# Fighting Future Flames: Modelling Forest Fire Vulnerability in Nova Scotia, Canada

by

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Table of Contents

1. Introduction ........ 1
1.1 Motivation ........ 1
1.2 Background ........ 2
1.3 Summary of Literature ........ 4
1.4 Introduction to Study ........ 4
1.5 Summary of Approach ........ 5
2. Literature Review ........ 6
3. Methods ........ 10
3.1 Study Areas ........ 10
3.1.1 History of Disturbance ........ 11
3.2 Overview of Data Sources ........ 12
3.3 Data Preparation and Analysis ........ 13
3.3.1 Fire Risk Variables ........ 13
3.3.2 Masking Coastal Waters ........ 16
3.3.3 Unsupervised Classification ........ 16
3.3.4 Burn Scar Generation and Validation ........ 17
3.3.5 Vulnerability classification validation ........ 18
4. Results ........ 20
5. Discussion ........ 24
6. Conclusion ........ 27
7. References ........ 29

List of Figures

Figure 1: Study Areas, Ecoregions and Counties Across Nova Scotia, sourced from Taylor et al., (2020) ..... 11
Figure 2: Difference in Vegetation Before and after the Forest Fires at both Study Areas ... 20
Figure 3: Validation results for the Upper Tantallon Study Area ..... 22
Figure 4: Map of the Validation Raster of the Barrington Study Area ..... 23

List of Tables

Table 1:Wavelength Range for Sentinel-2 Multispectral Satellite, source from Campbell et al. (2023), pp. 183 ..... 3
Table 2: Datasets used as inputs to the analysis ..... 13
Table 3: Summary of Potential Pixel Values Resulting from the Multiplication of the Reclassified Vulnerability Layer and the Burn Scar Raster ..... 18
Table 4: Accuracy assessment results for the Upper Tantallon Study Area ..... 22
Table 5:Accuracy Assessment results for the Barrington Study Area ..... 23

Abstract

Historically, fire has been, and continues to be, a natural driver of forest renewal and regrowth, shaping Earth's landscapes into what we see today. The complex relationship between changing climate patterns, fuel types, and human activity has contributed to an increase in the frequency of forest fires. An effective method to quantify and monitor the changes to a forest ecosystem is the use of integrated remote sensing and spatial analysis techniques. In the summer of 2023, Nova Scotia experienced their most devastating fire season with 220 fires burning 25,093 hectares of land, highlighting the growing importance of monitoring forest fire vulnerability. The goal of this study is to develop a suite of indicators that, when considered together, identify areas at potential high-risk of forest fires in Nova Scotia. Two study areas were considered: Upper Tantallon and Barrington fire locations from the summer of 2023 in Nova Scotia, Canada. An ISODATA unsupervised classification was performed to identify patterns of similar spectral characteristics among biophysical variables that was used to create a map of forest fire vulnerability using an ordinal scale. The input variables include spectral indices like Normalized Difference Vegetation Index, Normalized Difference Moisture Index, slope and proximity to human-built areas, as identified across several previous studies. The vulnerability scale was tested against a high accuracy burned area classification that was generated through band differencing Sentinel-2 derived NBR (kappa 0.905). In this validation there was a high level of agreement between burned and vulnerable areas in both the reference and the map at both locations. Therefore, a significant number of areas classified as vulnerable did burn in the resulting fire. There was low agreement between the not burned and not vulnerable areas in both the reference and the map at both locations; however, this could have been caused by fire control efforts in those areas. The results of this study will help improve future wildfire science towards forest fire prediction to increase disaster preparedness and decrease the damage of forest fires.

Keywords: Forest fire; Remote sensing; Vulnerability; Unsupervised classification; Nova Scotia

Abbreviations

NDVI: Normalized Difference Vegetation Index

NDMI: Normalized Difference Moisture Index

dNBR: Difference Normalized Burn Ratio

NBR: Normalized Burn Ratio

GIS: Geographic Information Systems

NASA: National Aeronautics and Space Administration

USGS: United States Geological Survey

ESA: European Space Agency

MSI: Multispectral Imaging

NIR: Near Infrared

SWIR: Shortwave Infrared

FWI: Fire Weather Index

WFPI: Wildland Fire Potential Index

CWFIS: Canadian Wildland Fire Information System

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Land Acknowledgment

I would like to acknowledge that Dalhousie University is located in Mi'kma'ki (MEEG-MA-GEE), the traditional (or ancestral) territory of the Mi'kmaq people. This territory is covered by the "Treaties of Peace and Friendship" which Mi'kmaq Wəlastəkwiyik (Maliseet), and Passamaquoddy Peoples first signed with the British Crown in 1726. The treaties did not deal with surrender of lands and resources but in fact recognized Mi'kmaq and Wəlastəkwiyik (Maliseet) title and established the rules for what was to be an ongoing relationship between nations.

## 1. Introduction

### 1.1 Motivation

Fire has shaped the Earth we know today (Zalzal, 2018), acting as a naturally occurring catalyst for the renewal and the regrowth of forest ecosystems (Szpakowski & Jensen, 2019). Now, forest fires are occurring more frequently a result of the interactions between changing climate and weather patterns, fuel types, and humans (Flannigan et al., 2009). In the past 21 years, human-caused fires have extended the average fire season in the United States from 21 to 154 days, tripling its length (Congressional Research Service, 2023). Over half of the fires across Canada are a direct result of human activity, including human driven climate change (MacCarthy et al., 2024). Population growth and urban expansion have been directly linked to an increase in human-caused wildfires, as more people settle near or within forested areas (Guo et al., 2024). This proximity increases the likelihood of fire ignitions due to human activity, such as recreation, infrastructure development, and land-use changes (Taylor et al., 2006). The growing population in wildland-urban interface regions has intensified these interactions (Radeloff et al., 2005), placing additional stress on forest ecosystems and elevating fire risk (Whitman et al., 2013). Living within these wildland urban interfaces increases the risk for forest fires that result in aggressive and costly control strategies (Taylor et al., 2006). In 2023, Canada experienced a record-breaking annual population growth of over 1.2 million people (Statistics Canada, 2024) with the population in suburbs and exurbs growing much faster than in the visible downtown cores (Gordon & Shrinkoff, 2014). In the same period, the province of Nova Scotia experienced its largest population growth since 1951 (Willick, 2023). This growth has accelerated a shift away from urban cores toward suburban areas, a trend known as suburbanization. Suburban developments in Nova Scotia are creating more areas where humans and forests intermingle, increasing the potential for human-caused ignitions of forest fires (Hammer et al., 2009). This increase in fire activity is particularly concerning given that Nova Scotia's forests are already fire-prone due to the abundance of woody shrubs and coniferous trees (Whitman et al., 2014).

The increasing frequency of forest fires poses a complex policy challenge, given their far-reaching consequences for ecological integrity, economic stability, and human health. Research by Taylor et al. (2006), concluded that 145 million hectares of Canada's land supports an $81.8 billion forestry industry, comprising approximately 40% of Canada's forests. Beyond the loss of resources to a significant industry, forest fire control is extremely costly. Between 2006 and 2015, an annual 2.6 million hectares of Canada's land were destroyed due to fire, with fire management costing an average of $800 million per year (Stocks & Martell, 2016). Over the past decade, the severity of forest fires in Nova Scotia has increased significantly, posing a significant threat to both human life and the ecological integrity of the Acadian-Wabanaki Forest (Whitman et al., 2014). Between May and August 2023, the areas of Barington Lake and Upper Tantallon experienced some of the largest forest fires in Nova Scotia history, devastating approximately 25,000 hectares of land and 260 homes (Calian Group, 2024).

## 1.2 Background

An effective method to quantify and monitor changes to a forest ecosystem is the use of remote sensing techniques (Navarro et al., 2017). Remote sensing is the process of obtaining information about the Earth's land and water surfaces using images obtained from satellites and using electromagnetic radiation reflected or emitted from the Earth's surface (USGS, 2022). Geographic information systems (e.g., ArcGIS™ and QGIS™) can be used to store, process, analyze and visualize data collected through remote sensing techniques (Longley et al., 2015.). Satellite-borne sensors can detect wavelengths across the electromagnetic spectrum, including both visible and non-visible ranges (e.g., near infrared, short-wave infrared, thermal infrared). Earth's features, for example, dry or wet soil, can be identified by their unique spectral response collected by a satellite (NASA, 2023). Remote sensing and Geographic Information Systems (GIS) methods can be used to quantify environmental changes ranging from local to regional and global scales, over multiple time periods. A user's ability to distinguish features on Earth's surface depends not only on the sensor's spatial resolution, the ground area represented by each pixel, but also the spectral and radiometric resolutions of the sensor, which affect how well the sensor detects and records variations in wavelength and reflectance (Campbell et al., 2023, pp. 154).

Multispectral optical remote sensing has played a critical role in Earth observation, enabling the detection and analysis of surface features by recording reflected sunlight and emitted longer infrared wavelengths across several discrete spectral bands (Campbell et al., 2023, p. 177). The Landsat program was initiated in 1972 by the National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS) to provide continuous multispectral imagery of Earth's surface and set the precedent for modern Earth observation missions. Building on this program, the Sentinel-2 satellite constellation (A, B, and recently C) was launched as a part of the European Space Agency's (ESA) and the Copernicus Earth Observation Program in 2015, working passively to monitor land and coastal areas (Sentinel Online, n.d.). The optical multispectral imagery collected from the Multispectral Imager carried by Sentinel-2 is useful to study ecosystems as it can differentiate between vegetation types and can be used to measure vegetation indexes and leaf moisture content. The Multispectral Imager (MSI) sensor carried on the Sentinel-2 platform collects 12-bit high resolution optical imagery (Thepaut et al., 2018), covering a 290km swath with a temporal resolution of 5 days (Campbell et al., 2023, pp. 182). Each sensor collects 13 discrete spectral bands (see Table 1) at varying spatial resolutions (Campbell et al., 2023, pp. 184).

