ASSESSING HISTORICAL LANDSCAPE PATTERNS FOLLOWING FIRE IN THE CANADIAN BOREAL FOREST USING REMOTE SENSING DATA

by

Ignacio San Miguel Sánchez
B.Sc. Universidad Politécnica de Madrid, 2010
M.Sc. Universidad de Valladolid, 2012

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The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

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submitted by Ignacio San Miguel Sánchez  in partial fulfillment of the requirements for
the degree of Doctor of Philosophy
in Forestry

Examining Committee:
Dr. Nicholas C. Coops
Supervisor
Dr. David W. Andison
Supervisory Committee Member
Dr. Bruce C. Larson
Supervisory Committee Member
Dr. Sarah E. Gergel
Supervisory Committee Member
Dr. Marwan Hassan
University Examiner
Dr. Sean Smukler
University Examiner
Dr. Santiago Saura Martinez de Toda
External examiner
Abstract

Understanding pre-industrial fire patterns, in particular unburned or partially burned vegetation remnants, has become a research and forest management priority in Canada and beyond. To achieve these goals, it is crucial to better understand the variability of spatial fire patterns, as well as the relative importance of the environmental controls at broad scales.

Open-source and freely available Landsat data has great potential to capture fire patterns in a repeatable and automated way across large and remote areas. However, critical challenges associated to (1) the reliance on very expensive field plot data for calibration/validation of the mortality maps; and (2) the lack of consistent spatial language and methods to analyze the spatial patterns, hindered the applicability of these methods across large areas and the comparability of the results obtained.

The objective of this dissertation is to develop, test and demonstrate the value of a novel framework to help improve our understanding of historical spatial fire patterns across the Canadian boreal forest. The research advances our understanding of the variability and causality of spatial fire patterns across large remote boreal regions addressing both scientific and management communities. Major contributions from this research include:

- Re-imagining how to capture and describe spatial fire patterns across large and remote areas of the boreal forest through an innovative and cost-effective framework that combines Landsat satellite data, polygons of mortality from aerial photo-interpretation and a consistent spatial language and metrics to capture key fire characteristics.
- A demonstration of this new framework and how it can be extrapolated to other landscapes beyond the original formulation area. In particular, this research produced a fire pattern database comprising 507 new fires and 2.5 Mha – far in excess of any other study to date for the same area.
- An examination of how the data generated could be used in combination with new tools and methods to reveal patterns of fire mortality not previously possible including (1) characterization and assessment of differences in fire pattern signatures between pre-defined ecological zonations, and (2) analysis of the interactions between spatial fire patterns and main biotic and abiotic environmental controls.
Lay Summary

A more complete understanding of historical fire patterns is required to inform management decisions across the Canadian boreal forest. However, the lack of comprehensive site-specific mortality maps and of tools to characterize spatial patterns makes difficult to interpret fire patterns across large areas.

The objective of this dissertation is to develop, test and demonstrate the value of a novel framework to improve our understanding of historical fire patterns across the Canadian boreal forest. The framework combines Landsat data, polygons of mortality from photo-interpretation, a consistent spatial language and pattern metrics. When applied the framework produced new information for 507 fires across 2.5 Mha that, when combined with a suite of tools, revealed new insights into fire mortality and fire burn behaviour not previously known. This research provides a framework that can be used to create a national fire pattern database and contribute to the knowledge required for disturbance-based management strategies.
Preface

This research was initially proposed by Dave W. Andison and Nicholas C. Coops and led, expanded and conducted by myself, collaboratively with my committee. Most of the research undertaken in this dissertation has been published in peer-review journals and presented in conferences. In those publications I conducted the research, data analysis, interpretation of the results, writing, and prepared the final manuscript. The publications are as follows:


The conferences where I presented the results of this research are as follows:

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List of Abbreviations

%IR – Percentage of island remnants

%LDP – Percentage of the largest disturbed patch

%MR – Percentage of matrix remnants

%TR – Percentage of total remnants

AB – Alberta

ACA – Average class accuracy

API – Aerial photographic-interpretation

BP – Boreal plains

BS – Boreal shield

CBI – Composite Burn Index

CHU – Clear Hills Upland

dBand4, dBand5 and dBand7 – Differenced version of the near and short-wave infrared Landsat bands (i.e. 4, 5 and 7 in Landsat Thematic Mapper)

