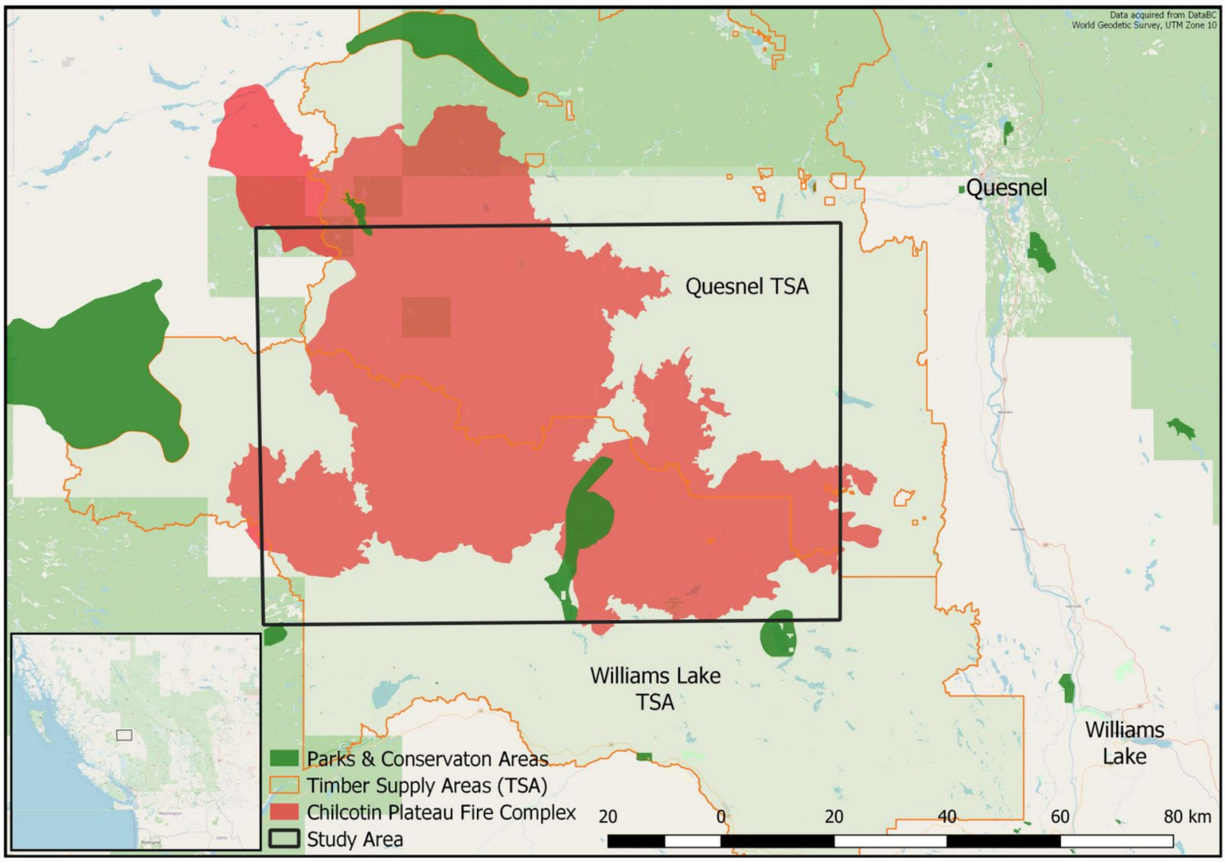
Post-Wildfire Landscape Metrics & Transition Characteristics in Cariboo Regional District, 2017

Table of Contents

1.0 Introduction

The summer of 2017 marked one of the worst fire seasons in British Columbia's history. By October, wildfires had covered approximately 1.2 million hectares, prompting the province to spend $649 million in fire suppression costs alone (Province of British Columbia, 2020). Accurate analysis of post-fire areas can facilitate decision making in forestry and environmental management. Applied over a longer period, these examinations can predict forest fire behaviour and guide fire response. The purpose of this experiment is to evaluate the effects of wildfires on local landscape metrics and analyze the characteristics of land cover change across the post-fire landscape. The 700,000 ha study area is situated southwest of Quesnel, centered on the Chilcotin Plateau fire complex which merged in July. The area is diverse in terrain and ecosystems, though coniferous forests prevail with a mixture of fir, pine, spruce and aspen meadows (Trail Ventures BC, 2020). In general, the flora and fauna found here are a mix of those found in B.C.'s coastal and interior regions (2020).



Map 1: Study area extent, lumber resources, parks, and nearby communities.

