Assessing the Association of Environmental Changes with Natural and Anthropogenic Stressors in the Oil Sand Area of Northern Alberta, Canada

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Abstract
This study analysed the association of natural and anthropogenic stressors with environmental changes detected between 2000 and 2020 in the Oil Sands Area (OSA) of northern Alberta, Canada. Building on earlier change detection analyses and on remote sensing imagery (classification and spectral indices), we developed Random Forest and Generalized Boosted models to assess the role of potential change drivers. Detected environmental changes occurred over a relatively small portion of the region and displayed clustered patterns that varied over space and time, exhibiting both positive sign (i.e., increases) and negative sign (i.e., decreases) across the region and throughout the time period. Anthropogenic stressors considered in the analysis included indicators of industrial activities, oil and gas extraction, and urban land use, while wildfire, forest damage, and precipitation differences were considered natural stressors. Model results showed that environmental changes in the region were associated with varying combinations of natural and anthropogenic stressors, with a general prevalence of anthropogenic stressors during the 2000-2010 interval. Within the project scope, analyses were conducted at relatively coarse analytical scales, both spatially and temporally. Despite limitations in scale, data availability, and modelling approach, this analysis constitutes a valuable tool to understand environmental change in this area, and our results provide valuable information for monitoring and managing environmental changes in the OSA. Furthermore, those analyses would be easy to replicate for other regions where environmental changes occurred due to different stressors.

Keywords: Anthropogenic and Natural Stressors, Environmental Change, Oil Sands Area, Pseudo Space-Time Modelling, Random Forest

1. Introduction

Environmental changes, also referred to as disturbances, can be associated with natural or anthropogenic events, which are categorized as pulses or presses, based on their intensity and duration [1] and [2]. Examples of sudden short-term events, or pulse disturbances [1] and [3] include major floods [4], rapid snowmelt events [5], hurricanes [6], insect outbreaks [7], or wildfires [8]. Examples of long-term or press disturbances, which permanently alter conditions [9], include land use changes, encompassing road development, infrastructure, urban development, timber harvesting, or industrial activities. It may not be possible to associate disturbances with specific categories or to accurately identify event types; however, measuring and classifying the physical landscape at certain spatial and temporal scales is helpful not only in identifying and categorizing disturbances [10], but also in assessing ecosystem functions, structure, and processes [11]. The complexity of environmental changes and their related disturbances cannot be tackled from a single perspective; hence, each study provides only a partial contribution to its understanding [12]. Our study area (Figure 1) encompasses the Oil Sands Area (OSA) of northern Alberta: a vast and heterogeneous region, well known within Canada and internationally for its bituminous sands, and the related oil and gas extraction activities. In recent years, the OSA has experienced significant environmental changes, ranging from the physical landscape to population dynamics, air quality, and climate change [13][14][15][16][17][18] and [19].

Environmental planning and policies for such a complex and dynamic region require the support not only of a comprehensive analysis of environmental changes, but also of their association with natural and anthropogenic disturbances and an evaluation of their mutual relationships [20].

The intent of this research is to identify and model potential drivers of the environmental changes that took place in the OSA over the two decades spanning 2000-2020. Previous analyses [21] assessed environmental changes in the OSA through the examination of landscape metrics and spectral indices over the 2000-2020 period [16][18] and [19]. Those analyses indicated that the prevailing vegetation cover, linked to the Forest class and greenness index, experienced the most significant change across the region and over the period, knowing that the boreal forest covers a substantial part of the OSA. Environmental changes associated with anthropogenic stressors such as agriculture, oil and gas extraction or forestry, can take various forms over time, due to both development and reclamation policies implemented by different industries; therefore, it can result in negative observed changes (in the mathematical sense of the term, i.e., decreases) as well as positive ones (i.e., increases). Further, industrial activity can exhibit varying associations with urban changes. During the study period, the OSA also experienced substantial change associated with natural stressors, including forest fires and climatic variability [13][14][15][16][17] [18] and [19].

Modelling these processes would aid their monitoring and management; however, their range and the complexity of their spatial, temporal, and spatio-temporal interactions make it difficult to model them with traditional statistical analytical methods. As these phenomena can only be known at discrete spatial and temporal samples, their statistical distribution is not entirely known. Furthermore, statistical distribution and correlations tend to vary across spatial and temporal scales, potentially biasing traditional statistical methods [22]. For these reasons, the current study employed Random Forest models, which was also the preferred choice of the project funder (i.e., at the time of inception, Alberta Environment and Parks–Oil Sands Monitoring Program). Indeed, Random Forest models [23] outperformed corresponding logistic regression models with parallel specification, identical data and virtually the same predictors [24]. Further, boosted regression tree models, primarily Generalized Boosted Models (GBM) [25] were computed.

This study considers the 2000-2020 period, subdivided into four 5-year intervals within, i.e., time-steps: 2000-2005, 2005-2010, 2010-2015, and 2015-2020. Building on our previous detection of environmental changes [21], the present analysis focused on portions of the OSA where changes were detected over each time-step. A pool of candidate variables was identified to represent a range of natural and anthropogenic stressors associated with positive and negative environmental changes in the OSA, i.e., the gain or loss of forest, built-up, and agricultural zones, as well as greenness, as an indicator of vegetation health, and bareness, as an indicator of bare lands such as built-up or burned areas. These variables were included in Random Forest and boosted regression tree models over each time-step, testing different model specifications. This analysis helps associate each change with both natural and anthropogenic stressors and identify stressors more likely associated with each change.

2. Study Area

Our study area (Figure 1) is the Oil Sands Area (OSA) within northern Alberta, which encompasses more than 20% of the entire province with a total area of 142,200 km^2 (i.e., an area approximately as large as Nepal, and half the size of Italy). The OSA has experienced significant environmental changes over several decades, associated with both natural and anthropogenic disturbances. This complex and heterogeneous area is home to diverse flora and fauna, to urban areas, and to a variety of settlements, including First Nations and Métis communities. Economic activities are not limited to oil and gas extraction, but encompass timber harvesting, livestock, and agriculture, as well as transportation, retail, and other urban and local functions. Located in northern Alberta, the area is characterized by relative isolation and exposed to a cold climate, which has experienced major changes and extreme events in recent years. Specifically, wildfires have grown in frequency and intensity, with the most notable events the 2011 Richardson fire and the 2016 Fort McMurray fire, which was one of the largest and most costly natural disasters in Canadian history [26].

While considering the entire spatial extent and all the time-steps, the analysis focuses on areas and periods where environmental changes were observed. Figure 2 (produced with [27] in R [28]) shows an example of temporal detected changes on the Greenness index defined in section 4.1.

3. Data

3.1 Spatial Units of Analysis: HUC Watersheds

The units of analysis, stipulated by the funder, are the Hydrologic Unit Code (HUC) units provided by Alberta Environment and Parks.

HUC units are a series of nested drainage basin feature classes forming five hierarchical levels (2, 4, 6, 8, and 10, where 2 is the coarsest scale and 10 is the finest) [29]. In total, the study area holds 658 HUC10 units, each one covering 216 km^2 on average (Figure 1).

3.2 Response Variables: Percentage of Landscape (Landscape Metric)

Five separate Land Use/Land Cover (LULC) maps were created at 30 m resolution for 2000, 2005, 2010, 2015, and 2020 [21]. A Random Forest (RF) classifier developed on the 2010 Landsat composites was applied to the other 4 composites; those composites were generated from orthorectified at-surface reflectance and harmonized [30] Landsat images collected at 30 m resolution for the May-September period of each year of interest. LULC maps should include 9 classes ("barren", "built-up", "agriculture", "water", "broadleaf/deciduous forest", "needleleaf/coniferous forest", "mixed forest", "treed wetland", and "vegetated open upland/wetland"); however, due to computing constraints, the two categories "barren" and "built-up" were aggregated into a single class named Built-Up and the three forested categories into a single class named Forest (Figure 1). The class "water" and the two "wetland" classes had to be excluded from modelling because of the high rate of misclassification: identifying different types of wetlands would require a specific algorithm aimed at detecting wetlands, and as no ground truth was available for the entire OSA, it was difficult to assess classification accuracy [31]and [32]. For each of these three classes, the "percentage of landscape" was calculated as the portion of each HUC10 polygon occupied by each class using ESRI ArcGIS Pro v2.8 (Esri Inc., Redlands, CA). The "raster to polygons" tool was applied to the classified images, followed by a "tabulate intersection" between the output land cover polygons and the HUC10 polygons to calculate the percentage of the class coverage within the nine polygons for 2000, 2005, 2010, 2015, and 2020; finally, the 5-year differences were calculated for each class and time-step at the HUC10 level.

