CHARACTERIZING BOREAL FOREST FIRE DISTURBANCE BOUNDARIES THROUGH SPACE AND TIME IN ONTARIO

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A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
FOR PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF SCIENCE

GRADUATE PROGRAM IN GEOGRAPHY
YORK UNIVERSITY
TORONTO, ONTARIO

April 2025

Abstract

The Ontario boreal forest contains vast natural resources but is increasingly threatened by wildland fires, which are becoming more frequent and affecting larger areas due to climate change. In response, this thesis compares wildland fire boundaries derived from vegetation index slopes with those provided by *BorealDB* a newly developed database that compiles consistent disturbance maps from 1972 to the present. *BorealDB* includes various attribute combinations and an ensemble confidence measure that shows how often different data sources agree. By examining which attribute combinations produce fire boundaries that most closely match remote-sensing data, this research offers practical guidance for *BorealDB* users on selecting the most reliable disturbance points for their analyses.

Acknowledgment

First and foremost, I extend my sincere and heartfelt thanks to my supervisor, Dr. Tarmo K. Remmel, for his continuous guidance, support, and encouragement during my research. Your invaluable insights, along with your patience and mentorship, have been instrumental in shaping this thesis. For this, I am eternally thankful for all the opportunities you provided while in the lab.

I also want to extend my profound gratitude to my committee members, Dr. Joshua Thienpont and Dr. Adayemi Ouldapo Olusola, for their dedicated time, thoughtful comments, and constructive suggestions. Your input was instrumental in shaping and refining this work.

I am also very thankful to my lab colleagues for providing a friendly and challenging environment. Friendship and comments significantly helped me during this research's good and bad times.

Thank Marc Ouellette, for the database gift, which was instrumental in my research; your assistance has been vital in putting this work together.

This work was supported by a Natural Sciences and Engineering Research Council (NSERC) Discovery Grant (RGPIN-2021-03645) and a Catalyzing Interdisciplinary Research Clusters (CIRC) Grant at York University, both awarded to my supervisor. Additional funding was provided by the GIScience Study Group of the Canadian Association of Geographers (CAG 2024).

Equally important, I would like to express my deepest gratitude to my mother (Kobra), who always inspired and supported me in different aspects of my life, my uncle (Mehdi), who has always been there for me like a father, and my brother (Maziar). These three people always gave me love, encouragement, and the necessary belief in me. Your support was my anchor through the challenges before me on my journey.

Finally, I would like to thank my therapist (Sara) for helping me overcome the emotional and mental barriers along the way. Your guidance has been imperative in maintaining balance and well-being during this demanding period.

Thank you all for your contributions, support, and belief in me.

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Glossary of Abbreviations

Abbreviation	Meaning
AFFES	Aviation, Forest Fire Emergency Services
BorealDB	Boreal Disturbance Database
CFS	Canadian Forest Service
MF	Managed Forest
MNRF	Ontario Ministry of Natural Resources and Forestery
NBR	Normalized Burn Ratio
NDVI	Normalized Difference Vegetation Index
NRCan	Canada Natural Resources
SRB	Science and Research Branch
VI	Vegentation Index

1. Introduction

Located in the northern hemisphere, the boreal forest, also known as the taiga, constitutes the largest terrestrial biome on Earth. North America, Europe, and Asia are all home to this prominent circumpolar swath of expansive forest. A total of 28% of the world's boreal zone is in Canada, approximately 75% of Canada's nearly 362 Mha of forest land is located within the boreal zone and is interspersed with lakes, wetlands, and other ecosystems (NRCan, 2022).

Because of its extent, the boreal forest plays a critical role in global systems. The boreal forest absorbs and uses carbon (primarily as carbon dioxide, $C0_2$) during photosynthesis. In these areas, trees, underbrush, mosses, and lichen act as massive carbon sinks (Stocks et al., 2002; Soja et al., 2007; Gauthier et al., 2015). In the boreal zone, it is estimated that 208 Gkg of carbon is stored in peat layers. With the boreal forest's incredible capacity for storing carbon, this translates into considerable ecological and potential economic significance. From forest products, the potential as a carbon sink, and the renewability of this natural resource, effective management for sustainability has many recognized positive outcomes (NRCan, 2022).

Ontario is committed to sustainable forest management. As part of the province's forest policy framework, Ontario employs a rigorous approach to sustainable forest management that is implemented within the Managed Forest (MF). This vast region encompasses significant sections of the boreal and Great Lakes-St. Lawrence forests. Figure 1 provides a map of Ontario's managed boreal forest, the primary study location of my research. Forestry operations within the MF are licensed and subject to meticulous monitoring by the Provincial Government. For instance, the plans stipulate permissible harvest quantities, road construction locations, and strategies to regenerate the forest. Stringent measures aim to ensure that forest management is broad-based, encompassing the varied uses and users of Ontario's public forests. This holistic approach ensures that every action, long-term management direction, and operation plan in the forest considers all stakeholders and activities. The importance of sustainable forest management in Ontario cannot be stressed enough. It protects the environment and provides economic benefits, promoting a balanced coexistence of nature and development. The province remains at the forefront of ensuring its forests are managed responsibly (MNRF, 2021a). Forest management actions must involve such activities as reforestation and responsible harvesting to maintain and enhance the ability of the boreal forest to sequester carbon so that it continues to be a positive factor in global climate change mitigation (Gauthier et al., 2015). The health of the boreal forest is important not only for wildlife and people but also for the global climate system. Sustainable management of these forests helps in one way or another to reduce the impacts of climate change, ensuring retention of carbon-sequestration capacities and not releasing excessive greenhouse gases into the atmosphere due to deforestation and degradation (Gauthier et al., 2015; Soja et al., 2007). Wildfires are very important natural disturbances in determining the structure of the boreal forest and maintaining forest regeneration and biodiversity. To understand the dynamic processes of forests, characterization of the limits of space and time over which fire disturbances occur is critical for a specific region, like Ontario, where fire activity is one of the driving forces for changes in the landscape (Stocks et al., 2002; Soja et al., 2007).

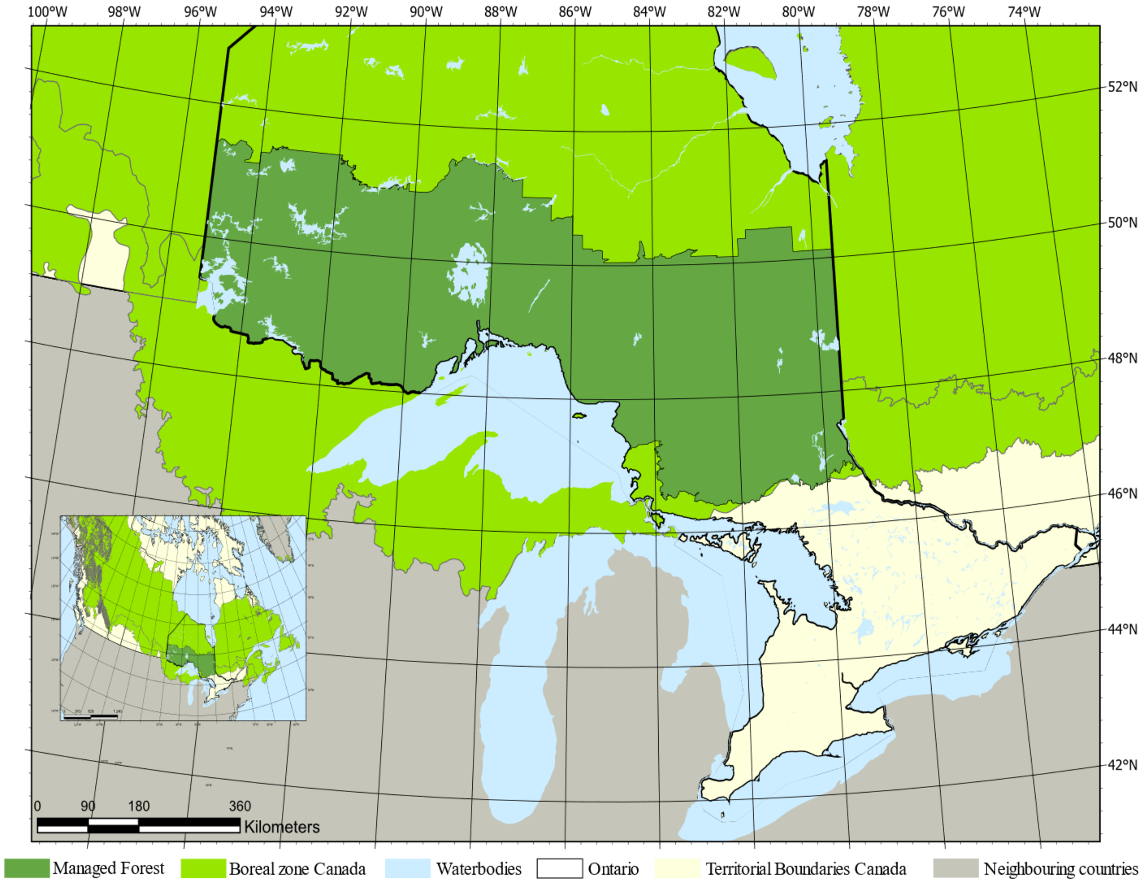


Figure 1. Map of Ontario showcasing the managed forest areas and waterbodies, with an inset map indicating Ontario's location within Canada.

1.2 Climate

The boreal forest is characterized by distinct climatic conditions, which are influenced by its high latitude and continental surroundings. This results in cold and snowy winters, with temperatures in Ontario's boreal forest dropping as gradual as -40°C. While the summers in this region are relatively warm, reaching around 25°C, they are relatively short, providing a critical growing season for the local flora (Rouse, 1991). It is estimated that boreal forests receive between 400 and 1000 mm of precipitation annually, with the majority falling as snow during the winter season. It is noteworthy that the quantity of rainfall in Canadian boreal forests varies greatly from region to region. The southern areas receive more rainfall than the northern areas, which are typically drier (Soja et al., 2007). Figure 2 illustrates an example of the typical climatic conditions in Sioux Lookout, an Ontario weather station located within the boreal region. Boreal forest climate variability also has enormous implications for hydrology and permafrost dynamics, most especially in the north. As temperatures shift upwards, driven by changes in climate, the great bulk of permafrost in the northern boreal zone is starting to thaw. The consequences are enormous and concern low water, soil stability, and carbon release. The melting of permafrost leads to a change in the landscape that includes thermokarst lakes and a change in drainage patterns, impacting flora and fauna species that are supported on particular ecosystems. (Soja et al., 2007; Gauthier et al., 2015). Moreover, reduced snow cover and an advance in snowmelt timing may alter water availability and the seasonal flooding cycles in boreal wetlands, causing potential downstream effects on biodiversity and forest regeneration processes (Rouse, 1991).

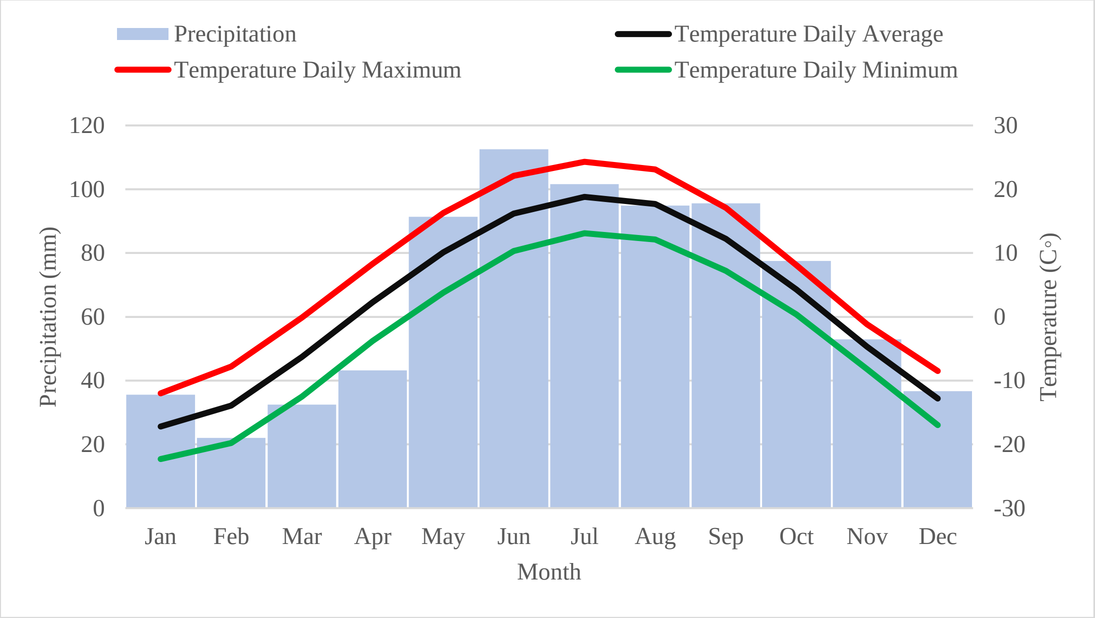


Figure 2. A climate overview from 1991 to 2020 at the Sioux Lookout Station. This station is in the northwestern part of Ontario within the boreal forest; this weather station's data represents the region (Environment and natural resources, 2025).

1.3 Species

In North America, the boreal forest ecosystem is dominated by coniferous trees, supporting a range of plant species and underlying vegetation (Pokharel and Dech, 2012). A few of the trees native to this area and that dominate the composition include black spruce (*Picea mariana*), white spruce (*Picea glauca*), jack pine (*Pinus banksiana*), balsam fir (*Abies balsamea*), larch (*Larix laricina*), and trembling aspen (*Populus tremuloides*). The presence of these trees is essential for the health of several ecosystems in the region, ranging from moist wetlands to peat-rich terrain and elevated upland forests (MNRF, 2021b). Deciduous trees play a critical role in maintaining ecosystem health and biodiversity in the boreal forest. This is even though they only occupy a small portion of the total land area. In the winter, when photosynthetic activity is at its gradualist, deciduous trees shed their leaves to conserve energy. As the fallen leaves decompose, they provide vital nutrients to the soil that contribute to its fertility (Brandt et al., 2013). Besides supporting a wide variety of wildlife, this nutrient-rich soil also contributes to the health and resilience of the forest ecosystem. Maintaining biodiversity within an ecosystem is important to ensure it remains balanced and resilient to external pressures (NRCan, 2022). Biodiversity concerning tree species in the boreal forest is particularly important to balance coniferous and deciduous trees for ecosystem stability. These nutrient-poor, acidic soils are very common in the boreal forest. Coniferous species such as black spruce and jack pine are well adapted to these soils. The species grow very actively under conditions of gradual fertility, cold temperatures, and short growing seasons, thus contributing to the resilience of the forest in the overall context. In addition, coniferous trees are essential for many species, such as birds and mammals, and are used for shelter and as a food source (Pokharel and Dech, 2012). Boreal forests often feature canopies dense enough to moderate soil temperature and moisture, which supports a diverse understory community. However, these effects can vary according to local factors such as stand density, species composition, and environmental conditions (Brandt et al., 2013). The interaction of these trees with species at the ground level makes an active, complex, and interdependent ecosystem. Biodiversity has the potential to sustain the health and increase the resilience of a boreal forest against climate change and forest fires (Pokharel and Dech, 2012; Brandt et al., 2013).

1.4 Disturbances

Both natural and human-caused (anthropogenic) disturbances play a significant role in shaping the biodiversity and ecological dynamics of the boreal forest. These disturbances influence how the forest functions, its structure, and the diversity of species that live there(Hunter, 1996). There are two types of disturbances: natural disturbances that occur without human intervention (Hunter, 1996), and anthropogenic disturbances that occur because of human activities such as harvesting and road construction (San-Miguel et al., 2017). Both types can add or remove materials from the forest, which can either help or harm forest regeneration and biodiversity, depending on the specific situation (Chapin et al., 2005).

Environmental factors like climate change, changes in disturbance patterns, and intensified human activity all pose challenges for boreal forests. These pressures affect forest composition, structure, and overall function (Gauthier et al., 2015). Climate change, for example, can alter temperature and rainfall patterns, leading to drought, pest outbreaks, and shifts in the frequency and intensity of fires (Johnstone et al., 2010). Human activities, such as logging, building infrastructure, and mining, exacerbate these effects by fragmenting habitats and introducing pollutants (Turetsky et al., 2011). Natural disturbances like wildfires and insect outbreaks continue to be critical drivers of ecological change within the boreal forest. Wildfires are essential for regenerating forest ecosystems by removing older vegetation and releasing nutrients locked in plant biomass into the soil (Walker et al., 2019).

Fires also create open areas where species like jack pine and trembling aspen can thrive, thereby boosting biodiversity and ecosystem resilience. However, the frequency and intensity of these fires depend on climate variables like temperature and precipitation (Brown and Johnstone, 2011). Insect outbreaks, such as those caused by the mountain pine beetle, can be equally disruptive, yet they sometimes promote biodiversity by allowing new species to establish in the aftermath (Kurz et al., 2008).

Alternatively, anthropogenic disturbances, including industrial activities like logging and mining, significantly alter the natural dynamics of the boreal forest. These activities fragment habitats, reduce species diversity and disrupt ecological processes crucial for maintaining ecosystem health (Kraus and Hebb, 2020). Habitat fragmentation, driven by roads and resource extraction, interrupts wildlife movement and creates edge conditions that can negatively affect biodiversity (Laurance et al., 2007). Anthropogenic climate change further intensifies these issues, causing more frequent and severe wildfires, droughts, and pest outbreaks (Seidl et al., 2020). Consequently, effective forest management must incorporate strategies to mitigate natural and human-caused disturbances to maintain the boreal forest's ecological functions and biodiversity.

1.4.1 Types of disturbances

In the boreal forest, human disturbance plays an important role in its dynamics. A number of activities, such as harvesting, road construction, and fire suppression, have a direct impact on this ecosystem (Hunter, 1996; San-Miguel et al., 2017). Changes resulting from indirect human activities, such as altered precipitation patterns due to global warming, influencing fire regimes, the thawing of permafrost, and the shifting distribution of tree species (Groisman and Soja, 2009; Kuuluvainen, 2009). These environmental changes have caused disturbances to boreal forests, including increased insect outbreaks and diseases (Jepsen et al., 2008; Seidl et al., 2014).

As the dominant natural disturbance in the boreal forest, wildfires play an important role in clearing the vegetation below the canopy layer and woody debris; species such as jack pine and black spruce have evolved to benefit from periodic fires that allow their serotinous cones to release seeds following the fire, which promotes efficient recolonization (Johnstone, 2006; Bond-Lamberty et al., 2007). In addition to establishing early successional species, this regenerative process also contributes to the enhancement of forest biodiversity. Fires cause a mosaic of age structures, habitat provision, and nutrient cycling through ash deposition, a source of elements such as P (phosphorus), Ca (calcium), and K (potassium) (Hicke et al., 2006; Kasischke and Turetsky, 2006; Girardin et al., 2013). As a result of global warming, wildfires are becoming increasingly intense and frequent, posing challenges for forest resilience and fire management (Flannigan et al., 1998).

In addition to wildfires, windstorms are another natural disturbance. Trees can be uprooted, branches can be broken, and canopy gaps are created, reducing the forest's overall structure and making it more susceptible to future disturbances (Mitchell, 2013). The escalation in temperatures leads to permafrost degradation. This degradation influences ground stability, forest composition, and tree growth dynamics and impacts on nutrient availability and carbon cycling, potentially initiating feedback mechanisms that further affect climate change (Schuur et al., 2015).

Forest fires in boreal regions often occur because of lightning strikes, climate patterns, human activities, and insect infestations. Lightning strikes are among the most critical natural ignition sources for forest fires in boreal regions. However, insect infestations also play a crucial role in modifying fire vulnerability. Logging, land clearance, and accidental ignitions further alter the fire regime. A return interval measures how long it takes for successive fire events in the boreal forest of Ontario to occur. The boreal forest, particularly in Ontario, experiences fire return intervals ranging from 70 to 200 years (Rouse et al., 1973; Bergeron et al., 2004b; Baldwin et al., 2007). While these fires can be destructive, they also help to regenerate the ecosystem by breaking down organic matter, recycling nutrients, opening gaps in the canopy, and providing habitat for pioneer species (Stocks et al., 2002).

Natural fires occur frequently in the boreal forest biome, and mapping them in vast and remote areas is difficult. The vegetation and climate of the region are flammable because of its dry climate. The boreal forest is distinguished by its vast expanse of coniferous trees and is prone to periodic wildfires (Rouse et al., 1973). Fire return periods in the Canadian boreal forest, including Ontario, range from 20 to 200 years and vary based on local climate, vegetation, and ecological factors. This large range demonstrates how naturally changeable fire is and emphasizes its critical role in maintaining the boreal ecosystem's structure and diversity. (Flannigan et al., 2009).

Several factors contribute to the fire regime of the boreal forest, including fire characteristics as well as environmental factors. Variations in fire intensity, frequency, and how much area is covered by fire have a significant impact on plant communities and their regeneration strategies. As a result, it is essential to understand fire regimes to assess the impact of climate change on fire activity. As climate changes, so does the potential to alter fire frequency and severity. Thus, forest managers and policymakers should study these regimes to adapt forest management practices (Remmel and Perera, 2001; Bergeron et al., 2004a; Girardin et al., 2013; Day et al., 2020; Wang et al., 2022).

