EXPLOITING OVERLAPPING LANDSAT SCENE CLASSIFICATIONS AND FOCAL CONTEXT TO IDENTIFY BOREAL DISTURBANCE MAPPING UNCERTAINTY

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Abstract

The BorealDB dataset is derived from a mosaic of Landsat scenes that were independently classified to identify historic fire and timber harvesting disturbances within Ontario. This thesis identifies and flags areas of classification uncertainty within BorealDB and scrutinizes them to assess classification confidence. The focal context of all orthogonal neighbour states was quantified to feed classification tree (CT) and random forest (RF) classifiers to predict focal disturbance classes. Uncertainty is deemed to exist where BorealDB and predicted CT or RF classes disagree. When RF and CT predictions were compared with the BorealDB classes, RF predicted more uncertainty (58%) than CT predictions (15%). Sampled locations compared with original satellite imagery and visual assessments suggested uncertainty depended on classifier, disturbance type, and spatial neighbours. Timber harvest disturbance classifications had the most uncertainty and CT predictions was the most consistent with neighbouring classifications and visual assessments indicating it is more effective than RF.

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Acronyms and abbreviations

AFFES:	Aviation Forest Fires and Emergency Services
BorealDB:	Boreal Disturbance Database
CART:	Classification and Regression Tree
CFF:	Coarse and Fine Filter Management Approach
CNDFB:	Canadian National Fire Database
CT:	Classification Tree
eFRI:	Enhanced Forest Resource Inventory
FMP:	Forest Management Plans
FRI:	Forest Resource Inventory
LFDB:	Large Fire Database
MA:	Managed Area
MNRF:	Ministry of Natural Resources and Forestry
NBR:	Normalized Burn Ratio
NDMNRF:	Ministry of Northern Development, Mines, Natural Resources and Mines
NDVI:	Normalized Difference Vegetation Index
NFT:	National Forest Inventory
NRCAN:	Natural Resources Canada
RF:	Random Forest

1. Introduction

The boreal forest is one of the world's largest biomes, it is characterized as disturbance prone, a cold climate, and widely distributed extending across multiple countries within the northern hemisphere (Brandt et al., 2013). The boreal forest is a valuable part of Canadian history, environment, economy, and culture (NRCan, 2019). Taking into consideration the environmental, economic, and cultural needs understanding the boreal in its entirety becomes a monumental task undertaken by forest managers who are responsible for the long-term health of the ecosystem. To accomplish this task historical data of the forest state is often used to inform forest management decision making often in the form of geospatial data (Drever et al., 2006). However geospatial data is often an abstracted and simplified representation of complex geographical realities (Zhang and Goodchild, 2002). Thus, geospatial data will often contain a degree of uncertainty.

Multiple attempts have been made to record historic disturbance data of Canada's Boreal Forest including the Forest Resource Inventory (FRI) (MNRF, 2021a) the Enhanced Forest Resource Inventory (eFRI) (MNRF, 2014), and the National Forest Inventory (NFI) (Gillis et al., 2005) and the Canadian National Fire Database (CNFDB) (NRCan, 2022) but these attempts were hampered by several limitations. First, existing historic data often lack standards for assembling and portraying the data, with varying data sources and definitions depending on the user (Gillis and Leckie, 1996). Secondly existing historic data is often aspatial, limited spatially, and/or temporally limited (Gerard et al., 2003; Eskelson et al., 2009; White et al., 2017). Finally existing data is often presented as deterministic (NRCan, 2022), despite natural disturbances having irregular edges as opposed to crisp boundaries (Remmel and Perera, 2009).

In recognition of these limitations, Ouellette et al. (2020) worked to overcome them by addressing them with the Boreal Disturbance Database[1], hereafter referred to as BorealDB, a disturbance database containing representations of large historic fire and timber harvesting boreal disturbances within the Ontario's Managed Area (MA), from 1972 to the present (Ouellette et al., 2020). BorealDB portrays disturbances as points, arranged in a regular grid-like pattern, derived from individually classified Landsat scenes. Spatial uncertainty within BorealDB was assessed by quantifying the focal contextual data of each point to identify areas of classification uncertainty caused by overlapping Landsat scenes. Note that when this research began, the area now referred to as the MA was labelled as the Area of Undertaking and hence older references and documents may contain this terminology, the area will be referred to as the MA throughout this thesis.

1.1 The Boreal Forest

The boreal forest is one of the world's most important bio-geoclimatic areas (Brandt, 2009). The boreal forest (known as Taiga within Eurasian countries) is distributed throughout the global north, extending across multiple high latitude countries such as Canada, USA (Alaska), Norway, Sweden, Finland, and Russia at high latitudes of between 45°N to 75°N (WWF, 2012). Despite all boreal forests sharing similar

[1] **(Remmel, T.K., Perera, A.H., Ouellette, M., 2020. Boreal Disturbance Database [WWW Document]. URL https://www.borealdb.ca/download.html)**

characteristics and latitudinal extents, regional differences exist within their ecological compositions. Comparing Canadian and Russian boreal forests, Canadian fire regimes were found to be more susceptible to crown fires than Russian forests which were more prone to surface fires. These differences are due to Canadian forest composition being predominately Black Spruce (*Picea mariana*), which have highly flammable foliage and low-lying branches that become ladder fuels that support the transition of surface fires to crown fires (de Groot et al., 2013). In comparison Russian forests contain a considerable amount of Larch (*Larix*) which have a high moisture content within their needles (de Groot et al., 2013).

Canada holds a significant percentage of Boreal Forest accounting for approximately 28% of the global boreal forest area (NRCan, 2019). Canada's boreal forests encompasses much of Northern Canada extending through many of its provinces and territories, the region is depicted in Figure 1. The characteristics of boreal forests are shaped predominately by climate influences which lead to differences between the regions within plant and animal taxa (Boonstra et al., 2016). Ontario's boreal forests are comprised primarily of coniferous and mixed wood forests with tree species such as Black Spruce, White Spruce (*Picea glauca*), Balsam Fir (*Abies basamea*), Trembling Aspen (*Populus tremuloides*), White Elm (*Ulmus americana*), Black Ash (*Fraxinus nigra*), and Tamarack (Larix laricina) (MacDonald, 1995). Canada's boreal forest acts as a habitat for various animal species including big wildlife such as: Black Bears, Caribou, Gray Wolves, and Moose (Franklin et al., 2019); insects such as: Springtails, Beetles and Centipedes (Ferguson and Berube, 2004); and birds such as:

Black-Capped Chickadees, Downy Woodpeckers, and Easter Bluebirds (Cullinane-Anthony et al., 2014); and various other types of wildlife.

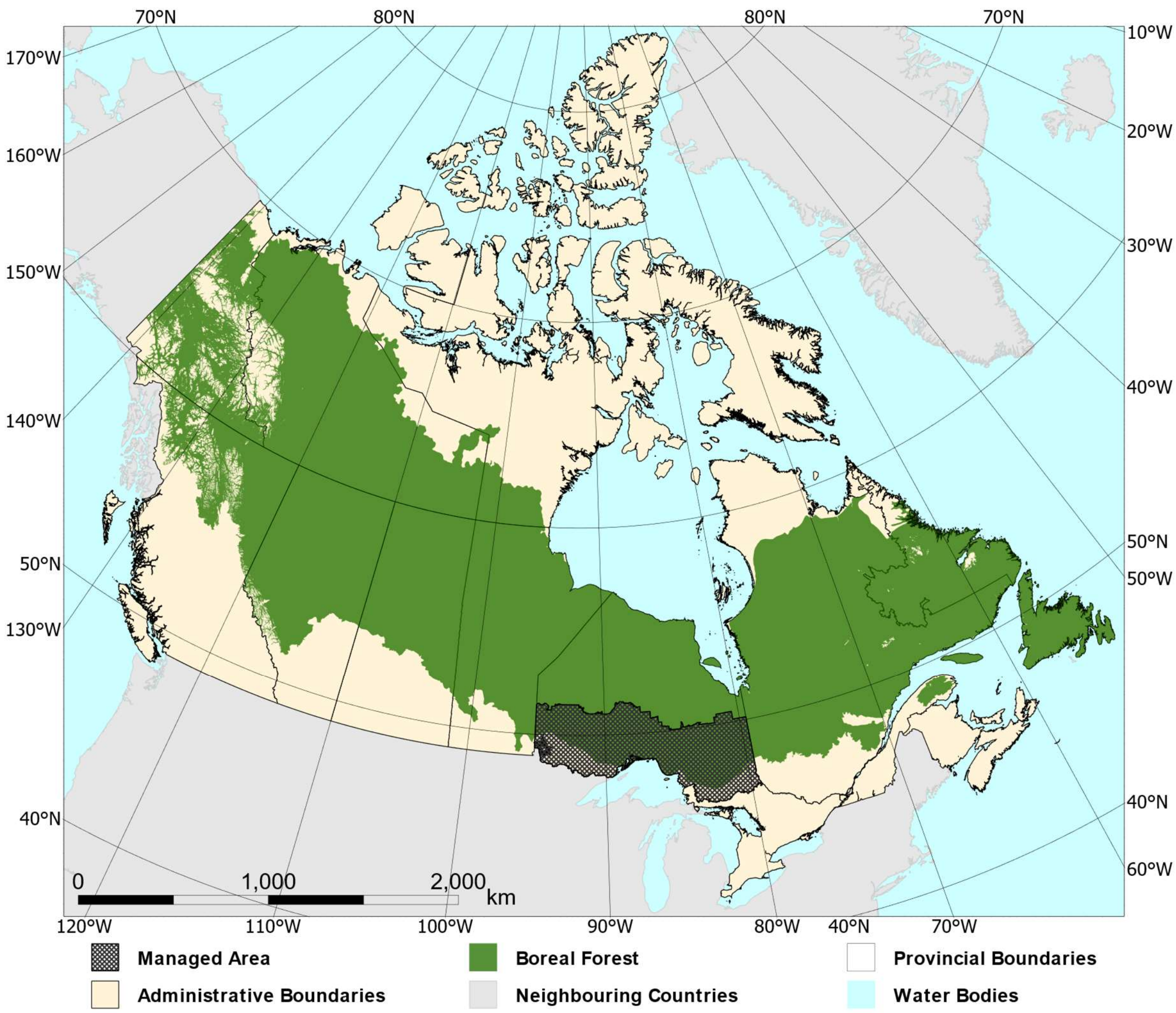


Figure 1. The extent of boreal forest within Canada. Data acquired from Brandt (2009) and Statistics Canada (2016).

Due to low temperatures, organic matter decomposition is inhibited within the boreal which leads to large quantities of carbon storage within soils (Schlesinger and Andrews, 2000) and peatland, which are commonly located within the Hudson Bay

Lowlands (Gorham, 1991). These carbon stores becomes problematic when taking into consideration the relationship between the stores and fire disturbances, which are capable of releasing large quantities of carbon into the atmosphere that are stored within older forested stands (Miquelajauregui et al., 2019).

1.1.1 Forest Disturbances

Forest disturbances are events within forested landscapes that drastically change the vegetation dynamics of the region, they are ecological processes intrinsic to the history and development of boreal forests. The abundance and distribution of wildlife is often influenced by the presence of forest disturbances in which their effects can vary regionally (DeMars et al., 2019). Forest fires are an important phenomenon that influence the global ecosystem (Bowman et al., 2009) with large crown fires capable of altering carbon cycling over large areas allowing for the release of carbon into the atmosphere (Kashian et al., 2006). To understand the influence of disturbances on landscapes, it is important to understand their causes.

Disturbances can be classified into two main categories. The first are natural disturbances, disturbances that occur without human influence (Hunter, 1996). Forest fires are a primary example of natural disturbances, they typically start from lightning strikes which spread due to abundances of biomass fuel (de Groot et al., 2009), favourable moisture conditions, and favourable wind conditions (Xavier Viegas, 1998). While fire disturbances can have anthropogenic origins, they often represent a small fraction of the total area burned. As an example within Ontario, in 2019 human activity caused fires burned 16,274 ha of forest while lightning caused fires burned 253,446 ha (National Forestry Database, 2020). Forest fires are the main stand replacing disturbance in Canadian forests impacting approximately 1.56 million ha of forest per year (Hermosilla et al., 2019). Within the MA between 2015 – 2019 approximately 774,279 ha of forest was consumed by fire with data showing a steady increase in area of forest burned annually (MNRF, 2021b). Forest fire disturbances are highly dependent on weather conditions and fuel availability. The fuel in question is partially decomposing organic matter which is derived from surface fuels such as leaf litter and woody debris, subsurface fuels predominated by decaying organic matter, coarse surface fuels such as downed trees, and canopy fuels such as foliage (Perera and Buse, 2014).

The fluctuations in the distribution and spatial scale of forest fires cause an inherent patchiness within the landscape (Hély et al., 2001). Forest fires are the most common natural disturbance within Ontario forests due to the wide availability of combustible fuel. The majority of the fires that occur within North America are crown fires that have high intensity and severity and affect large areas of forest (Perera and Buse, 2014).

The second category of disturbances are anthropogenic in origin; these involve human triggers such as timber harvesting disturbances which are connected through road construction (San-Miguel et al., 2017). Timber harvesting disturbances are the second most common disturbance within Ontario. Harvesting disturbances are driven by anthropogenic factors such as approved harvesting limits set out in forest management plans and the conditions of the forestry product market (MNRF, 2016). Due to forest management practices the area harvested annually within the MA has been consistent, averaging 120,000 ha between 2015 – 2019, an area within approved harvesting limits (MNRF, 2021b).

While boreal forest disturbances can cause drastic changes to the local environment, they are important to the overall ecological health of the ecosystem. It has been theorized that disturbances are required by forests in order to persist as being tree dominated communities (Perera et al., 2004). While forest disturbances can have wide impacts upon forested landscapes, the extent differs between disturbance events and types. Disturbance types have an impact on the spatial patterns of vegetation, fire disturbance scars have lower heterogeneity in landcover types but are larger and less patchy than timber harvesting disturbance scars (Schroeder and Perera, 2002).

Disturbances influence landscapes by characterizing disturbance regimes that describe how disturbance frequency and scale change through time (Girardin et al., 2013). Forest fire events are characterized by fire regimes, the generalized behaviour and effects of cumulative individual forest fire events in large areas over long periods of time (Ontario Forest Research Institute et al., 2006). Fire regimes describe the patterns and characteristics of various forest fire events within a set spatial and temporal window (Krebs et al., 2010). Fire regime behaviours include parameters such as spatial characteristics (fire size and shape), temporal characteristics (duration and return intervals), and fire characteristics (intensity and vegetation type) (Krebs et al., 2010). Differences in parameters such as intensity and fire size results in uneven burn areas within the landscape, resulting in boundaries with more discrete or gradual boundaries depending on changes in fire intensity (Jordan et al., 2005).

Timber harvesting disturbances are more influenced by human interaction, disturbance boundaries depend on harvesting method (e.g., clear cut, partially cut) (Steventon et al., 1998). Sustainable clear cutting follows natural landscape contours and forest boundaries while retaining individual trees and patches through the cut area (MNRF, 2001). Disturbance regimes differ depending on the types of disturbances that influence the landscape and the conditions surrounding them. Succession is the ecological progression of a forested ecosystem. Differing disturbance regimes result in forested patches with dissimilar successional stages which directly influence wildlife composition dynamics (Sousa, 1984; Steventon et al., 1998).

Due to the patchiness of the landscape caused by forest disturbances the boreal forest is comprised of a mosaic of forest stands with dissimilar successional stages (Foster, 1985). Vegetation growth post disturbance is influenced by a variety of factors, including the competition for nutrients and resources. Forest disturbances can play an important role of replenishing these disturbances through soil nutrients and increasing the availability of sunlight beneficial resources to growing plants due to a drop in resource competition between plants (Taylor et al., 2020).

Boreal forest disturbances are intrinsic to the boreal forest as the main drivers of ecological processes. Post disturbance the trajectories of ecological succession change as the forested ecosystem is sent to an earlier stage of development to a stage understood as secondary succession (Perera et al., 2004). Understanding the role of succession is important to understanding the effects and role of fire disturbances with regard for regrowth patterns within the boreal forest. Within the Boreal succession is dependent on fire with some species requiring fire to germinate, as an example Jack Pine (*Pinus banksiana*) has serotinous cones requiring high temperatures for cones to release its seeds (Gauthier et al., 1996). Changes in the fire regime affects the vegetation characteristics of the boreal (Weber and Flannigan, 1997), thus fire is a necessary and natural component of boreal ecology.

Boreal forest succession is driven by the forest structure, an interconnection of various elements derived before and after a forest disturbance (Mulverhill et al., 2019). In other words, the trajectory of regrowth for a forested stand is driven by its history. Self-replacement is one of the most common functional successional pathways post disturbances as recovery is based upon residual vegetation and buried seed stocks within the landscape. The initial development of a forested stand is influential to the future structure and growth of naturally regenerating forest stands (Angelstam and Kuuluvainen, 2004). As examples, trembling aspen forested stands often dominate post-disturbance landscapes due to the survival of high quantities of saplings (Ilisson and Chen, 2009) and the removal of old growth forests often increases sunlight and soil nutrient availability for young plant life (Taylor et al., 2020).

Age also affects how a forest burns, as forest age increases the susceptibility to disturbances increases due to a net accumulation of stored carbon (Kurz and Apps, 1999). Forest stand age can be found when examining post fire timelines, net primary production increased rapidly within early successional stages but decreases as time progresses (Bond-Lamberty et al., 2004). Thus, the patterns of regrowth for boreal forest stands vary depending on the historic conditions of the boreal forests. This over encompassing forest structure is beneficial to understanding the past, present, and the future of the boreal forest ecosystem.

1.2 Ontario Forest Management

The boreal forest has historically been important to the cultural identity of Canada. The boreal forest is stated by Natural Resources Canada (NRCan) to provide Canadians with a wealth of benefits such as providing jobs and supporting local economies, providing recreation opportunities (e.g., hiking, camping, bird watching), and having a strong cultural importance (NRCan and Canadian Forest Service, 2020). The Canadian identity has historically been tied to the north (Walton, 1990) with natural landscapes and icons often used as cultural symbols. Many first nations communities traditionally have their livelihoods shaped by these forests with hunting, fishing, gathering, and small-scale agriculture practices (Berkes and Davidson-Hunt, 2006).

The Canadian boreal landscape is predominately managed, 94% of all Canadian forest is Crown land, owned by the government allowing for the implementation and regulation of harvesting practices (MNRF, 2019). Of this Crown land, 90% of Canadian forests are owned by provinces and territories in which licensed and certified forestry companies are given management rights through provincially approved Forest Management Plans (FMP) (NRCan, 2015). The management of the Canadian boreal is the responsibility of provincial and territorial governments thus regulations are not necessarily consistent between jurisdictions. Provincial and territorial governments are responsible for setting and applying management plans and practices for forests within their boundaries. Ontario's boreal forest is managed by the Ministry of Northern Development, Mines, Natural Resources and Forestry (NDMNRF). Forest management within Northern Ontario occurs within the MA located within 45°N, 76°W, 52°N, 95°W and encompasses 45 million hectares of the region (MNRF, 2019). The extent of the

MA is depicted in Figure 2. As of the writing of this thesis the former Ministry of Natural Resources and Forestry (MNRF) had merged with the Ministry of Northern Development and Mines and has renamed itself the Ministry of Northern Development, Mines, Natural Resources and Forestry (NDMNRF). While this thesis refers to the NDMNRF as the MNRF they are the same entity, the use of the term MNRF is based on when the supporting documents were published.

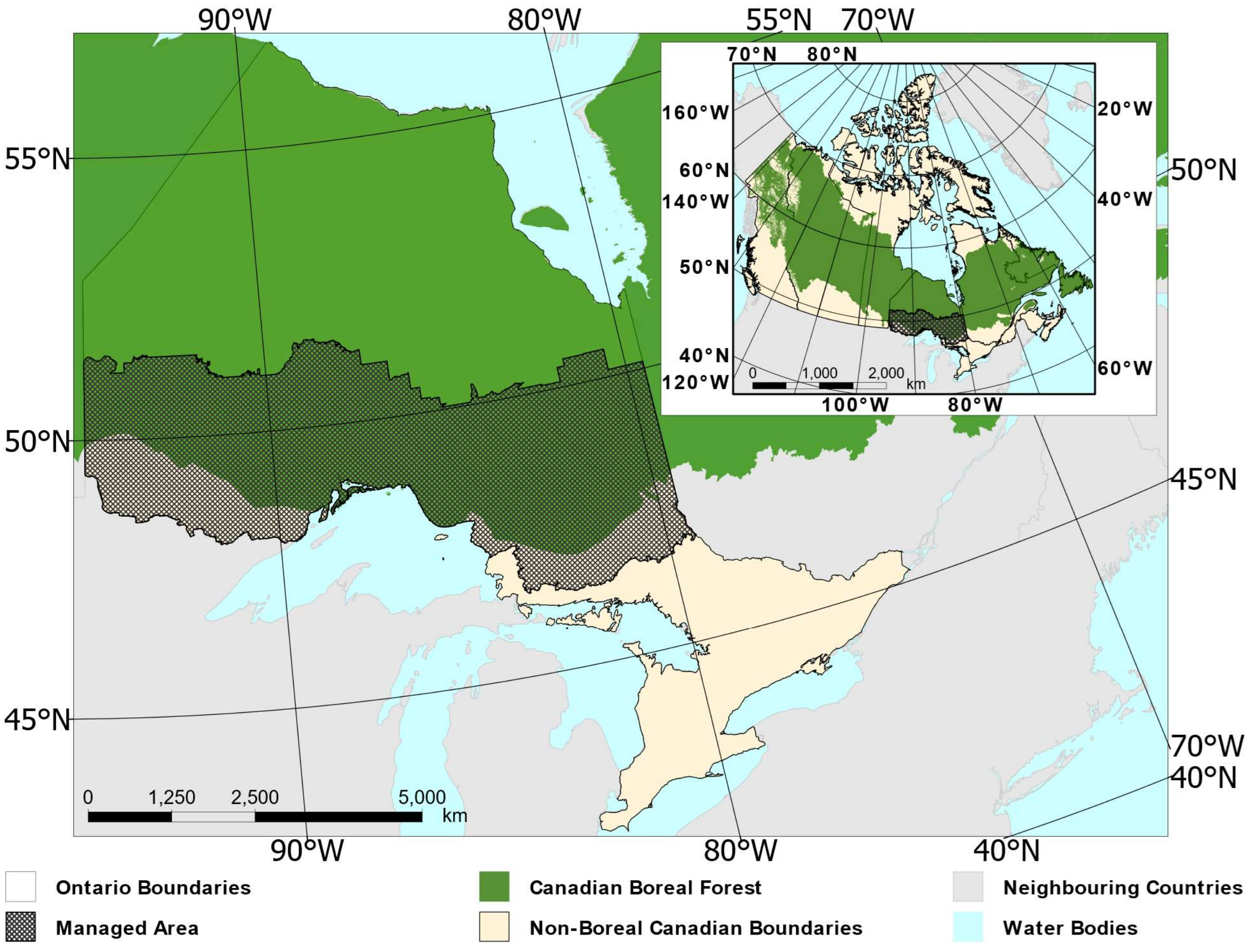


Figure 2. The study area for the proposed research, the Managed Area (Formerly known as AOU) within Ontario, Canada. The map in the corner depicts the extent of boreal forest within Canada. Data acquired from Brandt (2009) and Statistics Canada (2016).

The boreal has been a longstanding part of Canada's economy. Economic growth in the late 1880s lead to the development of Canada's forestry industry which would remain an important part of Canada's economy, producing various goods such as timber products for building, packaging material, pulp, and paper. At the time of this writing, during the COVID-19 pandemic, the forestry sector provided support through providing Canadians essential materials such as toilet paper, sanitation products, and personal protective equipment such as non medical masks or medical gowns (NRCan and Canadian Forest Service, 2020). The boreal sustains the livelihoods of many local economies. In 2020 the forestry sector accounted for 1% of total employment within Canada with 184,510 jobs (Statistics Canada, 2021), with approximately 7% of the workers being indigenous as of 2016 (NRCan and Canadian Forest Service, 2020) and contributing $23.7 billion to Canada's Gross Domestic Product in 2019 (NRCan, 2021). The boreal forest is integral to the history and lives of many Canadians, the management of the boreal requires understanding of not only the needs of the ecosystem but also the needs of all stakeholders (Côté and Bouthillier, 1999) whose needs are weighed against one another (Eyvindson et al., 2019).

For forest managers, considering the needs of various stakeholders on a provincial scale is impossible. Thus, forest management within the MA is divided into smaller management units which are managed by forestry corporations that have been granted sustainable forest licences. Corporations are responsible for the planning and implementation of FMPs that introduce the objectives and operations of a designated management unit for the following 10 years (MNRF, 2018). To ensure the longevity of its ecosystem the Crown Forest Sustainability Act was passed in 1994 (*Crown Forest Sustainability Act*, 1994) resulting in a shift towards a sustainable forestry management model which sought to "to meet [the] social, economic and environmental needs of present and future generations." (ECO, 2014). The idealized goals of sustainable forest management are to ensure Ontario forests remain healthy and conserve their biodiversity by protecting wildlife and to support the needs of all Ontarians.

Recent forest management approaches have been based upon understanding the dynamics of natural processes (Dhital et al., 2013). It has been argued that harvesting requires the accompaniment of fire suppression tactics due to situations involving high fire frequency causing a competition between harvesters and loggers (Bergeron et al., 2004). This need relates to a paradigm within forest management where fire management and forest management are treated as separate issues and as such are dealt with separately (Le Goff et al., 2005). Understanding between forest fire dynamics and forest management practices requires an integration of both management practices. Natural disturbances have long been established as fundamental to the development and structure of forest ecosystems, forest management should be based upon the understanding of disturbance processes (Attiwill, 1994). The emulation of natural disturbances is the notion that forest managers should design FMPs that apply specific management practices at scales that are suitable and appropriate enough to be structurally and functionally similar to post-disturbance ecosystems (Perera et al., 2004). Sustainable forest management is based upon the understanding of natural systems to maintain forest productivity, resilience, and biodiversity (Bergeron et al., 2002). Having a thorough understanding of natural disturbance regimes and the dynamics of the boreal ecosystem can be used to inform forest management practices (Fenton et al., 2009) and find a balance between economic, ecological, and social values (Kuuluvainen et al., 2021).

Prior to the shift towards sustainable forest management the dominant approach was the feature wildlife species approach, which operates under the assumption that addressing the needs of select species will accommodate the needs of most wildlife.

Since 2001 the MNRF recommended the Coarse and Fine Filter Management Approach (CFF) of forest management (Ontario and MNRF, 2014). The CFF approach essentially encapsulates the needs of as many species as possible through the usage of “filters”. The coarse filter broadly captures the needs for the majority of native species, providing habitat conditions that suit as many species as possible. Fine filters capture the needs of species that the coarse filter does not accommodate (Lemelin and Darveau, 2006). Within Ontario the emulation of disturbance patterns is used as the basis of the coarse filter while fine filters are specific habitat provisions for unaccommodated species (Ontario and MNRF, 2014).

Disturbances occur at multiple temporal and spatial scales, with thousands of different species residing within Ontario’s boreal forest a species-by-species conservation approach would be impossible (MNRF, 2001). CFF addresses this issue through guidelines established by ranking the needs of various species to be either coarse or fine filters (MNRF, 2001). The coarse filter is to ensure species representation by broadly encapsulating the needs of multiple species whereas the fine filter are more precise, directly addressing the needs of species not captured by the coarse filter (Lemelin and Darveau, 2006). While disturbance emulation is considered the most reasonable course for sustaining forest the MNRF identifies there is no guarantee of the methods effectiveness (MNRF, 2001), thus forest management methods continue to develop as new applicable science and information are developed (Ontario and MNRF, 2014).

Forest managers need to understand the ecological and socio-economic consequences of accumulating disturbances within Ontario’s boreal forests. As humans alter the type, severity, scale, and frequency of disturbances, it becomes necessary for forest managers to design FMPs that emulate disturbances and landscape patterns while minimizing adverse effects on ecological, social, and economic values and improve biodiversity (*Crown Forest Sustainability Act*, 1994). As one of the world's largest boreal forest ecosystems there has been a need for Canada to develop forest inventory and monitoring programs that could provide information in response to national and international concerns over the sustainable development of the boreal (Wulder et al., 2003). To track the progress of sustainable forest management and to better inform decision making forest managers would require information to be aggregated and accessible. The data would thus need to consider accessibility, availability, and recency.

1.2.1 Historical Disturbance Data

Historical disturbance data is often used by forest managers to support management decisions that maintain the boreal ecosystem's composition and structure (Hunter, 1993; Kaufmann et al., 1994; Drever et al., 2006; San-Miguel et al., 2017). Historic disturbance pattern information has been used to develop hydrological and topographic GIS models to predict residual shoreline forest patterns for shoreline forest management (Newaz et al., 2020), to assess the short term responses of small mammal community structure to fires (Ecke et al., 2019), and to characterize human interference upon natural fire regimes (Campos-Ruiz et al., 2018).