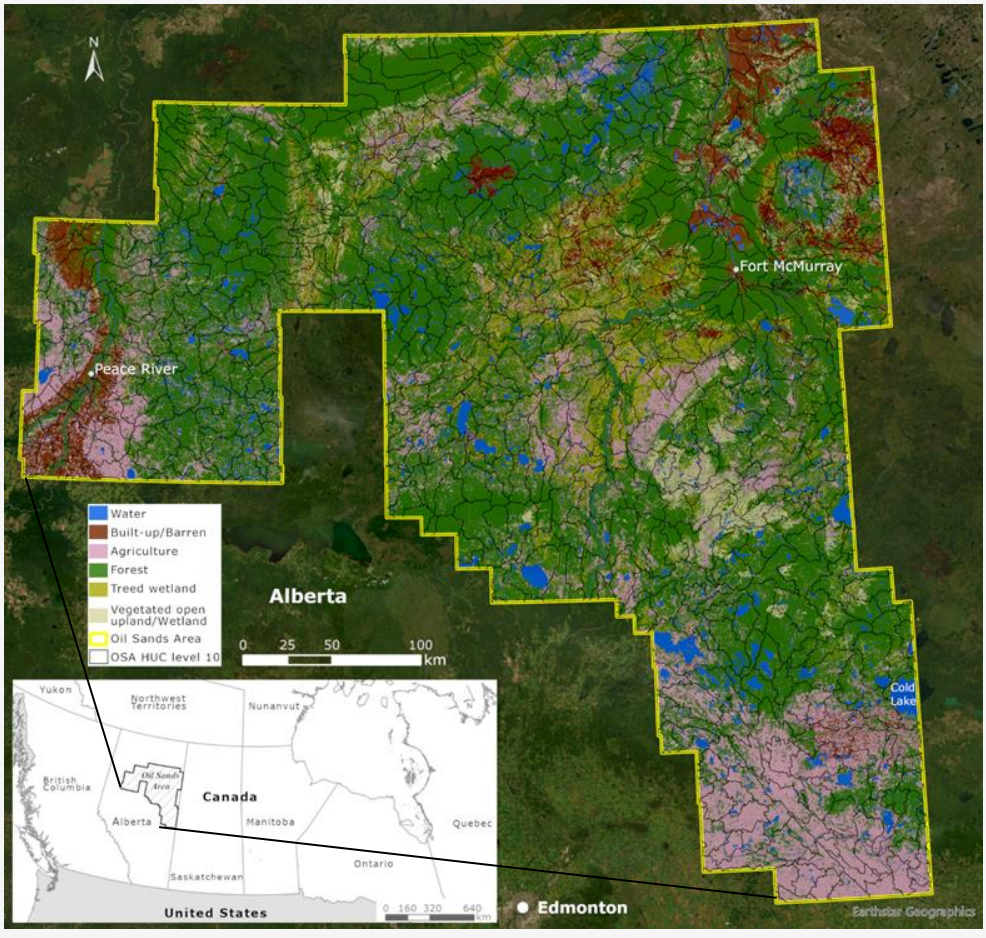

Figure 1: Oil sands area of northern Alberta, Canada

3.3 Response Variables: Change Detected on Spectral Indices

For each input year, five different indices were calculated from Landsat composites, and their median was computed over each HUC10 polygon. The indices selected for this study include the Normalised Difference Vegetation Index (Equation 1), the Modified Soil-Adjusted Vegetation Index (Equation 2) to minimize the effect of bare soil where there is low vegetation, the greenness component from a Tasselled Cap transformation (TCgreen) [33], the Normalised Burn Ratio (Equation 3) to identify burnt areas and their severity, and the Normalised Difference Built-up Index (Equation 4) [34] and [35].

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Equation 1

$$MSAVI = \frac{2NIR + 1 + \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}}{2}$$

Equation 2

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2}$$

Equation 3

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR}$$

Equation 4

For each index and time-step, the difference in zonal median between its end-year and start-year (e.g., 2005 minus 2000) was computed over each HUC10 polygon.

3.4 Predictor Variables: Wildfire

Shapefiles containing the boundaries of wildfires that occurred in the area between 1995 and 2020 were acquired from Alberta Agriculture and Forestry [36]. The proportion of burned areas and of partially burned areas within each HUC10 polygon was calculated and summed for the end-year of each time-step, based on the presence of wildfires over the five years up to and including each target year.

3.5 Predictor Variables: Forest Damage

Forest damage (FD) due to pests, such as Mountain Pine Beetle (*Dendroctonus ponderosae*) or Spruce Budworm (*Choristoneura*) [37], and abiotic agents, such as hail or flood, were acquired from the Aerial Overview Surveys for the 1998-2010 and 2011-2020 periods from the Government of Alberta Forest Health Conditions data [38]. For each time-step end-year, the sum of the Severity attributes (i.e., little, moderate, and severe) was calculated for each HUC10 polygon showing forest disturbances, along with the percentage of Forest Damage within those polygons.

3.6 Predictor Variables: Precipitation Differences

GeoPDF figures (see extracts in Online Resource Figure S1) having annual precipitation accumulations relative to long-term normal precipitation across Alberta were acquired from Alberta Agriculture and Forestry for 2000, 2005, 2010, 2015, and 2020 [39]. Precipitation accumulations were divided into 11 categories, ranging from wettest to driest, depending on their frequency of occurrence compared to the historical weather data for 1961-2020. The GeoPDFs were transformed into raster datasets and then cleaned (ex. Removing place names) using GIMP [40] and a GIMP plug-in: Resynthesizer v1.0-i686 (GitHub–bootchk/resynthesizer: Suite of gimp plugins for texture synthesis) (see example in Online Resource Figure S2). Those 11 categories were aggregated into five final groupings: (1) wettest (i.e., the single category including the most extreme wet instances); (2) wet (i.e., the sum of 3 categories ranging from extremely high to high precipitation); (3) normal precipitation (i.e., the sum of 3 categories ranging from moderately high to moderately low precipitation); (4) dry (i.e., the sum of 3 categories ranging from low to extremely low precipitation), and (5) driest (i.e., the single category including the most extreme dry instances). For each HUC10 polygon, first the percentage area covered by each grouping was calculated for each year, then the difference was calculated for each time-step. The latter differences are referred to as dwettest to ddriest (i.e., difference from each of the above final categories, e.g., dwettest = ($wettest_{2010}$-$wettest_{2005}$)).

3.7 Predictor Variables: Disturbed Land

Disturbed land shapefiles were acquired from the Government of Alberta Oil Sands Information Portal [41] for the years 1998 (used in place of 2000, which was not available), 2007 (in place of 2005, likewise), 2010, 2015, and 2020. The proportion of each of three land cover categories (Cleared, Disturbed, and Reclaimed) was calculated for each HUC10 polygon. As the sample size for each category would be too small for statistical modelling, the three classes were aggregated within each polygon and the difference for each time-step was calculated.

3.8 Predictor Variables: Oil and Gas Activities

Oil and gas activities data were acquired from several publicly available datasets obtained from the Alberta Energy Regulator (AER) including AER ST 37 list, ST102 Facility list, and Enhanced Pipeline files.

AER ST 37 is a monthly data product in shapefile format that holds information about all wells reported to the AER from which the surface hole well information was extracted [42]. ST102 is a complete list of facilities in Alberta that have a Petrinex Facility ID and have reported volumetric activity to the AER; it is available in shapefile format and is updated monthly [43]. The enhanced Pipeline dataset includes non-confidential data reported to the AER and is updated daily; it excludes low pressure distribution lines [44]. Upon inspection of the data, the Facility data in ST102 was disregarded from the study as data were only readily available after 2016. The Wells and Pipeline data were extracted by temporal groupings to capture changes for each of the four time-steps within the HUC10 polygons, resulting in separate Wells and Pipeline activity predictors.

4. Methods

4.1 Data Preparation

For the spectral indices outlined in section 3.3 and the percentage of landscape classes described in section 3.2, contiguous areas of significant change [21] were identified through a Getis-Ord Gi* hotspot analysis [45] with ESRI ArcGIS Pro v2.8. This analysis yields significant spatial clusters of features with high (hotspots) or low (cold spots) values, at confidence levels of 90%, 95% and 99% over a contiguous area. The hotspot analysis results for the spectral indices were then aggregated by summing their Gi-bin values (data classified into bins ranging from -3 (Cold Spot – 99% Confidence) to +3 (Hot Spot–99% Confidence), with 0 being non-significant) into two broad indicators of changes: a Greenness index, combining results from NDVI, MSAVI, and TCgreen, and a Bareness index, combining results from NBR and NDBI. Finally, binary variables were created where the Gi-bin values ≠ 0 corresponded to detected changes and Gi-bin values =0 to the no detected changes (see Figure 2 for an example for the Greenness index). These binary variables represented presence versus absence of significant environmental change at the HUC level 10 over the Oil Sands Area for the 4 time-steps of interest. Those binary variables were the response variables in all the multivariate models.