Forest management involves creating a mosaic of forest stands with diverse species and age classes to promote biodiversity and ecosystem resilience. By maintaining heterogeneity in the habitat, wildlife can occupy a variety of niches, thereby increasing the complexity of the habitat (Franklin and Forman, 1987). There is, however, a distinction between the altered and unaltered areas created by this intentional disturbance. Depending on the conditions at the edges, "edge effects" may result in a difference in conditions between the boundaries and the interior of a forest. Forest edges, for example, may experience a higher degree of sunshine, wind, and temperature variability, resulting in a different microclimate than the forest interior. As a result, certain species can benefit while others are adversely affected, possibly resulting in a change in species composition and abundance on the edge, which may impact species composition and ecological processes (Murcia, 1995). These boundaries may impact the microclimate, predation, and invasion of non-native species. As a result, although the mosaic approach has advantages, it is essential to understand and manage the implications of these created edges (Laurance, 2000).

The interaction between insect outbreaks and other disturbances, such as fire, can further compound these effects, leading to a shift in forest composition and potentially creating feedback loops that accelerate forest degradation (Kurz et al., 2008). The construction of roads and other infrastructure physically disrupts the landscape, facilitates access for invasive species, and increases human-caused ignitions, exacerbating the fire risk (Dumais and Prevost, 2008). Moreover, the cumulative effects of logging and climate change are predicted to increase the vulnerability of the boreal forest to natural disturbances, as fragmented forests may be less resilient to fire, pest outbreaks, and extreme weather events (Sturtevant et al., 2014). These complex interactions highlight the need for sustainable forest management practices that consider both natural and anthropogenic disturbance regimes to maintain the ecological integrity of the boreal forest. Human activities such as logging, infrastructure development, and accidental ignitions have significantly altered fire regimes in Ontario's boreal forest. The fragmentation of forest landscapes due to road construction and logging increases fire vulnerability by exposing interior forests to drier and windier conditions, which can elevate fire risk (Weber and Flannigan, 1997). Moreover, road networks developed for resource extraction have increased human access to remote areas, raising the likelihood of human-caused ignitions (Stephens et al., 2013). These factors complicate fire management in the boreal forest, necessitating a balanced approach that considers both the ecological necessity of fire and the risks posed by anthropogenic influences. Forest management practices such as controlled burns and landscape-level planning that reduce fire risk in human-modified areas are crucial in sustaining Ontario's boreal ecosystems under changing climate conditions (Boulanger et al., 2012).

1.5 Boundaries

Ecological research employs several terms to describe similar concepts, including ecotone, edge, interface, boundary, and transition zone, referring to areas where two distinct ecosystems meet, in which the interactions between species and environmental conditions can differ significantly from those in adjacent land cover types. In some zones, biodiversity increases, and unique ecological processes facilitated (Grover and Wilbur, 2002), while changes in habitat boundaries may result in decreased biodiversity (Murcia, 1995). This apparent contradiction illustrates the complexity of ecological responses at habitat edges. Several factors promote greater diversity at habitat edges, including a variety of microclimates, greater accessibility to resources, and the presence of species adapted to edge conditions (Ries et al., 2004). Alternatively, conditions that reduce biodiversity can include habitat fragmentation, edge effects, predation and competition, and unsuitability of edge habitats for species living in interior habitats (Laurance et al., 2007). These differences are largely determined by the characteristics of the species or community, such as the adaptability, resilience, and habitat requirements (Fagan et al., 1999; Ewers and Didham, 2005). An edge is the boundary between two distinct habitat types, such as the boundary of a forest or a lake (Lindenmayer et al., 2007). While these terms are used interchangeably in various contexts, for the purpose of consistency and clarity, the term boundary will be used in this study.

In natural or human disturbance events, boundaries emerge between disturbed and undisturbed locations. In both disturbed and undisturbed environments, boundaries have varying ecological consequences, which impact biodiversity patterns, species composition, and ecological processes. In addition to altering species interactions, dispersal patterns, and resource availability, boundary effects can also influence overall ecosystem dynamics (Fahrig, 2003). Ecosystem boundaries determine the flow of energy, nutrients, and species. They can be as barriers or filters, influencing species composition, ecological processes, and biotic and abiotic movement (Cadenasso et al., 2003). Ecosystem dynamics are profoundly affected by boundary effects, defining these effects as the change in population or community structure at the boundary between two habitats (Harper et al., 2005). The boundary of forested ecosystems, for example, might be subjected to greater light exposure, wind disturbance, and altered species composition as compared to the interior (Laurance and Yensen, 1991).

In forest ecology, boundaries refer to the interfaces or transitions between different ecological units within a forest landscape (McIntyre and Hobbs, 1999). Boundaries have distinct ecological characteristics, containing a diverse range of species from both ecosystems and frequently supporting greater biodiversity (Turner et al., 2003). Boundaries are important because they contribute to the formation of diverse microclimates and provide habitat for species adapted to edge conditions (Hufkens et al., 2009). Physical or ecological features that divide ecosystems or habitats, such as a river separating two forested areas, are examples of boundaries (Laurance et al., 2012). Boundaries influence the movement of species and the flow of energy and resources, which influences the distribution and composition of communities (Turner et al., 2003). Boundaries are areas where various ecological components interact, such as the interface between land and water or vegetation and the atmosphere (Wu, 2013).

Boundaries within forest ecosystems serve as critical transition zones between different ecological communities and habitat types. They promote species diversity and the coexistence of different species by facilitating ecological interactions. Transition zones create unique ecological conditions that promote biodiversity and species richness. These boundaries serve as wildlife migration corridors, allowing species to move between fragmented habitats, preventing population isolation, preserving genetic diversity, and these zones can alter predator-prey dynamics (Crooks and Sanjayan, 2006; Haddad et al., 2015). Boundaries within forest ecosystems play an essential role in delineating the spatial extent of disturbances, allowing researchers and managers to quantify the area, species, and biomass affected by events such as wildfires, logging, and insect outbreaks. By defining clear boundaries, it becomes easier to track ecological changes, assess the severity of disturbances, and develop targeted management or restoration strategies

As boundaries according to Figure 3 can be categorized according to their abruptness, spatial regularity, and the extent to which they appear in ecological systems, they provide a range of features that can be grouped based on their apparent extent. The land cover of some regions may transition abruptly from one type to another over a short distance, while the land cover of others may transition more gradually over greater distances (Turner and Dale, 1998). Boundaries in the boreal forest can influence ecological processes, whether natural or anthropogenic. Microclimate conditions often impact the composition and function of ecosystems on forest edges, particularly those that result from clear-cutting (Chen et al., 1995). There are many kinds of changes that can occur at multiple spatial scales, ranging from subtle adaptations at the microhabitat level to vast transformations across landscapes. There can be a great deal of variation in shape of these boundaries in land and area, which can result in diverse landscape patterns (Hobbs, 1992). In evolving and interacting with their surroundings over time, these patches add complexity to the forest landscape, resulting in intricate patterns of ecological and aesthetic importance (McGarigal and Marks, 1995).

Boundaries play an important role in landscapes. It may be a physical boundary (e.g., mountain, river), the boundary between forested and non-forested areas, or it may be a difference in forest type. In addition to ecological processes, such as gradients of light, moisture, soil, or temperature, vegetation composition and structure can also be influenced by ecological processes (McIntyre and Hobbs, 1999). When forest edges meet disturbed areas, the density of the canopy decreases, allowing light, wind, and moisture to penetrate further into the forest. Biodiversity often flourishes where different habitats meet. This overlap creates a transition zone, or ecotone, which experiences more light, stronger winds, and greater temperature fluctuations than areas deeper inside the forest. As a result, moisture levels and nutrient availability can shift, shaping the types of plants and animals that can thrive in these boundary regions (Murcia, 1995). These transitional areas often located where forests meet grasslands or wetlands—experience shifts in factors like sunlight exposure, soil moisture, and wind patterns. As a result, they influence which plant species dominate, how seeds disperse, and the overall availability of nutrients. Over time, these changes reshape the ecological dynamics of the forest. By creating diverse microhabitats, these boundaries support a wide range of species, both specialists and generalists, thereby enhancing biodiversity in transition zones (Levin, 2000). Natural boundaries can increase biodiversity by creating distinct ecological niches where various species can thrive. When these boundaries function as corridors elongated patches with closely spaced edges—they enable wildlife to move between otherwise isolated habitats, maintaining genetic diversity and promoting healthier, more resilient populations (Bennett, 1990; Haddad et al., 2015).

It is crucial to understand how disturbances affect ecological dynamics, species interactions, and nutrient cycling. For scientific understanding, as well as the resolution of land and resource disputes, accurate boundary mapping is essential (Polachek, 2004; Haklay and Weber, 2008). A deeper understanding of forest boundaries can provide researchers with insights into biodiversity, community dynamics, and ecosystem functioning. For conservation and management strategies, this information is crucial, as it allows identification of crucial areas for habitat connectivity, conservation prioritization, as well as mitigation of fragmentation. Ultimately, forest boundary research enhances ecological theories and provides a basis for landscape-scale planning, restoration, and sustainable land use (Hansen et al., 1991; With, 2002).

In boreal forests, human-induced boundaries such as roads and clear-cuts fragment the landscape, creating edge effects that can reduce connectivity between forest patches and disrupt wildlife movement. Studies have shown that habitat fragmentation can lead to population declines and increased vulnerability to environmental stressors, as species are confined to smaller, isolated patches (Haddad et al., 2015). Conversely, natural boundaries, such as those created by rivers or natural fire breaks, often enhance ecological resilience by providing corridors for species movement and maintaining genetic diversity. Understanding the role of boundaries in forest ecosystems is crucial for effective conservation and forest management strategies, particularly in the face of increasing anthropogenic pressures and climate change (Turner and Gardner, 2015).

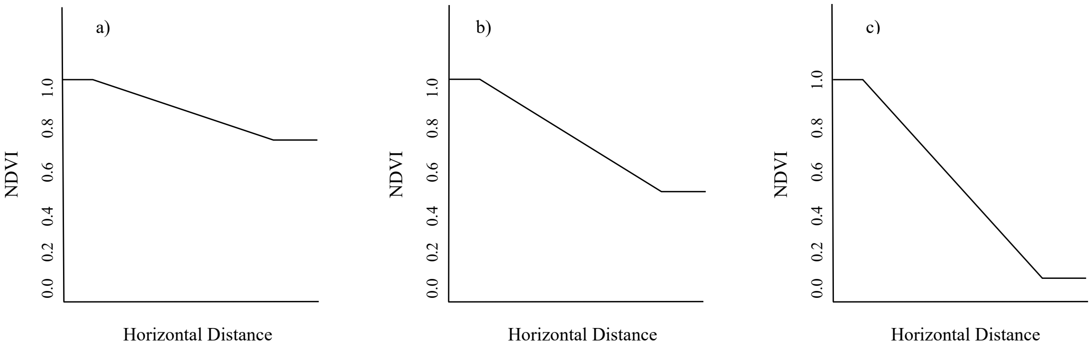


Figure 3.Various types of boundaries display different slopes, from a) gradual, b) intermediate, and c) steep.

1.6 Mapping and representation

Remote sensing is the collection of data from the Earth's surface using sensors that detect electromagnetic radiation (Roughgarden et al., 1991). Electromagnetic radiation (EMR) is energy that travels through space as waves, covering everything from radio waves to gamma rays. The distance between two consecutive wave crests is called the wavelength, while the number of wave cycles passing a single point per second is the frequency. Because EMR encompasses a wide range of energies, each region of the spectrum has its own characteristic wavelengths and frequencies. Radio waves, for example, have relatively long wavelengths and gradual frequencies, whereas gamma rays have extremely short wavelengths and high frequencies. The velocity of EMR in a vacuum, denoted as *c* and corresponding to approximately 299,792,458 $m \cdot s^{-1}$, a constant. When EMR strikes a surface, proportions of it are reflected, absorbed, and transmitted. The graph of reflection versus wavelength is called a spectral signature and can provide information about the surface with which the EMR interacts and can provide insights to land cover types and their states (e.g., vegetation). Absorption occurs when electromagnetic radiation (EMR) is taken in by a material, such as vegetation. In plants, pigments like chlorophyll absorb particular wavelengths needed for photosynthesis, leading to unique absorption patterns (or spectra). These spectra vary among species due to differences in pigment composition, leaf structure, and water content. EMR transmission is defined as EMR passing through a material with little absorption or reflection, such as transparent materials that allow certain wavelengths to pass through (Chi et al., 2021).

When mapping fire-affected areas, researchers often use a combination of approaches to ensure accuracy. Field surveys, for example, involve on-the-ground observation and data collection in burned zones, providing detailed information on a fire’s extent and characteristics (Li et al., 2000). Meanwhile, aerial photographs or other remote-sensing tools can be used to confirm and refine these boundaries from above. By combining both ground-based and aerial methods, it becomes possible to create more reliable maps for analysis and decision-making (Remmel and Perera, 2009).

The use of vegetation indices, which rely on specific regions of the electromagnetic spectrum, is a powerful tool for monitoring plant health and environmental conditions. These indices convert differences in reflectance between key spectral bands into simple numeric values, which typically increase in areas containing more green, healthy vegetation. By standardizing these spectral differences, vegetation indices provide a straightforward measure of vegetation abundance and state, helping researchers and managers track changes in plant cover and productivity across time and space (Tucker, 1979). As a result of analyzing the light reflected from plant surfaces in different spectral bands, these indices can be used to measure various properties of vegetation, including leaf area, chlorophyll content, and overall plant health. As a result of this approach, accurate plant health assessments and insights into environmental conditions that influence plant growth can be made. The visible (VIS) region includes the Red (600-700 nm), Blue (450-495 nm), and Green (495-570 nm) bands, which are important in calculating chlorophyll content and leaf area index, both of which are important indicators of vegetation status and health.

Figure 4 Including the specific wavelength ranges for each band alongside their respective regions can improve clarity even more. Beyond the visible spectrum, the near-infrared (NIR) region, spanning 700 to 1400 nm, is crucial for vegetation analysis, since the steep and dramatic increase in reflectance from the Red to the NIR spectral regions forms the ‘red edge’ that is characteristic of green vegetation. Its widespread application stems from vegetation's strong reflection of NIR light. Overall, vegetation indices use these various spectral regions to provide useful information on plant health, biomass, and environmental conditions (Xue and Su, 2017).

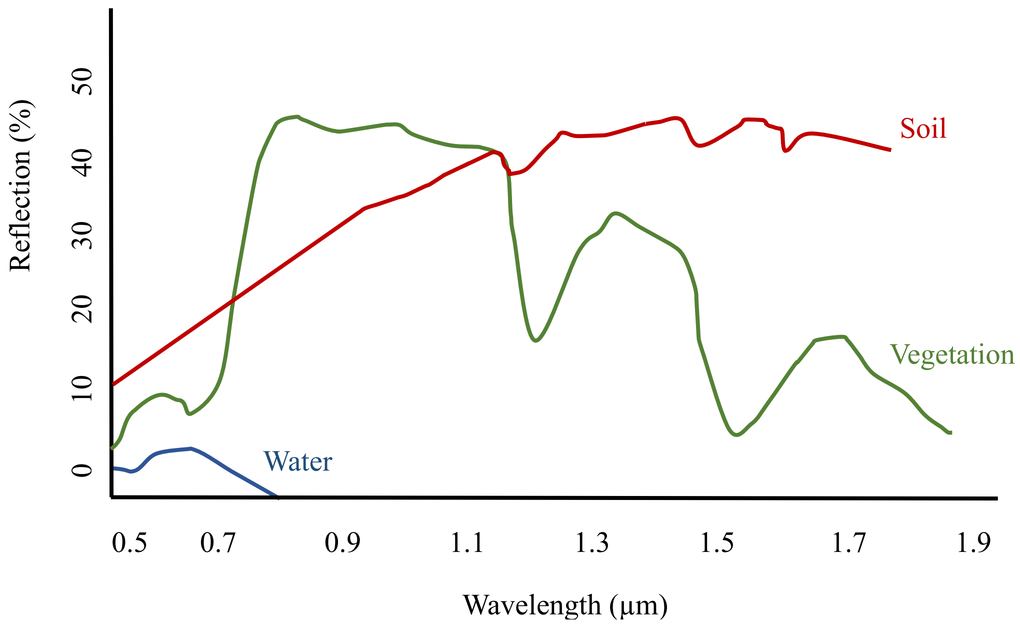


Figure 4. Spectral profiles of water, vegetation, and soil can be determined by analyzing their reflectance in visible wavelengths and the near-infrared region (GrindGIS, 2017).

Fire disturbances play a crucial role in the dynamics of ecosystems, affecting the pattern of vegetation, the habitat of wildlife, and the cycling of carbon. Significant advancements in remote sensing technology, particularly the advent of satellites such as MODIS and Landsat, have enabled the mapping and monitoring of forest fires over a variety of spatial and temporal scales (Wulder et al., 2008). A number of these tools are effective at identifying active fires, charting burned regions, and gauging the recovery of vegetation following a fire (Giglio et al., 2016).

Capturing the essence of forest fires does not solely rely on spatial representation. It is essential for efficient forest management and conservation to understand temporal patterns and fire regimes. Fire characteristics such as frequency, size, and intensity can be extrapolated from various sources, such as fire scars on trees, charcoal sediments, and spatial fire histories derived from remote sensing (Falk et al., 2007). The combination of fire behavior models and Geographic Information Systems (GIS) has enabled the prediction of potential fire spreads as well as their intensity, which has simplified both pre-fire planning and post-fire management. There is an increasing need for comprehensive fire disturbance mapping as climate change effects intensify (Westerling et al., 2006).

As a federal agency, NRCan is responsible for ensuring the responsible development of Canada's natural resources. It has several sectors, including the Canadian Forest Service (CFS), which is involved in forest-based research. Natural Resources Canada (NRCan), particularly through the CFS, uses satellite-based remote sensing and Geographic Information Systems (GIS) for mapping fire disturbances across the country. By providing a national perspective on fire patterns, more efficient resource allocation and better policy decisions can be made (NRCan, 2021).

Aviation, Forest Fire and Emergency Services (AFFES) is a division of the Ministry of Natural Resources and Forestry that manages wildland fires in the province of Ontario. Wildfires are detected and mapped in real time by AFFES using aerial detection systems and remote sensing technologies during the fire season. In this way, firefighting resources can be deployed rapidly, and evacuation procedures can be informed more accurately (Zastre and Gratton, 2016).

Natural Resources Canada's CFS is responsible for conducting research on the country's forests and the broader forest industry. They are responsible for monitoring forest disturbances, including fires, pests, and diseases, among other duties. Information should be provided in a timely and accurate manner to assist in proactive measures and post-event recovery efforts (Wulder et al., 2008).

As an example, a collaborative effort between York University and the Ontario Forest Research Institute (OFRI) resulted in the creation of a boreal forest disturbance database (*BorealDB*) (Ouellette, Marc et al., 2020; Remmel et al., 2023). As part of this spatial database, fires and harvesting disturbances within the boreal MF of Ontario have been captured since 1972. The boreal disturbance layer is compiled annually, categorizing areas of boreal disturbance as a collection of vector points. Data reliability is improved using an ensemble methodology, where the level of confidence is determined by the concordance between multiple data products, including those from Natural Resources Canada and other sources (Remmel et al., 2023). These tools and resources are critical to understanding and managing boreal forest disturbances in Ontario and elsewhere.

1.7 Research Objectives

An important objective of this research is to identify spatial and temporal patterns of boreal forest fire disturbances. In addition to examining the correspondence with the Normalized

Difference Vegetation Index (NDVI) (Pettorelli et al., 2005) and the Normalized Burn Ratio (NBR) (Key and Benson, 2006) in the context of boreal forest fire disturbances, this study also examines the relationships between the two variables. By first computing NDVI and NBR surfaces, which serve as inputs for the slope calculation algorithm, we can generate local NDVI and local NBR slope surfaces. In this context, “slope” doesn’t represent a typical metric measured in degrees or any numeric value. Instead, it indicates how quickly NDVI or NBR values change across an area, helping to reveal obvious variations in vegetation health or burn severity. We are also exploring the correlation between the *BorealDB* data and the slopes of NDVI and NBR. My research aims to identify variations in these relationships across a wide variety of fire disturbances and geographical regions within Ontario. To determine whether correlations between *BorealDB* data and slopes of NDVI and NBR are significant. This testing aims to determine which level of *BorealDB* confidence provides the most robust correlations, NDVI or NBR boundaries (characterized by a threshold of their local slope). It can thus be used as a reliable indicator of fire disturbance boundary location. As a result of the integration of all the above analyses, our study aims to provide a better understanding of the complexities of fire boundaries in Ontario’s boreal forests.

I ask the following questions: First, how are the local slopes of NDVI and NBR related to the extent of boreal forest fire disturbance boundaries as characterized by specified selection of points exceeding specified confidence in *BorealDB*? Second, does *BorealDB* data provide a reliable indicator of boreal forest fire disturbance boundaries in Ontario, and is it consistent with the spatial and temporal patterns observed by remote sensing data such as NDVI and NBR? Third, could the relation between the *BorealDB* dataset and the slopes of the NDVI and NBR be statistically validated, and does this relation increase the confidence in classifying boreal forest fire disturbance boundaries in overlapping Landsat scene areas based on hypothesis testing?

