anthropogenic disturbance (e.g., clusters 1, 15, 17) are spread across more NSRs, while clusters with lower anthropogenic disturbance – located predominantly in the more climatically extreme, rugged and protected areas (e.g., clusters 2, 3, 13, 14) – are more correspondent with a single NSR (Table 2).

### 3.2. Comparison of EcoAnthromes and Natural Subregions

Diversity of EcoAnthrome clusters was high (low class agreement) across nearly all NSRs (Fig. 4). The mixedwood NSRs were the most diverse in terms of EcoAnthromes, while the Foothills Parkland and Alpine NSRs were the least diverse (Fig. 4 and Table A3). Larger NSRs were more likely to be more diverse, though exceptions did exist (e.g., the Peace River Parkland).

The EcoAnthromes provided greater separation and explained more variance for the majority of vegetation and disturbance-related cluster input variables and the three other metrics compared to the NSRs, while maintaining moderate separation for climate input variables (Table 3, Figs. A2 and A3). The NSRs explained more variance of all climate and terrain variables except topographic position (TPI) and sediment thickness (SED). The largest difference between the two regionalizations were for disturbance of vegetation structure (NBR-sd) and forest connectivity (FOR), where the EcoAnthromes reduced RSE by 50% and 48%, respectively, and for growing degree days (DD > 5) and the summer-heat moisture index (SHM), where the NSRs reduced RSE by 78% and 51%, respectively (Table 3). Land cover classes alone explained little variance across all variables tested, but in general was more strongly related to climate, terrain and vegetation than to disturbance variables.

As anticipated, the EcoAnthromes more strongly reflected patterns in land cover classes compared to the NSRs (Fig. 5; also see Figs. 1 and 3 and Fig. A1). Few of the NSRs are dominated by a single land cover classes. Many are composed of mixed forest types along with shrubland, or combinations of agriculture and grassland. By contrast, several of the EcoAnthrome clusters represent relatively homogenous land cover types, especially those that are highly disturbed (e.g., Clusters 5, 8, 15 and 17 are primarily agriculture or developed) or relatively undisturbed (e.g., Clusters 13 and 19 are mostly barren; Clusters 9, 11 and 16 are mostly coniferous forest; and Cluster 12 is mostly broadleaf forest). EcoAnthromes with intermediate disturbance tended to be composed of more land cover classes.

### 3.3. Multivariate analysis of EcoAnthromes

Each principal component (PC) represents unit-scaled linear combinations of all the input variables used in the analysis, and they are transformed such that the first PC accounts for the largest possible variance in the dataset, the second for the largest possible remaining variance, and so forth. The first three PCs explained the majority of variance in the EcoAnthrome dataset (Fig. 6), and each of the other PCs composed < 7% of total variance (data not shown). Each PC rotation can be analyzed based on the loadings of the original variables (Table A4). Loadings are essentially a coefficient (positive or negative) indicating the weight of each variable on each PC, and variables with strong loadings (i.e., further from zero) within a PC capture a large portion of the dataset's variance and are strongly related to each other.

Along the first PC rotation, climate variables related to warmer temperature (e.g., DD > 5, MAT, INSOL) and standard deviation of greenness (GRN-sd) had strong negative loadings, while chilling degree-days (DD < 0), forest connectivity (FOR) and species intactness (SPP) had strong positive loadings (Fig. 6 and Table A4). This PC highlights the differences between areas most suitable for agriculture – those with lower values for PC 1 (e.g., Clusters 5, 15 and 17) – and other colder and less-arable climates with higher values (e.g., Clusters 2, 3 and 4).

Along the second PC rotation, the strongest loadings are related to climate and topographic wetness (TWI), with strong positive loadings for variables related to climate seasonality (e.g., TD, SHM) and TWI, and strong negative loadings for MAP. EcoAnthromes with low values along the second PC axis have low seasonality compared to the rest of the province – most notably in the alpine and subalpine areas (clusters 13 and 14) where precipitation is consistently high and temperatures consistently cool, and, to a lesser extent, in the foothills (clusters 11 and 12). Areas with positive values on the PC 2 axis have high seasonality, and can be separated into clusters with longer, hotter summers (e.g., clusters 7 and 15 in the far south) and clusters with longer, colder winters (e.g., cluster 4 in the far north).