DC – Drought Code

dNBR – Differenced Normalized Burn Ratio

dNDVI – Differenced Normalized Difference Vegetation Index

EA – Event area

EAs – Extended Assessment

EOSD – Earth Observation for Sustainable Development of Forests

ESPA – Center Science Processing Architecture

ETM+ – Landsat Enhanced Thematic Mapper

FSC – Forestry Stewardship Council
FWI – Fire Weather Index
HRFC – High Resolution Forest Change for Canada product
HRV – Historical Range of Variation
HSD – Tukey’s Honest Significant Difference
IQR – Interquartile range
KS – Kolmogorov-Smirnov test
MBL – Mid-Boreal Lowland
MBU – Mid-Boreal Uplands
MC – Montane cordillera
MDC – Monthly Drought Code
MSE – Mean squared error
MTBS – Monitoring Trends in Burn Severity project
NBR – Normalized Burn Ratio
NDP – Number of disturbed patches
NDPn – Normalized number of disturbed patches
NDVI – Normalized Difference Vegetation Index
NIR – Near-infrared
OLI – Landsat Operational Land Imager
OOB – Out-of-the-bag accuracy
PCA – Principal components analysis
RdNBR – Relativized differenced Normalized Burn Ratio
RF – Random Forest
SD – Standard deviation
SI – Shape index
SIn – Normalized shape index
SK – Saskatchewan
SRL – Slave River Lowlands
SRTM – Shuttle Radar Topography Mission
SWIR – Shortwave infrared
TCT – Tasseled Cap Transformation
TM – Landsat Thematic Mapper
TP – Taiga plains
TS – Taiga shield
USGS – United States Geological Survey
WAU – Western Alberta Upland
WL – Wabasca Lowland
WRS-2 – Landsat Worldwide Referencing System
WX – Wilcoxon Rank Sum test
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A mis padres, por enseñarme el camino.

Nunca habría llegado aquí sin vosotros.
Chapter 1

1. Introduction

1.1. The resilience of the Canadian boreal forest

Boreal forests are the largest terrestrial biome on Earth, accounting for approximately 30% of the world’s forest coverage (FAO, 2010). Brandt (2009) defined the boreal forest as ‘the broad, circumpolar vegetation zone of high northern latitudes covered principally with forests and other wooded land consisting of cold-tolerant tree species primarily within the genera Abies, Larix, Picea, or Pinus but also Populus and Betula’. Canada’s boreal represents 28% of the total global extent of boreal forest (Brandt, 2009). This dominant biome covers 552 Mha; of which 270 Mha supports forests, 39 Mha other wooded-land, 171 Mha other related land cover types with the remaining 71 Mha covered by lakes, ponds and rivers (Brandt, 2009).

Boreal forests are also important for the many ecosystem services they provide, including provisioning, regulating, cultural and supporting (Hassan et al., 2005). With respect to regulating services, boreal forested ecosystems play an important role in the global carbon cycle, storing 32% of the global carbon (Pan et al., 2011) and facilitating flows from the atmosphere to the biosphere (Kasischke et al., 1995). In terms of provisioning, the boreal ecosystems are fundamental to Canada’s resource-based economy, providing renewable forest resources, non-renewable mineral and energy resources, and hydroelectric production. Conservative estimates put the contribution of boreal forest resources into the Canadian forest economy at $40 billion in revenue and 128,000 jobs, or about 40% of the total forest economy (Bogdanski, 2008). The boreal ecosystem also represents a key opportunity for researchers to study natural ecosystem processes because of its relatively wild state due to its limited human occupation, few invasive species and many intact predator–prey processes (Brandt et al., 2013).

For the last seven thousand years frequent natural disturbances – fire, insects, diseases and their interactions – of variable magnitude have created and maintained a range of ecosystem conditions (Brandt et al., 2013) resulting in vegetation mortality and releasing available growing space (Oliver and Larson, 1996). During this time, boreal species have not only adapted to these spatial patterns of mortality but also have evolved to depend on many of these processes for their survival (Delong and Kessler, 2000).
In the Canadian boreal forest, fire is the most common natural disturbance since the last Ice Age (Rowe and Scootter, 1973; Weber and Flannigan, 1997; Wotton et al., 2010), burning on average 2 Mha or 0.7% of Canada’s surface yearly as a result of large and infrequent fires larger than 200 ha (Stocks et al., 2002). Post-fire effects are long-reaching and profound, with some areas of the boreal forest experiencing fire return intervals exceeding 300 years (Parisien et al., 2006, 2004). As a result, fire represents a critical process for much of the boreal forest biodiversity and is responsible for shaping landscape heterogeneity and influencing biogeochemical cycling and energy flows (Rowe and Scootter, 1973; Stocks et al., 2002; Wotton et al., 2010).