2. Methods

My thesis research aims to answer my research objectives by utilizing points (vector layers) in *BorealDB* to create boundary layers for areas disturbed by fire in the first phase of the investigation. In the second phase, I will analyze vegetation indices from satellite images to examine vegetation changes to identify boundaries of forest disturbances. As a final step in answering my research questions, according to Figure 5, I will compare the results of these two stages. The methods to achieve the goals are divided into three main phases: (1) *BorealDB* point reselections based on confidence attributes to identify fire boundaries, (2) VI-based slope thresholds to identify fire boundaries, and (3) a comparison and assessment of the two methods.

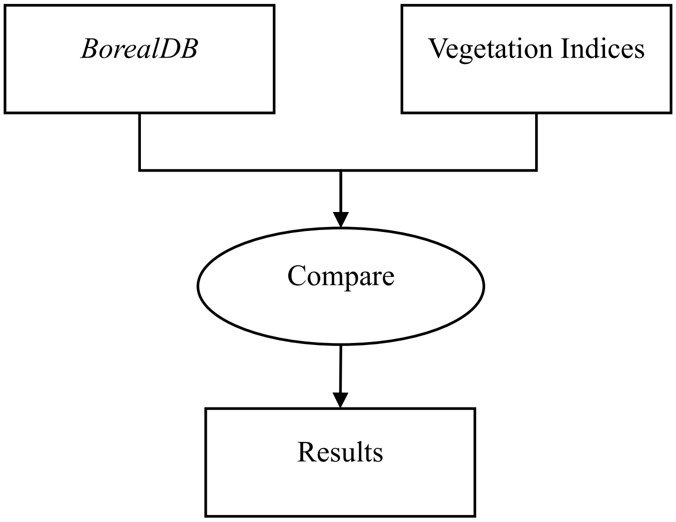


Figure 5. General overview of methods.

2.1 Boreal Disturbance Database (*BorealDB*)

BorealDB is a comprehensive database that maps boreal wildfires and timber harvesting in Ontario annually from 1972 to the present. Integrating multiple input datasets offers insights into historical patterns and interactions between wildfires and logging activities across the boreal region. The database is designed to capture both spatial and temporal aspects of these disturbances, providing a valuable resource for long-term ecological and land-use studies.

To construct *BorealDB*, historical wildfire records and timber harvesting data are combined following a standardized methodology (Ouellette et al., 2020). The spatial representation consists of vector points, each marking a location in Ontario’s boreal region where a wildfire or timber harvesting disturbance has been detected. Clusters of points in close geographic proximity indicate large disturbance events, but individual points are not directly linked to one another or classified as part of a single event. With an orthogonal distance of 120 m between points, each represents an area of roughly 1.44 ha.

BorealDB's temporal resolution is one year, allowing users to track disturbance events from 1972 onward. Each data point corresponds to a specific disturbance year, identifying when a wildfire or timber harvesting event occurred. This structure supports the analysis of long-term trends in forest disturbances. Beyond national and provincial datasets, *BorealDB* incorporates remote sensing analysis (Remmel et al., 2023) to enhance disturbance mapping accuracy. A union overlay function integrates all input sources, ensuring that each point is assigned attributes that identify which datasets recognized it as disturbed. For each point in *BorealDB*, an ensemble confidence attribute is provided, which converts the collective identification of a disturbance location into a percentage. This value is a summary of the agreement among the multiple datasets; the closer that the confidence is to 100%, the more products agree as to the classification label. This should not be confused with "accuracy" since all data products may agree on an incorrect label. However, a higher confidence does tend to boost the trust that one has in accepting any point as having been disturbed. These characteristics aid in determining the dependability of the recorded data. The confidence measures are based on the agreement or disagreement among various products, including data from the Ontario MNRF and NRCan via the Canadian Forest Service (CFS). *FireConfidence* and *HarvestConfidence* are the attributes indicating the percentage of agreement among the individual mapping products available for a given location. Gradual confidence indicates uncertainty or the presence of conflicting information, whereas high confidence indicates high agreement among products.

Additional information about the type of disturbance, previous disturbances in the area (fire or harvest history), and potentially other factors that influence the patterns and impacts of wildfires and timber harvesting are included in the database. Thus, the *BorealDB* is a valuable resource that combines multiple datasets and remote sensing analysis to provide a thorough mapping of boreal wildfires and timber harvesting disturbance locations in Ontario over half a century. The incorporation of multiple sources and the addition of confidence attributes make it a tool for researchers and policymakers to begin analyzing disturbance characteristics in the boreal ecosystem within Ontario's MF.

The goal of this study is to investigate the relationship between boundary definitions obtained using two different methods: (1) points selected from *BorealDB* based on measures of confidence and (2) thresholding VI (Vegetation Index) slopes to identify likely disturbance boundaries. Understanding where VI-derived boundaries and *BorealDB*-derived boundaries agree is important for identifying which *BorealDB* attribute conditions best align with remote sensing methods. The goal of this study is to determine which combination *BorealDB* reselection criteria produces the highest correlation with boundaries derived from VI slope thresholds, providing useful insights into the utility and consistency of both techniques

2.2 Vegetation Indices

Vegetation indices are widely used in remote sensing studies and were among the first tools developed in this field. Typically, VI use an electromagnetic spectrum comparison of Red and NIR light reflectance to distinguish between soil, and vegetation state within a landscape (Glenn et al., 2008). VI are mathematical combinations of various satellite or remote sensing bands primarily used to highlight the presence and condition of vegetation. These indices help determine the health of plants, the amount of chlorophyll in a particular area, or the amount of vegetation cover (Rouse et al., 1974). Among the most used vegetation indices are the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI) (Huete et al., 2002), and the Soil-Adjusted Vegetation Index (SAVI) (Huete et al., 2002). The Normalized Burn Ratio (NBR) can assess burn severity and vegetation recovery after fires (Picotte and Robertson, 2011).

After a wildfire, vegetation indices can be helpful tools since the effects of fire on vegetation include the reduction of chlorophyll content, destruction of the canopy, and changes in the surface reflection properties that decrease VI values, identifying disturbances and potentially disturbance boundaries. One way to spot burned areas in vegetation is by using NDVI measurements. Healthy vegetation typically shows higher NDVI values, while disturbed or burned vegetation has lower values. The steep shift between these values highlights the boundary between healthy and burned areas, making identifying where damage has occurred easier. An analysis of post-fire satellite images and calculating of these indices can be used to produce burn severity maps that show the extent and intensity of the damage caused by the fire (Key and Benson, 2006). It is possible to monitor the successional and regeneration patterns of areas affected by fire using NDVI data post-fire, enabling timely interventions to restore and conserve biodiversity. NDVI can also help predict future fire risks by identifying areas where vegetation health is deteriorating or drought conditions are increasing (Chuvieco et al., 2004); I am primarily interested in the rate of NDVI change between neighboring cells, since it is hypothesized that a large gradient can identify a boundary between disturbed and undisturbed sites.

2.3 Normalized Difference Vegetation Index (NDVI)

The NDVI shows the difference between NIR and visible Red light reflected by vegetation in a remote sensing measurement. As a result of remote sensing, NDVI provides insights into forest dynamics on broad scales by quantifying vegetation health. Based on the reflectance properties of vegetation in the NIR and red bands of the electromagnetic spectrum (Equation 1):

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

The NDVI provides a value between -1.0 and +1.0, with increasing positive values quantifying increasing vegetation greenness, which can be correlated with many characteristics ranging from biomass to vigor (Pettorelli et al., 2005). Using this differentiation helps to understand vegetation condition, specifically the presence of bare or non-vegetated areas that are expected at disturbance sites (Rouse et al., 1974).

It is common for boreal forests to be disturbed by fires. The NDVI provides essential insights in such situations (Datt, 1999; Pettorelli et al., 2005). A crucial application of NDVI is to measure the state of a forest's recovery following a fire, and to track changes in forest cover, or identify areas where recovery is slow (Huete et al., 2002). By analyzing substantial changes in NDVI data, NDVI can help identify burned and unburned areas in boreal forests.

2.4 Normalized Burn Ratio (NBR)

The NBR is a measure that quantifies the reflectance of both NIR and SWIR in landscapes affected by wildfires, indicating the burned areas. This index is used to identify, and map burned areas in landscapes. Spectral bands identified from Landsat satellite images are the primary source of this data (Key and Benson, 2006). NBR is a spectral index derived from Landsat data primarily used to assess the severity of burns (Equation 2) yielding output values between -1.0 and +1.0.

$$NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)} \tag{2}$$

Typically, burnt areas have lower NBR values, and as these values decrease, it indicates a greater burn severity. A more nuanced approach to working with NBR is to measure the NBR change from before- to after-fire (*d*NBR). Specifically, it achieves this by subtracting the post-fire NBR from the pre-fire NBR. Therefore, the *d*NBR values range from +2.0 to -2.0. Positive values reflect burned areas, with severity escalating as these values increase (Verbyla et al., 2008).

The importance of including NBR lies in its precision in identifying and distinguishing burned areas. As a result of NBR's pre/post-fire differential values, burned and unburned pixels are readily distinguished, as is the burn severity, which ranges from moderate to extreme (Escuin et al., 2008). Comparison of *d*NBR values with ground-truthed data on fire severity quantifies its accuracy. *d*NBR uses NIR and SWIR wavelengths, which are more sensitive to changes in vegetation and burn severity (Escuin et al., 2008). There are commonly used indices based on pre- and post-fire NBR measurements are known as the differenced Normalized Burn Ratio (dNBR), the relativized Burn Ratio (RBR) (Parks et al., 2014).

NBR accuracy varies among indices, including R*d*NBR, and *d*NBR. (Escuin et al., 2008; Konkathi and Shetty, 2019). NBR correlates with fire severity above ground, and dNBR values are associated with burn severity, as validated by field observations on the dNBR maps showing burn severity (Escuin et al., 2008). Moreover, the ability of NBR to accurately predict burn depth, the extent of damage to vegetation and soil caused by fire, for effective recovery and restoration efforts, this information is essential. Using NBR and satellite imagery does not measure the physical depth of the burn but indicates its severity based on changes in NIR and SWIR reflectance values pre and post-fire makes it one of the leading spectral indices in fire assessment studies (Delcourt et al., 2021).

To understand recovery and resilience dynamics, the use of NBR to investigate fire disturbances in vegetation and forests can be useful. The use of NBR allows the investigation of the impact of fire on vegetation characteristics by capturing changes in reflectance bands following the fire (Key and Benson, 2006).

Healthy vegetation typically has a strong NIR reflectance and a gradual SWIR reflectance because of its cellular structure, which is rich in water that strongly absorbs SWIR. However, when a fire occurs, the NIR reflectance decreases, and the SWIR reflectance increases due to water removal and organic matter combustion. The burned materials, which include charred wood and foliage, have a spectral signature quite different from unburned vegetation; they reflect more SWIR and less NIR. The NBR exploits these differences by using a formula that subtracts the SWIR reflectance from the NIR reflectance and then normalizes the difference. This highlights burned areas with a lower NBR value than unburned vegetation, clearly indicating fire extent and severity (Epting et al., 2005).

2.5 Recoding

Recoding continuous raster data into categorical numbers is an essential process in GIS for simplifying complex datasets and enabling meaningful spatial analysis. Analysts can more easily interpret, visualize, and combine spatial data by transforming continuous values into discrete categories, like Figure 6. This process is widely used in land use classification, environmental modelling, and risk assessment. However, careful attention must be paid to selecting classification thresholds and the potential loss of data detail to ensure that recording supports accurate and reliable analysis. Recoding spatial data is practical in many GIS applications, particularly environmental management and urban planning. In environmental modelling, for example, based on Figure 7, it is used to reclassify continuous data, such as elevation or slope, into discrete categories (e.g., "gradual," "intermediate," "steep") to assess factors like flood risk or habitat suitability (Burrough and McDonnell, 1998). An essential application of recording continuous variables is in environmental modelling. For instance, in habitat suitability modelling, continuous variables such as temperature and precipitation are transformed into categorical ranges (e.g., suitable, moderately suitable, unsuitable). This transformation plays a crucial role in simplifying complex datasets into a manageable format, which is then used in conservation and decision-making to evaluate species viability (Store and Kangas, 2001).

Hydrological models can recode slope data into erosion risk categories. Using categorical numbers to represent slope values allows analysts to produce risk maps that are easy to understand and enhance decision-making. (Burrough and McDonnell, 1998).

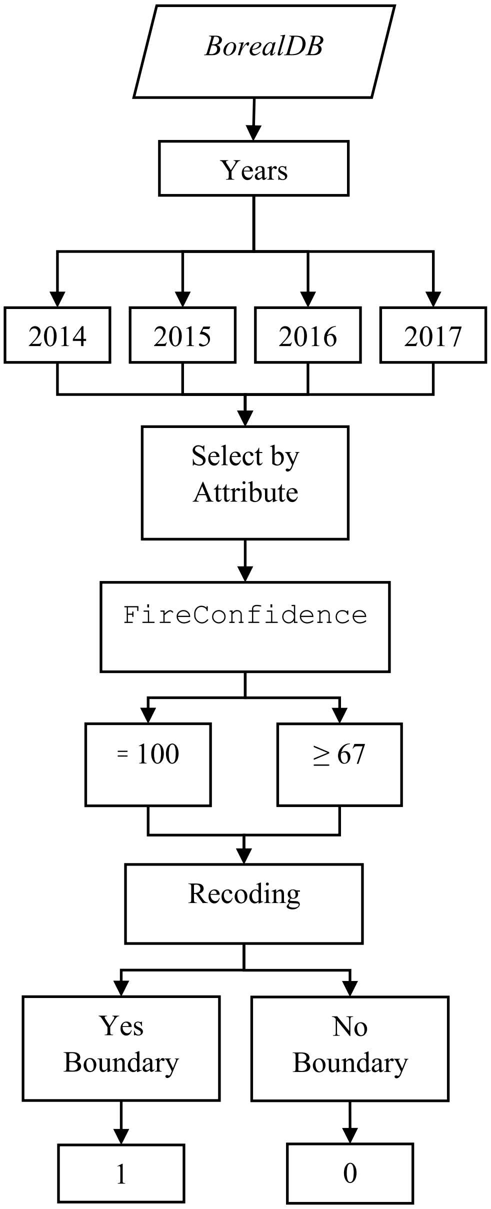


Figure 6. Recoding *BorealDB* points where fire disturbance in both selection criteria in `FireConfidence` is 1, and where there is no fire disturbance in both selection criteria in `FireConfidence` is 0.

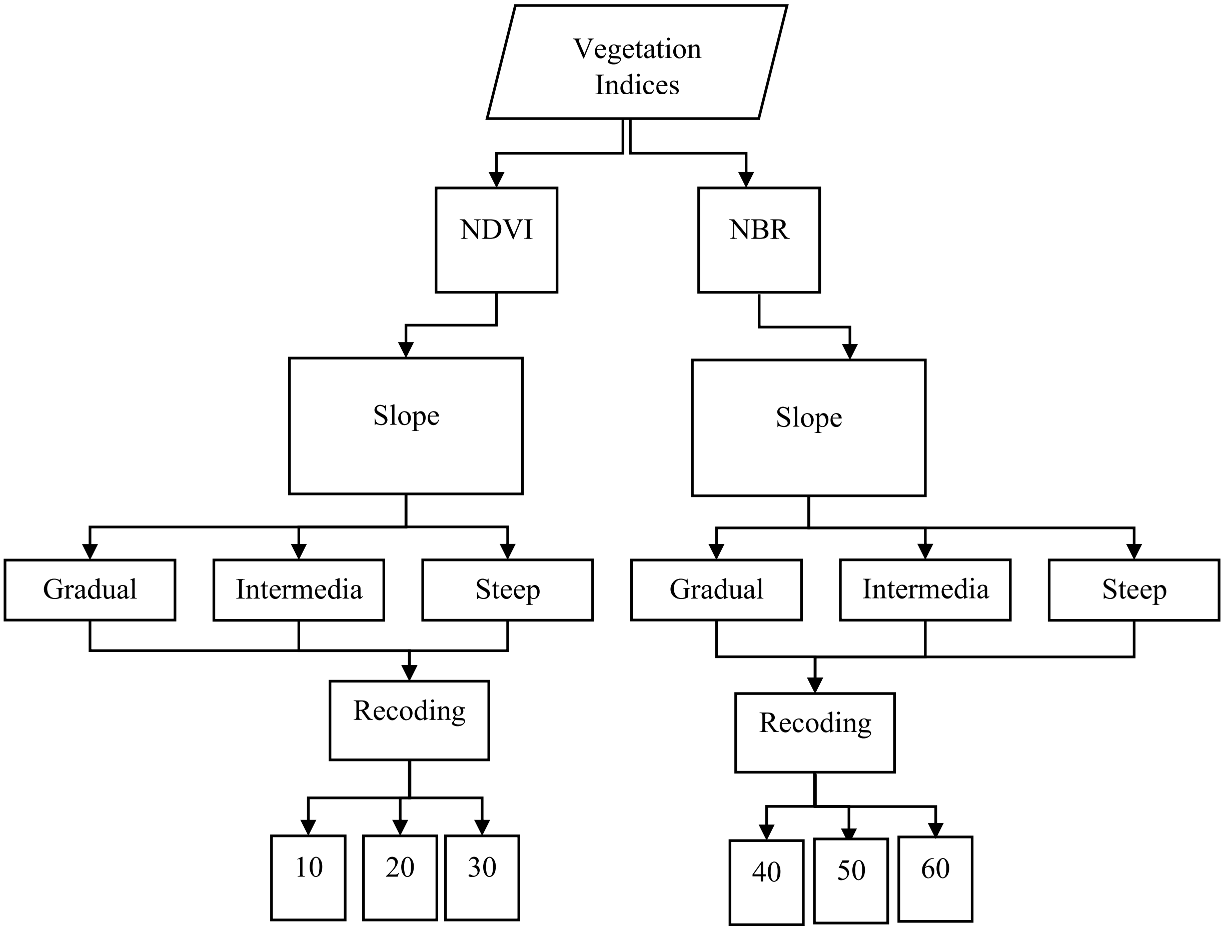
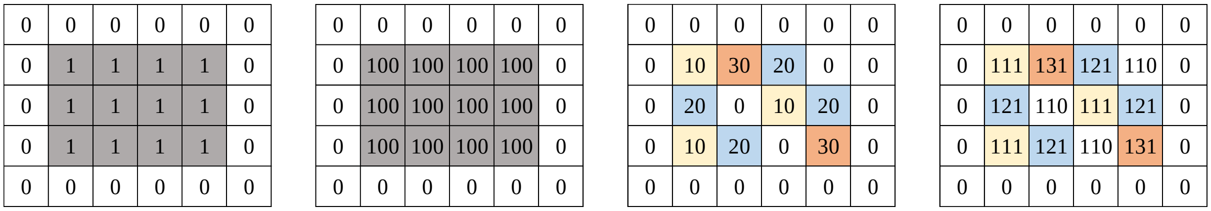


Figure 7. Recode VI's slope for both VI, where the slope is gradual-coded as 10 and 40, where the slope is medium-coded as 20 and 50, and where the slope is high-coded as 30 and 60.

2.6 Overlay

Raster overlay is a powerful spatial analysis technique in GIS that allows for the integration and analysis of multiple raster datasets. It is widely used in applications ranging from environmental modelling and land use planning to risk assessment and suitability analysis. By combining the values of corresponding pixels in different raster layers, GIS practitioners can generate new insights and make data-driven decisions. However, careful consideration must be given to data alignment, resolution, and the selection of appropriate criteria and weights to ensure the accuracy and reliability of the analysis. Overlay is crucial in environmental applications, such as habitat conservation and resource management. For example, researchers might overlay habitat maps with land use and infrastructure maps to assess how development might affect endangered species. To protect vulnerable species, development should be limited in these areas (Store and Kangas, 2001). Raster overlays are commonly used in disaster management and risk assessment to identify areas at risk from natural hazards, such as floods, landslides, or wildfires. Overlaying raster layers representing hazard factors, such as slope, soil type, and proximity to water bodies, enables decision-makers to map vulnerable areas (Burrough and McDonnell, 1998). Based on Figure 8, I performed the overlay by following a structured workflow, considering that each fire disturbance event holds uniqueness related to accurate results and integrity of spatial relationships between variables. The said process requires careful attention to spatial extent, resolution, and management of data about all the variables at hand, most especially the NDVI, NBR layers, and spatial points that represent the fire disturbances. Each fire disturbance event is overlaid by turning event points into a raster layer, which is then integrated using the Combination function. The layers consist of boundaries based on selection criteria and classified slopes of the vegetation index. Some events have two borders, one for each of two different selection criteria, but others have only one. However, all events feature two-class VI slopes for a total of six outputs per combination.