4.2 Modelling: Random Forest Models

A hierarchical zonal analysis of different spectral indices and selected landscape metric (percentage of landscape) was performed to examine the OSA based upon the HUC polygons. Random Forest (RF) models [23] were calculated in Python v2023.10.1 using the sklearn.ensemble [46] with the RF Classifier algorithm (sklearn.ensemble.RandomForestClassifier) for the Percent of Landscape Change Hotspot Outputs, and in R [28] using the "biomod2" package [47] for the Index Hotspot Outputs. RF models use multiple independent decision trees to predict an outcome with the response variable (i.e., environmental changes) and feature parameters standing for hypothesized influencing conditions (i.e., predictors described in sections 3.4-3.8). Ensemble RF models, which were used in this project, use sub-samples of the dataset to improve prediction accuracy and reduce over-fitting. As a result, individual data points may be used more than once in the model. Owing to the binary response variable, classification (i.e., not regression) RF models were computed.

4.2.1 Modelling: generalized boosted models

Generalized Boosted Models (GBM) were also computed for the Index Hotspot Outputs described in sections 4.1 within R [28] using the "biomod2" package [47]. This popular machine learning algorithm builds an ensemble of weak successive decision trees that learn and improve from previous ones, thus sequentially reducing errors and creating a very highly accurate prediction model [25]. This approach is unlike that of the Random Forest model, which builds many independent decision trees and then aggregates them into one; for this reason, the GBM was computed as a comparison with the Random Forest model.

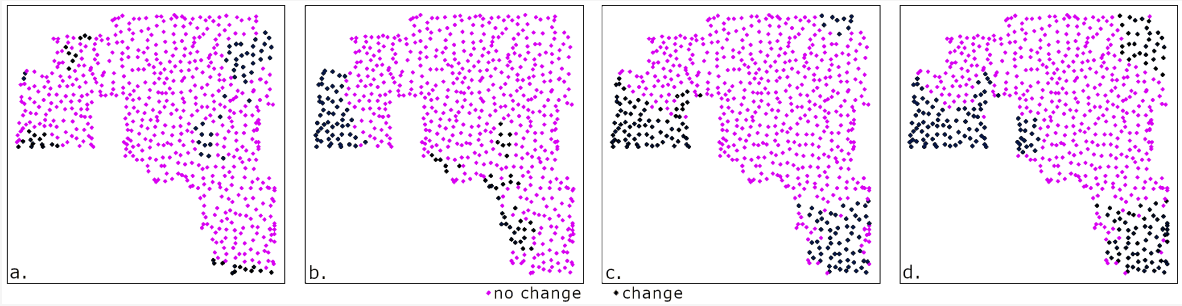

Figure 2: Detection of changes in the greenness index:
(a) 2000-2005, (b) 2005-2010, (c) 2010-2015, (d) 2015-2020

4.2.2 Model tuning and assessment

Tuning of RF and GBM models was implemented automatically, and results are presented in Tables S3 and S4. To assess RF classification models and evaluate their accuracy, the data were first split into training (70-75%) and test (25-30%) datasets. ROC (Relative Operating Characteristic) AUC [48] and Cohen's kappa [49] were calculated for the pairs of RF and GBM models computed on the Greenness and Bareness indices. The kappa assesses the model's ability to discriminate the binary classes. Further, the F1 scores [48] were calculated for the RF models computed on landscape classes. The evaluation metrics were performed via a 5-fold Cross-Validation (CV 5-fold) on the testing sets and the average metrics are reported. By combining training and CV 5-fold on testing, "better" models are easier to name [50] and [51].

5. Results

The results of the RF and GBM models on spectral indices are presented in Tables 1 and S1, and those of the RF models on percentages of land cover change in Tables 3, 4, and S2. A synopsis of all RF models is presented in Figure 3, which portrays, for each time-step, the relative percentage of variables of importance for each model in the outer circle, where the brown shades stand for individual anthropogenic stressors, while the yellow-green and blue shades stand for natural ones; in the inner circle shows the relative contribution of natural (dark green) versus anthropogenic (grey) stressors.

5.1 RF and GBM on Index

The RF and GBM models yielded consistent sets of variables of importance, with only minor differences in rank ordering and/or percentage explained for all the time-steps, and with RF ascribing lower percentages to each variable (Table 1). Values highlighted in orange in the table show the most important predictors: the darker the colour, the higher their importance in that model. Models were created using the R package "biomod2" [47]. Among the variables of importance, both natural and anthropogenic stressors yielded major contributions during the first decade, while in the second decade the contribution of anthropogenic stressors was marginal (Figure 3).

The overall contribution of natural stressors for 2000-2005 was 59% (RF) and 64% (GBM), while that of anthropogenic stressors was 36% (RF) and 48% (GBM). For 2005-2010, the overall contribution of natural stressors was 45% (RF) and 43% (GBM), while that of anthropogenic stressors was 50% (RF) and 26% (GBM). In both time-steps, natural variables of importance included wildfires (the largest contributor in 2000-2005, followed by difference in dryness), and forest damage (the largest contributor in 2005-2010); among anthropogenic variables, the contribution of disturbed land was the largest in 2000-2005 (21%), but decreased in 2005-2010, replaced by well (22%) and pipeline (16%) activity.

Table 1: Exploration of variable importances in greenness index using Random Forest and Generalized Boosted Models

	RF variables of importance (%)				**GBM variables of importance (%)**			
	2000-2005	**2005-2010**	**2010-2015**	**2015-2020**	**2000-2005**	**2005-2010**	**2010-2015**	**2015-2020**
Wildfire	36.50	7.40	8.10	3.20	37.50	4.00	9.80	-
Forest damage	1.00	15.60	1.20	8.40	-	18.00	0.70	2.60
dwettest	0.70	-	9.00	18.60	-	-	4.70	15.20
dwet	4.80	1.60	7.90	33.00	7.10	0.40	9.40	65.00
dnormal	3.60	6.00	28.40	4.40	2.90	6.10	49.80	3.80
ddry	12.20	6.90	7.00	3.80	16.90	10.60	3.40	0.10
ddriest	-	7.80	0.50	1.90	-	4.30	0.90	-
Wells activity	4.20	21.80	4.30	3.70	2.80	11.60	4.00	1.20
Pipeline activity	10.20	16.30	2.80	2.10	18.30	4.70	1.90	0.60
Disturbed land	21.20	11.70	-	0.20	27.00	9.60	-	-
on testing*	**14 (150)**	**20 (143)**	**36 (128)**	**50 (114)**	**14 (150)**	**20 (143)**	**36 (128)**	**50 (114)**
kappa	0.24	0.34	0.60	0.64	0.34	0.29	0.55	0.59
ROC AUC	0.74	0.78	0.92	0.89	0.74	0.81	0.92	0.89

For 2010-2015 and 2015-2020, according to both models, variables of importance consisted almost only of natural stressors; in 2010-2015 they included precipitation differences (i.e., from normal, with 28% and from wettest) and wildfire, while in 2015-2020 they included precipitation differences (i.e., from wet, with 33%, and from wettest with 19%) and forest damage. The ROC AUC for the RF models ranged between 0.74 and 0.92 on the testing set, indicating a good model performance in discriminating the binary classes, despite a low portion of change versus no change. The kappa ranged between 0.24 and 0.64 on testing. The portion of non-null values ranged between 14% and 18% in the first two time-steps, and between 28% and 44% in the last two. Lower kappa values reflect the imbalance between classes and the models' tendency to classify more accurately the polygons experiencing no changes. The GBM model showed similar values throughout the time-steps and sets. The number of non-null values in the testing set for the bareness index was negligible, i.e., 3%, 1.5%, 6%, and 2.5%. Owing to this disproportion, the model was deemed not meaningful, and its results are reported in Online Resource Table S1.

5.2 Random Forest Models on Landscape Metric (Percentage of Landscape)

GBM models yielded results that were mostly consistent with RF. For this reason, along with the recommendation of the project funder, only RF models are discussed below. Input parameters vary across models, as predictors were selected based on theoretical reasoning and depend on the class under examination.

