GEOG 471

Evaluating the Impact of Burn Severity on long-term Vegetation Regeneration in Okanagan Mountain Park, British Columbia and Slave Lake, Alberta

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Abstract

This research paper aims to assess the relationship between burn severity and vegetation regeneration in the Okanagan Mountain Park wildfire in 2003 and the Slave Lake wildfire in 2011. This study utilizes remote sensing data and a variety of methods, including the normalized difference vegetation index (NDVI), normalized burn ratio (NBR), and differenced normalized burn ratio (dNBR) in order to analyze vegetation regeneration over a 10-year period. The study areas were chosen based on specific criteria, such as the total area burnt, the date on which the major fire was observed and whether any major wildfires followed up after the initial event. The study's objective is to compare the differences in the vegetation regeneration results between the two wildfires while determining which driving factors can be used to predict long-term vegetation regeneration.

This research's methodology involves analyzing the pre-fire, post-fire, 2-year, 4-year, 6-year, 8-year and 10-year NDVI values for the two study areas to provide an estimation of the distribution of vegetation health available in an area. The dNBR of the two wildfires was obtained to derive the severity of fires as an index. This is done by looking at NBR values pre-fire and post-fire, which represent the severity of each fire. For Slave Lake, the dNBR values did not correlate with the NDVI values, while Okanagan Mountain Park had strong correlation. Additionally, elevation, slope, northerly value, and easterly value were obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) as they are key factors that directly impact vegetation regeneration. Linear regression models were used to analyze how these factors affect long-term vegetation regeneration for each study area.

The results of this study provide valuable insights into the factors that affect vegetation regeneration. Significant relationships between the different regression variables were established. The difference in the results for the two study areas is interesting. Although both wildfires did significant damage to each respective study area, vegetation regeneration is very different between them. Slave Lake makes a full recovery within the first 4 years while Okanagan Mountain Park seems to never recover. The results highlight the importance of considering burn severity when developing effective post-fire management strategies.

This research paper provides important information regarding the impacts of wildfires on vegetation regeneration, which could be used to have a better understanding of vegetation recovery when considering post-fire management practices.

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Introduction

1.1 Introduction

Wildfires have become an increasingly critical issue globally due to their destructive effects on both human and natural environments. The impacts of such fires ranging from property loss to environmental destruction, can be felt for years, causing long-term damage to affected areas. Understanding the processes and dangers of wildfires is important in reducing their effects and developing effective post-fire management strategies. However, many variables come into play which are uncontrollable when assessing the impacts of wildfires, making it challenging to fully comprehend their long-term effects. Similarly, research studies that evaluate the impact of wildfire on vegetation regeneration are of significant importance in managing the effects of wildfires.

The study areas selected for this research are Okanagan Mountain Park in British Columbia and Slave Lake in Alberta. The areas were chosen based on specific criteria, including the total area burnt, when the fire initially occurred and whether any major wildfires followed up after the initial event. These two study areas met these conditions even though they are very different in every aspect. This difference allows for a more diverse analysis.

An important aspect of this study is in order to evaluate the impact of burn severity on long-term vegetation regeneration in Okanagan Mountain Park, British Columbia, and Slave Lake, Alberta, the study utilized differenced normalized burn ratio (dNBR) as an index to measure burn severity through remote sensing. dNBR is a commonly used index to measure burn severity due to its ability to differentiate between areas of high and low-severity burns by comparing pre-fire and post-fire NBR (normalized burn ratio) values. Although it is a commonly used index, it seems that previous papers do not seem to take dNBR into consideration.

Understanding the regeneration process of vegetation following a wildfire and identifying areas that require intervention in order to reduce further damage are essential in the development of effective post-fire management strategies. This research aims to contribute to a better understanding of the impacts of wildfires on vegetation regeneration in Okanagan Mountain Park, British Columbia and Slave Lake, Alberta. By analyzing the impact of burn severity on vegetation regeneration over a 10-year period, useful data could be provided to policymakers to assist in developing strategies for post-wildfire management.

To answer the research questions, several different methods were considered for this study. The results were obtained through the use of valuable tools and a variety of techniques, such as Google Earth Engine, remote sensing data, and thorough analysis. In order to select the appropriate methods to achieve a comprehensive evaluation, each factor influencing vegetation regeneration was researched to determine a feasible and robust analysis. In the end, processes employed in this study included using indices like normalized difference vegetation index (NDVI) and normalized burn ratio (NBR), as well as analysis methods such as linear regression to determine which factors influence vegetation regeneration the most. Additionally, several pieces of literature were reviewed to enhance the decision process of these methods and to subsequently support the findings of this study. The first part of the analysis was to use Landsat 5 and 8 images to compose a map of NDVI values over time for the two selected study areas. NDVI is a widely used method to measure vegetation regeneration, especially when it comes to post-fire assessment (Ireland & Petropoulos, 2015a; Eckert et al., 2015). This index was used to provide an estimation of the distribution of vegetation health present in an area, making it a useful tool for monitoring ecosystem productivity. In this study, the NDVI values of pre-fire, post-fire, 2-year, 4-year, 6-year, 8-year, and 10-year were obtained and compared. Next, using the same datasets, the dNBR (differenced Normalized burn Ratio) of the two wildfires was acquired. This is a frequently used method to derive the severity of fires as an index, which provides an idea of how much damage was done by each fire (Giddey et al., 2022). Further data was obtained from The Advanced Spaceborne Thermal Emission and Reflection Radiometer (Aster) Global Digital Elevation Model (GDEM). This elevation model supplied other vegetation regeneration influencing variables such as elevation, slope, northerly value, and easterly value. These are key factors that directly impact vegetation regeneration since the topography highly influences variables like the amount of sunlight and precipitation an ecosystem will receive, further impacting other driving factors such as the spread of soil moisture (Martín-Alcón & Coll, 2016). Lastly, to bring it all together, using numerous linear regression models, it will allow for the analysis of how these distinct factors affect long-term vegetation regeneration (Liu et al., 2022). Through the combination of these methods and the use of supporting literature, this research paper aims to provide a better understanding of post-wildfire vegetation regeneration. More specifically, to verify that burn severity plays a significant part in an ecosystem's ability to regrow. As well as determine how much the specifically chosen factors influence regeneration, and the consequences that accompany these fires.

1.2 Research Objectives

1. To assess the relationship between burn severity and vegetation regeneration in the 2003 Okanagan Mountain Park wildfire and the 2011 Slave Lake wildfire.
2. To compare the differences in the vegetation regeneration results between the two wildfires while determining which driving factors can be used to predict long-term vegetation regeneration.
3. To evaluate the long-term effects of these wildfires with regard to ecological and climatic consequences.

Methods

In this section, the methods that were used for this study will be explained and supported. An outline of the study areas and datasets that were chosen for this paper will be provided, in addition to the strategies employed for measuring vegetation regeneration and classifying fire severity for these selected study areas. Information and reasoning behind how NDVI, NBR, dNBR, and Aster GDEM data were utilized will be explained. There are details about the data analysis methods used, including linear regression, and a description of how these techniques were applied to gain a comprehensive understanding of the factors that affect vegetation regeneration. In general, this section will provide all the details required to re-create this analysis. The general processes followed for the methodology can be observed in Figure 2.1 below.

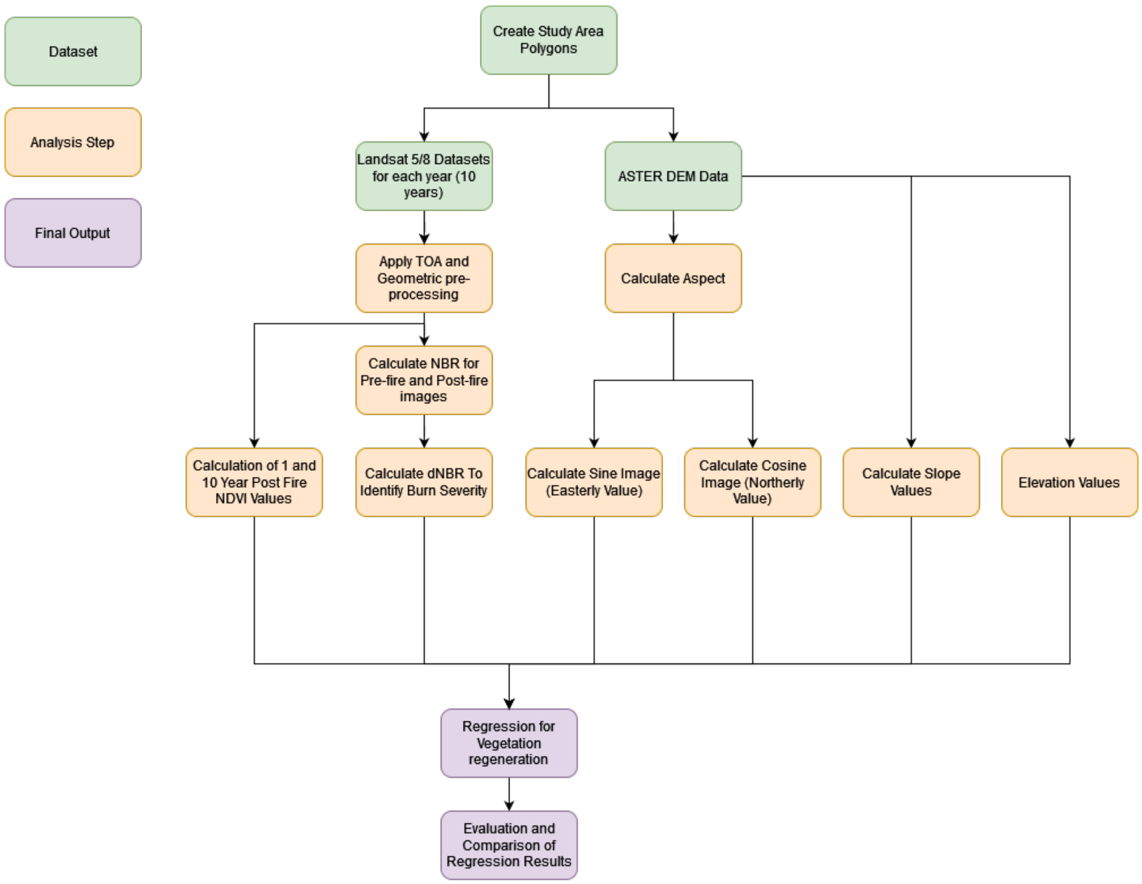

Figure 2.1: Methodology

2.1 Study Area

For this study, two areas were selected for comparison in terms of vegetation regeneration following wildfires. The study areas selected for analysis in this research are the Okanagan Mountain Park, which experienced a wildfire in 2003, and the Slave Lake Fire, which occurred in 2011 in Alberta, Canada. These two areas were chosen for their unique and contrasting characteristics in terms of vegetation types, climate, and topography. The location and extent of these study areas can be seen in Figure 2.2 below.

Figure 2.2: Study Area

The study areas were selected based on specific criteria, including the requirement that the wildfires occurred over a decade ago in order to evaluate the rate of vegetation regeneration over a longer period of time. Additionally, the wildfires had to affect an area greater than 5000 acres which would place them in the largest class according to NWCG's size classification for wildfires. Similarly, the areas had to be unaffected by any significant wildfires since the initial burning; this was done to prevent additional fires from affecting the natural rate of vegetation regeneration measured within the study period. To conduct a comprehensive analysis, the areas needed to be larger than 5000 acres as this would allow for a more extensive dataset, resulting in a better understanding of the vegetation regeneration process. Larger areas also meant that a more representative sample of the ecosystem could be captured; aiding in the evaluation of the long-term impacts of wildfires on vegetation.

The first study area is the Okanagan Mountain Park located in British Columbia. In 2003, this region experienced significant damage from a wildfire outbreak, making it an ideal case study for examining vegetation regrowth over a period of ten years (2003-2013). Most of the park's landscape consists of coniferous forests with grassy and shrubby regions found in lower areas. The average elevation is around 983 meters and the slopes range from 0 to 89° (Ireland & Petropoulos, 2015b). On August 16, 2003, a lightning strike started a fire that burned a total area of 64,030 acres in the Okanagan Mountain Park (Brennan, 2012). The Okanagan Valley experiences a mild and continental climate with warm and sunny summers, while winters can range from moderate to cold extremes at higher elevations (Brennan, 2012).

Okanagan Mountain Park would be an interesting area to study due to the severe and long-lasting impacts of the fire on the local community, infrastructure, tourism industry and environment, as well as the potential effects of fire suppression on future wildfires. Okanagan Mountain Park matched the criteria of this study due to several reasons. Firstly, the wildfire occurred in 2003, which is over 10 years ago, making it suitable to evaluate the rate of long-term vegetation regeneration. Secondly, the affected area of the wildfire is greater than 5000 acres and at last, the areas have not been affected by any significant wildfires since the initial burning.