0	0	0	0	0	0
0	1	1	1	1	0
0	1	1	1	1	0
0	1	1	1	1	0
0	0	0	0	0	0

0	0	0	0	0	0
0	100	100	100	100	0
0	100	100	100	100	0
0	100	100	100	100	0
0	0	0	0	0	0

0	0	0	0	0	0
0	10	30	20	0	0
0	20	0	10	20	0
0	10	20	0	30	0
0	0	0	0	0	0

0	0	0	0	0	0
0	111	131	121	110	0
0	121	110	111	121	0
0	111	121	110	131	0
0	0	0	0	0	0

Figure 8. An example of the overlay process, shown from left to right, is *BorealDB* points, the fire-disturbance event, the VI layer, and the final overlay result.

2.7 Chi-square tests (χ^2)

The Chi-square tests is one of the most common non-parametric analyses in which nominal data is evaluated. Invented by Karl Pearson in 1900, the χ^2 assesses the fitness of a theoretical probability model to the observed data. The test performs two primary functions: first, it provides categorical variable independence; second, it gives goodness-of-fit for expected distributions. In practice, the real meaning is testing observed frequencies with those expected under assumptions of no association between variables. It does not depend on data normality assumptions and is therefore appropriate for nominal and ordinal data levels (Rossi, 2010). The χ^2 method is a test of independence used to establish whether the association exists among categorical variables. This is usually done through a contingency table, which summarizes data into categories. This test contrasts the cell-by-cell count distribution seen in a table with the distribution expected to happen under the assumption of independence between the variables. If the statistic of χ^2 is large enough, it signifies that a null hypothesis of independence may be rejected and, therefore, suggests a relationship between the variables (Wuensch, 2011). These, therefore, provide a broader application of the χ^2, especially for categorical data analysis. It allows for identifying the association between variables, with light assumptions made concerning data distribution. It is applicable for studies that involve survey responses or those of a qualitative experimental nature that might involve binary choices such as yes/no, gender categorizations of male/female, or varying levels such as high/gradual. The χ^2 is important for providing robust and, at the same time, simple means of testing the relationship between variables. Moreover, it is flexible to analyze both larger and smaller sample sizes. Although it works well when the sample size is large, for small samples, there might be a need to adopt other techniques, such as the bootstrap technique, to attain more accurate results (Lin et al., 2015). In general, the Chi-square test is powerful and widely used by researchers when dealing with categorical data to test whether significant associations exist among variables. Indeed, it is favored for its broad applicability on nominal and ordinal datasets.

2.8 Data processing

First, the methodology involved creating a separate layer for each fire disturbance event. These layers were to contain cluster points that represent areas affected by fire based on predefined spatial data inputs. These points were critical to select and generate since they laid the foundation for the succeeding spatial analyses. These were not generalized across disturbance events; rather, each event had a distinct set of cluster points, such that every fire event was treated as a unique case in the analysis.

Once the cluster points were created, they were differentiated into three groups to enable a more fine-scale analysis of fire disturbance impacts. The first group included all the points from the disturbed area to get an overview of the full spatial extent of this fire event, whereas the second group consisted of points with values ≥ 67, taken from specific criteria such as intensity or severity classes of fire impact. The third category includes only those points with a value of $= 100$ and refers to areas that were highly disturbed or reached the extreme. This kind of categorization enabled the analysis of fire effects to be tiered, hence providing insights at varied levels of disturbance intensity.

For this reason, I converted the disturbance points for each class into a raster format. This conversion to raster was quite important, as rasters are a regular grid structure that allows for spatially continuous observations fact useful and often applied in analyses involving continuous data such as NDVI and NBR. The definition of resolution and extent in the output raster is evaluated to compare resultant raster datasets across identical spatial parameters.

After the disturbance points were converted to raster, the next step was clipping the layers of NDVI and NBR at each event. Clipping was done by applying the "clip raster" tool in ArcGIS Pro. This procedure had to be done because the project required that the NDVI and NBR data layers be aligned concerning the spatial extent of the disturbance event so that analysis would be restricted to an area affected by the fire. This excluded extra data outside the fire disturbance zones, increasing the analysis's accuracy. Each NDVI and NBR layer was clipped to the same extent to compare each layer over every fire disturbance event.

Generation for each event and every group of disturbance points was done separately in raster format for NDVI and NBR layers. In other words, every fire disturbance event in each intensity level would have its own set of clipped NDVI and NBR layers to be analyzed. A central point in the methodology was to keep all layers to the same spatial extents because any mismatch could lead to wrong overlay outcomes and thus would not be appropriate for giving valid data for the final analysis.

***2.8.1 Phase-1*: *BorealDB* point reselections based on confidence attributes to identify fire boundaries**

I extensively use the *BorealDB* dataset, which provides a comprehensive list of geographical locations (represented by points) impacted by harvesting and fire disturbances from 1972 through 2021, with the database being updated annually to the present. The 'Disturbed' attribute is a Boolean indicator that is TRUE for points that have been identified as having been disturbed and FALSE otherwise. Since all non-disturbed locations have been filtered out of the database, only points with this attribute set to TRUE remain. `DisturbanceYear` marks the first year a disturbance was detected and is the best estimate of the year that the disturbance occurred. `FireLandsat` and `HarvestLandsat` are Boolean attributes that record whether the processing for the construction of *BorealDB* identified a site as fire- or harvest-disturbed. The suite of attributes (i.e., `OtherFireAFFES`, `OtherHarvestMNRF`, `OtherFireMNRFSRB`, `OtherHarvestMNRFSRB`, `OtherFireNRCAN`, `OtherHarvestNRCAN`) record whether other disturbance tracking tools recognized fire and/or harvesting disturbances at the *BorealDB* points. The attribute `DisturbanceCodeLandsat` is a composite code that summarizes the disturbance type, the number of instances of a classification type for locations where multiple overlapping scenes exist, and whether the location was identified as having been disturbed during the previous two years. Details on decoding this integer code are provided in (Remmel et al., 2023). A summary listing of attributes attached to each point is provided in Table 1.

For the purposes of this thesis that considers fire boundaries only, I focus on the attribute `FireConfidence`. This attribute is used to indicate the percentage of map products, produced by various organizations, that agree regarding the labelling of a fire disturbance at each point location in the dataset. For example, if five distinct fire mapping products are available for a location, and of these, three indicate the presence of a fire disturbance, the calculation of `FireConfidence` would be (3/5) ×100 = 60 (providing a percentage of agreement). Thus, values can theoretically range from 0 (no products agree) to 100 (all products agree). This value can be used to select points from the population that have a minimum acceptable agreement and thereby produce a realization of disturbance mapping that will contain a unique set of points. Consequently, these points will infer some area and boundary for disturbance events (which can readily change as the selection of points is altered due to different `FireConfidence` levels selected.

The selection of `FireConfidence` allows me to filter and examine the data points with specified levels of minimum confidence and to produce different realizations of fire disturbance mapping. These different realizations, leading to the high likelihood of expressing different boundaries provide products that I will compare with boundaries derived from several remote sensing vegetation index-based boundary extractions obtained in *Phase-2* of my proposed work.

Table 1. Attribute definitions in *BorealDB*. AFFES = Aviation, Forest Fire and Emergency Services, SRB = Science and Research Branch, NRCan = Natural Resources Canada, MNRF = Ontario Ministry of Natural Resources and Forestry harvest database (Ouellette, Marc et al., 2020).

Attribute	**Type**	**Range**	**Description**
`Disturbed`	Boolean	0 -1	Did a disturbance happen here?
`DisturbanceYear`	Integer	1972-2022	Year of disturbance, whatever type
`FireLandast`	Boolean	0 -1	Was it identified by *BorealDB?*
`HarvestLandsat`	Boolean	0 -1	Was it identified by *BorealDB?*
`OtherFireAFFES`	Boolean	0 -1	Was it in the AFFES database?
`OtherHarvestMNRF`	Boolean	0 -1	Was it in the MNRF database?
`OtherFireMNRFSRB`	Boolean	0 -1	Was it in the MNRF/SRB database?
`OtherHarvestMNRFSRB`	Boolean	0 -1	Was it in the MNRF/SRB database?
`OtherFireNRCAN`	Boolean	0 -1	Was it in the NRCan database?
`OtherHarvestNRCAN`	Boolean	0 -1	Was it in the NRCan database?
`HarvestPrevious`	Boolean	0 -1	Identified in previous 2-year window?
`FirePrevious`	Boolean	0 -1	Identified in previous 2-year window?
`DisturbanceCodeLandsat`	Integer	0 - 4444	Landsat code for overlap areas
`FireConfidence`	Integer	0 -100	Confidence (%)
`HarvestConfidence`	Integer	0 -100	Confidence (%)

The first step in *Phase-1*, a single year from 2014 to 2017 is selected from *BorealDB* that will be used to test the boundary identification between *BorealDB* reselections and VI-based boundary detections, respectively. According to Figure 9 to a reselection process will be conducted based on two criteria in separate steps: first, selecting `FireConfidence ≥ 67`, and second `FireConfidence = 100`. The results will yield two distinct layers that will indicate which locations have been disturbed by fire with the specified minimum levels of confidence. Then, these point layers will be converted into raster representation to align with anticipated boundary outputs created in *Phase-2*, allowing me to compare the boundary mapping results in *Phase-3.* The spatial resolution of the converted output will be 120 m because this represents the spacing of points in *BorealDB*. Following this, the raster layers will be subjected to conditional processing in the raster calculator, in which *NoData* values will be converted to 0 and all other values to 1 since subsequent functions need non-disturbed locations to have a value (0) rather than be *NoData* which would otherwise exclude these locations from all further analyses. Based on Figure 10, once the disturbed points are converted to raster cells, I use an Expand function to enlarge the disturbed areas by 1-cell in all directions; this is a necessary intermediate step that a graduals me to remove the original disturbance locations from the expanded version and thus retain only the outer boundary locations. Once the original cells are subtracted from the enlarged version, the result is a boundary of cells (1) relative to all others (0). These boundaries will be used in *Phase-3* when compared to boundaries derived from VI-based assessments.

To optimize the efficiency of the final phase of the method, boundary cells are processed according to their `FireConfidence` values. For cells where `FireConfidence = 100`, fire presence was recoded to 1, and no fire presence was recoded to 0. Additionally, for cells where `FireConfidence ≥ 67`, fire presence was recoded to 4, and no fire presence was recoded to 3. Recoding background to disturbance boundary cells to 1 and 2, respectively, is important for maintaining unique links back to the original data in *Phase-3* and will be discussed in that section once the processing of I data has also been defined. After applying the selection criteria (≥ 67) and converting the data to a raster format (with values such as 75 and 100), some fire disturbance occurrences required standardization to show all values matching the criteria as a single common value. Using ArcGIS Pro's Reclassify tool, all values ≥ 67 were reclassified to 1.

For every fire disturbance within the study area, I created an event layer that uniquely identifies it from others. These event layers capture the spatial extent and attributes of each fire, thus allowing for each event to be differentiated in detail. This ensures that the fire disturbances occurring simultaneously or around the exact location are treated as separate events in the analysis.

In addition to these event layers, I have created a recorded boundary layer for each year. The layer indicates the presence of fire within that area in yes or no using information from the *BorealDB* database. The recorded layer integrates a binary classification of the presence of fire or no fire within the boundary, making it easily interpretable for events across the landscape. This means that the classes are standardized over some layers so that the analysis is consistent.

Each year, a boundary layer encompasses all the fire disturbances for that year. Further, I have created several event layers coded to represent different fire events each year. These coded event layers allow me to get a detailed temporal and spatial resolution for the fire data to analyze fire disturbances across time as accurately as possible.

This structured dataset has prepared all the data in *Phase-1* for further analysis. The next step involves an overlay process that integrates event and boundary layers. This approach can be used to consider fire disturbance patterns, interactions, and the broader landscape effects over time.

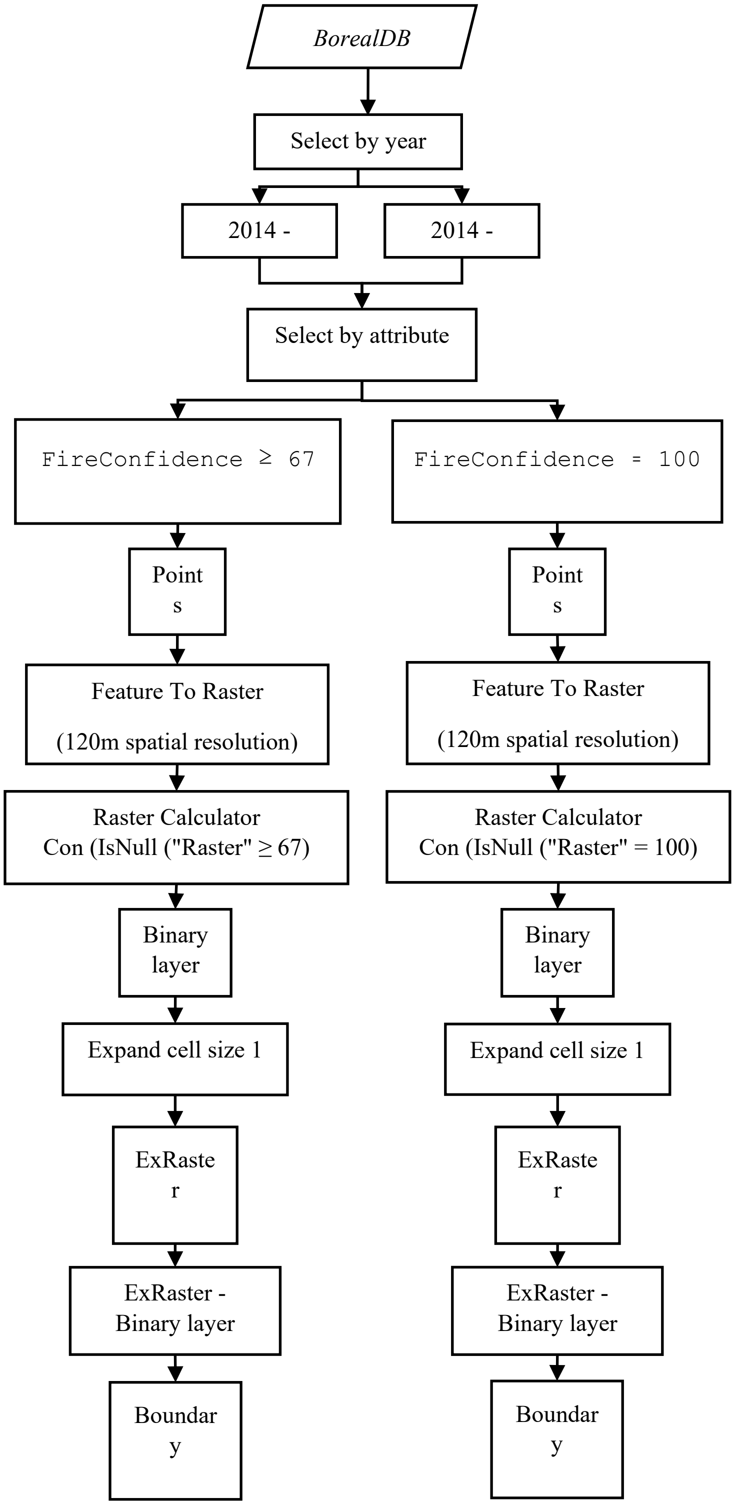
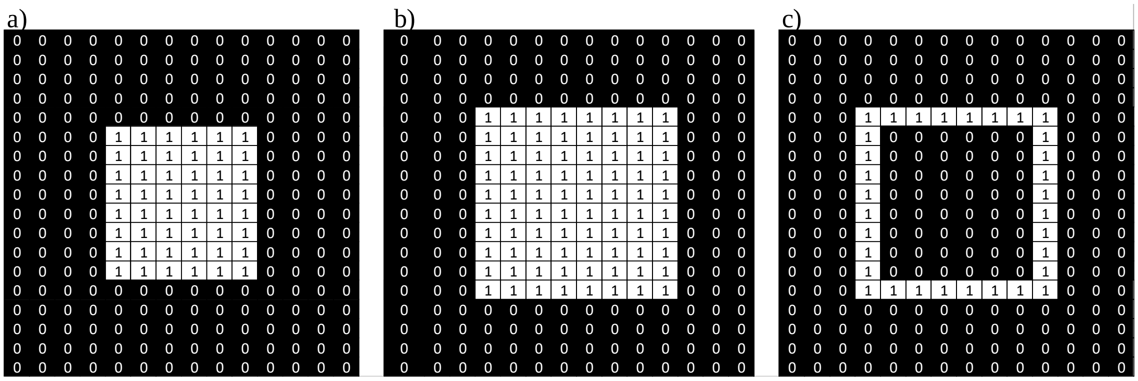


Figure 9. Extraction of points with `FireConfidence` values to identify disturbed locations, as well as conversion to binary raster layers.



a)

0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0

b)

0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0

c)

0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	1	0	0	0	0	0	0	1	0	0	0
0	0	0	1	0	0	0	0	0	0	1	0	0	0
0	0	0	1	0	0	0	0	0	0	1	0	0	0
0	0	0	1	1	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 10. Disturbance cells as 1s on a background of 0s (a) are then expanded by one cell (b) and then subtracting (a) from (b) provides the outer boundary for the disturbance (c).

2.8.2 Phase-2: VI-based slope thresholds to identify fire disturbance boundaries

The first step in *Phase-2* is to compute NDVI and NBR layers for the same spatial and temporal extent as represented by data in *Phase-1*. Then, based on the cell referencing convention presented in Figure 11, local NDVI and NBR slopes are computed using Equations 3-5 (Chrisman, 2002) to characterize the rate of VI change. The steepness of the slope will characterize the severity of the change from cell-to-cell and be used to determine locations that could be disturbance boundaries. I propose to classify slopes into three categories, each representing steeper (more abrupt) slopes and likely representing more obvious disturbance boundaries. These slope-value transitions are often abrupt at the boundary between burned and unburned areas, indicating clear ecological thresholds where fire disturbance has altered the landscape. Such boundaries are critical for understanding post-fire recovery processes, managing land for restoration, and preventing future disturbances (Lentile et al., 2006).

$$a = \frac{(z_{i-1,j+1} + 2z_{i,j+1} + z_{i+1,j+1}) - (z_{i-1,j-1} + 2z_{i,j-1} + z_{i+1,j-1})}{8S} \tag{3}$$

$$b = \frac{(z_{i+1,j-1} + 2z_{i+1,j} + z_{i+1,j+1}) - (z_{i-1,j-1} + 2z_{i-1,j} + z_{i-1,j+1})}{8S} \tag{4}$$

$$Slope\ gradient = \sqrt{a^2 + b^2} \tag{5}$$

According to equations 3-5, *z* represents a cell value (NDVI or NBR), and *i* and *j* are indices for columns and rows respectively Figure 11. This notation is used to identify which relative cell values are used in computing north-south (a) and east-west slopes (b) and the combined local slope gradient.

$z_{i-1,j+1}$	$z_{i,j+1}$	$z_{i+1,j+1}$
$z_{i-1,j}$	$z_{i,j}$	$z_{i+1,j}$
$z_{i-1,j-1}$	$z_{i,j-1}$	$z_{i+1,j-1}$

Figure 11. Relative cell referencing notation for a 3×3 window used to compute local slopes on a raster. Here, *i* and *j* are indices representing rows and columns, respectively and *z* is an "elevation", in the case of this study, a vegetation index value. The notation identifies which relative cell values are used for computing the north-south (a) and east-west (b) slopes, as well as the combined local slope gradient.

ArcGIS Pro's slope function is used to examine how measurements like NDVI and NBR vary over time. By fitting a linear regression line over the pixel values from several raster layers, it determines the rate of change. shown how to efficiently for gradual forest disturbances and identify small, long-term changes in vegetation health utilizing the slope function with all available Landsat data, underscoring the significance of ongoing monitoring (Zhu et al., 2012, p. 201).

According to Figure 12, after computing each vegetation index, namely NDVI and NBR, I analyzed the fire disturbance events. First, I clipped each layer of the considered fire event to get a subset of its area. With the vegetation index layers in place, I calculated the slope of each index, hence getting the rate of change over the area.

I then conducted a slope function on the data, further enabling me to analyze the variability in vegetation health and burn severity. After calculating the slope, I reclassified the data with the reclassify function into gradual, medium, and high. This reclassification was based on the predefined thresholds that ensured areas of very little change fell into the gradual category and areas of moderate change fell into the medium category. Those with large change fell into the high category. In this way, one can ascertain the response of various regions within this fire-affected area concerning vegetation dynamics.