The third PC rotation represents strong negative loadings for variables related to vegetation productivity (GRN, NBR,WET), human access features (ACC) and nighttime lights (NTL). Moderately negative loadings were also present for forest connectivity and temperature,

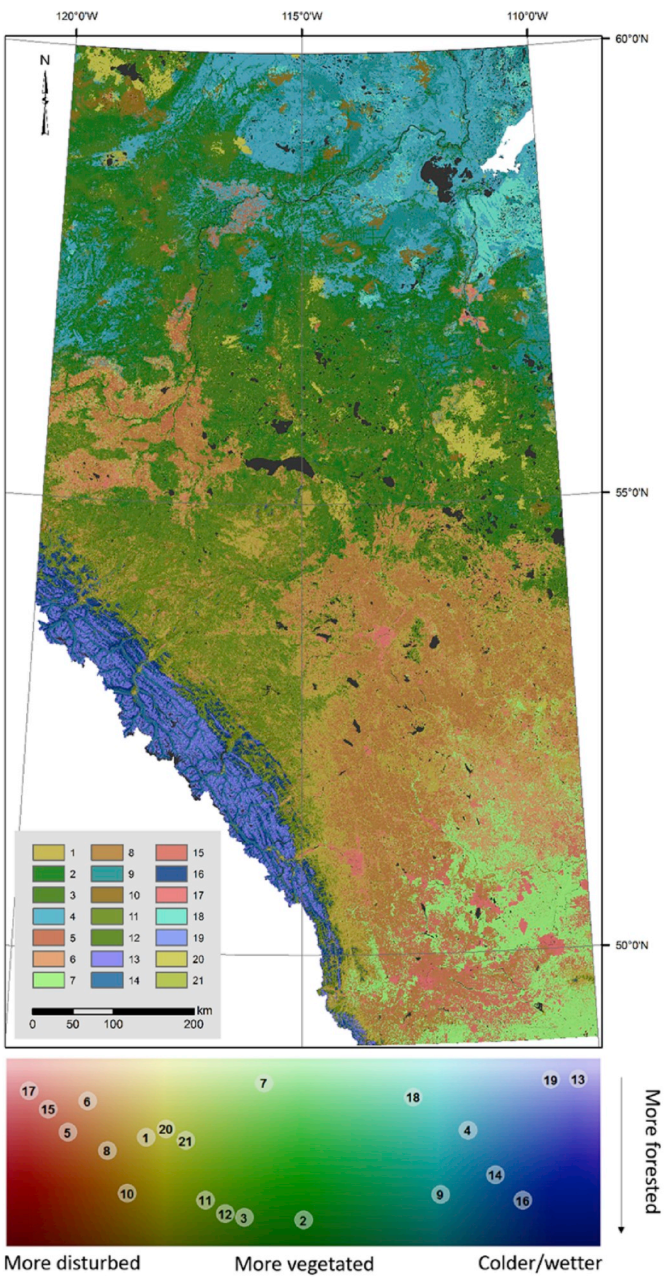


**Fig. 3. EcoAnthrome regionalization of Alberta with 21 clusters**. Output of the two-stage clustering algorithm (cut at 21 clusters), using vegetation, disturbance and human activity input variables (see Table 1 for a complete list). Numbers are randomly assigned to each EcoAnthrome. Colors are discreetly assigned to each cluster within the color space, such that red indicates increasing human activity and disturbance, green indicates increasing vegetation greenness, and blue indicates increasing precipitation and decreasing temperature. The color value (i.e., brightness) is adjusted such that darker colors indicate higher forest connectivity. Black areas are a mask of large waterbodies and ice fields. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

whereas moderately positive loadings were found for species intactness (SPP). EcoAnthromes with positive loading on this PC therefore represent areas with low forest connectivity, low human disturbance and high species intactness, such as those representing recent fire disturbance (clusters 10, 18 and 20), alpine regions (clusters 13 and 14), and natural grasslands (cluster 7). Areas with negative values for this PC likely represent areas of high natural forest productivity, overlapping with widespread anthropogenic activity.

Plotting these PC's together shows distinct patterns among the EcoAnthromes. For example, in Fig. 6b, the lower right quadrant (positive for PC 1 and negative for PC 3) represents clusters with low anthropogenic disturbance and high forest productivity and connectivity, whereas the lower-left quadrant represents clusters with high levels of disturbance and high forest productivity, but low connectivity – likely forests managed for logging. The upper two quadrants in Fig. 6b are clusters with low forest productivity. Highly disturbed grasslands and agriculture are in the upper-left quadrant, and extremely cold alpine outcrops and subarctic shrublands are in the upper-right. Fig. 6c shows recently fire-disturbed EcoAnthromes in the upper-right quadrant, where seasonality is high and current forest productivity low. Variability between and within the three broad cluster groups can be seen in Fig. 7 and the Supplementary Material.