The southern half of the study area lies within the Williams Lake TSA (Timber Supply Area), lying between the Coast Mountains in the west and the Cariboo Mountains to the east. The northern half covers part of the Quesnel TSA. The area is a valuable source of lumber; 3 million cubic metres are cut annually (2020). The study area also contains Nazko Lake Park, While Pelican Park, and the Narcosli Lake Ecological Reserve. To the east are the communities of Williams Lake and Quesnel.

2.1 Materials & Workflow

Two Landsat 8 OLI images from August 2016 and September 2017 were acquired from USGS for the primary analysis. Auxiliary data describing historical fires, logging areas, and land cover from DataBC provided background information. Aerial images from Google Earth provided some rudimentary ground truth data. Much of the geoprocessing was performed in a QGIS environment, though the classification and accuracy assessment were accomplished using RandomForest and caret (Classification and Regression Training). Landscape metrics were computed with FRAGSTATS, and a transition matrix was created using MOLUSCE (Modules for Land Use Change Simulations).

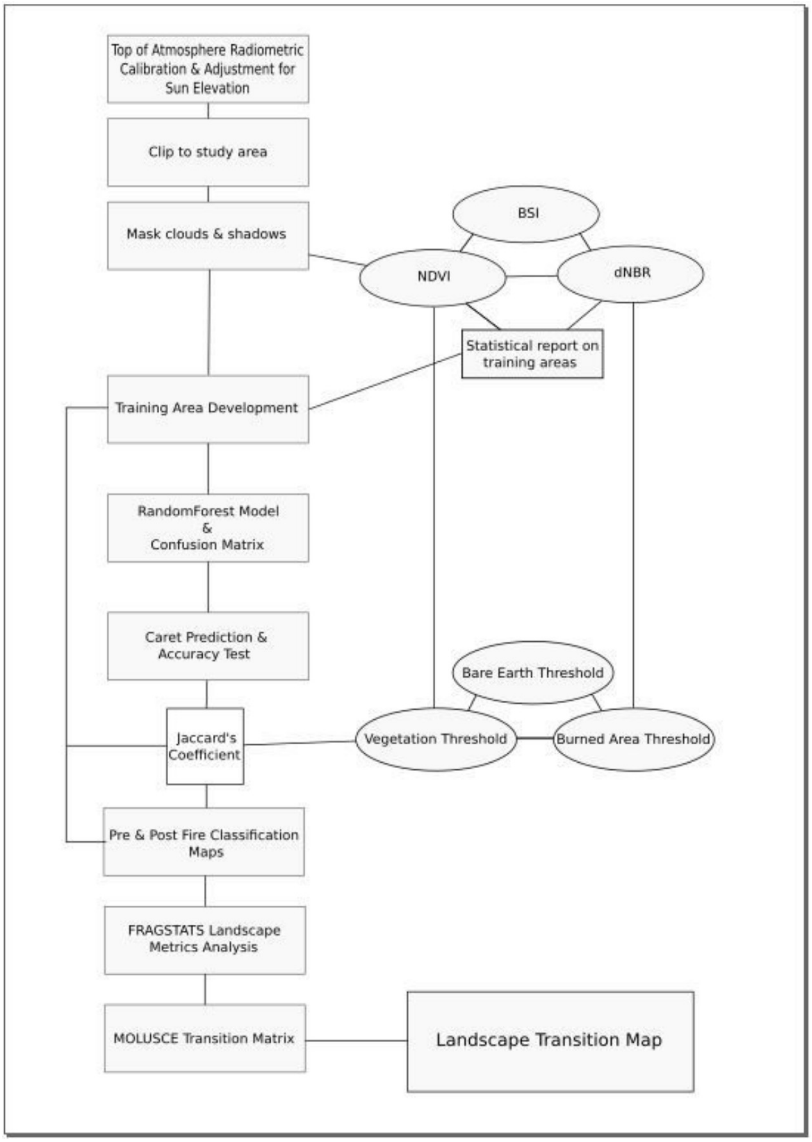
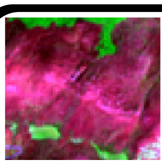
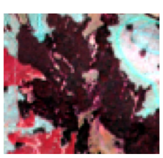


Image 1: Workflow design. Correlation with vegetation, soil and fire indices was an important part of ensuring training areas captured only land cover represented by their respective class.



Burned Areas was easily recognized using band combination 7-5-2. This combination is commonly used for visualizing forest fire burn scars; short-wave infrared bands are less susceptible to smoke and haze generated by fires.