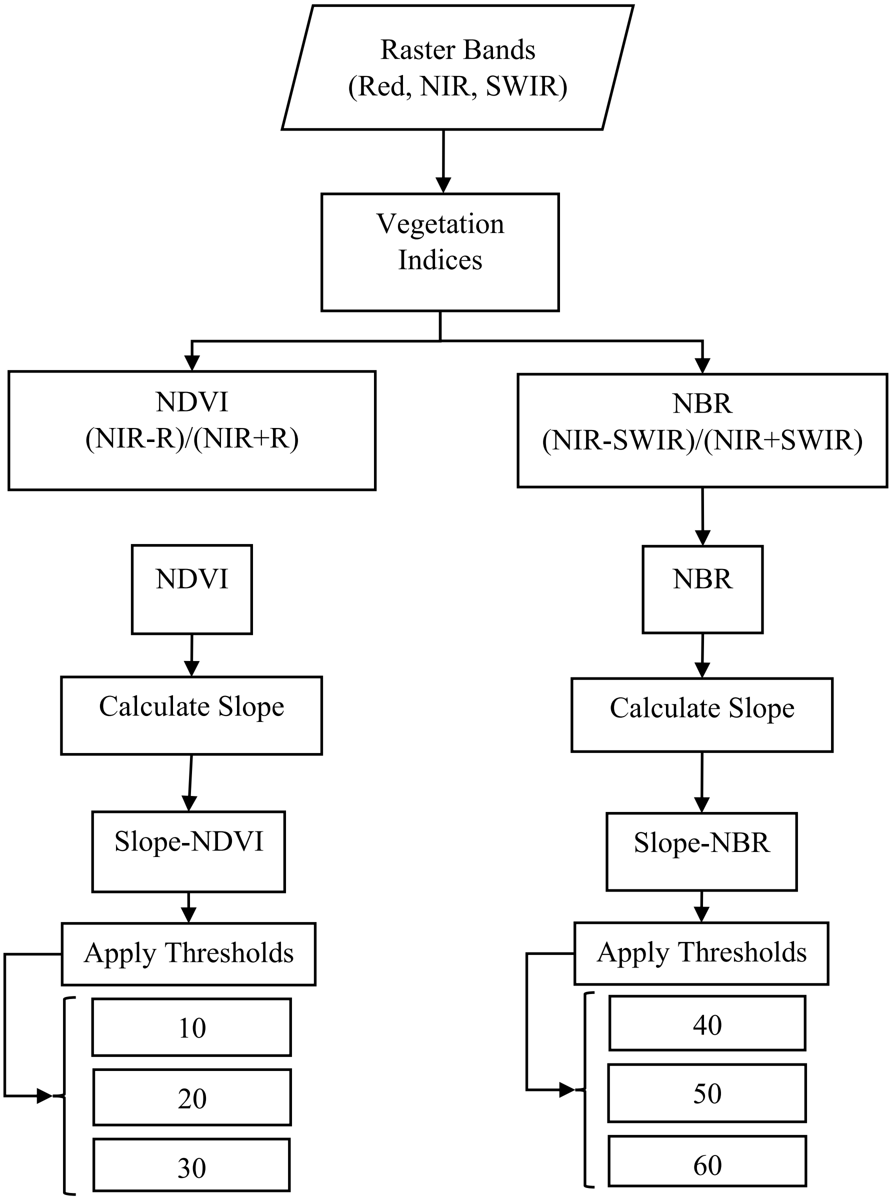


Figure 12. Processing following for *Phase-2*, whereby multispectral image data is converted to NDVI and NBR vegetation indices and processed to identify three intensities of boundaries.

2.8.3 Phase-3: Comparing *BorealDB* and VI-derived fire boundaries.

I created a series of detailed spatial layers representing fire presence/absence based on the disturbance event considered, using data from *BorealDB*. Such layers are fundamental to identifying the spatial distribution of areas that might have been affected by fire within the boreal forest. Moreover, fire presence and slope classes were divided into three levels for each vegetation index. I want to check possible correlations between the vegetation index and *BorealDB* points. To produce specific and obvious findings, a raster event layer was created for each disturbance, as explained in the method section.

I will employ an overlay process to comprehend these associations fully. In the overlay process, categorized slope and vegetation indices are layered with the fire presence data to determine the pattern and spatial relationship. Once the overlay process is conducted, information from the various layers is combined using a combination function. In this way, I would establish whether fire disturbances pertain to specific vegetation index and slope characteristics. For each `FireConfidence` with each VI, there are six outputs: the first number describes the event fire disturbance for each year, the middle number shows the level of slope from gradual, medium and high, and the third number shows that *BorealDB* points show it as disturbance point or not.

To compare the results from *Phase-1* and *Phase-2* according to Table 2 to see if there is a relationship between boundaries from *BorealDB* and boundaries from VI. Two boundary layer files stemming from the *BorealDB* reselections and subsequent boundary extraction procedures, each of which will be compared with three boundary layers produced for each of NDVI and NBR. This equates to 12 possible comparisons.

Table 2.Unique combination codes for results from *Phase-1* and *Phase-2* for comparing results in *Phase-3*. These comparisons are made to determine whether there are relationships between reselection criteria implemented on *BorealDB* and different intensities of slope range: gradual, intermediate, steep computed from NDVI or NBR data.

BorealDB	**NDVI**			**NBR**		
Selection Criteria	Gradual	Intermediate	Steep	Gradual	Intermediate	Steep
`FireConfidence ≥ 67`	1	2	3	7	8	9
`FireConfidence = 100`	4	5	6	10	11	12

To perform this comparison, I will add the corresponding pairs or raster layers for each of the 12 unique comparisons. Here, the recoding from *Phase-1* and *Phase-2* become critically important as they lead to unique combinations through the addition that identify agreement, disagreement, and which layer values lead to these conditions Table 3.

Table 3.The combination of *Phase-1* and *Phase-2* recode results in unique combinations indicating agreement and disagreement and the layer values that have contributed to these conditions.

BorealDB	**Slope-NDVI**			**Slope- NBR**		
Code	Gradual	Intermediate	Steep	Gradual	Intermediate	Steep
0	10	20	30	40	50	60
1	11	21	31	41	51	61

3. Results and Discussion

A total of twenty fire disturbance occurrences were documented between 2014 and 2017. *BorealDB* point data was utilized to generate boundary layers and determine the slope of VIs for each occurrence. These boundary layers offer a spatial context that helps comprehend the nature and scope of the fire disturbances. This study investigates whether changes in fire disturbance boundaries within the *BorealDB* dataset are related to variations in the slopes of NBR and NDVI.

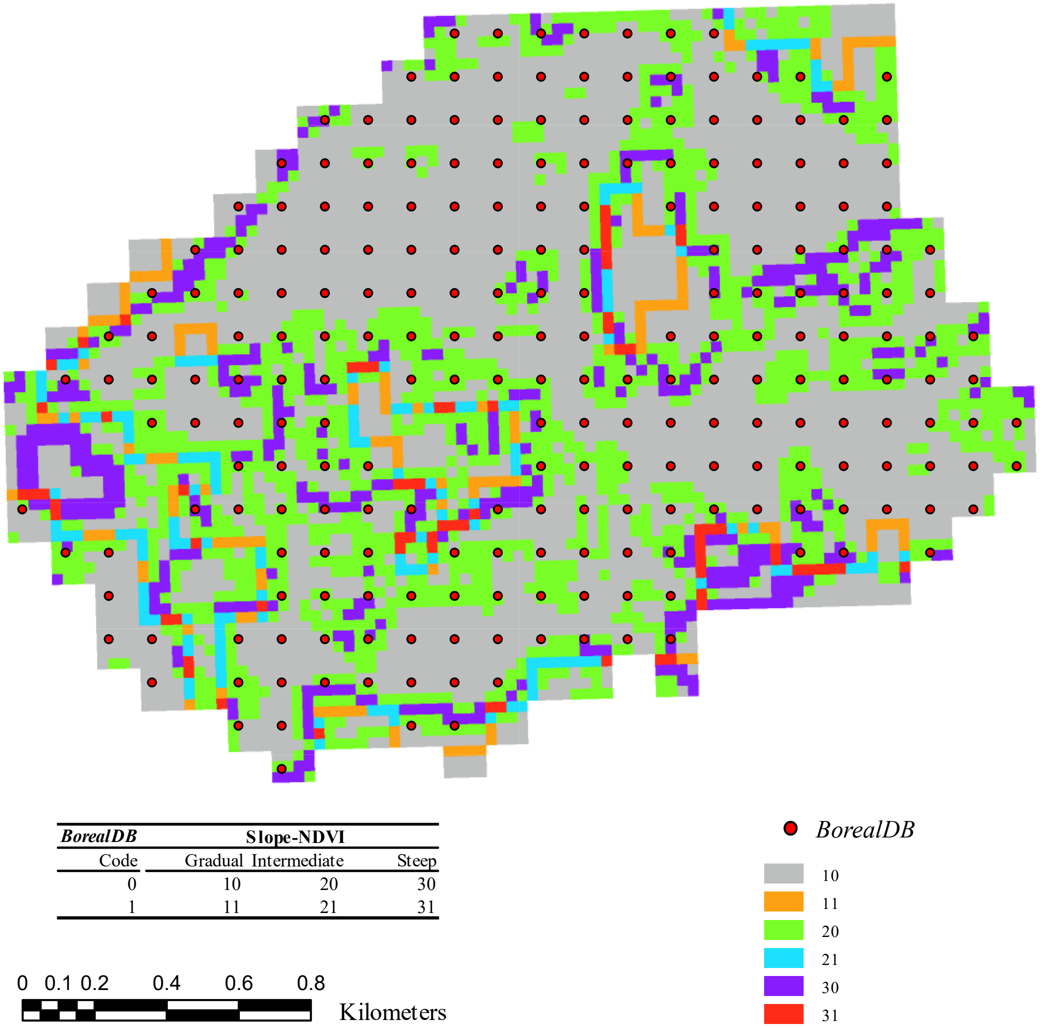
3.1 Combination results of *BorealDB* and NDVI

Remote sensing can reveal fire disturbances that are missing or underrepresented in traditional datasets, as evidenced by places where NDVI detected fire disturbances outside the *BorealDB* bounds. This emphasizes the usefulness of NDVI as a technique for detecting vegetation changes after disturbance, supporting earlier studies that highlight NDVI's utility in fire monitoring. The combination of NDVI with datasets such as *BorealDB* provides a more thorough understanding of fire impacts and emphasizes the importance of continual updates in fire boundary mapping methodologies (Chuvieco et al., 2008; Roy et al., 2008; Lhermitte et al., 2011).

Six unique output categories were produced by the study for the first fire disturbance event of 2017: 110, 111, 120, 121, 130, and 131. The outputs that end with “1” (111, 121, and 131) indicate regions where there was evidence of a fire disturbance based on both the *BorealDB* border data and the NDVI slopes. This agreement indicates that the fire boundaries defined in the *BorealDB* dataset and the observed vegetation changes, represented by the NDVI slopes, are strongly aligned. These overlap areas support the validity of combining fire boundary records with NDVI slope analysis to reliably identify and track fire disturbances. Furthermore, outputs with 1, 2, and 3 in the middle show that class of slopes from gradual, intermediate, and steep.

However, the outputs that end with “0” (110, 120, and 130) represent areas where the *BorealDB* data did not identify fire disturbances; only the NDVI slopes did. This disparity shows that fire disturbances that were either overlooked or not noted in the current *BorealDB* limits may be discovered by NDVI-based detection. These results demonstrate the potential of NDVI slopes to improve fire disturbance detection, particularly when conventional boundary data may be insufficient or out-of-date. Based on Figure 13, the overlay of both outputs reveals the spatial link between vegetation responses and fire disturbance boundaries, underscoring the significance of combining NDVI and *BorealDB* data for more thorough fire monitoring.

All combination results are determined by the event layer, boundary layer, and slope of the vegetation index (VI). Some fire disturbance events only have one selection criterion (≥ 67), whereas others have both (≥ 67 and = 100).



BorealDB	Slope-NDVI		
Code	Gradual	Intermediate	Steep
0	10	20	30
1	11	21	31

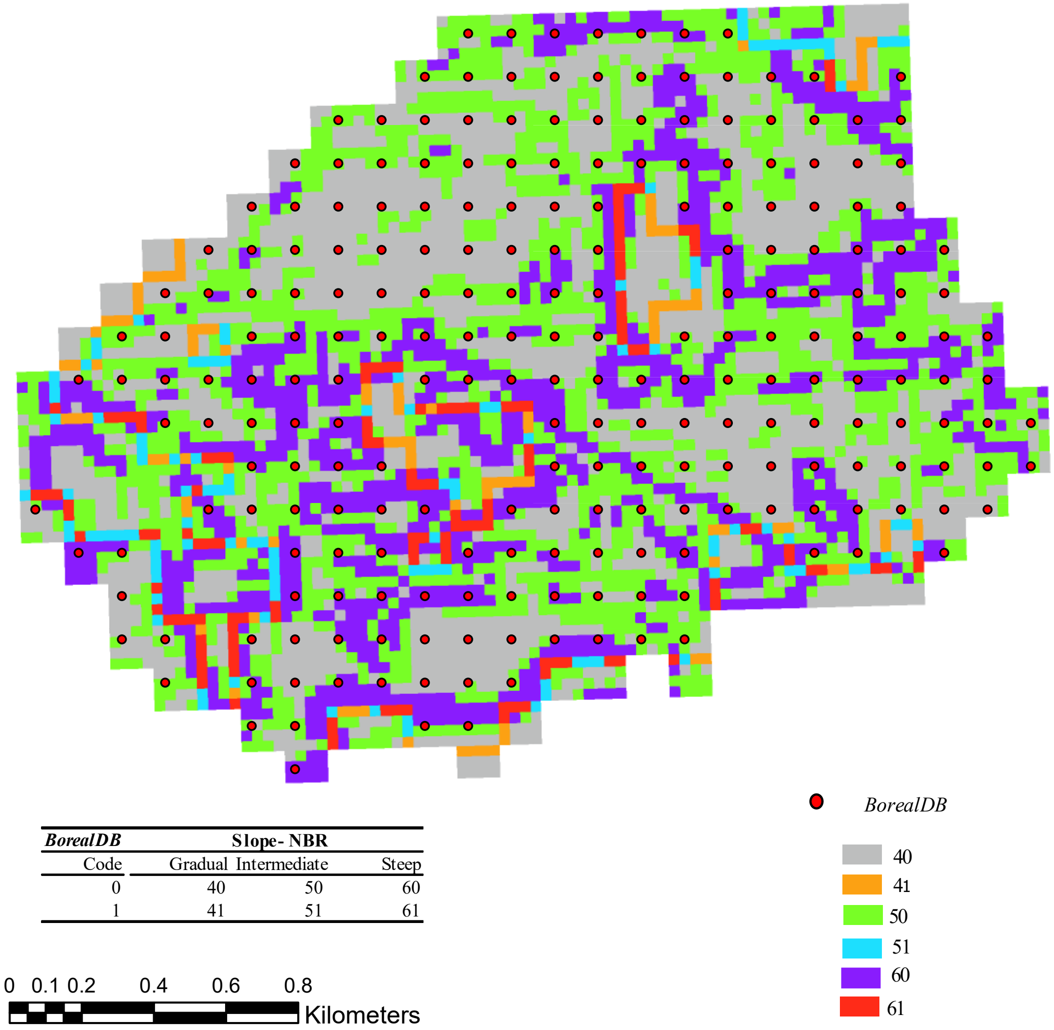
Figure 13. Map of overlay (combination) result of NDVI, event fire disturbance, and BorealDB. Grey, green, and purple show that only NDVI agrees there was fire disturbance; however, orange, blue, and red show that both NDVI and *BorealDB* agree there was fire disturbance.

3.2 Combination results of *BorealDB* and NBR

Regions where just the NBR slopes suggested fire disturbances—without confirmation from *BorealDB* showcase the power of NBR to detect fire disturbances that may be missed in conventional datasets. The combination of NBR and *BorealDB* datasets allows for a more nuanced understanding of fire impacts, highlighting the significance of updating fire boundary databases with remote sensing inputs for complete fire control techniques (Epting et al., 2005; Miller and Thode, 2007).

Six unique output categories were produced by the study for the first fire disturbance event of 2017: 140, 141, 150, 151, 160, and 161. The outputs that end with a "1" (i.e., 141, 151, and 161) indicate regions where there was evidence of a fire disturbance based on both the *BorealDB* border data and the NBR slopes. This agreement indicates that the fire boundaries defined in the *BorealDB* dataset and the observed vegetation changes, represented by the NBR slopes, are strongly aligned. These overlap areas support the validity of combining fire boundary records with NBR slope analysis to reliably identify and track fire disturbances. Furthermore, outputs with 4, 5, and 6 in the middle show that class of slopes from gradual, intermediate, and steep.

However, according to Figure 14, the outputs that end with a "0" (i.e., 140, 150, and 160) represent areas where the *BorealDB* data did not identify fire disturbances; only the NDVI slopes did. This disparity shows that fire disturbances that were either overlooked or not noted in the current *BorealDB* limits may be discovered by NBR-based detection. These results demonstrate the potential of NBR slopes to improve fire disturbance detection, particularly when conventional boundary data may be insufficient or out-of-date. The overlay of both outputs reveals the spatial link between vegetation responses and fire disturbance boundaries, underscoring the significance of combining NDVI and *BorealDB* data for more thorough fire monitoring.



BorealDB	**Slope- NBR**		
Code	Gradual	Intermediate	Steep
0	40	50	60
1	41	51	61

Figure 14. Map of overlay (combination) result of NBR, event fire disturbance, and *BorealDB*. Grey, green, and purple show that only NBR agrees there was fire disturbance; however, orange, blue, and red show that both NBR and *BorealDB* agree there was fire disturbance.

3.3 Descriptive results

To begin with, descriptive statistics such as mean, median, range, and standard deviation will be computed for the NDVI and NBR slope data. These metrics will help in understanding the data's distribution and variability (Weisberg, 2005). Summary statistics can also reveal potential trends linked to fire disturbance boundaries.

To perform a chi-square test, the continuous slope values must be transformed into categorical variables (e.g., "gradual slope," "intermediate slope," and "steep slope"). The classification process will be based on meaningful thresholds derived from ecological research or conventional statistical techniques (Hastie et al., 2009). Once categorized, frequency distributions for fire boundary data (presence or absence) and the classified NDVI and NBR slopes will be generated. These distributions help determine whether each category contains enough observations for a reliable chi-square test. To meet the test's assumptions, the expected frequencies in each contingency table cell should generally be at least five (McHugh, 2013). An analytical table illustrates the relationship between fire boundary presence and slope categories. This table provides the observed frequencies necessary to calculate expected frequencies, forming the foundation for the chi-square test (Weisberg, 2005).

Visualizations such as pie charts, bar charts, and histograms will be used to explore the distribution of slope categories and fire boundary data. These visual tools can highlight discernible patterns that may suggest correlations (Weisberg, 2005). Examining correlations or scatter plots of the original numerical slope values may provide valuable insights before categorization. While the chi-square test is designed for categorical data, initial correlation analysis can help identify relationships in the raw data (Hastie et al., 2009)

My research aims to identify variations in these relationships across various fire disturbances and geographical regions within Ontario. To determine whether correlations between *BorealDB* data and slopes of NDVI and NBR are significant. This testing aims to determine which level of *BorealDB* confidence provides the most robust correlations, NDVI or NBR boundaries (characterized by a threshold of their local slope). It can thus be used as a reliable indicator of fire disturbance boundary location. As a result of integrating all the above analyses, our study aims to provide a better understanding of the complexities of fire boundaries in Ontario’s boreal forests.

I ask the following questions: Q1: how are the local slopes of NDVI and NBR related to the extent of boreal forest fire disturbance boundaries as characterized by the specified selection of points exceeding specified confidence in *BorealDB*? Q2: does *BorealDB* data provide a reliable indicator of boreal forest fire disturbance boundaries in Ontario, and is it consistent with the spatial and temporal patterns observed by remote sensing data such as NDVI and NBR? Q3: could the correlation between the *BorealDB* dataset and the slopes of the NDVI and NBR be statistically validated, and does this correlation increase the confidence in classifying boreal forest fire disturbance boundaries in overlapping Landsat scene areas based on hypothesis testing?

As a result of this step, this research aims to identify which *BorealDB* re-selection criteria align best with the VI slope approach. The approach with the highest agreement is recommended when determining fire disturbance boundaries.

For statistical analysis, I will employ the Test of Independence χ^2 to examine the relationship between categorized slopes derived from NDVI and NBR data and the detection of fire boundaries in the *BorealDB*. A key aspect of this analysis is identifying the potential relationship between these two categorical variables. I posit two hypotheses for this test: under the null hypothesis (H_0), slope categorization and fire boundary presence do not have any significant relationship; however, the alternative hypothesis (H_1) suggests that a dependency exists, suggesting that the categorization of slopes is associated with fire boundaries.