## 4. Discussion

### *4.1. Description of EcoAnthromes*

Our EcoAnthrome mapping approach highlights three distinct types or groups of ecological conditions in Alberta. The first broad group consists of areas with low levels of human impact, located in the extremely cold, barren, sodden, or high-elevation regions (e.g., alpine, subalpine, subarctic, rocky and wetland areas), or within protected parks. Here, species intactness tends to be high (see Fig. 7e), likely due to minimal anthropogenic disturbance. Forest connectivity is generally low due to climatic and soil limitations and/or frequent or recent fires. One exception is cluster 14, which represents the montane valleys of the Rocky Mountains, many of which are found within protected parks.

The second broad group includes mostly forested areas with intermediate levels of disturbance relative to the other two broad groups. Forest connectivity and species intactness is generally high, but variable, as these areas include clusters with different forest types and varying levels of disturbance. These areas represent the modern nexus between anthropogenic and wild ecosystems, and are perhaps the most important areas for EcoAnthrome mapping and monitoring. They are rapidly changing as new infrastructure is developed and natural resource extraction continues, resulting in increased landscape change with potential impact on habitat, biodiversity and ecosystem function. Furthermore, they tend to be managed for complex and, at times, contrasting outcomes, such as wildlife conservation, recreation, ecosystem services such as carbon and water storage and resource development.

The third broad group includes areas with widespread and intensive human activity, largely in the form of urban and agricultural centers and industrial sites such as mining, oil and gas and forestry. These EcoAnthromes are widespread across the flatter, warmer and more arable landscapes such as the grassland, parkland and lower foothills areas. They are, however, more geographically fragmented and concentrated around urban, agricultural and industrial centers. Here forest connectivity and species intactness is generally low, and many of these areas may be ‘novel’ ecosystems that are unlikely to occur in the absence of anthropogenic activity (Morse et al., 2014).

Within each of the three EcoAnthrome groups, we can find distinct sub-groupings and gradients across individual EcoAnthromes. For example, within the mostly forested EcoAnthromes in Group 2 there is both a productivity gradient, corresponding to changes in climate, and a fragmentation gradient, generally corresponding to increasing anthropogenic disturbance within the most productive forests in the Rocky Mountain foothills adjacent to protected parks. These gradients highlight how the EcoAnthromes approach differs from a land cover map (e.g., Fig. 1) where differences in productivity or disturbance are not captured within a single land cover (e.g., coniferous forests). A complete description of the 21 individual EcoAnthromes is provided in the Supplementary Material.

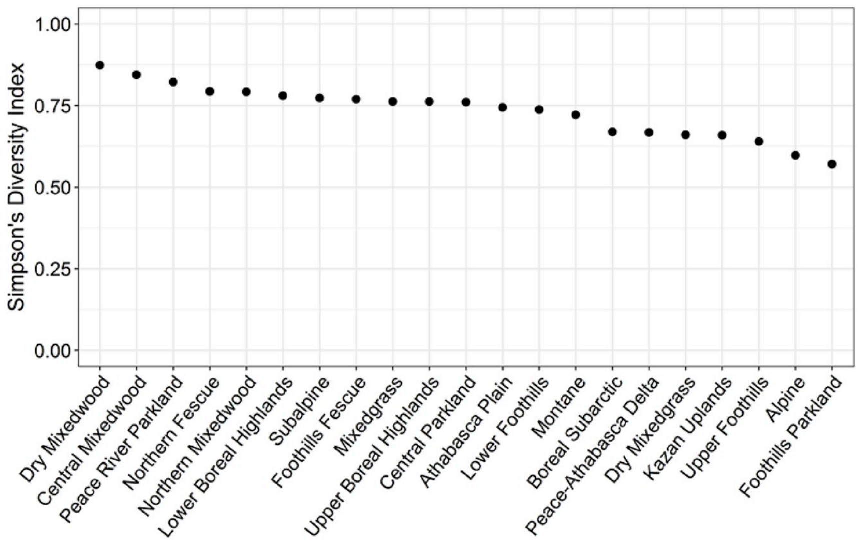


**Fig. 4. Diversity of EcoAnthromes within each Natural Subregion**. Simpson's diversity index of EcoAnthrome clusters within each of the Natural Subregions of Alberta, ordered by decreasing diversity.

### 4.2. Ecological patterns captured by EcoAnthromes

The broad EcoAnthrome groups in Alberta reflect the pattern of anthropogenic activity observed at the global scale – essentially, wildlands in which anthropogenic disturbance is absent primarily exist only in extremely cold, dry or barren landscapes, or within protected areas (Ellis et al., 2010). Within Alberta, these areas tend to coincide, meaning that the protected landscapes are relegated to some of the least productive and potentially least biodiverse regions, again reflecting patterns observed within Canada (Andrew et al., 2011) and globally (Martin et al., 2014; ONeill and Abson, 2009). The area of the anthropogenic EcoAnthromes in Group 3 exceeds that of Developed, Agricultural and Barren/Exposed land covers (Fig. 1) by over 90,000 km$^2$ (about 14% of Alberta's land area), demonstrating how estimates of human disturbance based on land cover alone may be misleading.