Dense/Healthy Vegetation areas appear in vibrant shades of reds using bands 5-4-3. Coniferous trees usually appear dark. This reflectance is based on water and chlorophyll absorption in the leaves.

Sparse/Degraded Vegetation in the 5-4-3 band combination appears light red and pinkish due to the small difference in reflection of visible and infrared wavelengths. There are lower levels of chlorophyll absorption and/or less vegetation.

Open/Bare Earth area are easily distinguishable in the true colour 4-3-2 band combination. Roads, empty fields and recently logged areas all exhibit somewhat similar wavelength signatures.

Image 2: Band combinations used in supervised classification

Bands 2 to 7 from each image were stacked and clipped to the study area. Top-of-atmosphere radiometric values were calibrated and corrected for sun elevation. Clouds and shadows were masked out, and training sites created. Bare Soil Index (BSI), Normalized Difference Vegetation Index (NDVI) and difference Normalized Burn Ratio (dNBR) were calculated to refine classification training sites according to thresholds set through research and ground-truth data.

Classification was divided into four broad land cover categories. 'Burned Areas' encompasses areas directly affected by fire with no vegetative regrowth. Open/Bare Earth represents areas covered mostly by soil, rocks, and trace amounts of vegetation. Sparse/Degraded Vegetation represents unproductive grasslands and sparse, degraded forests. Healthy/Productive Vegetation delineates areas of dense forests, productive fields and thick foliage.

The landscape was modeled through Random Forest and accuracy was assessed using caret. Random Forest uses many decision trees to predict classes based on a set of data (Yiu, 2019). Functions within caret partition data, train models, and evaluate model performance using a confusion matrix. Testing points throughout the classification maps are compared to aerial imagery acquired to assess map accuracy.

FRAGSTATS provided a landscape metrics system to evaluate ecosystem degradation and habitat suitability. MOLUSCE quantified land cover changes and transition characteristics between different time periods, revealing patterns of fire expansion. The final product reveals which types of areas were affected most, and category conversion trends between classes.

2.2 Normalized Spectral Indices

Spectral Indices are used to automatically outline landscape features like soil, water, and vegetation. Normalized indices were chosen in order to minimize detrimental effects due to topography. NDVI is a good indicator of forests and productive vegetation (Buma, 2011). Higher values reveal areas of more productive flora due to increased infrared energy reflectance and red band absorption. Healthy vegetation is usually above .65, but studies in temperate forests in Canada have shown that forests can have values as low as .36 (He et al, 2012). BSI uses blue, red, near-infrared and short-wave infrared bands to capture soil variations (Earth Observation University, 2020) It is useful in soil mapping and crop identification. Bare soil values hover around zero, and the presence of vegetation causes the value to rise. Classification of soil-covered areas can be improved by searching for areas with near zero BSI and low NDVI values (Diek et al, 2017).

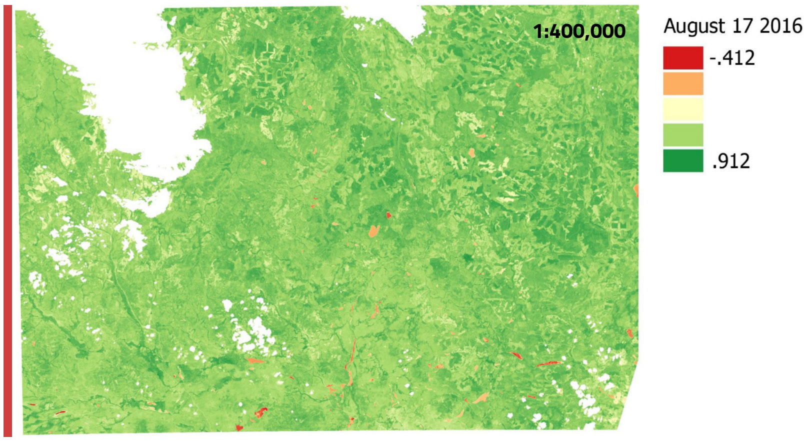


Image 3: NDVI 2016: August is the peak growing season, so NDVI values are high. The time of day, precipitation and amount of received sunlight also factor in index values.