The FRI was developed in the 1950s to localize information and aid managers to inform planning, harvesting, and evaluation decisions. This data was derived from stand level data via questionnaires and maps derived from aerial photography interpretation in which data collection was intended to occur in 10-20 year cycles (Gillis et al., 2003). In 1981 Canada's Forest Inventory was comprised of aggregated data acquired from management agencies containing location specific data on the characteristics and quality of the forest resources (Gillis et al., 2005). In 2005, the FRI developed into the eFRI which shortened the inventory cycle to 10 years, include the usage of high-resolution multispectral imagery, and made use of new geoscience technologies and software during inventory production (Bilyk et al., 2021). The eFRI has changed since it's inception, with each major iteration followed large scale policy shifts within forest management, but has been argued that inventory had been taken out of it's intended purpose (Bilyk et al., 2021). Eventually the NFI was developed which additionally addressed policy, national and international reporting allowing for better assessments on indicators of sustainable forest management (Gillis et al., 2005). Despite the improvements within the NFI there were still issues regarding accessibility. One of the causes for the inventory's replacement was the lack of consistency within the data, forest managers of various sites would have differing reporting styles which was problematic when integrating the data nationally (Gillis et al., 2003).

Forest managers require detailed disturbance pattern information to support disturbance-based management decisions. Characterizing the spatial and temporal dynamics of the ecosystem is important as the forest cannot be characterized by static attributes (Kneeshaw and Gauthier, 2003). Having historic context improves the understanding of how disturbances would affect other boreal forest processes including the hydrological regime (Buttle and Metcalfe, 2000), the carbon cycle (Lasslop et al., 2019), and plant succession (Hunt et al., 2003). Better understanding the relationships within Ontario forests, managers can improve wood volume production and shorten harvesting intervals. Despite the wealth of information on the boreal, there is a lack of consistency and standardization towards how data is presented or referred to within scientific literature. This lack of standards means that within the literature there is consensus on a concept but uncertainty in its application/execution. As an example, Andison (2012) found that despite a general understanding of the complexity and variability of fire scars there was low agreement among details such as the percent area of unburned residuals, or the influence of vegetation type to burning. Conversely the MNRF found that the definition of fire size distribution is often used interchangeably with terms such as area burned, burned area, and surface burned within literature (Ontario Forest Research Institute et al., 2006). To develop FMPs requires specific, clearly defined management goals and information for the specific management unit (Landres et al., 1999). Inconsistency adds ambiguity into the development of FMPs and for the reporting of boreal data in an already complex ecosystem.

Ontario MA disturbance data products have historically been recorded by various sources but are archived into a single collection. The CNFDB is a collection maintained by the Canadian Forest Service of Natural Resources Canada (NRCAN) using forest fire data products provided by fire management agencies (NRCan, 2022). One such data product is the Large Fire Database (LFDB) which was replaced by the CNFDB. The LFDB depicts fire location, size, date, and cause for fires larger than 200 ha between 1959 – 1997 within the Canadian landscape (Stocks et al., 2002). The issue with the database is that the accuracy and uniformity of the data varies based upon the source, year, and mapping techniques applied to contributing data products. Within the

CNFDB metadata it is noted that the data is incomplete, with varying accuracy due to differing mapping techniques across agencies, the completeness and quality of data depending on the contributor (NRCan, 2020). The problem with the accuracy of the data is addressed by multiple studies that attempt to map boreal disturbances within Canada (Goetz et al., 2006; White et al., 2017). Despite improvements, there are three main barriers to existing boreal disturbance data.

First, is the lack of standards toward data assemblage and portrayal. While contemporary studies made use of satellite data the method of data extraction varies between them. Some studies use a tasseled cap index (Frazier et al., 2015) while others use the Normalized Difference Vegetation Index (NDVI) (Goetz et al., 2006) or Normalized Burn Ratio (NBR (White et al., 2017). In addition, there is a need to consider the data that is used for the mapping. Factors such as spatial resolution, data format, classification scheme, and boundary assessment method influence the definition of a disturbed boundary (Remmel and Perera, 2017). The lack of set standards within available boreal disturbance data means the quality and presentation of data will vary causing issues of standardization, in the situation multiple data products are required it is possible that they may have different representations.

The second barrier includes the spatial and temporal gaps within historical coverage within the MA. Boreal data within Ontario relies on compilations of data derived from jurisdictional sources. The inconsistency in the completeness and quality of CNDFB is due to data being contributed from various agencies, data accuracy varies due to agencies applying different mapping techniques (NRCan, 2022). Spatial and temporal gaps can exist with respect to the resources available at the time of data collection. Prior to the availability of satellite coverage, large areas of Canada were not monitored because many provinces did not document fires in remote northern regions (Stocks et al., 2002). Additionally fires were monitored by hand sketching perimeters on hard copy maps requiring a fixed-wing or helicopter flight over the disturbed region (Remmel and Perera, 2009). Another issue is the lack of data due to cloud artifacts and shadows within satellite data, which could result in falsely detected fire identifications (Remmel and Perera, 2001). Subsequently cloud screenings would be required to improve accuracy but at a cost of losing assess to multiple data sets. Accurate historic boreal disturbance data requires a dedicated effort towards a specific goal of disturbance mapping that can be consistently updated.

The final barrier involves the deterministic presentation of the data. The CNFDB depicts forest fire locations as points and fire boundaries as polygons across Canada (NRCan, 2020) while studies utilizing Landsat data presented their data in a raster format (Baumann et al., 2014; Frazier et al., 2015; White et al., 2017). Due to characteristics of forest fire boundaries being driven by the data and research questions, there is disagreement over the definition of what constitutes a forest fire boundary. Forest fires events heterogeneously affect the disturbed area despite the complexity, features more prominent within the landscape are mapped more accurately regardless of the mapping platform (Remmel and Perera, 2017). Traditionally fire-polygon mapping lacks explicit standards which overly simplifies the extent of fire disturbances (Remmel and Perera, 2009). The characteristics of forest fire boundaries are often driven by the data and the research questions as such the issue is the notion that burn patches are delineated as crisp boundaries. Residuals refer to vegetation patches of various scales that have been spared by forest fires which often represent small proportions of the burned area (Cullinane-Anthony et al., 2014; Perera and Buse, 2014; Araya et al., 2016). Peninsular residual patches are defined as unburned forest outside of the footprint that comprise parts of the fire perimeter, The MNRF defined two types of peninsular residual patches type 1, which exists outside of forest fire boundaries due to the convolution of perimeters, and type 2, which exist within forest fire boundaries occurring within 20 m from the boundary (Figure 3) (Perera and Ontario Forest Research Institute, 2009). Previous disturbance mapping methods recommended by the MNRF include peninsular residual patches as parts of disturbances despite the area essentially not existing within the disturbed area, these areas would be delineated as discrete boundaries that clearly indicate the end points of fire disturbances (MNRF, 2001). A similar case can be made for insular residual patches, unburned patches within fire footprint boundaries with a minimum area ≥ 0.25 ha and ≥ 20 m from the boundary (Figure 3) (Perera and Ontario Forest Research Institute, 2009), the presence of fire residuals is often the result of a complex interaction of multiple factors as such what belongs within a fire footprint can greatly vary (Araya et al., 2016). In reality a fire may have progressively burned out leading to a more gradual change in space as a fuzzy boundary (Jordan et al., 2005).

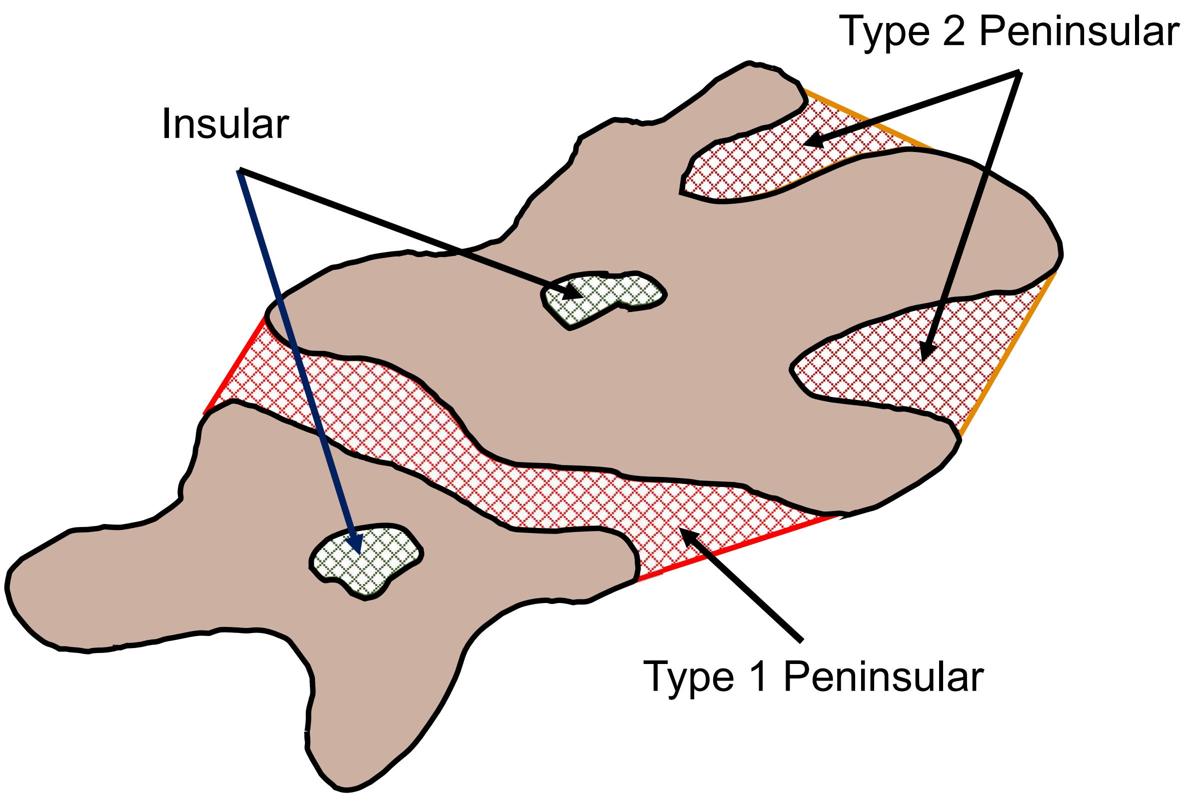


Figure 3. Peninsular and Insular Patches. Despite being considered residuals by the MNRF peninsular patches do not exist within the burned area.

1.2.2 Boreal Disturbance Database

This research uses BorealDB (Ouellette et al., 2020), a spatially comprehensive database compiled in a joint effort between York University and the Ontario Forest Research Institute as an archive of all fire and timber harvesting boreal forest disturbances within Ontario's MA from 1972 to the present.

Multispectral imagery requires specific sensors that can detect the spectral reflectance of objects, this data is stored for individual pixels on spatially coincident layers. Each layer represents a specific and defined spectral band. This data is used to identify features within captured landscapes. The features are identified by examining their spectral characteristics, the way different features interact with different wavelengths of electromagnetic radiation (Gamon and Qiu, 1999). Using of multispectral imagery is common when mapping forest disturbances (Roy et al., 2006; Collins et al., 2018) as the data allows a comprehensive exploration of temporal land cover changes (Hermosilla et al., 2015).

One source of multispectral imagery is from the Landsat satellite missions which began in 1972. The evolution of the Landsat missions through time (Table 1) saw improvements to existing satellites, and the addition of new sensors onboard the satellite platforms. A single pixel in a Landsat scene accounts for the spectral characteristics of a given 30 × 30 m area with each scene being approximately 190 × 180 km in size (USGS, 2019). Since 1972, the consistency and longevity of the Landsat mission makes the data appealing to researchers. Landsat data is freely available for use and has been used to support local testimonials concerning environmental change with varied applications from wetland conservation in developing countries (Kovacs et al., 2001), to detect levels of harvesting disturbances in forested stands in Maine (Wilson and Sader, 2002), to characterize forest disturbance recovery of Canadian forests (White et al., 2017), and to develop an index to detect wetland stress (Walter and Mondal, 2019).

Table 1. The sensors used for each Landsat satellite mission (USGS, 2020).

Satellite Mission	Sensors	Years
Landsat 1-5	Multispectral Scanner System (MSS)	1972 – 1978 (Landsat 1) 1975 – 1983 (Landsat 2) 1978 – 1983 (Landsat 3)
Landsat 4-5	Thematic Mapper (TM)	1982 – 1993 (Landsat 4) 1984 – 2013 (Landsat 5)
Landsat 7	Enhanced Thematic Mapper (EMT+)	1999 – Present (Landsat 7)
Landsat 8	Operational Land Imager (OLI)	2013 – Present (Landsat 8)

BorealDB is compiled from multiple data products; accompanying data products were acquired from the NRCAN and the MNRF in the form of various organizational branches (Table 2). The primary data product within BorealDB is an unsupervised classification derived from Landsat scenes. The approach used by Ouellette et al. (2020) extracted disturbance data by classifying Landsat scenes from various missions (MSS, TM, ETM+, OLI). First training areas were identified on pre-processed (water, cloud, and shadow masks) and atmospherically corrected scenes to ensure standardized comparisons. Training areas were manually selected by referencing existing MNRF fire and harvest databases and visual selection. An unsupervised ISOData classification, a method commonly used within studies examining forest landscape changes (Kovacs et al., 2001; Wilson and Sader, 2002; Jin and Sader, 2005), was performed on the training areas to produce clusters that would form scene-wide training signatures. The ISOData clusters became the training input for a maximum likelihood supervised classification to produced preliminary fire and harvesting disturbance maps. These maps were spatially degraded to 1.44 ha spatial resolution, to match standard reporting scales, and converted to regularly spaced points encoded with attributes related to disturbance type, timing, and confidence. The workflow established by Ouellette et al. (2020) allows for annual updates to be assessed and incorporated on an ongoing basis.

Table 2. Boreal disturbance database data products used to determine confidence

Data Product	**Description**
FireLsat	Landsat Derived Fire Classification
HarvLsat	Landsat Derived Harvest Classification
OFireAFFES	Fire classifications derived from the AFFES (Aviation Forest Fires and Emergency Services), a division of the MNRF
OHarvMNRF	Harvest classifications derived from the MNRF
OFireSRB	Fire classifications derived from the Science and Research Branch of the MNRF
OHarvSRB	Harvest classifications derived from the Science and Research Branch of the MNRF
OFireNRCAN	Fire classifications derived from NRCAN
OHarvNRCAN	Harvest classifications derived from NRCAN

Ouellette et al. (2020) a methodological framework documents all decisions being made to ensure reproducibility that meets the standards for the database. In comparison to previous data products Ouellette et al. (2020) hopes to address deterministic portrayal of the data by presenting the data as points with degrees of confidence. BorealDB makes use of an ensemble assessment of confidence which delineates the likelihood a data point is delineated as a disturbance. Using a fuzzy membership function allows for users to devise multiple definitions of a fire disturbance based upon their ecological interpretations in which pixels can be included or excluded depending on how they define it (Remmel and Perera, 2009).

The development of BorealDB was based upon the recognition of: the lack of generalized standards in place for the assembly and portrayal of annual historical disturbance information, the existence of spatial temporal gaps within the historical coverage of the MA, existing data is presented deterministically without estimates of error or variability (Ouellette et al., 2020). BorealDB addresses the increasing need for reliable and defensible boreal disturbance information. The primary objective of BorealDB was to compile a spatially and temporally comprehensive data set that detects past fire and timber harvesting disturbances of the MA (Ouellette et al., 2020). For each year, an annual disturbance layer is produced in which boreal disturbances are presented as vector disturbance points that are classified based on their disturbance type.

The database is currently available for download and has been acquired for the purposes of completing this research. With the increased need for accurate boreal disturbance data there is a need to ensure BorealDB is as correct as possible. As such the research project proposes to aid in the processing of the boreal forest fire disturbance database by minimizing classification uncertainties that result from overlapping Landsat scenes to increase classification confidence.

BorealDB portrays disturbances as clusters of point data in a grid-like pattern, where points are positioned at the vertices of a 120 m regular grid. Each disturbance point contains attribute information regarding their disturbance classification (Ouellette et al., 2020). BorealDB used the point approach to ensure manageable file sizes, the ability to focus on identified disturbance locations as opposed to delineating complex boundaries, and to ensure each point can have measures of confidence based upon an ensemble assessment of agreement (Ouellette et al., 2020). Four disturbance classes are encoded in BorealDB (Table 3): Current year fire disturbances (`1`), current year harvest disturbances (`10`), fire disturbances within the last two years (`100`), and harvest disturbances within the last two years (`1000`). Using this method each Landsat identified disturbance point will have a classification. While the method provides a classification to each point, uncertainty occurs when an individual disturbance point has multiple conflicting classifications, one on each overlapping scene covering the same location in time.

Table 3. The Landsat disturbance code utilized within the boreal disturbance database. A single disturbance point can have multiple classifications.

Disturbance Type	**Disturbance Code**
Fire (Current Year)	1
Harvest (Current Year)	10
Previous Fire (Previous 2 Years)	100
Previous Harvest (Previous 2 Years)	1000

The cause of these conflicting classifications is overlap along Landsat scene margins. Due to each scene being individually classified, there is potential for disturbances within overlapping areas to have different classifications on each scene. To encompass the MA, BorealDB incorporates multiple overlapping scenes. A graphical representation of the overlap is shown in Figure 4.

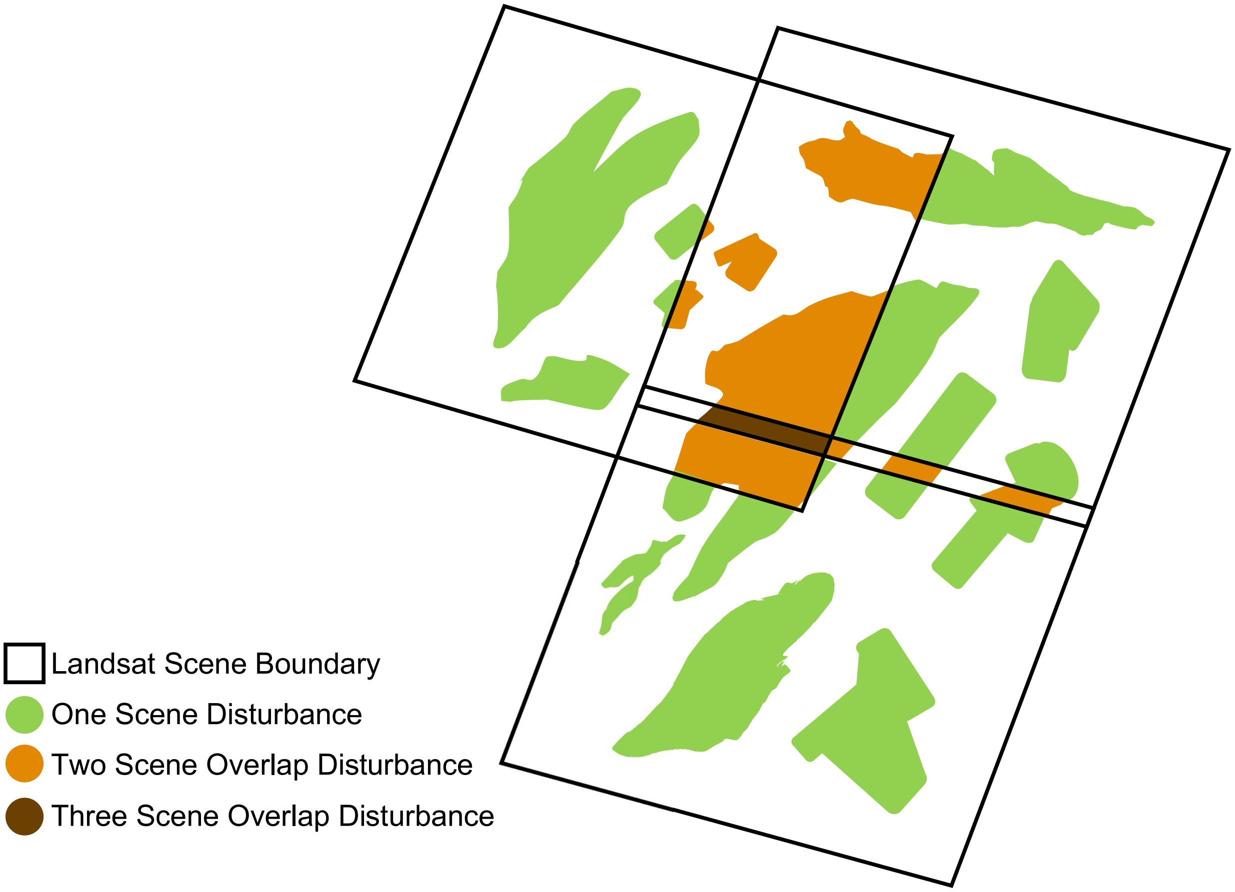


Figure 4. Sites of uncertainty caused by overlapping Landsat scenes. These hypothetical disturbances demonstrate how disturbances can exist within multiple overlapping spaces.

Due to the overlap along scene margins and that Ouellette et al. (2020) had independently classified each scene there is a potential for 1 to 4 scenes to have conflicting disturbance classifications for the same disturbance (Ouellette et al., 2020). The overlap produces uncertainty within the database by producing multiple classifications for disturbance points that do not always agree. A single disturbance point near scene corners has the potential to have up to four different classifications. Referring to Table 3, each disturbance point is encoded to show agreement amongst scene classifications as up to 4 scenes may have separate disturbance classifications and form a disturbance code composite. As an example, a disturbance point that exists on an overlap between three scenes that was classified as a forest fire (`1`) in two overlapping scenes but classified as a timber harvest (`10`) on one would have a disturbance code composite of `12` (`10` + `1` + `1`) in BorealDB.

1.3 Classification Confidence

1.3.1 Uncertainty and Accuracy

A clarification to be made is the differences between uncertainty and accuracy within BorealDB. Uncertainty is described by Zhang and Goodchild (2002) as a measure of the difference between the actual contents of data, and the contents that the current user would have created by direct and perfectly accurate observation of reality. The role and impact of uncertainty within geographic data is well understood within the literature (Zhang and Goodchild, 2002; Foody, 2010; Zhang and Zhang, 2019). Uncertainty can be understood as the variation between a geographic data representation relative to its appearance in the real world. Uncertainty inherently exists within all aspects of geospatial data, occurring due to noisy or mixed pixels within remote sensing imagery or even issues derived from the classification process itself (Zhang and Zhang, 2019). Within BorealDB, uncertainty can be understood as the lack of confidence in a classification label that has been applied to a disturbed point as to whether the label reflects its location in geographic reality. With each point there is a vagueness and ambiguity as to whether the classification reflects geographic reality. In representing the realities of a forest fire there is a consistent challenge in the presentation of geographic data due to the inherent complexity of the real world and the necessary simplistic presentation of data.

Accuracy tests “correctness” to obtain a better representation of the data as reality. Traditionally maps were produced as crisp sets in which boundaries are more clearly delineated within the data which leaves potential for errors in map accuracy and area estimation (Woodcock and Gopal, 2000). Classification accuracy refers to a classification’s degree of ‘correctness’, the extent to which an image classification agrees with reality (Foody, 2002). Land cover maps are convenient sources of land cover information, but often are of insufficient quality for operational applications due to disagreements between the map and reference data (Foody, 2002). To assess the “correctness” of the data the results are often compared as matrices in an accuracy assessment. An accuracy assessment relies on information that can validate the geographic data, the accuracy of the data is then represented as an error matrix (Congalton, 1991). Despite this an accuracy assessment is limited by resources available (Cihlar, 2000), issues such as: costs, accessibility, human error, and technological shortcomings, means that validation data will require low degrees of error as it has been previously found that small errors can result in large biases within the data set (Foody, 2010).

BorealDB is a historical database comprised of decades of historical MA disturbance data, due to the passage of time and the large area needed for validation it becomes impossible to assess the accuracy of the data using conventional means. Classification uncertainty within BorealDB refers to the classification labels that have been applied to each disturbance point within the database. Uncertainty exists when disturbance points are assigned multiple classification labels allowing for the occurrence of conflicting classifications. BorealDB determines classification confidence using an ensemble assessment of confidence which overlaps other existing data products to identify areas of agreement (Ouellette et al., 2020). While the ensemble assessment also uses “reference data” there is no guarantee that other data products have a better reflection of reality, the approach instead determines the likelihood of a disturbance’s existence by comparing its existence with all other data products. The use of an ensemble assessment to identify classification confidence is due to the inability to assess the classification accuracy of BorealDB. Thus, minimize the classification uncertainty within BorealDB means increasing the classification confidence.

1.3.2 Confidence

Due to the database being based on historic data field validation is infeasible, as a result an ensemble approach was utilized in which each disturbance point was given a measure of correctness. BorealDB makes use of data products from NRCAN and the MNRF in addition to the primary data set. Confidence within the database is essentially the measure of how likely a disturbance point belongs to a class based upon an ensemble decision making method in which each data product has an equal weight. Classification confidence is like fuzzy set theory, the notion in which objects in reality can not be clearly categorized as there is often ambiguity surrounding how objects should be classified. To address this objects are given a membership which determines the degree in which the object belongs to a particular class (Zadeh, 1965). In doing so the assessment of confidence for a disturbance is derived from whether data products agree or disagree. Classification confidence is determined by the presence and absence of a classification. Confidence varies annually due to the availability of data products thus there is potential for an annual disturbance layer to have two data products while a disturbance layer for a different year has four. The highest confidence measures a disturbance point can have is 100% while the lowest confidence measure will always be greater than 0%, because all points are designated as disturbed by at least one data product. For each annual disturbance layer, the highest confidence measure is divided by the number of data products within the layer and the divided value is assigned equally to each data product as a weight. This variability ensures the confidence value can change as additional data products are included in the confidence calculation. The equation (1) below summarizes the confidence measure, which is the weighted percent agreement (C) between binary indicators (D_i) of disturbances by n data products (Ouellette et al., 2020).

$$C = 100 \sum_{i=1}^{n} \frac{D_i}{n} \tag{1}$$

In an example depicted within Figure 5, the hypothetical disturbance is derived from an annual disturbance layer with three different data products, thus each product would hold a weight of 33%. If a single disturbance point was classified as a fire with two out of the three data products recognize the disturbance point as a fire, then the confidence level would be 66%.

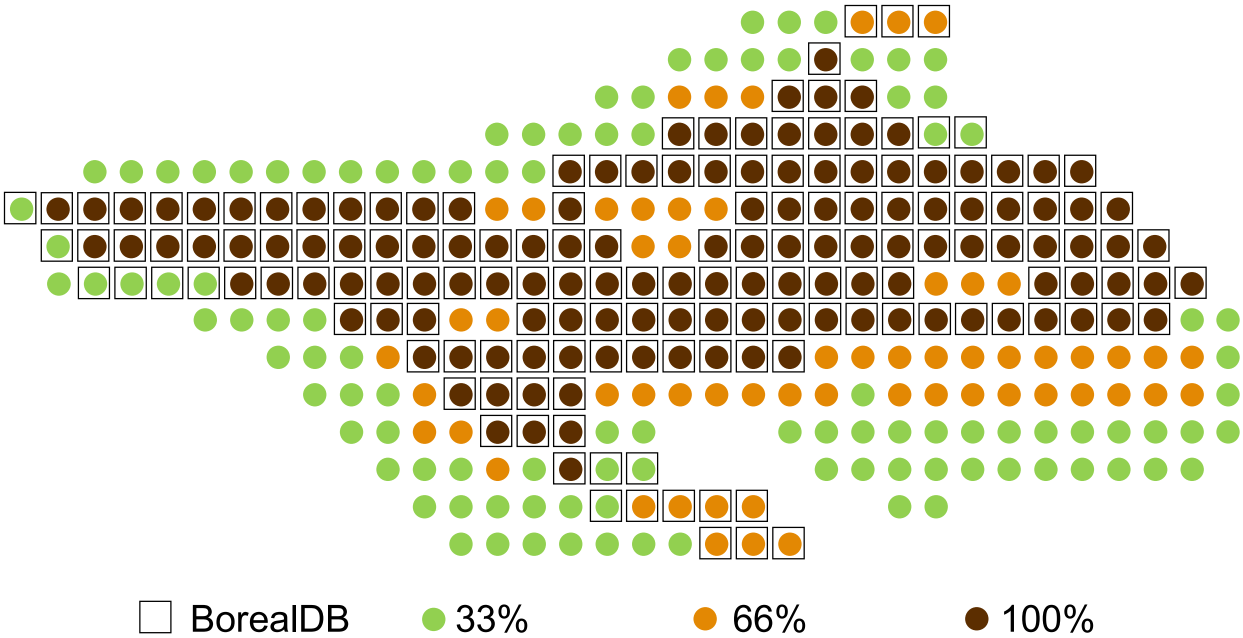


Figure 5. A hypothetical example of a BorealDB disturbance cluster. A disturbance point's confidence level with three data products. 33% means a single data product agrees that a disturbance occurred at a point. 67% means two data products agree that a disturbance occurred at a point. 100% means all three data products agree. Points classified by the BorealDB data product are enclosed within squares.