Multi-variate analysis of ecological drivers and outcomes shows how ecological patterns are being strongly driven by human activities, and how the EcoAnthromes capture both anthropogenic and natural patterns. Remotely sensed vegetation indicators were more strongly

**Table 3**

Explained variance of environmental and land-cover/disturbance variables by regionalization. Results are from regression analysis for each dependent variable, with each regionalization/classification used separately as the independent variable. $R^2$ is the coefficient of determination of each regression test. Natural Subregions were developed by Natural Subregions Committee (2006) and 2010 Land Cover classes were developed by ABMI (2013). Variable descriptions and units are provided in Section 2 and in Table 1.

| | Variable | EcoAnthromes | Natural Subregions | Land Cover (2010) |
|---|---|---|---|---|
| | | ***$R^2$*** | | |
| ENVIRONMENT | *Climate* | | | |
| | Mean Annual Precipitation (MAP) | 0.66 | 0.81 | 0.02 |
| | Mean Annual Temperature (MAT) | 0.75 | 0.84 | 0.24 |
| | Temperature Difference (TD) | 0.74 | 0.82 | 0.11 |
| | Summer Heat:Moisture Index (SHM) | 0.59 | 0.83 | 0.14 |
| | Growing Degree Days (DD > 5) | 0.73 | 0.92 | 0.08 |
| | Chilling Degree Days (DD < 0) | 0.74 | 0.80 | 0.28 |
| | *Terrain* | | | |
| | Solar Insolation (INSOL) | 0.63 | 0.72 | 0.16 |
| | Topographic Wetness Index (TWI) | 0.45 | 0.54 | 0.22 |
| | Topographic Position Index (TPI) | 0.61 | 0.22 | 0.00 |
| | Sediment thickness (SED) | 0.57 | 0.13 | 0.05 |
| LAND COVER & DISTURBANCE | *Land Cover and Vegetation* | | | |
| | Average spectral Brightness (BRT) | 0.69 | 0.48 | 0.03 |
| | Average spectral Greenness (GRN) | 0.64 | 0.40 | 0.13 |
| | Average spectral Wetness (WET) | 0.73 | 0.45 | 0.16 |
| | Average of Normalized Burn Ratio (NBR) | 0.72 | 0.45 | 0.19 |
| | Forest Connectivity (FOR) | 0.84 | 0.39 | 0.08 |
| | *Disturbance* | | | |
| | Standard deviation of GRN (GRN-sd) | 0.72 | 0.38 | 0.01 |
| | Standard deviation of NBR (NBR-sd) | 0.71 | 0.15 | 0.03 |
| | *Human Activity* | | | |
| | Nighttime lights disturbance index (NTL) | 0.30 | 0.24 | 0.00 |
| | Access disturbance index (ACC) | 0.50 | 0.49 | 0.07 |
| OTHER | *Other Metrics* | | | |
| | Fire intensity (FIRE) | 0.40 | 0.13 | 0.01 |
| | Harvest intensity (HRVST) | 0.07 | 0.05 | 0.00 |
| | Species Intactness (SPP) | 0.63 | 0.52 | 0.17 |