The second study area is Slave Lake located in Alberta. In 2011, a wildfire known as the Slave Lake Fire occurred in this area with a significant impact on the town of Slave Lake. In comparison to Okanagan Mountain Park, Slave Lake has lower peak elevation levels ranging from 500m to 1000m, with an average of 590m. The Slave Lake Fire, caused by arson, destroyed 374 homes and caused widespread damage over an area of 1200 acres, mainly consisting of Boreal forests and residential areas (Kulig, 2012). The aftermath of the fire led to the allocation of $189 million for rebuilding and implementing a wildfire recovery plan. Although different in cause and impact, the Slave Lake Fire provides another area of interest to study vegetation regeneration following a wildfire. Despite the differences in vegetation types, both areas provide valuable insights into vegetation regeneration following a wildfire. Thus, this study aims to compare the post-fire vegetation recovery of these two contrasting ecosystems and to provide a better understanding of the factors affecting the regeneration of vegetation in these areas.

2.2 Datasets

The images and datasets acquired for this study were obtained from Landsat 5, Landsat 8, and The Advanced Spaceborne Thermal Emission and Reflection Radiometer (Aster) Global Digital Elevation Model (GDEM). Firstly, the calculation to obtain Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio (NBR) values requires using the reflectance values of the near-infrared and red bands, and the near-infrared and shortwave-infrared bands, respectively (Kim et al., 2021). These 3 bands can be found on Landsat satellites. For this study, the chosen time frame for assessing long-term vegetation regeneration is 10 years. Given that the wildfires occurred in 2003 and 2011, this means the images to be acquired need to be within the 2003 to 2013 range for the first fire and the 2011 to 2021 range for the second fire. While trying to use freely available data and simultaneously cover the temporal scale without having to change satellites, Landsat was the best fit in order to keep the data and images as consistent as possible within the two study areas. The reasoning behind this is that Landsat 5 has been providing data from 1984 to 2012 and Landsat 8 has been active since early 2013, both of which nearly cover the entire time frame for the two study areas (Li et al., 2021). This satellite also allows for a great selection of images given that Landsat 5 and 8 have a 16-day repeat cycle (Landsat Missions, n.d.-a,-b). Additionally, Landsat provides high spatial resolution data; the reflectance bands have a resolution of 30m (Landsat Missions, n.d.-a,-b). These characteristics are important because wildfires tend to create a significant amount of smoke which interferes with the data returned from the satellite bands, further resulting in analysis errors (Wang et al., 2022). Having the ability to pick a clear image that was taken soon after the fire allows for more consistent and accurate results. Additionally, the datasets derived from these satellites are readily available on Google Earth Engine, a crucial tool that was utilized in this research. Referring to Table 2.1, more information can be found about the details of the satellite and the specific collections used in this study.

Landsat 5 and 8 were used to evaluate the NDVI values at 2-year increments until the 10th year was reached and to obtain the NBR values required for calculating dNBR. By using Landsat 5 and Landsat 8, the datasets obtained were easily accessible, accurate, and provided several different images of the study area throughout the 10-year time frame, allowing the data used for the analysis to remain as consistent as possible. Furthermore, the images used for calculating NDVI were all carefully selected to fall within the summer months, primarily in July and August, to keep the values as comparable to each other as possible.

In order to obtain the rest of the data for the linear regression model, Terra Aster GDEM was the selected dataset. The rest of the independent variables for the linear regression analysis were gathered from this dataset. This includes the elevation, slope, northerly values, and easterly values of the study areas. Just like NDVI and NBR, the data was calculated using Google Earth Engine. Aster GDEM was a well-fit choice for this research as it has a high spatial resolution just like the Landsat satellites sitting at 30m, it covers the required temporal scale, it is freely available and easily accessible maintaining the results as consistent as possible (NASA/METI/AIST/Japan Spacesystems & U.S./Japan ASTER Science Team, 2019). Overall, Landsat 5, Landsat 8, and Aster GDEM were the datasets that were used in the analysis portion of the research paper to measure vegetation regeneration and classify fire severity, as well as to obtain topographic information.

Table 2.1: Satellite Details
(Landsat Missions, n.d.-a,-b; NASA/METI/AIST/Japan Spacesystems & U.S./Japan ASTER Science Team, 2019)

Satellite	**Landsat 5 and Landsat 8**	**Aster GDEM**
Use:	Calculating NDVI and NBR	Obtaining elevation, slope, northerly value, and easterly value
Collection Details:	Level 2, Collection 2, Tier 1	ASTER GDEM Version 3 (ASTGTM)
Spatial Resolution	30m	30m
Description:	Atmospherically corrected surface reflectance data.	Terra ASTER Global Digital Elevation Model
Source:	USGS	USGS
More Information:	Additional Infomation about the satellites can be found in the Earth Engine Data Catalog Landsat 5: USGS Landsat 5 Level 2, Collection 2, Tier 1 Landsat 8: USGS Landsat 8 Level 2, Collection 2, Tier 1	Additional Information can be found here

2.3 Data Processing

In this section, the data processing methods used in to answer the research questions are described. The section outlines how the datasets above were leveraged to construct a meaningful analysis. Information, such as why these methods were chosen will be explained. Further details on the analysis will be provided, including how NDVI, NBR, dNBR, and other regression variables were obtained. Overall, this section will provide a deeper explanation of how the results were conducted. A majority of the analysis was conducted using Google Earth Engine, and all the code can be found in the Appendix A.

2.3.1 Pre-processing

Data Preparation for NDVI and NBR

There are numerous pre-processing steps that are taken in order to prepare the data for analysis. These procedures are nearly identical for NDVI and NBR as both calculations use the same Landsat dataset. Since all Landsat datasets were obtained from Google Earth Engine's catalogue, some pre-processing had already been applied. As stated in Table TBD above, the chosen Landsat collection has atmospherically corrected surface reflectance-ready data. Therefore, these processes did not have to be manually applied and additional information can be found in the Google Earth Engine Data Catalog. Further pre-processing included filtering through data to only display images taken during the summer months, give or take a month when there was an insufficient number of suitable images available. This needs to be done because NDVI is influenced by climate, which seems appropriate as NDVI is an index used for classifying the vegetation of an area (Verbyla & Kurkowski, 2019). The summer time frame for measuring the values of these indices is fitting given that vegetation is most dense, and cloud cover is significantly lower during the warmer months allowing for a greater selection of clear images (Gryning et al., 2021). The second pre-processing step for the two indices was filtering through images that had low cloud cover, specifically setting the filter to return images that had 20% cloud cover or less. The purpose of this is to gather images that are as clear as possible because cloud cover interferes with data extracted from optical remote sensing satellites which in turn affects the values gathered from the reflectance bands (Moran et al., 2002). Considering that the calculation for both of these indices utilizes reflectance bands, it is important to limit atmospheric interference as much as possible (Sofan et al., 2016). In order to obtain accurate values, certain steps had to be taken to account for the scale factor and the pixel offset that is specifically attached to Landsat Collection 2 datasets (Landsat Missions, n.d.-c). For each image extraction in Google Earth Engine, all reflectance bands that were used for NDVI and NBR calculations were multiplied by the scale factor of 0.0000275, then the offset of -0.2 was added to account for the surface reflectance scaling factor (Landsat Missions, n.d.-c). Once the image that fit all of the necessary requirements was found, it was then clipped to the study area polygon. At that point, the data is ready to be processed.

Pre-processing ASTER GDEM

The data that was utilized from Aster GDEM to obtain some of the independent variables for the regression analysis only had to undergo one manual pre-processing step. That step was clipping the data to the study area polygons created in Google Earth Engine. No other pre-processing steps were required since the dataset comes prepared for analysis as cloud masking is already applied to this DEM to exclude pixels that have cloud interference (Abrams et al., 2020). Therefore, besides importing the data into Google Earth Engine and clipping it to the frames, no other steps were required to prepare this dataset.

2.3.2 Processing and Post-processing

NDVI

Normalized difference vegetation index (NDVI) was the chosen index to interpret vegetation growth and regeneration over time. NDVI is one of the utmost used indices to measure vegetation density in a large area using remote sensing, providing highly significant results (Huang et al., 2021). Additionally, NDVI can be easily obtained as most satellites are equipped with the necessary multispectral sensors and said satellites often offer free high-resolution imagery (Huang et al., 2021; Li et al., 2021). These reasons are precisely why this index was selected to measure vegetation recovery among the two study areas.

The calculation of NDVI returns an index value between -1 and 1, which can be computed by taking the near-infrared bands (NIR) and the red bands as shown in Figure 2.3 below (Costa et al., 2020).

This formula returns a value between -1 and 1 for each pixel, which is used to classify what that area represents. After reviewing several different pieces of literature, it was determined that this range can be classified into many categories depending on the use case. For this study, the range was classified into 4 different categories as shown in Table 2.2 below. The categorization was decided based on a few kinds of literature that had similar

$$\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})}$$

Figure 2.3: NDVI Formula
(Costa et al., 2020)

applications for NDVI. Any values that fell below 0.1 were classified as non-vegetation, this includes urban areas, rocks, cloud cover, smoke, snow, sand, etc. Values that were between 0.1 and 0.39 are considered shrub and grassland, which can be referred to as low-vegetated areas. Above 0.39 but below 0.59 fell into the deciduous or moderately vegetation areas. Finally, values above 0.6 refer to areas that have healthy vegetation (Remote Sensing Phenology, 2018; Al-doski et al., 2013; Ebinne et al., 2020). These categories and ranges are among the best-fit classifications when trying to assess vegetation rates over time.

Table 2.2: NDVI Category Classification
(Remote Sensing Phenology, 2018; Al-doski et al., 2013; Ebinne et al., 2020)

Category	**Value Range**
Non-vegetation	<0.1
Shrub and Grassland	0.1 to 0.39
Deciduous/Moderate Vegetation	0.4 to 0.59
Healthy Vegetation	0.6 to 1

Once the calculation is complete for all images during the selected years, this raw data can be transformed into information. At this point, the distribution of NDVI across the two study areas is acquired. This includes the results for pre-fire, post-fire, and every 2 years after the fire until the 10th year was reached. For each study area, there were 7 NDVI maps that were used to interpret the change of vegetation 10 years after the wildfire. Using these maps and tools like ArcGIS Pro, a time slide of the maps was formed in order to create a visual representation of how the vegetation reacted to the fire.

Further calculations were accomplished to obtain more significant information. This included determining how much area had healthy vegetation (NDVI $\geq$ 0.6) in each image for both study areas. This calculation was done by taking the pixel count of healthy vegetation (NDVI ≥ 0.6) and multiplying them by the area of a single Landsat pixel. A single pixel in a Landsat image is 30m by 30m and thus, the area of a single pixel is $900m^2$. Once the pixel count is multiplied by the area, a simple conversion from meters to hectares returns the results of the healthy vegetated area for each image. Finally, this information can be used to display the recovery rates as a percentage. More information about these processes can be found by referring to the appendix (see Appendix A and Appendix B).

NBR and dNBR

In order to measure burn severity, differenced normalized burn ratio (dNBR) was used. dNBR is an index commonly used to measure burn severity through remote sensing (Hislop et al., 2020). There are multiple different indexes which have been used to measure burn severity such as differenced normalized difference vegetation index (dNDVI), and relativized differenced normalized burn ratio (RdNBR). dNBR was chosen due to it being the most common index used to measure burn severity and due to the fact that there are conflicting studies on which index is the most accurate in measuring burn severity (Miller et al., 2023).

dNBR is calculated by first calculating the normalized burn ratio (NBR) for the pre-fire and post-fire images of the study area, ideally with the least time between the two images as possible using the following formula:

$$\text{NBR} = \frac{\text{NIR-SWIR}}{\text{NIR+SWIR}}$$

Figure 2.4: NBR Formula
(Cocke et al., 2005)

NBR calculates the normalized difference between the near-infrared and short wave infrared bands resulting in a value ranging from -1 to 1 (Cocke et al., 2005). NBR values can be used to highlight burnt regions in an area but can vary depending on the types of vegetation, atmospheric effects, and sensor used (Escuin et al., 2008). Pre-fire NBR values must be considered in order to accurately detect and classify burn severity to account for these factors (Escuin et al., 2008). The pre-fire NBR values are then subtracted by the post-fire values resulting in the dNBR as shown in the following formula:

$$dNBR = NBR_{pre\text{-}fire} - NBR_{post\text{-}fire}$$

Figure 2.5: dNBR Formula
(Cocke et al., 2005)

dNBR is generally considered as a more accurate index than dNDVI as NDVI takes into account all vegetation loss while the normalized difference between NIR and SWIR bands focus more on burn specific vegetation loss (Miller et al., 2023). dNBR values range from -2 to 2 with higher values signifying greater burn severity. The USGS has recommended specific burn severity classifications based on dNBR values as seen in 2.3. For the purposes of the regression analysis, the raw dNBR numbers were used.

Table 2.3: dNBR Classification Table
(Lutes et al., 2006)

Severity level	dNBR value range
Enhanced regrowth, high (post-fire)	–0.500 to –0.251
Enhanced regrowth, low (post-fire)	–0.250 to –0.101
Unburned	–0.100 to +0.099
Low severity	+0.100 to +0.269
Moderate–low severity	+0.270 to +0.439
Moderate–high severity	+0.440 to +0.639
High severity	+0.640 to +1.300

Elevation/Aspect/Slope

ASTER GDEM was used to obtain aspect, slope, and elevation values for both study areas. Google Earth Engine's terrain and aspect functions were used to calculate slope, and aspect values. The slope and aspect values are measured in degrees, with a slope range of 0° to 90° and an aspect range of 0° to 360°. The aspect values are oriented in cardinal directions, with 0° indicating north, 90° indicating east, 180° indicating south, and 270° indicating west (Google Developers, n.d.). The sine aspect value was calculated to represent the easterly direction, whereas the cosine aspect value was calculated to represent the northerly direction in each study area. Easterly and northerly aspect values were calculated in order to convert the aspect variable to a linear variable to be used in the linear regression analysis.