BorealDB is heavily reliant on agreement between the multiple data products to illustrate confidence. Identifying areas of classification uncertainty within overlaps and assessing confidence levels allows disturbance features to be more clearly delineated. As such this thesis sought to assess uncertainty by using an ensemble approach with a point's orthogonal states to predict the optimal classifications for the database.

1.4 Research Objectives

The purpose of this thesis is to identify and flag areas of classification uncertainty within BorealDB so that they may be further scrutinized to assess classification confidence. To accomplish this a workflow was produced to quantify the focal context of disturbance point classifications to feed Classification Tree (CT) (Ripley, 2019) and

Random Forest (RF) (Breiman, 2001) classifiers. By assessing the relationship between the BorealDB disturbance classifications and those predicted by the CT and RF algorithms classification uncertainty is deemed to exist in areas where BorealDB and the CT and RF predictions disagree. It can be hypothesized that classes with low agreement will have higher classification uncertainty. The objectives of this thesis are: (1) to identify all areas with overlapping classifications that have uncertainty, (2) to examine the focal context and characterize neighbouring influences, (3) to assess classification uncertainty by comparing BorealDB with the contextual classifiers (CT and RF), and (4) to compare classifier results to identified sampled locations on the original satellite imagery to test the effectiveness of each classifier. Using this knowledge, we can assess the confidence of a disturbance point's classification to minimize classification uncertainty.

2.Methods

2.1 Focal Context

To identify areas containing classification uncertainty the focal context of individual disturbance points was examined. Focal context is related to Tobler's first law of geography, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970), points that are closer to one another are likely to have a stronger relationship with each other than points that are further away. Applying this concept to BorealDB implies that disturbance points within proximity will have a greater relationship than disturbance points that are further away, thus it can be expected that disturbance points adjacent to one another are of the same class.

The uncertainty of disturbance points is derived from contradictory classifications within overlapping scenes. Ascertaining the uncertainty of disturbance points, requires understanding of the focal neighbourhoods of disturbance points. Focal context refers to the nearest spatial neighbours of a focal point. Examining uncertainty on the focal scale refers to the immediate neighbourhood of a central point of interest that is being processed (Hamunyela et al., 2016). An advantage of a focal scale approach is that it derives information from an aggregation of pixels in comparison to individual pixels (Chubey et al., 2006). Focal approaches include moving window approaches, which calculate a value for a focal cell based upon a window of specified shape and size, object-based analyses which delineates objects made up of several pixels to transform them into usable spatial objects (Blaschke, 2010), and classification methods such as spatial autoregression assign labels to a focal location based on the class labels of surrounding locations (Shekhar et al., 2002).

Focal approaches have been used in analyses to minimize data uncertainties. As an example digital elevation models encounters uncertainties such as measurement accuracy and vegetation shadowing, applying statistical calculations over a user defined window can be effective at mitigating the errors (Castillo et al., 2021). The focal approach has been applied to improve early deforestation detection within remote sensing studies (Hamunyela et al., 2016), to enhance statistical analysis methods such as change detection (Lv et al., 2016; Cui et al., 2019), to characterize gully geometries (Castillo et al., 2021), and to analyze the neighbourhood characteristics of land use (Verburg et al., 2004).

Within this thesis focal context examines the nearest orthogonal neighbours of a focal point to assess confidence. The decision to focus on the nearest neighbours was for a couple of reasons, first applying the concept to a focal point’s nearest neighbours ensures proof of concept, secondly nearer points are more likely to belong to the same disturbance, and finally having less disturbance points to feed into the contextual classifier means less computational power is needed. BorealDB's points appearing within a row and column format with each point containing information regarding every disturbance the point has been classified as. As such the current classifications of surrounding pixels can be compared with the focal pixel and an optimal class can be determined based upon the results of the ensemble. Thus, focal context within this thesis is defined as the Landsat disturbance code classifications of a focal point's orthogonal neighbours (Figure 6).

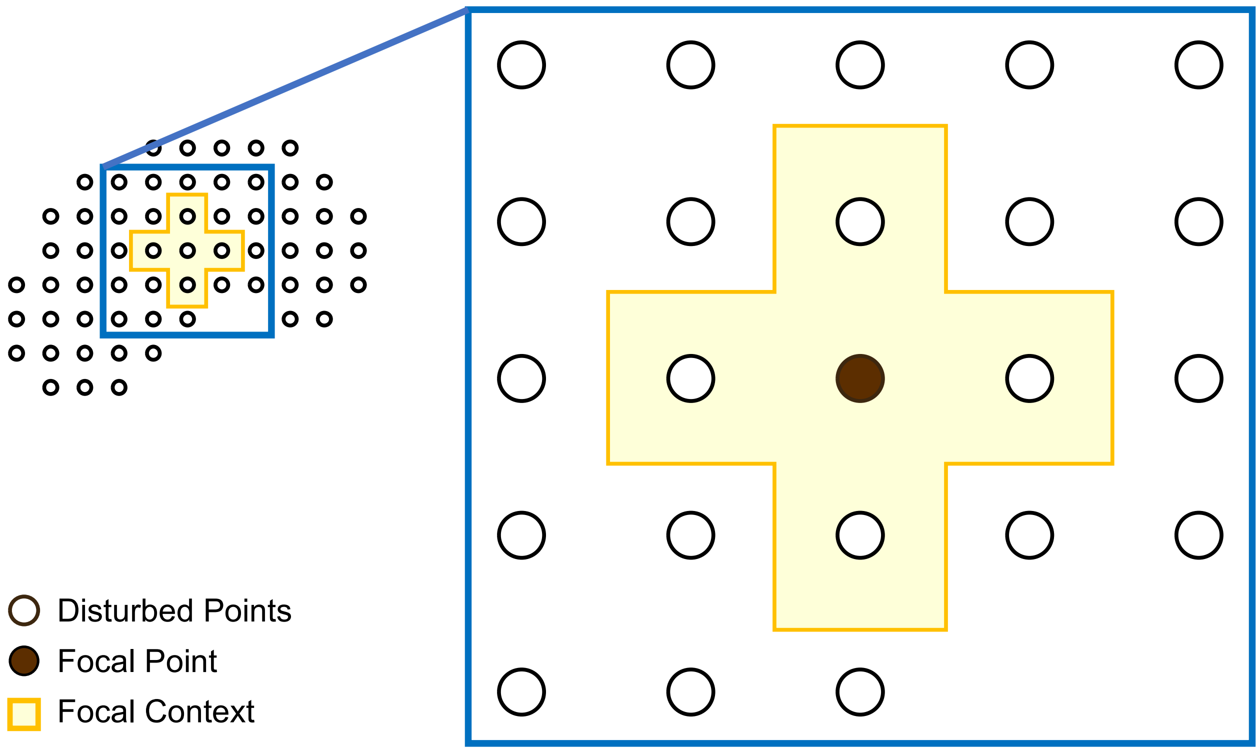


Figure 6. Focal context based on classifications of immediate neighbours. The blue box shows a sampled region within a hypothetical disturbance cluster. The focal context can be observed as encompassing the focal points nearest neighbours, points in its orthogonal directions.

The focal context method is applicable due to the data points in the database being derived from the centroids of pixels that were detected as a type of forest disturbance within Landsat data. Clusters of disturbance points represent different disturbance events meaning that neighbouring disturbance points have a high likelihood of being part of the exact same disturbance.

2.1.1 Focal Context Model

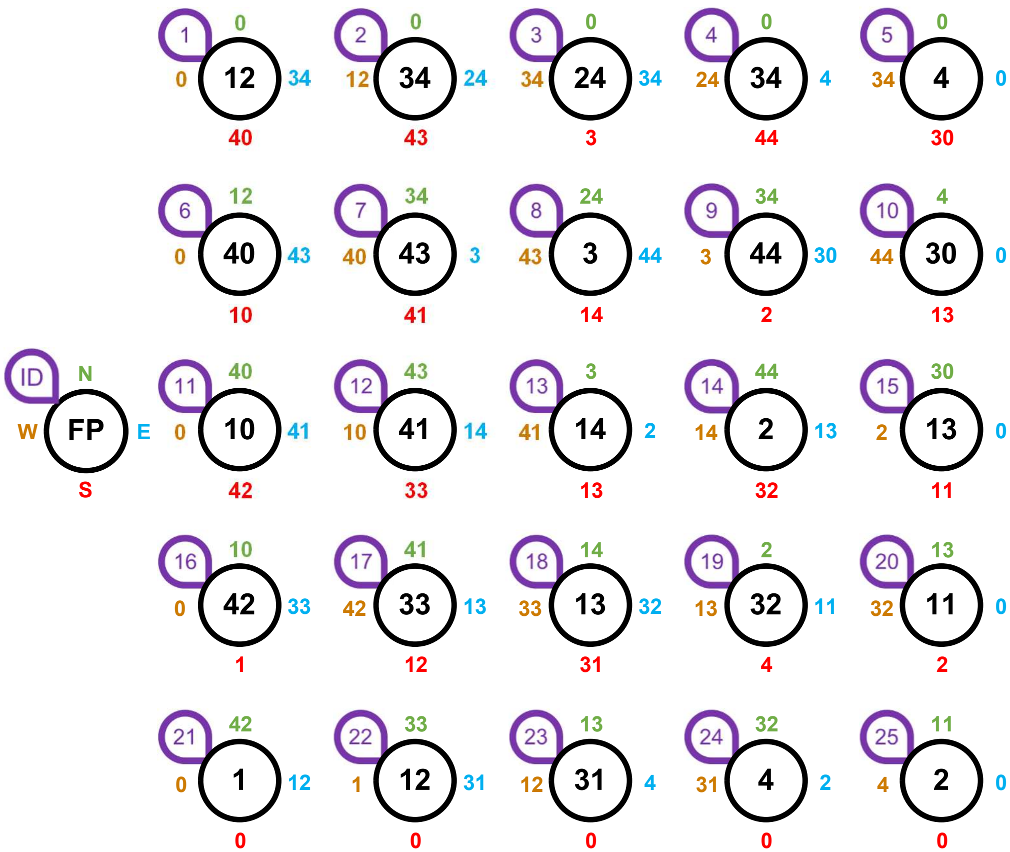
To encoded BorealDB disturbance points with contextual data there was a need to detect the neighbourhood values, while the spatial database is recorded in a tabular format it is necessary to discern the accuracy of a focal disturbance point's classification based upon its surroundings. The data collection method needed to consider a disturbance point’s location in space relative to other points. To this end it is required to utilize geographic information system software to analyze the geospatial database. ArcMap is used for its suite of geoprocessing tools and model builder which creates a manipulatable workflow of tools within software that is comprehensible and intuitive. The following section deconstructs the workflow, decisions, and motivations at each step made towards its construction. The process will be broadly organized in two steps: the detection phase which discusses the method used to acquire neighbouring attribute information and the geoprocessing step which indicates the tools within ArcMap that were applied within the workflow.

The first step of discerning the focal context is to determine a way to observe the attribute information of adjacent points. The method needs to fulfil several conditions:

1. Due to the vast amount of data points, it would be impossible to individually identify the classifications of a focal point’s neighbours as such it is necessary to utilize a method that can be applied reliably on a large scale.
2. The method should have minimal error, due to there being such a large amount of data any issues within the database would be difficult to identify and fix.
3. The method should also be easily replicable, due to the database being segmented annually the method needs to ensure the collection method can consistently collect the data with the same results.
4. Finally, the collection method must be adaptable, if the collection of more attribute information was required then the method should not require drastic changes to the model.

Based on these conditions the method used is the collection of attributes through the geometric intersection of a focal point and a copy of a neighbouring disturbance point that had been geographically shifted to overlap with the focal point. The horizontal distance between disturbance points is 120 m, being an exact copy the disturbance points between two databases overlap, shifting the copy by ±120 m along the *x*- or *y*-axis means that the neighbouring point will now directly overlap the original focal point. The direct overlap allows for a geometric intersection to be calculated on the database and its copy. The geometric intersection calculates overlap between the two input databases and encodes the necessary attributes of the copy on to the original database. The newly added attribute can then be renamed to reflect the direction of the neighbouring disturbance point. A visualization of this process is described below in Figure 7.

a)



b)

ID	FP	N	E	S	W
1	12	0	34	40	0
2	34	0	24	43	12
3	24	0	34	3	34
4	34	0	4	44	24
5	4	0	0	30	34
6	40	12	43	10	0
7	43	34	3	41	40
8	3	24	44	14	43
9	44	34	30	2	3
10	30	4	0	13	44
11	10	40	41	42	0
12	41	43	14	33	10
13	14	3	2	13	41
14	2	44	13	32	14
15	13	30	0	11	2
16	42	10	33	1	0
17	33	41	13	12	42
18	13	14	32	31	33
19	32	2	11	4	13
20	11	13	0	2	32
21	1	42	12	0	0
22	12	33	31	0	1
23	31	13	4	0	12
24	4	32	2	0	31
25	2	11	0	0	4

Figure 7. a) A hypothetical diagram demonstrating the shifting ideology on disturbance points. Each point is colour-coded based upon a given attribute. Purple represents the identification number, black represents the focal point's (FP) classification value, green represents the classification value of the point directly north of the FP, blue represents the classification value of the point directly east of the FP, red represents the classification value of the point directly south of the FP, and finally orange represents the classification value of the point directly west of the FP. b) the tabular form of the values in the hypothetical diagram.

The copy-contextual analysis method is ideal due to its reproducibility, accessibility, and the lack of extensive calculations. The encoded disturbance point's neighbourhood attributes are fed into the CT and RF model. Focal context is based upon spatial autocorrelation which measures the similarities of nearby observations. In the scenario of this thesis, adjacent disturbance points with the same classifications means the spatial autocorrelation is positive. Using focal context improves the correctness of the database as disturbance labels will no longer be based upon the classification of a single point but instead on an ensemble Figure 8. By considering the neighbouring classifications, the confidence label of a disturbance point will be improved as the classifications of neighbouring points serves as data validation.

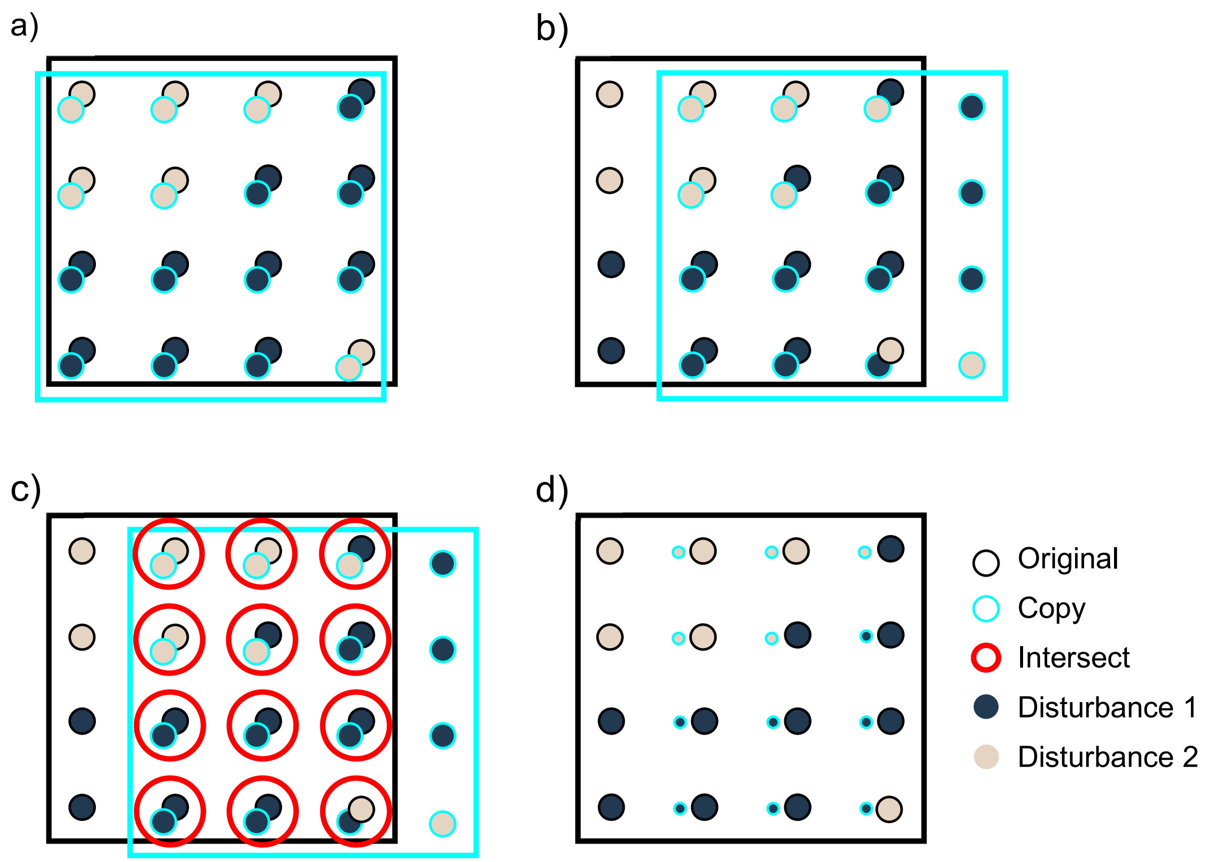


Figure 8. Focal Context. In this example the copy and original are slightly offset to show the differences: a) Create a copy of the original data set with the exact same geographic coordinates; b) Geographically shift the copy towards the opposite direction of the desired neighbour attribute; c) Geometrically intersect the copy and originals that overlap; d) Record the neighbouring values on the disturbance point.

2.2 CART

A decision tree was used to test the robustness of the model by predicting classifications based upon the focal context of disturbance points. Classification and regression trees (CART) are defined as a binary repetitive partitioning technique that processes either categorical or numeric variables (Steinberg, 2009). Classification trees are made up of three main components (Figure 9). Decisions along the trees are represented as nodes, the node at the top of a tree is called the root node. Nodes are connected by branches which represent the relevant pathing for a decision, depending on the decision made at a connecting node the variable will follow a branch to a different node. Finally once the data has been categorized the final nodes are known as leaves (terminal nodes) which represent the final groupings or end classifications of the variables set through the tree (De'ath and Fabricius, 2000).

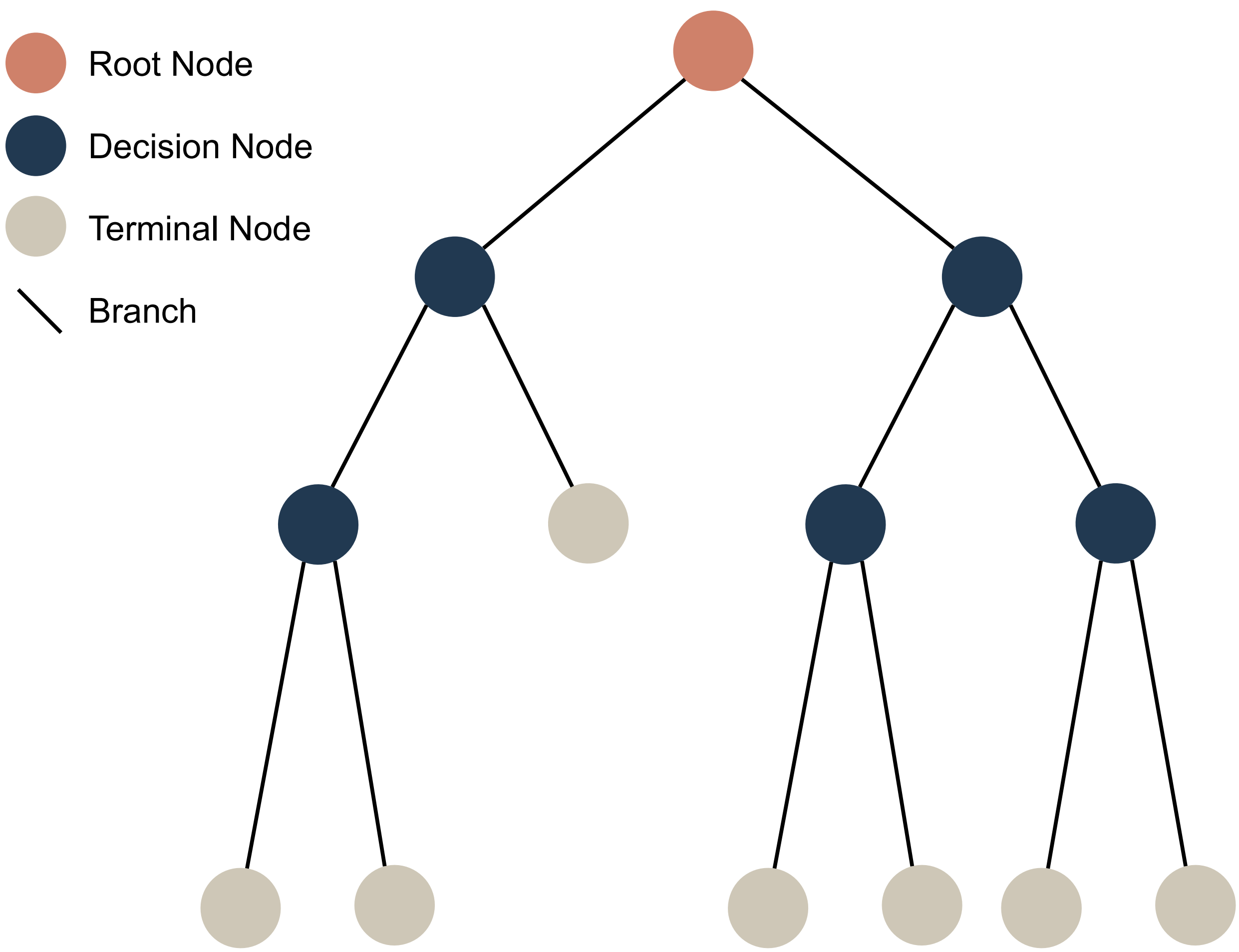


Figure 9. Terminology of a classification tree model.

CART is suitable for a few reasons, first they are suitable for the analysis of ecological data. Ecological data notably has complex non-linear relationships and can contain missing values due to the relationships between variables being convoluted, CART is utilized for its flexibility allowing for interactive exploration, description, and prediction between variables while being accommodating for different types of predictor values (De'ath and Fabricius, 2000). Secondly CART is non-parametric meaning the method makes no assumptions of the distribution of the input data (Friedl and Brodley, 1997). Finally, CART is easy to use and represents information intuitively in a manner that is easy to visualize (Naghibi et al., 2016) ensuring its replicability. This thesis makes use of the CT model as BorealDB's disturbance classifications are stored as categorical data.

The construction of CART is data driven, trees are grown using training data set containing "correct" classifications with attribute inputs used to inform binary decisions at each node (Bittencourt and Clarke, 2003). For a tree each decision is made using the best split among variables at its current level (Liaw and Wiener, 2002). The binary decisions at each partition of a tree are the orthogonal neighbour states of disturbance points. The CT model was run using the statistical programing language R with RStudio being used as the integrated development environment using the `Tree` package (Ripley, 2019). Growing a CT algorithm with BorealDB will: (1) grow a replicable CT applicable to any year of BorealDB that is not computationally intensive, (2) provide a CT derived classification for each disturbance point based upon their orthogonal neighbours, and (3) allows a comparison between the CT classifier with BorealDB's original classifications to assess the effectiveness of the focal context method.

2.2.1 Model Outline

The CT classifier is grown using binary recursive partitioning based upon orthogonal direction inputs (Figure 10). The training data is a sample from an aggregation of all annual layers. To grow the CT classifier the training data would need enough “correct” classifications to show agreeing orthogonal states. The rationale is that with an optimal sample size the CT would be less likely to overfit and that the model will be less computationally intensive.

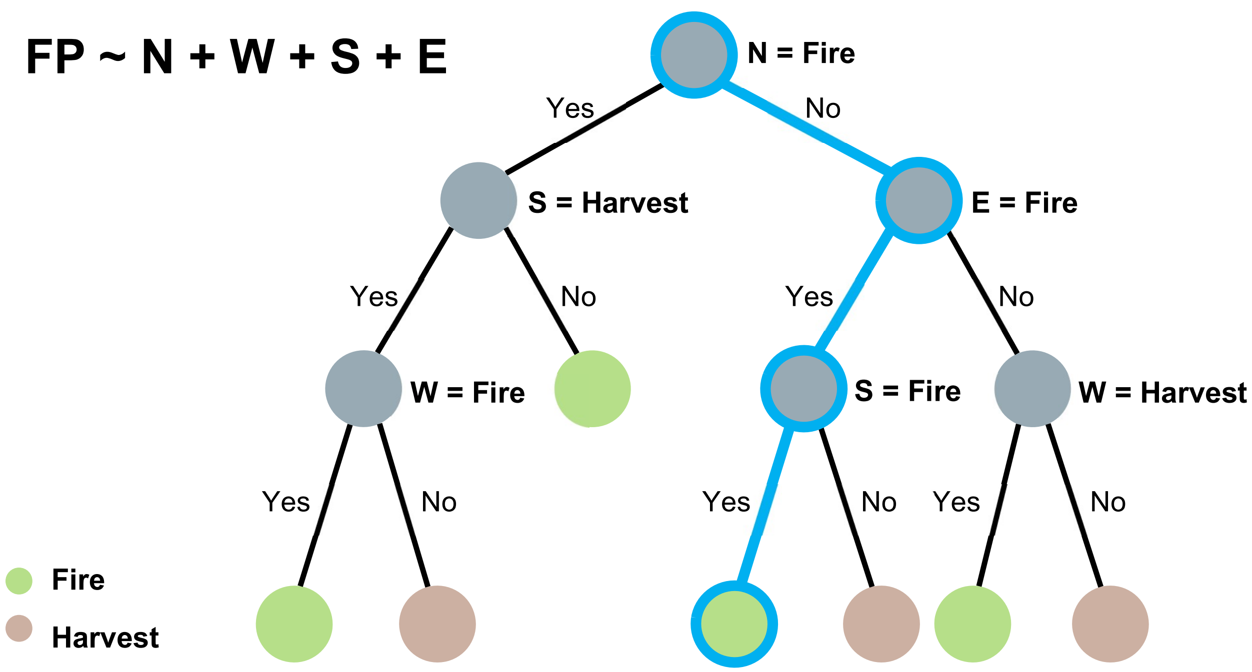


Figure 10. How the classification tree formula is used to plot a hypothetical tree which depicts how orthogonal states are fed into the CT model. Where FP is the focal point, N is the northern point, W is the western point, S is the southern point, and E is the eastern point. The formula indicates how the orthogonal states are used to predict the focal point.

Overfitting occurs when the model closely resembles the structure of its training data (Khoshgoftaar and Allen, 2001), leading to classification errors and poorer performance when the model is applied to unknown data. Pruning is used to reduce classification errors and duplication, the most common approach to pruning is the cross-validation method (Venables and Ripley, 1999). The cross-validation method however is computationally intensive, due to the database having almost 27 million disturbance points and hardware limitations a cross-validation could not be applied to the CT model at this time. Instead, the optimal sample size was tested by calculating the misclassification and deviance rate of many trees at multiple sample sizes.

Using the `prune.tree` function the misclassification and deviance at each decision split are calculated and aggregated into box plots where the shapes of each plot are visually assessed for significant differences. If the plot shapes were visually similar, then the sample sizes would not matter whereas if the shapes are widely different, samples sizes would be reassessed. Once an optimal sample size has been established a CT is constructed (Appendix A). To test overfitting the misclassification and deviance at each decision node (of the final CT) would be assessed to determine the necessity of pruning the classification tree. To start, four initial sample sizes were chosen: 25%, 30%, 35%, and 40%. If results prove inconclusive then additional sample sizes would be included. For each sample size 1000 samples were taken and grown into trees. For each sample size a set of trees are grown, with each tree in a set having training data derived from random selections made from the aggregated dataset.

2.3 Sample Size

For each sample size set the misclassification (Figure 11) and deviance (Figure 12) were aggregated into box plots. Each box plot compares the deviance or misclassification for each terminal node within a tree. Misclassification refers to the number of times a disturbance point has been assigned into the wrong class. Tree size refers to the number of splits within the decision tree. Deviance is a measure of how well the model fits the data.

Comparing the four misclassification box plots shows similarities between the various sample size sets. Comparing the 25% sample set with the 40% sample set, both plots have the same structure. Each of the misclassification plots show that as the tree size gets larger there is a decrease in misclassifications, plateauing at size 15. While the range and median of the box plots decrease with increasing size, size 16-18 trees have greater misclassifications. All deviance box plots show the exact same plot structure. From these box plots two conclusions can be made. Growing a CT with any of the four sample sizes will yield consistent results, each of the initial sample sizes has sufficient data to grow the CT classifier. In addition, the increase in misclassification in tree sizes greater than 15 means that any split greater than 15 should be pruned. Based upon the previous results, the CT classifier was grown with a sample size of 30%, outputting a tree with 15 splits. Plotting the misclassification and deviance at each decision split showed results consistent with the box plots but the results did not plateau, thus the tree was not pruned. The tree grown with BorealDB can be seen in Appendix A. The nearest orthogonal disturbance classes of each point were fed into the tree, the tree would predict the disturbance code value for each focal point based upon this data.