**Table 1:** *Wavelength Range for Sentinel-2 Multispectral Satellite, source from Campbell et al. (2023), pp. 183*

| Band | Wavelength (µm) | Spatial Resolution |
|---|---|---|
| 1 | 0.4322-0.4527 | 60 m |
| 2 | 0.4594-0.5251 | 10 m |
| 3 | 0.5418-0.5770 | 10 m |
| 4 | 0.6494-0.6801 | 10 m |
| 5 | 0.6966-0.7116 | 20 m |
| 6 | 0.7330-0.7466 | 20 m |
| 7 | 0.7728-0.7897 | 20 m |
| 8 | 0.7799-0.8858 | 10 m |
| 8A | 0.8542-0.8750 | 20 m |
| 9 | 0.9351-0.9537 | 60 m |
| 10 | 1.3619-1.389 | 60 m |
| 11 | 1.5682-1.6574 | 20 m |
| 12 | 2.1149-2.2782 | 20 m |

### 1.3 Summary of Literature

Previous studies integrating remote sensing and spatial analysis techniques to examine forest fire vulnerability and/or to predict fire behaviour are well established in the United States, Asia, Europe and some Mediterranean countries (e.g., Akinola & Adegoke, 2018; Moghadam et al., 2024; Rasooli et al., 2018). Several studies (e.g., Navarro et al., 2017) were conducted using nationwide burn indices, such as the normalized burn ratio (NBR), derived from coarse spatial resolution satellite images. Recent studies in remote sensing have began exploring the use of machine learning algorithms in environmental risk modelling (Nikolaychuk et al., 2024; Coughlan et al., 2021; Truong et al., 2023). Despite being well established in other regions, there has been limited forest fire vulnerability modelling applied to Nova Scotia using classification methods. The model currently used for fire danger ratings across Nova Scotia is the Fire Weather Index (FWI). This model is used by the Nova Scotia Department of Natural Resources and Renewables is largely based on weather conditions but does not consider differences of risk, fuel or topography, which have been critical in the application of other models (Gulcin & Deniz, 2020; Ji et al., 2024; Lahmar & Akakba, 2024).

### 1.4 Introduction to Study

As the global climate changes, it is becoming increasingly important to estimate and monitor forest fire vulnerability. Between 2018 and 2022, the number of forest fires burned in Nova Scotia did not change significantly, but the size of the burned area increased exponentially. In 2018, 190 fires burned through 251 hectares of land and in 2022, 152 fires burned through 3,389 hectares of land (Department of Natural Resources and Renewables, 2023). In the summer of 2023, Nova Scotia experienced their most devastating fire season with 220 fires burning 25,093 hectares of land (Department of Natural Resources and Renewables, 2023). The goal of this study is to develop a suite of indicators that, when considered together, identify areas at potential risk to forest fires in Nova Scotia. Given this context, this study aims to answer the question: to what extent can optical satellite imagery be used to identify areas vulnerability to forest fires in Nova Scotia, Canada?

## 1.5 Summary of Approach

The research question will be addressed through the application of remote sensing and spatial analysis techniques to analyze biophysical variables that will be used to classify forest fire vulnerability. Because forest fires are a global concern, remote sensing techniques are increasingly employed to track environmental factors that may increase fire risk on a global scale. This study focuses on two areas previously affected by forest fires in Nova Scotia. Within each study area, a cluster analysis is applied using biophysical variables to identify patterns of fire hazard. For this research, optical multispectral satellite imagery of the Barrington and Upper Tantallon fire locations will be obtained through the Copernicus Dataspace Ecosystem. The imagery, collected by the Sentinel-2A satellite platform, will be analyzed using geographic information systems and remote sensing packages (e.g., ArcGIS Pro™, Catalyst Professional™). The research question will be addressed by performing an ISODATA unsupervised classification algorithm using variables to identify 6 potential clusters of very low, low, moderate, high, and extreme vulnerability. The biophysical variables used in the analysis include a normalized difference vegetation index (NDMI), a normalized difference moisture index (NDMI), topographic slope, and proximity to human-built areas, as outlined in several previous studies (Navarro et al., 2017; Anikola & Adegoke, 2018; Rasooli et al., 2018). To validate the model, an error analysis using a confusion matrix was used to estimate the agreement between vulnerability classes and pixels representing the burned area to validate the model's accuracy.

## 2. Literature Review

This literature review explores remote sensing and spatial analysis techniques and its role in mapping forest fire vulnerability across various environments. Very few articles were found to model forest fire vulnerability in Nova Scotia, revealing a clear knowledge gap. This review is informed by the literature found in an array of peer-reviewed scientific journals and high-level government documents. I conducted searches through the Environment Complete database, Novanet, and Google Scholar using key terms such as: forest, forest fire, wildland fire, wildfire, vulnerability, prediction, susceptibility, modelling, remote sensing, and Senitnel-2. Given the resources available and time constraints for this study, the contemporary methods found in this literature review were used to inform the most suitable method to map forest fire vulnerability in locations across Nova Scotia.

Future fire activity in Canada is expected to increase with global climate change (Johnston et al., 2020). Predicted climate changes for Nova Scotia were defined by Whitman et al., (2014) as increased temperatures during fire season and increased evaporation creating dryer fuels. By 2040, forest fire seasons are expected to last an average 30 days longer, occur 25% more often, and burn 46% more land (Public Health Agency of Canada, 2018). These changes are expected to exceed our fire response capacity resulting in more fires per season escaping control efforts and resulting in more burned land (Johnston et al., 2020).

Forests provide our world with ecosystem services that allow life on Earth to exist (Dickinson & Ramalho, 2022). Some effects of forest fires, such as habitat loss and reductions in soil, air, and water quality, are short-term, whereas changes to ecological processes like carbon cycling can be long-lasting or permanent (Gralewicz et al., 2012). Furthermore, shifts in forest species composition and age-distribution due to changing wildfire regimes have already been observed (Johnston et al., 2020). In addition to ecological impacts, wildfires pose substantial economic and social challenges. From 2006 to 2015, wildfires burned an average of 2.6 million hectares annually in Canada, with suppression efforts costing approximately $800 million per year (Stocks & Martell, 2016). Canada's $81.8 billion forestry industry is also at risk, highlighting the broader economic implications of fire events (Taylor et al., 2006). Beyond economic losses, affected communities often face serious public health concerns, including increased incidence of cardiovascular and respiratory illness, mental health impacts, and in extreme cases, fatalities (Public Health Agency of Canada, 2018).

Remote sensing and spatial analysis are foundational methods being used in wildfire vulnerability models. Remote sensing techniques have been used to analyze the negative impacts of forest fires since the mid-1980s (Navarro et al., 2017) given the many advantages of remote sensing in natural disaster assessment and mitigation. Remote sensing technology provides large scale data acquisition across many spatial and temporal scales (Qu et al., 2020). This is done by using satellite sensors to collect fire locations and quantify the intensity of forest fires (Chen et al., 2024). GIS has been useful to store, analyze, transform and manage imagery collected from satellites (Gai et al., 2011). Environmental variables such as vegetation type, normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), elevation derivatives like slope, and surface temperature can all be derived from satellite imagery (Gulcin & Deniz, 2020; Shadrin et al., 2024; Moghadam et al., 2024). The coupled use of remote sensing and GIS allows for both the qualitative and quantitative spatial analysis of forest ecosystems to identify and monitor forest fires (Gulcin & Deniz, 2020).

Government agencies in North America have built several different open-access forest fire maps that are used to inform forestry management across the globe. The United States Geological Survey (USGS) created the Wildland Fire Potential Index (WFPI) (USGS, 2017) that assign an index of vegetation flammability derived from satellite-based vegetation data, weather forecast data, and landcover, at 1 km spatial resolution (Woody, 2023). Another program used by the USGS is LANDFIRE, which uses spatial data to map vegetation, fire and fuel across the United States, with 30 m spatial resolution (USGS, 2023). In Canada, the Canadian Wildland Fire Information System (CWFIS) maps fire hotspots, fire behavior and weather, across Canada (Natural Resources Canada, 2020). The results of the CWFIS are a rough estimate, due to coarse spatial resolution, therefore there is limited accuracy in the outputs of the fire hotspots (Natural Resources Canada, 2022). The model currently used for provincial fire danger ratings in Nova Scotia is the Fire Weather Index (FWI). The FWI is one of the most widely used fire danger rating systems (De Jong et al., 2016). This model is used by the Nova Scotia Department of Natural Resources and is only based on weather conditions but does not consider differences of risk, fuel or topography, which have been critical in the application of other models (Gulcin & Deniz, 2020; Ji et al., 2024; Lahmar & Akakba, 2024).

A recent trend in remote sensing literature is the emerging application of machine learning methods in natural disaster mitigation. Logistic regression, a supervised shallow machine learning algorithm, was one of the first methods used for regional forest fire predictions, demonstrated by Fan et al. (2007) with 70% accuracy. With technological advancements, other machine learning algorithms like convolutional neural networks emerged and more accurate predictions of forest fire vulnerability were realized. For example, studies like Nikolaychuk et al. (2024) using random forest with 89% accuracy; Coughlan et al. (2021) using a decision tree, an AdaBoost and random forest with 78% accuracy, and Chen et al. (2023) using random forest with 87.5% accuracy. The integration of machine learning, GIS and remote sensing allows for forest fire trends, patterns and vulnerability to be analyzed effectively at large scales (Mishra et al., 2024).

Digital image classification is a process that groups pixels in satellite imagery based on their spectral and/or spatial characteristics and assigns them to meaningful categories, known as informational classes (Campbell et al., 2023, p. 315). Supervised classification methods are commonly used to map forest fire areas, where a set of training data, pixels with known land cover types, is used to teach the algorithm how to recognize and classify areas with similar characteristics in the rest of the image (Liu & Mason, 2013). Unsupervised classification does not require training data, instead the algorithm will classify groups or clusters based on the pixel values (Pacheco et al., 2023). No studies were found to be using ISODATA unsupervised classification method in forest fire vulnerability modelling. There are studies using K-Means clustering, which ISODATA is derived from, to predict forest fires and analyze litter flammability (Sevinç, 2022 & Li et al., 2023).