2.3.3 Regression Variables

In order to evaluate the impact of burn severity on long-term vegetation regeneration in the study areas, we built linear regression models for each study area using established variables from previous research, in addition to burn severity. The dependent variable in our model was the 10-year post-fire NDVI levels, which we chose to analyze because this time frame provides a suitable measure of the long-term impact of burn severity on vegetation regeneration. A table of the regression variables used can be seen in 2.4.

Table 2.4: Variables Used in Regression Models

Variables		Description
Dependent	NDVI Year (10 years)	Long-term vegetation greenness
Independent	NDVI After Fire (1 year)	Short-term vegetation greenness
	Normalized Burn Index	Burn Severity of Pixel
	Elevation	Elevation Value of Pixel
	Slope	Slope Value of Pixel
	Northerly Value	Northerly Value value of Pixel
	Easterly Value	Easterly Value value of Pixel

Elevation was included as a variable in our models as it has been previously used in studies regarding vegetation regeneration (Casady et al., 2010). Higher elevations tend to have cooler temperatures, and more moisture which can aid in vegetation growth (Mei et al., 2021). Aspect, which is represented by easterly (sine of aspect) and northerly (cosine of aspect) variables was also included in our model. Aspect can affect vegetation regeneration by influencing factors such as sunlight exposure and temperature, and has been found to be relevant in previous studies (Viana-Soto et al., 2017). Slope was another independent variable included in our model as it can influence soil moisture and nutrient availability which can impact vegetation growth (Sterner et al., 2022). Early NDVI values were also included as an independent variable in our regression model as they can provide insight into the initial state of vegetation following a fire and may influence its long-term regeneration (Viana-Soto et al., 2017). Burn severity was included in order to evaluate the impacts it has on long-term regeneration. Forest fires may aid in vegetation regrowth due to the release of nutrients from burned organic material such as leaves and branches into the soil (Halofsky et al., 2020). This increased nutrient availability can stimulate plant growth and regeneration, though high burn severity may also negatively impact vegetation regeneration by causing extensive damage to the soil structure, reducing soil fertility, and altering soil nutrient availability (Halofsky et al., 2020). This can lead to a decreased capacity for vegetation regrowth in the affected area.

We chose to omit variables such as soil moisture, number of temperature anomalies, and precipitation levels from our regression model, as they were not consistently observed across all studies in our literature review, unlike the other variables we included, which had a more prevalent presence in the literature.

2.3.4 Statistics and Analysis

Ordinary least squares (OLS) linear regression was chosen to evaluate the impact of burn severity on long-term vegetation regeneration. OLS is a commonly used regression method that estimates the parameters of a linear regression model by minimizing the sum of squared residuals between the observed and predicted values (Burton, 2021). This method was chosen because it allowed for the exploration of the relationships between burn severity and vegetation regeneration while controlling for other variables that might influence this relationship. Linear regression has also been used in previous vegetation regeneration studies to explore the impact of different factors such as topography, and climate on post-fire vegetation recovery (Viana-Soto et al., 2017).

After creating the regression models residual plots will be created which can reveal any non-linear patterns in the data (Cook, 1994). The coefficient of determination (R^2) will then be used to assess the goodness of fit of the models and determine the accuracy of the predictions.

To determine the order of importance for each independent variable, standardized coefficients were used. These coefficients represent the standardized effect size of each independent variable on the dependent variable (Bring, 1994). Standardized coefficients are calculated by subtracting each independent variable by their own mean and dividing them by their standard deviation (Bring, 1994). The order of importance can then be determined by ranking the standardized coefficients from greatest to least by their absolute value. Standardized coefficients allow for the comparison of coefficients as the values have been standardized which can be used to determine the most influential variables and evaluate their impact on vegetation regeneration.

Results

The results of our study provide valuable insights into the factors that affect vegetation regeneration. In this section, the data obtained from the methods section will be explained and turned into information. This will include any graphs and maps that were created to better interpret the data. Any significant relationships between the different regression variables will be displayed along with simple descriptions to provide a deeper understanding of the analysis. The difference in the results for the two study areas is interesting. Although both wildfires did some significant damage, the outcome happened to be incredibly different for each study area.

3.1 Okanagan Mountain Park, BC

For the Okanagan Mountain Park wildfire, in British Columbia, the number of acres that were destroyed was immense. Nearly all the burned land was vegetation prior to the fire. In Figure 3.1 below, the change in NDVI over the 10 years can be assessed. This figure provides a visual interpretation of how the NDVI values changed from pre-fire, and post-fire, to 10 years after the fire. Through the figure alone, it is evident that a lot of vegetation burned and that some areas regenerated. However, to gain a better understanding of how much healthy vegetated area actually burned, Figure 3.2 was constructed to give a deeper representation of where the vegetation was in comparison to where it is now. Finally, to see the trend of the NDVI value range, a plot graph (see Figure 3.3) was used. From these three figures, it is evident that vegetation significantly receded when comparing pre-fire and 10 years after the fire.

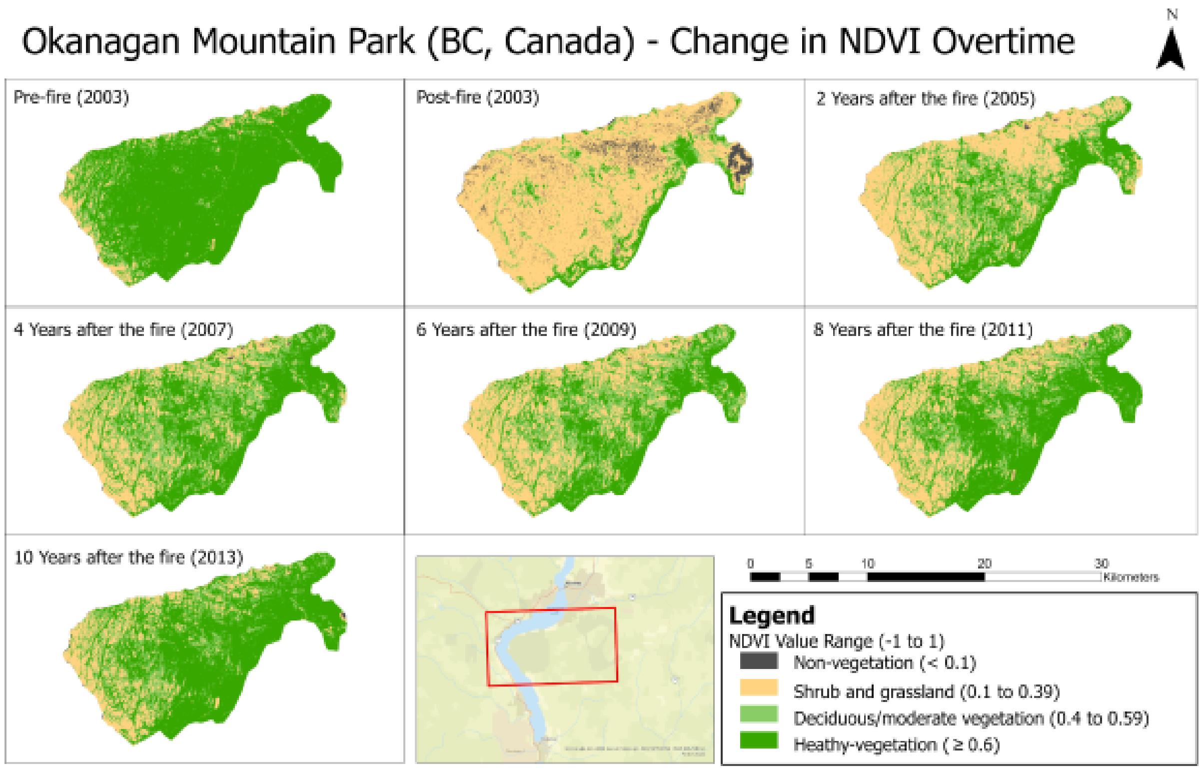

Figure 3.1: Change in NDVI Overtime for Okanagan Mountain Park Wildfire (BC, Canada)

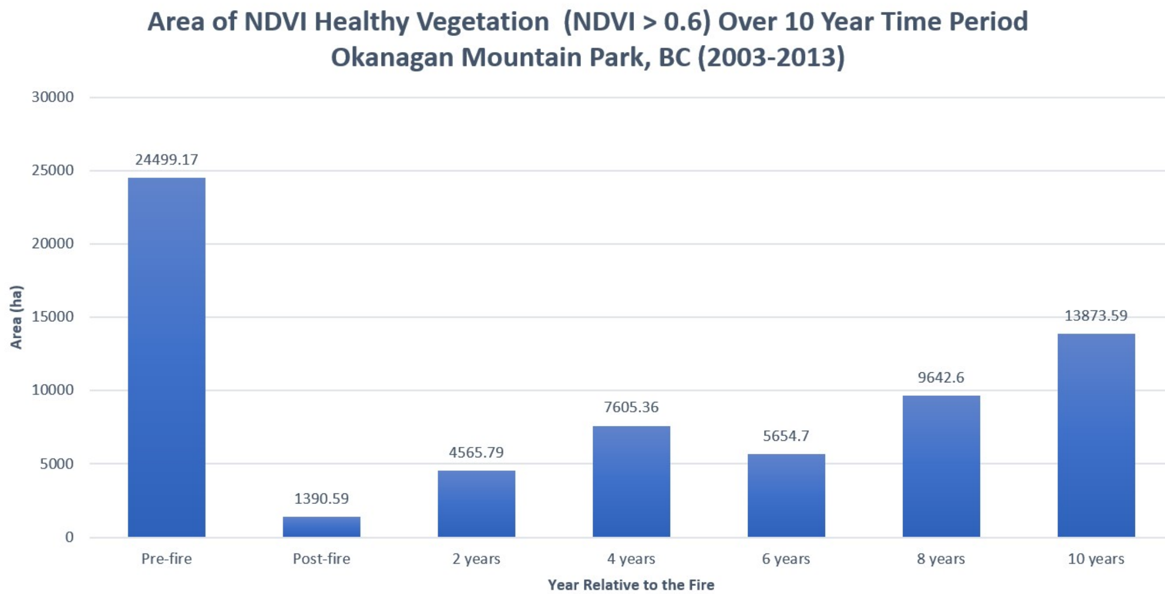

Figure 3.2: Area (ha) of Healthy Vegetation (NDVI $\geq$ 0.6) Over 10-year time period for Okanagan Mountain Park Wildfire (BC, Canada)

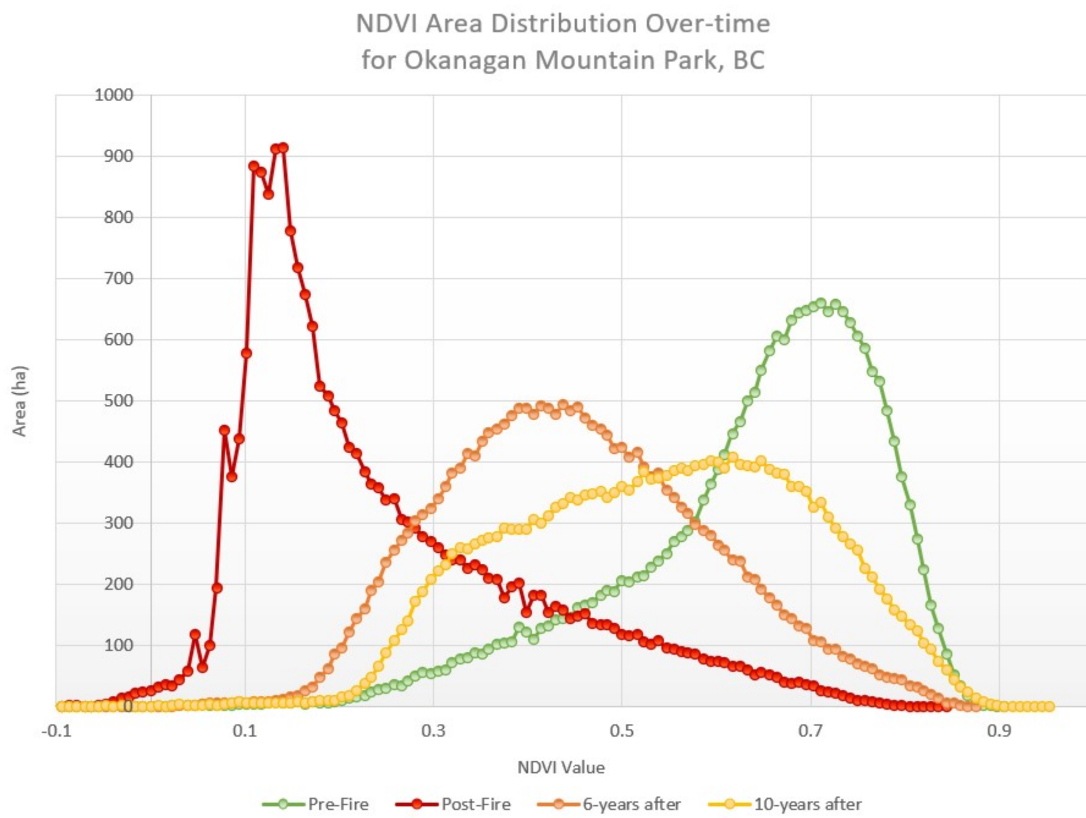

Figure 3.3: NDVI Area Distribution Over Time for Okanagan Mountain Park Wildfire (BC, Canada)