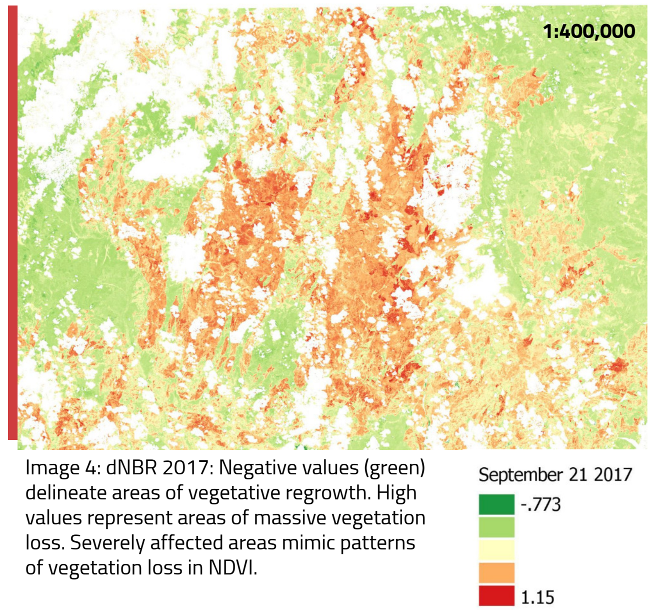


Image 4: dNBR 2017: Negative values (green) delineate areas of vegetative regrowth. High values represent areas of massive vegetation loss. Severely affected areas mimic patterns of vegetation loss in NDVI.

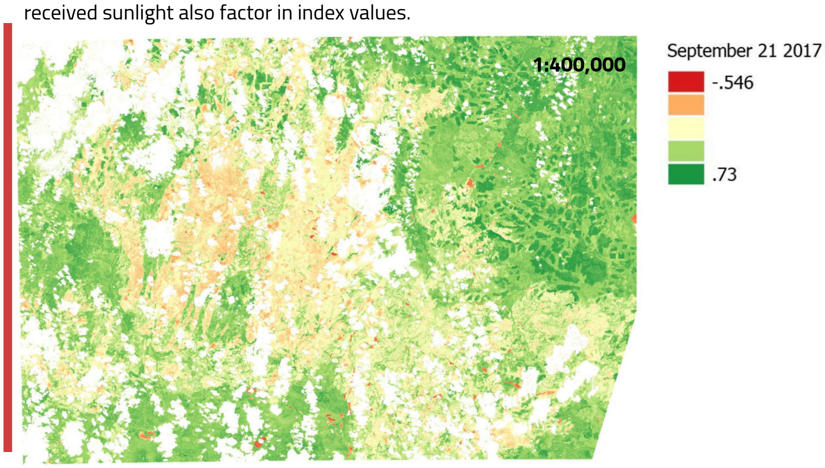


Image 5: NDVI 2017: September is past the peak growing season, and the image was captured later in the evening. NDVI values reflect these changes even in areas unaffected by fire.

NBR uses the ratio between near-infrared and short-wave infrared bands to detect recently burned areas (UNOOSA, 2020). Shortwave infrared reflectance increases greatly following a fire due to losses in canopy shadow and moisture (Wu, 2015). The dNBR is the difference between pre-fire and post-fire images: higher values depict areas more severely burned and greater loss of vegetation. dNBR is best used immediately after the fire before there has been a chance for vegetation to regrow.

	BSI		dNBR		NDVI	
Indices	2016	2017	2016	2017	2016	2017
Burned Areas	0.21 - 0.28	-0.10 - 0.02	-0.34 - -0.27	< 0.27	0.19 - 0.24	-0.03 - 0.07
Open/Bare Soil	0.01 - 0.14	-0.07 - 0.13	0.04 - 0.25	0.02 - 0.19	.28 - 0.53	0.18 - 0.33
Sparse/Degraded Vegetation	-0.09 - 0.10	-0.14 - -0.03	0.12 - 0.38	-0.09 - 0.07	0.45 - 0.63	0.27 - 0.411
Healthy/Dense Vegetation	-0.28 - -0.08	-0.39 - -0.21	0.37 - 0.58	-0.15 - 0.05	0.62 - 0.76	< 0.411

Table 1: Index Thresholds:: Threshold limits were calculated by averaging the maximum and minimum values of pixels in validated areas for each class. If correlation with indices was poor, then training sites were rebuilt to exclude extreme values.

3.1 **Classification & Map Accuracy**

Index correlation was measured using Jaccard's Coefficient; it compares areas which satisfy both the index and class to those which satisfy only one. NDVI and dNBR correlated well with Healthy/Dense Vegetation and Burned Areas respectively, but the Open/Bare Soil matched poorly with the BSI. The Random Forest model was very accurate: training sites successfully predicted classes in dedicated testing areas. Caret described strong performance for the classification models as well. Kappa, a measure of concordance for categorical data that measures agreement relative to what would be expect by chance, remained high in both maps as well (Kuhn, 2008).150 random points were generated in each classified landscape and compared to aerial imagery in order to obtain map accuracy. Although map accuracy was high, there were difficulties in discerning Sparse/Degraded Vegetation from Healthy/Dense Vegetation. Water was occasionally classified as a severely burned area, due to similar reflectance values in the short-wave infrared band.