Collectively in the literature reviewed, vegetation, topography, climate, and land use were the dominant biophysical variables used in forest fire modelling. One particular study used the analytic hierarchy process (AHP) to find that precipitation, temperature, elevation, and non-photosynthetic vegetation were the main influencing factors in the occurrence of forest fires in the Anning River Valley in China (Ji et al., 2024). Another study using AHP found that the most important factors to influence forest fire modelling were NDVI and surface temperature (Lahmar & Akakba, 2024). Furthermore, human activities are a major source of ignition and are considered in different models (Zhou et al., 2023). The ranking of variables used in some studies was not uniform across different parts of the world. This difference is because topography, climate, and vegetation are all location dependent.

One article was found to study forest fire risk within Nova Scotia in two communities in the Halifax Regional Municipality (Whitman et al., 2013). In the study by Whitman et al., (2013) it was found that the majority (51.1% and 67.2%) of the two study areas did not burn, indicating low susceptibility to forest fire. However, Whitman et al., (2013) used an outdated version of the BurnP3 model. Burn-P3 was developed by the Canadian Forest Service in 2005 and has since been updated to the BurnP3+. The BurnP3+ estimates wildfire susceptibility using a Monte Carlo simulation modelling approach using fire ignition, weather and biophysical variables to create a raster grid of burn probability and fire-size distribution (Forest Service, 2019). Some challenges associated with the use of Monte Carlo methods have been identified, particularly in the context of fire modelling (Beverly & McLoughlin, 2019). It was found that map symbology impacts the appearance and the corresponding accuracy of the burn probability maps. These findings suggest that burn probability maps may have limited applicability at finer spatial scales (Beverly & McLoughlin, 2019).

The literature found focused on the different methods being used across the globe and 3 main themes. Firstly, the weighted value of the variables being used to map forest fire vulnerability is a decision the analyst must make in the process of creating these models. Furthermore, the integration of machine learning, GIS and remote sensing allows for forest fire trends, patterns and vulnerability to be analyzed on large or possibly fine scales. Finally, it was concluded that these methods should be more thoroughly studied within Nova Scotia to assess any knowledge gaps for effective future forest fire mitigation strategies within the province.

# 3. Methods

## 3.1 Study Areas

This research examined two separate locations of the largest forest fires recorded in Nova Scotia, Canada (Figure 1) during the summer of 2023. The study areas represent a sample within the 39 ecodistricts in Nova Scotia with distinct ecological landscapes (Nova Scotia Department of Natural Resources, n.d.). The fires occurred near the community of Barrington within Shelburne County, and in the Upper Tantallon area within the Halifax Regional Municipality. The Barrington fire area represents 23,525 hectares of burned land (Nova Scotia Natural Resources and Renewables, 2023) located at the most south-western point of Nova Scotia in the Sable ecodistrict (Department of Lands and Forestry, 2019b). Softwood species dominate over half of the forest cover in the Sable ecodistrict, with black spruce growing in the poorly drained soils and red spruce, eastern hemlock, and white pine in areas with well-draining soils. Softwood species growing in coarse-textured soils are found to be more susceptible to fire disturbances (Gajewski et al., 2023). The elevation in this region reaches a maximum height of about 110m. The Upper Tantallon fire was located west of Downtown Halifax and was estimated to be 969 hectares of burned land. Upper Tantallon is a part of the St. Margarets Bay ecodistrict, where the vegetation varies between red spruce, white pine and black spruce in the drier regions, and some hardwood species growing in more fertile soils (Department of Lands and Forestry, 2019a). Elevation in this region reaches approximately 220 meters and, alongside tree species composition and ecodistrict characteristics, serves as a key factor influencing forest disturbance regimes as elevation can facilitate or inhibit wildfire spread (Taylor et al., 2020).

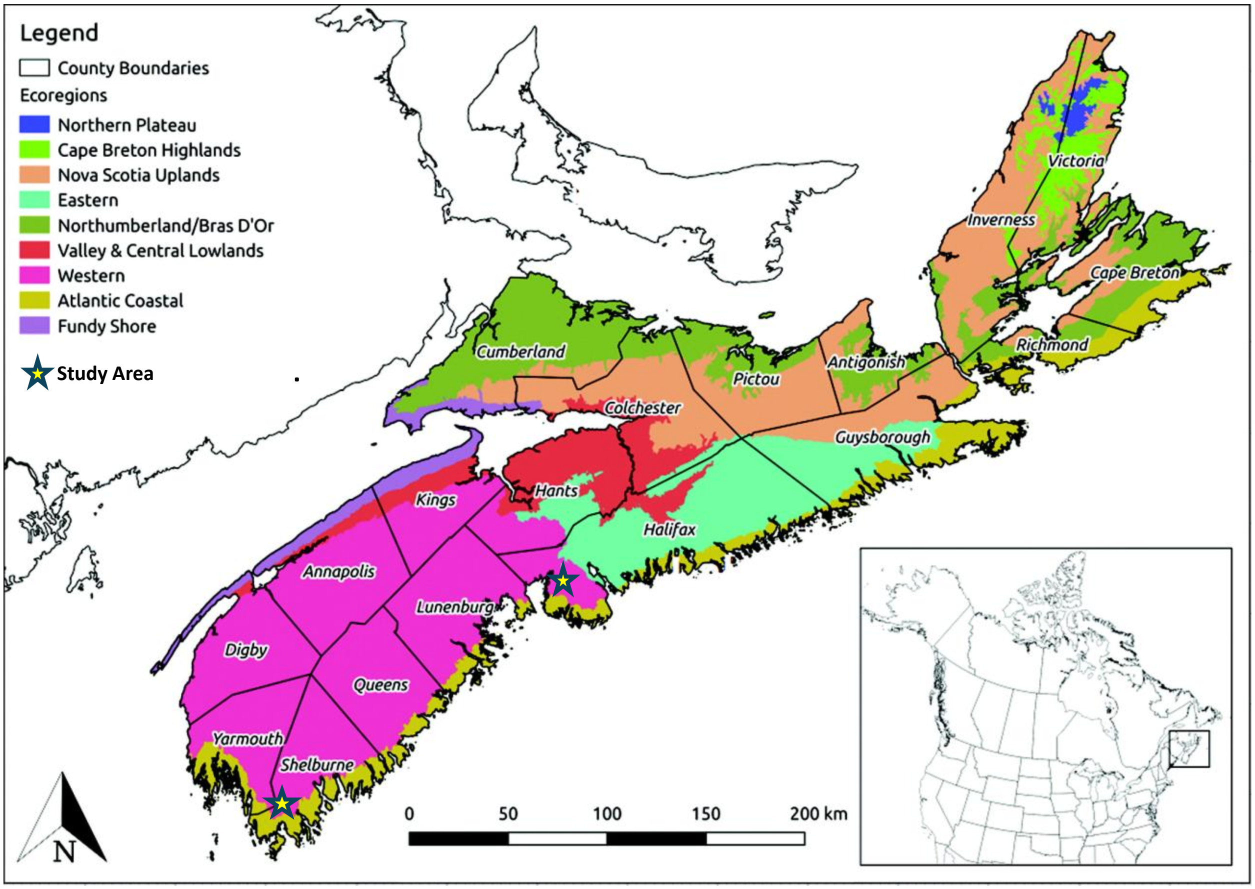


**Figure 1:** Study Areas, Ecoregions and Counties Across Nova Scotia, sourced from Taylor et al., (2020)

3.1.1 History of Disturbance

Paleontological records of Nova Scotia indicate the presence of large forest fires 11,000 to 6,000 years before present (Green, 1981). Fire is the most dominant kind of disturbance in the Shelburne County region (Basquill et al., 2001), disturbance being a human or naturally induced change to the original condition of an ecosystem (Department of Lands and Forestry, 2019a). Setting fires to increase blueberry growth and other wildlife food was common practice by the Mi'kmaq in Shelburne County (Department of Lands and Forestry, 2019a). The reoccurrence of fires in this region of Nova Scotia created barren lands where fire resistant species are scarce (Taylor et al., 2020). Among others, strong winds and hurricanes are of known influence in the Nova Scotia forests (Taylor et al., 2020). Due to the location's proximity to the Bay of Fundy and the Atlantic Ocean, hurricanes are the dominant disturbance in the Upper Tantallon region (Department of Lands and Forestry, 2019b). Local fire behaviors are heavily influenced by winds, as well as vegetation, soil properties and firebreaks (Edmonds et al., 2011). Historically and presently, fire has adverse effects on forest composition and species diversity. The original conditions of the Acadian-Wabanaki Forest, preserved through Mi'kmaq oral traditions and settler records, have since been altered by centuries of land use and resource extraction (Loo & Ives, 2003). The difference between past and present fire patterns, influenced by humans, may result in unpredictable effects (Wein & Moore, 1979).

## 3.2 Overview of Data Sources

The optical multispectral imagery collected by the Sentinel-2 satellite platform of the Barrington and Upper Tantallon locations was obtained through the Copernicus Dataspace Ecosystem. The three Sentinel satellites, Sentinel-2A, Sentinel-2B, and Sentinel-2C, were developed by the European Space Agency (ESA) to monitor changes on Earth's surface. The imagery used in this study was obtained from the Copernicus platform, based on pre-fire and post-fire acquisition dates corresponding to the selected study areas. The imagery of the study areas was collected on May 23 and 28, 2023. A search criterion of no more than 20% cloud cover was used to filter out any low-quality images. Too much cloud cover can disrupt the reflectance signal and obstruct the view of Earth's surface (Meraner et al., 2020). Imagery was then imported into ArcGIS Pro™ for further analysis.