5.2.1 Forest

The forest percentage of landscape is not only the largest landscape class within the OSA, encompassing between 39 and 47% of the study area, but it also showed the greatest changes during the study period [21]. In the RF models (Table 2), the contribution of anthropogenic stressors was 45% in 2000-2005, peaked in 2005-2010 (50%), decreased moderately in 2010-2015 (42%), and more drastically in 2015-2020 (35%). In Table 2 the values highlighted in orange show the most important predictors, where the darker the colour, the higher the importance it has in that model. A corresponding inverse trend was seen for natural stressors, with contributions of 56% in 2000-2005, 47% in 2005-2010, 58% in 2010-2015, and 65% in 2015-2020. For the first three time-steps, top-ranking variables were anthropogenic, with pipeline activity as the top variable of importance, contributing 22-26%, and well activity as the second or third variable of importance, contributing 16-20% (Figure 3). Among the natural stressors, forest damage consistently ranked in the top three predictors, peaking in 2005-2010 (21%), and ranking as top contributor in 2015-2020 (18%). Wildfires ranked second (except in the last time-step), though with modest and overall decreasing contributions (14%, 12%, 6%, and 8%). Period over period, the precipitation variables fluctuate in importance. Difference from normal was generally the highest in all periods except for 2005-2010 where it ranked near the bottom. Difference in wet and wettest alternate importance over the time periods except in 2015-2020 when both are equal contributors, and the difference in normal, wet, and wettest have a cumulative impact of 35% on the model.

Table 2: Exploration of variable importances in Forest class using Random Forest

	2000-2005	**2005-2010**	**2010-2015**	**2015-2020**
Wildfire	13.70	11.70	5.70	8.20
Forest Damage	13.40	20.80	14.80	18.30
dwettest	0.10	0.50	9.30	11.10
dwet	10.30	8.40	2.90	10.50
dnormal	9.10	4.50	13.40	13.40
ddry	8.90	0.50	7.90	3.30
ddriest	0.00	0.00	3.60	0
Wells activity	16.50	20.30	17.60	13.80
Pipeline activity	26.00	23.60	22.00	13.50
Disturbed land	2.00	5.90	2.70	7.90
on testing*	**68 (141)**	**72 (137)**	**64 (144)**	**79 (124)**
Mean ROC AUC	0.73	0.73	0.75	0.66
kappa	0.33	0.32	0.24	0.26
F1 on changed	0.50	0.53	0.38	0.41
F1 on no changed	0.82	0.79	0.83	0.79

The influence of difference from dry is low at 1-9% and difference from driest is miniscule at 4% or null (Figure 3). The models' performance was consistent throughout the period, with ROC AUC scores between 0.66 and 0.75 for the testing set, while kappa ranged from 0.24 to 0.33, owing to the imbalanced classes. F1 suggests that the models performed better for null values, as F1 on no changes scored consistently around 0.8 while on changed units, it ranged from 0.38 to 0.53. The models for the 2 first time-steps performed better.

5.2.2 Agriculture

According to the RF model (Table 3), natural stressors contributed slightly more (i.e., 52% to 65%) than anthropogenic (i.e., 35% to 48%). Like in previous models, anthropogenic exerted greater importance in the 2000-2015 interval, though, unlike in greenness and forest models, their contribution in 2005-2010 was lower than over its contiguous time-steps. The largest difference between natural and anthropogenic stressors was in 2015-2020, with 65% (natural) versus 35% (anthropogenic). Notwithstanding overall contributions, top-ranking variables were mostly anthropogenic throughout the period.

Among variable of importance, pipeline activity consistently ranked first, apart from 2005-2010, when it was outranked by wildfire (29%); its 2015-2020 contribution was a modest 17%, compared to the previous 22%, 21%, and 26%. This predictor was closely followed by well activities, only outranked by forest damage (17%) in 2005-2010, and by wildfire (14%) in 2015-2020. Among natural stressors, forest damage contributed 16% - 17% between 2000 and 2015, decreasing to 10% in 2015-2020. Further to the 29% peak in 2005-2010, wildfire yielded modest contributions (6% in 2000-2005, and 8% in 2010-15), and a larger 14% in 2015-2020. Difference in normal precipitation contributed 6% to 8% in the first half of the period, and 11% to 13% in the second half. Difference in dry was the third-ranking contributor in 2000-2005, with 17%, followed by 6%, 8%, and 4%, in the next time-steps. Difference in extreme dry yielded null contribution throughout. Difference in wet contributed 7% in 2000-2005, 2% in 2005-2015, and 12% in 2015-2020. Difference in extreme wet contributed 6% in 2010-2015 and 12% in 2015-2020 (Figure 3). ROC AUC scored between 0.66 and 0.80 for the testing set while kappa ranged from 0.11 to 0.22. F1 suggests that the models performed better for null values, as F1 on no change scored consistently around 0.8 while on changed, it ranged from 0.23 to 0.32.

5.2.3 Built-up

For these models, the predictor pool encompassed only one natural stressor, i.e., wildfire, in addition to the three anthropogenic stressors. With very low portions of non-null values (i.e., 14%, 8.3%, 10,2%, and 8.9%), models predicted null values, rather than change; hence, they were deemed invalid, and their results are presented in Online Resource Table S2.

6. Discussion

6.1 Natural versus Anthropogenic Predictors; Spatial and overall Trends

Owing to constraints in data availability and funder's stipulations, the association of environmental changes with natural versus anthropogenic stressors was explored through a smaller set of predictors than what may adequately representing the range of phenomena affecting the OSA over two decades.

Table 3: Exploration of variable importances in Agriculture class using Random Forest

	2000-2005	2005-2010	2010-2015	2015-2020
Wildfire	5.70	28.70	7.80	14.30
Forest Damage	11.30	16.60	17.10	10.40
dwettest	0.00	0.70	6.30	12.00
dwet	6.50	2.00	1.90	12.10
dnormal	7.70	5.60	11.10	12.70
ddry	18.10	5.60	8.10	3.60
ddriest	0	0	0	0
Wells activity	22.58	13.80	18.60	9.70
Pipeline activity	25.28	21.20	26.00	16.70
Disturbed land	2.80	5.80	3.10	8.40
on testing*	**58 (149)**	**75 (132)**	**61 (146)**	**68 (139)**
Mean ROC AUC	0.80	0.72	0.68	0.66
kappa	0.15	0.18	0.11	0.22
F1 on changed	0.23	0.32	0.23	0.31
F1 on no changed	0.84	0.79	0.82	0.83

Anthropogenic stressors were represented by indicators of industrial development (specific to oil and gas extraction), directly resulting from purposeful human action. However, stressors classified as natural may embed anthropogenic disturbances, as wildfires and forest damage may be, partially, unintended consequences of human action, and precipitation amounts may vary in relationship with climate change. The relative contribution of predictors and stressors across models and time is summarized through pie charts in Figure 3.