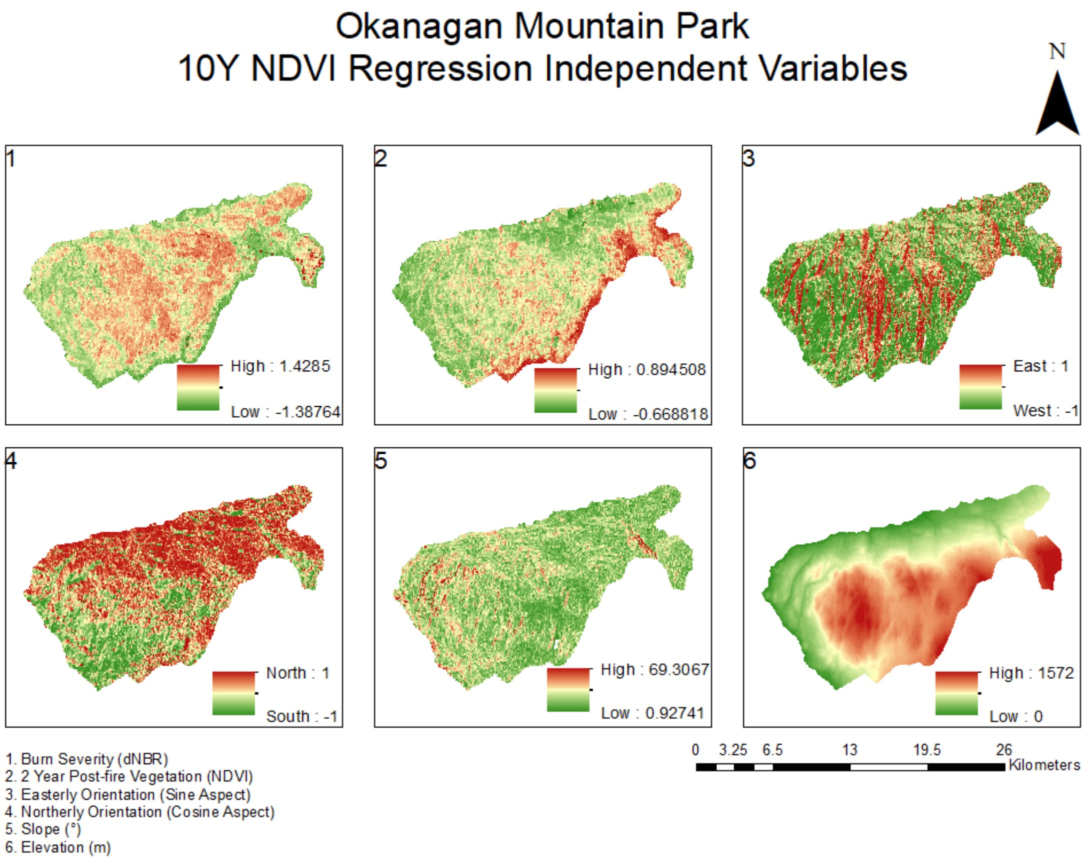

Figure 3.4: Maps of Independent Variables for Okanagan Mountain Park Wildfire (BC, Canada)

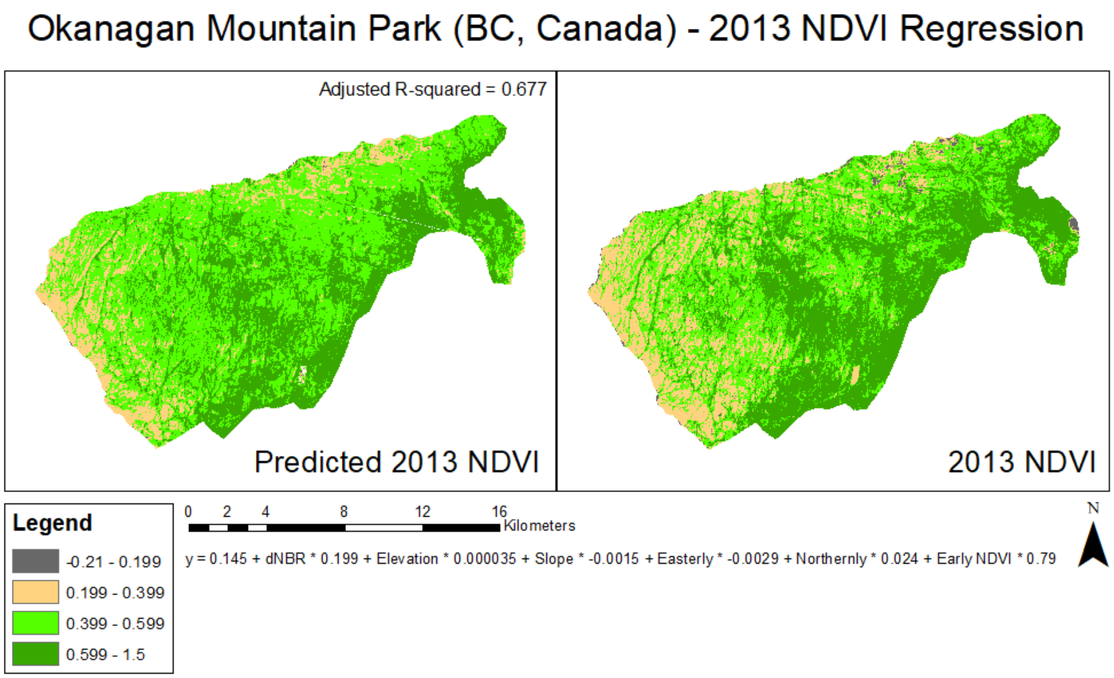

Figure 3.5: Map of Regression Result for Okanagan Mountain Park Wildfire (BC, Canada)

Table 3.1: Regression Summary of Okanagan Mountain Park Wildfire (BC, Canada)

Coefficients	Estimate	Standardized	t value	Pr(>|t|)
Intercept	0.145	N/A	207.1	<0.0000000000000002
dNBR	0.199	0.19	187.6	<0.0000000000000002
Elevation	0.000035	0.0726	66.35	<0.0000000000000002
Slope	-0.0148	-0.0821	-84.66	<0.0000000000000002
sinImage (Easterly)	-0.00287	-0.0128	-13.56	<0.0000000000000002
cosImage (Northerly)	0.0242	0.1032	106.5	<0.0000000000000002
Early NDVI	0.7931	0.7494	694.4	<0.0000000000000002

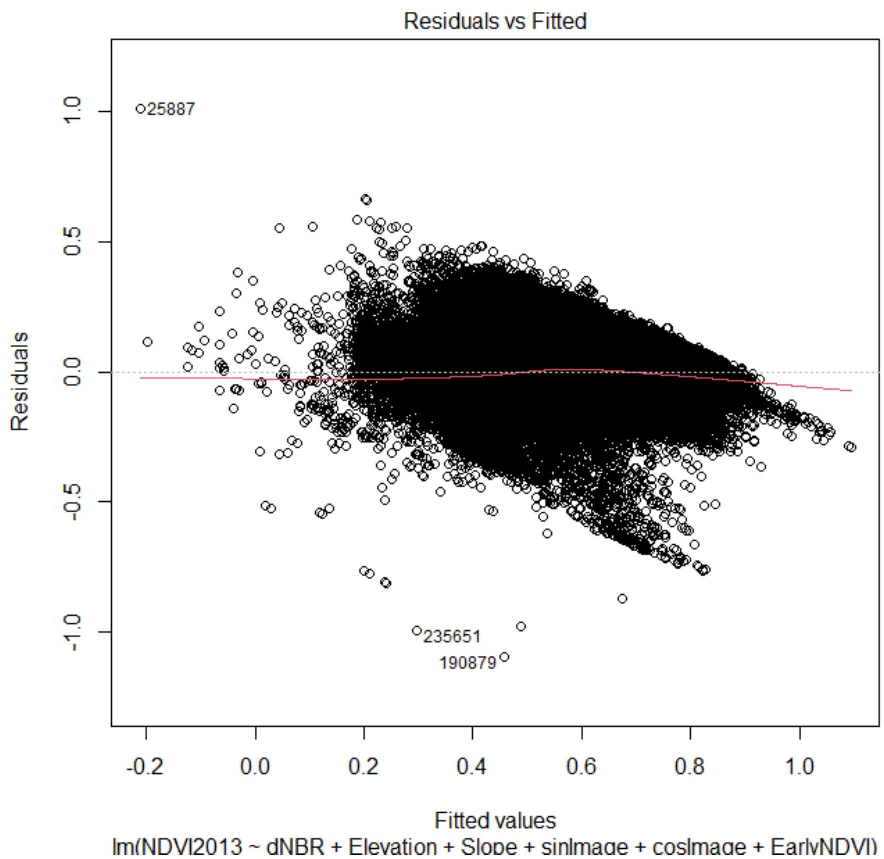

Figure 3.6: Residuals vs. Fitted Plot of Okanagan Mountain Park Wildfire (BC, Canada)

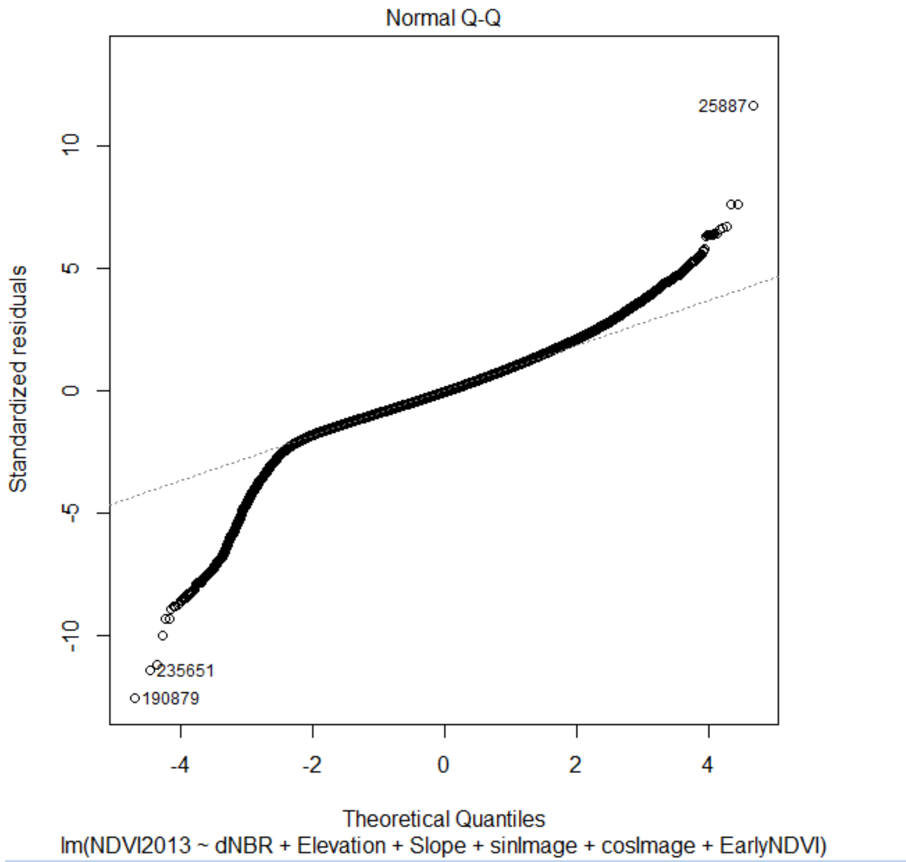

Figure 3.7: Q-Q Plot of Okanagan Mountain Park Wildfire (BC, Canada)

Maps of all regression variables used were created in order to visualize the differences between the two study areas which can be seen in 3.4. 3.5 is a map of the resulting regression equation that was also created in order to visually assess the degree of correlation and the overall fit of the model. The summary of the regression results in 3.1 is seen which lists the standard coefficients, t-values, and p-values of the model. All variables in this model had a p-value of < 0.05 which signifies that there is a correlation between the variables. The fitted vs residual value chart in 3.6 and the Q-Q plot in 3.7 are used to examine the linearity of the model.

3.2 Slave Lake, AB

The Slave Lake wildfire analysis went through the same process as the Okanagan Mountain Park fire, but the results are different. To map out NDVI change over the 10 years, the same map was made, using the same classification ranges and categories to allow for study area comparison (see Figure 3.8). For Slave Lake, the vegetation bounced back rather quickly, which is why this figure does not provide much information. To attain a better understanding, the same bar graph that was created for Okanagan Mountain Park was developed which can be seen below in Figure 3.9. This representation presents a more clear view of what occurred before, during, and after the wildfire in terms of vegetation health. Lastly, the plot graph for showing the area distribution of NDVI was produced to display what happened to the vegetation over the 10-year time frame (see Figure 3.10). Both study areas show immensely different reactions to their wildfire in terms of vegetation regeneration.