**Table 2:** *Datasets used as inputs to the analysis*

| Name | Format | Source | Purpose | Data Currency |
|---|---|---|---|---|
| Sentinel-2A | TIF File | Copernicus Dataspace Ecosystem | Generate spectral indices | 5/28/2023 |
| Elevation | TIF File | USGS TNM Download (v2.0) | Generate slope | 2022 |
| Built area - European Space Agency Land Cover (2021) | Tiled Imagery Layer | ESRI Environment Living Atlas | Generate distance accumulation | 5/22/2024 |
| Road Network | Shapefile | Nova Scotia Road Network Map | Generate distance accumulation | 1/1/2025 |
| Nova Scotia Provincial Boundary | Shapefile | Statistics Canada Census (2021) | Mask coastal waters | 2020 |

## 3.3 Data Preparation and Analysis

### 3.3.1 Fire Risk Variables

The study areas can be characterized by various vegetation types, topography, and land use. To identify different features on Earth's surface, remote sensing is used to measure and compare the brightness of objects over a range of wavelengths (Campbell et al., 2023, pp. 47). This allows for the identification of different crop types, soils and other chemical and physical properties of an object. Through comprehensive literature review, biophysical variables are selected based on their known influence on forest fire occurrence. These variables include vegetation indices, topography, and proximity to human development. All datasets used in this study were processed using a consistent, user-defined processing extent to ensure spatial alignment across layers. This processing extent was created by generating a minimum bounding rectangle around a 5 km buffer of each burned area. The coordinate system was set to match the native spatial reference system of the Sentinel-2 Imagery (i.e., WGS 1984 UTM Zone 20N) and the processing extent was applied before any analyses were conducted to standardize the spatial reference and analysis area for all datasets.

#### 3.3.1.1 Vegetation

Vegetation provides fuel for fire and is an important factor in determining forest fire severity (Mohajane et al., 2021). A normalized difference vegetation index (NDVI) was calculated using Equation (1), this ratio calculates photosynthetic activity in vegetation with values closer to zero indicating low canopy cover. A normalized difference moisture index (NDMI) was calculated using Equation (2), this ratio calculates moisture levels in leaves with values closer to zero indicating high water stress. These calculations were executed in the Raster Calculator tool in ArcGIS Pro™. The NDVI and NDMI raster outputs were rescaled by 20,000 (meaning each pixel value was multiplied by 20,000) in order to match the numerical range of the other input variables to be used in the cluster analysis.

(1) $NDVI = \frac{Band\ 8 - Band\ 4}{Band\ 8 + Band\ 4} = \frac{NIR - Red}{NIR + Red}$

(2) ) $NDMI = \frac{Band\ 8A - Band\ 11}{Band\ 8A + Band\ 11} = \frac{NIR - SWIR1}{NIR + SWIR1}$

Band 4 represents the red portion of the visible spectrum. Changes in the NIR are especially noticeable when vegetation is under stress, such as from moisture deficiency. Band 8 in the Sentinel-2A satellite represents spectral reflectance in the near-infrared (NIR) and is captured at a 10-meter resolution. This band is used in vegetation monitoring as healthy plants strongly reflect NIR light, making it useful for detecting plant vigor and stress. Band 8A also falls within the NIR range but has a slightly narrower bandwidth and with a 20-meter spatial resolution, offering additional sensitivity to vegetation structure (Campbell et al., 2023, pp. 47). Band 11 captures shortwave infrared (SWIR) reflectance, making it ideal for monitoring canopy moisture levels (Campbell et al., 2023, pp. 433). Since Band 11 has a spatial resolution of 20 meters, the resulting NDMI raster was resampled to 10-meter resolution using bilinear interpolation to match the finer resolution of other input layers. It is important to recognize, however, that the limitation of upscaling the data from 20m to 10m is that data volume increases without improving the amount of detail in an image. This can potentially affect the classification analysis outcomes.

### 3.3.1.2 Topography

Topography has been identified across multiple studies to influence fire behavior (Johnston et al., 2020; Ji et al., 2024; Zühal Özcan et al., 2024). Terrain complexity can be a critical influence on the spread of fire across landscapes (Guo et al., 2024). Although, topographically, the study areas remain relatively simple, topography has been noted to be the most important biophysical variable analyzed across many studies modelling forest fire vulnerability (Epstein et al., 2024; Valdez et al., 2017; Zahra Parvar et al., 2024). In this study, 10-meter spatial resolution raster-based DEMs for both study areas were obtained from the USGS National Map datasets. Slope was then derived from the DEMs in ArcGIS Pro™ and expressed as percent rise. Flat areas are thought to have the highest risk for forest fire ignition (Gulcin & Deniz, 2020). Although, lightning induced fires occur more frequently on mountain ridges and high slopes (Zhang et al., 2024), a study by Zhou et al. (2023) suggests that human activity usually occurs in areas with slopes less than 10 degrees leading to more frequent forest fires. In this study, slopes will be considered to be inversely related to fire risk, with flatter areas at higher risk of ignition as human activity has been a significant cause of recent forest fires.

#### 3.3.1.3 Human Interaction

Human activity plays a significant role in both the occurrence and spread of forest fires (Rasooli et al., 2018). In this study, human interaction is represented by the proximity to anthropogenic features, specifically roads and built-up areas. A vector dataset for roads and a raster dataset for land cover were obtained from the Nova Scotia Road Network and ESRI Living Atlas. The roads were extracted to match the processing extent of the study areas using the Extract by Mask tool. The built areas were extracted from the land cover layers. The roads were then converted from polyline to raster dataset based on Object ID and reclassified using the Reclassify tool in ArcGIS Pro™. This process produced a binary raster in which cells representing roads and built-up areas were assigned a value of 1, and all other land types were assigned a value of 0. The binary raster was then used in a distance accumulation analysis to calculate the distance in meters from each pixel to the nearest human-developed feature. Areas closer to roads and built environments were considered more vulnerable to fire ignition due to increased human presence.

### 3.3.2 Masking Coastal Waters

To exclude coastal waters from the Barrington study area, a land-only mask was applied using the Nova Scotia provincial boundary from the 2016 Census. This vector boundary was used to restrict the spatial extent of the analysis, ensuring that only land within the defined processing extent were included in the results. The mask was applied before conducting further analyses to avoid the inclusion of non-burnable areas such as ocean and coastal water.

### 3.3.3 Unsupervised Classification

Each pixel in the study area was classified as either inland water surfaces, very low, low, moderate, high, or very high vulnerability to fire using the Iterative Self-Organizing Data Analysis Technique (ISODATA) unsupervised classification tool in ArcGIS Pro™. This tool groups pixels based on the similarity of their values across several input layers, including spectral indices (e.g., NDVI, NDMI), slope, and distance to human-built areas. In this context, similarity means that pixels with comparable combinations of input values are grouped into the same category or cluster based on the pixel's distance to the cluster centre. Forest fire vulnerability is the informational class of interest that is identified by the analyst using the results of the classification method.

The model was parameterized using four variables identified through literature review and expected to be strong influences on an area's vulnerability to fire ignition. The expected number of clusters was informed by the preferred levels of forest fire vulnerability to be considered. Five vulnerability clusters were chosen to represent inland water surfaces, very low, low, moderate, high, and very high vulnerability to wildfire if exposed to a source of ignition. The ISODATA classification algorithm is an unsupervised classification method provided in ArcGIS Pro™. The method began by plotting each variable on its own axis (i.e., multidimensional space). Cluster centers were distributed equally throughout the point cloud. After the initial cluster centers are defined, each pixel is assigned to the cluster whose center is closest to it in terms of Euclidean distance across all input variables. With each iteration, the algorithm recalculates new cluster means and reassigns pixels, accordingly, based on any changes in class membership. Clusters that are closer than the user defined minimum distance will merge, and those points will be reclassified based on the new mean center. The process is repeated through several iterations until clusters of pixels with similar values across the input layers are formed. The initial number of clusters, the minimum class size and the sample interval are chosen by the user. The minimum class size was set to 20, and the sample interval to 10, retaining the default parameters of the ISO Cluster tool. After running the classification algorithm, the results were interpreted based on the mean values of each variable in a cluster and by visually interpreting the satellite imagery, and each cluster was assigned to a level of vulnerability. The vulnerability classification was then validated against known burned areas using a pixel-by-pixel comparison and accuracy assessment created in ArcGIS Pro™ and Excel.

### 3.3.4 Burn Scar Generation and Validation

The difference normalized burn ratio (dNBR) is an index used to measure the difference between pre and post fire conditions in both study areas and can be calculated using Equation 4. The dNBR is useful in this study to identify the burned areas and create a boundary around where the fire burned at each location. Dead vegetation reflects SWIR more strongly and therefore dNBR can clearly detect the difference between burned and not burned vegetation.

(3) $NBR = \frac{Band\ 8 - Band\ 12}{Band\ 8 + Band\ 12} = \frac{NIR - SWIR2}{NIR + SWIR2}$

(4) dNBR = NBRprefire – NBRpostfire

Thresholding of the dNBR layer was performed by classifying it into two categories, burned and not-burned, based on a visually selected break value that best distinguished fire-affected areas. The resulting binary raster assigned a value of 1 to not-burned pixels and 2 to burned pixels. An accuracy assessment was then performed on the burn scar to determine the strength of the burn scar delineation by the dNBR index. Using ArcGIS Pro™, a stratified random sample of 400 accuracy assessment points were created for the Tantallon burn scar, and 500 points were created for the Barrington burn scar. The Barrington burned area is much larger than Tantallon, therefore there were more points created for this area. A reference classification was created by visually identifying burned or not-burned conditions at each sample point. User accuracy, producer accuracy, overall accuracy, and the kappa statistic were all calculated in a confusion matrix using ArcGIS Pro™.

### 3.3.5 Vulnerability classification validation

Validating the results of the vulnerability assessment against the burned area required reclassifying the vulnerability output to a binary raster. A binary vulnerability raster was created by reclassifying pixels with very low to low vulnerability to a value of 1 and moderate or higher vulnerability to a value of 10. To assess the accuracy of the vulnerability classification against the actual burned areas, the binary vulnerability raster was multiplied with the burn scar raster using the raster calculator tool (see Table 3). Examples of this operation are illustrated in Figures 3 and 4.