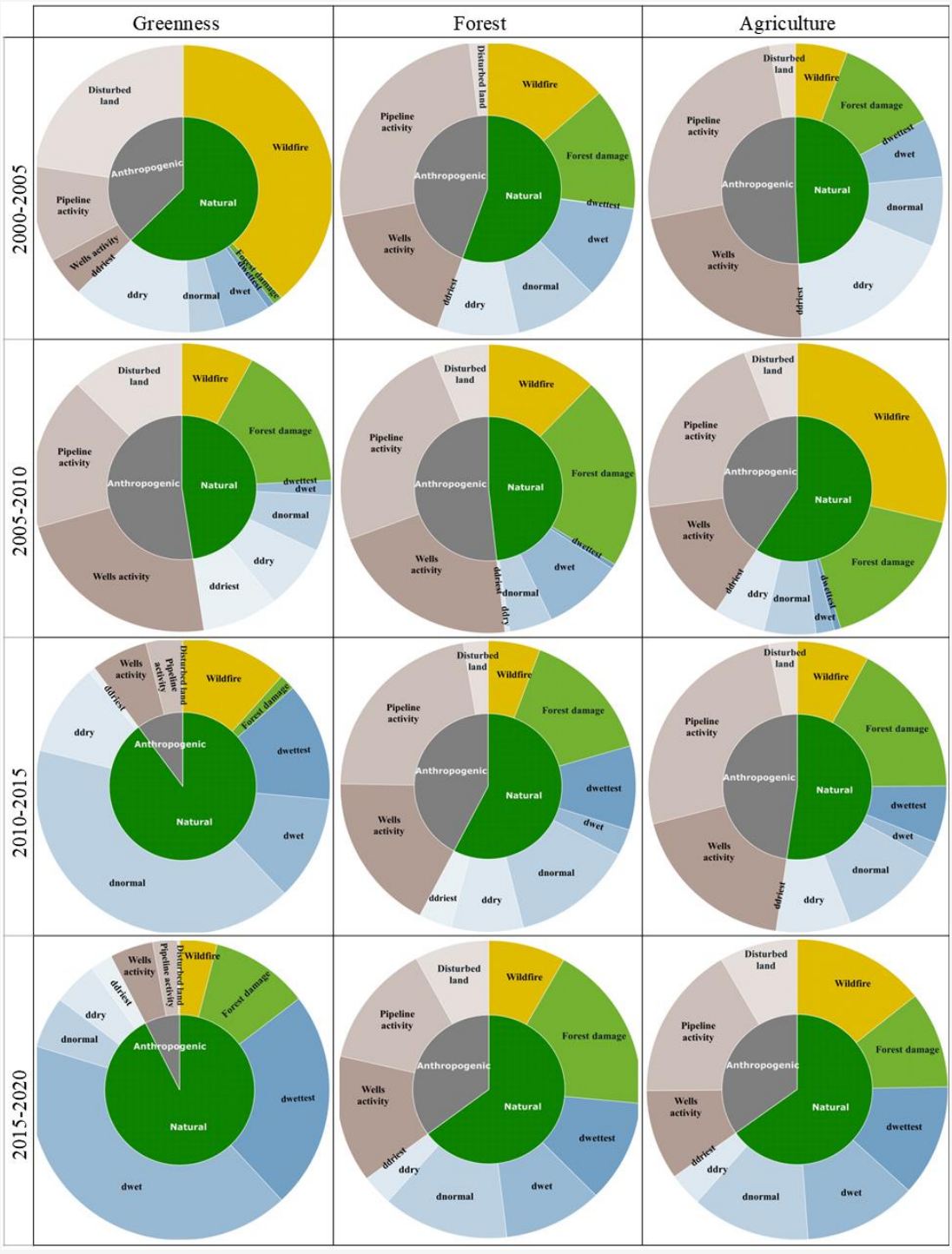

Figure 3: Relative contribution of anthropogenic and natural stressors to detected environmental changes through Random Forest models

Despite differences across models, the charts suggest that the significant role of anthropogenic stressors in 2000-2005 expanded through 2005-2015 and declined in 2015-2020. Pipeline activity was generally the largest of these contributors, followed by well activity; however, the increased importance of disturbed land in 2015-2020 may prelude to future well and pipeline expansion (i.e. negative changes in greenness or Forest) or land reclamation (i.e. positive changes). The effect of drought conditions in the early periods [52] are shown by the combined importance of wildfire and differences in dry, while wet conditions are growing in importance in the latest periods. The importance of forest damage exhibits an increasing trend.

Environmental changes (positive and negative) occurred within existing land uses, which lie in distinct areas, within the vast extent of the OSA: while forest covers between 39 and 47% the study area, agriculture occurs primarily in the south-west and south-east, and built-up areas in local clusters. Hence, for example, precipitation amounts may exhibit spatial variations large enough to impact landscape classes differently, compounding with local stressors. The increased importance of natural stressors in 2010-2020 may result not only from the decreased importance of anthropogenic stressors, but also from increased frequency and intensity of extreme events, consistent with climate change. All the analyzed anthropogenic stressors constitute long-term disturbances, while those considered natural include both short-term and long-term disturbances. These stressors, which may embed anthropogenic sources, exert their impact, chronologically, after the long-term anthropogenic disturbances, potentially compounding with them.

6.2 Forest, Agriculture, and Greenness

During the study period, the forested portion of the OSA fluctuated in size by about 12,000 Km^2, with both negative changes (i.e., decreases) and positive changes (i.e., increases) occurring in varying clustered patterns [21]. Up to 50% (2005-2010) of the combined changes were associated with anthropogenic stressors, including up to 26% with pipeline activity and up to 20% with well activity. Wildfire, drought, and forest damage, i.e., the next contributors, may relate indirectly to anthropogenic stressors, e.g., via fragmentation, or climate change. Agricultural land, on a smaller area, experienced modest changes [21], associated with anthropogenic stressors in the first three time-steps (up to 51% in 2000-2005), with the largest contributions by pipeline and well activities. Wildfire was a major contributor in 2005-2010 (consistent with forest), and in 2015-2020, the latter in combination with differences in both dryness and wetness. Forest damage contributed mostly in 2005-2015, i.e., a period of minor changes. Like in the forest models, the importance of anthropogenic stressors declined overall in 2015-2020, despite a remarkable increase of disturbed land.

The changes detected in greenness exhibit dichotomous associations in 2000-2010 versus 2010-2020. The contribution of anthropogenic stressors rose from 36% in 2005-2010 to 50% in 2005-2010, declining to 7% and 6% in the last periods. The 2005-2010 increase is primarily linked to wells activity, i.e., 4% to 22% (versus 10% - 16% for pipeline activity and 21% to 12% for disturbed land). Among the natural stressors, differences in precipitation yielded the largest contributions, i.e., dnormal (28%) in 2010-2015, while in 2015-2020 differences in wet (33%) and wettest (19%) contributed jointly more than 50%; over that period, the latter stressors were also important in forest and agriculture models.

In summary: larger changes in forest and greenness in the early periods were mostly associated with anthropogenic stressors (mainly wells and pipeline activities), along with wildfire and drought, while lesser changes in the latest periods were mainly associated with precipitation and other natural stressors. These results are consistent with the recent history of the OSA, which underwent a phase of expansion in extraction activities, accompanied by infrastructure development, in the 2000-2010 period [53]. These activities declined following the 2008 global recession and the decline in oil prices [54] and [55]. Changes in greenness and forest over 2010-2020 may be partly associated not only with stalling industrial development, but also with reclamations mitigating the industry's impact. In 2000-2010 natural stressors, i.e., wildfires, drought, and pests, also contributed to the decline in forest and green areas, likely compounding with anthropogenic stressors. Conversely, increased precipitation in 2010-2020 may have contributed to positive changes, i.e., forest and green area regeneration, strengthening purposeful anthropogenic action, aided by relatively lower forest damage. Consistent trends affected agriculture, despite overall lower changes, possibly related to greater accessibility of agricultural land; further, the impact of varying precipitation amounts and pests may have been mitigated by standard interventions, e.g., irrigation and pesticides.

6.3 Built-Up and Barren and Bareness

Built-up areas mostly hold urban and industrial land use, while barren includes diverse extents of barren rock and soil, areas cleared for future industrial or commercial use, and areas cleared by natural events such as flooding or wildfire.

Overall, these areas cover a modest extent of the OSA which, at the HUC10 level, displayed very few changes, resulting in an overwhelming proportion of null values, which severely affected the models. Most natural stressors were not pertinent in built-up models, and the paucity of predictors was worsened by the unavailability of census indicators for the entire study period and all the inhabited portions of the OSA. The only pertinent natural stressors were precipitation differences (for bareness and barren) and wildfire. The former contributed to changes in bareness in 2010-2020, while the latter was a sporadic contributor, reflecting the impact of major events, including the 2011 Richardson fire and the 2016 Fort McMurray fire. Notwithstanding their limitations, these models yielded a message consistent with other models, i.e., a larger contribution of anthropogenic stressors in 2000-2010, followed by their sharp decline through 2010-2020. Also, disturbed land increased in importance, becoming the top-ranking predictor in 2015-2020, with the potential implications noted for forest and agriculture.

6.4 Modelling Approach, Limitations, and Future Work

Within the project scope, detected environmental changes over the entire OSA and 20-year period were modelled as function of hypothesized predictors by RF and GBM models. However, changes were detected on median values of HUC10 polygons; hence, response variables were affected by classification and detection uncertainty, sample size, and analytical scale. Additionally, aggregation level and analytical scale, constrained by the size of the study area and the scope of the work, affect all the variables, masking changes that may have occurred at finer scale. Significant clusters of changes, either positive or negative, were localized over small portions of the OSA, with most polygons showing no change (i.e., null value) [21]. Hence, the number of polygons displaying changes was exceedingly low compared to the sum of those with no-changes and changes of opposite sign. Therefore, positive and negative changes were combined into a single category representing change versus no-change. While this operation was necessary to improve the numerical balance, it makes it harder to ascribe associations to positive or negative changes. Despite these limitations, according to ROC AUC and kappa, the greenness models achieved greater accuracy in 2010-2020, probably due to a greater portion of non-null values in the testing sets. Forest and agriculture models, with percentages of non-null values constantly in the 30s%, achieved consistent results, though with greater accuracy on no-change (F1 scores). These results should be complemented and confirmed by explicitly spatial approaches, e.g., geographically weighted and spatially autoregressive models, to assess local associations with positive versus negative changes. Future research can improve the current classification and detection uncertainty, with high-quality classification products becoming available. Models would benefit from additional variables, representing a wider range of natural and anthropogenic stressors.

Despite its limitations, this analysis yielded associations of change with natural versus anthropogenic stressors that are consistent with the recent history of the region; hence, it provides a promising predictive tool, potentially useful in management and policy making, to aid depict plausible scenarios based on recent trends. Finally, we wish to emphasize that this quantitative study necessarily forms only a partial contribution to capturing the complexity of the environmental changes that took place in a region as large as the OSA over two decades. The OSA is home to First Nations and Métis communities, to local communities and seasonal workers. In advocating for a local approach to complement our analysis (including finer-scale analyses over areas most affected by change), we also wish to communicate that this type of analysis can benefit by traditional environmental knowledge, by local expert opinion, and by studies of landscape change.