Fires within boreal forested ecosystems have traditionally been viewed as severe, killing most of the trees within the fire perimeter, and thus homogenizing age-class distributions (e.g. Johnson et al. (1998)). In fact, this argument has been used to justify low retention levels in harvesting planning (Seymour and Hunter Jr., 1999). Recent studies however have shown that not all the boreal forests fires are severe in nature (Johnson et al., 1998), nor all the vegetation is killed within the fire perimeter (Eberhart and Woodard, 1987). Fire events can leave as much as 40% to 60% of remnant, unburned vegetation (Andison and McCleary, 2014; Pickell et al., 2015; Soverel et al., 2010), which results in a mosaic of different age-class distributions, structure and composition within the fire perimeter (Turner and Romme, 1994) (see Figure 1.1). These vegetation remnants provide critical compositional and structural complexity that help in the reassembly of the biotic community post-fire (Drever et al., 2006), via enhancing tree regeneration by providing adjacent seed sources (Perera and Buse, 2014), maintaining habitat connectivity for large mammals such as caribou (Courtois et al., 2004) or providing refugia for in-situ recolonization of small mammals with reduced dispersal capabilities (Banks et al., 2011). Moreover, evidence suggests not only is the presence of vegetation remnants important, but also their spatial configuration. For example, Turner and Romme (1994) found that the rate of reestablishment of plants that depend on the dispersal of propagules was influenced by the size of the burned patch, the distance to the nearest unburned forest patch, and the amount and spatial distribution of burn severities within a given patch; and Oliver (1981) suggested that areas with high-edge contrast between burned and unburned patches facilitate tree re-establishment by providing shade, wind protection and a propagules.

1.2. The new management paradigm

In order to maintain the critical compositional and structural complexity created by fire across the boreal forest, it has been suggested that forest management patterns should be modelled after the Historical
Range of Variation (HRV) (Attiwill, 1994; Hunter, 1993; Johnson et al., 1998), where HRV is defined as the variability of ecological conditions experienced by a fairly intact ecosystem, for a given time period and extent (Landres et al., 1999). The objective is to maintain a range of ecosystem conditions within the HRV, so that the structure and function of these ecosystems will be maintained in the long term with a reduced risk of negatively affecting biodiversity and other ecosystem services (Landres et al., 1999).

There has been considerable interest in HRV to support sustainable forest management across the boreal regions. This is particularly evident in Canada, while in the Eurasian boreal forest the majority of the information to-date remains theoretical (Kuuluvainen and Grenfell, 2012). In particular, in the last two decades multiple management agencies and certification bodies in Canada required forest management plans to include some level of natural pattern approximation. This generally involves to apply knowledge of spatial mortality patterns created by fire as coarse-filter indicators to guide forest harvesting (Perera and Buse, 2014). Several provincial guidelines have been implemented at the provincial level to emulate fire disturbances via characterizing the size of the clearcuts and the amount and spatial distribution of the tree vegetation remnants, such as in British Columbia (BCMF 1995), Alberta (ASRD, 2008) and Ontario (OMNR 2010). Also certification agencies such as the Forestry Stewardship Council (FSC) have included fire pattern indicators as part of their requirements for the Canadian boreal region (FSC, 2004). In addition to guiding harvesting planning, there is an increasing interest in HRV to assess the risk of biodiversity loss via analyzing departure from the natural state of multiple anthropogenic activities (Pickell, 2012).

Regardless of the application, a key requirement for the implementation of HRV approaches is the definition and characterization of the variability of spatial patterns created and maintained by fire (Boulanger et al., 2013, 2012), as well as the abiotic and biotic controls associated to those patterns across large areas of the boreal forest (Parisien et al., 2006).

Spatial patterns of fire can be quantified in various ways, depending on the objective. According to Keane et al. (2009) ideal variables to quantify fire patterns for HRV are measurable, representative and appropriate for the management objectives. For instance, a thematic map of tree mortality classes (e.g. unburned, partial and complete mortality) based on measurements of canopy loss can be used to map fire patterns with relevance to harvesting planning.

Characterizing HRV across large areas of the boreal forest requires (1) methods that are cost-effective at mapping large extents, (2) a consistent spatial language to characterize the fire events, (3) a consistent suite of metrics that capture the key fire characteristics and (4) robust statistical and visualization methods that can be applied to summarize and compare fire patterns metrics across and within regions.
First, any method to characterize HRV across the boreal needs to be cost-effective at mapping large areas. Spatial mortality patterns are the result of a range of fire behaviours controlled by the local environment – fuels, topography and climate – at multiple spatial and temporal scales (Turner and Romme, 1994; Wotton et al., 2010). In the vast and heterogeneous forests of the Canadian boreal this results in highly variable fire patterns within and among regions (e.g. Andison and McCleary, 2014; Burton et al., 2008; Parisien et al., 2004), which means that characterizing HRV requires large amounts of site-specific fire pattern data.

Second, a consistent spatial language to define fire perimeters and within patch-types is required to guarantee the comparability of the results across studies (Andison and McCleary, 2014). For example, Andison (2012) demonstrated that even subtle changes to the definition of a fire perimeter can have dramatic impacts on the measured amount of fire vegetation remnants.
Figure 1.1. Managing for ecosystem resilience with fire.