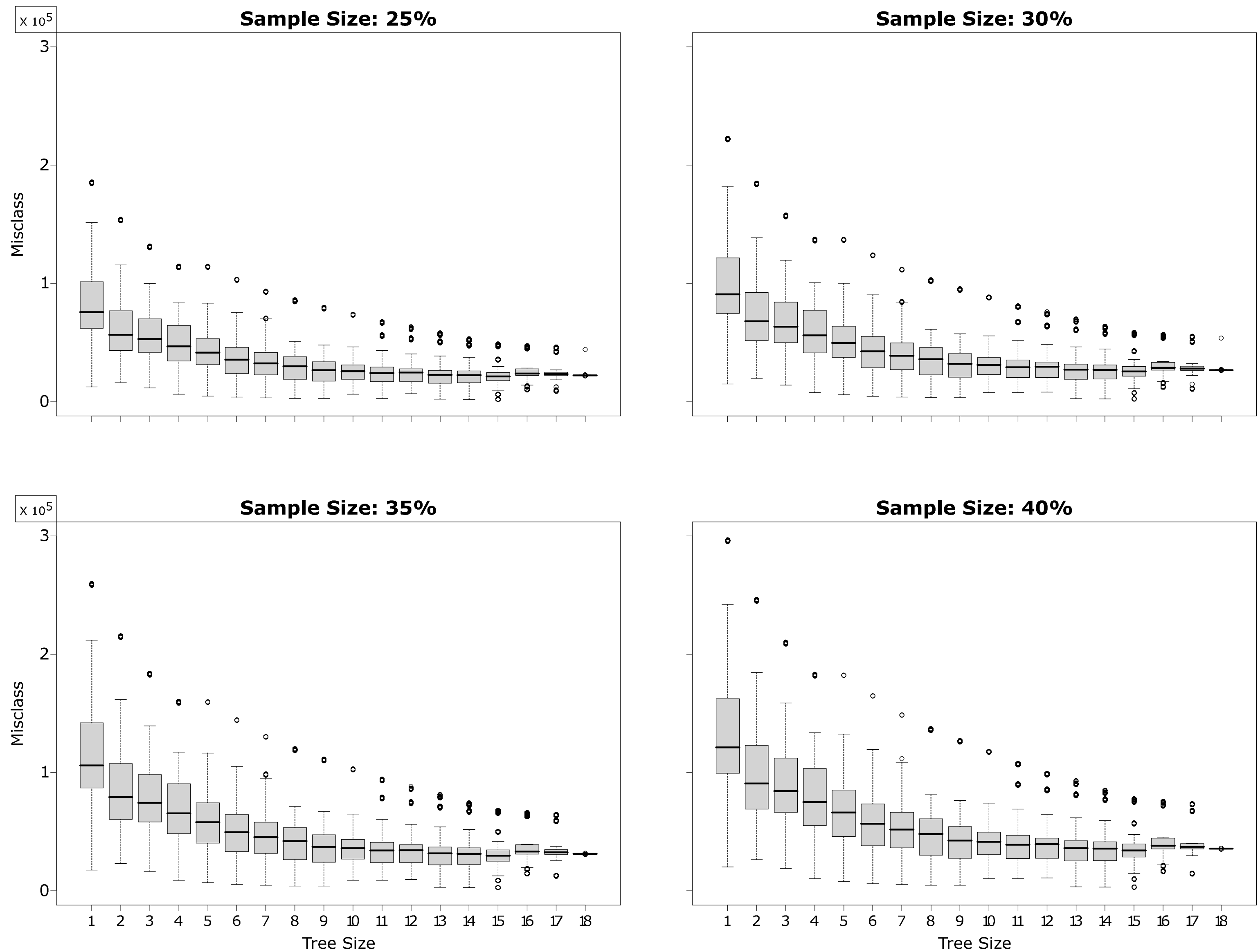


Figure 11. Overfitting test for 1000 trees, misclassification. Disturbance classification tree size to misclassification.

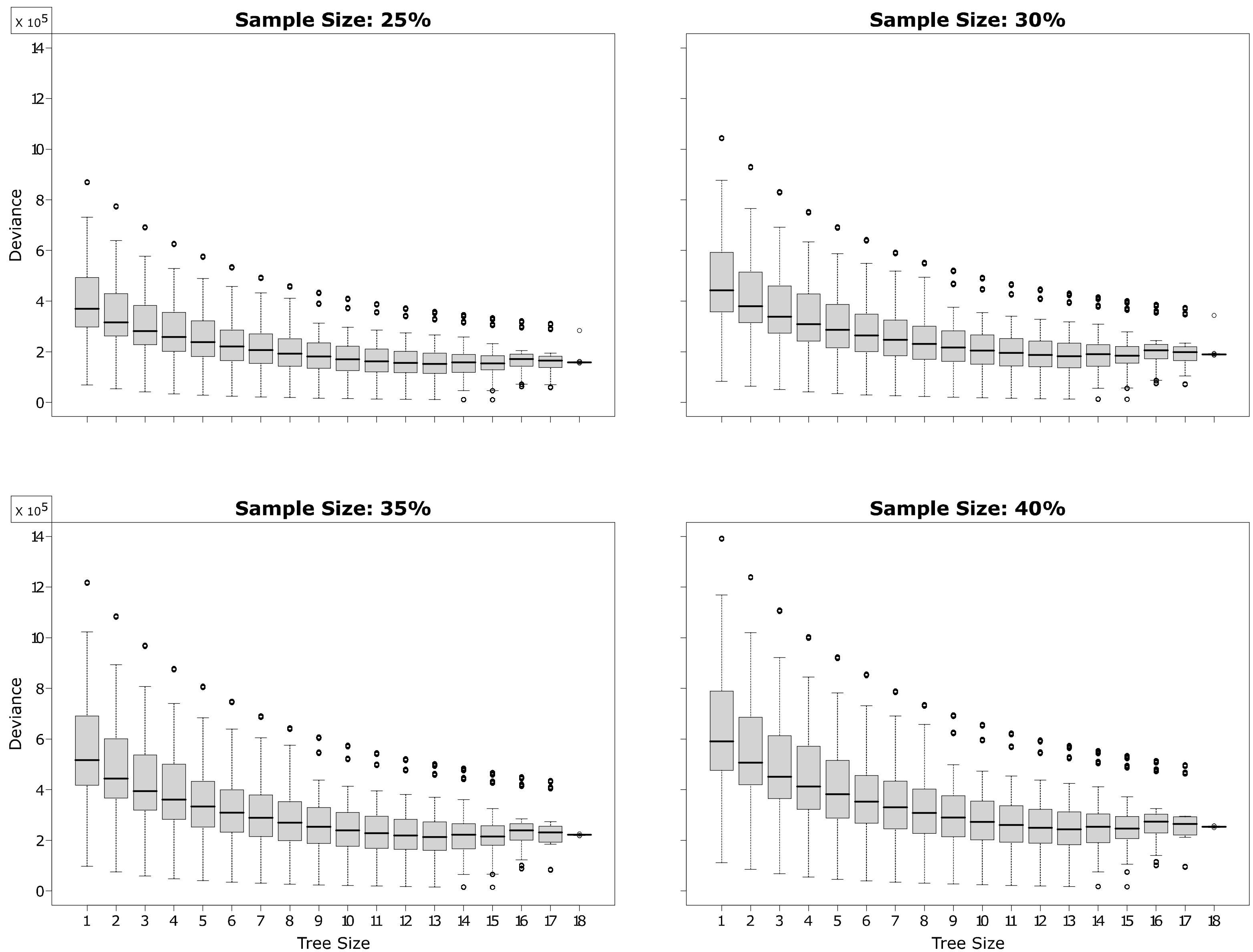


Figure 12. The overfitting test with 1000 trees, deviance. Disturbance classification tree size to deviance.

2.4 Random Forest

RF is a classification algorithm consisting of various decision trees that vote for an optimal classification. It is an ensemble method made up of a large number of decision trees that predict a class for each variable using a weighted vote (Breiman, 2001; Pal, 2005). The algorithm uses bagging, the aggregation of many bootstrap samples from a single data set (Breiman, 1996), which ensures the structure for each tree within a RF is different. Unlike standard CTs the best split is determined by a random subset chosen at the node (Liaw and Wiener, 2002). With this additional randomness RF makes for an effective classifier that is robust against overfitting due to the law of large numbers (Breiman, 2001). A RF model benefits the study as it is an ensemble technique that is non-parametric, makes no assumptions of the distribution of the input data (Wu et al., 2018), is user friendly algorithm with few parameters required (Liaw and Wiener, 2002), does not overfit due to the law of large numbers (Breiman, 2001), and can be used to improve classification accuracy (Ko et al., 2016).

RF is a popular algorithm that has frequent usage within ecological research (Araya et al., 2016; Collins et al., 2018; Huo et al., 2019; Silveira et al., 2019; Wang et al., 2019); RF is often used because it produces a large number of trees with results often better than CART due to decisions being randomized (Ghimire et al., 2012). When compared to other ecological classifiers it was found that two key factors differentiated RF from other classifiers (Cutler et al., 2007). First RF does not experience the shortcomings of traditional classification methods such as selecting single variables among a group of highly correlated predictors. Secondly is the wide variety of analyses that can be performed using the method. Due to its effectiveness as a tool of prediction

RF is used within this research. The RF algorithm makes use of the aggregated BorealDB sample and orthogonal neighbour classifications, incorporating them as parameters within the model. Just like with CT, the nearest orthogonal disturbance classes of each point were fed into RF and predicted the disturbance code value for each focal point based upon this data. The RF model is run in the R environment (R Core Team, 2019) using the `ranger` package which is more computationally and memory efficient than alternative RF packages (Wright and Ziegler, 2017).

2.5 Visual Assessments

After predicting the CT and RF classifiers the most stable classification method was determined by visually assessing disturbance clusters, conglomerates of disturbed points, against original satellite imagery for various sample years (1989, 1990, 1991, 1993, 1994, 1995, 1996, 1997, 1998, 2001, 2003, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2013, 2014, 2015, 2016, 2017, 2018, 2019). BorealDB was derived from Landsat scenes encompassing the MA (Ouellette et al., 2020). Two scenes were selected (Table 1), one scene is located in north-western Ontario while the other scene is located in north-eastern Ontario (Figure 13). The scenes were selected because they are completely within the MA.

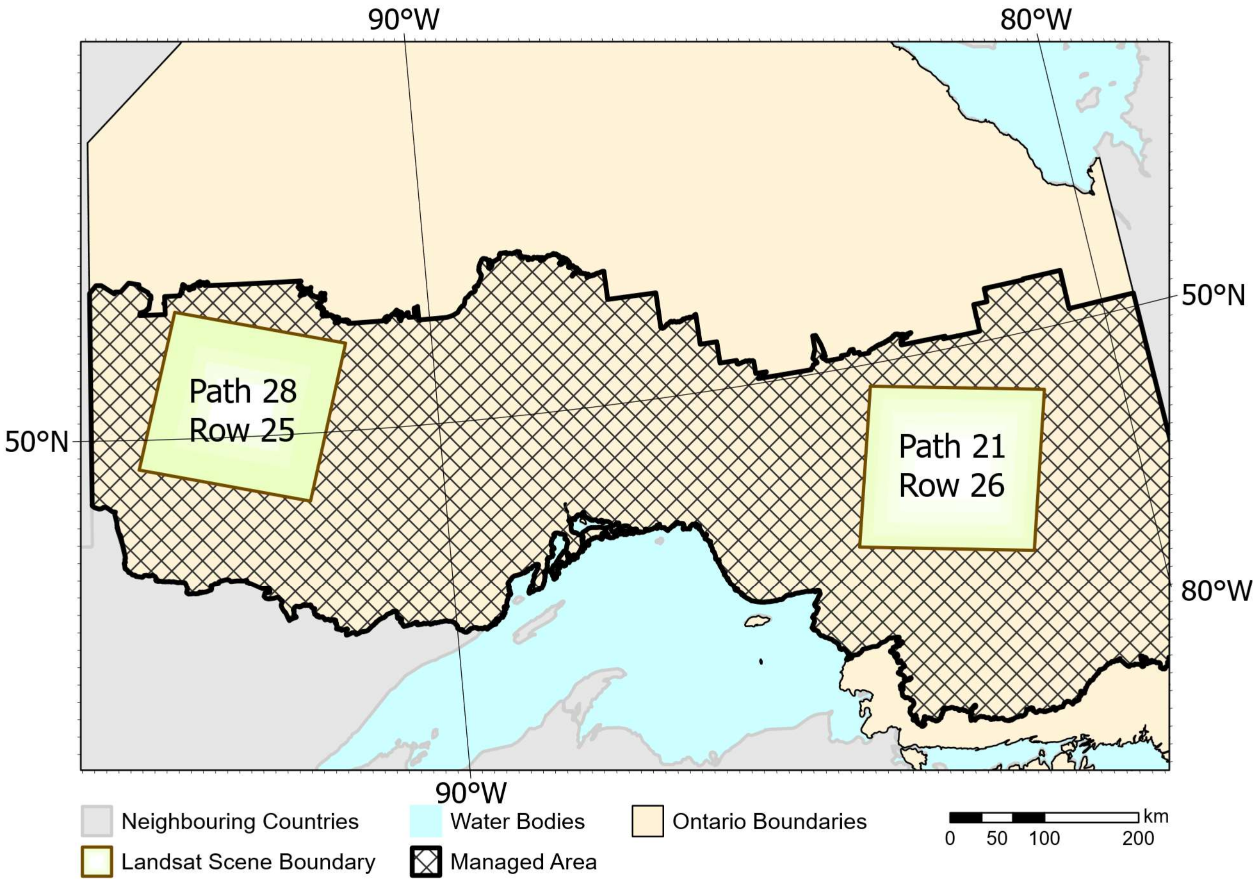


Figure 13. Landsat scenes that were used for visual assessments. Visual assessment samples were acquired from 1989 – 2019.

Sample disturbance clusters were randomly selected to be analyzed. These samples were compared with the original satellite imagery to assess which classification is most reasonable and use this knowledge to suggest the most stable classification method. For each sample the original Landsat images used to classify the disturbance points was used to assess whether the same geographic space a disturbance point occupied was disturbed. The visual assessment determined whether BorealDB identified an existing disturbance and how the disturbance compared to classifiers. Visual assessments compared disturbed clusters with original satellite imagery, identifying point locations overlapping areas burned, areas harvested, and roads for harvests. The disturbance types can be identified visually because harvest disturbances often have clearer spectral values than fire disturbances as depending on fire severity they often leave residual vegetation as well as mixed woody debris (Schroeder et al., 2011). For each disturbance a set of maps and matrices were used to comparing the visual assessment with each classifier. Based upon these comparisons the most stable classifier would be determine by comparing results.

3. Results

3.1 Classifier Results

Areas with overlapping classifications were discerned by comparing the classifier results. Using matrices areas of uncertainty were flagged as areas of disagreement between classifier results, the three classifiers analyzed against each other are:

1. BorealDB, the original classification derived by Ouellette et al. (2020), the basis for the orthogonal states.
2. CT, the tree derived classification based upon orthogonal neighbours.
3. RF, the random forest derived classification using orthogonal neighbours.

The disturbance classes used to classify the data were the disturbance types based upon the disturbance code. To simplify classification, the codes were aggregated to six classes with four as 1st order classes and two as 2nd order (Table 4). Aggregations were based upon a simple majority, where points are aggregated based upon the most frequent classification in a disturbance code composite. The 1st order classes are classified as disturbed by BorealDB: “Fire” representing forest fire events within the current year, “Harvest” representing timber harvesting events in the current year, “Previous Fire” which represent fire events two years prior, and “Previous Harvest” which represents timber harvesting events two years prior. Whereas 2nd order classes lack a definitive classification. First is “Unassigned” which represent disturbance points without a Landsat disturbance code but are recognized as disturbed by the NRCAN or MNRF data sets. As such, the points were labelled as “0” indicating points are disturbed but were not identified as such by BorealDB. “Uncertain” represents disturbance points with conflicting classifications, disturbance code composites with an unclear class majority are labeled as “Uncertain”.

Table 4. Definitions of disturbance classifications.

Order	Class	Definition	Disturbance Code
1st Order	Fire	Forest fire events in within the current year.	1, 2, 3, 4, 12, 1002, 1003
	Harvest	Timber harvesting events in the current year.	10, 20, 21, 30, 31, 40, 120, 130
	Previous Fire (Prev Fire)	Forest fire events within the two years prior.	100
	Previous Harvest (Prev Harvest)	Timber harvesting events within the two years prior.	1000
2nd Order	Unassigned	Disturbance points that lacking a Landsat disturbance code due to being identified as disturbed in an additional data set.	0
	Uncertain	Points that lack a class majority in a disturbance code composite.	11, 22, 110, 1001, 1100

The classifier results were compared using matrices to assess agreement (Table 5), CT did not classify any disturbance points as “Uncertain” thus this label is not included as part of the classifier. For each comparison the agreement, when classifier results agree, and disagreement, when the classifier results disagree, will be discussed.

Table 5. Distribution of disturbance point classifications for each classifier.

		Unassigned		Fire		Harvest		Prev Fire		Prev Harv		Uncertain	
		f	%	*f*	%	*f*	%	*f*	%	*f*	%	*f*	%
Classifier	**BorealDB**	6498326	24	3603799	13	2853090	11	7205664	27	6380663	24	233901	1
	Tree	7787430	29	3221526	12	3193756	12	6727314	25	5845417	22	0	0
	RF	8196403	31	3481118	13	2487778	9	8102063	30	76813	0	4431268	17

Among classifiers (BorealDB, CT, and RF) there were minor differences between current year classifications but noticeable differences in previous year classes, particularly with the RF classifier. “Unassigned” was the most dominant class, with the number of classifications increasing with CT and RF. Comparing BorealDB with RF, “Unassigned” increased by 7%. “Fire” and “Harvest” classifications remained stable with minimal changes between classifiers. Specifically, there was a slight decrease in “Fire” for CT and RF whereas “Harvest” increased for CT but decreased for RF. “Previous Fire” was also a dominant class, with each classifier having similar numbers of classifications. “Previous Harvest” had the most noticeable differences, the number of “Previous Harvest” points predicted by the RF classifier greatly decreased with less than a <1% of disturbance points belonged to this grouping. In contrast CT predicted 22% of disturbance points belonged to “Previous Harvest”, like BorealDB’s 24%. “Uncertain” also had noticeable differences with RF predicting 17% of classifications belonging to “Uncertain” while CT didn’t classify any.

3.2 Neighbouring Points

To discern the effectiveness of the classifiers, predictions were compared with their neighbours in each orthogonal direction. As discussed in section 2.1 points in proximity are more likely to belong to the same disturbance, therefore a disturbed points nearest neighbours should belong to the same class. High levels of agreement serve as an indicator of classifier effectiveness because models are derived from contextual information. Orthogonal neighbour classifications are derived from BorealDB, representing the contextual information that were fed into the CT and RF models. As an example, comparing a point classification with its nearest neighbours (Table 6), many of the point classifications agree with their neighbours. This indicates that the majority of disturbance points belong to clusters of the same class, implying a proximity based relationship between points and thus agreeing with Tobler’s first law of geography (Tobler, 1970).

Table 6. Orthogonal direction agreement tables for BorealDB classifications.

		BorealDB Classification											
		Unassigned		**Fire**		**Harvest**		**Prev Fire**		**Prev Harvest**		**Uncertain**	
		f	**%**	***f***	**%**	***f***	**%**	***f***	**%**	***f***	**%**	***f***	**%**
Northern Class	**Unassigned**	6183377	23	1864748	7	1569719	6	3701875	14	3378707	13	65823	0
	Fire	83525	0	1676043	6	7109	0	30652	0	7816	0	17848	0
	Harvest	159956	1	6536	0	1140312	4	9215	0	113681	0	13608	0
	Prev Fire	25611	0	31846	0	9724	0	3402462	13	23296	0	41791	0
	Prev Harvest	43809	0	7619	0	112079	0	21989	0	2827837	11	28020	0
	Uncertain	2048	0	17007	0	14147	0	39471	0	29326	0	66811	0
Eastern Class	**Unassigned**	6171867	23	1872335	7	1572215	6	3709201	14	3386695	13	66345	0
	Fire	85329	0	1668905	6	6889	0	31726	0	7660	0	17395	0
	Harvest	168341	1	6880	0	1138887	4	9712	0	112163	0	13967	0
	Prev Fire	25129	0	30184	0	9042	0	3391324	13	22545	0	40367	0
	Prev Harvest	45552	0	7894	0	112629	0	22949	0	2823492	11	29128	0
	Uncertain	2108	0	17601	0	13428	0	40752	0	28108	0	66699	0
Western Class	**Unassigned**	6180557	23	1871224	7	1571481	6	3712202	14	3384571	13	67313	0
	Fire	85621	0	1668905	6	6880	0	30184	0	7894	0	17601	0
	Harvest	160140	1	6889	0	1138887	4	9042	0	112629	0	13428	0
	Prev Fire	25349	0	31726	0	9712	0	3391324	13	22949	0	40752	0
	Prev Harvest	44669	0	7660	0	112163	0	22545	0	2823492	11	28108	0
	Uncertain	1990	0	17395	0	13967	0	40367	0	29128	0	66699	0
Southern Class	**Unassigned**	6169806	23	1864331	7	1569738	6	3696545	14	3383119	13	67139	0
	Fire	84322	0	1676043	6	6536	0	31846	0	7619	0	17007	0
	Harvest	170121	1	7109	0	1140312	4	9724	0	112079	0	14147	0
	Prev Fire	25673	0	30652	0	9215	0	3402462	13	21989	0	39471	0
	Prev Harvest	46279	0	7816	0	113681	0	23296	0	2827837	11	29326	0
	Uncertain	2125	0	17848	0	13608	0	41791	0	28020	0	66811	0

As a note, a large percentage of the neighbours belong to the “Unassigned” class. This does not necessarily indicate that a disturbance point is adjacent to a “Unassigned” point as the value includes points with no neighbours which affects the actual number of points assigned as “Unassigned”. Thus, while discussing nearest neighbours the “Unassigned” class will be predominately ignored.

3.2.1 CT Neighbours

Comparing CT predictions nearest neighbour classes found almost all neighbours belonged to the same class as the focal point (Table 7) with points to the north and south of the focal point having the most agreement. Every “Harvest” and “Previous Harvest” point predicted by CT, except for “Unassigned”, agreed with the northern point class. A similar trend is observed with the southern points, every disturbance point neighbouring a “Fire” or “Previous Fire” point was of the same class. Disturbance points to the east and west of the focal point had lower agreements, with predictions being more distributed among classes. Disturbance points with the most disagreement were the eastern neighbours of “Harvest” classified points, where approximately 16% of “Harvest” predictions neighboured a “Fire” point, which is higher relative to other disagreements.

Table 7. Orthogonal direction agreement tables for Classification tree predictions.

		Classification Tree Predictions									
		Unassigned		**Fire**		**Harvest**		**Prev Fire**		**Prev Harvest**	
		f	**%**	***f***	**%**	***f***	**%**	***f***	**%**	***f***	**%**
Northern Class	**Unassigned**	7787428	29	1331153	5	1769058	7	3045903	11	2830707	11
	Fire	2	0	1798652	7	0	0	24339	0	0	0
	Harvest	0	0	10496	0	1424698	5	8114	0	0	0
	Prev Fire	0	0	25039	0	0	0	3509691	13	0	0
	Prev Harvest	0	0	7278	0	0	0	19365	0	3014710	11
	Uncertain	0	0	48908	0	0	0	119902	0	0	0
Eastern Class	**Unassigned**	7787269	29	1627251	6	1489861	6	3068939	11	2805338	10
	Fire	143	0	1494909	6	280505	1	34466	0	7881	0
	Harvest	18	0	17412	0	1294141	5	21025	0	117354	0
	Prev Fire	0	0	30221	0	7840	0	3461569	13	18961	0
	Prev Harvest	0	0	15602	0	107888	0	45116	0	2873038	11
	Uncertain	0	0	36131	0	13521	0	96199	0	22845	0
Western Class	**Unassigned**	7787288	29	1348443	5	1776802	7	3070466	11	2804349	10
	Fire	127	0	1769860	7	5123	0	33979	0	7996	0
	Harvest	14	0	15977	0	1288654	5	20030	0	116340	0
	Prev Fire	0	0	32386	0	7985	0	3458646	13	22795	0
	Prev Harvest	0	0	14851	0	105288	0	49731	0	2868767	11
	Uncertain	1	0	40009	0	9904	0	94462	0	25170	0
Southern Class	**Unassigned**	7780274	29	1334531	5	1755023	7	3062303	11	2818547	11
	Fire	0	0	1823373	7	0	0	0	0	0	0
	Harvest	14	0	11490	0	1350989	5	14647	0	76352	0
	Prev Fire	0	0	0	0	0	0	3529462	13	0	0
	Prev Harvest	0	0	12016	0	78292	0	36001	0	2921926	11
	Uncertain	7142	0	40116	0	9452	0	84901	0	28592	0

3.2.2 RF Neighbours

Comparing RF predictions against nearest neighbours predominately found disagreement (Table 8). Despite low agreement distribution of agreement was consistent amongst directions. “Fire” was the most consistent agreement with predictions agreeing with approximately 93% of neighbouring classification in each direction. Harvest type classes consistently have the lowest agreement. For example, “Previous Harvest” predictions had approximately 10% of neighbouring classifications agreeing. Instead, points classified by RF as “Harvest” predominately neighbour “Previous Harvest” points. “Previous Fire” predictions often neighbour “Harvest” and “Previous Harvest” points. Of the contextual classifiers CT has the highest overall agreement with its neighbours, indicating CT predictions are more alike nearest neighbour classes than the RF.

Table 8. Orthogonal direction agreement tables for Random Forest predictions.

		Random Forest Predictions											
		Unassigned		Fire		Harvest		Prev Fire		Prev Harvest		Uncertain	
		f	**%**	***f***	**%**	***f***	**%**	***f***	**%**	***f***	**%**	***f***	**%**
Northern Class	**Unassigned**	7791333	29	1631818	6	947881	4	5331323	20	42277	0	1019617	4
	Fire	225	0	1722562	6	70943	0	10839	0	4379	0	14045	0
	Harvest	5193	0	61319	0	13961	0	1319875	5	6673	0	36287	0
	Prev Fire	35	0	15160	0	15891	0	528159	2	2711	0	2972774	11
	Prev Harvest	399455	1	20154	0	1377719	5	898642	3	3176	0	342207	1
	Uncertain	162	0	30105	0	61383	0	13225	0	17597	0	46338	0
Eastern Class	**Unassigned**	8183895	31	1655750	6	682904	3	4488971	17	15587	0	1751551	7
	Fire	945	0	1713368	6	73266	0	11946	0	5668	0	12711	0
	Harvest	5151	0	37832	0	22150	0	1288282	5	27599	0	68936	0
	Prev Fire	12	0	17384	0	28071	0	963589	4	6190	0	2503345	9
	Prev Harvest	648	0	25733	0	1631793	6	1329558	5	2266	0	51646	0
	Uncertain	5752	0	31051	0	49594	0	19717	0	19503	0	43079	0
Western Class	**Unassigned**	7789564	29	1624831	6	359606	1	5672874	21	32779	0	1307694	5
	Fire	253	0	1708616	6	70955	0	16322	0	4539	0	16400	0
	Harvest	654	0	57712	0	13363	0	1294774	5	13123	0	61389	0
	Prev Fire	15	0	23134	0	18712	0	528601	2	6527	0	2944823	11
	Prev Harvest	405710	2	24059	0	1965885	7	576265	2	3784	0	62934	0
	Uncertain	207	0	42766	0	59257	0	13227	0	16061	0	38028	0
Southern Class	**Unassigned**	8185054	31	1628427	6	612900	2	4797869	18	25639	0	1500789	6
	Fire	894	0	1721249	6	71710	0	7843	0	4668	0	17009	0
	Harvest	20	0	48335	0	30724	0	1309214	5	20970	0	44229	0
	Prev Fire	6	0	21873	0	17913	0	971582	4	2401	0	2515687	9
	Prev Harvest	5798	0	26748	0	1695453	6	1000070	4	5155	0	315011	1
	Uncertain	4631	0	34486	0	59078	0	15485	0	17980	0	38543	0

3.3 BorealDB versus Classification Tree

The BorealDB and CT classifiers have the highest agreement between classifiers at 84.88% (Table 9) indicating BorealDB's classifications agree with CT predictions derived from the focal context. Meaning 15% of classifications can be assessed as areas of classification uncertainty. Individual class agreements range from 70% to 95%, with previous year classes having higher agreement than current year classes. This is observed with the high agreement of both "Previous Fire" (94.8% of CT with 88.5% BorealDB) and "Previous Harvest" (93.3% of CT with 84.4% BorealDB). "Harvest" has the lowest agreement with only 80.1% of points classified by BorealDB agreeing with 71.5% of CT predictions. Despite "Harvest" agreement being low relative to other classes the majority still agrees, indicating orthogonal neighbour derived classifications gives confidence to BorealDB's classes within the confines of the CT model.