7. Conclusion

This paper analyzed the natural and anthropogenic stressors associated with environmental changes detected at 5-year intervals (i.e., time-steps) over a 20-year period in the Oil Sands Area (OSA) of northern Alberta, Canada. Building on previous change detection analyses and on classified remote sensing imagery, it employed Random Forest (RF) and Generalized Boosted Regression (GBM) to model spectral indices, i.e., greenness and bareness, and landscape classes, i.e., forest, agriculture, and built-up and barren. Predictors included anthropogenic stressors, encompassing industrial and extraction activities, and stressors deemed natural, including wildfire, forest damage, and precipitation. Models of greenness, forest, and agriculture yielded more reliable results than models of bareness, built-up and barren, as they relied on larger samples and greater proportions of non-null changes.

Despite differences across land classes and spectral indices, all models consistently show that anthropogenic variables were important contributors in 2000-2010, in several cases with overall contributions no less than 50%. Among anthropogenic stressors, well and pipeline activities were the largest contributors in the central time-steps, while disturbed land was more important in the initial and final stages, potentially preluding to further future developments. Of the stressors considered natural, wildfire and drought were important in early time-steps, difference in wetness was more important in later intervals, and forest damage was important throughout. Models yielded satisfactory accuracies, despite uncertainties in classification and change detection and a limited pool of predictors. As the OSA is a remarkably large region, both spatial and temporal analytical scale were relatively coarse. These results are consistent with the recent history of the OSA, yielding information that can be integrated into a framework for monitoring and managing environmental changes in this complex region. Environmental management and monitoring are important to protect and keep ecosystem integrity for future generations and this methodology is applicable to any region undergoing environmental changes at different scales. The use of natural and anthropogenic stressors in the models reflects the drivers of change in this model and may vary across ecosystems depending on what is driving the change.

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References

[1] Collier, K. J. and Quinn, J. M., (2003). Land-Use Influences Macroinvertebrate Community Response Following a Pulse Disturbance. *Freshwater Biology*, Vol. 48(8), 1462–1481. https://doi.org/10.1046/j.1365-2427.2003.01091.x.

[2] Delcourt, H. R., Delcourt, P. A. and Webb, T., (1982). Dynamic Plant Ecology: The Spectrum of Vegetational Change in Space and Time. *Quaternary Science Reviews*, Vol. 1(3), 153-175. https://doi.org/10.1016/0277-3791(82)90008-7.

[3] Parminter, J. and Daigle, P., (2000). *Crown Publications Online Catalogue - Extension Note 10 - Landscape Ecology and Natural Disturbances: Relationships to Biodiversity*. [Online]. Available: https://www.crownpub.bc.ca/Product/Details/7610000191_S. [Accessed Feb. 27, 2024].

[4] Milner, A. M., Robertson, A. L., McDermott, M. J., Klaar, M. J. and Brown, L. E., (2013). Major Flood Disturbance Alters River Ecosystem Evolution. *Nature Climate Change*, Vol. 3(2), 137–141. https://doi.org/10.1038/nclimate1665.

[5] Pomeroy, J., Fang, X. and Ellis, C., (2012). Sensitivity of Snowmelt Hydrology in Marmot Creek, Alberta, to Forest Cover Disturbance. *Hydrological Processes*, Vol. 26(12), 1891-1904. https://doi.org/10.1002/hyp.9248.

[6] Imbert, D. and Portecop, J., (2008). Hurricane Disturbance and Forest Resilience: Assessing Structural Vs. Functional Changes in a Caribbean Dry Forest. *Forest Ecology and Management*, Vol. 255(8–9), 3494–3501. https://doi.org/10.1016/j.foreco.2008.02.030.

[7] Dodds, K. J., Garman, S. L. and Ross, D. W., (2006). Landscape Analyses of Douglas-Fir Beetle Populations in Northern Idaho. *Forest Ecology and Management*, Vol. 231(1–3), 119–130. https://doi.org/10.1016/j.foreco.2006.05.023.

[8] Faustini, A., Alessandrini, E. R., Pey, J., Perez, N., Samoli, E., Querol, X., Cadum, E., Perrino, C., Ostro, B., Ranzi, A., Sunyer, J., Stafoggia, M., Forastiere, M. and The MED-PARTICLES Study Group, (2015). Short-Term Effects of Particulate Matter on Mortality During Forest Fires in Southern Europe: Results of the MED-PARTICLES Project. *Occupational and Environmental Medicine*, Vol. 72(5), 323-329. https://doi.org/10.1136/oemed-2014-102459.

[9] Glasby, T. M. and Underwood, A. J. (1996). Sampling to Differentiate between Pulse and Press Perturbations. *Environmental Monitoring and Assessment*, Vol. 42(3), 241-252. https://doi.org/10.1007/BF00414371.

[10] Lung, T. and Schaab, G., (2006). Assessing Fragmentation and Disturbance of West Kenyan Rainforests by Means of Remotely Sensed Time Series Data and Landscape Metrics. *African Journal of Ecology*, Vol. 44(4), 491–506. https://doi.org/10.1111/j.1365-2028.2006.00663.x.

[11] Syrbe, R. U. and Walz, U., (2012). Spatial Indicators for the Assessment of Ecosystem Services: Providing, Benefiting and Connecting Areas and Landscape Metrics. *Ecological Indicators*, Vol. 21, 80-88. https://doi.org/10.1016/j.ecolind.2012.02.013.

[12] Chen, Z., Xu, B. and Devereux, B., (2014). Urban Landscape Pattern Analysis Based on 3D Landscape Models. *Applied Geography*, Vol. 55, 82–91. https://doi.org/10.1016/j.apgeog.2014.09.006.

[13] Wasser, S. K., Keim, J. L., Taper, M. L. and Lele, S. R., (2011). The Influences of Wolf Predation, Habitat Loss, and Human Activity on Caribou and Moose in the Alberta Oil Sands. *Frontiers in Ecology and the Environment*, Vol. 9(10), 546-551. https://doi.org/10.1890/100071

[14] Gibson, J. J., Birks, S. J., Yi, Y. and Vitt, D. H., (2015). Runoff to Boreal Lakes Linked to Land Cover, Watershed Morphology and Permafrost Thaw: A 9-Year Isotope Mass Balance Assessment. *Hydrological Processes*, Vol. 29(18), 3848–3861. https://doi.org/10.1002/hyp.10502.

[15] Brook, J. R., Cober, S. G., Freemark, M., Harner, T., Li, S. M., Liggio, J., Makar, P. and Pauli, B., (2019). Advances in Science and Applications of Air Pollution Monitoring: A Case Study on Oil Sands Monitoring Targeting Ecosystem Protection. *Journal of the Air and Waste Management Association*, Vol. 69(6), 661–709. https://doi.org/10.1080/10962247.2019.1607689.

[16] Russell, M., Hakami, A., Makar, P. A., Akingunola, A., Zhang, J., Moran, M. D. and Zheng, Q., (2019). An Evaluation of the Efficacy of Very High Resolution Air-Quality Modelling over the Athabasca Oil Sands Region, Alberta, Canada. *Atmospheric Chemistry and Physics*, Vol. 19(7), 4393–4417. https://doi.org/10.5194/acp-19-4393-2019.

[17] McEachern, P., Prepas, E. E., Gibson, J. J. and Dinsmore, W. P., (2000). Forest Fire Induced Impacts on Phosphorus, Nitrogen, and Chlorophyll a Concentrations in Boreal Subarctic Lakes of Northern Alberta. *Canadian Journal of Fisheries and Aquatic Sciences*, Vol. 57(S2), 73-81. https://doi.org/10.1139/f00-124.

[18] Chasmer, L., Lima, E., M., Mahoney, C., Hopkinson, C., Montgomery, J. and Cobbaert, D., (2021). Shrub Changes with Proximity to Anthropogenic Disturbance in Boreal Wetlands Determined Using Bi-Temporal Airborne Lidar in the Oil Sands Region, Alberta Canada. *The Science of the Total Environment*, Vol. 780. https://doi.org/10.1016/j.scitotenv.2021.146638.

[19] Masud, B., Cui, Q., Ammar, M., E., Bonsal, B., R., Islam, Z. and Faramarzi, M., (2021). Means and Extremes: Evaluation of a CMIP6 Multi-Model Ensemble in Reproducing Historical Climate Characteristics across Alberta, Canada. *Water*, Vol. 13(5). https://doi.org/10.3390/w13050737.

[20] de Groot, R., (2006). Function-Analysis and Valuation as a Tool to Assess Land Use Conflicts in Planning for Sustainable, Multi-Functional Landscapes. *Landscape and Urban Planning*, Vol. 75, 175–186. https://doi.org/10.1016/j.landurbplan.2005.02.016.