Table 2: Accuracy of results

	2016	2017
Map Accuracy	85%	83%
BSI	54%	47%
NDVI	89%	82%
dNBR*	-	74%
Caret Accuracy	.9888	.9525
Kappa	.9802	.9147

* There is no dNBR for August 2016; it is ia a comparison of two dates.

Image 6: September 21 2017 Classification

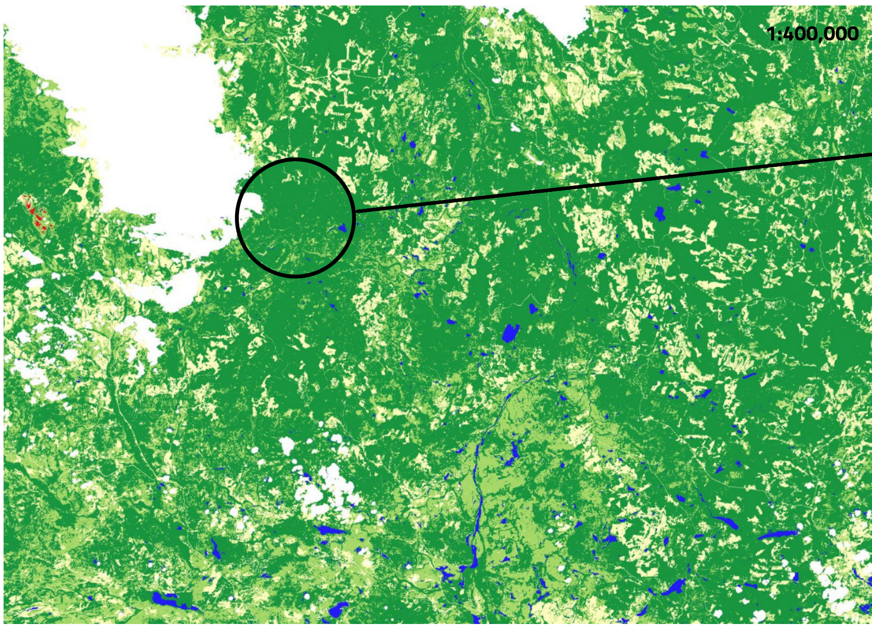


Image 8: August 17 2016 Classification of Healthy/Dense Vegetation. Forests and productive fields dominate the landscape.

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Image 7: September 21 2017 Classification