Table 9. Class frequencies of BorealDB and classification tree predictions.

		Classification Tree				
		Unassigned	**Fire**	**Harvest**	**Prev Fire**	**Prev Harvest**
BorealDB	**Unassigned**	5701816	168302	445604	64959	117645
	Fire	371269	2910110	257649	53221	11550
	Harvest	318024	24249	2284639	30975	195203
	Prev Fire	734307	45428	14603	6378858	32468
	Prev Harvest	657648	22275	174463	74382	5451895
	Uncertain	4366	51162	16798	124919	36656
Agree	**BorealDB**	87.74%	80.75%	80.08%	88.53%	85.44%
	Tree	73.22%	90.33%	71.53%	94.82%	93.27%
	Overall	84.88%				

Most disagreement (15%) is concentrated within “Unassigned” and “Uncertain” (Table 10). Points classified by BorealDB as “Fire”,” Harvest”, “Previous Fire”, and “Previous Harvest” are predominately classified by CT as “Unassigned”. In addition, current year classifications often classify as previous year counterparts as well as the reverse. The exception are points classified by BorealDB as “Fire” which CT frequently predicted as “Harvest”.

Table 10. Class agreement between BorealDB and classification tree predictions.

			Classification Tree				
			Unassigned	Fire	Harvest	Prev Fire	Prev Harvest
BorealDB	**Unassigned**	**BorealDB**	87.74%	2.59%	6.86%	1.00%	1.81%
		Tree	73.22%	5.22%	13.95%	0.97%	2.01%
	Fire	**BorealDB**	10.30%	80.75%	7.15%	1.48%	0.32%
		Tree	4.77%	90.33%	8.07%	0.79%	0.20%
	Harvest	**BorealDB**	11.15%	0.85%	80.08%	1.09%	6.84%
		Tree	4.08%	0.75%	71.53%	0.46%	3.34%
	Prev Fire	**BorealDB**	10.19%	0.63%	0.20%	88.53%	0.45%
		Tree	9.43%	1.41%	0.46%	94.82%	0.56%
	Prev Harvest	**BorealDB**	10.31%	0.35%	2.73%	1.17%	85.44%
		Tree	8.44%	0.69%	5.46%	1.11%	93.27%
	Uncertain	**BorealDB**	1.87%	21.87%	7.18%	53.41%	15.67%
		Tree	0.06%	1.59%	0.53%	1.86%	0.63%

3.4 BorealDB versus Random Forest

Agreement between BorealDB and RF is the lowest amongst classifiers (42.43%) (Table 11). Indicating approximately 58% of classifications can be assessed as areas of classification uncertainty. Class agreements predominately disagreed except for “Fire” and “Unassigned” classes. Of the 1st order classes 85.08% of points classified as “Fire” by BorealDB agreed with 88.08% of RF’s predictions, followed by “Previous Fire” (34.10% of BorealDB to 30.32% of RF), “Harvest” (2.07% of BorealDB to 2.38% of RF), and “Previous Harvest” (0.09% of BorealDB to 7.10% of RF) with the lowest overall agreement. The “Unassigned” class found 87.85% of points classified by BorealDB agreed with 69.65% of points predicted by RF. “Uncertain” classifications found 27.96% of points classified by BorealDB agreeing with 1.48% of points predicted by RF. While the difference between the percentages is high it highlights that RF classified more disturbance points as “Uncertain” than BorealDB.

Table 11. Class frequencies of BorealDB and random forest predictions.

		Random Forest					
		Unassigned	**Fire**	**Harvest**	**Previous Fire**	**Prev Harvest**	**Uncertain**
BorealDB	**Unassigned**	5708972	193497	33168	525058	7917	29714
	Fire	371756	3066139	90948	36248	12362	26346
	Harvest	329317	80134	59156	2293796	28815	61872
	Prev Fire	736581	52598	40546	2456805	5743	3913391
	Prev Harvest	1043446	44240	2203517	2749466	5450	334544
	Uncertain	6331	44510	60443	40690	16526	65401
Agree	**BorealDB**	87.85%	85.08%	2.07%	34.10%	0.09%	27.96%
	Random Forest	69.65%	88.08%	2.38%	30.32%	7.10%	1.48%
	Overall	42.43%					

Classification disagreement was unevenly distributed amongst classes, predictions were often concentrated within a few classes. This can be observed with RF “Harvest” predictions where disagreement was distributed amongst 1st order classes (Table 12). 88.57% of RF “Harvest” predictions were classified by BorealDB as “Previous Harvest”. Similarly, 80.40% of BorealDB “Harvest” classifications were predicted by RF as “Previous Fire”. Another instance was with RF “Uncertain” predictions where 88.31% of points were classified by BorealDB as “Previous Harvest”. The exception is RF “Previous Fire” predicted classes where disagreement was divided amongst BorealDB “Harvest” (80.40% of BorealDB to 28.31% of RF) and “Previous Harvest” (43.09% of BorealDB to 33.94% of RF) classifications.

Table 12. Class agreement between BorealDB and random forest predictions.

			Random Forest					
			Unassigned	Fire	Harvest	Prev Fire	Prev Harvest	Uncertain
BorealDB	**Unassigned**	**BorealDB**	87.85%	2.98%	0.51%	8.08%	0.12%	0.46%
		RF	69.65%	5.56%	1.33%	6.48%	10.31%	0.67%
	Fire	**BorealDB**	10.32%	85.08%	2.52%	1.01%	0.34%	0.73%
		RF	4.54%	88.08%	3.66%	0.45%	16.09%	0.59%
	Harvest	**BorealDB**	11.54%	2.81%	2.07%	80.40%	1.01%	2.17%
		RF	4.02%	2.30%	2.38%	28.31%	37.51%	1.40%
	Prev Fire	**BorealDB**	10.22%	0.73%	0.56%	34.10%	0.08%	54.31%
		RF	8.99%	1.51%	1.63%	30.32%	7.48%	88.31%
	Prev Harvest	**BorealDB**	16.35%	0.69%	34.53%	43.09%	0.09%	5.24%
		RF	12.73%	1.27%	88.57%	33.94%	7.10%	7.55%
	Uncertain	**BorealDB**	2.71%	19.03%	25.84%	17.40%	7.07%	27.96%
		RF	0.08%	1.28%	2.43%	0.50%	21.51%	1.48%

3.5 Classification Tree versus Random Forest

Agreement between CT and RF is at 50.04%, indicating approximately half of all disturbance classifications agree (Table 13). Class agreements between CT and RF show similarities with agreements between BorealDB and RF with “Fire” (94.50% of CT to 87.46% of RF) and “Previous Fire” (37.67% of CT to 31.28% of RF) having higher agreement than other classes. Harvest type classes have the lowest agreement, with “Harvest” (0.88% of CT to 1.14% of RF) overall having less agreement than “Previous Harvest” (0.10% of CT to 7.94% of RF).

Table 13. Class frequencies of classification tree and random forest predictions.

		Random Forest					
		Unassigned	**Fire**	**Harvest**	**Prev Fire**	**Prev Harvest**	**Uncertain**
Tree	**Unassigned**	7784760	1045	14	1608	0	3
	Fire	1222	3044490	99720	23645	31881	20568
	Harvest	5215	361861	28250	2728079	31533	38818
	Prev Fire	5745	42498	99469	2534507	7300	4037795
	Prev Harvest	399461	31224	2260325	2814224	6099	334084
Agree	**Tree**	99.97%	94.50%	0.88%	37.67%	0.10%	0%
	Random Forest	94.98%	87.46%	1.14%	31.28%	7.94%	0%
	Overall	50.04%					

The distribution of disagreement between CT and RF is concentrated within 1st order classes (Table 14). Classification disagreement was unevenly distributed amongst classes, predominately concentrated into a single class. RF “Harvest” predictions found the majority of disagreement concentrated within CT “Previous Harvest” predictions (90.86% of RF). Similarly, 85.42% of CT “Harvest” predictions were classified by RF as “Previous Fire”. Another instance is RF “Uncertain” where 91.12% of predictions belonged to CT “Previous Fire” predictions. The exception is points classified by RF as “Previous Fire”, unlike previous examples disagreement was divided more evenly amongst CT “Harvest” (33.67% of RF) and “Previous Harvest” (34.73% of RF) predictions.

Table 14. Class agreement between classification tree and random forest classifiers

Classification Tree			Random Forest: Unassigned	Fire	Harvest	Prev Fire	Prev Harvest	Uncertain
	Unassigned	Tree	99.97%	0.01%	0.00%	0.02%	0.00%	0.00%
		RF	94.98%	0.03%	0.00%	0.02%	0.00%	0.00%
	Fire	Tree	0.04%	94.50%	3.10%	0.73%	0.99%	0.64%
		RF	0.01%	87.46%	4.01%	0.29%	41.50%	0.46%
	Harvest	Tree	0.16%	11.33%	0.88%	85.42%	0.99%	1.22%
		RF	0.06%	10.39%	1.14%	33.67%	41.05%	0.88%
	Prev Fire	Tree	0.09%	0.63%	1.48%	37.67%	0.11%	60.02%
		RF	0.07%	1.22%	4.00%	31.28%	9.50%	91.12%
	Prev Harvest	Tree	6.83%	0.53%	38.67%	48.14%	0.10%	5.72%
		RF	4.87%	0.90%	90.86%	34.73%	7.94%	7.54%

3.6 Visual Assessment

To determine the most stable classifier the sampled locations were visually assessed against the original satellite imagery. Visually assessing sample locations means the effectiveness of the classifiers, the potential causes of uncertainty within the data, and BorealDB's ability to identify disturbances can be assessed. This analysis scrutinizes the effectiveness of the classifiers for determine potential improvements that can be applied to future research. Agreement within this section is understood as the degree to which a classifier resembles its disturbed state in the satellite imagery. Samples were chosen randomly amongst disturbance clusters, with each sample being current year disturbances.

Each sample has maps to depict classifier results, and a map depict a visual comparison between the point clusters and its geographic location's disturbed state. These maps were analyzed to assess the relationship between disturbed point classifications and their representations. The results of the samples are organized in the tables below (Table 15, Table 16, Table 17, Table 18, Table 19, Table 20, Table 21, and Table 22).

Table 15. All Path 21/Row 26 timber harvesting disturbance samples collected before 2001.

		1989		1990		1991		1993		1995		1997		1998	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	0	245	15	217	0	0	931	903	0	0	2	40	6	557
	Fire	0	0	0	248	0	0	0	0	0	0	0	0	0	7
	Harvest	1	587	0	94	0	130	1	480	0	99	0	24	0	107
	P-Fire	0	0	0	0	0	72	0	0	0	0	0	0	0	0
	P-Harv	31	4	39	1363	0	146	0	162	0	16	0	0	0	11
	Uncertain	0	0	0	109	0	6	0	0	0	0	0	0	0	16
Classification Tree	Unassigned	1	285	21	195	0	55	910	471	0	6	2	24	6	452
	Fire	0	0	1	391	0	0	0	0	0	0	0	0	0	37
	Harvest	0	549	1	137	0	100	19	825	0	89	0	40	0	188
	P-Fire	0	0	0	0	0	74	0	0	0	0	0	0	0	0
	P-Harv	31	2	0	1308	0	125	3	249	0	20	0	0	0	21
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	2	10	22	256	0	61	910	488	0	6	2	24	6	452
	Fire	11	32	2	536	0	0	0	0	0	0	0	13	0	33
	Harvest	0	0	13	506	0	46	0	68	0	8	0	0	0	5
	P-Fire	0	39	14	608	0	186	22	987	0	96	0	17	0	185
	P-Harv	1	11	0	40	0	1	0	0	0	0	0	6	0	21
	Uncertain	0	13	3	85	0	60	0	22	0	4	0	1	0	6

Table 16. All Path 21/Row 26 timber harvesting disturbance samples collected from 2001 to 2010.

		2001		2003		2005		2006		2007		2009		2010	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	0	0	3	367	0	7	0	22	0	0	0	0	4	200
	Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harvest	0	239	0	478	0	17	0	818	0	7	0	14	0	118
	P-Fire	0	0	6	0	0	0	0	0	4	2	0	0	0	0
	P-Harv	0	226	0	0	0	89	5	51	3	118	0	91	0	18
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Classification Tree	Unassigned	0	28	6	147	0	7	1	120	1	120	0	15	4	195
	Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harvest	0	222	1	698	0	19	0	719	0	719	0	12	0	127
	P-Fire	0	0	2	0	0	0	0	0	0	0	0	0	0	0
	P-Harv	0	215	0	0	0	87	4	52	4	52	0	78	0	14
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	0	43	6	147	0	11	1	123	1	123	0	21	4	196
	Fire	0	2	0	45	0	0	0	0	0	0	0	0	0	4
	Harvest	0	69	0	0	0	45	0	9	0	9	0	20	0	2
	P-Fire	0	319	3	634	0	45	2	752	2	752	0	52	0	131
	P-Harv	0	2	0	9	0	0	0	0	0	0	0	0	0	2
	Uncertain	0	30	0	10	0	12	2	7	2	7	0	12	0	1

Table 17. All Path 21/Row 26 timber harvesting disturbance samples collected from 2011 to 2020.

		2011		2013		2014		2015		2017		2018		2019	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	0	0	18	422	19	846	7	389	0	0	0	0	0	0
	Fire	0	0	0	0	0	0	43	168	0	0	0	0	0	0
	Harvest	0	129	0	36	0	64	0	61	23	100	0	216	1	56
	P-Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	P-Harv	0	29	0	160	0	0	0	0	0	0	0	68	0	0
	Uncertain	0	0	0	0	0	0	0	29	0	0	0	0	0	0
Classification Tree	Unassigned	0	10	17	412	15	739	8	216	2	12	0	27	1	6
	Fire	0	0	0	0	0	0	39	301	0	0	0	0	0	0
	Harvest	0	116	0	35	4	171	3	130	0	0	0	199	0	48
	P-Fire	0	0	0	0	0	0	0	0	21	88	0	0	0	0
	P-Harv	0	32	1	171	0	0	0	0	0	0	0	58	0	0
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	0	11	17	423	15	739	8	216	2	12	0	30	1	8
	Fire	0	0	0	0	0	0	41	259	0	0	0	0	0	0
	Harvest	0	6	0	59	0	0	0	0	0	0	0	12	0	0
	P-Fire	0	134	1	124	4	171	1	137	21	88	0	0	0	48
	P-Harv	0	0	0	0	0	0	0	35	0	0	0	0	0	0
	Uncertain	0	7	0	12	0	0	0	0	0	0	0	0	0	0

Table 18. All Path 28/Row 25 fire disturbance samples collected before 2001.

		1989		1990		1991		1995		1997		1998	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	1	27	0	16	0	46	855	1738	110	655	1	19
	Fire	13	0	0	874	28	946	0	16	4	1607	34	838
	Harvest	0	78	0	3	0	0	0	154	0	0	0	550
	P-Fire	0	0	0	0	0	0	0	0	0	0	0	0
	P-Harv	0	0	0	19	4	101	32	1018	0	0	0	45
	Uncertain	0	0	0	2	1	143	0	0	0	0	0	52
Classification Tree	Unassigned	2	10	0	93	1	31	862	1588	49	148	4	170
	Fire	11	0	0	731	24	1087	0	29	54	2037	26	1024
	Harvest	1	95	0	53	4	38	0	348	11	77	5	495
	P-Fire	0	0	0	0	0	0	0	0	0	0	0	0
	P-Harv	0	0	0	17	4	80	25	961	0	0	0	35
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	2	10	0	93	1	32	862	1650	49	148	4	171
	Fire	11	32	0	807	29	1185	0	37	15	336	29	788
	Harvest	0	0	0	1	0	3	3	488	50	1778	0	5
	P-Fire	0	39	0	12	2	14	20	682	0	0	2	574
	P-Harv	1	11	0	0	0	0	0	0	0	0	0	182
	Uncertain	0	13	0	1	1	2	2	69	0	0	0	4

Table 19. All Path 28/Row 25 fire disturbance samples collected after 2001.

		2001		2007		2010		2011		2015		2018	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	0	0	0	0	0	0	0	0	0	0	0	0
	Fire	106	0	20	11	582	0	248	54	74	441	64	133
	Harvest	0	0	0	5	0	0	0	0	0	0	0	0
	P-Fire	0	0	0	0	0	0	51	21	0	0	0	0
	P-Harv	0	0	0	20	0	0	0	0	0	0	0	0
	Uncertain	0	0	0	6	0	0	0	0	0	0	0	0
Classification Tree	Unassigned	98	0	0	2	74	0	31	9	6	35	3	12
	Fire	3	0	18	15	464	0	198	42	63	382	59	114
	Harvest	0	0	2	8	44	0	21	5	5	24	2	7
	P-Fire	0	0	0	0	0	0	49	19	0	0	0	0
	P-Harv	0	0	0	17	0	0	0	0	0	0	0	0
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	5	0	0	3	0	0	31	9	6	35	3	12
	Fire	101	0	20	23	74	0	220	47	68	406	61	121
	Harvest	0	0	0	2	508	0	0	0	0	0	0	0
	P-Fire	0	0	0	13	0	0	19	10	0	0	0	0
	P-Harv	0	0	0	0	0	0	0	0	0	0	0	0
	Uncertain	0	0	0	1	0	0	29	9	0	0	0	0

Table 20. All Path 28/Row 25 timber harvest disturbance samples collected before 2001.

		1991		1994		1995		1996		1997		1998		2000	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	209	241	36	118	13	178	177	214	23	122	2	51	30	238
	Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	Harvest	0	91	7	262	0	94	0	114	0	58	0	48	0	152
	P-Fire	0	0	0	0	0	0	0	0	0	0	0	0	23	20
	P-Harv	0	0	0	0	0	0	0	1	0	165	0	4	0	12
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	5
Classification Tree	Unassigned	196	163	23	27	8	98	171	149	16	85	0	21	28	156
	Fire	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	Harvest	13	169	20	353	5	174	6	177	7	101	2	78	7	234
	P-Fire	0	0	0	0	0	0	0	3	0	0	0	0	18	27
	P-Harv	0	0	0	0	0	0	0	0	0	168	0	4	0	10
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	196	163	23	27	23	27	171	149	16	85	0	21	28	158
	Fire	0	0	5	68	5	68	0	0	0	0	0	0	0	0
	Harvest	0	0	0	1	0	1	0	0	0	107	0	0	0	3
	P-Fire	13	169	15	220	15	220	6	180	7	148	2	82	18	248
	P-Harv	0	0	0	23	0	23	0	0	0	0	0	0	0	0
	Uncertain	0	0	0	40	0	42	0	0	0	6	0	0	7	18

Table 21. All Path 28/Row 25 timber harvest disturbance samples collected after 2000.

		2001		2003		2005		2006		2008		2011		2015		2016	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	7	6	374	469	17	3	34	128	0	94	0	0	12	25	2	0
	Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harvest	0	54	6	845	19	145	0	121	0	105	0	37	0	179	0	65
	P-Fire	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0
	P-Harv	2	71	0	934	9	103	0	72	0	32	0	24	0	107	3	86
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Classification Tree	Unassigned	7	6	309	279	3	17	30	53	0	44	0	9	11	27	2	4
	Fire	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harvest	0	54	68	1015	25	129	4	193	0	157	0	30	1	185	0	59
	P-Fire	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0
	P-Harv	2	71	3	954	17	105	0	75	0	30	0	22	0	99	3	88
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	7	15	309	342	5	19	30	61	0	48	0	9	11	35	3	11
	Fire	0	15	11	104	0	0	1	31	0	51	0	0	0	53	0	13
	Harvest	0	11	0	479	3	42	0	26	0	9	0	4	0	35	2	36
	P-Fire	2	73	53	1164	37	175	3	178	0	88	3	46	1	155	0	81
	P-Harv	0	3	5	26	0	0	0	10	0	19	0	0	0	11	0	0
	Uncertain	0	14	2	133	0	15	0	15	0	16	5	2	0	22	0	10

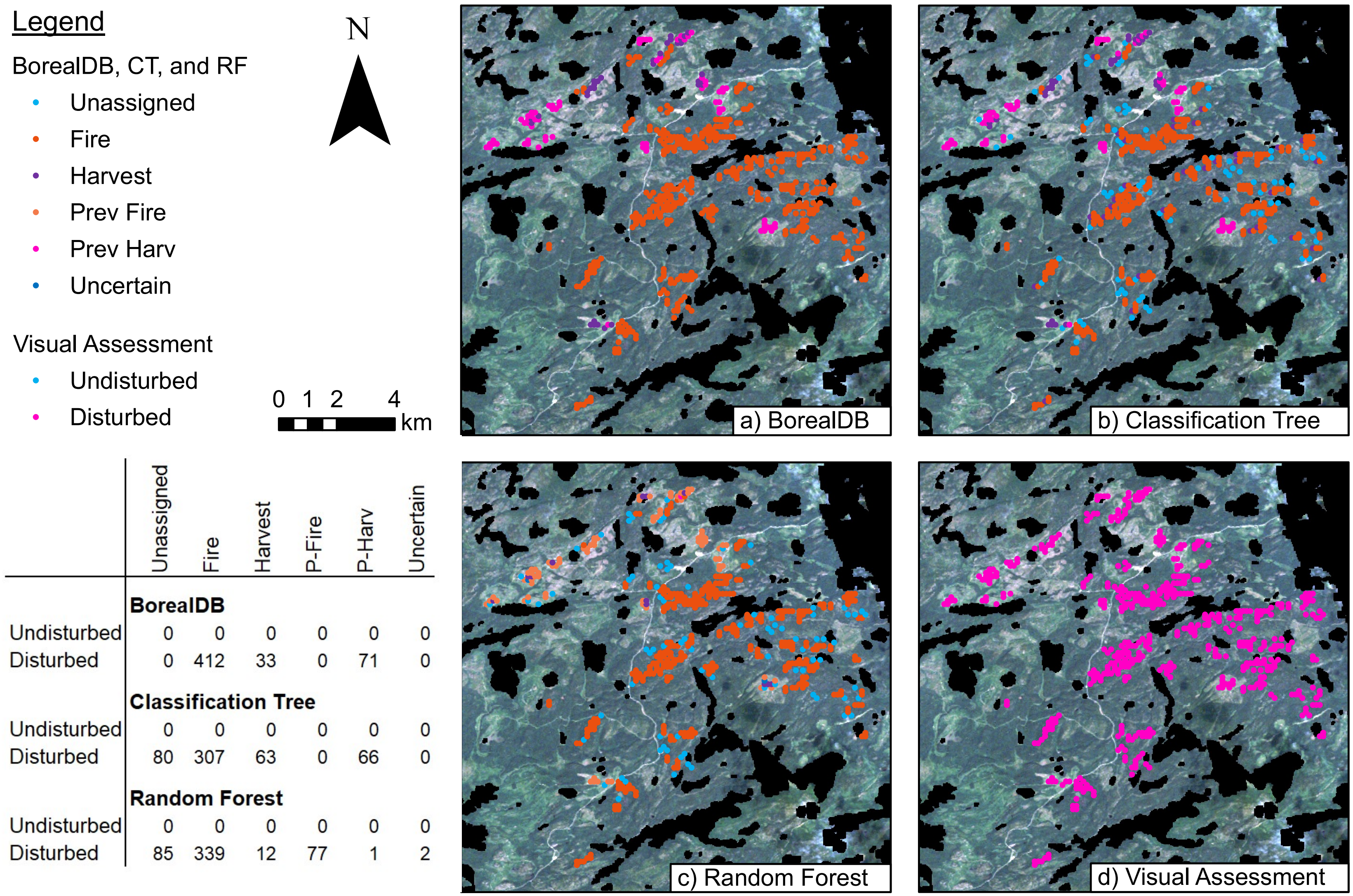
Table 22. All Path 28/Row 25 fire disturbance samples.

		1995		1996		1997		2001		2006		2011	
		Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed	Undisturbed	Disturbed
BorealDB	Unassigned	3184	0	20	88	0	0	1	0	586	96	0	0
	Fire	0	2640	12	605	69	497	22	1429	0	886	0	412
	Harvest	0	0	0	0	0	0	0	0	0	0	0	33
	P-Fire	0	0	23	953	0	0	0	0	0	0	0	0
	P-Harv	0	0	6	0	0	0	2	0	0	0	0	71
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0
Classification Tree	Unassigned	1541	46	3	30	2	10	4	148	214	56	0	80
	Fire	1497	2513	16	602	64	470	18	1173	330	902	0	307
	Harvest	146	81	1	28	3	17	3	107	42	24	0	63
	P-Fire	0	0	35	986	0	0	0	1	0	0	0	0
	P-Harv	0	0	6	0	0	0	0	1	0	0	0	66
	Uncertain	0	0	0	0	0	0	0	0	0	0	0	0
Random Forest	Unassigned	1541	46	3	30	2	10	4	148	216	58	0	85
	Fire	1643	2594	19	602	67	487	21	1280	135	216	0	339
	Harvest	0	0	2	0	0	0	0	0	235	708	0	12
	P-Fire	0	0	17	147	0	0	0	1	0	0	0	77
	P-Harv	0	0	0	0	0	0	0	0	0	0	0	1
	Uncertain	0	0	20	867	0	0	0	0	0	0	0	2

3.6.1 Visual comparisons

Visual assessments are analyses of a disturbance cluster sample's classification against the original satellite imagery used to classify the data. For each sample disturbance points are compared visually with the original satellite imagery to determine whether the disturbed point belongs to the disturbance. The visual comparisons were encoded to each sample to determine whether the disturbed point agreed. Each cluster is designated a disturbance type based upon the majority of its point classes. If a disturbance cluster contains a hundred disturbance points and eighty are classified as harvest, then the cluster would be a timber harvesting disturbance. For a disturbance cluster the number of disturbance points belonging to a class varies depending on the classifier, by comparing the results of the classifiers the cluster that agrees the most with the visual assessment is the classifier that best fits. The effectiveness of a classifier means to determine the classifier that best fits the visual assessment. Using the previous example, if one classifier contains more "Harvest" classified points than any other classifier for a timber harvest disturbance then that classifier best fits the visual assessment.

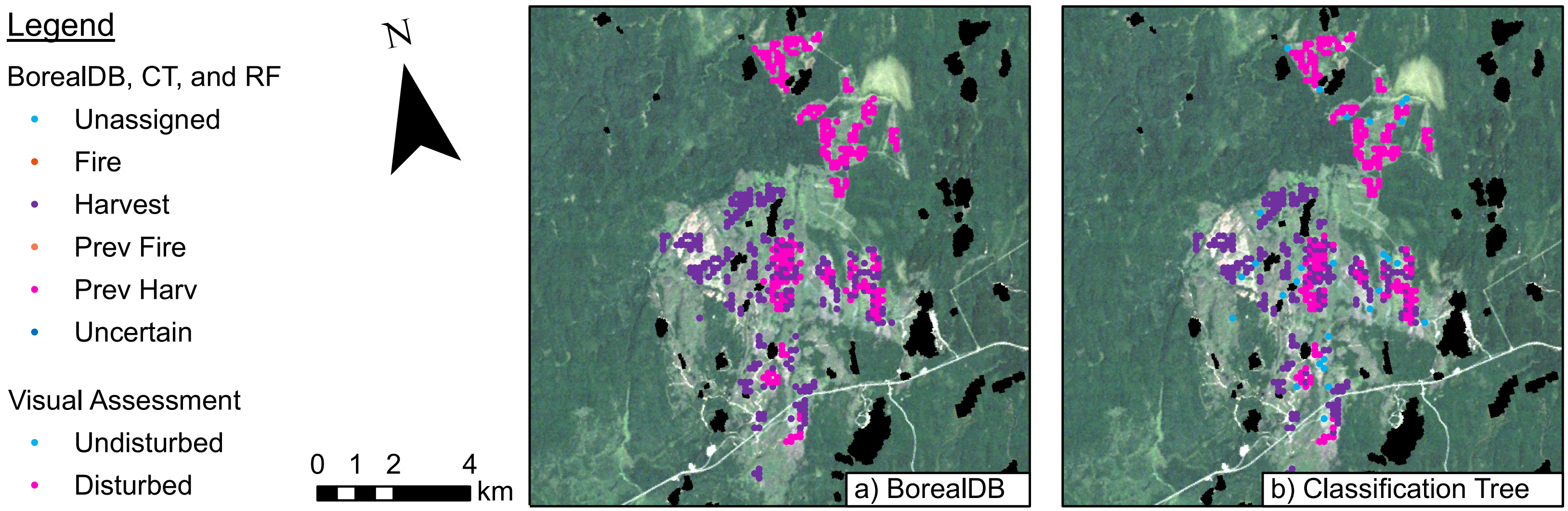
Many visual assessments were found to agree with classifiers, but results varied depending on the classifier. As an example, Figure 14 shows overall agreement that fire was the primary disturbance. This can also be seen within Table 18 (1991), Table 19 (2007), and Table 22 (1997). Amongst visual assessments agreement fire disturbances were the most consistent. Most disagreement can be observed in harvesting disturbance assessments where BorealDB and CT agree, and RF disagree.