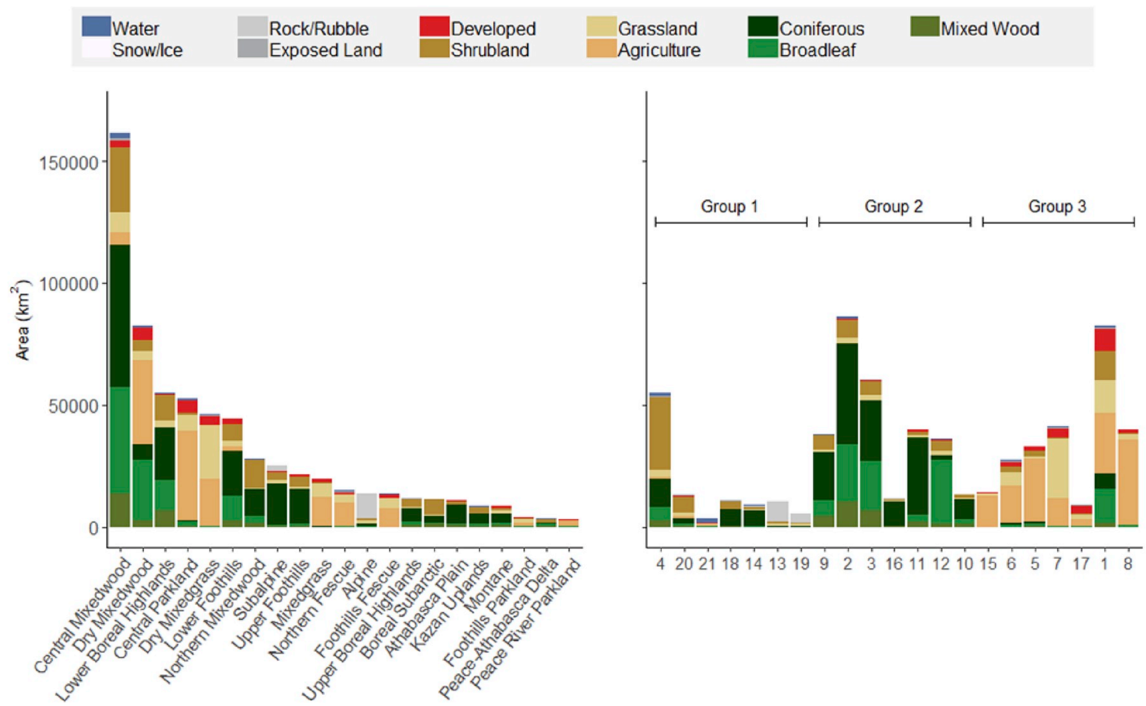


**Fig. 5. Land cover distribution of Natural Subregions and EcoAnthromes**. Area of each Natural Subregion (left) and EcoAnthrome cluster (right), stratified by 2010 land cover classes (ABMI, 2013). Natural Subregions are ordered by total area. EcoAnthrome clusters are ordered by group (also see dendrogram in Fig. 2). Color legend corresponds with Fig. 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

related to human activity than to climatic gradients, indicating that anthropogenic disturbance is a key driver of vegetation structure and composition. This trend is especially strong in warmer areas with a longer growing season, where vegetation productivity is highest and agricultural production and forest harvesting are profitable. Within these regions, species intactness was strongly related to forest connectivity, and inversely related to remotely-sensed indicators of anthropogenic disturbance (e.g., GRN-sd, NTL). Species intactness is highest outside of these productive areas, in the coldest regions where seasonality is high and winters are long and cold.

Geographic fragmentation was observed for disturbance-driven EcoAnthromes. These include fire-related disturbances (e.g., Clusters 10, 18 and 20) and anthropogenic activity (e.g., Clusters 5, 6, 15 and 17). Both of these groups span relatively large areas and climatic ranges (see Fig. 3 and Fig. A2) and represent ecosystems that are not well captured by traditional regionalization approaches. The anthropogenically-driven group includes impacted and potentially novel ecosystems that would not otherwise exist in the absence of human intervention (Morse et al., 2014). These, as well as the more anthropogenically disturbed and fragmented clusters from Group 2 (e.g., Clusters 10, 11 and 12), could be good candidates for future research on how ecosystems and individual species are responding to direct human impacts. Meanwhile, other EcoAnthromes could act as important reference sites and locations to study less direct human impacts, such as climate change. Assessments of how species assemblages differ between EcoAnthromes would elucidate the magnitude and permanence of anthropogenic ecosystem impacts.

### 4.3. Strengths, limitations and applications of the EcoAnthromes approach

While qualitative approaches do offer distinct benefits (Omernik and Griffith, 2014), it is not practical to update expert-delineated maps frequently to reflect recent ecosystem changes, or to assess change over time. The temporal and spatial resolutions afforded by a quantitative remote-sensing based regionalization can complement expert-based approaches to support numerous applications for which this information is required. For example, species recovery planning and monitoring for grizzly bears and range planning efforts for woodland caribou – both of which are listed threatened species in Alberta – could integrate EcoAnthrome classifications into habitat models. The spatial resolution of our classification enables analysis of connectivity within and between distinct ecological regions and could support the prioritization needs of decision makers, such as where to undertake highway mitigations for wildlife permeability (Alberta Environment and Parks, 2016). The EcoAnthromes will also support efforts to understand the cumulative impacts of different disturbance types on wildlife. This is a key component for setting disturbance thresholds such as those under development in Alberta's Provincial Woodland Caribou Range Plan (Government of Alberta, 2017b).

It is worth noting that characterizing landscapes around anthropogenic influence could have unintended consequences if interpretation and application is not carried out in tandem with other contextual information. For example, some decision makers may seek to push future development into more disturbed areas in order to protect more 'natural' habitat elsewhere, potentially at the expense of less charismatic species that are thriving in that area despite the influence of (or as a result of) human activity. Additionally, using linear access and electrified features as proxies for anthropogenic actions may not capture foraging, hunting and other subsistence activities taking place in areas we have highlighted as relatively 'untouched'. Efforts to protect such areas (e.g., for species conservation) may undermine the ability of indigenous peoples to carry out traditional practices. However, these potential pitfalls of EcoAnthrome interpretation are not inherent to the clustering process, and any number of variables could be included the regionalization for specific applications.