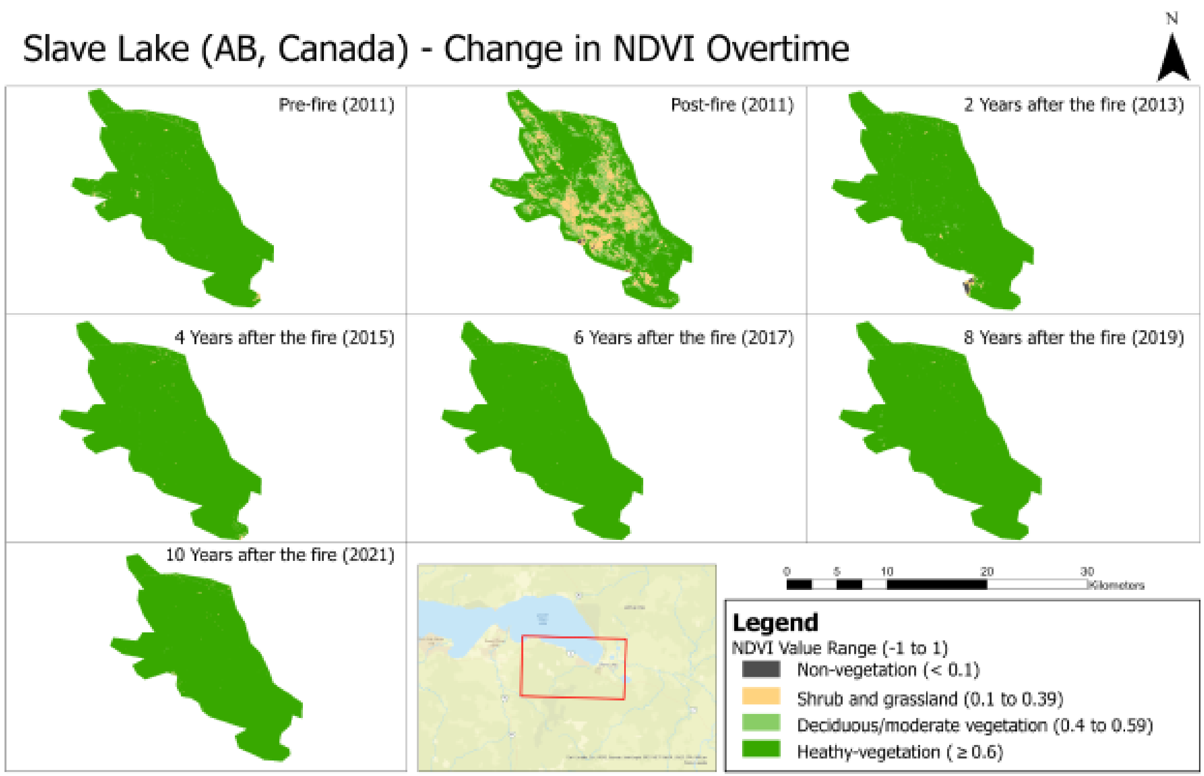

Figure 3.8: Change in NDVI Overtime for Slave Lake Wildfire (AB, Canada)

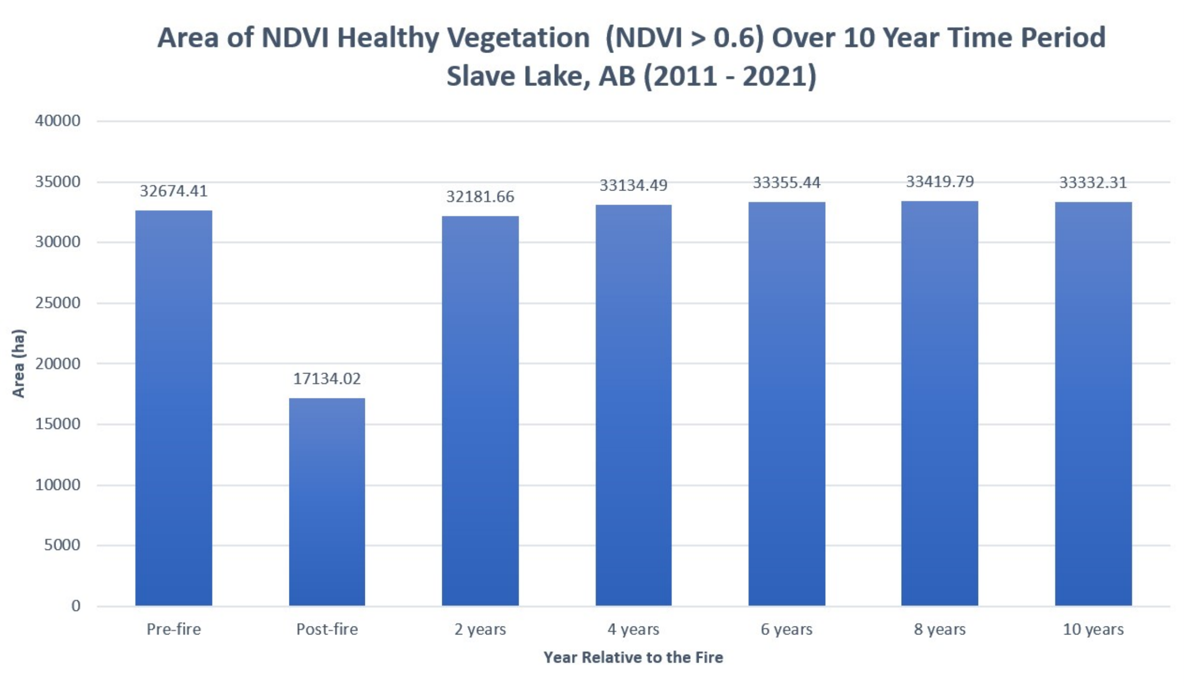

Figure 3.9: Area (ha) of Healthy Vegetation (NDVI ≥ 0.6) Over 10 year time period for Slave Lake Wildfire (AB, Canada)

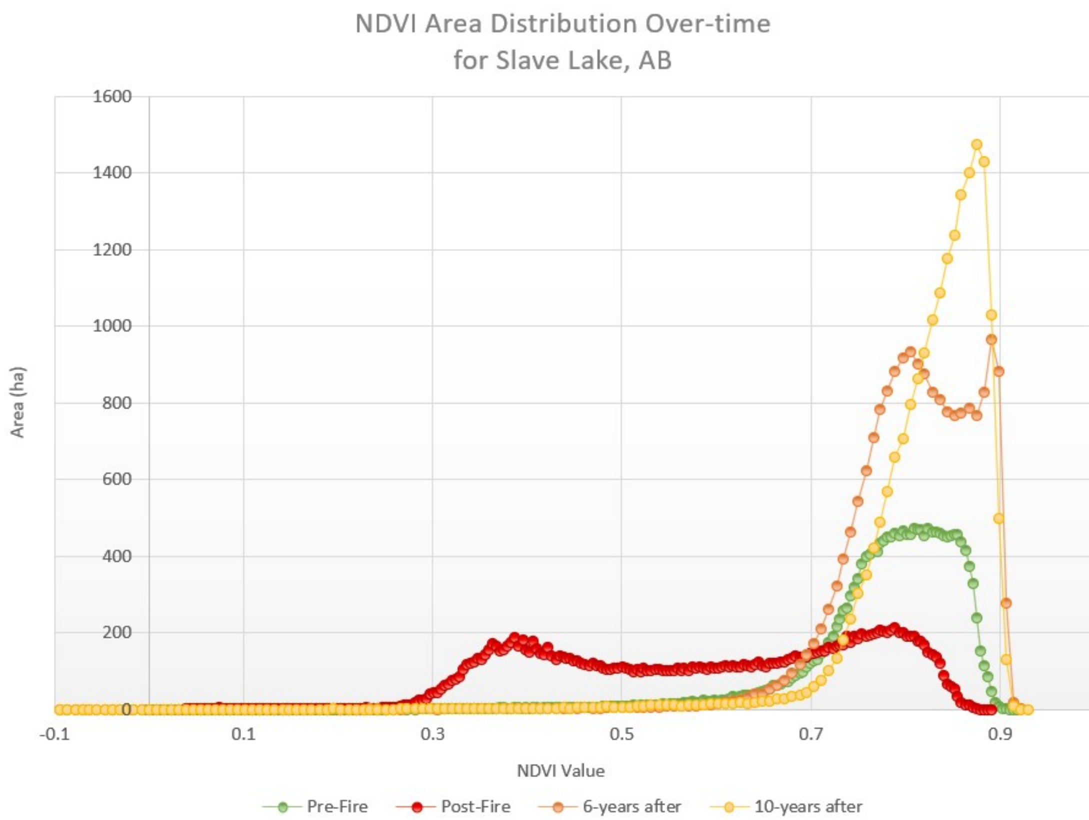

Figure 3.10: NDVI Area Distribution Over Time for Slave Lake Wildfire (AB, Canada)

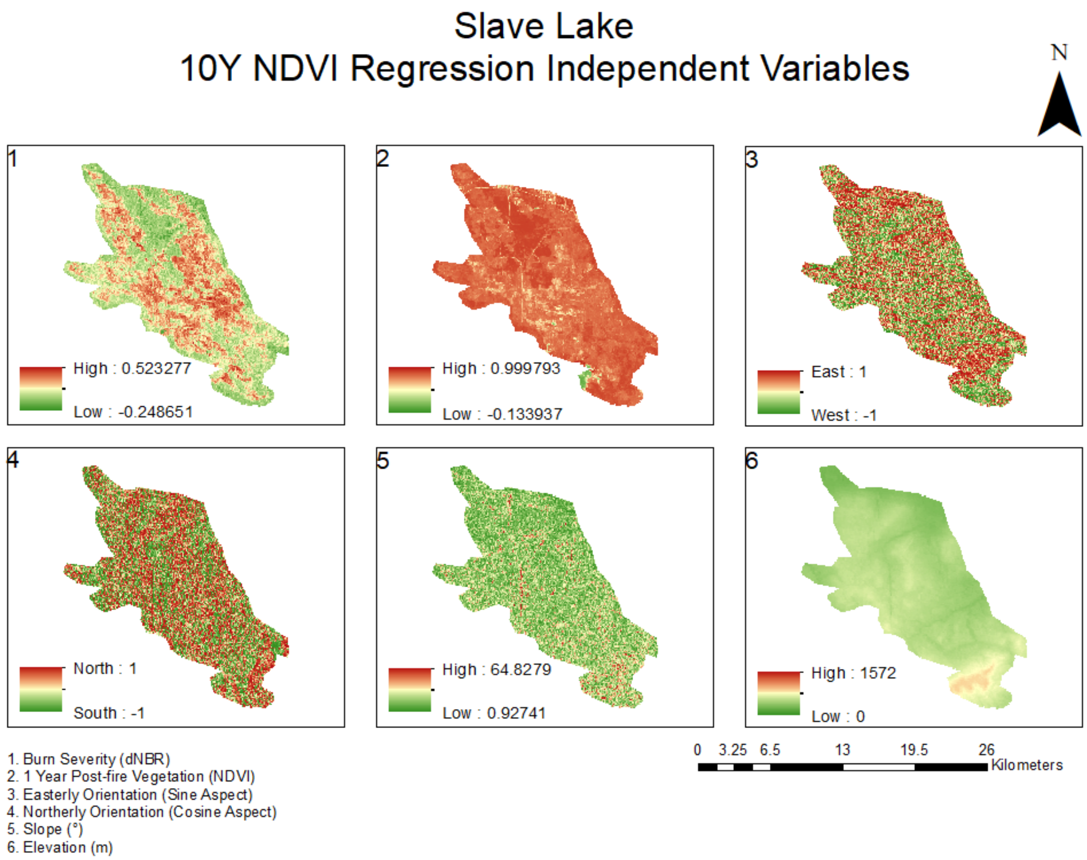

Figure 3.11: Maps of Independent Variables for Slave Lake Wildfire (AB, Canada)