This photo taken by my from a helicopter on September of 2014 shows the landscape mosaic after 20 years of using the knowledge of fire patterns as benchmarks for harvesting planning near La Ronge in the province Saskatchewan, Canada. This approach focuses on emulating the amount and spatial configuration of unburned vegetation patches after fire events to enhance tree regeneration, maintaining habitat connectivity and providing refugia for in-situ recolonization after harvesting events.
Third, making HRV an operational reality in the boreal forest of Canada requires a suite of robust and consistent fire pattern metrics that represent the spatial and temporal distribution of fire patterns on the landscape and that serve as benchmarks against which to compare (Keane et al., 2009). Many metrics can be generated to quantify landscape patterns, with the most relevant often depending on the application (Landres et al., 1999). Fire mortality pattern can be quantified through metrics describing composition and configuration (Li and Reynolds, 1995). Composition metrics are not spatially explicit and include the amount or proportion of each patch type within disturbances (Mcgarigal and Marks, 1994). These metrics are often used as baseline information to layout emulation templates, and are therefore essential to support any human disturbance planning that utilizes fire patterns. For example, the total area of a fire event, and the proportional area of vegetation remnants not only capture key patterns of natural fire behaviour, but also inform management planning on the size of the harvest cutblocks or the amount of tree retention (Andison, 2012). Configuration metrics provide spatial context for composition metrics, such as the distribution, arrangement or spatial relationship of the patches of a given class or across classes (Mcgarigal and Marks, 1994). For example, the shape index captures the sinuosity of a disturbance event, and can be used by managers to define the total amount of edge for a harvest compartment. Likewise the size-distribution and number of burned patches can inform on the patchiness within the fire event.

Lastly, there is a need for robust statistical methods to summarize and compare fire pattern metrics within and across regions, as well as improving our understanding of the environmental conditions when they occur. Some of these analyses may include to compare frequency distributions for a given metric through deviances in median values or differences in the distribution shape (e.g. Pickell et al. (2013)).

1.3. Remote sensing to assess fire patterns

The HRV of natural fire patterns has been often studied based on mortality maps derived from different data sources (Morgan et al., 2001). Mortality maps can be produced from plot or transect data collected in the field, which is the most precise technique, however is labour intensive and expensive making it unsuitable for mapping mortality across even moderately-sized areas (Chuvieco et al., 2006). Remote sensing, from satellite or other aerial platforms, has significant potential for studying fine-scale heterogeneity of mortality following fire across large areas, and has been commonly applied to map both the perimeter of fires as well as the configuration of burnt patches and unburnt vegetation remnants.
1.3.1. Manual interpretation of aerial photography

The oldest source of remotely sensed and spatial data for mapping fire patterns is aerial photography (Morgan et al., 2010), which became available starting in 1940’s with regular flights for mapping and forestry inventory in Canada. High-quality aerial photos are spatially detailed and using aerial photographic-interpretation (API) can provide information on fire size, type, and spatial arrangement of within-fire mortality patterns. Given this history, the longest fire pattern databases in Canada are API derived. However, API is also time-consuming, requires very specific expertise, and to acquire the photographs is expensive and only available on an ad-hoc basis in the Canadian boreal forest, which means that only a subset of all fires can be analyzed (Morgan et al., 2010). A western boreal fire dataset of 129 wildfires (30–25,000 ha) that burned between 1940 and 2010 across Alberta and Saskatchewan, Canada (Andison and McCleary, 2014), offers a prime example of these detailed and valuable databases.

1.3.2. Semi-automated methods using the Landsat data archive

Another remotely-sensed data source from which mortality maps are generated is satellite imagery. Since the mid 1980’s, numerous remote sensing techniques have been developed to assess fire patterns on both local and regional scales (Key and Benson, 2006). When vegetation is burned, there is a drastic reduction in visible-to-near-infrared surface reflectance (i.e. 0.4–1.3μm) associated with the charring and removal of vegetation at the 30 m spatial resolution of Landsat sensors. This is often accompanied by an increase in short-wave infrared reflectance (i.e. 1.6–2.5μm), as a compounded effect of increased soil exposure and radiation absorption by burned vegetation, and a decrease in the evapotranspiration (Lentile et al., 2006). Based on those sensitivities, multi-temporal approaches that apply image ratios and image differencing have been developed to detect changes associated to burned vegetation (Eidenshink et al., 2007), which are then validated against ground-truth estimates (see Chapter 4 for more information about satellite-derived spectral indices).

Most fire pattern studies have been conducted with multispectral Landsat sensor imagery (Chuvieco et al., 2006) since its large area coverage (185 km wide swath for single scenes) and moderate spatial resolution (30 m) is well suited to capture changes in tree condition at the stand level across landscape scales (White et al., 2014). The recent opening of the United States Geological Survey (USGS) archive of Landsat imagery (Woodcock et al., 2008) has provided users with high-quality data processed to stringent radiometric and geometric standards that is suitable for time-series analysis of vegetation condition (Zhu and Woodcock, 2014). The increased data availability has enabled the development of multiple algorithms to detect and mask noise and data fusion techniques to guarantee spectral
consistency across the time series (White et al., 2014). For example, the Fmask algorithm developed by Zhu and Woodcock (2012) is now routinely applied to the entire Landsat data archive providing a user-ready mask with information about water, clouds, shadows and other atmospheric distortions (see https://espa.cr.usgs.gov/). Similarly, the development of pixel-compositing approaches to combine and summarize dense and noisy time-series imagery into seamless spectrally consistent, cloud-free images can be used to detect and quantify changes in vegetation condition (White et al., 2014). Together these advancements make possible the detection and delineation of fires across unprecedented spatial scales (Hermosilla et al., 2016; White et al., 2017), the detailed characterization of changes in vegetation condition (Eidenshink et al., 2007), and the study of recovery trends after disturbance (Kennedy et al., 2010).