**Table 3:** *Summary of Potential Pixel Values Resulting from the Multiplication of the Reclassified Vulnerability Layer and the Burn Scar Raster*

| Pixel Value | Description |
|---|---|
| 1 | Not vulnerable, not burned |

| | |
|---|---|
| 2 | Not vulnerable, burned |
| 10 | Vulnerable, not burned |
| 20 | Vulnerable, burned |

For this component of the study, a modified accuracy assessment was conducted not to test agreement between equivalent reference classes (e.g., forest classified as forest), but to evaluate the percent agreement between the vulnerability classification and the observed burned areas. This approach provided insight into the model's ability to identify areas susceptible to ignition. However, a key limitation of this method is the use of burned areas as a proxy for ignition locations. Since fires often spread beyond their point of origin, this may result in over or underestimating the model's predictive accuracy.

4. Results

Sentinel-2A multispectral imagery was used to generate the NBR and dNBR outputs to identify areas affected by forest fires in Upper Tantallon and Barrington, Nova Scotia. The change in vegetation before and after the fires is illustrated in Figure 2. The accuracy assessment done on the burn scars resulted in high Kappa statistics of 0.905 for Upper Tantallon and 0.948 for Barrington, indicating a highly accurate delineation of the burned areas. Kappa values range between 0 and 1, where 0 indicates the chance of class existence and 1 indicates perfect agreement between two data sets.

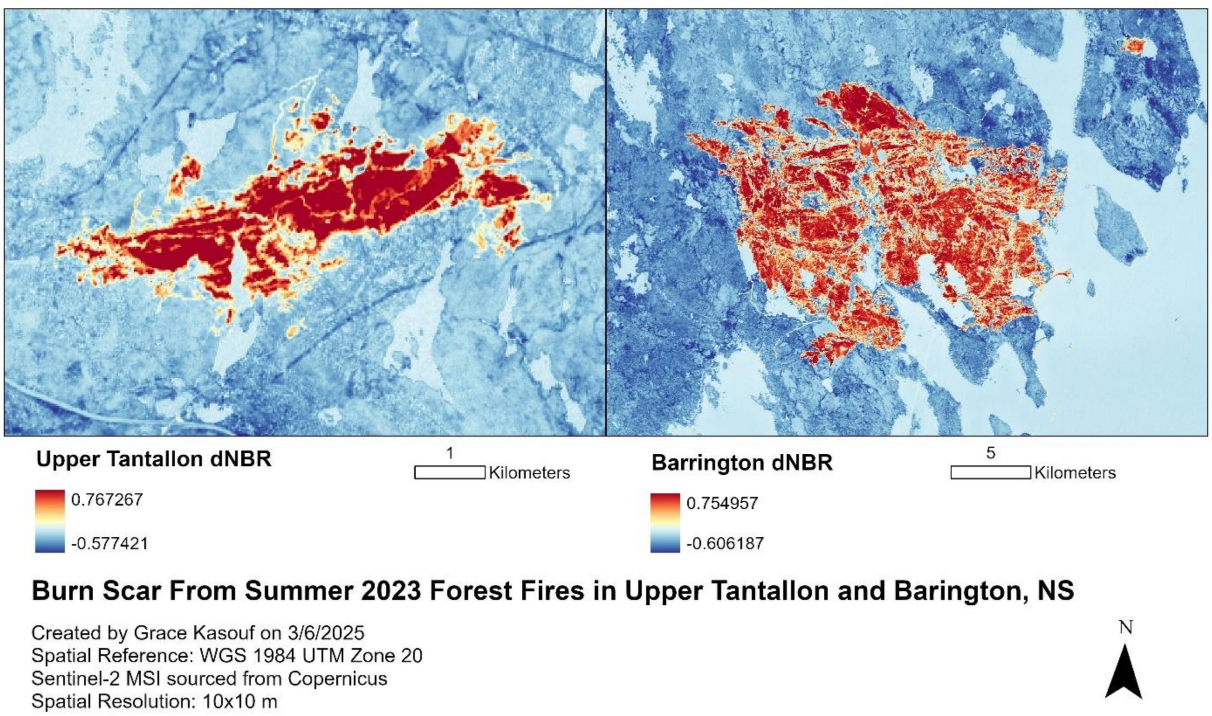


**Figure 2:** Difference in Vegetation Before and after the Forest Fires at both Study Areas

The results of multiplying the binary vulnerability raster with the burn scar are presented in Figures 3 and 4. The modified accuracy assessment of vulnerability serves as a proxy for evaluating the effectiveness of the vulnerability classification in an actual burn scenario. The classification's performance was evaluated using a confusion matrix, that includes standard metrics such as true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In this study, the reference data is the burned area, rather than actual fire vulnerability meaning two different classifications are being compared. Conventional accuracy assessments typically compare classified imagery to a reference dataset of known ground truth, such as land cover. However, in this study, the classified variable is fire vulnerability, which is not directly observable in satellite imagery. As a result, a post hoc comparison was used, evaluating how well the vulnerability classification aligned with the areas that ultimately burned. This approach introduces some uncertainty, as areas may be highly vulnerable but remain unburned simply because no ignition occurred. The accuracy results for both study areas were derived from the confusion matrix, as shown in Tables 3 and 4.

The model's ability to classify vulnerable areas that also burned in the Upper Tantallon fire is reflected in a 64% accuracy rate (see Table 3). The user's confidence in the model's ability to correctly identify vulnerable areas that burned on the ground is reflected in a 71% accuracy rate. The confusion matrix results indicate low agreement between the not burned and not vulnerable classifications, with an accuracy of 15% in the map and 19% in the reference data.

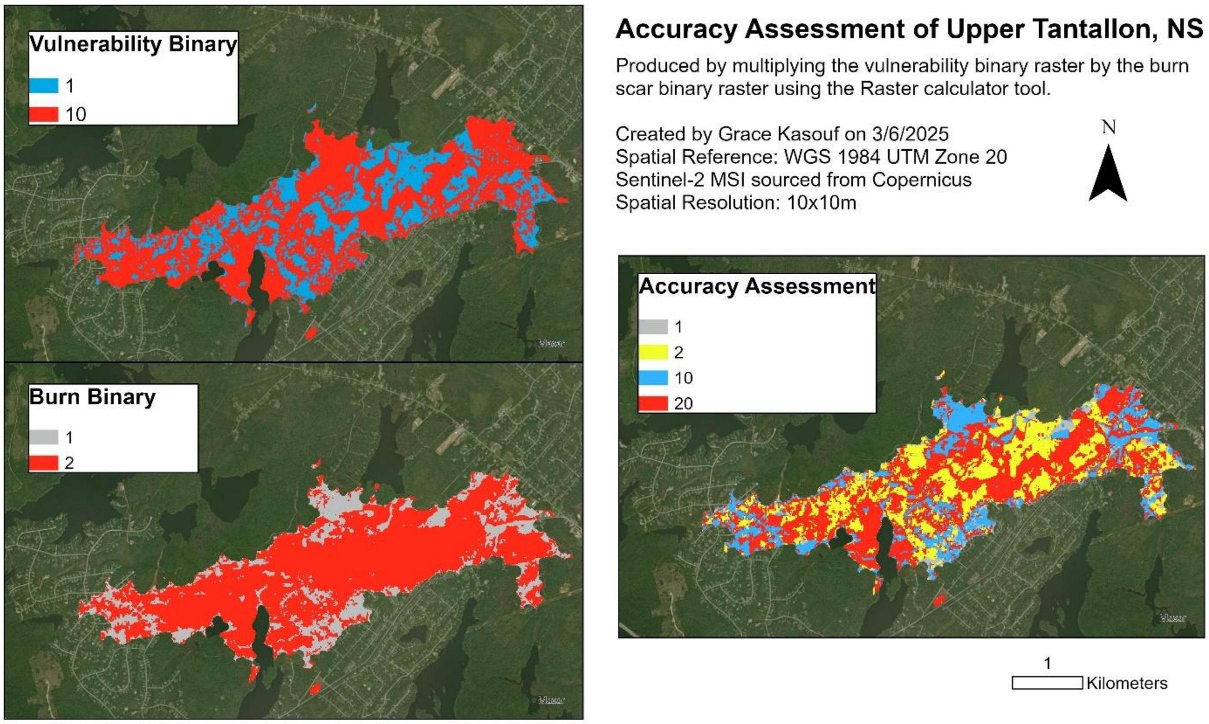


**Figure 3:** Validation results for the Upper Tantallon Study Area

**Table 4:** *Accuracy assessment results for the Upper Tantallon Study Area*

| | Burned | Not burned | Marginals | Agreement |
|---|---|---|---|---|
| Vulnerable | 38710 | 15683 | 54393 | 71% |
| Not Vulnerable | 21679 | 3778 | 25457 | 15% |
| Marginals | 60389 | 19461 | 42488 | |
| Agreement | 64% | 19% | | |

The model demonstrated strong accuracy in classifying vulnerable areas that burned in the Barrington fire, with a 95% agreement (see Table 4). The user's confidence in the model's ability to correctly identify vulnerable areas that burned on the ground is 83%. These results indicate a high level of agreement between vulnerable and burned areas, with a 95% match in the map and 83% in the reference data. The results also indicate a low level of agreement between the not burned and not vulnerable classifications, consistent with the findings from the Upper Tantallon study area.