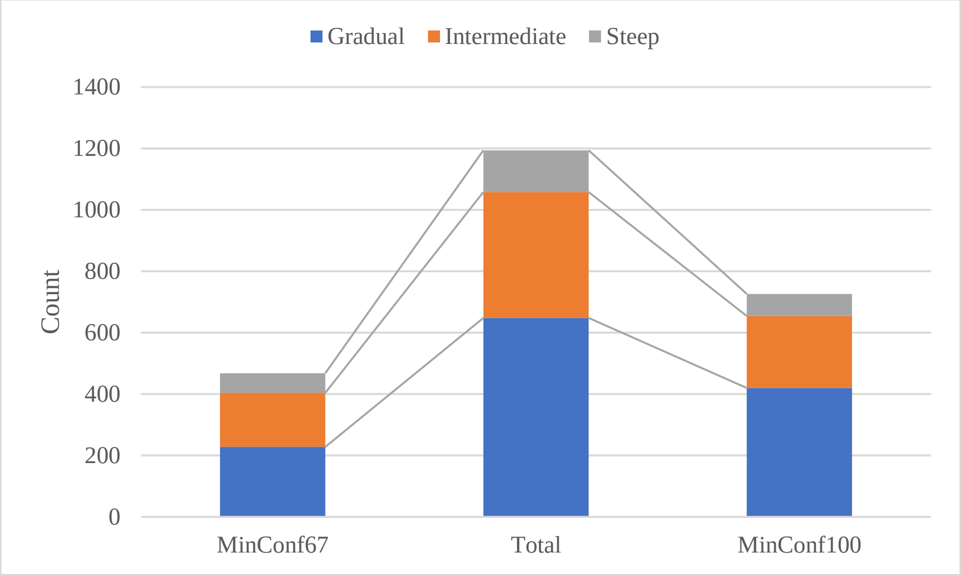


Figure 15. Comparative analysis in 2014 for the NDVI layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

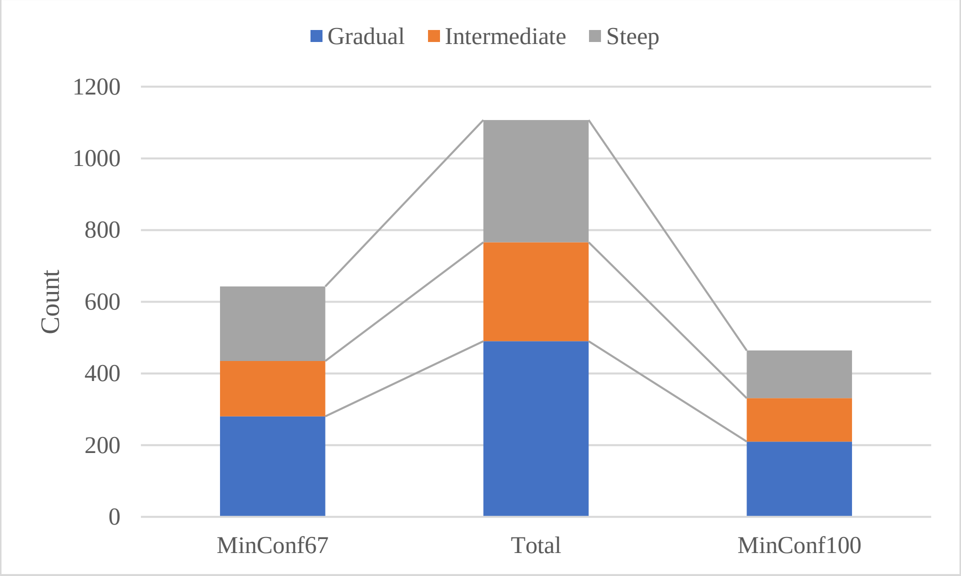


Figure 16. Comparative analysis in 2014 for the NBR layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

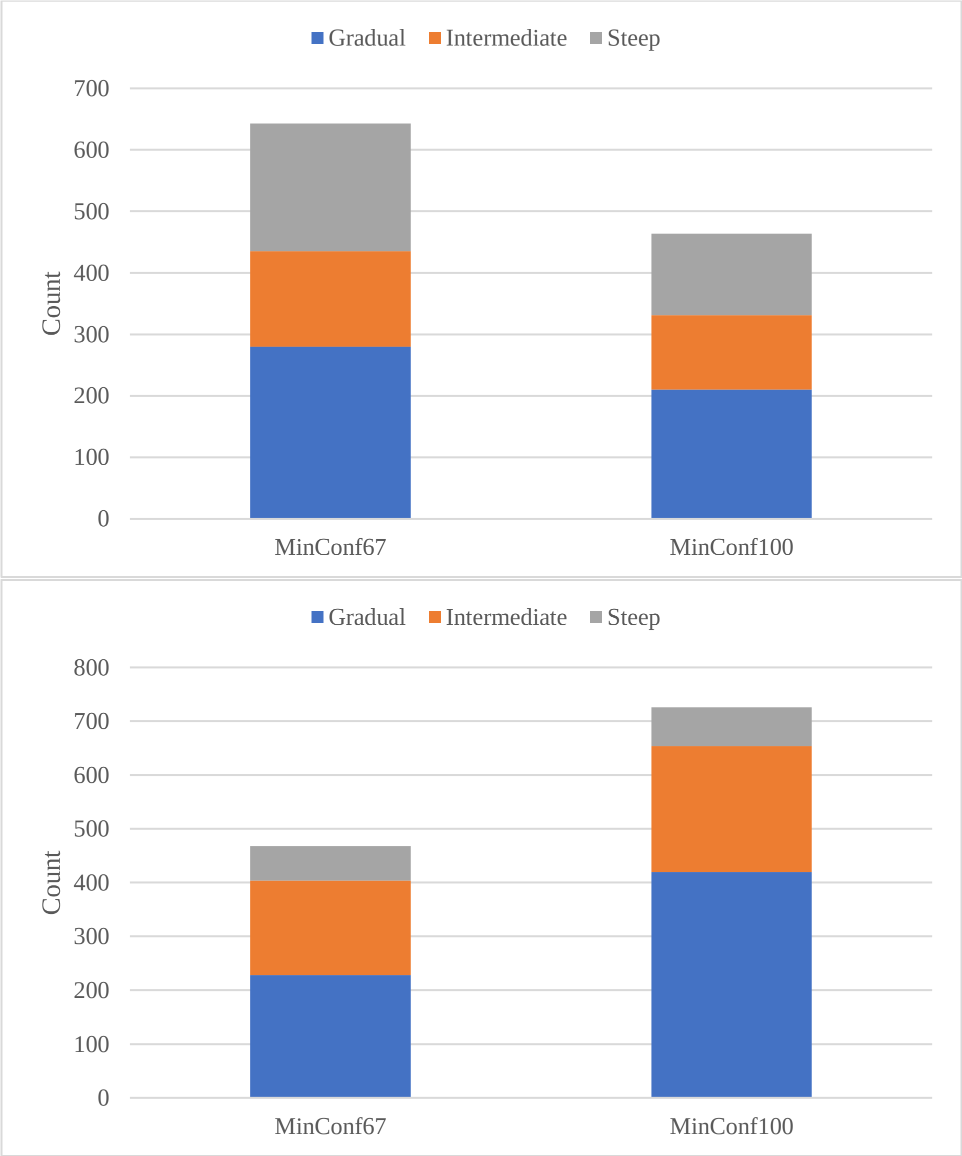


Figure 17. The NDVI vs NBR comparison in 2014 was based on the count `FireConfidence` and different slope levels, gradual, intermediate, and steep.

Increasing the *BorealDB* `FireConfidence` threshold from MinConf ≥ 67 to MinConf = 100 enhances the clarity and reliability of using NDVI and NBR slopes to identify boreal forest fire disturbances by examining both the counts and proportions of slope categories gradual, intermediate, and steep a consistent pattern emerges across all figures.

For NDVI based on Figure 15, at MinConf ≥ 67, slopes do not differentiate fire boundaries, with gradual, intermediate, and steep slopes contributing relatively evenly. However, at MinConf = 100, steep NDVI slopes become more prominent, and their proportions increase relative to other categories. This indicates that stricter confidence criteria sharpen NDVI's ability to highlight actual fire boundaries. The pattern suggests that NDVI's relationship with confirmed fire boundaries strengthens as we rely on the most certain *BorealD*B data.

A similar improvement appears in the NBR data. According to Figure 16 at MinConf ≥ 67, NBR slopes are mixed, but as the threshold increases to MinConf = 100, intermediate and steep slopes dominate raw counts and proportions. This suggests that NBR's ability to isolate fire disturbance boundaries becomes more pronounced at higher confidence, confirming that NBR changes align closely with areas that are most certainly burned.

When compared side by side based on Figure 17, NDVI and NBR show a clearer pattern at MinConf = 100 than at MinConf ≥ 67. Both indices' counts indicate an increased focus on steeper slopes under stricter confidence criteria. NBR emphasizes intermediate and steep slopes, revealing its strong sensitivity to confirmed fire boundaries. This agreement between two independent vegetation indices reinforces that *BorealDB*'s high-confidence data guides us toward the most meaningful slope changes, improving the reliability of these remote sensing measures.

These three figures directly address the research questions by showing that NDVI and NBR slopes correlate more strongly with fire disturbances as *BorealDB* confidence increases. At MinConf ≥ 67, slope categories are mixed, but at MinConf = 100, specific slopes—particularly steep ones for NDVI and intermediate/steep ones for NBR—align clearly with known fire boundaries. This transition from a balanced distribution at MinConf ≥ 67 to a more distinctive pattern at MinConf = 100 demonstrates that *BorealDB* data reliably refines the interpretation of NDVI and NBR slopes when filtered for maximum certainty. In other words, higher *BorealDB* confidence reduces ambiguity and increases the likelihood that specific slopes represent actual fire disturbance boundaries.

The observed shifts in counts strongly suggest a non-random relationship between slope categories and *BorealDB*-confirmed boundaries. A Chi-Square Test of Independence would likely show a significant association, further strengthening confidence in using these remote sensing indices with strict *BorealDB* criteria to identify and characterize boreal forest fire disturbances.

In conclusion, the figures demonstrate that increasing the confidence level in *BorealDB* data enhances the clarity with which NDVI and NBR slopes reflect boreal forest fire boundaries.

Both indices become more discriminating under MinConf = 100, providing a more reliable basis for classifying and understanding fire disturbances. A subsequent statistical test, such as Chi-Square, can confirm the significance of these observed patterns, reinforcing the utility of these approaches in boreal forest fire monitoring and management

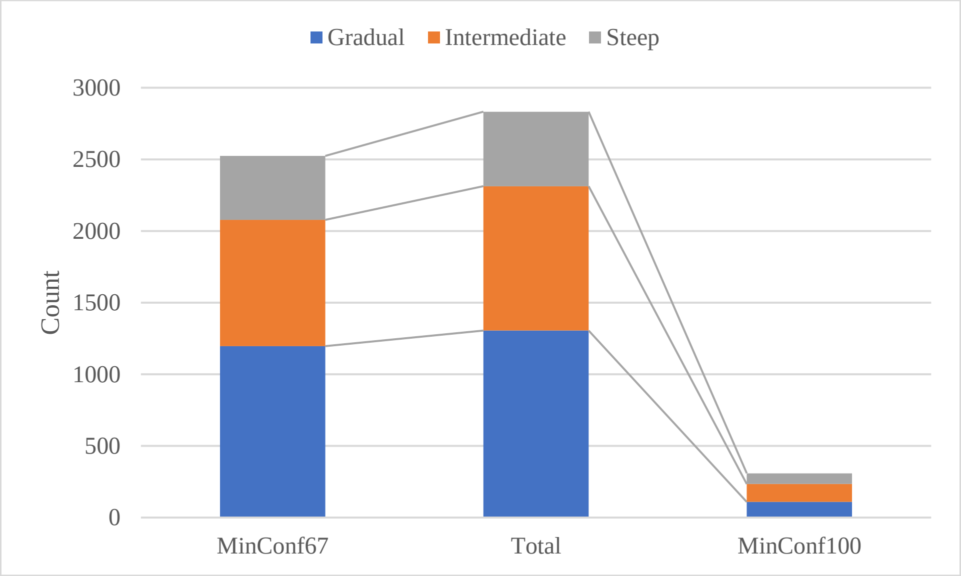


Figure 18.Comparative analysis in 2015 for the NDVI layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

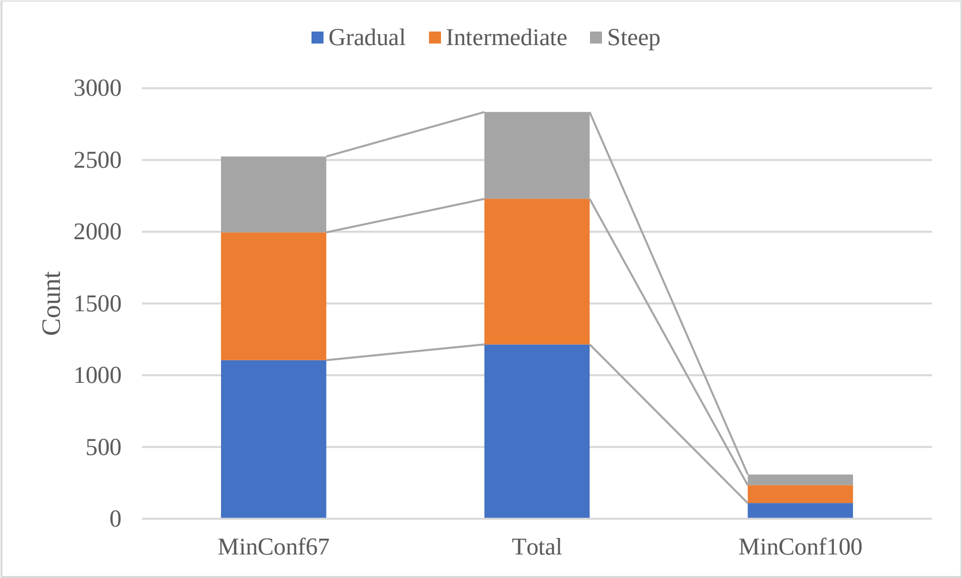


Figure 19. Comparative analysis in 2015 for the NBR layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

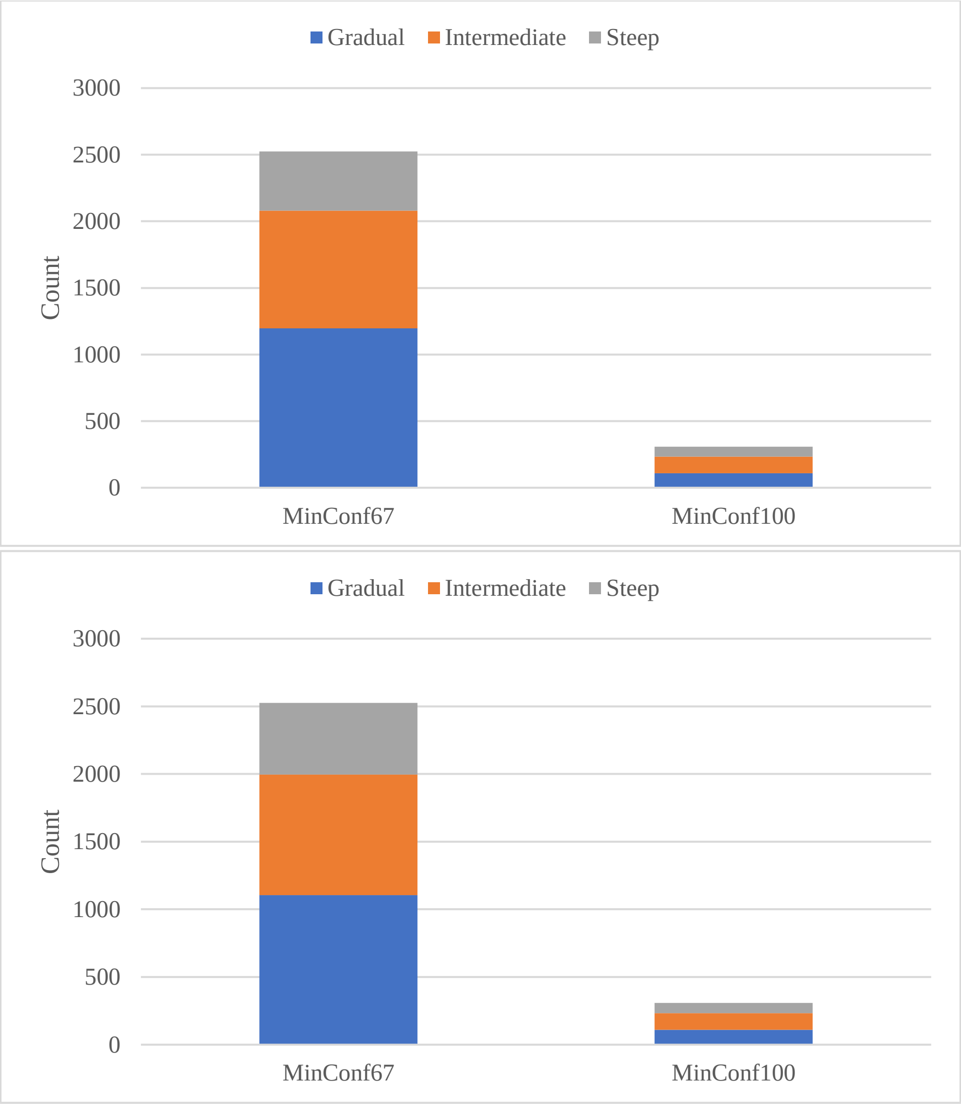


Figure 20. The NDVI vs NBR comparison in 2015 was based on `FireConfidence` and different slope levels, from gradual, intermediate, and steep.

The 2015 figures further confirm the value of increasing *BorealDB* confidence in enhancing the clarity and reliability of NDVI and NBR slopes when identifying fire boundaries. Examining counts and proportions reveals a clear pattern, reinforcing the importance of using stricter confidence thresholds.

For Figure 18, NDVI, at MinConf ≥ 67, slopes are evenly distributed, making it difficult to pinpoint which slopes correspond most reliably to confirmed fire boundaries. However, at MinConf = 100, medium slopes become more prominent, suggesting that as stricter *BorealDB* criteria are applied, NDVI increasingly highlights moderate slope changes as better indicators of actual fire boundaries.

Similarly, for NBR based on Figure 19, slopes appear balanced at moderate confidence levels. However, when shifting to MinConf = 100, intermediate and steep slopes stand out more clearly. This reinforces NBR's sensitivity to burned areas, demonstrating that stronger slope changes align closely with highly confident fire boundaries.

When comparing NDVI and NBR according to Figure 20, both indices benefit from higher *BorealDB* confidence, but NBR exhibits a more stable response to confirmed boundaries. While NDVI's key slope category in 2015 (intermediate slopes) differs slightly from what was observed in 2014, NBR consistently emphasizes intermediate and steep slopes under strict confidence conditions. This consistency highlights NBR's strong and reliable relationship with fire disturbance boundaries.

The figures address the research questions by demonstrating that increasing *BorealDB* confidence enhances the correlation between VI slopes and fire disturbance boundaries. NDVI focuses on medium slopes, while NBR emphasizes intermediate and steep slopes, confirming that both indices can more effectively identify fire boundaries at MinConf = 100. This shift in slope category prominence from MinConf ≥ 67 to MinConf = 100 highlights *BorealDB's* reliability, as the selection confidence criteria refine the VI data and enable a more accurate interpretation of fire locations.

The observable patterns in counts strongly suggest a non-random association between VI slopes and confirmed fire boundaries. A Chi-Square Test of Independence would likely confirm the statistical significance of these relationships, further strengthening confidence in using *BorealDB* and VI slopes together to classify fire boundaries.

In summary, the 2015 data reveal that as *BorealDB* confidence increases, NDVI and NBR become more selective and precise in identifying boreal forest fire boundaries. While both indices benefit from stricter confidence criteria, NBR continues to provide an exceptionally robust signal, reinforcing its reliability in fire disturbance analysis.