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
BorealDB						
Undisturbed	0	0	0	0	0	0
Disturbed	0	412	33	0	71	0
Classification Tree						
Undisturbed	0	0	0	0	0	0
Disturbed	80	307	63	0	66	0
Random Forest						
Undisturbed	0	0	0	0	0	0
Disturbed	85	339	12	77	1	2

Figure 14. Visual assessment for a fire sample disturbance at P28/R25 in 2011. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

Comparing the classifier results with reference disturbances found BorealDB and CT agreed the most with reference disturbances while RF generally disagreed. It was found that samples predicted by RF often contain a variety of classes, introducing classes that were not originally identified by BorealDB. This could be observed in multiple samples such as Figure 15, Table 15 (1995, 1997), Table 16 (2001), and Table 22 (1996).



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
BorealDB						
Undisturbed	0	0	0	0	0	0
Disturbed	0	0	239	0	226	0
Classification Tree						
Undisturbed	0	0	0	0	0	0
Disturbed	28	0	222	0	215	0
Random Forest						
Undisturbed	0	0	0	0	0	0
Disturbed	43	2	69	319	2	30

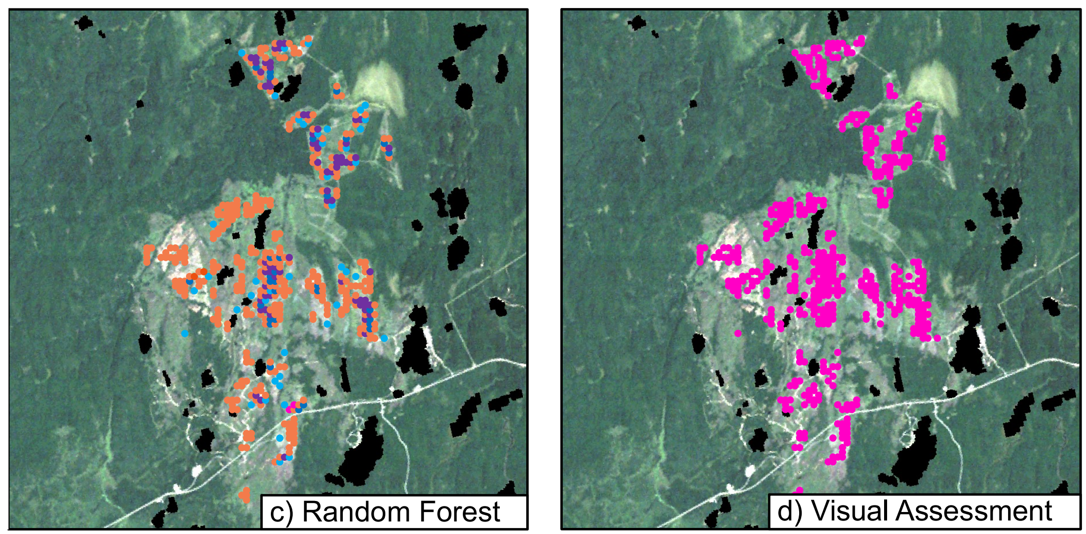
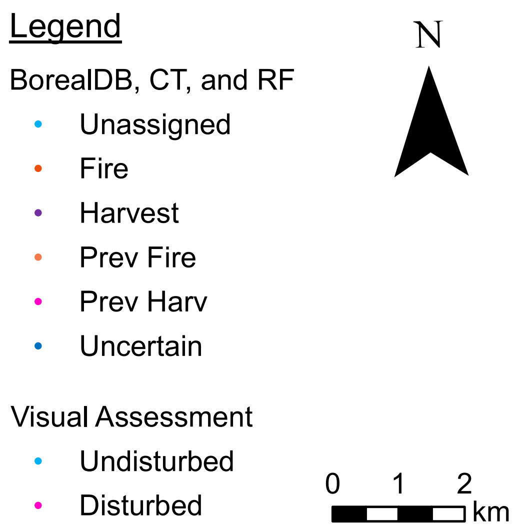


Figure 15. Visual assessment for a harvest sample disturbance at P21/R26 in 2001. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

Within these samples RF predictions often contradict the visual assessment results. As an example, within a harvest disturbance sample (Figure 15) BorealDB and CT point classifications are divided between two classes, “Harvest” and “Previous Harvest” with “Harvest” being the majority while RF identifies the disturbance as a previous fire. Another example of this is Figure 16 which depicts a fire disturbance, while BorealDB and CT classifiers identifies the disturbance as a fire the RF classifier identifies the disturbance as a harvest disturbance.



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
BorealDB						
Undisturbed	586	0	0	0	0	0
Disturbed	96	886	0	0	0	0
Classification Tree						
Undisturbed	214	330	42	0	0	0
Disturbed	56	902	24	0	0	0
Random Forest						
Undisturbed	216	135	235	0	0	0
Disturbed	58	216	708	0	0	0

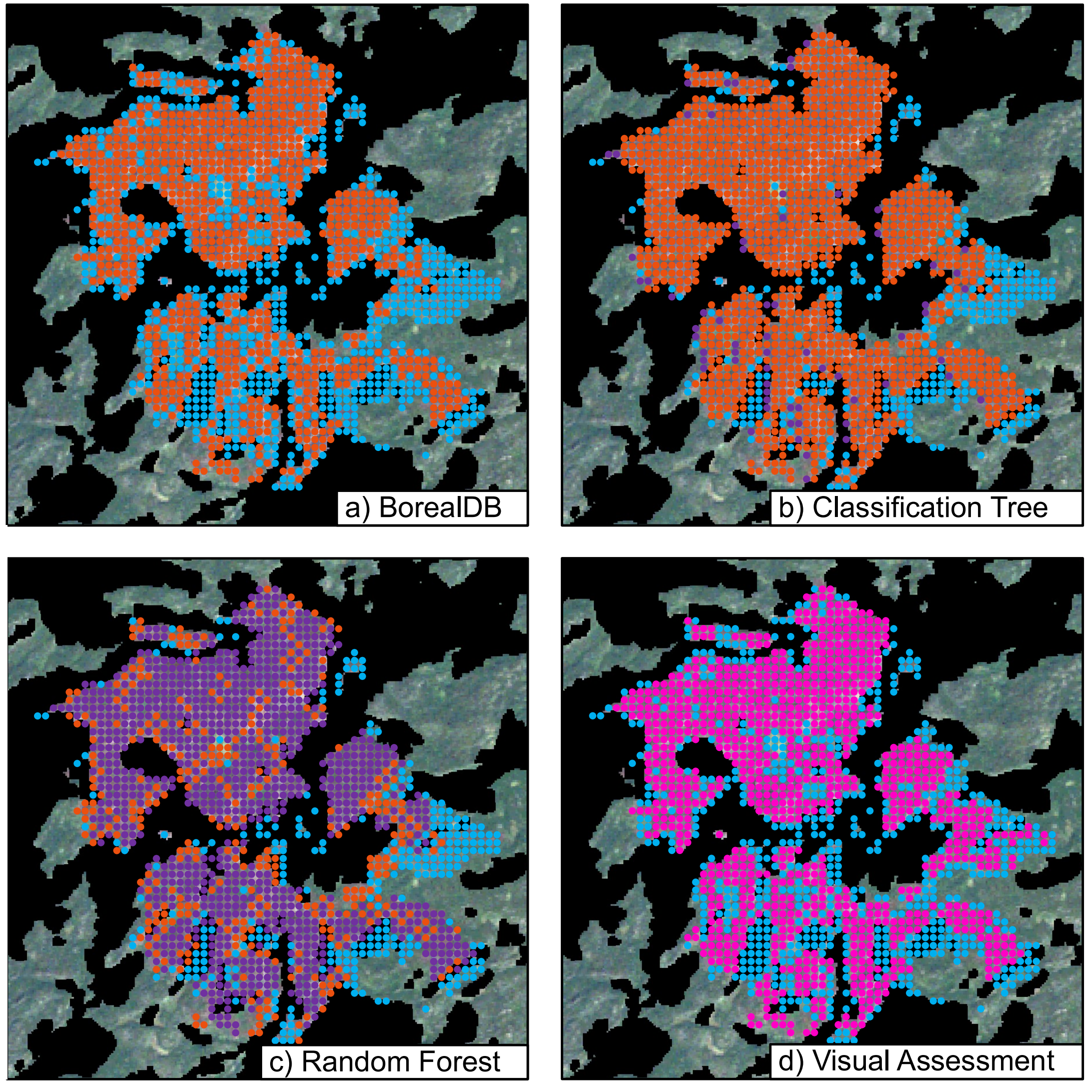
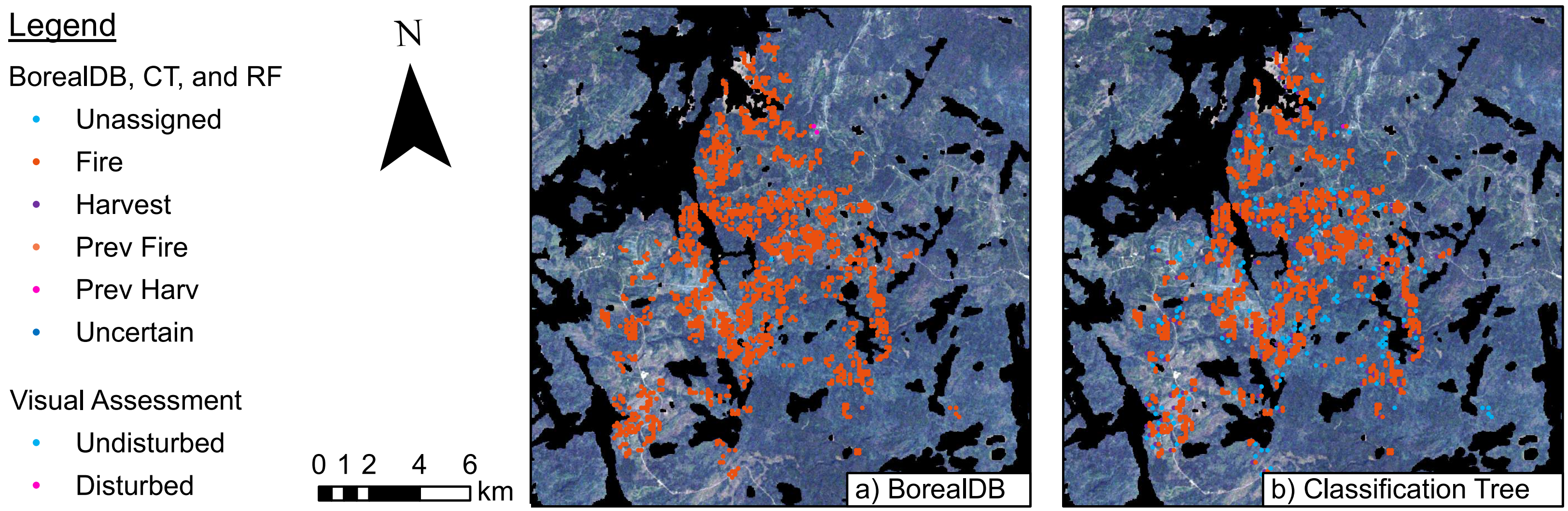


Figure 16. Visual assessment for a fire sample disturbance at P28/R25 in 2006. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

This trend would be a common occurrence, the RF classifier would frequently classify a disturbance differently from the other classifiers and the visual assessment while BorealDB and CT had disturbance points that are more consistent with the surrounding disturbances. This is best illustrated in many of the harvesting samples identified by visual assessment as harvest where RF predicted multiple disturbances as previous fire. This can be observed in Table 15 (1990, 1995, 1997), Table 20 (1991), and Table 21 (2001). This relation between the classifiers however is not surprising as this exact situation was previously observed when comparing the RF classifier with the BorealDB and CT classifier in section 3.3 and 3.4.

Based on these results BorealDB and CT are more effective classifiers for the data than RF. Despite this, there were instances in which RF had higher agreement than the other classifiers. This would however only occur in a few instances with fire disturbances. This can be seen within Table 19 (2015, 2018), and Table 22 (2001). It can be examined that RF predictions had more uniformity than CT. Within a fire disturbance sample (Figure 17) CT and RF agree a disturbance is “Fire” but RF has more point predictions. The difference between RF’s harvest and fire predictions indicate that the effectiveness of the classifier varies depending on the disturbance.



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
	BorealDB					
Undisturbed	1	22	0	0	2	0
Disturbed	0	1429	0	0	0	0
	Classification Tree					
Undisturbed	4	18	3	0	0	0
Disturbed	148	1173	107	1	1	0
	Random Forest					
Undisturbed	4	21	0	0	0	0
Disturbed	148	1280	0	1	0	0

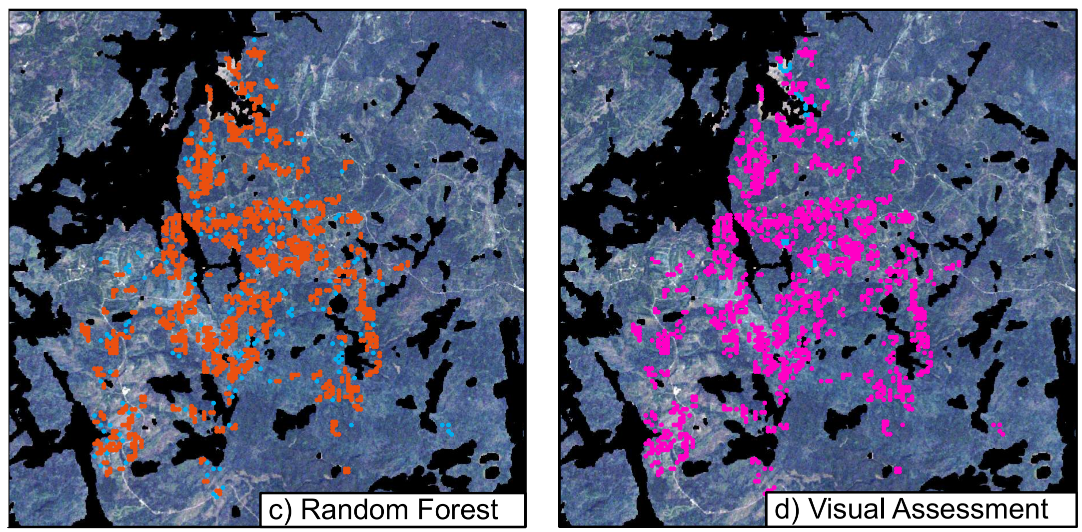


Figure 17. Visual assessment for a fire sample disturbance at P28/R25 in 2001. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

3.6.2 Missing disturbances

Within the visual assessments there were instances where disturbances identified by BorealDB did not appear on the original satellite imagery. There were a few instances amongst samples (Table 19 (2010) and Table 22 (1997)). The lack of a disturbance indicates the event had yet to transpire at the time the satellite imagery had been captured. This occurs due to the overlap between Landsat scenes (Figure 2). While multiple scenes overlap each image is captured at a different point in time, thus there is a possibility that a disturbance simply had not occurred at the time the scene was captured. Landsat missions capture scenes along a near polar-orbit (USGS, 2020) thus, it is possible for a disturbance to be visible on only some west-east overlapping satellite imagery. This can be verified by examining the satellite imagery of the same region in later years, Figure 18 depicts a disturbance appearing more visible in the following year.

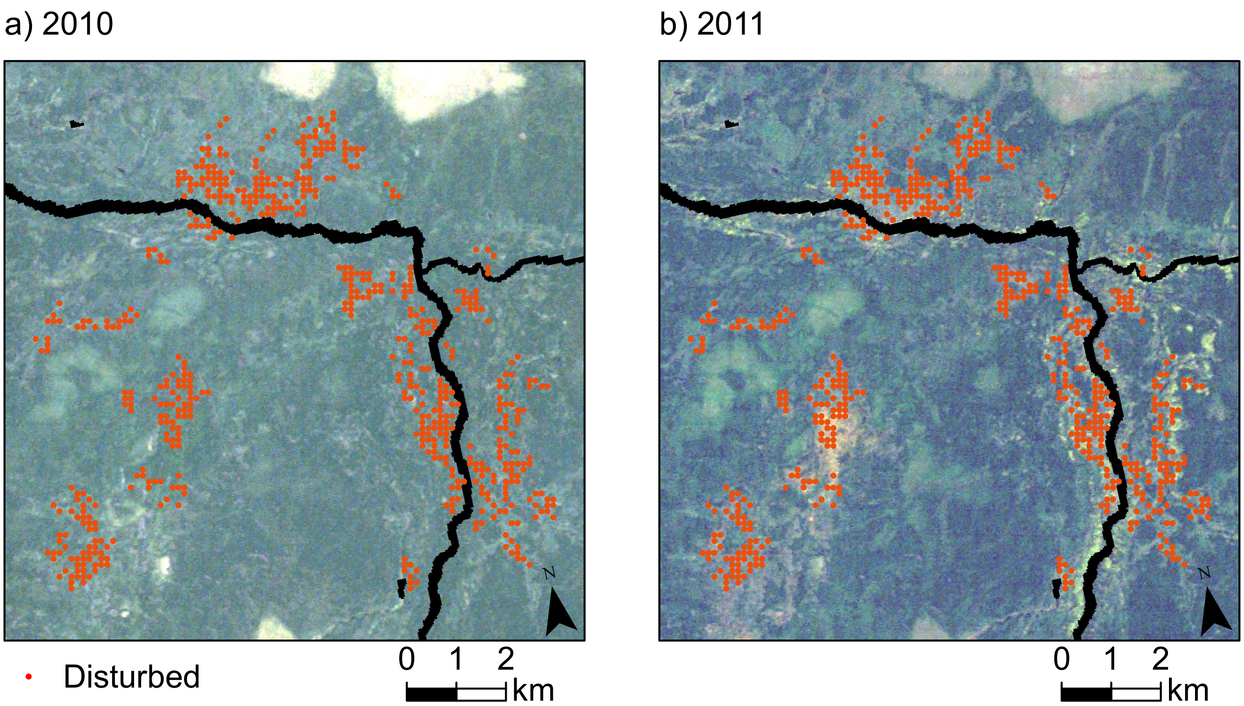


Figure 18. Disturbances appearing more visible in later years. The point data sample is taken from the 2010 data set.

Similarly, there were samples where only sections of disturbance clusters are visible within the landscape. These instances are often due to disturbances having been identified with a different data product which encapsulates disturbance data for the year whereas BorealDB is limited to disturbances visible within the imagery. This is due to imagery in later years often containing missing sections of disturbance clusters and disturbance points within missing sections often being classified as “Unassigned” indicating that BorealDB did not identify these areas as disturbed. This trend was noticeable with harvesting disturbances. Figure 19 depicts this occurrence, showing disturbance points in 1996 encompassing areas undetected by BorealDB in the current year but being visible in later years.

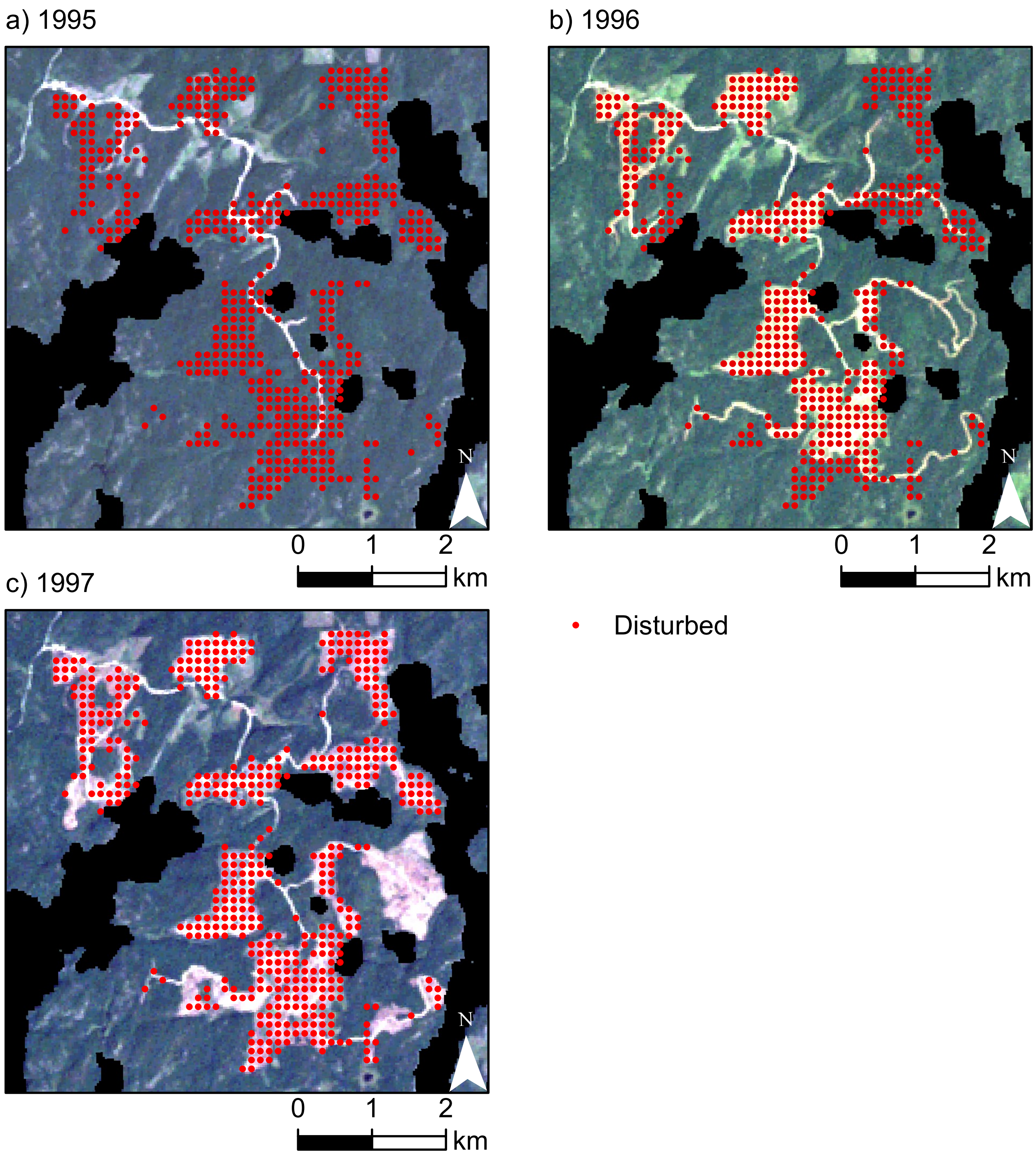
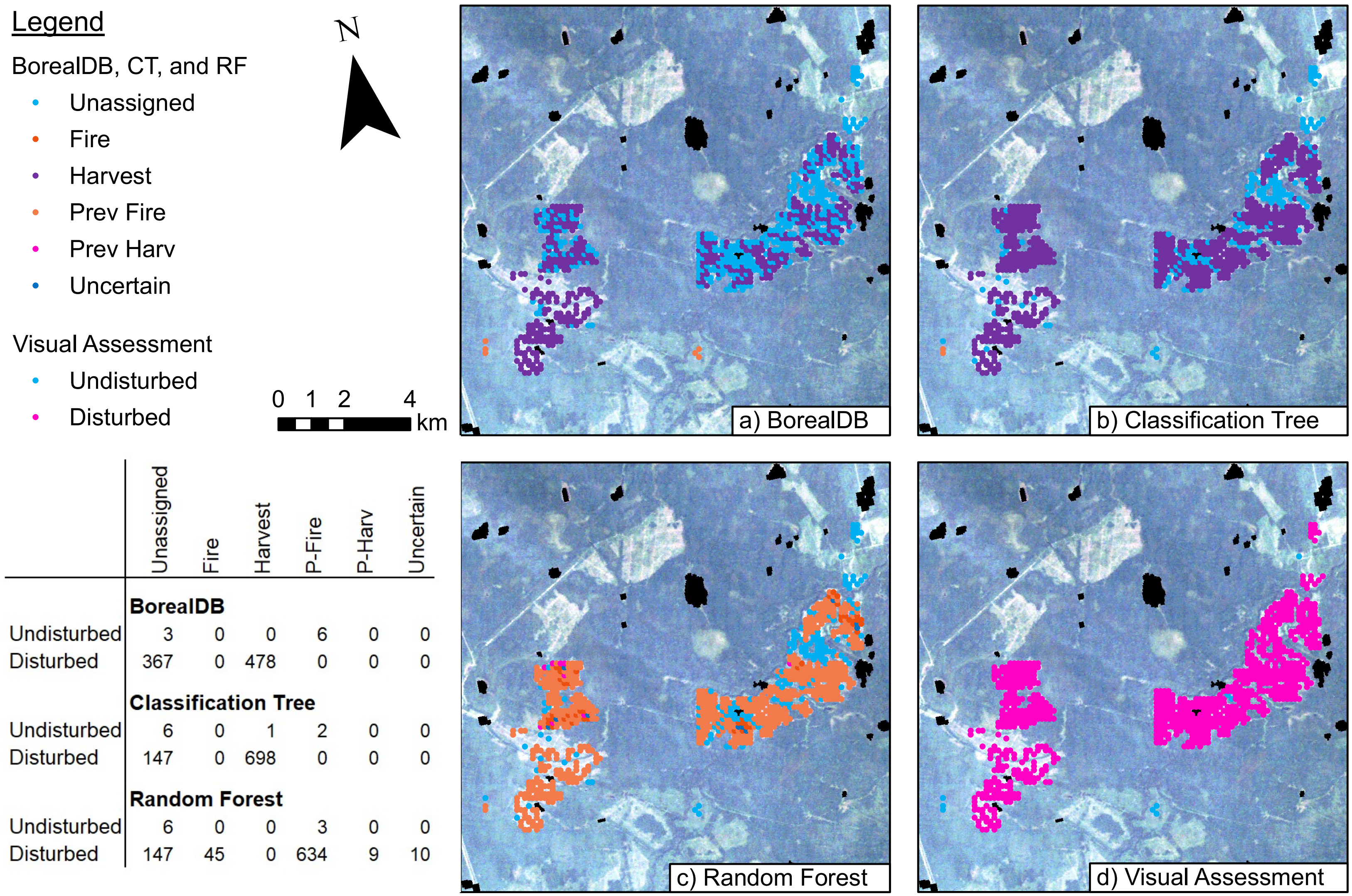


Figure 19. How a disturbance sample can contain disturbance data that is visible across multiple years. The point data sample is taken from the 1996 data set showing that areas identified in 1997 as disturbed were identified by additional data sets as disturbed in 1996.

3.6.3 Contextual information

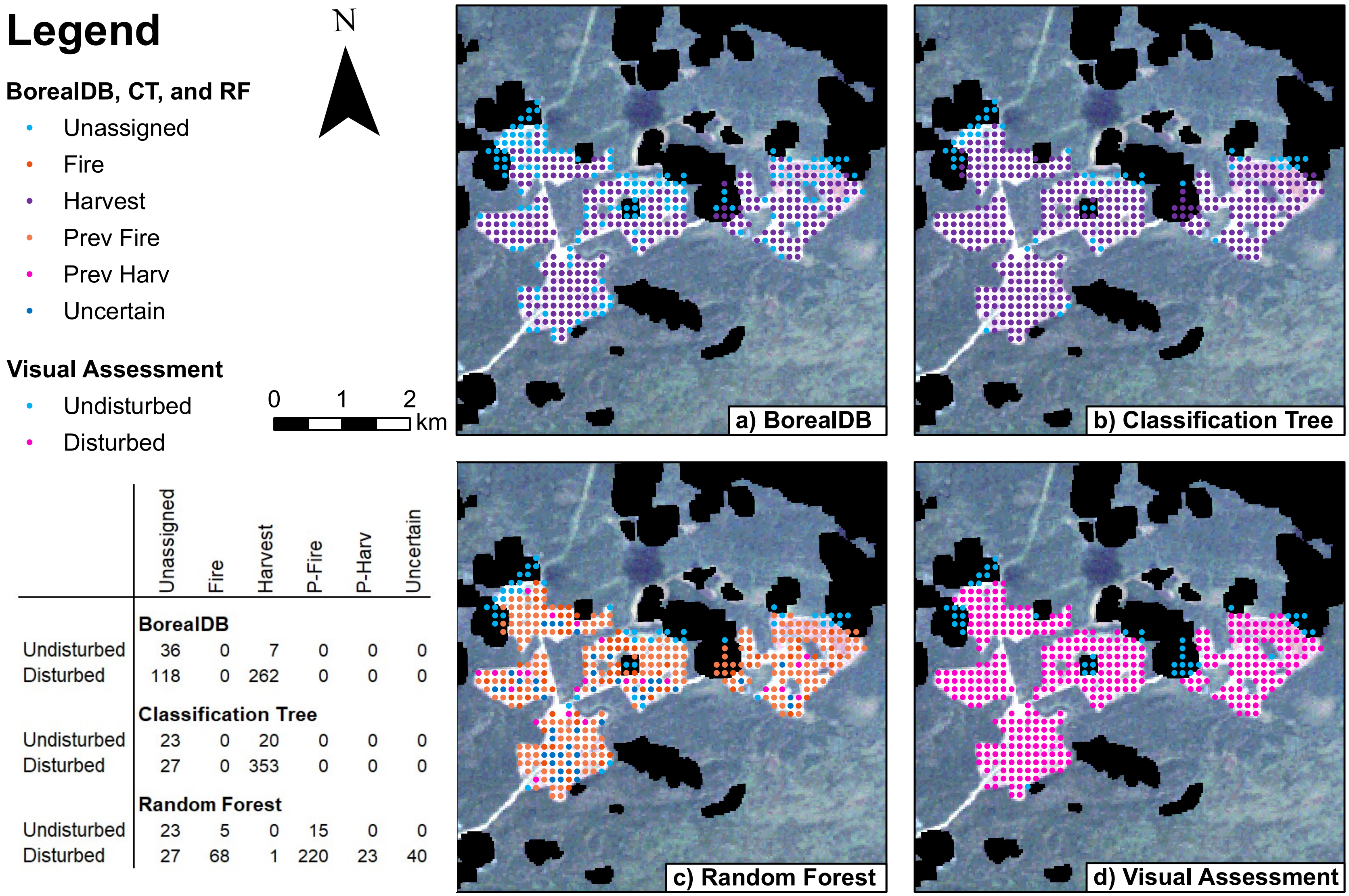
Of the contextual classifiers CT had the highest agreement with visual assessments. Compared with BorealDB, CT was found to reduce classification uncertainty at disturbed sites with large patch sizes. The CT classifier reduces classification uncertainty by homogenizing disturbance clusters with mixed classifications, leading to disturbance clusters comprising of singular classes. In some samples it could be observed that disturbance clusters with mixed classifications BorealDB were often classified more consistently by CT. This can be observed in Table 15. (1998), Table 20 (1994, 1998), and Table 21 (2015). As an example, within a harvesting disturbance (Figure 20) this homogenizing effect can be observed.