Our quantitative clustering approach utilized primarily remotely sensed inputs, offering some level of objectivity and repeatability. The majority of the data we used as inputs was derived from freely available satellite imagery and could therefore be developed for any area globally, including data-poor and remote regions. Our area of interest, the province of Alberta, experienced widespread and intensive vegetation disturbances during the study period and contains an extensive amount

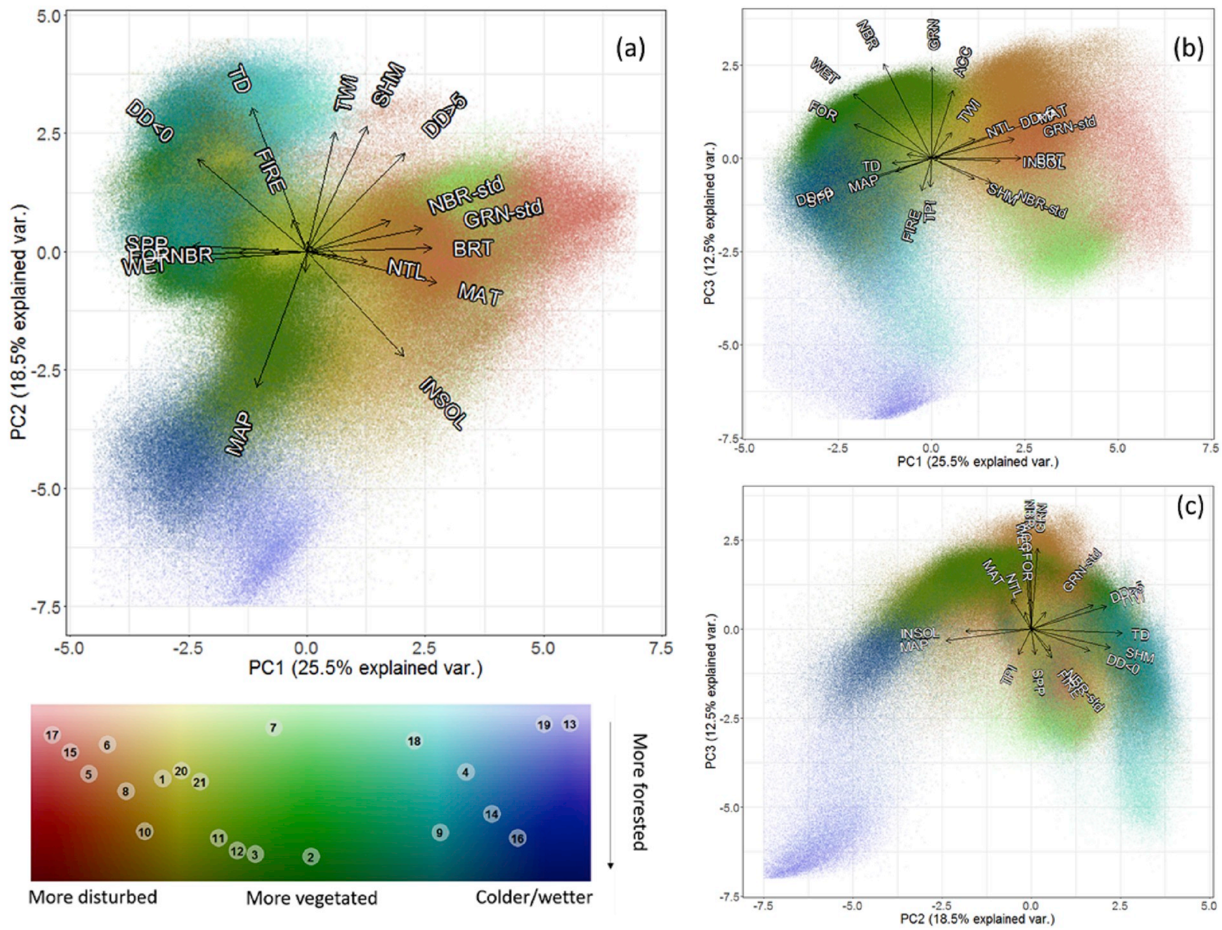


**Fig. 6. Distance bi-plots of the first three principal components (PC's) of inputs and metrics**. Bi-plots are (a) PC 1 vs. PC 2, (b) PC 1 vs. PC 3, and (c) PC 2 vs. PC 3. Colored points represent a stratified random sample of cells within each cluster. The color legend corresponds to the map in Fig. 3 and is relative to the most disturbed (red), most vegetated (green) and coldest/wettest (blue) clusters. Color value (i.e., brightness) is adjusted such that darker areas indicated increasing forest connectivity. Variable abbreviations are given in Table 2. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of electrified infrastructure detectable with NTL imagery. In regions where anthropogenic disturbance concerns are less associated with changes in vegetation or electrified infrastructure (e.g., non-point source water contamination, air pollution, poaching, etc.), different or additional input data is likely required to produce useful EcoAnthromes.