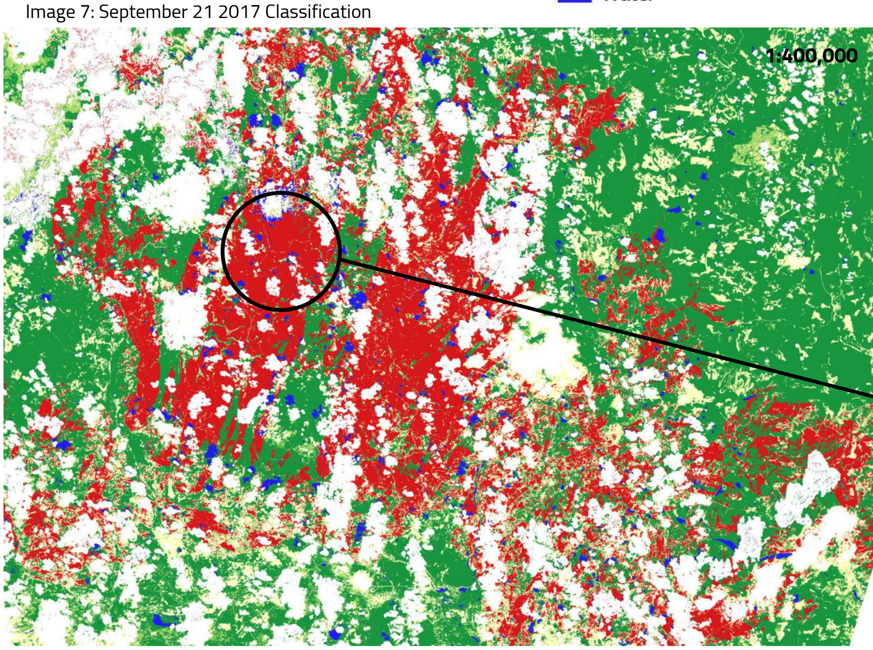
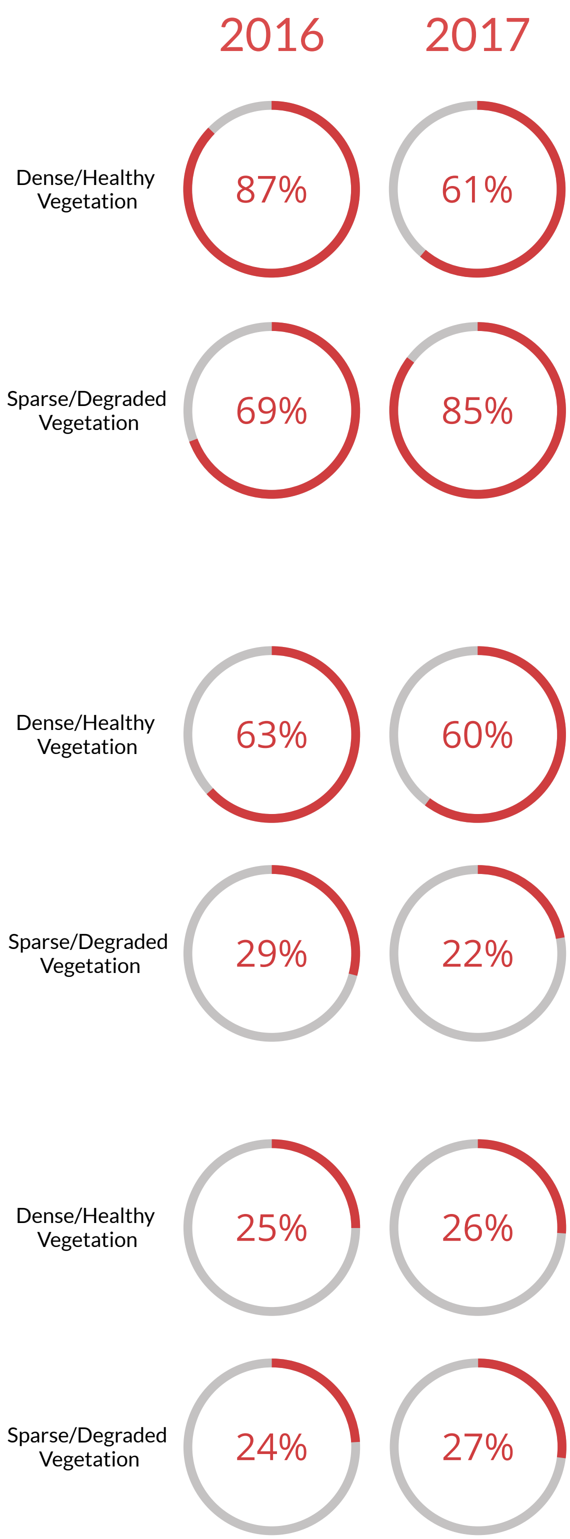


Image 9: Previously heavily vegetated areas after the fire. There is little regrowth in vegetation so. soon after the fires had subsided

3.2 **FRAGSTATS Metrics & Quantifying Spatial Patterns**

FRAGSTATS is a research tool which contains a plethora of metrics for defining and quantifying patterns in natural landscapes. It was founded on the notion that the patterning of landscape elements (patches) strongly influences ecological processes (McGarigal & Marks, 1994). Three metrics were chosen and normalized to analyze the broad pattern of change in vegetation classes as a result of the 2017 wildfire. Bare/Open Areas were excluded because they hold less value to stakeholders and rebound relatively quickly after fires. Metric values were compared to their theoretical maximum to reach a percentage expression. By analyzing the patch shape, core area, and mean distance between patches, researchers can gain a broad interpretation of remaining ecosystem habitability and gauge the potential disturbance to local species.



Core Shape Index

Patch shape has been shown to influence inter-patch processes amongst wildlife and woody plant colonization. This is due to the 'edge-effect', the zone where two distinct ecosystems meet. The shape index measures the complexity of patch shape compared to a standard circular shape; a shape index approaching 0 is increasingly complex as the ratio of edge distance to patch area increases. This has negative effects on the breeding success of birds and leads to degradation of forest fragments (Harper et al, 2005). While dense and healthy vegetation area shapes became more complex, sparser areas retained a more basic shape.

Core Area Index

Core Area Index is defined as the area within a patch beyond some specified edge distance or buffer (McGarigal & Marks, 1994). It is the core area outside the effects of the edge influence, in this case a buffer of 60 metres. Core area size is a central issue in the protection of forest-interior species, and is often a useful predictor of the presence and abundance of area-sensitive species (Hennenberg et al, 2008). A core area index value approaching 1 implies a less fragmented landscape. Core area size in both classes slightly decreased, more so in sparse and degraded areas.