There are inherent limitations of using Landsat data for fire pattern mapping. First, the 30 m spatial resolution of Landsat certainly limits our ability to capture the details related to individual tree condition or areas where there is high spatial variability in fire effects at the subpixel level (van Wagtendonk et al., 2004). This is particularly problematic when mapping sparsely forested areas, or areas where fire effects are more dispersed and vary at the individual tree scale (e.g. Miller and Yool (2002)). Second, Landsat imagery is captured by a passive optical sensor, which makes it suitable to capture fire effects on overstory vegetation (Fraser et al., 2017; Miller and Thode, 2007; Smith et al., 2007) but less so under the obscured sub-canopy (Cocke et al., 2005). Third, and despite the stringent radiometric and geometric standards implemented by the USGS, the Landsat imagery is subjected to some degree of misregistration error that can result in a false detection of change (Verbyla and Boles, 2000). Likewise, undetected clouds, smoke or haze from single date cloud detection (Zhu and Woodcock, 2012) or changes in reflectance due to phenology can also lead to a false detection of change. Lastly, limiting fire pattern data only back to 1985 compromises the ability to capture the full temporal range of variability in fire patterns.

1.3.3. Challenges of fire pattern studies using Landsat data

Despite the availability and potential of Landsat data, there have been no studies that captured detailed vegetation remnants patterns and partial mortality with reasonable accuracy across more than a very small sample size of the Canadian boreal forest. One of the major reasons for this lack of comprehensive studies is that satellite-based approaches require an independent source of data for calibration and validation of the mortality maps. Without this, it is not possible to evaluate the accuracy of the mortality maps, rendering the results undefendable for managers (e.g. Burton et al. (2008)).
Composite Burn Index (CBI) field data (Key and Benson, 2006) has become the standard for mapping fire patterns as a quick method to assess ground measurements of fire effects for map calibration and accuracy assessment (Eidenshink et al., 2007). CBI plots record rankings from 0 (unburned) to 3 (most severe) across different strata (soil, understory, shrub, intermediate trees and overstory trees), which are then averaged to a unitless value (Key and Benson, 2006). A number of studies across the Canadian boreal forest have used Landsat and CBI data with relative success (Boucher et al., 2017; Hall et al., 2008; Soverel et al., 2011, 2010). However, there are some challenges to using CBI data. Collecting CBI data over remote areas is highly expensive and time-consuming and would require a vast network of plots to capture the variability of conditions in highly heterogeneous Canadian boreal landscapes (Fraser et al., 2017). The result is a series of scattered studies with low sample sizes (<10) (Boucher et al., 2017; Hall et al., 2008; Soverel et al., 2011, 2010) that offer little context to interpret the variability of fire patterns within and among fires even across moderately-sized areas. Other challenges to utilizing CBI for fire pattern studies include that its visual assessment is somewhat subjective and highly variable among observers (Lentile et al., 2006) and lacking a clear agreed-upon biometric definition (Kolden et al., 2016), which hinders the comparability and interpretability of the results. Given the applied nature of the fire mortality pattern information to forest management, regulatory, and certification agencies, incomplete or inaccurate fire pattern estimates are not defendable, and thus of limited value.

1.3.4. Challenges associated to spatial language and methods

Other challenges associated with fire pattern studies in general are that they differ in their methods, data quality and type, and spatial language, which makes it difficult for managers to understand and compare fire patterns across both small areas (because small studies may not capture the full variability of fire patterns) and larger areas (because the data, methods and assumptions from different studies are not comparable). What is needed is a universal combination of data sources, methods and spatial language that can be applied to generate a large enough sample size – of sufficient accuracy – to differentiate the signature of within zone fire patterns from those between zones. This information can then be used to quantify how fire pattern metrics vary among and within pre-defined ecological zonations (e.g. Parisien et al. (2004)), to define areas where spatial fire patterns are relatively homogeneous (Boulanger et al., 2012), or to better understand the relationship between fire pattern metrics and various environmental controls (Morgan et al., 2001). If broad-scale patterns are found to exist, it would increase the robustness of statistical inferences across the boreal forest ecosystems in support to management efforts.
1.4. Objectives and research questions

The main objective of this dissertation is to develop, test and demonstrate the value of a novel framework to help improve our understanding of historical fire patterns across the Canadian boreal forest. To meet this objective I address the following research questions:

- To what level of detail can a Landsat-derived model be used to predict tree mortality?
- To what level of detail can three-class mortality maps derived from Landsat data be used to predict seven fire patch metrics?
- Can a Landsat-derived model be used to generate a sufficiently large sample size as to detect differences in fire patterns within and across sub-regions of the boreal plains ecozone?
- What are the relative roles of disturbance history, climate, vegetation, and topography and their complex interplay on resulting fire patterns across boreal plains?