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
	BorealDB					
Undisturbed	3	0	0	6	0	0
Disturbed	367	0	478	0	0	0
	Classification Tree					
Undisturbed	6	0	1	2	0	0
Disturbed	147	0	698	0	0	0
	Random Forest					
Undisturbed	6	0	0	3	0	0
Disturbed	147	45	0	634	9	10

Figure 20. Visual assessment for a fire sample disturbance at P21/R26 in 2003. Landsat image used is a false colour composite image shown in RGB for TM Bands 543. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

Figure 20 shows BorealDB “Unassigned” classifications at the center of disturbance clusters were reclassified by CT as “Harvest”. Another example can be seen within Figure 21. The harvest disturbance is made up of five disturbance clusters, comparing the BorealDB and CT classifiers shows CT predicted clusters have more homogenous classifications. These results indicate that CT is effective at assessing classification uncertainty since classification derived from orthogonal neighbours agree with BorealDB. However, the reason these contextual classifiers are effective in the examples is due to focal disturbance points having sufficient contextual information.



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
BorealDB						
Undisturbed	36	0	7	0	0	0
Disturbed	118	0	262	0	0	0
Classification Tree						
Undisturbed	23	0	20	0	0	0
Disturbed	27	0	353	0	0	0
Random Forest						
Undisturbed	23	5	0	15	0	0
Disturbed	27	68	1	220	23	40

Figure 21. Visual assessment for a harvest sample disturbance at P28/R25 in 1994. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

When focal disturbance points lack contextual information, they are often misclassified by CT and RF. This can be observed with disturbance points on the edges of disturbance clusters and points that lack orthogonal neighbours. As an example, a fire disturbance depicted within Figure 22 shows that BorealDB had classified every point in the disturbance as a “Fire”, when comparing to CT and RF many disturbance points were predicted as “Unassigned”. Additionally, it can be observed that multiple points classified as “Fire” by BorealDB are classified by CT as “Harvest”. Closely examining these points shows they lack orthogonal neighbours thus, lacking the contextual information to properly classify. This lack of contextual information is a prevalent issue within the CT and RF classifiers and is evident due to every disturbance classification introducing “Unassigned” disturbance point classifications in scenarios while BorealDB did not identify any (Table 5).

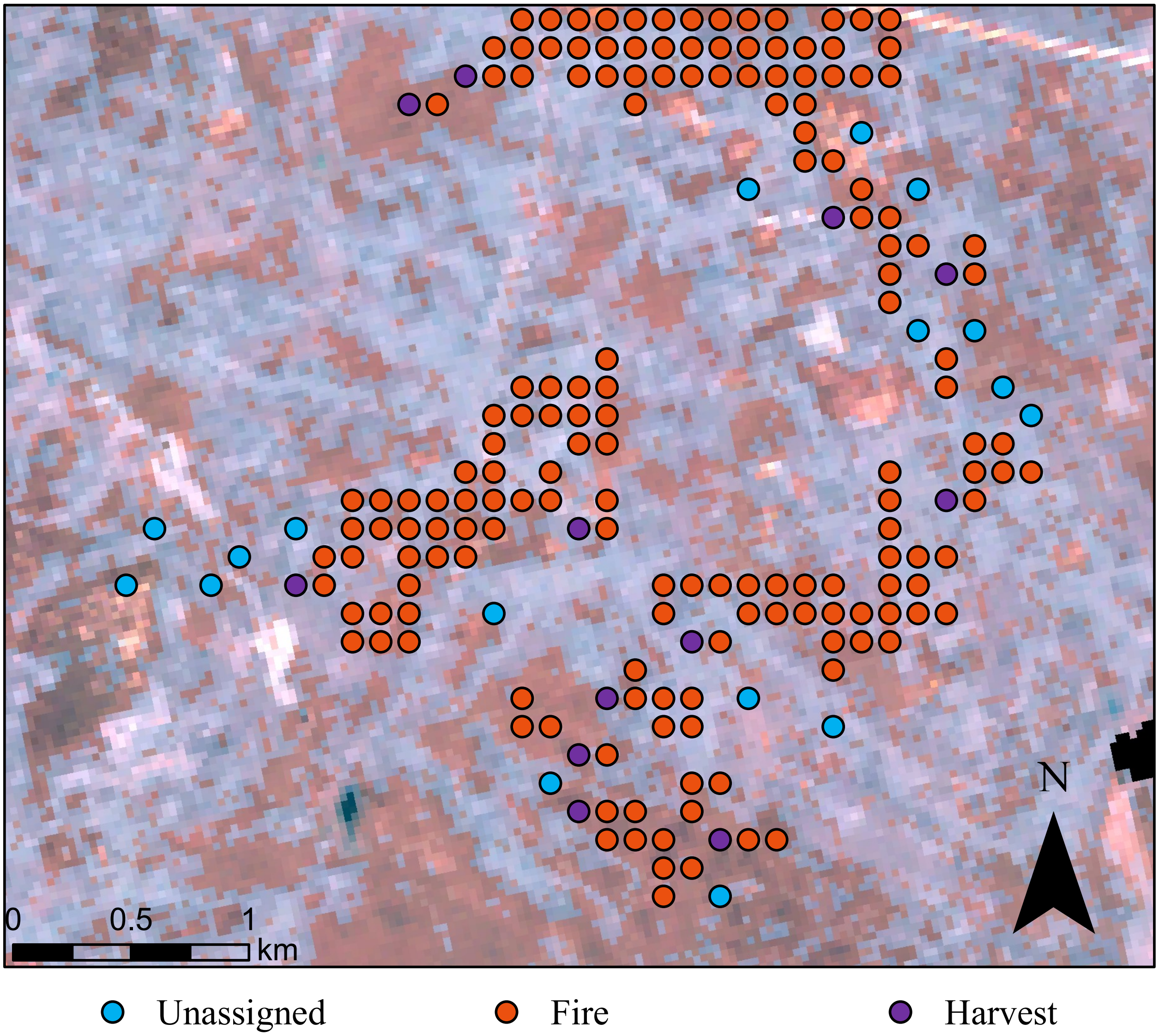
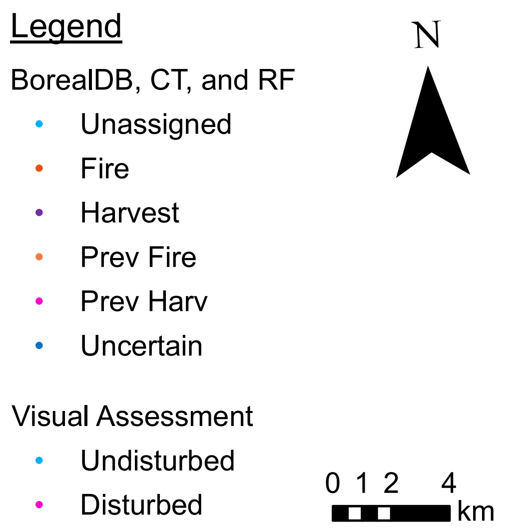
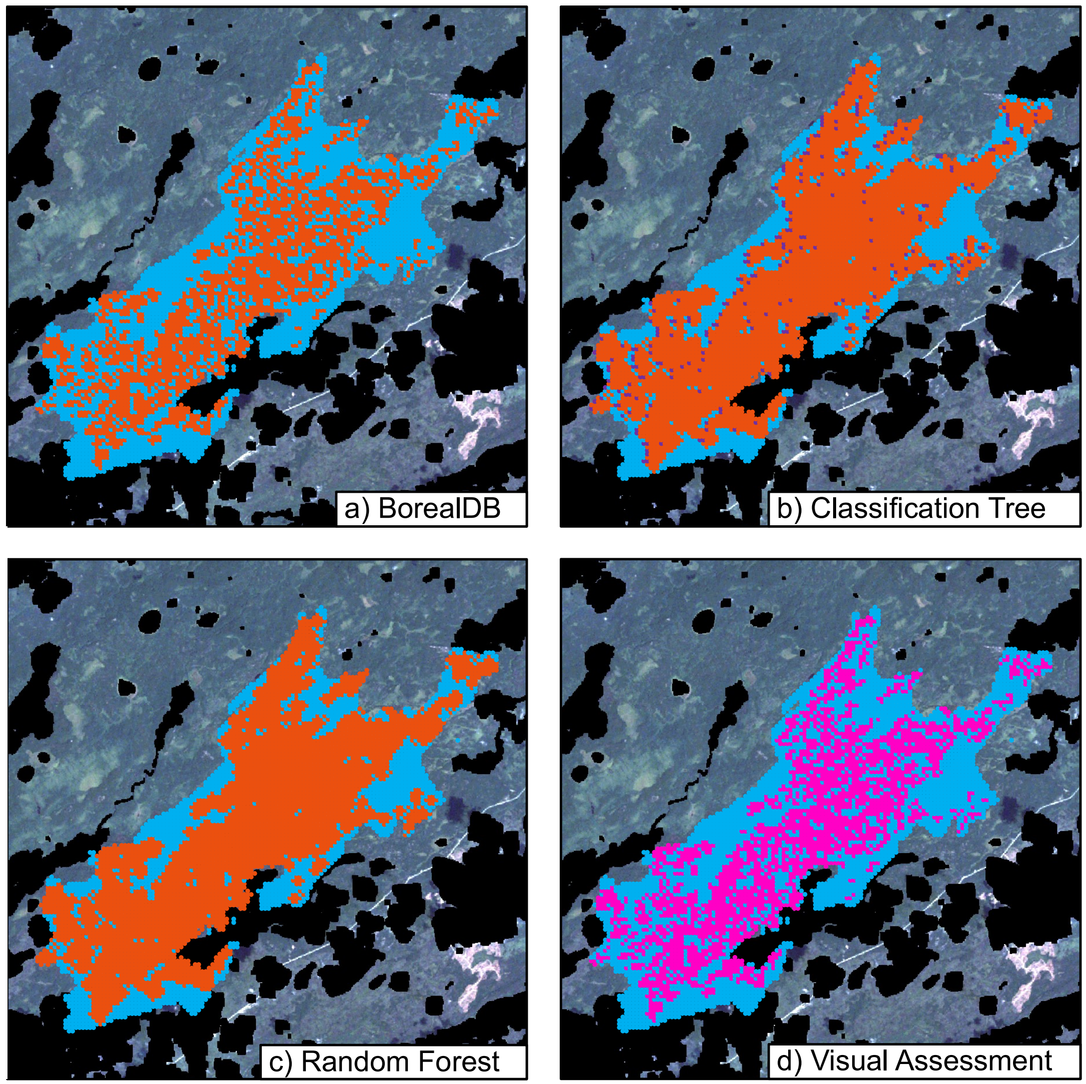


Figure 22. The influence of contextual information. Within this sample from 2015 in P21/R26 a fire disturbance is classified using the CT classifier. Points with no neighbours were classified as unassigned because their orthogonal neighbours were labelled “0” by default which is the same disturbance code value as unassigned. All points that only have an eastern fire class neighbour were classified as harvest.

However, despite the need for contextual information it does not necessarily benefit the classification. As an example, if a fire disturbance has patches of unburned forest encompassed by burn scars, then these unburned areas may instead by classified as burned instead. This is due to additional data product classifications which identify areas as disturbed. Within Figure 23 the area for a fire disturbance is depicted by the AFFES data product as being much larger than the area identified by the visual comparisons. When using the CT and RF classifiers it can be observed that the center of the disturbance cluster become more homogenous, resulting in fewer undisturbed patches that disagree with visual assessments.





	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
	BorealDB					
Undisturbed	3184	0	0	0	0	0
Disturbed	0	2640	0	0	0	0
	Classification Tree					
Undisturbed	1541	1497	146	0	0	0
Disturbed	46	2513	81	0	0	0
	Random Forest					
Undisturbed	1541	1643	0	0	0	0
Disturbed	46	2594	0	0	0	0

Figure 23. Visual assessment for a fire sample disturbance at P28/R25 in 1995. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

When classifying “Uncertain” points the contextual classifiers was shown to have reduced effectiveness, even with sufficient contextual information. Within Figure 24 it could be observed that “Uncertain” points, surrounded by “Previous Harvest” points, were classified by CT as “Fire”. RF would show similar results, with multiple points being also classifying as “Fire” or “Previous Fire”.

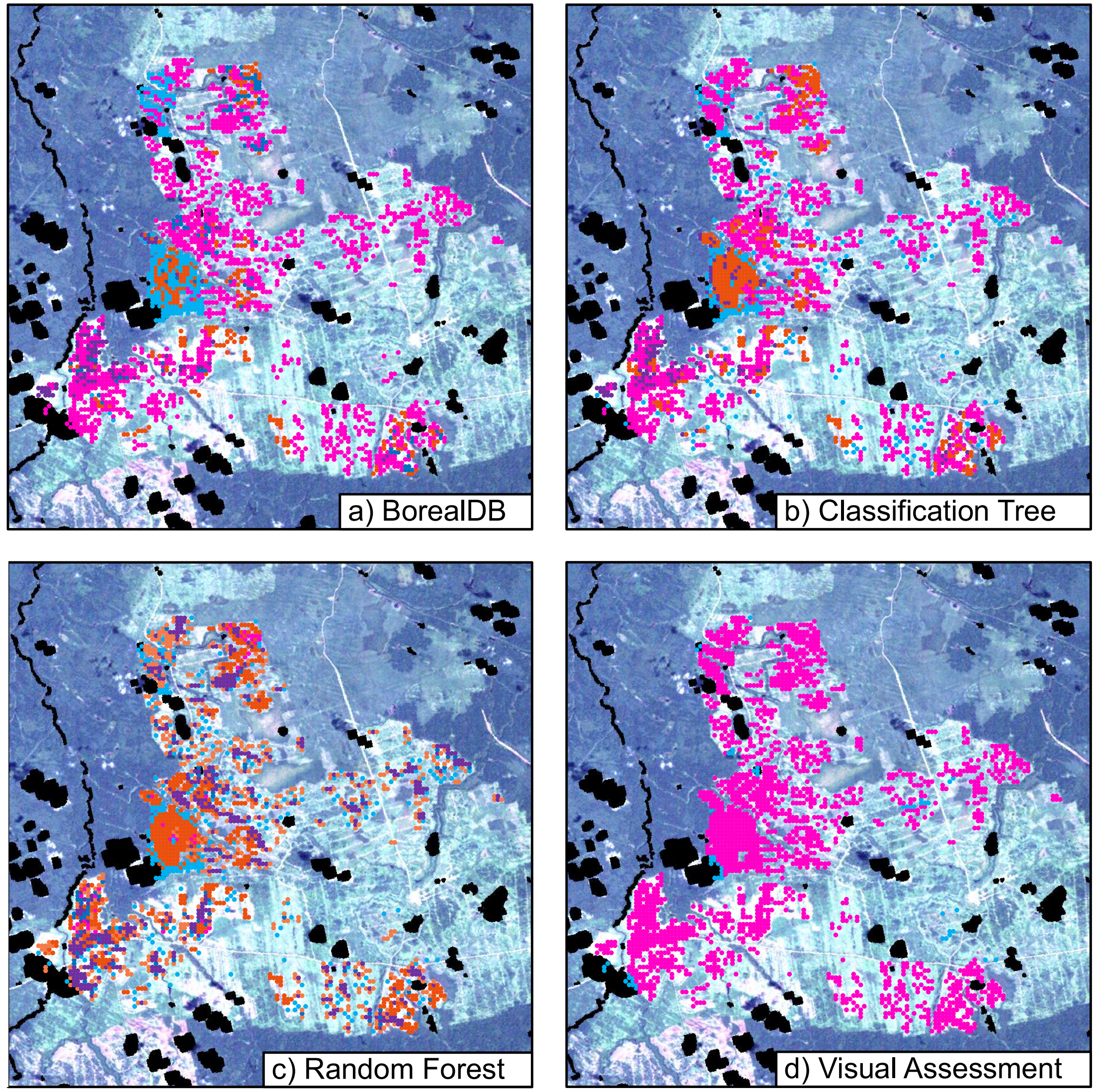
Legend

BorealDB, CT, and RF

- Unassigned
- Fire
- Harvest
- Prev Fire
- Prev Harv
- Uncertain

Visual Assessment

- Undisturbed
- Disturbed



	Unassigned	Fire	Harvest	P-Fire	P-Harv	Uncertain
BorealDB						
Undisturbed	15	0	0	0	39	0
Disturbed	217	248	94	0	1363	109
Classification Tree						
Undisturbed	21	1	1	0	0	0
Disturbed	195	391	137	0	1308	0
Random Forest						
Undisturbed	22	2	13	14	0	3
Disturbed	256	536	506	608	40	85

Figure 24. Visual assessment for a fire sample disturbance at P21/R26 in 1990. Landsat image used is a true colour composite image shown in RGB for TM Bands 321. Black spots represent areas masked out. a) depicts BorealDB classification, b) depicts CT classification, c) depicts RF classification, d) depicts the visual comparison.

4. Discussion

4.1 Analysis

Using the contextual classifiers, areas of classification uncertainty were identified within BorealDB to be further scrutinized to assess classification confidence. CT and RF models were fed a disturbance point's nearest orthogonal neighbours to test whether knowing a point's neighbours could predict its disturbance state. Using the predictions, classification uncertainties were identified by comparing the classifiers (BorealDB, CT, and RF) to identify areas of disagreement as indicators of uncertainty. The classifiers were then visually assessed against the original satellite imagery to determine which classifier best fit the reference satellite data. An advantage of the contextual classifier method is that it allows the user to assess a classifier's effectiveness at using information that is already encoded within the database, the method's ease of use means successive years and additional data products can be added to BorealDB without the need for extensive processing.

The contextual context model improved classification confidence as points with the same disturbance label are likely to be within proximity to one another, thus disturbance clusters are likely to be comprised of points of the same class. This is expected as landscapes do not exist in isolation and are distinguished by the spatial relationships of their components (McGarigal and Marks, 1995). This is evident as the majority of BorealDB's orthogonal neighbours agreed with focal point classifications (Table 6) indicating a relationship between a focal disturbance point and its nearest neighbours. Using the contextual data to improve the classification required a means to quantify it, however there is no guarantee that the means would be free of uncertainty. By having multiple classifiers, the classification confidence is more robust as each classifier could hold accountability for each other. This point is apparent when comparing class distribution of points for each classifier.

The comparison found the degree of classification uncertainty identified depends on the classifiers being compared. As established in section 1.3.2 the absolute accuracy of BorealDB cannot be assessed thus classification confidence is used as a proxy to estimate the likelihood of a disturbance's existence. By comparing BorealDB with the contextual classifiers, which predict a disturbance point's class based on its nearest neighbours, areas of uncertainty are identified when they disagree. It was found that BorealDB and the CT classifier, which had an 84.88% agreement, had more similarities with each other than with RF. Of these comparisons RF had the most disagreement, with the classifier having no more than 50% of point classifications agreeing with BorealDB or CT. Based upon these results the lack of agreement between RF and the other classifiers implies that more than half of the database's disturbance points should be scrutinized for classification uncertainty.

Of the 1st order classes "Harvest" had the highest classification uncertainty, consistently having one of the lowest class agreements. Points classified by BorealDB were frequently in disagreement with class predictions derived from their orthogonal neighbours. The majority of this disagreement was with RF predictions which found that over 90% of disturbance points within harvest type classes disagreed and were reclassified into a separate class. Compared with CT "Harvest" had the lowest agreement amongst 1st order classes, points would often misclassify if their only orthogonal neighbour was an eastern "Harvest" classification (Figure 22). Due to the overall lower agreement amongst classifiers the cases imply harvest disturbance clusters are less uniform that fires, disagreement with orthogonal neighbours indicates that harvest disturbances detected by BorealDB have greater spatial variability.

The relationship between classifiers could be more clearly seen when comparing individual classes; the contextual classifiers are more effective at predicting “Fire” classifications than any other class because they consistently have the highest agreement. The analysis would also highlight the extreme differences between classifiers, while the “Harvest” class consistently had the lowest agreement within comparisons, RF related comparisons always had agreement levels far lower than expected.

Unexpectedly, it was observed that RF’s class distributions had a wider range of disagreement than BorealDB or CT’s distributions. RF predictions increase the proportion of “Uncertain” classifications and greatly decrease the proportion of “Previous Harvest” classifications. Less than a percent of all RF predictions was labelled as “Previous Harvest”. It was found that BorealDB and CT classified “Previous Harvest” points were often labelled by RF as “Harvest” and “Previous Fire”. This development is unusual as the lack of “Previous Harvest” points means RF found that less than a percent of all identified disturbances shows a harvest disturbance recovering. Landsat imagery has been used to characterize forest recovery (Frazier et al., 2015), this method is applied by BorealDB to identify areas that are recovering from fire or harvesting disturbances. Since BorealDB identifies recovering harvest disturbances the lack of agreement completely contradicts the reason for the “Previous Harvest” class. This assertion can be made due to the design of BorealDB, the “Previous Harvest” class is meant to classify recovering timber harvesting disturbances (Ouellette et al., 2020).

Boreal forests recover from disturbances due to the inherent resilience of the ecosystem (Perera and Cui, 2010). The lack of “Previous Harvest” classifications means that the entirety of Ontario’s Managed Area lacks this recovery process which is not the case which implies the RF classifier is ineffective at identifying “Previous Harvest” classifications. The absence of “Previous Harvest” classifications also implies that relative to other classes “Previous Harvest” neighbours were less frequent, potentially indicating classifications of “Previous Harvest” within BorealDB were poor.

The contextual classifiers would sometimes predict classes that did not agree with the classifier predicting classes that did not exist within the sampled disturbance. This can be observed in Figure 16 where both CT and RF predictions introduced classes that did not appear within the BorealDB classifications. The “Unassigned” class is the most prominent, occurring along the edges of disturbance clusters. RF would introduce classes more extensively with classifications that reintroduce uncertainty (Figure 18c), this issue occurs predominately within harvest disturbance samples. This result parallels the observations within the classifier comparisons in that BorealDB and CT classifications are often more similar to one another than to RF. The analysis highlights that RF classifications often disagree with the visual assessments, implying that within the context of the visual assessments RF is an ineffective contextual classifier. This lack of agreement is surprising as the general consensus found that RF studies performed well in land cover classification studies (Pal, 2005; Wang et al., 2019) and outperformed CT classifications (Gislason et al., 2006; Ghimire et al., 2012).

However, while RF is ineffective as a classifier it may be useful at identifying uncertainty. This implication is similar to (Gislason et al., 2006) who found that RF is able to detect outliers which in the case of BorealDB are “Uncertain” classifications. The “Uncertain” class is comprised of disturbed points with multiple conflicting classifications, an increase in this class means disturbed point classifications are adjacent to neighbours that disagree. In addition, it was observed that most “Uncertain” classified points were labelled as “Previous Fire” by BorealDB and CT. This increase in “Uncertain” points implies the RF model determined that BorealDB point clusters containing “Previous Fire” points were likely to have more varied neighbours.

This connection between “Uncertain” and “Previous Fire” was not only visible in comparisons relating to RF, the BorealDB and CT comparison found most points classified as “Uncertain” by BorealDB were labelled as “Previous Fire” by CT. Thus, the connection implies that within BorealDB, disturbed points with the “Previous Fire” label are more likely to be located within areas of uncertainty as well as that disturbance points are not as influenced by orthogonal neighbours.

The analysis revealed the contextual classifier method is an effective predictor if the method is able to quantify spatial neighbours. By examining the agreement between the focal neighbours of disturbed points the results indicated for the CT classifier that most of the neighbouring disturbed points belonged to the same class as the prediction. Orthogonal point classifications belonging to the same class as CT predictions indicate there is a relationship between CT predictions and its nearest neighbours, which in a sense, demonstrates the effectiveness of CT as a predictor correlating with the results of the visual assessments and the classifier comparisons.

Analyzing the visual assessments found that between contextual classifiers CT predictions agreed with sampled disturbances the most consistently. This would occur within large disturbance clusters where CT predictions homogenize disturbance classifications, causing clusters with mixed classifications to be comprised of a single class. This result is similar to the findings of Lv et al. (2016) who found classifications in locations with lots of noise tended to misclassify but were improved by considering contextual information. This would most frequently occur with “Unassigned” disturbance points derived from additional data product. This could be observed in Figure 18b, CT predictions found that many of the “Unassigned” disturbance points within BorealDB were predicted as CT as Harvest, the resulting prediction was shown to produce a classification that agreed better with the visual assessment than BorealDB. This scenario also occurred with RF predictions but only with fire disturbance types (Figure 15c). However, while CT is able to properly relabel “Unassigned” points it had a reduced effectiveness with “Uncertain” points. This was observed in Figure 24 which had samples of BorealDB “Uncertain” classifications being predicted by CT as “Previous Fire” despite being surrounded by harvest type classifications. BorealDB classifications show that the “Uncertain” classifications reside in a cluster made up of “Previous Fire” and “Previous Harvest” disturbance points. Thus, the results indicate that while the contextual classifiers can predict optimal classes for “Unassigned” disturbance points but has reduced effectiveness for points with “Uncertain” classifications.

This concentration of “Uncertain” classifications within “Previous” disturbance clusters could be due to the decrease in disturbance detectability over time. Despite this, Schroeder et al. (2011) notes that fire and harvesting disturbance events can still be accurately classified up to four years after the event. Given that BorealDB detects disturbance up to two years after its occurrence this conclusion may not be likely.

However, due to the time lag between west-east scene overlap and the possibility that a disturbance had not occurred at the time of scene capture, disturbance clusters may contain both current and previous year classifications. This would explain both the reason why many “Uncertain” classifications are comprised of current and previous year classes (Table 4) and the overall low accuracy in “Harvest” disturbances and it’s connection with “Previous Harvest”.

A lack of sufficient information is reflected within the increase in “Unassigned” classifications for both CT and RF, which indicates that a number of disturbed points either had no orthogonal neighbours or had a neighbour with the “Unassigned” label. As discussed previously, many disturbance points along the edge of disturbance clusters were classified as “Unassigned”. This could be observed in various visual assessments samples which found disturbance points lacking orthogonal neighbours were classified as “Unassigned”. Another example can be observed in Figure 16 where “Fire” disturbance points were classified by CT as “Harvest” with many disturbed points only having “Fire” as the nearest eastern neighbouring point. This example is also evident when examining the nearest eastern neighbour classifications against CT predictions where “Fire” is the most prominent disagreement with “Harvest” (Table 7).

While sufficient contextual information is important to the classification process predictions differed depending on the classifier. The strong agreement between CT derived classifications and its nearest neighbours, indicates that the neighbours of disturbed points are of the same classification meaning most disturbance points likely belong to clusters composed of the same classification. In contrast agreement between RF predictions and nearest neighbour classes was much weaker (Table 8). Examining

BorealDB's nearest neighbours it could be observed that current year "Fire" and "Harvest" disturbance points would frequently neighbour their previous year counterparts. The link between BorealDB's current and previous year seem to imply that disturbance clusters consist of classifications of the same type. This link can also be observed within the classifier results as the second highest agreement amongst the 1st order classes for BorealDB and CT.