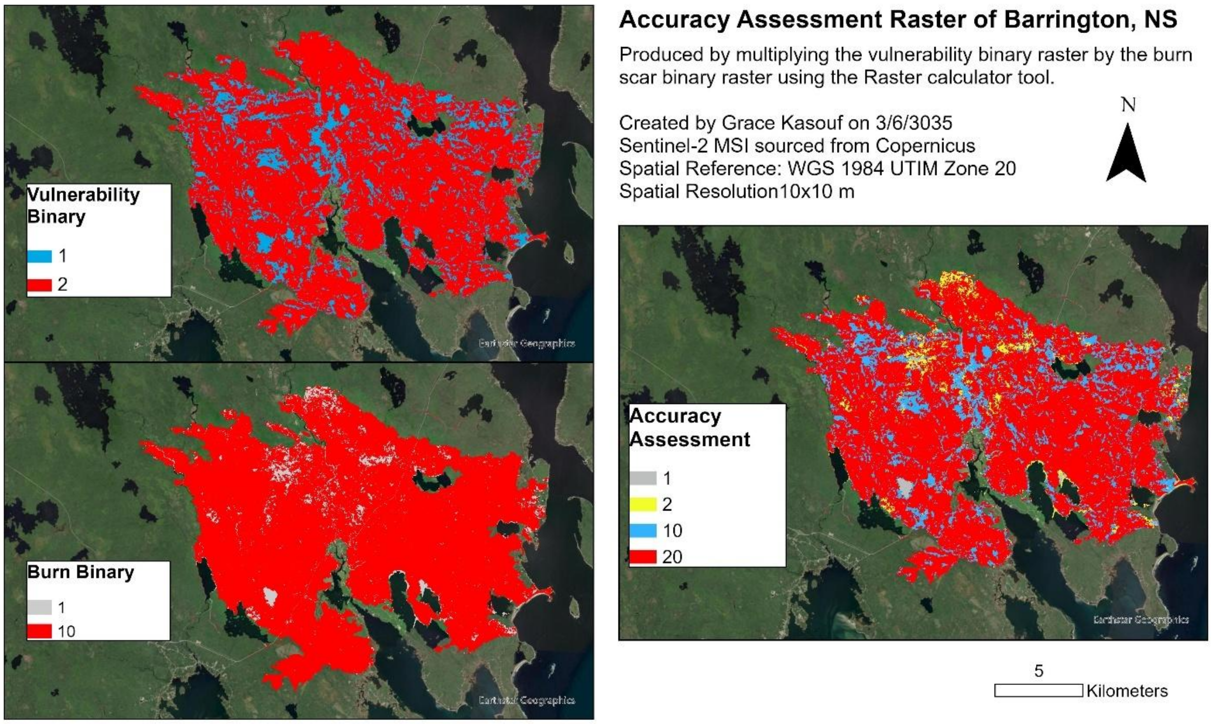


**Figure 4:** Map of the Validation Raster of the Barrington Study Area

**Table 5:** *Accuracy Assessment results for the Barrington Study Area*

| | Burned | Not Burned | Marginals | Agreement |
|---|---|---|---|---|
| Vulnerable | 1733545 | 352249 | 2085794 | 83% |
| Not vulnerable | 80756 | 29556 | 110312 | 27% |
| Marginals | 1814301 | 381805 | 1763101 | |
| Agreement | 95% | 8% | | |

## 5. Discussion

The strong agreement between vulnerable and burned areas highlights the potential of optical satellite imagery to identify areas vulnerable to forest fires. The confusion matrices confirm that the model effectively identified areas at risk of burning using NDVI, NDMI, slope, and proximity to human-built areas. These findings support existing research on fire behaviour, which emphasizes the role of vegetation, topography, and human accessibility in influencing ignition risk (Yang et al., 2007). However, additional environmental variables such as temperature, precipitation, humidity, aspect, vegetation type, and crown closure have been used in other fire risk models (Ji et al., 2024; Rabiei et al., 2022; Akay & Erdoğan, 2017), they were excluded from this study due to data accessibility constraints. Instead, this model uses publicly available resources, allowing it to be easily replicated and accessed by policymakers and resource managers. While the model effectively identifies ignition risk, it does not account for factors influencing fire behavior and spread, such as wind. This limitation reflects a broader challenge in wildfire modelling, as ignition points are inherently difficult to predict (Yang et al., 2007).

Among these selected variables, human proximity was particularly influential in the difference in study area sizes, reinforcing previous research on the relationship between human activity and fire susceptibility (Gulcin & Deniz, 2020; Gralewicz et al., 2012; Erni et al., 2023). Large wildfires are most likely to ignite 100–300 km from populated areas (Gralewicz et al., 2012), which is consistent with the remote location of the Barrington study area. Although the Upper Tantallon fire began within the community, contradicting Gralewicz et al. (2012), these findings contribute to ongoing research on the wildland-urban interface (WUI), where human access increases ignition risk while also increasing response efforts.

The Barrington fire ignited in a remote part of Nova Scotia with minimal built infrastructure, limited human resources, and restricted emergency response access. As a result, the fire spread largely uncontrolled, consuming a much larger area. The fire began on May 26, with fourteen emergency service personnel dispatched that evening. Despite aerial firefighting efforts, conditions worsened the following day, leading to significant fire growth (Calian Group, 2024). Consequently, a greater proportion of areas classified as vulnerable burned at the Barrington site, and the larger burn scar encompassed both vulnerable and non-vulnerable areas. These findings highlight the importance of integrating fire vulnerability assessments into land-use and emergency response planning, particularly in rural regions where delayed access can lead to uncontrolled fire spread.

In contrast, the Upper Tantallon fire remained relatively contained due to its urban setting. The fire was reported at 15:28 on May 28, with an update on two burning homes at 15:31, prompting an emergency response by 15:36 (Calian Group, 2024). Fires in urban areas, such as Upper Tantallon, pose a higher risk to homes and human life, making rapid response critical. The influence of human presence on fire occurrence is closely linked to population density and accessibility (Yang et al., 2007). While densely populated areas are at higher risk of ignition due to human activity, they are also where emergency services can respond most quickly.

Nova Scotia's current use of the Canadian FWI operates at a 100 km spatial resolution. This study demonstrates the value of higher-resolution fire vulnerability models that incorporate both environmental and human variables. Such models can improve decision-making in both fire prevention and response by providing risk assessments that can complement, rather than replace, coarse-scale weather-based systems.

There was low agreement seen between the areas classified as not burned and not vulnerable in both the map and reference data. The lower agreement in non-vulnerable classifications may be because regions categorized as low vulnerability are less likely to ignite; however, once a fire reaches high intensity, these areas can still serve as fuel. Additionally, fire suppression efforts, such as fire hoses, aerial firefighting, or even chance, may have played a role in limiting fire spread, further affecting classification accuracy. This indicates a key limitation in the use of post hoc validation as agreement metrics may underestimate model performance in cases where fire behavior relies on unpredictable ignition points and factors not included in the model, such as human response and mitigation efforts. It also highlights the challenge of using binary classifications (vulnerable/not vulnerable) to assess wildfire risk. Future research should consider incorporating probabilistic models or continuous vulnerability indices to better capture the variability of fire risk and account for suppression efforts and fire spread dynamics.

There are several limitations to consider when replicating this study. Factors such as data accessibility, image quality, and the analyst's expertise may impact replication efforts. The temporal resolution of satellites plays a critical role, as it determines the dates of available imagery. In this study, Sentinel-2A's five-day revisit period ensured that temporal limitations had minimal impact on the results. Furthermore, proxies such as a specific ignition source are not used in this model, therefore, it cannot be used to predict exact locations of ignition or spread. Environmental conditions such as cloud cover should be considered on the day satellite images are collected as it can affect analysis quality. To mitigate this, only images with less than 20% cloud cover were used, ensuring sufficient clarity for reliable analysis. Finally, human error remains a potential constraint on replication. While the use of unsupervised classification helps minimize human error when generating spectral classes, errors can still occur when assigning these classes to meaningful informational categories. In this study, vulnerability levels were determined by labeling spectral clusters based on their mean values, therefore the analyst's judgment was essential to ensure that these classifications accurately reflected fire vulnerability.

## 6. Conclusion

This study set out to determine whether optical satellite imagery could be used to effectively identify areas vulnerable to fire ignition in Nova Scotia. The results demonstrate that using Sentinel-2 optical satellite imagery, combined with site-specific variables such as NDVI, NDMI, slope, and proximity to human-built areas, can successfully highlight areas vulnerable to ignition. The strong agreement between vulnerability and the observed burned areas confirms the potential of this approach to support forest fire preparedness efforts.

These findings have significant implications for researchers as it contributes to the growing field of research applying machine learning methods to environmental risk modelling. It highlights the value of open-access tools that can be used to assess fire risk without relying on expensive or proprietary data. The method is also adaptable over time, as only the vegetation indices change seasonally and can be easily updated in the model. These findings also offer a more spatially detailed alternative to the currently used Fire Weather Index (FWI) system, which operates at a coarse resolution and does not account for variability in fuel type, topography, or human access. This model can be applied at the county scale by stakeholders to support fire mitigation strategies, land-use planning, and emergency response coordination.

While this model effectively identifies areas prone to forest fire ignition, it could be made more useful if combined with a fire spread or predictive modelling framework. This integration could make it possible to not only identify where a fire might start, but also where it may spread. Additionally, combining vulnerability outputs with fire suppression efforts could further improve resource allocation in both rural and urban areas. While rural fires like Barrington can spread rapidly due to slower emergency response times, urban fires, like the one in Upper Tantallon, require more resources and real-time monitoring to protect surrounding communities. This emphasizes the need to incorporate vulnerability mapping into emergency response planning to ensure that areas with limited built areas aren't ignored in provincial fire risk strategies. It also highlights the need for better coordination between land-use planning and fire management to reduce forest fire occurrence in growing communities.

Future research should explore the use of this method in larger study areas to assess its performance in different landscapes and fuel environments. Evaluating the influence of study area size on the unsupervised classification algorithm will be critical in determining its scalability. Furthermore, testing the model with lower-resolution satellite imagery could provide insights into its applicability in data-limited regions or under operational constraints. As climate change increases fire frequency and intensity, developing accessible, data-driven tools is essential to support proactive wildfire management and risk strategies.