The variables we chose to represent disturbances captured disturbance-related landscape patterns relevant to Alberta, such as agricultural activity, urban and industrial development, recent fires and, to a lesser extent, harvesting. Applications to other regions, or at different scales, may need to use different variables to produce a regionalization relevant to their objectives. In our application, EcoAnthromes represent varying levels of disturbance and post-disturbance recovery, especially for fires. Variance of forest harvesting intensity was not captured as clearly by the clusters (Fig. A4), perhaps due to the high heterogeneity of harvesting practices, locations and timing. In general, areas harvested in the latter half of the study period (2011–2015) were grouped into clusters with recent fire disturbance (Clusters 10 and 20), areas harvested in the first half (2006–2010) were grouped with agricultural and urban clusters where GRN and NBR were low and variable (Clusters 5, 6 and 17), and areas harvested prior to 2006 were broadly grouped with road margins, sparsely treed areas and fragmented broadleaf forests (Clusters 1 and 12). More work is needed to determine the degree to which harvested areas indeed share characteristics with these clusters. It is possible that more complex forest disturbance and fragmentation metrics (e.g., patch size, edge density) would better capture the ecological outcomes of forest harvesting and regeneration (Wulder et al., 2008).

Finally, the two-stage approach allowed us to create a hierarchical clustering framework that would not otherwise be possible due to computational limitations. This framework helped to understand and interpret ecological patterns and provides flexibility for scaling EcoAnthrome classification as appropriate for specific applications. We chose a 21-class regionalization for intuitive comparison against the 21 NSRs of Alberta. Examination of the dendrogram (Fig. 2) and cluster validity metrics (data not shown) suggest that increasing the number of clusters to between 26 and 34 could further improve results at the provincial scale. The two-stage approach provides the flexibility to delineate EcoAnthromes at various scales to meet research and management objectives. More research is needed to evaluate the applicability of the hierarchical clustering structure developed at a broad scale (e.g., the provincial level) to landscape characterization at local scales, and to determine when new clustering should be performed to meet scale-specific management objectives.

## 5. Conclusion

Our example of an EcoAnthrome regionalization for Alberta achieved our stated goal to develop a quantitative, 30 m spatial resolution regionalization approach that identifies areas with unique ecological characteristics related to both natural and anthropogenic disturbances. The two-stage approach allowed for EcoAnthrome