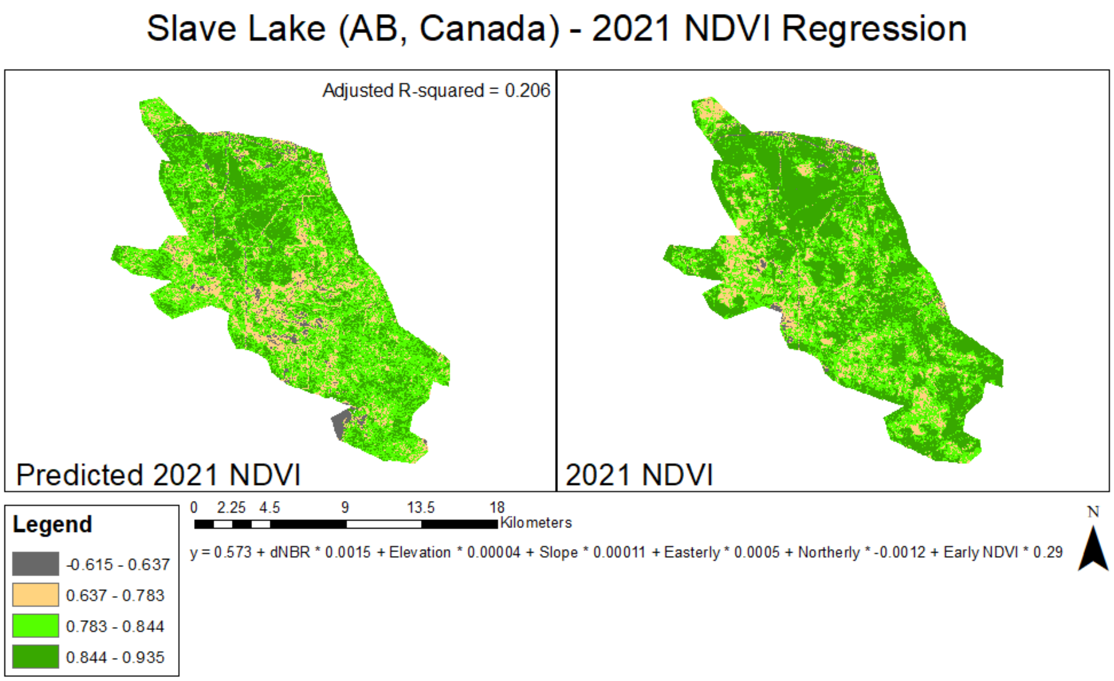

Figure 3.12: Map of Regression Result for Slave Lake Wildfire (AB, Canada)

Table 3.2: Regression Summary of Slave Lake Wildfire (AB, Canada)

Coefficients	**Estimate**	**Standardized**	**t value**	**Pr(>|t|)**
Intercept	0.5733	N/A	456.8	<0.0000000000000002
dNBR	0.00145	0.00267	1.706	0.087934
Elevation	0.0004	0.05298	34.48	<0.0000000000000002
Slope	0.000115	0.01095	7.185	<0.0000000000000002
sinImage (Easterly)	0.000479	0.00567	3.768	0.000165
cosImage (Northerly)	-0.00123	-0.01375	-9.111	<0.0000000000000002
Early NDVI	0.2895	0.45568	289.2	<0.0000000000000002

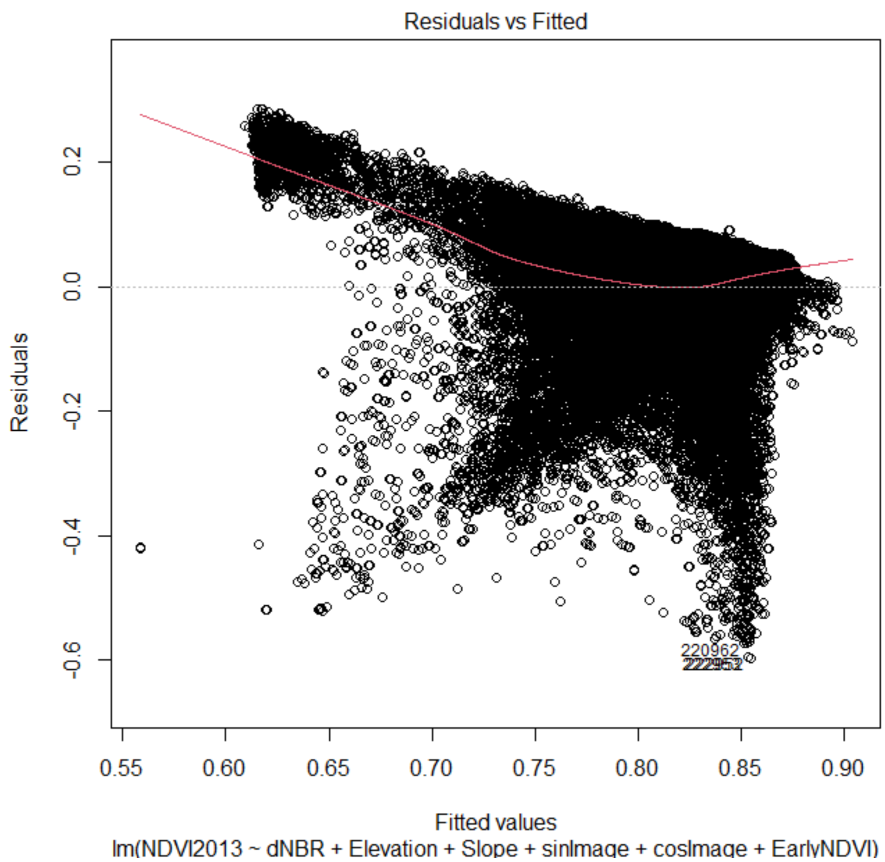

Figure 3.13: Residuals vs. Fitted Plot of Slave Lake Wildfire(AB, Canada)

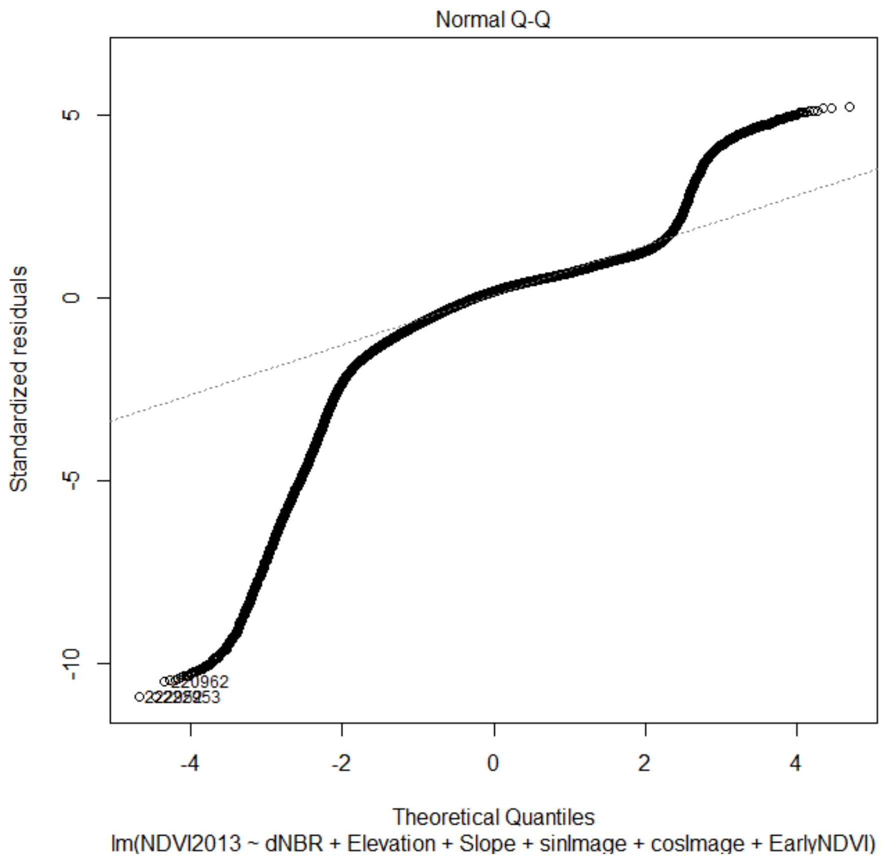

Figure 3.14: Q-Q Plot of Slave Lake

The same maps of variables and regression outputs were created for Slave Lake in order to visualize the data distributions and overall fit of the model in 3.11 and 3.2. In the regression summary of Slave Lake, it can be seen that dNBR had a p-value of 0.0879 signifying that it is not significantly correlated with NDVI values. The order of absolute values of standardized coefficients also differ when compared to Okanagan Mountain Park. Residual versus Fitted and Q-Q plots were also created for Slave Lake in order to test for linearity as seen in 3.13 and 3.14.

Discussion

In this section of the research paper, the results will be interpreted in the context of the research objectives and what it means. This is to provide a comprehensive understanding of what this study is trying to bring to light. Details that could have made this research more thorough will be described, along with the limitations that accompany the methods and analysis present. Overall, this section aims to provide a critical analysis and highlight the implications for the betterment of future research.

4.1 Interpretation of Results

The findings of this research paper will provide a deeper explanation of how burn severity impacts vegetation regeneration. When assessing the starting point of both study areas, it is clear that a majority of the land is covered by healthy vegetation. This can be seen in the pre-fire images of Figures 3.1 and 3.8 above. When evaluating the state that the fire left the area in (see post-fire images in Figure 3.1 and Figure 3.8), it is evident that Okanagan Mountain Park sustained a more significant amount of damage than Slave Lake did. Before the wildfire, the area of healthy vegetation in Okanagan Mountain Park covered approximately 24499.17ha. Post-fire, that area of healthy vegetation went down to 1390.59ha as shown in Figure 3.2 above. This means that 94.32% of the area, or 23108.58ha, that was considered healthy vegetation (NDVI ≥ 0.6) is no longer present. In comparison, the Slave Lake study area had around 32674.41ha of healthy vegetation pre-fire, which dropped to 17134.02ha post-fire as displayed in Figure 3.9 The rate of healthy vegetation dropped by 47.56%, meaning 15549.39ha was damaged. This is the first indicator that the Slave Lake wildfire caused less harm than the Okanagan Mountain Park fire did in terms of damage to vegetation. This is further apparent when analyzing the NDVI area distribution for both study areas (see Figures 3.3 and 3.10). By reviewing the dispersal of NDVI values before (displayed in green) and after the fire (displayed in red), it is clear that a more significant amount of moderate and healthy vegetation (NDVI ≥ 0.4) was reduced to shrubbery and non-vegetated (NDVI < 0.4) area in the Okanagan Mountain Park wildfire. Whereas in the Slave Lake fire, the damage was less substantial, maintaining the area majority of the categorization between moderate or healthy vegetation, with some extent being classified as shrubbery and an insignificant amount being non-vegetated. These results further signify that the Okanagan Mountain Park area experienced considerably more destruction to vegetation.

Focusing on the Okanagan Mountain Park wildfire, it is worth mentioning that the area of healthy vegetation actually recedes when comparing the 4th year post-fire to the 6th year (see images in Figure 3.1). This incident is explainable by analyzing the weather leading up to the images. Temperature and precipitation play an important role when it comes to the restoration of ecosystems (Hao et al., 2022). The temperature history of the two years (2007 and 2009) can be seen in Figure 4.1 and Figure 4.2 below. The red markings indicate the date of the Landsat image used in the analysis for that year. When looking at the average temperature (grey area), both graphs present relatively similar values hovering between 12°C to 20°C prior to the date of the image. However, when looking at the low values, the 2009 temperatures are steadily lower in comparison to 2007. This is insufficient evidence to rule out that this is the sole cause for the receding vegetation as the temperature is not the only driving factor. In Figure 4.3 and Figure 4.4, the weather patterns can be seen for both years. In 2007, there was significantly more rainfall in the prior days leading up to the image, whereas in 2009, the early summer season was relatively dry. This is to further show that the additional factors contributing to vegetation regeneration affect the end results. This phenomenon was a drawback for Okanagan Mountain Park. Each year, the area of healthy vegetation was growing by about 3000 to 4000 hectares as seen in Figure 3.2. Between 2007 and 2009, the area receded by 2000 hectares. The final recovery area at the end of the 10 years was 13873.59ha in comparison to the pre-fire number of 24499.17ha. This means that after 10 years, the healthy vegetation regenerated about 56.63% of its original area. If the drawback had not occurred and the area continued to follow the same pattern, recovering about 3000-4000ha each year, the final recovery area would be roughly hovering around 16600ha to 19600ha, or 67% to 80% recovered.