## 7. References


Akay, A. E., & Erdoğan, A. (2017). GIS-based multi-criteria decision analysis for forest fire risk mapping. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *IV-4/W4*, 25–30. https://doi.org/10.5194/isprs-annals-iv-4-w4-25-2017

Akinola, O. V., & Adegoke, J. (2018). Assessment of forest fire vulnerability zones in Missouri, United States of America. *International Journal of Sustainable Development & World Ecology*, *26*(3), 251–257. https://doi.org/10.1080/13504509.2018.1551815

Basquill, S., Woodley, S., & Pardy, A. B. (2001). *The history and ecology of fire in Kejimkujik National Park* (Vol. 29). Parks Canada.

Beverly, J. L., & McLoughlin, N. (2019). Burn probability simulation and subsequent wildland fire activity in Alberta, Canada – Implications for risk assessment and strategic planning. *Forest Ecology and Management*, *451*, 117490. https://doi.org/10.1016/j.foreco.2019.117490

Bitek, D., Sanli, F. B., & Erenoglu, R. C. (2024). Spatial and statistical analysis of burned areas with Landsat-8/9 and Sentinel-2 satellites: 2023 Çanakkale forest fires. *Environmental Monitoring and Assessment*, *197*(1). https://doi.org/10.1007/s10661-024-13474-5

Calian Group. (2024, March 8). 2023 Nova Scotia wildfires. Nova Scotia. https://novascotia.ca/nova-scotia-wildfires-2023-after-action-report.pdf

Campbell, J. B., Wynne, R. H., & Thomas, V. A. (2023). *Introduction to remote sensing* (6th ed.). The Guilford Press.

Chen, Y., Morton, D. C., & Randerson, J. T. (2024). Remote sensing for wildfire monitoring: Insights into burned area, emissions, and fire dynamics. *One Earth*, *7*(6), 1022–1028. https://doi.org/10.1016/j.oneear.2024.05.014

Congressional Research Service. (2023). *Wildfire statistics*. https://sgp.fas.org/crs/misc/IF10244.pdf

Coughlan, R., Di Giuseppe, F., Vitolo, C., Barnard, C., Lopez, P., & Drusch, M. (2021). Using machine learning to predict fire-ignition occurrences from lightning forecasts. *Meteorological Applications*, *28*(1). https://doi.org/10.1002/met.1973

De Jong, M. C., Wooster, M. J., Kitchen, K., Manley, C., Gazzard, R., & McCall, F. F. (2016). Calibration and evaluation of the Canadian Forest Fire Weather Index (FWI) System for improved wildland fire danger rating in the United Kingdom. *Natural Hazards and Earth System Sciences*, *16*(5), 1217–1237. https://doi.org/10.5194/nhess-16-1217-2016

Department of Lands and Forestry. (2019a). *Ecological landscape analysis: South Shore Ecodistrict 830 – Part 1: Overview of ecodistrict; Part 2: Linking the landscape to the woodlot*. https://novascotia.ca/natr/ELA/pdf/ELA_2019part1_2/830SouthShoreParts1&2_2019.pdf

Department of Lands and Forestry. (2019b). *Ecological landscape analysis: St. Margaret's Bay Ecodistrict 780*. https://novascotia.ca/natr/ELA/pdf/ELA_2019part1_2/780StMargaretsBayParts1&2_2019.pdf

Department of Natural Resources and Renewables. (2023). *Annual wildfire statistics 2023*. https://novascotia.ca/natr/forestprotection/wildfire/wildfire-statistics-2023.pdf

Dickinson, D. C., & Ramalho, C. E. (2022). A balancing act: Biodiversity and human wellbeing considerations in the management of urban forest in a global biodiversity hotspot. *Urban Forestry & Urban Greening*, *74*, 127656. https://doi.org/10.1016/j.ufug.2022.127656

Edmonds, R. L., Agee, J. K., & Gara, R. I. (2011). Fire as a physical process. In *Forest health and protection* (pp. 49–101). Waveland Press.

Epstein, M. D., Seielstad, C. A., & Moran, C. J. (2024). Impact and recovery of forest cover following wildfire in the Northern Rocky Mountains of the United States. *Fire Ecology*, *20*(1). https://doi.org/10.1186/s42408-024-00285-9

Erni, S., Wang, X., Swystun, T., Taylor, S., Robinne, F. S., Boulanger, Y., Oliver, J., Armitage, B., & Flannigan, M. D. (2023). Mapping wildfire hazard, vulnerability, and risk to Canadian communities. *International Journal of Disaster Risk Reduction*, *101*, 104221. https://doi.org/10.1016/j.ijdrr.2023.104221

ESRI. (n.d.). *ArcGIS | Geospatial platform – GIS software for business & government*. https://www.esri.com/en-us/arcgis/geospatial-platform/overview

Fan, H., Di, L., Yang, W., Bonnlander, B., & Li, X. (2007). Use of binary logistic regression technique with MODIS data to estimate wild fire risk. *Proceedings of SPIE – The International Society for Optical Engineering*. https://doi.org/10.1117/12.774737

Flannigan, M. D., Krawchuk, M. A., de Groot, W. J., Wotton, B. M., & Gowman, L. M. (2009). Implications of changing climate for global wildland fire. *International Journal of Wildland Fire*, *18*(5), 483–507. https://doi.org/10.1071/WF08187

Forest Service. (2019). *BurnP3+ SyncroSim package*. https://burnp3.github.io/BurnP3Plus/

Gai, C., Weng, W., & Yuan, H. (2011). GIS-based forest fire risk assessment and mapping. In *2011 Fourth International Joint Conference on Computational Sciences and Optimization*. https://doi.org/10.1109/cso.2011.140

Gajewski, K., Neil, K., Ponomarenko, E., Ershova, E., Stewart, B., Neily, P., & Quigley, E. (2023). Climate, fire disturbance regime, and vegetation response of the past 2500 years for central Nova Scotia. *Ecosphere*, *14*(11). https://doi.org/10.1002/ecs2.4710

Gralewicz, N. J., Nelson, T. A., & Wulder, M. A. (2012). Factors influencing national scale wildfire susceptibility in Canada. *Forest Ecology and Management*, *265*, 20–29. https://doi.org/10.1016/j.foreco.2011.10.031

Green, D. G. (1981). Time series and postglacial forest ecology. *Quaternary Research*, *15*(3), 265–277. https://doi.org/10.1016/0033-5894(81)90030-2

Gordon, D., & Shirokoff, I. (2014, July). *Suburban nation? Population growth in Canadian suburbs, 2006–2011*. https://www.canadiansuburbs.ca/Gordon_Shirokoff_2011.pdf

Gulcin, D., & Deniz, B. (2020). Remote sensing and GIS-based forest fire risk zone mapping: The case of Manisa, Turkey. *Turkish Journal of Forestry | Türkiye Ormancılık Dergisi*, *21*(1), 15–24. https://doi.org/10.18182/tjf.649747

Guo, Y., Wang, J., Ge, Y., & Zhou, C. (2024). Global expansion of wildland–urban interface intensifies human exposure to wildfire risk in the 21st century. *Science Advances*, *10*(45). https://doi.org/10.1126/sciadv.ado9587

Hammer, R. B., Stewart, S. I., & Radeloff, V. C. (2009). Demographic trends, the wildland–urban interface, and wildfire management. *Society & Natural Resources*, *22*(8), 777–782. https://doi.org/10.1080/08941920802714042

Ji, C., Yang, H., Li, X., Pei, X., Li, M., Yuan, H., Cao, Y., Chen, B., Qu, S., Zhang, N., Chun, L., Shi, L., & Sun, F. (2024). Forest wildfire risk assessment of Anning River Valley in Sichuan Province based on driving factors with multi-source data. *Forests*, *15*(9), 1523. https://doi.org/10.3390/f15091523

Johnston, L. M., Wang, X., Erni, S., Taylor, S. W., McFayden, C. B., Oliver, J. A., Stockdale, C., Christianson, A., Boulanger, Y., Gauthier, S., Arseneault, D., Wotton, B. M., Parisien, M.-A., & Flannigan, M. D. (2020). Wildland fire risk research in Canada. *Environmental Reviews*, *28*(2), 164–186. https://doi.org/10.1139/er-2019-0046

Lahmar, B., & Akakba, A. (2024). Forest fire detection based on earlier pre-fire conditions using analytic hierarchy process (AHP) in a semi-arid climate: A case study of Belezma National Park, Algeria. *Acta Geographica Lodziensia*, *114*. https://doi.org/10.26485/agl/2024/114/3

Li, S., Zhang, Z., Zheng, J., Hou, G., Liu, H., & Cui, X. (2023). Evaluation of litter flammability from dominated artificial forests in Southwestern China. *Forests*, *14*(6), 1229. https://doi.org/10.3390/f14061229

Liu, J. G., & Mason, P. J. (2013). *Essential image processing and GIS for remote sensing*. Wiley-Blackwell.