[21] Couloigner, I., Fallah, B., Hanes, A., Mirzaei, M., Dempsey, D. and Bertazzon, S., (2024). Multiscale Space-Time Analysis of Environmental Changes in the Oil Sands Area (Alberta, Canada). *International Journal of Geoinformatics*, Vol. 20(4), 56–73. https://doi.org/10.52939/ijg.v20i4.3151.

[22] Brunsdon, C. and Comber, A., (2020). Big Issues for Big Data: Challenges for Critical Spatial Data Analytics. *Journal of Spatial Information Science*, Vol. 21, 89–98. https://doi.org/10.5311/JOSIS.2020.21.625.

[23] Hastie, T., Tibshirani, R. and Friedman, J., (2009). *The Elements of Statistical Learning*. New York, NY: Springer New York. https://doi.org/10.1007/978-0-387-84858-7.

[24] Cushman, S. A. and Wasserman, T. N., (2018). Landscape Applications of Machine Learning: Comparing Random Forests and Logistic Regression in Multi-Scale Optimized Predictive Modeling of American Marten Occurrence in Northern Idaho, USA [Chapter 9]. *In: Humphries, G.; Magness, D.; Huettmann, F., eds. Machine Learning for Ecology and Sustainable Natural Resource Management. Springer, Cham,* 185-203. https://doi.org/10.1007/978-3-319-96978-7_9.

[25] Friedman, J. H., (2001). Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics*, Vol. 29(5). https://doi.org/10.1214/aos/1013203451.

[26] Dmitrieva, K., (2016). Alberta Wildfires Costliest Insured Disaster Ever in Canada. *Bloomberg.com*. [Online]. Available: https://www.bloomberg.com/news/articles/2016-07-07/alberta-wildfires-cost-insurers-c-3-58-billion-industry-group. [Accessed Feb. 11, 2025].

[27] Pedesma, E., (2016). sp Gallery. Retrieved February 29, 2024, From: https://edzer.github.io/sp/.

[28] R: The R Project for Statistical Computing. *R: A Language and Environment for Statistical Computing*. [Online]. Available: https://www.r-project.org/. [Accessed Dec. 12, 2022].

[29] Watersheds of Alberta (MapServer). *Alberta Environment and Parks*. [Online]. Available: https://geospatial.alberta.ca/titan/rest/services/environment/watersheds_of_alberta/MapServer. [Accessed Jun. 15, 2022].

[30] Roy, D. P., Kovalskyy, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S. and Egorov, A., (2016). Characterization of Landsat-7 to Landsat-8 Reflective Wavelength and Normalized Difference Vegetation Index Continuity. *Remote Sensing of Environment*, Vol. 185, 57–70. https://doi.org/10.1016/j.rse.2015.12.024.

[31] Mahdavi, S., Salehi, B., Granger, J., Amani, M., Brisco, B. and Huang, W., (2017). Remote Sensing for Wetland Classification: A Comprehensive Review. *GIScience & Remote Sensing*, Vol. 55(5), 623-658. https://doi.org/10.1080/15481603.2017.1419602.

[32] Amani, M., Brisco, B., Mahdavi, S., Ghorbanian, A., Moghimi, A. and DeLancey, E. R., (2021). Evaluation of The Landsat-Based Canadian Wetland Inventory Map Using Multiple Sources: Challenges of Large-Scale Wetland Classification Using Remote Sensing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 14, 32-52. https://doi.org/10.1109/JSTARS.2020.3036802.

[33] Baig, M. H. A., Zhang, L., Shuai, T. and Tong, Q., (2014). Derivation of a Tasselled Cap Transformation Based on Landsat 8 At-Satellite Reflectance. *Remote Sensing Letters*, Vol. 5(5), 423-431. https://doi.org/10.1080/2150704X.2014.915434.

[34] Jensen, J., R., (2007). Chapter 11 Remote Sensing of Vegetation. *Remote Sensing of the Environment: An Earth Resource Perspective 2nd Edition*. Upper Saddle River: Pearson Prentice Hall.

[35] Senf, C., Seidl, R. and Hostert, P., (2017). Remote Sensing of Forest Insect Disturbances: Current State and Future Directions. *International Journal of Applied Earth Observation and Geoinformation*, Vol. 60, 49–60. https://doi.org/10.1016/j.jag.2017.04.004.

[36] Wildfire Maps and Data. *Alberta.Wildfire*. [Online]. Available: https://www.alberta.ca/wildfire-maps-and-data [Accessed Jan. 15, 2021].

[37] Bright, B. C., Hudak, A. T., Meddens, A. J. H., Egan, J. M. and Jorgensen, C. L., (2020). Mapping Multiple Insect Outbreaks across Large Regions Annually Using Landsat Time Series Data. *Remote Sensing*, Vol. 12(10), 1-20. https://doi.org/10.3390/rs12101655.

[38] Forest Health Conditions–Surveys and Reports. *Forest Health* [Online]. Available: https://www.alberta.ca/surveys-and-reports. [Accessed Oct. 8, 2022].

[39] Alberta Climate Information Service (ACIS). *Alberta Climate Information Service (ACIS)*. [Online]. Available: https://acis.alberta.ca. [Accessed Jun. 13, 2022].

[40] GIMP- GNU Image Manipulation Program. *GIMP*. [Online]. Available: https://www.gimp.org. [Accessed: Feb. 27, 2022].

[41] St. Clair, C. C., Habib, T. and Shore, B., (2011). OSIP - Data Library. Text. [Online]. Available: https://osip.alberta.ca/library/Dataset/Details/159. [Accessed Oct. 16, 2022].

[42] Alberta Energy Regulator ST37: List of Wells in Alberta. [Online]. Available: https://www1.aer.ca/ProductCatalogue/10.html. [Accessed Feb. 2, 2023].

[43] Alberta Energy Regulator ST 102: Facility List. [Online]. Available: https://www1.aer.ca/ProductCatalogue/35.html. [Accessed Feb. 2, 2023].

[44] Alberta Energy Regulator: Enhanced Pipeline Graphics File. [Online]. Available: https://www1.aer.ca/ProductCatalogue/35.html. [Accessed Feb. 2, 2023].

[45] Ord, J. K. and Getis, A., (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, Vol. 27(4), 286-306. https://doi.org/10.1111/j.1538-4632.1995.tb00912.x.

[46] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M. and Duchesnay, E., (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, Vol. 12, 2825–2830. http://jmlr.org/papers/v12/pedregosa11a.html.

[47] Thuiller, W., Georges, D., Engler, R. and Breiner, F., (2016). *biomod2: Ensemble Platform for Species Distribution Modeling.* [Online]. Available: https://biomodhub.github.io/biomod2/. [Accessed May 28, 2023].

[48] Sokolova, M. and Lapalme, G., (2009). A Systematic Analysis of Performance Measures for Classification Tasks. *Information Processing and Management*, Vol. 45(4), 427-437. https://doi.org/10.1016/j.ipm.2009.03.002.

[49] Congalton, R., Oderwald, R. and Mead, R., (1983). Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Statistical Techniques. *Photogrammetric Engineering and Remote Sensing*, 1671-1678.

[50] Picard, R. R. and Cook, R. D., (1984). Cross-Validation of Regression Models. *Journal of the American Statistical Association*, Vol. 79(387), 575–583. https://doi.org/10.1080/01621459.1984.10478083.

[51] Kohavi, R., (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *Proceedings of the 14th International Joint Conference on Artificial Intelligence*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc. Vol. 2, 1137-1143.

[52] History of Drought in Alberta., *Alberta Water Portal*. [Online]. Available: https://albertawater.com/history-of-drought-in-alberta/. [Accessed May 28, 2023].

[53] McKeown, L., Bristow, C. and Caouette, A., Canada's Shifting Sands: Oil Production, Distribution and Implications, 2005 to 2014. *Government of Canada*. [Online]. Available: https://www150.statcan.gc.ca/n1/pub/16-002-x/2016001/article/14629-eng.htm. [Accessed Feb. 27, 2024].

[54] Leach, A. Why this Oil Crash could be Worse for Alberta than the one in 2008. *Macleans.ca*. [Online]. Available: https://macleans.ca/economy/economicanalysis/why-this-oil-crash-could-be-worse-for-alberta-than-the-one-in-2008/. [Accessed Apr. 27, 2023].

[55] Market Snapshot: Oil Sands Production Likely to Continue Growing in the Short Term. *Canada Energy Regulator*. [Online]. Available: https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/market-snapshots/2015/market-snapshot-oil-sands-production-likely-continue-growing-in-short-term.html [Accessed Feb. 27, 2024].