The proposed framework leverages both the availability of free, open-access Landsat data as well as aerially-derived fire mortality maps for calibration, application of a consistent spatial language and the derivation of a suite of key fire metrics and methods to analyze the observed patterns. This research lays down a framework that can potentially be used to create a national fire pattern database and contribute to the knowledge required for disturbance-based management strategies, with important ramifications for fire management, conservation planning, and climate-change adaptation in the Canadian boreal region.

1.5. Dissertation overview

This thesis can be viewed through three overarching research themes: ‘model development’, ‘model testing’ and ‘model demonstration’ (Figure 1.2). In addition to the research chapters described below, Chapter 2 describes the study area and data and Chapter 3 describes the spatial language used throughout the thesis. A brief description of the research Chapters is included below:

- ‘Model development’ involved the conceptualization, calibration and validation of an innovative and cost-effective framework to capture and describe spatial fire patterns across large and remote areas of the Canadian boreal forest. With this framework I both analysed and communicated fire pattern information within and between the scientific and management communities to support disturbance-based management. The framework combines Landsat satellite data, polygons of mortality from aerial photo-interpretation and a consistent spatial language and metrics to capture key fire characteristics. In Chapter 4 I evaluated the accuracy of a Landsat spectral model to predict
tree mortality at different levels of detail and with different predictor variables. In Chapter 5 I compared multiple fire-patch metrics derived from a Landsat model to those derived from aerial photo-interpretation.

- ‘Model testing’ involved a demonstration of how this new framework can be extrapolated to other landscapes, not in the original formulation area, to produce new fire pattern information cost-effectively. In Chapter 6 I produced a fire pattern database comprising 507 new fires and 2.5 Mha – far in excess of any other study to date for the same area and created summaries of the data.

- ‘Model demonstration’ involved a demonstration that showed how the data generated in Chapter 6 could be used in combination with new tools and methods to help reveal an entirely new layer of research possibilities and interesting patterns that was not previously possible. In Chapter 6 I characterized and assessed differences in fire pattern signatures between pre-defined geographical divisions across the boreal plains; while in Chapter 7 I assessed the relative importance and complex interplay of abiotic and abiotic environmental on resulting post-fire patterns.

![Figure 1.2. Conceptualization of the research Chapters.](image-url)
Chapter 2

2. Study area and data

2.1. The Canadian boreal plains ecozone

The boreal plains ecozone (BP) of western Canada (Ecological Stratification Working Group, 1996) (Figure 2.1) is the third largest ecozone in Canada (Canadian Forest Service, 2013) with the fourth highest annual burn rate (Stocks et al., 2002), covering parts of Alberta, Saskatchewan and Manitoba, with smaller extensions into north-eastern British Columbia and south-central Northwest Territories. Climate is humid and continental characterized by cold winters and moderately warm summers. Average annual precipitation typically increases from north to south and east to west, ranging from 300-500 mm (Environment Canada, 2018). The topography is composed of flat to gently rolling plains with low-lying valleys between approximately 200 m to 800 m in elevation above sea level. Typically, the forest productivity and species diversity increases from north to south. The dominant vegetation is dense to sparse coniferous and mixedwood forests, with a mosaic of trees, shrubs, herbs, wetlands and lakes (Ecological Stratification Working Group, 1996). The main tree species are black spruce (*Picea mariana* P. Mill.), white spruce (*Picea glauca* Moench), jack pine (*Pinus banksiana* Lamb.) and tamarack (*Larix laricina* Du Roi), where broadleaf species, such as trembling aspen (*Populus tremuloides* Michx.), white birch (*Betula papyrifera* Marshall) and balsam poplar (*Populus balsamifera* L.), are more abundant towards the southern portion of the ecozone (Ecological Stratification Working Group, 1996). Over three quarters of the ecozone is dedicated to forestry, with small contributions of agriculture and exploration for oil and gas (Canadian Forest Service, 2013). Fire patterns in the ecozone are highly spatially variable due to latitudinal variability in climate and vegetation, and variable anthropogenic influences (Parisien et al., 2004). Anthropogenic disturbances – via landscape fragmentation, fire suppression and ignitions – are more common in southern areas of the ecozone (Pickell et al., 2015). This is the result of a greater accessibility, older and more common harvest tenures, and more aggressive fire suppression over the last 60 years (Cumming, 2005). The BP is divided into ten ecoregions, or broad recurring vegetation and landform patterns, within the regional climatic context of the ecozone (Table 2.1).
Figure 2.1. The boreal plains ecozone of western Canada.
Table 2.1. Physical and biological characteristics of the ecoregions within the boreal plains ecozone.