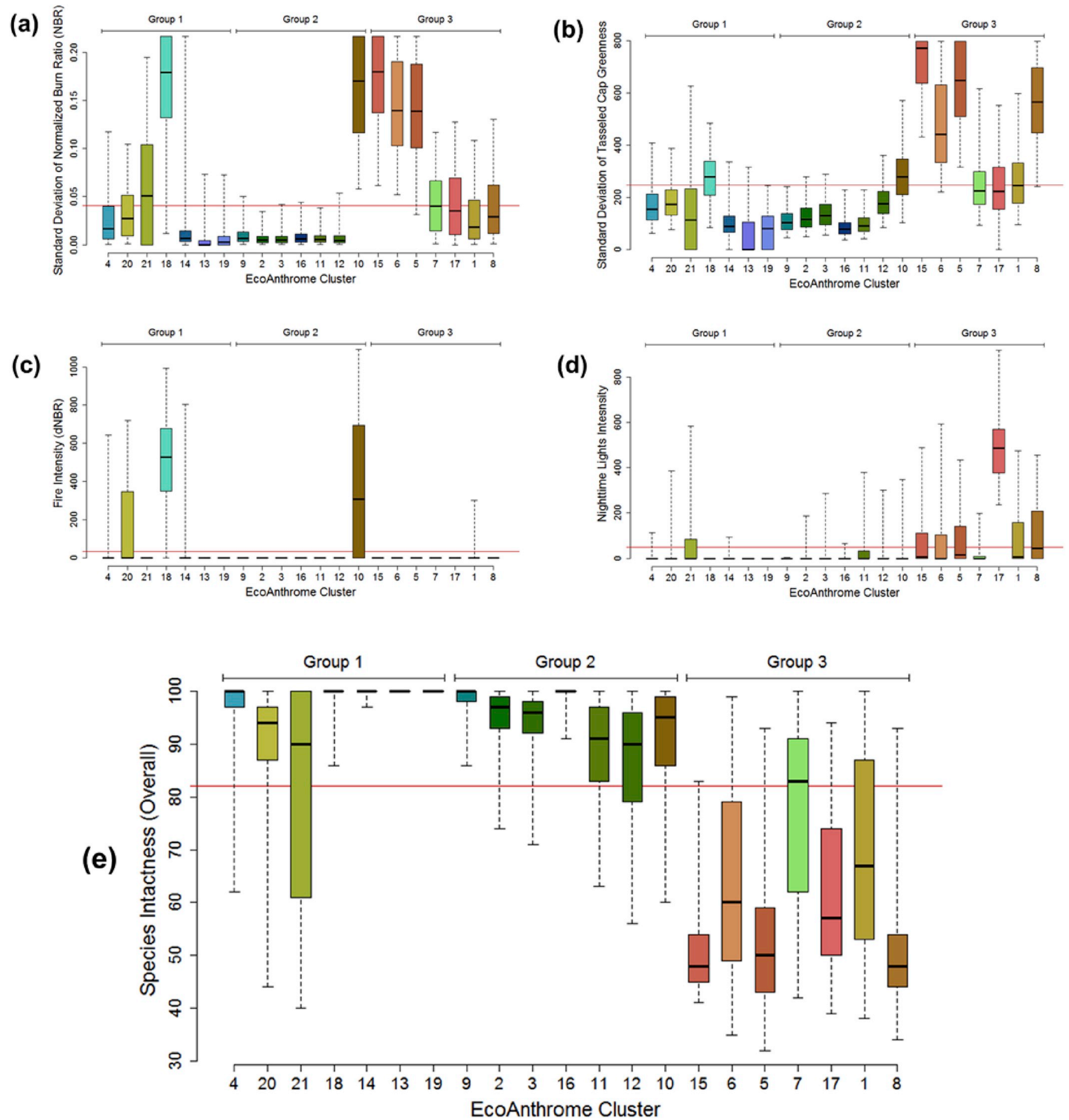


**Fig. 7. Box and whisker plots of disturbance and biodiversity across EcoAnthromes**. Sample distributions for select variables related to disturbance (a, b, c), built infrastructure (d) and overall species intactness (e). Black lines represent class medians, boxes are the 25th to 75th percentiles and whiskers are the 2.5th and 97.5th percentiles of the sample distribution. Horizontal red lines indicate the overall observed mean across all classes. Colors correspond to the map in Fig. 3 and are relative to the most disturbed (red), most vegetated (green) and coldest/wettest (blue) clusters. Groupings are derived from the hierarchical clustering process and are described in Section 3.1 and 4.1 (also see Fig. 2).

clustering at moderately-high spatial resolution across a broad extent using a large number of input variables, and the hierarchical framework provided greater insight and flexibility for use at multiple scales. Nearly all input variables were derived from freely available remotely sensed data. Furthermore, the approach is flexible insofar as input variables and their weightings can be adjusted depending on the scale and objectives of a given application. As the accessibility and spatio-temporal resolution of spaceborne, airborne (e.g., drone imagery, airborne laser scanning) and crowdsourced (e.g., camera traps, mobile app inputs) spatial data continues to increase, so too will our ability to incorporate disturbance and human activity into ecological regionalizations. This is important as conservation biologists increasingly call for biodiversity protection in habitats under direct human influence (Martin et al., 2014).

Compared to the expert-derived Natural Subregions in Alberta, the EcoAnthromes showed greater class separation and explained more variance for an assortment of variables related to land cover, disturbance and species intactness. The EcoAnthromes represent important ecological conditions that are defined by complex assemblages of topography, climate and disturbance, ranging from intact gravel-bed river valleys, boreal forests and grasslands to post-fire recovery areas to highly disturbed agricultural, industrial and urban landscapes. The disturbance-informed EcoAnthrome approach complements, rather than replaces, existing ecological regionalizations. We anticipate that it will prove valuable to support ecosystem management and conservation applications in Alberta (e.g., planning and monitoring for the recovery of threatened species), and encourage application and testing of disturbance-informed ecological regionalization approaches elsewhere.

## Acknowledgements

This research was supported by the Grizzly-PAW project (NSERC File: CRDPJ 486175–15, Grantee: N.C. Coops, FRM, UBC), in collaboration with fRI Research and FRIAA, Alberta Newsprint Company, Canfor, Cenovus, Repsol, Seven Generations Energy, Shell Canada, TransCanada Pipelines, Teck Resources, West Fraser, Westmoreland Coal, and Weyerhauser. More information can be found at http://paw.forestry.ubc.ca/.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2018.12.076.

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