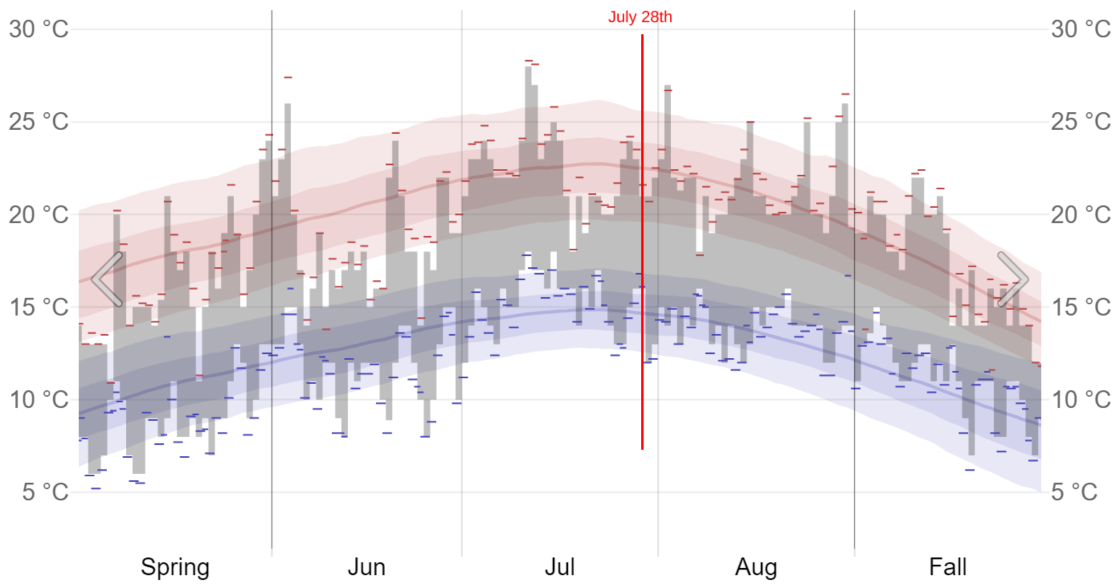

Figure 4.1: 2007 Temperature History
(Vancouver International Airport, 2007)

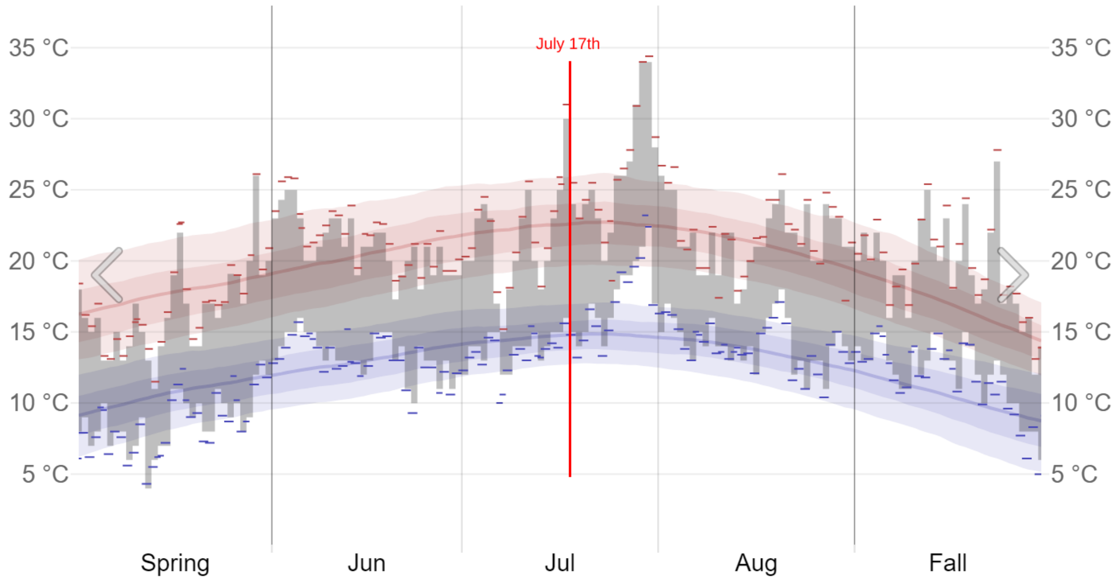

Figure 4.2: 2009 Temperature History
(Vancouver International Airport, 2009a)

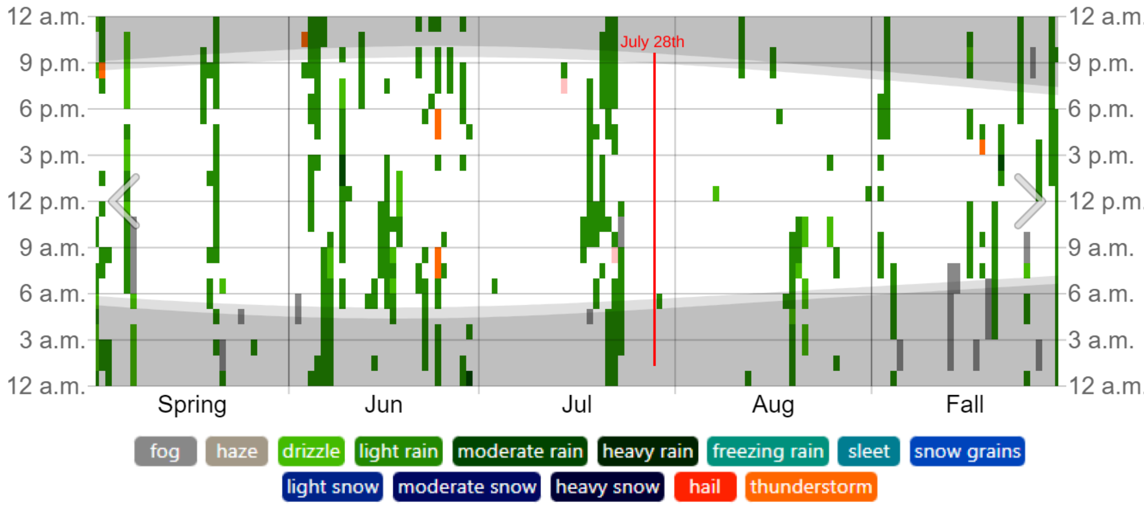

Figure 4.3: 2007 Weather History
(Vancouver International Airport, 2009b)

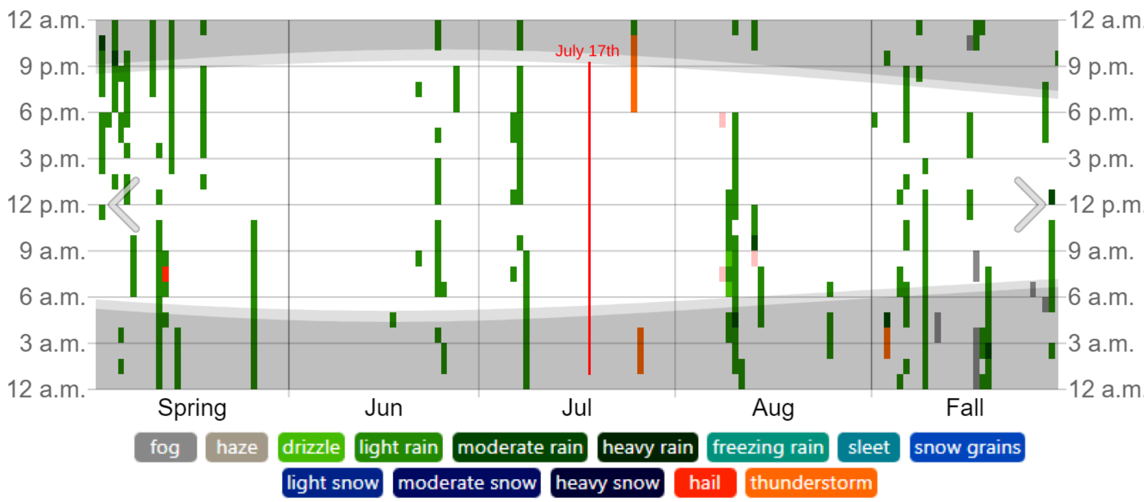

Figure 4.4: 2009 Weather History
(Vancouver International Airport, 2009c)

Slave Lake, however, had an entirely different result. The area that was affected by the wildfire was not harmed to the same degree that Okanagan Mountain Park was. Within 2 years after the fire, the healthy vegetated area went from 32674.41ha to 32181.66ha (see Figure 3.9). This means that the area had already recovered 98.49% of its original state. After the 4th year, this same area had already recovered to 33134.49ha or 101.41%. By the 10th year, this recovery rate had reached 102.01% with some minor shifts in the year between. It is no doubt that Slave Lake was able to recover significantly faster than Okanagan Mountain Park which is appropriate considering the differences between the topographic characteristics and the wildfire severity.

Burn severity is one of the major influencing factors for vegetation regeneration as shown when comparing the two study areas (Martín-Alcón & Coll, 2016). The ranges of NBR can be obtained by focusing on image 1 of Figures 3.4 and 3.11. Here, the burn severity can be compared between the two areas. The NBR values of Okanagan Mountain Park go up to 1.42, whereas these values only reach 0.52 for Slave Lake, indicating that Slave Lake burn severity was not nearly as severe. There are several explanations for why that is. The first and most obvious is the date of the wildfires. Slave Lake's wildfire occurred in May when temperature and weather conditions are not as optimal for fire spread as they are during summer months (Perry et al., 2022). According to this study done by European Geosciences Union, highly severe wildfires are typically focused during the summers that experience dry weather (Perry et al., 2022). The Okanagan Mountain Park's wildfire having occurred in August would line up well with why that fire was especially severe. The weather and temperatures can create perfect wildfire conditions. With Okanagan Mountain Park, the conditions were dry and the area was experiencing constant winds, allowing the fire to continuously grow with ease (Judd, 2013). Further explanation of why Slave Lake's burn severity was low is correlated with the fact that a significant part of the fire was within the city boundaries(Derworiz, 2021). The urban was not considered for this study since the objective is to measure vegetation regeneration. Therefore, including urban land would skew the vegetation data. Finally, the topography of the study areas, more specifically slope, is a driving factor for wildfire spread where a higher slope correlates to higher fire hazard conditions (Heisig et al., 2022; Environment and Climate Change NWT, n.d.). In Figures 3.4 and 3.11, image 5 shows the slope of each study area. Okanagan Mountain Park is more mountainous, whereas Slave Lake consists of small hills. This provides additional explanation for how the fire was able to spread and consequently do more damage in Okanagan Mountain Park.

The question still remains about why Slave Lake was able to regenerate so quickly. Wildfires are natural disasters that can be a contributing factor to an ecosystem (Moret-Soler et al., 2022). Fires with high severity cause large amounts of destruction and often do more harm than good for a functioning ecosystem. These large fires cause economic and ecological damage that seriously impacts both wildlife and human life (Hao et al., 2022). However, low-severity fires can actually have a positive ecological impact. They release nutrients stored in the forest floor, further stimulating new growth by allowing sunlight to reach the upper layer of the forest (Natural Resources Canada, 2022). These forest fires can enable an ecosystem to undergo natural regeneration and benefit the ecosystem by increasing species diversity (Hao et al., 2022). Therefore, since burn severity in the Slave Lake wildfire was relatively low, the vegetation was able to regenerate rather quickly in comparison to the Okanagan Mountain Park fire.

Assessing linearity of the regression model of Okanagan Mountain Park

In 3.6, it can be seen that the distribution of residuals are not even throughout all the fitted values. Residuals versus fitted value plots are commonly used to detect outliers non-linearity in regression models (Cook, 1994). An ideal residual versus fitted value plot would have an even distribution throughout the fitted value with no discernable trend. Although the trendline is relatively flat, there is a slight trend of lower residuals as the fitted NDVI value increases. This distribution signifies an unequal error variance which signifies a possible non-linear fit between the dependent and independent variables.

As seen in 3.7, the overall distribution of the Q-Q plot lies flat on the trendline which signifies a relatively normal distribution, though the Q-Q plot has heavy-tailed ends. This indicates more data is located at the extremes than a normal distribution.

Assessing linearity of the regression model of Slave Lake

The distribution of residuals in 3.13 for Slave Lake signifies a non-linear relationship. The trendline in red is curved with higher residuals on lower fitted values which signify a very unequal error distribution and a non-linear relationship.

As seen in figure 3.14, the Q-Q plot of the Slave Lake regression model has extremely tailed ends, and varies extremely far from the fitted line. This signifies a non-linear correlation between the variables. There is a significant tail in the lower theoretical quantile values which signifies a negative skew in the data.

The non-linear relationships of both study areas may be due to multiple reasons. One possibility is high levels of spatial autocorrelation in both study areas. Spatial autocorrelation refers to the tendency for nearby locations to have similar values (Koenig, 1999). Given the nature of the variables, spatial autocorrelation is present in all of the variables used for this analysis. As a result, it can lead to abnormalities in both the distribution of data and the linearity of their relationships. A global OLS regression model does not account for any spatial autocorrelation which can result in non-linearity of the resulting model (Charlton et al., 2009). The independent variables may also not have a linear relationship with the dependent variable, even if spatial autocorrelation were to be accounted for. Although these variables have all been used in previous studies using OLS regression models, their linearity may differ based on study area (Viana-Soto et al., 2017). Okanagan mountain park showed much lesser non-linearity signs in their diagnostic plots than Slave Lake which may be due to different environmental factors such as vegetation type, topography, and climate.

Regression Results

The resulting regression model for Okanagan Mountain Park had a coefficient of determination (R^2) score of 0.677 signifying 67.7% of the variation can be explained by the independent variables. Even though the Q-Q plots and residual versus fitted value plots seen in 3.7 and 3.6 signified a non-linear relationship, this is a relatively good fit. Slave Lake on the other hand had an R^2 score of only 0.206 representing a poor fit. As the Slave Lake diagnostic plots in 3.14 and 3.13 showed much more severe signs of non-linear correlations, the poor fit can be attributed to the possible non-linear correlations and the lack of spatial autocorrelation.

Looking at the coefficients of each variable, burn severity (dNBR) has a positive correlation with long-term vegetation values. This signifies that areas which had a higher burn severity correlated with higher levels of vegetation. Burn severity was expected to be negatively correlated with long-term vegetation levels as seen in previous studies but the opposite was found in both study areas (Viana-Soto et al., 2017). One possible reason for this is the positive effects wildfires have on vegetation regrowth which includes increased nutrient availability, reduced competition, and increased exposure to sunlight (Halofsky et al., 2020). It is important to note that a correlation between burn severity and long-term vegetation growth does not necessarily imply causation. Areas with high burn severity are likely to be areas with high vegetation levels prior to the fire which may signify optimal areas for vegetation growth because of other factors such as optimal soil moisture levels and climate. Accounting for additional relevant variables may change the coefficient of dNBR to a negative value.