Based on the Terrestrial Ecozones of Canada (Wiken, 1986).

<table>
<thead>
<tr>
<th>Ecoregion name</th>
<th>Ecoclimate</th>
<th>Mean temperatures for year/summer/winter (°C)</th>
<th>Precipitation (mm)</th>
<th>Vegetation</th>
<th>Topography</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slave River Lowlands</td>
<td>Sub humid mid-boreal</td>
<td>-2/13/-17</td>
<td>300-400</td>
<td>Closed stands of trembling aspen, balsam poplar, and jack pine with white and black spruce, and balsam fir in late successional stages. Tamarack and black spruce dominate fens and bogs with ericaceous shrubs and mosses</td>
<td>Flat to gently rolling</td>
<td>50% of the area is peatlands</td>
</tr>
<tr>
<td>(SRL)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Clear Hills Upland</td>
<td>Sub humid mid-boreal</td>
<td>-1/13/-17</td>
<td>400-600</td>
<td>Lodgepole pine with white spruce and fir in the uplands. Black spruce dominates in the poorly drained valley bottoms</td>
<td>Steep to gently rolling</td>
<td>Ecotone between boreal and cordilleran vegetation</td>
</tr>
<tr>
<td>(CHU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Boreal Uplands</td>
<td>Sub humid mid-boreal</td>
<td>-1/14/-14</td>
<td>400-550</td>
<td>Closed stands dominated by trembling aspen with balsam poplar with understory of tall shrubs and herbs. White and black spruce, and balsam fir occur in late successional stages. Deciduous stands have an understory of tall shrubs and herbs while coniferous have feathermoss. Tamarack and black spruce dominate fens and bogs</td>
<td>Flat to gently rolling</td>
<td>Accounts for most area burnt in the boreal plains (Parisien et al., 2004)</td>
</tr>
<tr>
<td>(MBU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wabasca Lowland</td>
<td>Sub humid mid-boreal</td>
<td>1/13/-13</td>
<td>350-500</td>
<td>Closed stands of trembling aspen and balsam poplar. White and black spruce, and balsam fir, occur in late successional stages. Tamarack and black spruce dominate fens and bogs</td>
<td>Flat to gently rolling</td>
<td>50% of the area is peatlands</td>
</tr>
<tr>
<td>(WL)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Western Alberta Upland</td>
<td>Sub humid mid-boreal</td>
<td>1.5/12/-10</td>
<td>450-600</td>
<td>Closed stands dominated by lodgepole pine, trembling aspen and white spruce with some balsam poplar, paper birch and balsam fir. Drier sites are most often covered by stands of aspen or open lodgepole pine forest; while on wet sites tamarack and black spruce are more prevalent. Higher elevations of the foothills are dominated by conifers and lower plains with aspen</td>
<td>Flat to gently rolling</td>
<td>Ecotone between mid-boreal and mid-cordilleran vegetation</td>
</tr>
<tr>
<td>(WAU)</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Boreal Lowland</td>
<td>Sub humid mid-boreal</td>
<td>-1/13/-17</td>
<td>375-625</td>
<td>Closed stands of trembling aspen, balsam poplar, and jack pine with white and black spruce, and balsam fir in late successional stages. Black spruce and willows dominate fens and bogs</td>
<td>Flat</td>
<td>50% wetlands</td>
</tr>
<tr>
<td>(MBL)</td>
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</tbody>
</table>
2.2. Remotely sensed data

Multiple sources of remote sensing data were used throughout the thesis, which included: (1) the western boreal aerial photo-interpreted fire dataset, (2) the Landsat data archive, and (3) pre-fire forest inventory data.

2.2.1. The western boreal aerial photo-interpreted fire dataset

In this study I used as reference data the western boreal aerial photo-interpreted (API) fire dataset which consists of 129 fires (30–25,000 ha) that burned between 1940 and 2010 across Alberta and Saskatchewan, Canada (Andison and McCleary, 2014). The extent of the fires covers >100 Mha of the western Canadian boreal across several major ecological zones including the montane cordillera, boreal plains, boreal shield, taiga shield and taiga plains according to the Canadian ecological classification system (Ecological Stratification Working Group, 1996). These ecozones represent a large range of conditions, from mountain to continental to sub-arctic climate, and dense conifer to mixedwoods to open-grown vegetation. Currently this database represents the largest spatial fire pattern database in Canada and costs more than 1M$ to produce (David W. Andison, personal communication).

The API process used aerial photos of scale 1:30,000 or finer acquired within four years of each fire event to delineate polygons of six tree mortality classes (i.e. 0%; 1–25%; 26–50%; 51–75%; 76–94% and >94%) by identifying burnt and dead tree and other vegetation directly from the most recent fire event (Andison, 2012) (Figure 2.2). Tree mortality was defined as percentage of crown mortality or lesser vegetation consumption attributable to the most recent fire. The expert interpreter was familiar with the process since the six mortality classes defined are routinely used by governmental agencies in Canada to map fire effects. To maximize the consistency and comparability of the results the same person interpreted all 129 fires.