Appendix Section

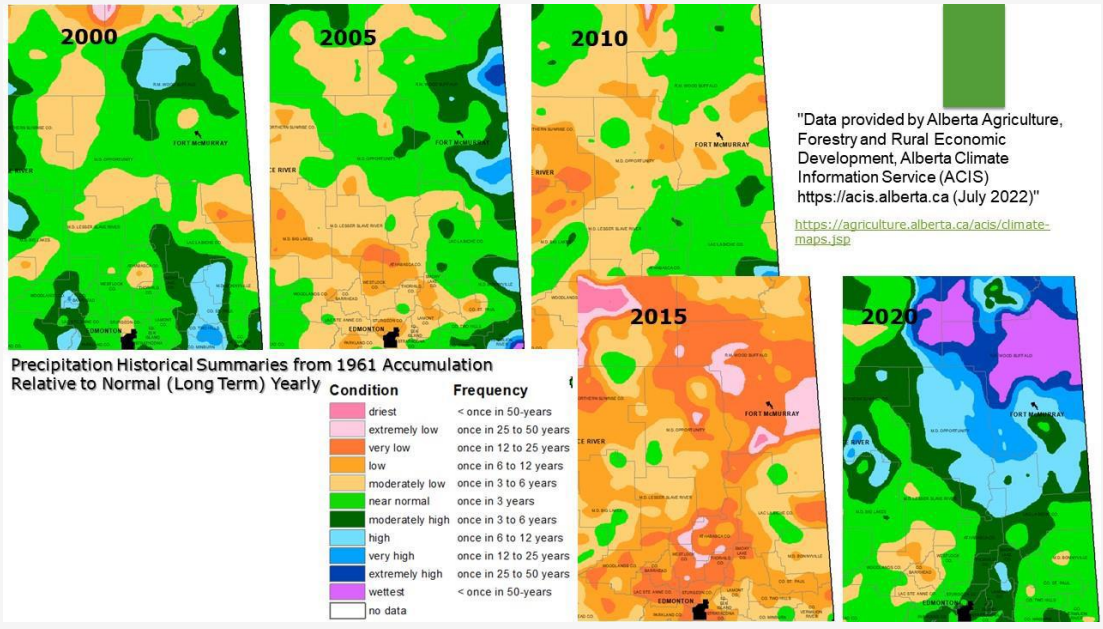

Figure S1: Extract, encompassing the OSA, of the yearly precipitation accumulations compared to long term normal precipitation GeoPDF (AAF, 2021) for the years of interest

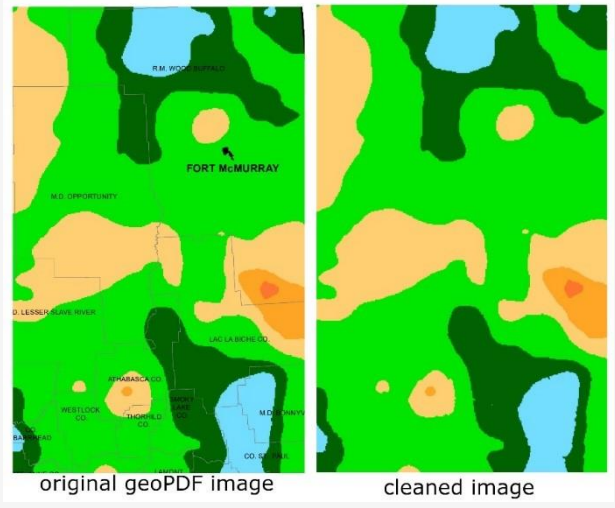

Figure S2: An example of yearly precipitation accumulations compared to long term normal precipitation from the original GeoPDF (AAF, 2021) to the cleaned one using GIMP and the resynthesizer plug-in

Table S1: Exploration of variable importance in bareness using Random Forest

	RF variable of importance (%)				GBM Variables of importance (%)			
	2000- 2005	2005- 2010	2010- 2015	2015- 2020	2000-2005	2005-2010	2010-2015	2015-2020
Wildfire	10.2	25.1	18.0	5.6	8.2	97.1	19.7	1.5
Forest damage	4.5	3.7	3.1	8.4	0.2	-	4.0	2.4
dwettest	-	-	4.5	35.3	-	-	1.2	83.6
dwet	8.1	0.2	0.1	26.6	7.1	-	-	4.3
dnormal	14.0	4.6	10.5	22.1	20.8	-	3.9	0.6
ddry	3.2	3.8	32.6	0.1	0.5	-	67.6	-
ddriest	-	-	1.5	-	-	-	-	-
Wells activity	28.0	40.9	18.3	10.4	41.9	-	20.4	8.0
Pipeline activity	19.0	31.6	3.1	4.3	24.5	-	0.3	-
Disturbed land	1.9	1.9	0.9	0.1	2.2	-	0.3	-
on testing*	**6 (191)**	**3 (225)**	**12 (185)**	**5 (192)**				
kappa	-0.03	0.11	0.20	0.31	-0.02	0.00	0.12	0.18
ROC	0.48	0.66	0.82	0.81	0.46	0.78	0.82	0.86

**Number of changed (no changed) HUC polygons within OSA*

Table S2: Exploration of variable importance in built-Up/bare using Random Forest

	2000-2005	2005-2010	2010-2015	2015-2020
Wildfire	4.10	10.10	25.70	17.70
Wells activity	52.00	16.10	47.90	20.10
Pipeline activity	29.10	51.40	21.20	28.60
Disturbed land	14.80	22.40	5.20	33.60
on testing*	**22 (135)**	**13 (144)**	**16 (141)**	**14 (143)**
Mean ROC AUC (training)	0.95	0.93	0.95	0.95
Mean ROC AUC	0.77	0.66	0.63	0.69
kappa	0.12	0	0	0
F1 on changed	0.15	0	0	0
F1 on no changed	0.92	0.96	0.95	0.95

**Number of changed (no changed) HUC polygons within OSA*

Table S3 and S4

Results of the automatically tuned models via biomod2:: BIOMOD_tuning(myBiomodData, models=c("RF","GBM"), env.ME = myExpl, n.bg.ME = ncell(myExpl)) in R

RF model	mtry	criterion	Resampling method
00-05_Greenness	2	max ROC	CV 10 fold
05_10_Greenness	3	max ROC	CV 10 fold
10-15_Greenness	3	max ROC	CV 10 fold
15_20_Greenness	2	max ROC	CV 10 fold
00-05_Bareness	6	max ROC	CV 10 fold
05_10_Bareness	3	max ROC	CV 10 fold
10-15_Bareness	3	max ROC	CV 10 fold
15_20_Bareness	5	max ROC	CV 10 fold

GBM model	n.trees	interaction.depth	shrinkage	m.minobsin node	criterion	Resampling method
00-05_Greenness	2500	9	0.005	10	max ROC	CV 10 fold
05_10_Greenness	2000	1	0.01	10	max ROC	CV 10 fold
10-15_Greenness	1250	5	0.005	10	max ROC	CV 10 fold
15_20_Greenness	2000	2	0.001	10	max ROC	CV 10 fold
00-05_Bareness	200	4	0.01	10	max ROC	CV 10 fold
05_10_Bareness	7500	1	0.05	10	max ROC	CV 10 fold
10-15_Bareness	300	7	0.001	10	max ROC	CV 10 fold
15_20_Bareness	5000	2	0.005	10	max ROC	CV 10 fold

Results of the automatically tuned models via sklearn.model_selection.GridSearchCV(rf, param_grid, cv=5) with param_grid = {'n_estimators': [80,100,130],'max_depth': [2,3,4,5],'max_leaf_nodes':[3,4,5,6,8,10,12], min_samples_split':[5,10,20,30,40],'criterion': ['entropy', 'gini']}

RF Model	max_depth	max_leaf_nodes	min_samples_ split	n_estimators	Accuracy (training)	Accuracy (testing)	Best CV-Score	Criterion
00-05_Forest	2	3	5	80	0.87	0.87	0.87	entropy
05-10_Forest	5	8	40	100	0.77	0.71	0.71	entropy
10-15_Forest	5	12	30	80	0.82	0.73	0.75	gini
15-20_Forest	5	10	10	100	0.76	0.69	0.72	entropy
00-05_Agriculture	5	12	5	80	0.78	0.74	0.76	gini
05-10_Agriculture	5	12	5	80	0.77	0.70	0.73	gini
10-15_Agriculture	5	12	3	130	0.79	0.71	0.76	gini
15-20_Agriculture	5	12	5	130	0.76	0.72	0.70	gini
00-05_Built-up/Bare	3	4	20	130	0.93	0.87	0.90	gini
05-10_Built-up/Bare	4	5	20	80	0.96	0.92	0.95	gini
10-15_Built-up/Bare	2	3	5	80	0.95	0.90	0.93	entropy
15-20_Built-up/Bare	2	3	5	80	0.94	0.91	0.93	entropy