The existence of a disturbance for a current year relies on the data product detecting it at the time. It was found that additional data products would detect disturbances that were not detected by either BorealDB or the original satellite images. At the time the satellite image was taken the locations detected by additional data products had not yet been disturbed on the imagery (Figure 19) with areas classified as "Unassigned" by BorealDB not being detected as disturbed in later years. What these leads into is a discussion on influence of additional data products and the vagueness surrounding how disturbance boundaries are defined.

Neighbouring disturbance points of different boundary definitions were found to affect classifier predictions. Disturbed areas identified only by additional data products often impacted the results of the classification. As discussed previously, disturbed points surrounded by "Unassigned" were predicted to be "Unassigned" the reverse of this was also found to be true, "Unassigned" points surrounded by disturbed points were predicted to be disturbed. This issue commonly occurred in disturbance clusters with insular patches. The implications are that classifier may predict undisturbed area as disturbed because it was identified by an additional product as being disturbed. The results also demonstrate the issues of inconsistency in boundary definitions discussed in section 1.2.1.

While the contextual classifier approach is a means to minimize classification uncertainty it also assesses disturbance points membership by comparing its neighbours. It is important to note that high agreement between classes alone does not indicate that CT is a more effective classifier instead, it simply means that there is substantial overlap between BorealDB and CT. Assessing the effectiveness of a classifier requires insight into the relationship between classifier predicted points and its orthogonal neighbours, as well as how the predicted points compare to the original satellite imagery the classes were derived from. Thus, while point agreement alone does not indicate that CT is the more effective contextual classifier it was observed that the RF classifier predicted point classes that disagree with their orthogonal neighbours often contradicted the results of the visual assessment samples. When visually assessing sampled disturbance classifications it could be observed that the results of the CT classifier closely resembled the sampled disturbances. The RF classifier would often introduce contradictory classifications or misclassify entirely particularly with harvest disturbances. The results indicate that RF predictions often shows information that is contradictory to its neighbours and to its reference disturbance; unlike the CT predictions which were shown to have high agreement with neighbours and reference disturbances. While the RF predictions were shown at times to classify fires better than CT, the CT predictions were more consistent. Based upon these results CT is the more effective contextual classifier. Despite this however, the RF predictor was able to identify areas of potential uncertainty which seem to be linked predominately to "Harvest" and previous classes.

Going forward, this thesis opens opportunities for future research. First, the classifiers were only fed the orthogonal data of BorealDB derived classifications. The thesis serves as a proof of concept demonstrating that predictions derived from the focal scale can reinforce BorealDB's classification confidence. Due to lack of uniformity in defining the boundaries of a disturbance additional data products influenced the classifier results. The accuracy and uniformity of the data varies based upon the source, year, and various mapping techniques applied towards contributing data products. Thus, feeding additional orthogonal data based upon other attributes, such as disturbance confidence and additional data product classifications, acts as an extension of the classifier confidence measure used within BorealDB as it incorporates contextual data. Nearest neighbour metrics have been used to fill in observational records of forest inventory and monitoring databases (Eskelson et al., 2009), supplementing detailed stand level information into the orthogonal neighbour model can be used to increase classification confidence as well as fill in missing information at the stand level. In addition to this, future research could expand the focal neighbourhood. The shape of the neighbourhood can influence classification results (Verburg et al., 2004), while the research was focused solely on the neighbouring disturbance points in the cardinal directions additional research can incorporate the ordinal directions as well, providing more samples to feed the contextual classifiers.

Another potential opportunity is to examine the relationship between disturbance years. Time is an important aspect of BorealDB, disturbances are only identified if a data product detects it. As such, some disturbances identified by BorealDB did not agree with other data products due to the disturbance having yet to occur at the time of the disturbance. Knowing how disturbance classifications for a given disturbance cluster changes through time helps conceptualize the relationship between disturbances and their previous counterparts. This data can then be used to assess the relationship between class labels and disturbance year which can determine whether certain classes are more susceptible to having uncertainty or not.

4.2 Limitations

Limitations due to hardware limitations led to a cross validation of the CT being infeasible due to the entire processing being too computationally intensive. Second, samples were limited by detected disturbances on the sampled scene. While samples were chosen at random, the number of samples depended on whether an annual disturbance layer had detected the disturbance type. Third, contextual data fed into the classifier was acquired solely using the classification data from BorealDB. Disturbed point predictions heavily rely on the presence of neighbours. Using more of the data encoded, such as the disturbance classifications of additional data products, would potentially provide a prediction that could provide more weight to the classification confidence. Finally, the inability to perform a ground validation, due to the vast geography and historic nature of the database, meant visual assessments were required to discern the presence of a disturbance. In addition, limitations due to the presence of clouds in available imagery led to masked-out areas and hence it was impossible to identify disturbed areas.

5. Conclusions

Areas of classification uncertainty were identified using the contextual classifiers; however, the extent of uncertainty varied depending on the classifier being compared. Approximately 50% of the CT and RF predictions differed, when classifiers were compared with BorealDB, CT predictions (84.88%) were found to have higher agreement than RF (42.43%). The results indicate 15% of BorealDB disagreed with CT while 58% of BorealDB disagreed with RF, between classifiers RF identified more classification uncertainty than CT. Areas of disagreement were found to occur primarily in “Harvest” disturbed clusters, which had the highest classification uncertainty, and clusters comprised of “Unassigned” points, which were often homogenized by neighbouring disturbances.

Orthogonal neighbours frequently belonged to the same class as the focal point, implying that disturbance clusters are comprised of points of the same class. This could be observed with the high agreement between BorealDB and its orthogonal neighbours. Similar observations were made with all CT classifications and the “Fire” RF classification.

Despite agreeing with orthogonal neighbours, the contextual classifier was found to be an effective predictor only if there was sufficient neighbouring influence. Neighbouring classification points disagreed with the classifier if surrounding points did not exist. This issue often led to classifiers predicting classes that did not match the sampled disturbance. This effect was noticeable along the edges of disturbances which were frequently classified as “Unassigned”. Classifiers would also have difficulty classifying disturbance points if neighbours were of multiple classes.

Similarly, classifiers were influenced by boundary definitions with disturbed areas identified by additional data products often impacting results. When “Unassigned” points were surrounded by disturbed points they would reclassify as disturbed, indicating that undisturbed areas may be classified as disturbed if an additional data product identifies it as such.

Of the 1st order classes “Harvest” had the highest classification uncertainty. Most of the uncertainty was found from classifier comparisons involving RF. The result implies harvest disturbance clusters are less uniform that fires which consistently had one of the highest agreements. Orthogonal neighbour disagreement demonstrated harvest disturbances have greater spatial variability, indicating that timber harvesting disturbance clusters were more likely to be comprised of multiple disturbance types.

Of the classifiers, the degree of classification uncertainty was highest in classifier comparisons related to the RF model. The distribution of RF classes was notably of a wider range of disagreement than BorealDB or CT in which the “Previous Harvest” class notably had almost no predictions. The absence of “Previous Harvest” classifications implies that relative to other classes “Previous Harvest” neighbours were less frequent, potentially indicating classifications of “Previous Harvest” within BorealDB were poor. In contrast the CT classifier was found to more closely resemble BorealDB predictions. This similarity was further exemplified when examining classifier relationships with the orthogonal neighbours fed into the classifier which found RF to frequently disagree with its nearest neighbour classifications.

Between the classifiers CT performed the most consistently as a predictor that could be used to identify classification uncertainty within BorealDB. Due to the classifier having high agreement with orthogonal neighbours and visual assessments CT was shown to be the most effective classifier. The RF classifier often disagrees with its orthogonal neighbours and visual assessments, only showing high agreement with fire disturbances. Whereas the agreement between BorealDB and CT indicates many point classifications within BorealDB are supported by predictions derived from their orthogonal neighbour classifications. BorealDB's low agreement with RF could also imply that disturbances were not as widely influenced by their orthogonal neighbours, within context of the orthogonal neighbour comparisons and the visual assessments however this seems unlikely.

The boreal forest is a complex ecosystem that is important to Canada's history, environment, economy, and culture. Ontario's boreal landscape is predominately a managed landscape and is integral to the lives of many Canadians. Within the Managed Area, forest managers need to consider the needs of the ecosystem as well as the needs of all stakeholders. To inform management decision making forest managers requires historical disturbance data that is accessible to maintain historical variability. The BorealDB database was compiled to address the increasing need for reliable and defensible boreal disturbance data. The goal of this thesis was to assess classification uncertainty caused by overlapping scene classifications used to construct BorealDB. To this end the relationship between BorealDB classifications and those predicted by the CT and RF classifiers, using its orthogonal neighbours, areas of uncertainty were identified as areas of disagreement. This thesis identified areas with overlapping classification uncertainty, to examine the influence of neighbour, to assess classification uncertainty within the contextual classifiers, and to compare the classifier results to identified sampled locations to test the effectiveness of each classifier. Ultimately assessing the confidence of a disturbance point's classification based upon the classifier results.

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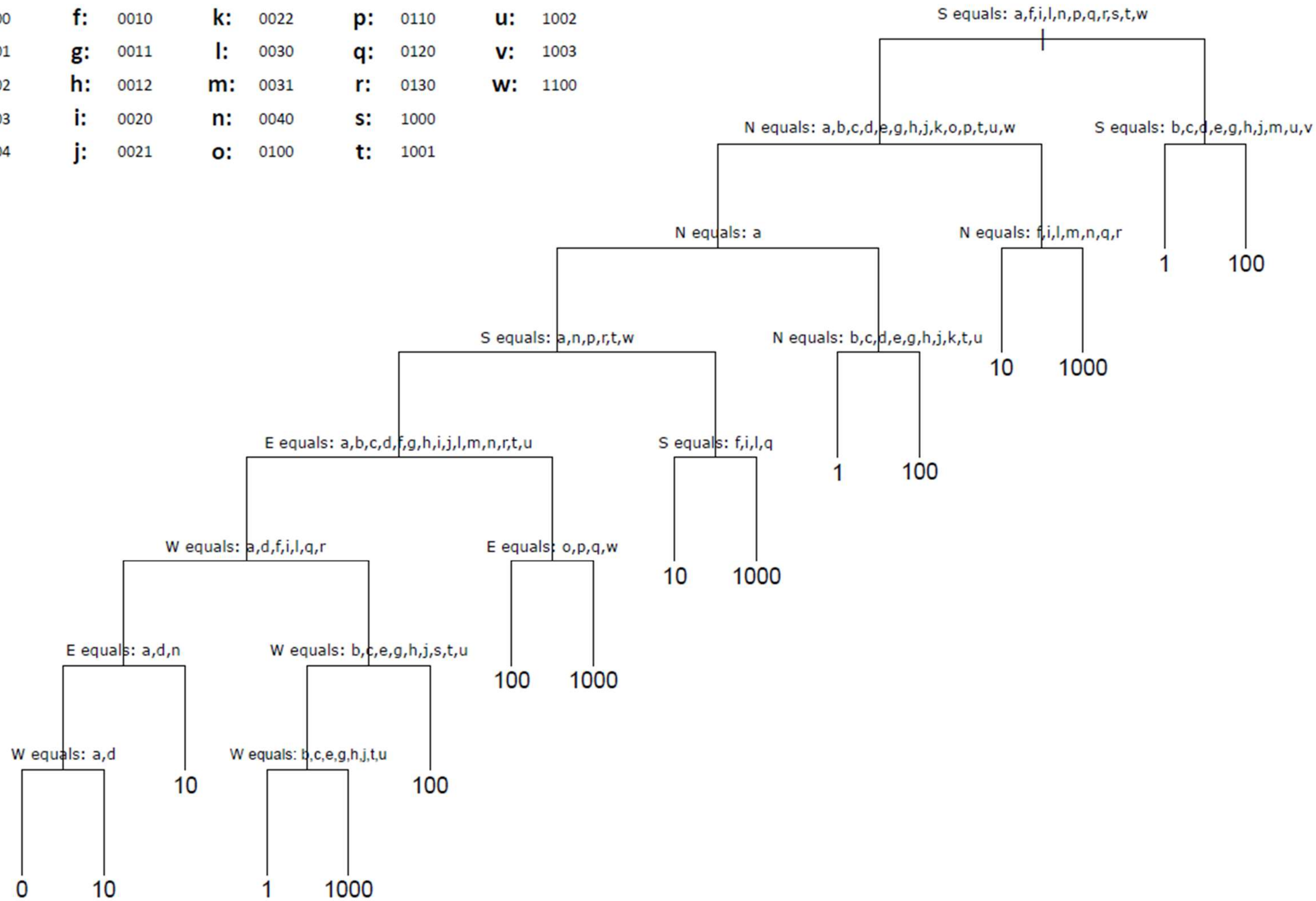
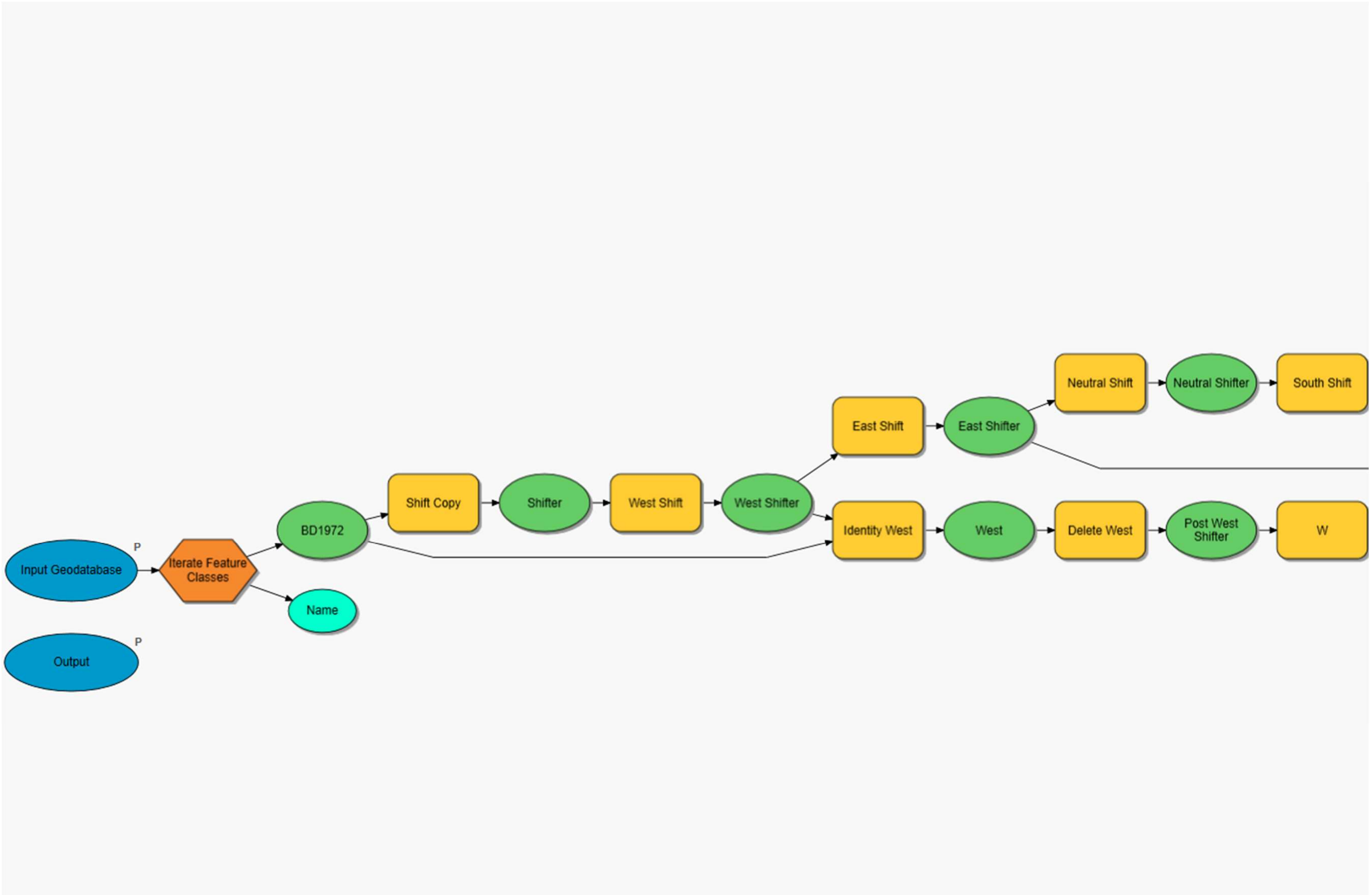
Appendix A

a:	0000	**f:**	0010	**k:**	0022	**p:**	0110	**u:**	1002
b:	0001	**g:**	0011	**l:**	0030	**q:**	0120	**v:**	1003
c:	0002	**h:**	0012	**m:**	0031	**r:**	0130	**w:**	1100
d:	0003	**i:**	0020	**n:**	0040	**s:**	1000		
e:	0004	**j:**	0021	**o:**	0100	**t:**	1001		

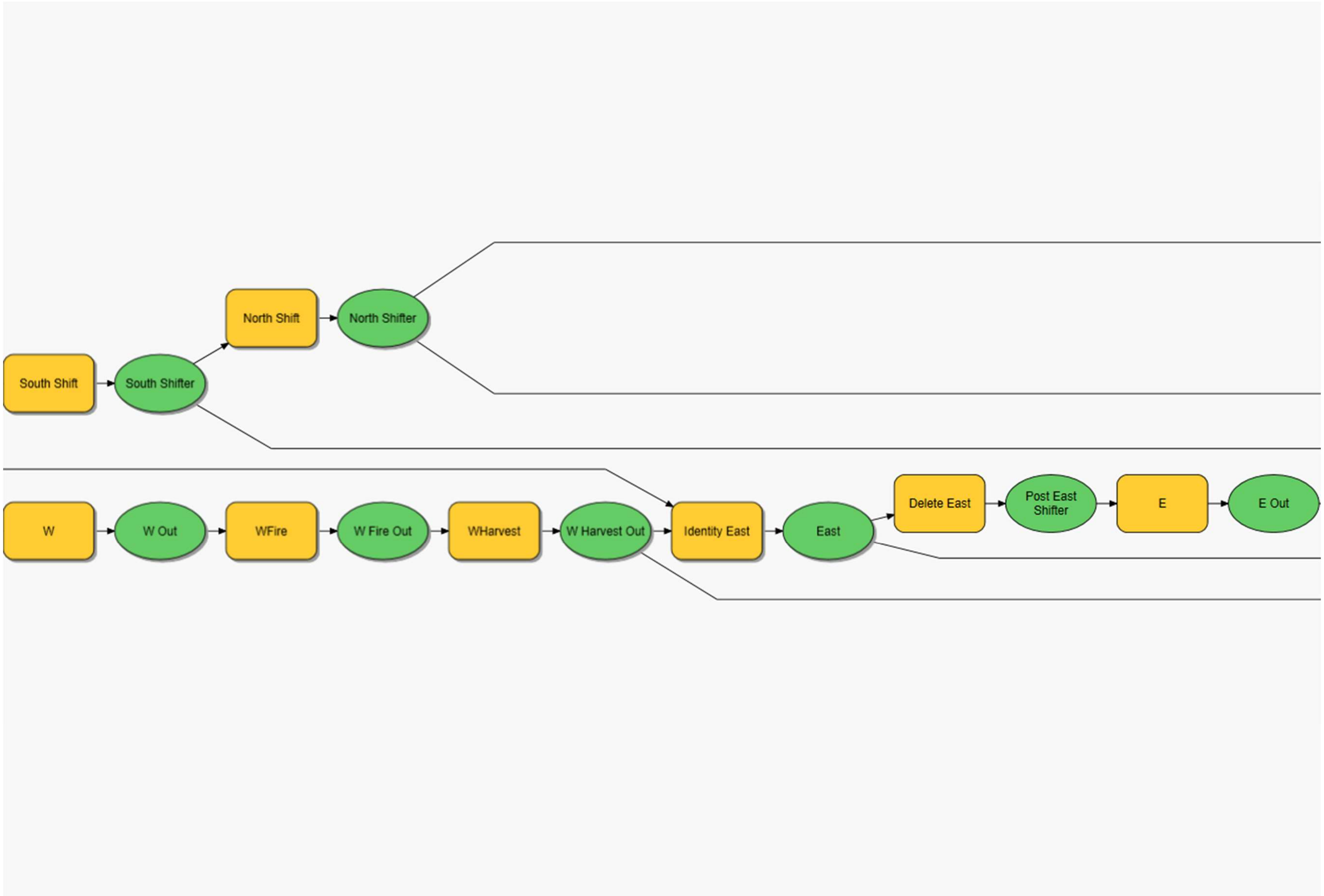


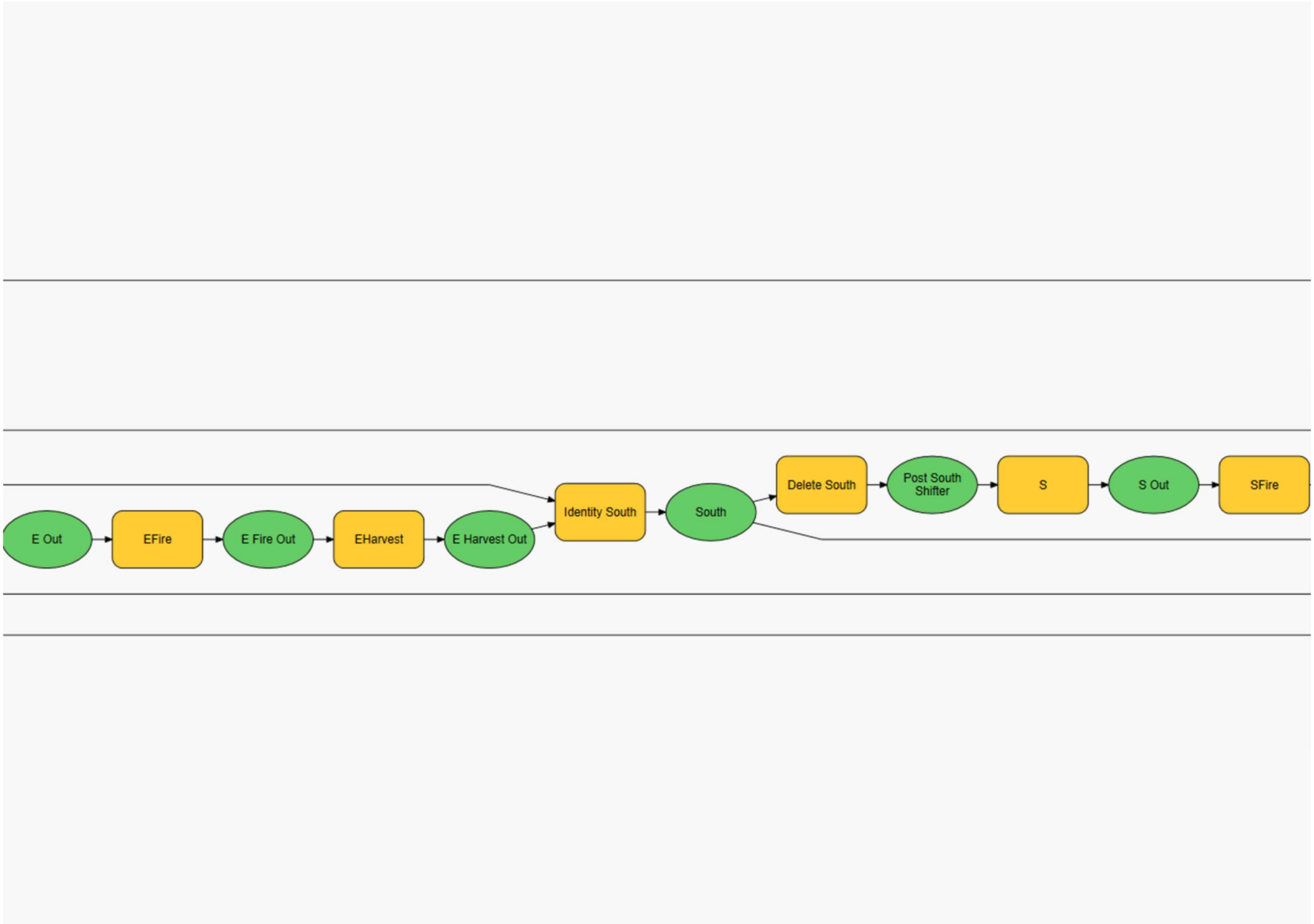
Appendix A. Classification Tree used to predict BorealDB classification.

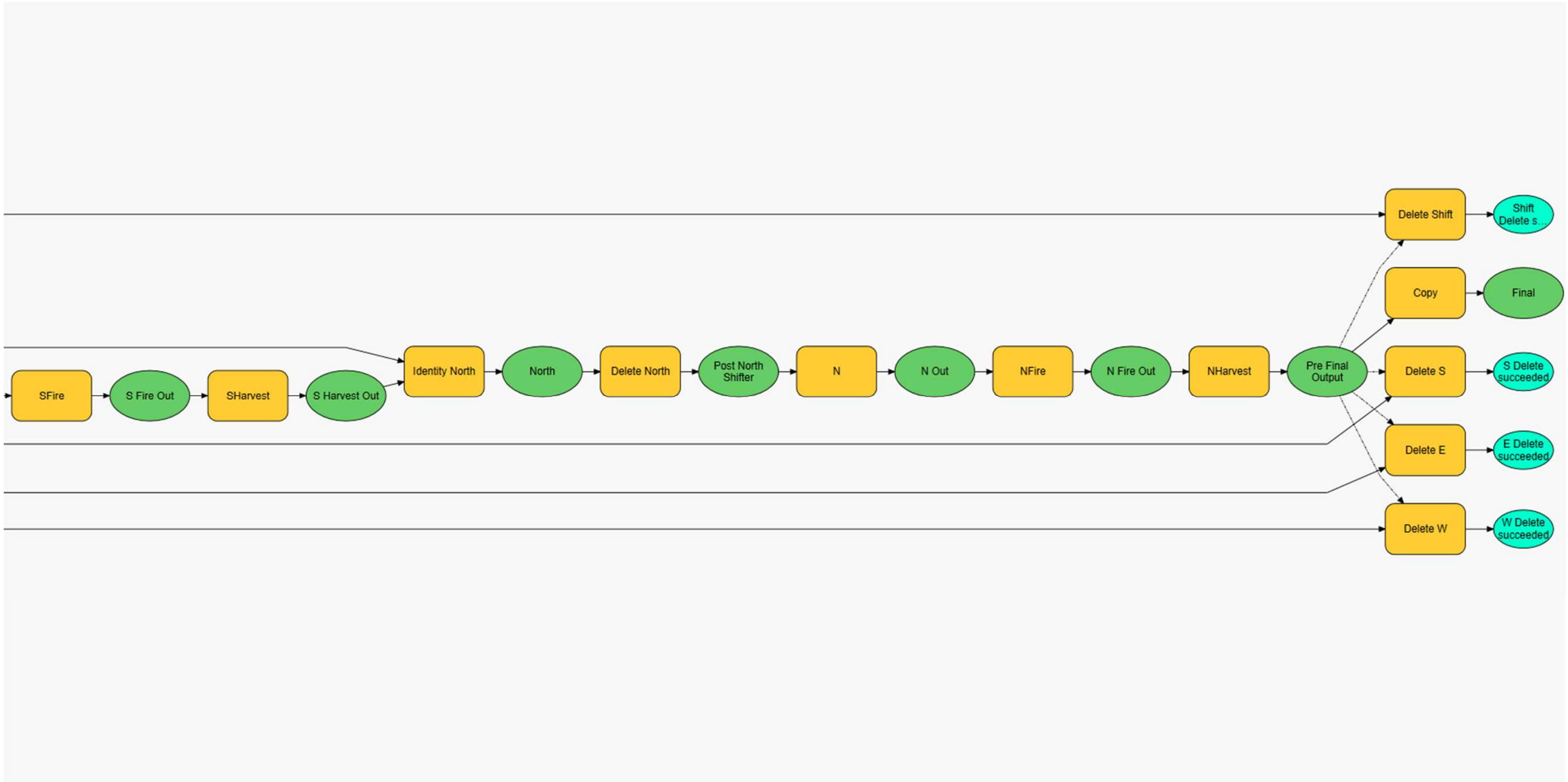
Appendix B



Input Geodatabase
P
Iterate Feature Classes
BD1972
Name
Output
P
Shift Copy
Shifter
West Shift
West Shifter
East Shift
East Shifter
Neutral Shift
Neutral Shifter
South Shift
Identity West
West
Delete West
Post West Shifter
W


North Shift
North Shifter
South Shift
South Shifter
W
W Out
WFire
W Fire Out
WHarvest
W Harvest Out
Identity East
East
Delete East
Post East Shifter
E
E Out


E Out
EFire
E Fire Out
EHarvest
E Harvest Out
Identity South
South
Delete South
Post South Shifter
S
S Out
SFire



Appendix B. Shift model used to encode nearest orthogonal neighbour point classifications.