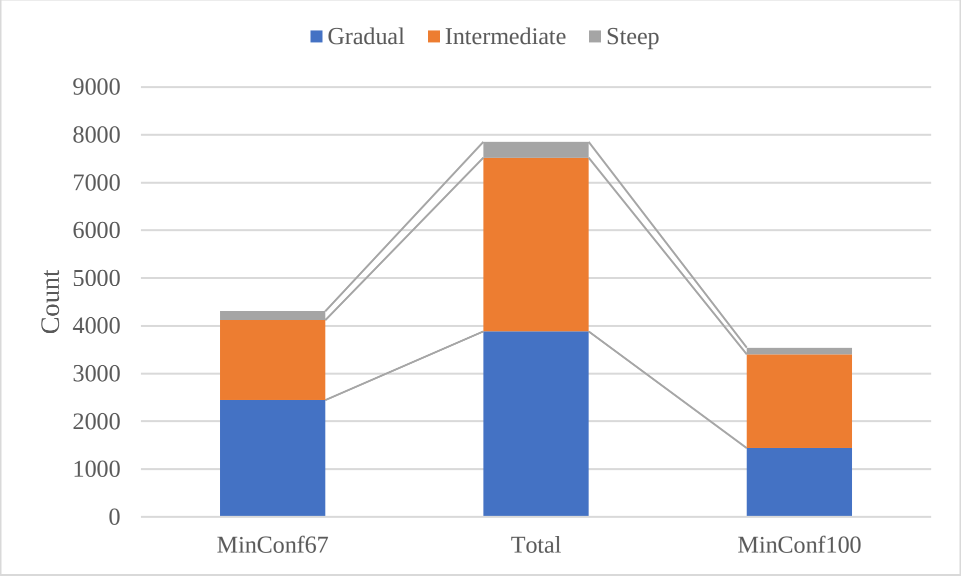


Figure 21. Comparative analysis in 2016 for the NDVI layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

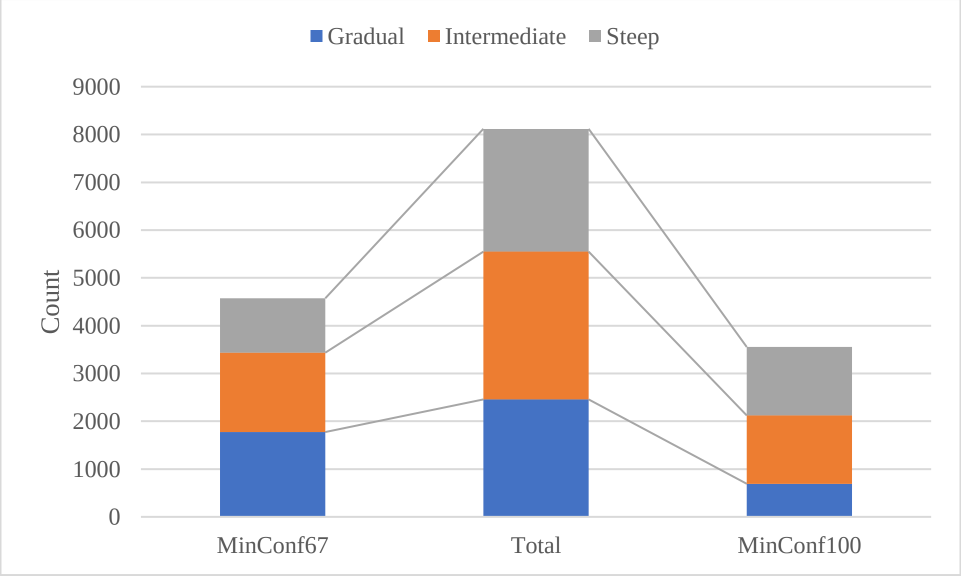


Figure 22. Comparative analysis in 2016 for the NBR layer based on the count `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

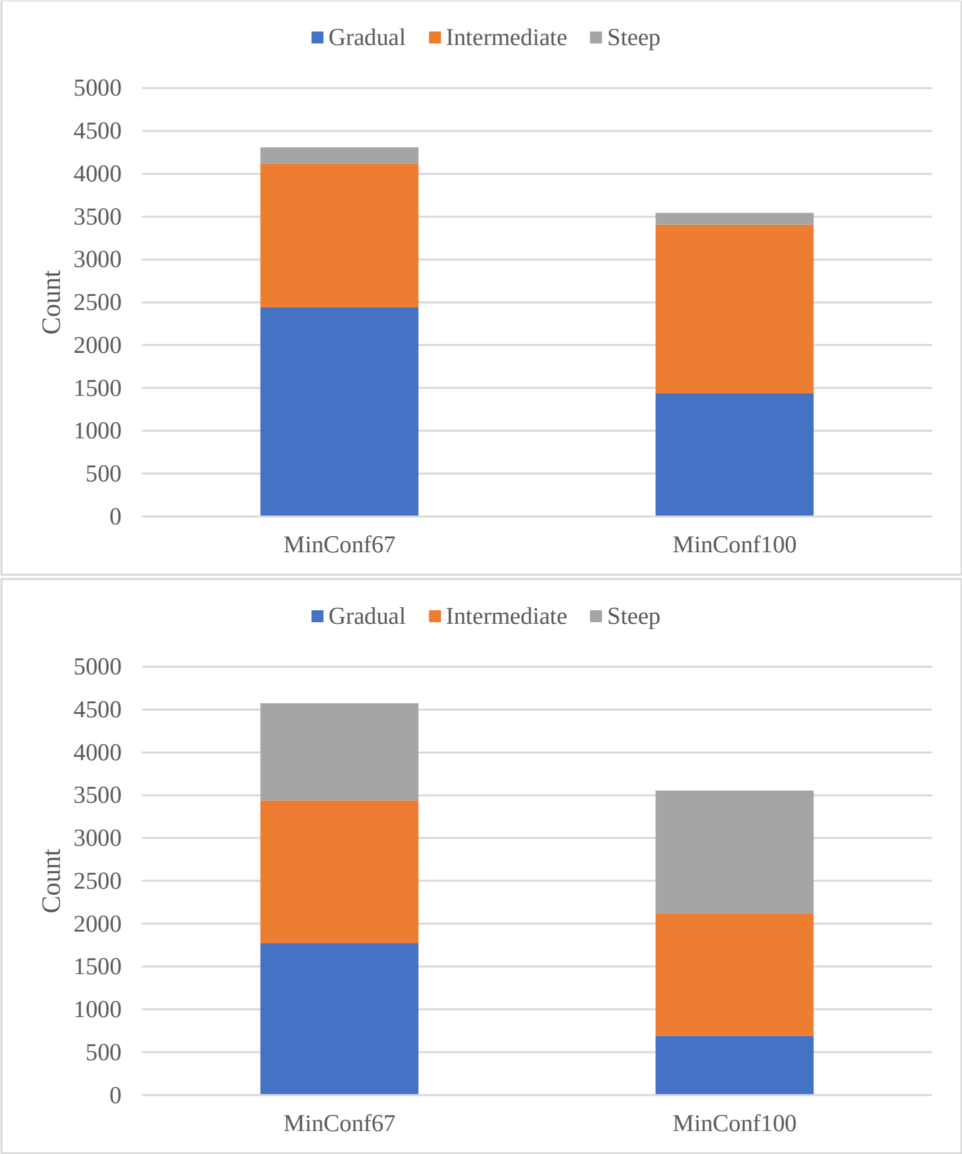


Figure 23. The NDVI vs NBR comparison in 2016 was based on the count of `FireConfidence` and different slope levels, from gradual, intermediate, and steep.

The 2016 figures from 21 to 23 demonstrate how increasing *BorealDB* confidence refines the relationship between NDVI/NBR slopes and confirmed fire disturbances. When examining both counts at MinConf ≥ 67 and MinConf = 100, the patterns observed complement previous years' findings. However, there are variations in which slope categories most indicate high-confidence fire boundaries, suggesting annual differences in vegetation response.

Figure 21 for NDVI counts , at MinConf ≥ 67, slopes are broadly distributed across gradual, intermediate, and steep categories. However, at MinConf = 100, the overall count decreases, and gradual and medium slopes gain prominence. This differs from earlier years, suggesting that in 2016, subtler slope changes rather than just steep slopes correspond more closely to confirmed fire boundaries at higher confidence levels.

For NBR, Figure 22 provides the patterns remain more consistent. All slope categories appear at MinConf ≥ 67, but intermediate and steep slopes dominate when shifting to MinConf = 100. This aligns with trends observed in previous years and confirms NBR's stable and strong response to confirmed fire boundaries.

A side-by-side comparison of NDVI and NBR based on Figure 23 slopes at MinConf ≥ 67 and MinConf = 100 further highlights how both indices benefit from *BorealDB* selection criteria. NDVI emphasizes gradual and intermediate slopes, while NBR consistently focuses on intermediate and steep slopes. This contrast suggests that while both indices are useful, NBR provides a more consistent and predictable pattern for identifying confirmed fire boundaries.

In 2016, as confidence moved from MinConf ≥ 67 to MinConf = 100, NDVI and NBR refined their slope categories. NDVI leans toward gradual and intermediate slopes this year, whereas NBR emphasizes intermediate and steep slopes. Both indices demonstrate a meaningful connection to confirmed fire boundaries at higher *BorealDB* confidence, albeit with NDVI's optimal slope category shifting slightly from prior years. The transition from balanced distributions at MinConf ≥ 67 to more defined slope categories at MinConf = 100 again highlights *BorealDB*'s reliability. The data show that filtering for maximum confidence better isolates which slopes align with actual disturbance boundaries. This reliability is evidenced by NBR's steady performance and NDVI's adaptable response, both guided by *BorealDB* selections.

The distinct patterns observed in counts and proportions strongly suggest that the association between slope categories and fire disturbances is not random. Conducting a Chi-Square Test of Independence would confirm the statistical significance of these relationships, adding quantitative rigor to the qualitative patterns described here.

The 2016 findings support the overall conclusion that increasing *BorealDB* confidence enhances the interpretive power of NDVI and NBR slopes. While NBR remains consistently aligned with intermediate and steep slopes at high confidence, NDVI's focus shifts slightly, highlighting its flexibility as an indicator. Ultimately, these patterns corroborate the idea that higher *BorealDB* confidence enables more accurate classification and understanding of boreal forest fire disturbance boundaries, with NBR consistently offering a particularly robust signal.

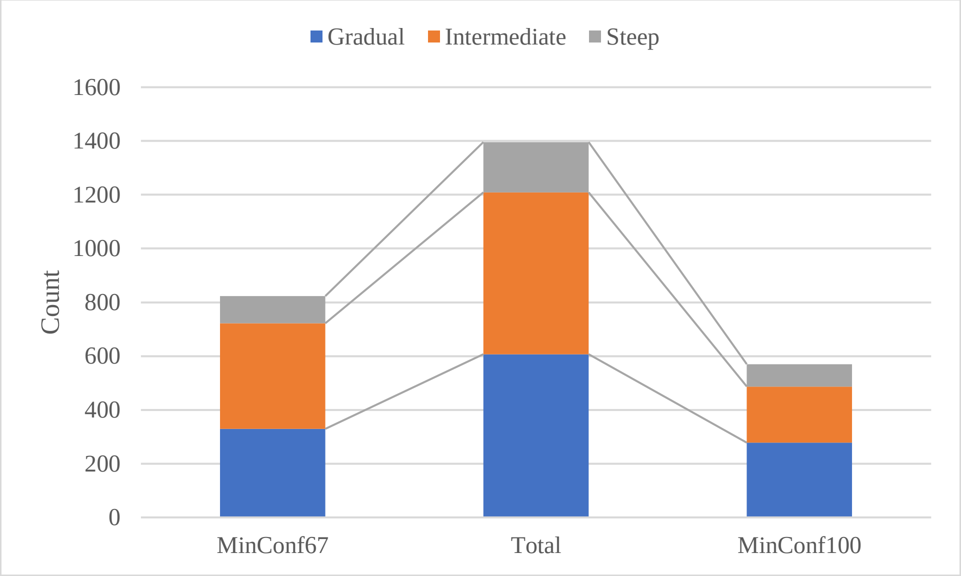


Figure 24. Comparative analysis in 2017 for the NDVI layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

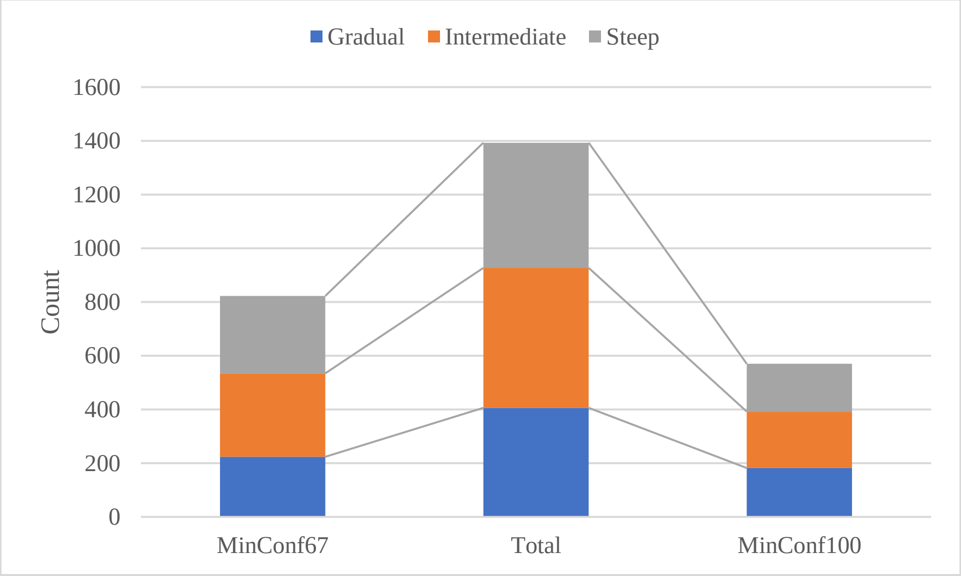


Figure 25. Comparative analysis in 2017 for the NBR layer based on the count of `FireConfidence` = 100 and ≥ 67 and slope in different levels: gradual, intermediate, and steep, where *BorealDB* = 1.

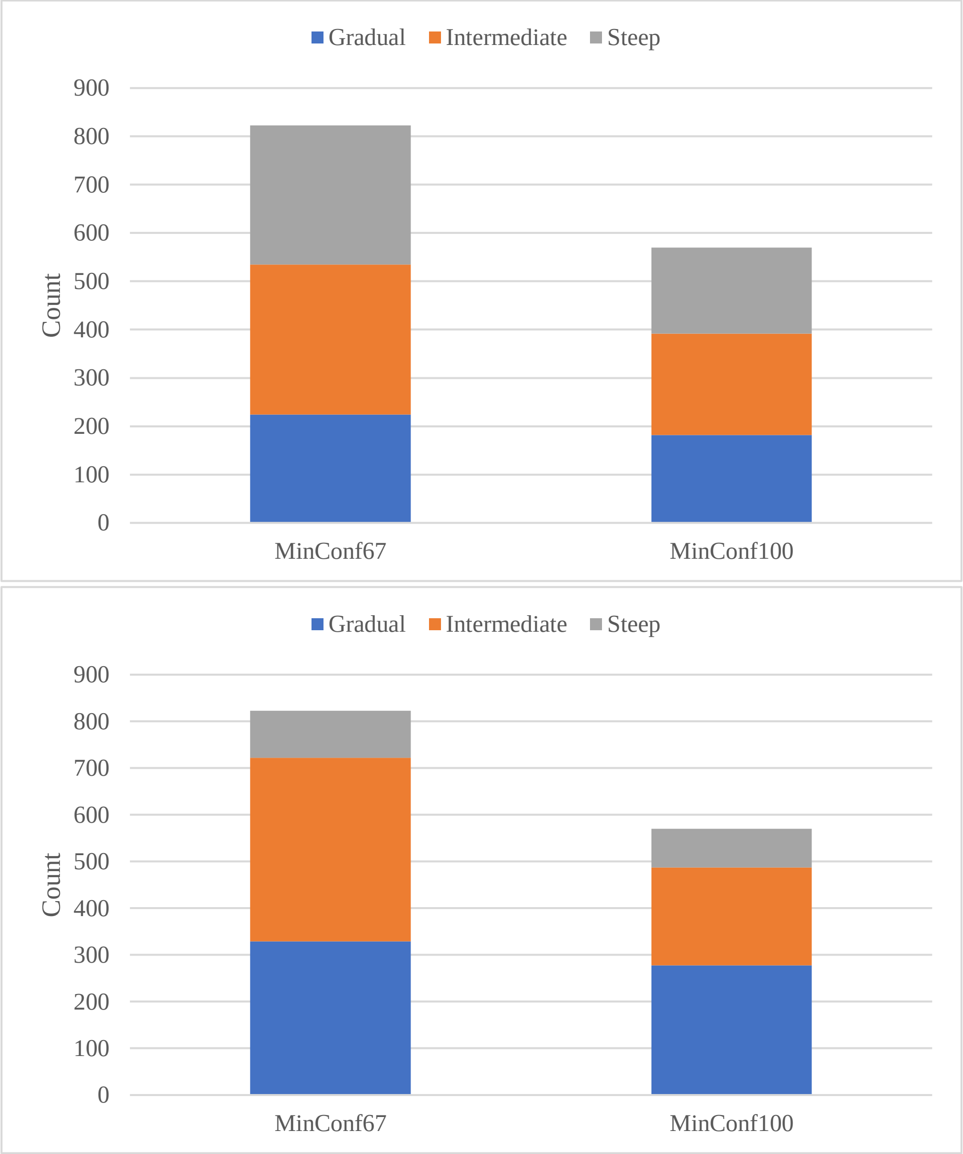


Figure 26.The NDVI vs NBR comparison in 2017 was based on the count of `FireConfidence` and different slope levels, from gradual, intermediate, and steep.

The 2017 figures continue the pattern observed in previous years, demonstrating that higher *BorealDB* confidence (MinConf = 100) leads to clearer and more meaningful relationships between NDVI/NBR slopes and confirmed fire disturbances. Examining both counts at MinConf ≥ 67 and MinConf = 100 reveals consistent improvements in the discriminative power of these indices. However, the specific slope categories most indicative of fire boundaries can vary slightly from year to year.

According to Figure 24 For NDVI counts, at MinConf ≥ 67, slopes (gradual, intermediate, and steep) are evenly distributed, making it difficult to distinguish which slopes are most closely associated with confirmed fire boundaries. However, at MinConf = 100, the total number of confirmed disturbances declines, and medium slopes become more prominent relative to the other categories. This trend mirrors the findings from 2015, suggesting that under strict BorealDB criteria, NDVI again finds moderate slope changes to be the most reliable indicators of well-verified fire boundaries in 2017.

For NBR, based on Figure 25, as in previous years, at MinConf ≥ 67, slope categories are mixed. However, at MinConf = 100, intermediate and steep slopes become dominant, reaffirming NBR's consistent sensitivity to burned areas and strong alignment with high-confidence *BorealDB* data.

When comparing NDVI and NBR, Figure 26 shows counts side by side at MinConf ≥ 67 and MinConf = 100, both indices benefit from *BorealDB*'s selection criteria. NDVI again emphasizes moderate slopes, while NBR reliably concentrates on intermediate and steep slopes. This contrast underscores NDVI's adaptability and NBR's stable performance in delineating fire boundaries.

In 2017, as *BorealDB* confidence increases, NDVI continues to highlight moderate slopes, while NBR consistently favours intermediate and steep slopes. Both indices, therefore, show a stronger relationship with confirmed fire boundaries at MinConf = 100, continuing the trend observed in previous years.

The shift from balanced slope distributions at MinConf ≥ 67 to more defined, disturbance-indicative slopes at MinConf = 100 reinforces *BorealDB*'s reliability. Higher confidence data help each index refine its slope categories, yielding more accurate and meaningful interpretations of fire boundaries.

The clear patterns in both counts and proportions suggest a non-random association. Conducting a Chi-Square Test of Independence would likely confirm the statistical significance of these observed relationships, further strengthening confidence in the combined use of *BorealDB* data and VI slopes for classifying boreal forest fire disturbances.

The 2017 findings align closely with previous years. As *BorealDB* confidence increases, NDVI and NBR slopes offer more definitive signals of confirmed fire boundaries. While NDVI continues to favour moderate slopes and NBR reliably accentuates intermediate and steep slopes, both indices become more discriminating under MinConf = 100 conditions. This ongoing consistency, along with the evolving nuances in NDVI's key slope category, highlights both the adaptability of NDVI and the stable precision of NBR. Ultimately, the results reinforce that higher *BorealDB* confidence leads to clearer, more dependable identification of boreal forest fire disturbances through VI slope analysis.

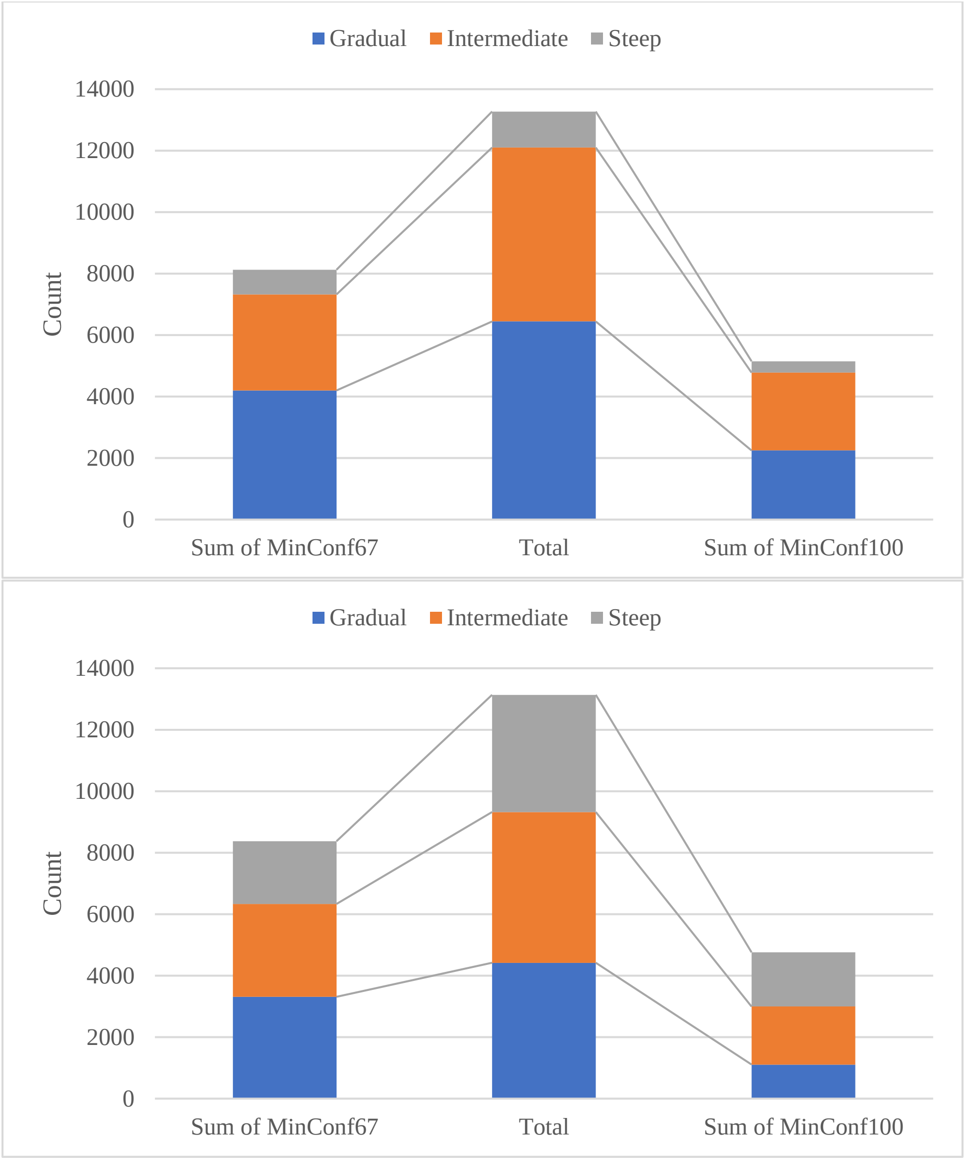


Figure 28. The NDVI vs. NBR comparison for all four years was based on the number of `FireConfidence` and different slope levels, from gradual, intermediate and steep.