Loo, J., & Ives, N. (2003). The Acadian forest: Historical condition and human impacts. *The Forestry Chronicle*, *79*(3), 462–474. https://doi.org/10.5558/tfc79462-3

Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2015). *Geographic information science & systems* (4th ed.). John Wiley & Sons. https://app.knovel.com/hotlink/toc/id:kpGISSE001/geographic-information/geographic-information

MacCarthy, J., Tyukavina, A., Weisse, M. J., Harris, N., & Glen, E. (2024). Extreme wildfires in Canada and their contribution to global loss in tree cover and carbon emissions in 2023. *Global Change Biology*, *30*(6). https://doi.org/10.1111/gcb.17392

Meraner, A., Ebel, P., Zhu, X. X., & Schmitt, M. (2020). Cloud removal in Sentinel-2 imagery using a deep residual neural network and SAR-optical data fusion. *ISPRS Journal of Photogrammetry and Remote Sensing*, *166*, 333–346. https://doi.org/10.1016/j.isprsjprs.2020.05.013

Mishra, M., Guria, R., Baraj, B., Nanda, A. P., Silva, S., & Tri, A. (2024). Spatial analysis and machine learning prediction of forest fire susceptibility: A comprehensive approach for effective management and mitigation. *Science of the Total Environment*, *171713*. https://doi.org/10.1016/j.scitotenv.2024.171713

Mohajane, M., Costache, R., Karimi, F., Pham, Q. B., Essahlaoui, A., Nguyen, H., Laneve, G., & Oudija, F. (2021). Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area. *Ecological Indicators*, *129*, 107869. https://doi.org/10.1016/j.ecolind.2021.107869

NASA. (2023). *What is remote sensing?* Earthdata. https://www.earthdata.nasa.gov/learn/backgrounders/remote-sensing

Natural Resources Canada. (2020). *Canadian Wildland Fire Information System*. https://cwfis.cfs.nrcan.gc.ca/home

Natural Resources Canada. (2022). *Canadian Wildland Fire Information System: Metadata*. https://cwfis.cfs.nrcan.gc.ca/datamart/metadata/fm3buffered

Navarro, G., Caballero, I., Silva, G., Parra, P.-C., Vázquez, Á., & Caldeira, R. (2017). Evaluation of forest fire on Madeira Island using Sentinel-2A MSI imagery. *International Journal of Applied Earth Observation and Geoinformation*, *58*, 97–106. https://doi.org/10.1016/j.jag.2017.02.003

Nikolaychuk, O., Pestova, J., & Yurin, A. (2024). Wildfire susceptibility mapping in Baikal Natural Territory using random forest. *Forests*, *15*(1), 170. https://doi.org/10.3390/f15010170

Nova Scotia Department of Natural Resources. (n.d.). *Ecodistrict profile: St. Margaret's Bay Ecodistrict 780*. Retrieved November 24, 2024, from https://novascotia.ca/natr/ELA/pdf/700/780StMargaretsBayProfile.pdf

Nova Scotia Natural Resources and Renewables. (2023, June 13). *Barrington Lake wildfire under control* | Government of Nova Scotia News Releases. https://news.novascotia.ca/en/2023/06/13/barrington-lake-wildfire-under-control

Pacheco, A. da P., Junior, J. A. da S., Ruiz-Armenteros, A. M., Henriques, R. F. F., & Santos, I. de O. (2023). Analysis of spectral separability for detecting burned areas using Landsat-8 OLI/TIRS images under different biomes in Brazil and Portugal. *Forests*, *14*(4), 663. https://doi.org/10.3390/f14040663

Public Health Agency of Canada. (2018). *Climate change, forest fires and your health*. https://www.canada.ca/en/public-health/services/health-promotion/environmental-public-health-climate-change/climate-change-public-health-factsheets-forest.html

Qu, T., Tian, G., & Tang, M. (2020). Research on methods and application of remote sensing technology in geological hazard monitoring and management. *IOP Conference Series: Earth and Environmental Science*, *514*(2), 022075. https://doi.org/10.1088/1755-1315/514/2/022075

Rabiei, J., Khademi, M. S., Bagherpour, S., Ebadi, N., Karimi, A., & Ostad-Ali-Askari, K. (2022). Investigation of fire risk zones using heat–humidity time series data and vegetation. *Applied Water Science*, *12*(9). https://doi.org/10.1007/s13201-022-01742-z

Radeloff, V. C., Hammer, R. B., Stewart, S. I., Fried, J. S., Holcomb, S. S., & McKeefry, J. F. (2005). The wildland–urban interface in the United States. *Ecological Applications*, *15*(3), 799–805. https://doi.org/10.1890/04-1413

Rasooli, S. B., Bonyad, A. E., & Pir Bavaghar, M. (2018). Forest fire vulnerability map using remote sensing data, GIS and AHP analysis (Case study: Zarivar Lake surrounding area). *Caspian Journal of Environmental Sciences*, *16*(4), 369–377. https://doi.org/10.22124/cjes.2018.3205

Sentinel Online. (n.d.). *Sentinel-2 – Satellite description*. https://sentinel.esa.int/en/web/sentinel/missions/sentinel-2/satellite-description

Sevinç, V. (2022). Mapping the forest fire risk zones using artificial intelligence with risk factors data. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-022-22515-w

Shadrin, D., Illarionova, S., Gubanov, F., Evteeva, K., Mironenko, M., Levchunets, I., Belousov, R., & Burnaev, E. (2024). Wildfire spreading prediction using multimodal data and deep neural network approach. *Scientific Reports*, *14*(1), 2606. https://doi.org/10.1038/s41598-024-52821-x

Statistics Canada. (2024, March 27). *Canada's population estimates: Strong population growth in 2023*. https://www150.statcan.gc.ca/n1/daily-quotidien/240327/dq240327c-eng.htm

Stocks, B. J., & Martell, D. L. (2016). Forest fire management expenditures in Canada: 1970–2013. *The Forestry Chronicle*, *92*(03), 298–306. https://doi.org/10.5558/tfc2016-056

Szpakowski, D. M., & Jensen, J. L. R. (2019). A review of the applications of remote sensing in fire ecology. *Remote Sensing*, *11*(22), 2638. https://doi.org/10.3390/rs11222638

Taylor, A. R., Boulanger, Y., Price, D. T., Cyr, D., McGarrigle, E., Rammer, W., & Kershaw, J. A. (2017). Rapid 21st century climate change projected to shift composition and growth of Canada's Acadian Forest Region. *Forest Ecology and Management*, *405*, 284–294. https://doi.org/10.1016/j.foreco.2017.07.033

Taylor, A. R., MacLean, D. A., Neily, P. D., Stewart, B., Quigley, E., Basquill, S. P., Boone, C. K., Gilby, D., & Pulsifer, M. (2020). A review of natural disturbances to inform implementation of ecological forestry in Nova Scotia, Canada. *Environmental Reviews*, *28*(4), 387–414. https://doi.org/10.1139/er-2020-0015

Taylor, S. W., Stennes, B., Wang, S., & Taudin-Chabot, P. (2006). *Integrating Canadian wildland fire management policy and institutions: Sustaining natural resources, communities and ecosystems*. Canadian Council of Forest Ministers.

Thepaut, J.-N., Dee, D., Engelen, R., & Pinty, B. (2018). The Copernicus Programme and its Climate Change Service. In *IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium*. https://doi.org/10.1109/igarss.2018.8518067

Truong, T. X., Nhu, V.-H., Phuong, D. T. N., Nghi, L. T., Hung, N. N., Hoa, P. V., & Bui, D. T. (2023). A new approach based on TensorFlow deep neural networks with ADAM optimizer and GIS for spatial prediction of forest fire danger in tropical areas. *Remote Sensing*, *15*(14), 3458. https://doi.org/10.3390/rs15143458

USGS. (2022). *What is remote sensing and what is it used for?* https://www.usgs.gov/faqs/what-remote-sensing-and-what-it-used

USGS. (2023). *LANDFIRE technical documentation*. https://doi.org/10.3133/ofr20231045

USGS. (2017). *Wildland Fire Potential Index (WFPI)*. U.S. Geological Survey. https://www.usgs.gov/fire-danger-forecast/wildland-fire-potential-index-wfpi

Valdez, M. C., Chang, K.-T., Chen, C.-F., Chiang, S.-H., & Santos, J. L. (2017). Modelling the spatial variability of wildfire susceptibility in Honduras using remote sensing and geographical information systems. *Geomatics, Natural Hazards and Risk*, *8*(2), 876–892. https://doi.org/10.1080/19475705.2016.1278404

Wein, R. W., & Moore, J. M. (1979). Fire history and recent fire rotation periods in the Nova Scotia Acadian Forest. *Canadian Journal of Forest Research*, *9*(2), 166–178. https://doi.org/10.1139/x79-031

Whitman, E., Rapaport, E., & Sherren, K. (2013). Modeling fire susceptibility to delineate wildland–urban interface for municipal-scale fire risk management. *Environmental Management*, *52*(6), 1427–1439. https://doi.org/10.1007/s00267-013-0159-9

Whitman, E., Sherren, K., & Rapaport, E. (2014). Increasing daily wildfire risk in the Acadian Forest Region of Nova Scotia, Canada, under future climate change. *Regional Environmental Change*, *15*(7), 1447–1459. https://doi.org/10.1007/s10113-014-0698-5

Willick, F. (2023, July 31). Nova Scotia's population is suddenly booming. Can the province handle it? *CBC News*. https://www.cbc.ca/news/canada/nova-scotia/nova-scotia-population-boom-1.6899752

Woody, C. (2023, October 4). USGS fire danger: Additional program updates. *USGS Land Imaging Report*. https://eros.usgs.gov/doi-remote-sensing-activities/2022/usgs/usgs-fire-danger-additional-program-updates

Yang, J., Healy, H. S., Shifley, S. R., & Gustafson, E. J. (2007). Spatial patterns of modern period human-caused fire occurrence in the Missouri Ozark Highlands. *Forest Science*, *53*(1), 1–15. https://doi.org/10.1093/forestscience/53.1.1

Zahra Parvar, S., Saeidi, S., & Mirkarimi, S. (2024). Integrating meteorological and geospatial data for forest fire risk assessment. *Journal of Environmental Management*, *358*, 120925. https://doi.org/10.1016/j.jenvman.2024.120925

Zalzal, K. (2018, January 9). A flammable planet: Fire finds its place in Earth history. *Earth Magazine*. https://www.earthmagazine.org/article/flammable-planet-fire-finds-its-place-earth-history

Zhang, Z., Tian, Y., Wang, G., Zheng, C., & Zhao, F. (2024). A forest fire prediction method for lightning stroke based on remote sensing data. *Forests*, *15*(4), 647. https://doi.org/10.3390/f15040647

Zhou, X., Yang, J., Niu, K., Zou, B., Lu, M., Wang, C., Wei, J., Liu, W., Yang, C., & Huang, H. (2023). Assessment of the forest fire risk and its indicating significances in Zhaoqing City based on Landsat time-series images. *Forests*, *14*(2), 327. https://doi.org/10.3390/f14020327

Zühal Özcan, İ., Caglayan, İ., & Kabak, Ö. (2024). A comprehensive taxonomy for forest fire risk assessment: Bridging methodological gaps and proposing future directions. *Environmental Monitoring and Assessment*, *196*(9). https://doi.org/10.1007/s10661-024-12982-8