Inter-patch Distance

Inter-patch distance is defined as the distance from a patch to the nearest neighbouring patch of the same type, based on edge-to-edge distance. It is a main factor of landscape distribution, and influences a number of important ecological processes. A greater inter-patch distance translates to greater patch isolation and fragmentation in ecosystems (McGarigal & Marks, 1994). The average distance between patches in both classes remained relatively unchanged.

3.3 **MOLUSCE & Landscape Transition**

MOLUSCE is an open-source extension capable of analyzing and distinguishing the land use change characteristics between two different years (Yusryzal & Ibrahim, 2015). The software produces a change map which indicates the location of area changes. Shifts in landcover are recorded in a transition matrix, displaying the total proportions of each class and their direction of transformation. The classification model yielded results similar to the outbreak patterns given by DataBC, though there are gaps of untouched areas in the center of the study area. Approximately 120,000 ha experienced moderate to severe burning, and areas with healthy or dense vegetation decreased by 80,000 ha. Areas with little or no vegetation increased by almost 23,000 ha, though some of this is probably due to incorrect classification: areas with minimal burn scarring mimic the spectral signature of areas dominated by soil cover, while some sparsely vegetated areas may simply be experiencing lower levels of production due to the season. Sparse/Degraded Vegetation zones also decreased by approximately 66,000 ha. Overall, the region has experienced significant losses in valuable forest resources and biomass-producing areas.

	2016		2017	
	Area (ha)	%	Area (ha)	%
Burned Area	110	0.02	120,067	24.81
Open/Bare Areas	67,851	14.02	90,467	18.69
Sparse/Degraded Vegetation	86,727	17.92	19,120	3.95
Healthy/Dense Vegetation	324,129	66.99	243,498	50.32

Table 3: Landcover class transitions in hectares and proportions of total landscape area

Healthy/Dense Vegetation was the largest contributor to Burned Areas; 21.9% of the class area was converted to the burned class. Sparse/Degraded Vegetation also contributed 34.3% of its initial expanse to Burned Areas. Approximately half of Open/Bare Areas remained unchanged, though a significant portion (27.8%) was converted to Burned Areas. Although the area remains dominated by areas represented by the Healthy/Dense Vegetation class, it will take decades for the area to reach pre-fire levels of biomass production.