There are also similar differences between the easterly and northerly aspect values between both study areas. As both study areas reside in the Northern Hemisphere, it was expected that both study areas would have a positive correlation with the same aspects but the opposite was true for both variables. Okanagan Mountain Park has more vegetation in west and north-facing slopes while Slave Lake has more in east and south slopes. Slave Lake is a relatively flat area while Okanagan Mountain Park is extremely mountainous. These differences in terrain may explain the differences seen in the regression equation as they may interfere with the amount of sunlight in each aspect.

Table 4.1: Order of Variable Importance in Okanagan Mountain Park and Slave Lake

Study Area	**Order of Variable Importance (Greatest -> Least)**
Okanagan Mountain Park	Early NDVI, dNBR, cosImage (North Value), Slope, Elevation, sinImage (East Value)
Slave Lake	Early NDVI, Elevation, cosImage (North Value), Slope, sinImage (East Value), dNBR

By comparing the absolute values of the standardized residuals seen in 3.1 and 3.2 for Okanagan Mountain Park and Slave Lake, respectively, it is possible to determine the order of importance of each independent variable in the regression model. The order of importance for each study area can be seen in 3.5 and 3.12. The results show that both study areas share Early NDVI as the most significant variable, which is consistent with previous research on the topic (Viana-Soto et al., 2017). This variable reflects the initial response of vegetation to the fire and can be a good predictor of long-term recovery (Viana-Soto et al., 2017). However, there are some differences in the order of importance of the other variables between the two study areas.The primary difference being how dNBR the the second most important variable in Okanagan Mountain Park but is not even a significant variable in Slave Lake.

The difference in burn severity importance may be due to the different characteristics of the fires in the two study areas, such as their size, intensity, or timing. Fire severity in Okanagan Mountain Park was much more severe than in Slave Lake with Slave Lake not sustaining any burns classified as high-severity leading to a stronger correlation between dNBR and vegetation recovery in the former study area. The significant nonlinearity discovered of the variables in Slave Lake in conjunction with the low R^2 score may also lead to an inaccurate representation of the importance of each variable. Another possibility is the differences in environmental factors which have not been measured such as vegetation type, human recovery efforts, and climate. As these variables have not been included, they may explain the decreased significance of burn severity.

4.2 Limitations

This section will introduce and describe the limitations of the dataset and analysis methods used in this research. Specifically, limitations related to the satellites used, the images selected for the analysis, and the other factors influencing vegetation regeneration which were not considered. Any discrepancies that may have existed due to atmospheric interference will be brought forth. It is important to note that these limitations likely have had an impact on the accuracy of the results as determining the driving factors for vegetation regeneration can be a highly complex task.

4.2.1 Dataset Limitations

The dataset limitations of this research begin with the fact that the Landsat 5 and 8 images used for the analysis were not taken on the same day. There are two major reasons for this. The first is that given Landsat's 16-day revisit time, the images available every year don't fall on the exact same day. Secondly, cloud cover has a significant impact when trying to calculate NDVI (Jiao et al., 2021). Therefore, selecting an image that was mostly cloud-free was a higher priority than selecting an image closer to the same day as in previous years. While efforts were made during the pre-processing stage to search for ideal images that had little to no atmospheric interference, some discrepancies may still exist due to cloud cover in some of the images. Although selecting low cloud-cover images were more important, all the selected images are still kept within the range of summer months. Some were, however, taken during late spring (June) meaning that there may have been climatic differences or spikes in harsh weather conditions between the images, which could have affected the accuracy of the results. Regardless, this is a limitation worth mentioning as we can see it occur quite drastically in some images for both study areas. You can see these errors highlighted in the red box found in Figure 4.5 below. These limitations may have had an impact on the accuracy of the results obtained from the analysis. Further research may be necessary to confirm the findings and to obtain more accurate results. Despite these limitations, the data processing methods employed in this research allowed for a comprehensive understanding of how fire severity and other factors affect vegetation regeneration.

In terms of the limitations that arise from datasets obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM), there is one known issue that can potentially and slightly alter the results of this study. The data gathered from version 3 of the ASTER GDEM that this research utilized is known to have values that overlap by one pixel in every direction (North, East, South, and West) not affecting the results a majority of the time, but there remains the possibility that some pixels do not reflect accurate values (NASA/METI/AIST/Japan Spacesystems & U.S./Japan ASTER Science Team, 2019). Nonetheless, ASTER GDEM, specifically version 3, to this day is among one of the most accurate digital elevation models that is also freely sourced (Du et al., 2016; MHAMDI et al., 2023).

4.2.2 Analysis Limitations

There are several limitations that should be acknowledged regarding the analysis of this study. One limitation is the exclusion of other possible factors that could impact vegetation regeneration, such as temperature, climate, and soil moisture. As long-term vegetation regeneration can be influenced by an extremely large number of factors, there are multiple conflicting studies on what variables can have an impact. Temperature and soil moisture are relatively prevalent, but are not represented in the same way consistently. Temperature has been represented in regression analysis differently in multiple studies such as maximum and minimum temperature anomalies and averaged value of temperature anomalies during regrowth years (Viana-Soto et al., 2017; Bring, 1994). These variables were not included in the regression analysis due to data availability constraints, as well as the fact that their

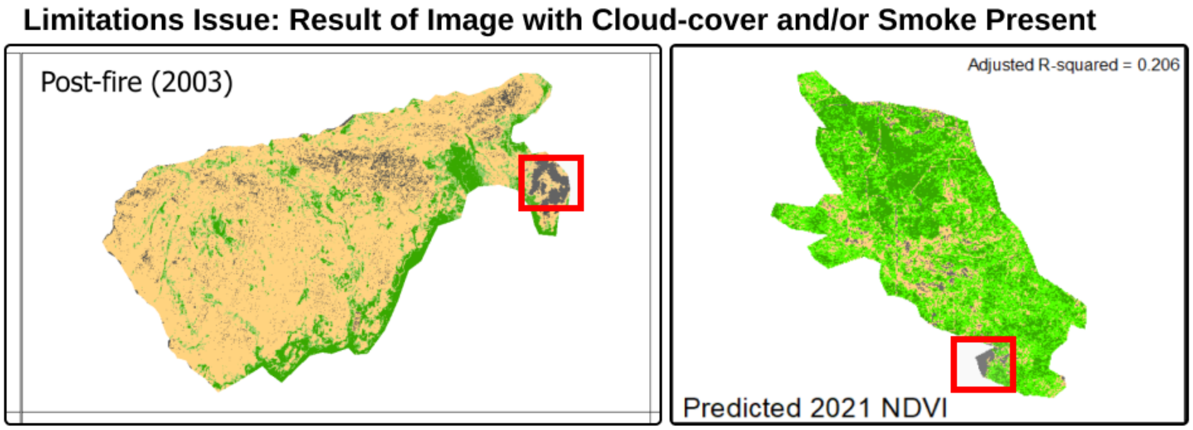

Figure 4.5: Example of Cloud-cover and Smoke Limitations in the Analysis

prevalence and significance in other research on vegetation regeneration was not clear. However, many factors could have had a significant impact on vegetation regeneration in the study areas which may have explained additional variance. For future analysis, exploratory regression analysis could be conducted for each study area in order to identify the most impactful factors in order to achieve a better model fit.

Another limitation of this study is the amount of human intervention and post-fire management practices. Okanagan Mountain Park saw a recovery committee formed post-fire while recovery while Slave Lake had over $50 million spent in recovery efforts (City of Kelowna, n.d.; Sands, n.d.). Slave Lake is also located extremely close to residential neighborhoods which may have been a factor when dealing with what types of post-fire management were implemented. It is extremely difficult to evaluate the effects of such interventions as specific post-fire management practices are not carried out in a consistent manner, and little to no public information on the specific post-fire management practices for each wildfire exists.

Both study areas included varying amounts of unburned regions, which can introduce inconsistencies in the regression analysis. Although the study areas were created around burnt areas, the density of each fire can vary, leaving many areas unburned within each study area. It is possible that the presence of unburned areas could have introduced bias into the regression model and impacted the accuracy of the regression results. Future studies could consider conducting a more precise spatial analysis to better account for the presence of unburned areas and improve the accuracy of the analysis.

dNBR was used to represent burn severity in the study, but it is not a perfect indicator of burn severity. dNBR has been shown to have extremely varying correlations to field measurements of burn severity (Soverel et al., 2010; Cai & Wang, 2022). There are multiple different methods commonly used to classify burn severity such as relativized differenced normalized burn ratio which may improve accuracy of burn severity, but also has inconsistent and conflicting opinions from other research papers (Miller et al., 2023). Burn severity itself is a relatively subjective measurement as the most common method for field measurements consists of an average score of burn severity of different vegetation types (Cocke et al., 2005). As there is no consistent method for both field measurements of burn severity or an agreed upon method for measuring burn severity using remote sensing, there is a significant amount of uncertainty regarding burn severity itself. As OLS regression was used in this analysis, it does not account for any possible spatial autocorrelation (Kala et al., 2017). The use of geographically weighted regression (GWR) can account for spatial autocorrelation by creating separate OLS regressions for each location allowing coefficients to vary based on location (Kala et al., 2017). GWR could have produced a better fit than a global OLS regression in this analysis as vegetation regeneration and burn severity have a degree of spatial autocorrelation (Viana-Soto et al., 2017).

4.3 Addressing the Sustainable Development Goals (SDG)

The Sustainable Development Goals (SDGs) are a set of 17 goals established by the United Nations. These goals are meant to be guidelines for achieving a more sustainable future for all. The SDGs aim to address global challenges such as poverty, inequality and climate change (Pradhan et al., 2017).

This research contributes to SDG 13: Climate Action by providing insights into how burn severity affects long-term vegetation regeneration. Climate change is causing an increase in the frequency and intensity of wildfires worldwide (Mansoor et al., 2022). Understanding how different levels of burn severity impact vegetation regeneration can inform better land management strategies to reduce the impacts of wildfires.

Similarly, this research also contributes to SDG 15: Life on Land by providing insights into the long-term effects of wildfires on vegetation regeneration. A key component of this SDG is land management practices that promote the restoration and conservation of ecosystems, which this research directly informs. By understanding the factors that contribute to successful regeneration of vegetation after a wildfire, biodiversity protection could be promoted.

Conclusion

In conclusion, this study aimed to evaluate the impact of burn severity on long-term vegetation regeneration in Okanagan Mountain Park, British Columbia, and Slave Lake, Alberta. The results of this study suggest that burn severity has a significant impact on vegetation regeneration in both areas. In Okanagan Mountain Park, high-severity burns resulted in lower vegetation recovery while in comparison, moderate-severity burns had a positive effect on vegetation regeneration in Slave Lake.

This research used remote sensing data that were obtained from Landsat 5 TM and Landsat 8 OLI satellite imagery in order to determine recovery in the two areas over a 10-year period following the wildfires. The results showed that in Okanagan Mountain Park, high-severity burns resulted in a lower vegetation recovery rate. While on the other hand, low-severity burns had a positive effect on vegetation regeneration. In Slave Lake, the results were different as moderate-severity burns had a positive effect on vegetation regeneration. The low-severity burns resulted in an increase in vegetation. The high-severity burns resulted in lower vegetation recovery; similar to Okanagan Mountain Park.

In terms of vegetation regeneration, this study found that Okanagan Mountain Park was unable to regenerate fully while Slave Lake's vegetation was able to restore completely within four years. The study also found that Okanagan Mountain Park was only able to restore 56.63% of healthy vegetation. This difference in regeneration can likely be due to the fact that burn severity was significantly higher for Okanagan Mountain Park than it was for Slave Lake.

The models used in the study were not entirely linear. The model used for Okanagan Mountain Park was mostly linear while the model used for Slave Lake was pretty non-linear. This nonlinearity can be partially explained by the fact that the study did not account for spatial autocorrelation, which refers to how areas close to each other are related to each other. The study found that burn severity was positively correlated for both Okanagan and Slave Lake, likely due to the fact that other variables were not accounted for. Burn severity was also found to be highly impactful for Okanagan Mountain Park, but not for Slave Lake. More research may need to be done accounting for spatial autocorrelation, possibly using geographically weighted regression, and including additional variables such as temperature and soil moisture.

It is important to remember that burn severity is a complex variable affected by a variety of factors and circumstances. This study only focuses on two rather different study areas. While the results that this study provided offer insightful information on how burn intensity affects vegetation regeneration, more research is necessary to fully understand the complex relationships between burn severity and vegetation regeneration. Similarly, it is important to consider that other factors may influence regeneration when evaluating the impact of burn severity on vegetation regeneration; two important aspects being climate and soil moisture. Future research could offer a better understanding of the effect of burn severity on vegetation regeneration by taking such variables and spatial autocorrelation into account.

Appendix

Note A. NDVI Okanagan Mountain Park Google Earth Engine Code. Link

Note B. NDVI Slave Lake Google Earth Engine Code. Link

Note C. NBR and dNBR Okanagan Mountain Park. Link

Note D. NBR and dNBR Slave Lake. Link

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