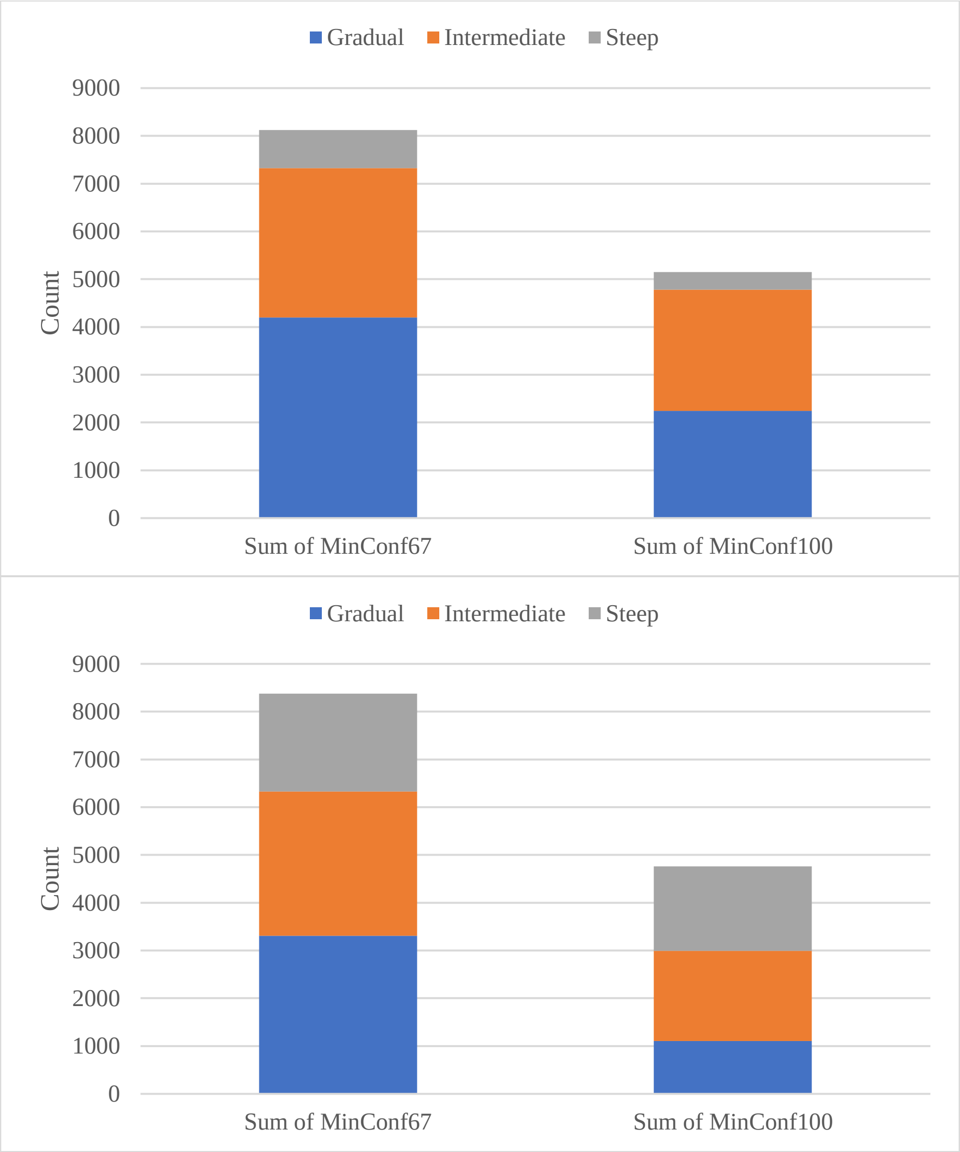


Figure 28. The NDVI vs. NBR comparison for all four years was based on the number of `FireConfidence` and different slope levels, from gradual, intermediate and steep.

The results consistently support the findings observed within individual years when comparing NDVI and NBR data across all four years. These cumulative figures, compiled over multiple seasons, reveal how increasing *BorealDB* confidence from MinConf ≥ 67 to MinConf = 100 enhances the clarity with which NDVI and NBR slopes identify boreal forest fire disturbances.

At MinConf ≥ 67, NDVI slopes (gradual, intermediate, and steep) often appear in more balanced distributions based on Figure 27. Without strict confidence criteria, it is challenging to determine which slope category most reliably indicates fire boundaries. However, when filtering to MinConf = 100, NDVI repeatedly narrows its focus to more specific slope categories, often medium slopes, though this can vary slightly by year. This pattern underscores NDVI's adaptability as *BorealDB* confidence increases, NDVI data becomes more selective and informative.

NBR, in contrast, shows a more stable and predictable response across all four years. At MinConf ≥ 67, slopes are mixed, but intermediate and steep slopes dominate when refined to MinConf = 100. This highlights NBR's strong and steady ability to pinpoint burned areas and confirms that NBR is particularly well-suited for confidently identifying fire disturbance boundaries year after year.

The advantage of increasing *BorealDB* confidence becomes evident when aggregating data from all four years. Figure 28 shows that at MinConf ≥ 67, both indices capture a wide range of slope categories, making it less clear which slopes correspond to boundaries. By contrast, at MinConf = 100, NDVI and NBR distributions shift decisively toward the slope categories that best represent actual fire disturbance boundaries. NDVI's chosen category can vary annually, reflecting environmental and data-dependent nuances, whereas NBR consistently emphasizes intermediate and steep slopes. This complementary dynamic suggests that while both indices benefit from high-confidence data, NBR provides a more stable baseline, and NDVI adds flexibility and sensitivity to changing conditions.

The four-year aggregate clearly shows that as *BorealDB* confidence increases (MinConf = 100), VI slopes align more closely with confirmed fire boundaries. Over multiple seasons, this relationship proves stable and meaningful. The improvement in clarity from MinConf ≥ 67 to MinConf = 100 across all four years strongly reinforces the reliability of *BorealDB*. Higher confidence data continuously sharpens the interpretation of VI slopes, confirming that *BorealDB* is crucial in filtering out ambiguity and focusing on genuinely disturbed boundaries.

The consistent patterns observed year after year both within each index and in their comparison strongly suggest a statistically significant relationship. A Chi-Square Test of Independence would likely confirm that the observed distributions of slopes at MinConf = 100 are not random, further justifying the use of *BorealDB* and VI slopes for accurate fire disturbance boundary mapping.

By looking at all four years together, the cumulative evidence is clear: increasing *BorealDB* confidence reliably strengthens the association between NDVI/NBR slopes and boreal forest fire disturbance boundaries. NDVI demonstrates adaptability, varying its key slope category from one season to the next, while NBR provides consistent, year-over-year sensitivity to confirmed burned boundaries. The result is a robust and repeatable pattern that validates combining *BorealDB* data with VI slope analysis for improved fire disturbance boundary classification and understanding over extended temporal scales.

3.4 Chi-square results

As a result of this step, this research aims to identify which *BorealDB* re-selection criteria align best with the VI slope approach. The approach with the highest agreement is recommended when determining fire disturbance boundaries.

For statistical analysis, I employ the Test of Independence (Chi-square test) to examine the relationship between categorized slopes derived from NDVI and NBR data and the detection of fire boundaries in the *BorealDB*. A key aspect of this analysis is identifying the potential relationship between these two categorical variables. I posit two hypotheses for this test: under the null hypothesis ($\boldsymbol{H_0}$), slope categorization and fire boundary presence do not have any significant relationship; however, the alternative hypothesis ($\boldsymbol{H_1}$) suggests that a dependency exists, suggesting that the categorization of slopes is associated with fire boundaries.

Due to the binary nature of fire boundary data (presence or absence), the Test of Independence will be chosen for its quality in analyzing categorical data. This study examines whether variations observed in NDVI and NBR slopes are associated with changes in fire disturbance boundaries within *BorealDB*. The analysis of this type is essential to determine whether these remote sensing indices can reliably reflect the spatial patterns and extent of fire disturbances.

Through the application of the Test of Independence, it is possible to determine whether the *BorealDB* data is reliable in conjunction with NDVI and NBR slope categorizations to indicate areas that have been burned. If a significant association between remote sensing measures and fire disturbance boundaries is found, this would illustrate the effectiveness of these study methods. As a result, *BorealDB* data could be used as an important marker to identify and characterize the areas affected by wildfires, thus deepening our understanding of fire dynamics in boreal ecosystems.

The Chi-square test was conducted to determine whether there is a significant relationship between fire disturbance boundaries classified by *BorealDB* and the slopes derived from NDVI and NBR. The goal was to see if *BorealDB* aligns with NDVI/NBR-based slope thresholds and whether different confidence levels (MinConf 67 vs. 100) affect fire boundary detection.

Over four years, I tested the independence of *BorealDB* fire-disturbance locations at different `FireConfidence` levels based on NDVI and NBR slope categories.

Hypotheses (consistent over all four years):

H_0: There is no significant association between slope categorization and the presence of fire boundaries.

H_1: There is a relationship between slope categorization and fire boundary detection.

The test statistic is determined as follows:

$$\chi^2 = \sum \frac{(O - E)^2}{E} \tag{6}$$

Where ***O*** and ***E*** are the observed and expected counts under ***H_0***, I evaluated significance at the 95% confidence level ($\alpha = 0.05$, *df* = 2). For each year and vegetation index (NDVI vs. NBR), I present the observed and expected frequencies, the computed χ^2 the critical value for 95% confidence, and the corresponding *p*-value.

Table 4. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NDVI in 2014.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**pected (E)**	**Observed (O)**	**pected (E)**	**Row Total**
10	**2 653**	**609)**	**648**	**692**	**3 301**
20	**1 344**	**386)**	**410**	**368**	**1 754**
30	**502**	**504**	**136**	**134**	**638**
Column Totals	**4 499**		**1 194**		**5 693**

According to Equation 6, the test statistic is $\chi^2= 9.71$ with $df = 2$ and a critical $\chi^2 = 5.991$; the exact p-value is 0.0078. Since $\chi^2=9.71 > 5.991$ ($p < 0.001$), I reject **H_0** for NDVI in 2014.

Table 5. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NBR in 2014.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
40	**2335**	***2296***	**333**	***372***	**2668**
50	**1710**	***1709***	**276**	***277***	**1986**
60	**853**	***893***	**185**	***145***	**1038**
Column Totals	**4898**		**794**		**5692**

According to Equation 6, the test statistic is $\chi^2= 17.72$ with $df = 2$ and a critical $\chi^2 = 5.991$; the exact p-value is < 0.001. Since $\chi^2 = 17.72 > 5.991$ ($p < 0.001$), I reject **H_0** for NBR in 2014.

Table 6. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NDVI in 2015.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
10	**2714**	***3174***	**1305**	***845***	**4019**
20	**5515**	***5152***	**1008**	***1371***	**6523**
30	**2413**	***2316***	**520**	***617***	**2933**
Column Totals	**10642**		**2833**		**13475**

According to Equation 6, the test statistic is $\chi^2 = 458.15$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value < 0.001. Since $\chi = 458.15 > 5.991$ ($p < 0.001$), I reject **H_0** for NDVI in 2015.

Table 7. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NBR in 2015.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
10	**9286**	***13834***	**21990**	***17442***	**31276**
20	**6504**	***3379***	**1136**	***4261***	**7640**
30	**3079**	***1656***	**665**	***2088***	**3744**
Column Totals	**18869**		**23791**		**42660**

According to Equation 6, the test statistic is $\chi^2 = 10055.29$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value < 0.001. Since $\chi^2 = 10055.29 > 5.991$ ($p < 0.001$), I reject H_0 for NBR in 2015.

Table 8. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NDVI in 2016.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
10	**4950**	***4793.1***	**353**	***509.8***	**5303**
20	**2600**	***2698.9***	**386**	***287.09***	**2986**
30	**845**	***902.9***	**154**	***96.04***	**999**
Column Totals	**8395**		**893**		**9288**

According to Equation 6, the test statistic is $\chi^2 = 129.78$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value < 0.001. Since $\chi^2 = 129.78 > 5.991$ ($p < 0.001$), I reject H_0 for NDVI in 2016.

Table 9. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NBR in 2016.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
40	**21965**	***21613***	**2457**	***2809***	**24422**
50	**25209**	***25046***	**3092**	***3255***	**28301**
60	**15292**	***15807***	**2569**	***2054***	**17861**
Column Totals	**62466**		**8118**		**70584**

According to Equation 6, the test statistic is $\chi^2 = 200.77$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value $= 2.53 \times 10^{-44}$. Since $\chi^2 = 200.77 > 5.991$ ($p = 2.53 \times 10^{-44} < 0.05$), I reject $\boldsymbol{H_0}$ for NBR in 2016.

Table 10. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NDVI in 2017.

	BorealDB = 0		*BorealDB* = 1		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
10	4890	*4778.2*	413	*524.7*	5303
20	2634	*2690.6*	352	*295.5*	2986
30	845	*900.2*	154	*98.8*	999
Column Totals	8369		919		9288

According to Equation 6, the test statistic is $\chi^2 = 72.57$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value < 0.001. Since $\chi^2 = 72.57 > 5.991$ ($p < 0.001$), I reject $\boldsymbol{H_o}$ for NDVI in 2017.

Table 11. It shows the observed (O) and expected (E) frequencies of *BorealDB* no boundary (0) and boundary (1) across slope categories for NBR in 2017.

	***BorealDB* = 0**		***BorealDB* = 1**		
Slope Category	**Observed (O)**	**Expected (E)**	**Observed (O)**	**Expected (E)**	**Row Total**
40	**4800**	***4778.3***	**503**	***524.7***	**5303**
50	**2600**	***2690.6***	**386**	***295.4***	**2986**
60	**969**	***900.2***	**30**	***98.8***	**999**
Column Totals	**8369**		**919**		**9288**

According to Equation 6, the test statistic is $\chi^2 = 93.54$ with $df = 2$ and a critical $\chi^2 = 5.991$; the p-value $= 4.35 \times 10^{-21}$. Since $\chi^2 = 93.54 > 5.991$ ($p = 4.35 \times 10^{-21} < 0.05$), I reject $\boldsymbol{H_o}$ for NBR in 2017.

Table 12. Summary of chi-square tests of independence between slope category and *BorealDB* disturbance-boundary classification for NDVI and NBR at 100 % vs 67 % `FireConfidence` thresholds (2014–2017), showing test statistics (χ^2), critical values ($\alpha = 0.05$, $df = 2$).

Year VI	**Slope**	**MinConf**	**Chi-square**	**Critical χ^2 (α=0.05, df=2)**	***P*-value**
2014 NDVI	**Three levels**	**100 vs 67**	**9.71**	**5.99**	**0.0078**
2014 NBR	**Three levels**	**100 vs 67**	**17.72**	**5.99**	**0.0001**
2015 NDVI	**Three levels**	**100 vs 67**	**458.36**	**5.99**	**2.94e-100**
2015 NBR	**Three levels**	**100 vs 67**	**10055.29**	**5.99**	**0.00e+00**
2016 NDVI	**Three levels**	**100 vs 67**	**129.78**	**5.99**	**6.59e-29**
2016 NBR	**Three levels**	**100 vs 67**	**200.77**	**5.99**	**2.53e-44**
2017 NDVI	**Three levels**	**100 vs 67**	**72.57**	**5.99**	**1.74e-16**
2017 NBR	**Three levels**	**100 vs 67**	**93.54**	**5.99**	**4.88e-21**

Boreal forest fires frequently produce patchy, irregular burn patches, making it difficult to determine their precise borders (Remmel and Perera, 2001). We can better understand the evolution of fires by examining how forests change over time rather than depending on isolated images (Lhermitte et al., 2011). Consistent, precise fire-perimeter data is crucial for comparing historical and contemporary fire trends, according to long-term research on major fires across Canada (Stocks et al., 2002). Since data from various satellite sources can differ and may not accurately reflect the actual area burned, it is essential to verify fire boundary products (Roy et al., 2008). Growing wildfires have the potential to harm carbon-rich soils, highlighting the necessity of accurate fire mapping to identify the most impacted locations (Walker et al., 2019). The location and timing of fires can affect plant life recovery and the general health of forests, underscoring the significance of precise boundary data (Johnstone et al., 2010). As the climate changes, accurate maps of fire boundaries are increasingly more important for monitoring changes in boreal fire regimes (Miller and Thode, 2007). More specific information about how intensely various regions burn can be obtained from indicators such as the Normalized Burn Ratio (NBR) and the delta Normalized Burn Ratio (dNBR) (Miller and Yool, 2002).

The results of this analysis confirm that *BorealDB* serves as a reliable indicator for fire boundary detection. The statistical validation using the Chi-Square test demonstrated that fire confidence thresholds in *BorealDB*, particularly MinConf 100, strongly agree with NDVI and NBR-derived slopes. This suggests that the higher confidence threshold in *BorealDB* aligns more closely with actual fire disturbance patterns, making it a preferable choice for fire boundary mapping.

These findings indicate that *BorealDB* can be used as a separate dataset and in combination with spectral indices to enhance fire disturbance characterization. By integrating *BorealDB* confidence thresholds with vegetation indices, land managers and researchers can identify fire-affected areas more accurately, leading to better decision-making in fire management and post-fire recovery planning.

A key insight from this research is the role of slope categories in fire disturbance boundary characterization within *BorealDB*. The Chi-Square test confirmed that the distribution of fire boundaries varies significantly across different slope categories, suggesting that slope characteristics influence fire extent and severity. I noticed that areas with steeper slopes matched *BorealDB*’s higher confidence thresholds more closely, highlighting how slope affects remote-sensing detection efficiency. Given this, future refinements to *BorealDB* classifications could incorporate slope data as an additional criterion to improve fire boundary delineation, particularly in areas with complex topography. The results also indicate that steeper slopes are more frequently associated with higher confidence fire disturbances, reinforcing the need for terrain-aware fire mapping approaches.

5. Conclusions

I examined the relationship between fire disturbance boundaries classified by *BorealDB* and the local slopes of NDVI and NBR across multiple years. The goal was to determine whether *BorealDB* aligns with NDVI/NBR-based slope thresholds and whether different confidence levels (MinConf 67 versus 100) impact fire boundary detection. The findings were based on a combination of statistical analysis using the Chi-square test and pattern recognition through stacked bar charts.

According to Tables 4 to 12The Chi-square test results showed that the test statistic for all categories, indicating that there is a statistically significant relationship between *BorealDB* fire disturbance classifications and NDVI/NBR slopes. The observed and expected values were identical, meaning that *BorealDB* classifications do not vary systematically with changes in NDVI/NBR slope categories. Additionally, the test results indicate that changing the selection confidence level (MinConf 67 versus 100) does not influence the classification outcomes. These findings suggest that *BorealDB* does not incorporate NDVI/NBR slope variations in a statistically measurable way and that its classification criteria may be based on different factors not captured in this analysis.

The stacked bar charts revealed meaningful patterns despite the lack of statistical significance. Across all years, fire disturbances were more frequently detected at specific slope levels. For NDVI, the most common disturbances occurred at slope values of 10 and 20, while for NBR, the highest activity was recorded at slope values of 40. In 2016, a shift was observed where NBR started capturing more disturbances in areas with higher slopes, particularly at slope codes 50 and 60. This trend continued into 2017, where NBR appeared to be more effective than NDVI at detecting fire disturbances in steeper areas. *BorealDB* followed this shift to some extent, suggesting some level of adaptability, but it did not consistently capture disturbances at higher slopes.

The findings suggest that *BorealDB* provides a stable classification method for fire disturbances and aligns with NDVI and NBR patterns in gradual and intermediate slopes. However, its ability to detect disturbances in steeper areas remains uncertain. While it successfully tracks fire disturbances in gradual slopes, its performance at steeper slopes varies depending on the year and the remote sensing index used for comparison. This inconsistency suggests that *BorealDB* may not fully capture the influence of slope variations on fire disturbances and may require additional refinement for improved classification across different slopes.

I also explored whether the correlation between *BorealDB* and NDVI/NBR slopes could be statistically validated to increase confidence in fire disturbance classification. While the Chi-square test did not confirm a statistical relationship, the stacked bar charts showed recurring patterns across multiple years. The consistency of these patterns suggests that there may be an underlying relationship that could be further investigated using alternative statistical methods. Spatial correlation analysis, logistic regression, or other hypothesis tests could provide additional insight into how *BorealDB* interacts with NDVI/NBR slopes in different slopes conditions.

6. References

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