4.0 **Conclusions**

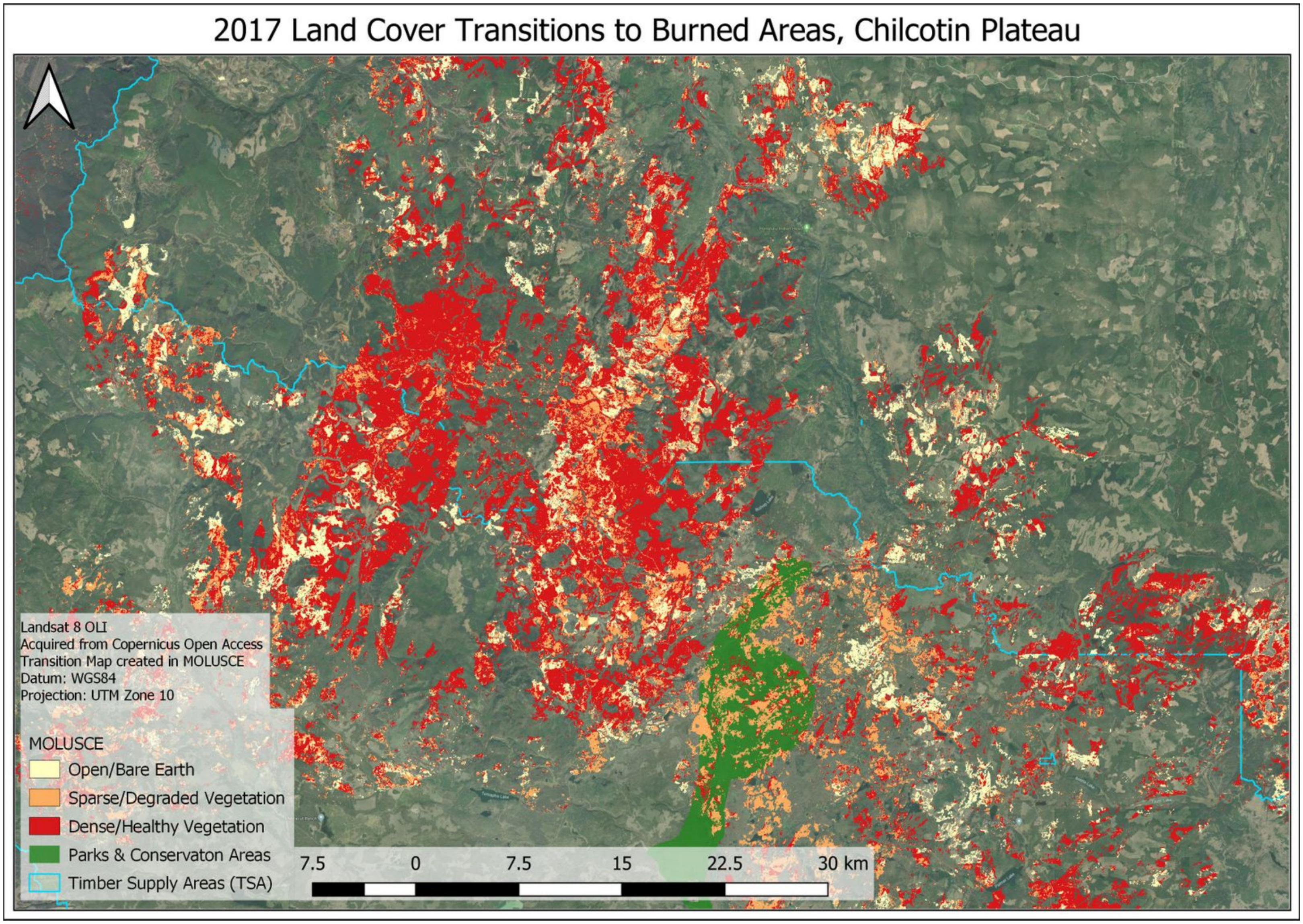
The study shows that heavily vegetated areas bore the brunt of the damage from the fire outbreak, and the extent of fire-affected areas roughly coincides with independent data. There is significant damage to TSA areas as well as provincial parks. As a result, the remaining productive vegetation areas have become more complex, fragmented, and isolated. These broad changes potentially further stress local wildlife and inhibit recovery rates, as well as introducing additional access challenges for logging entities operating in the area.

The research methods performed moderately well at discerning basic differences in broad classes. Map accuracy and index correlation were relatively successful as well. The Random Forest model also reliably predicted the correct classes based on spectral signatures. However, the study has some significant shortcomings. Individual indices were not sufficient in predicting land cover: although stacking them improved results, class spectral signatures proved to be more complex and

From/ To	Burned Areas	Open/Bare Areas	Sparse/Degraded Vegetation	Healthy/Dense Vegetation
Burned Areas	11.2%	76.5%	1.1%	4.4%
Open/Bare Areas	27.8%	47.0%	6.9%	17.5%
Sparse/Degraded Vegetation	34.3%	23.7%	7.8%	32.6%
Healthy/Dense Vegetation	21.9%	11.5%	2.3%	62.2%

Table 4: Transition proportions to and from each class

varying than limited thresholds of several bands. The Landsat data was unable to produce meaningful distinctions in land cover which could provide valuable information to stakeholders. For example, Sparse/Degraded Vegetation and Healthy/Dense Vegetation were occasionally classified interchangeably, and the types of vegetation that make up these classes (coniferous trees, deciduous trees, shrubs, grasses) could not confidently discerned. The inclusion of radar data could detect changes in vegetation structure, providing a means of differentiating between tree species. It could also discern canopy height from ground elevation, providing information on timber stock losses. Furthermore, Landsat data is limited by cloud cover; 27% of the September 2017 image was discarded to account for clouds and shadows, while the August 2016 set suffered about 20%. While map accuracy was high, ground-truth data was limited to aerial imagery available



Map 2: Spatial extent of transformations from each class into Burned Areas. There were more transition patterns that have been excluded in order to highlight the patterns primarily concerned with the study. For example, there were significant amount of Dense/Healthy Vegetation and Sparse/Degraded Vegetation zones that were converted into Open/Bare Areas.

through Google Earth: the inclusion of surveys or LiDAR data would provide a more reliable method of obtaining true map accuracy. Similar studies in the future could be improved by implementing initial unsupervised classification techniques, such as the K-Means method which produces spectral classes representing clusters of similar image values. Overall, the study is a useful first step in evaluating damages inflicted on forest resources in a wildfire scenario and showcases how private and public stakeholders can quickly calculate and present these changes using open-source software.

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