Three selection criteria were used to select and interpret the aerial photos: (1) local high quality, first-generation aerial photos / negatives available within five years after the fire, (2) no substantial fire control activities, and (3) no cultural disturbance before the fire, or post-fire salvage logging before the photos were taken. The minimum mapping resolution was 0.01 ha, or 10 m², which represents a clump of about three live trees (Andison and McCleary, 2014). However, the quality of the photos or negatives allowed clear identification of individual tree condition.
The value of the API data to this study was twofold; first, it was used to define HRV for a suite of ten fire pattern metrics in support of HRV requirements for harvesting planning (Andison and McCleary, 2014), analyzing departure from the natural state (Pickell et al., 2013), understanding burn pattern differences between different ecological regions (Andison and McCleary, 2014), and understanding where and when different parts of a fire survive as vegetation remnants (Ferster et al., 2016).

Figure 2.2. Example of polygons of mortality from aerial photo-interpretation and of the Landsat differenced Normalized Burn Ratio (dNBR) for the fire Cone.
2.2.2. Pre-fire forest inventory data

I used pre-fire forest inventory data to characterize the structure and composition of pre-existing vegetation as it greatly conditions the amount and arrangement of the available fuels and thus fire behaviour and resulting mortality patterns (Cumming, 2001; Kafka et al., 2001; Leduc et al., 2007). This dataset is a compilation of information with a main focus on timber production, used to help plan where, what, and when to harvest by the forest industry. Thus, the coverage includes forest disturbances, such as burned areas, and detailed information on tree species, density, height, stand ages, understory vegetation, non-forest types, and soil moisture. The inventory data was derived from API of 1:15-20,000 aerial photographs taken within five years prior to the date of each fire with a minimum mapping unit of two ha (AVIS, 2005; SFVI, 2004). To increase mapping accuracy, and depending on data availability, the photo-interpreter was aided by information from previous field checks, forest inventories, fire maps and records, sample plots and reforestation records. The area mapped included the fire perimeter plus a 100 m buffer to capture adjacent unburned areas. More detailed information on the photo-interpretation process and associated field checks is described in AVIS (2005) and SFVI (2004).

2.2.3. The Landsat data archive

This research has been made possible by recent free and open-access to the imagery in the Landsat data archive (Woodcock et al., 2008), which represents an opportunity to study fine-scale heterogeneity in tree mortality after fire across large areas (e.g. Eidenshink et al. (2007)). Landsat satellites have a semi-polar, sun-synchronous orbit at a nominal altitude of 705 km over the equator and collect multispectral information with a 16 days re-visit time and 30 m spatial resolution. Landsat sensors have collected information since the 1984 in what represents the longest and most-comprehensive on-going satellite data archive to-date (White and Wulder, 2014). Multiple Landsat sensors have collected information along the years. The Thematic Mapper (TM) instrument has recorded multispectral data from 1984 to 2011; the Enhanced Thematic Mapper (ETM+) instrument has been recording observations since 1999 and the Operational Land Imagery (OLI) since 2014. The ETM+ sensor however had an operational malfunction, which resulted in decreased acquisition capabilities (i.e. scan-line corrector off) since 2003.

Theoretically Landsat provides suitable spectral bandwidths to capture fire-induced changes on vegetation at the landscape level (Chuvieco et al., 2006), which was the reason why I chose Landsat data as the main data source in this study to derive tree mortality maps. In particular, Landsat sensors collect information in the near-infrared (NIR) and shortwave-infrared (SWIR) portions of the electromagnetic
spectrum that are most sensitive to spectral changes in burned areas (Pereira et al., 1999). This sensitivity has led to the development of a variety of spectral indices to map fire effects (i.e. combinations of different sensor bands) that are described in more detail in Chapters 4 and 5. In addition, Landsat imagery lends itself for time-series change detection analysis as it provides users with high-quality surface reflectance products processed to stringent radiometric and geometric standards (Zhu and Woodcock, 2014).

In addition to using raw surface reflectance Landsat imagery, I also utilized a number of Landsat-derived products for this thesis, which are described in detail in the corresponding research Chapters. These include thematic maps of land cover and the perimeter and year of fire events for the full length of the Landsat record.
3. Spatial language for describing fire patterns

3.1. Introduction

The study of spatial fire patterns requires thematic maps of mortality that identify areas with relatively homogeneous fire effects (Key and Benson, 2006). It also requires of a consistent spatial language to translate the thematic maps of mortality into simplified and spatially-discrete units, or patches, whose patterning can be described via different key attributes, or landscape metrics (Mcgarigal and Marks, 1994). This generally involves the definition of the area of influence of a fire and the different patch-types within. Concepts such as ‘fire perimeter’ or ‘island remnant’ may be intuitively obvious but they have resulted in a range of spatial interpretations that make comparing or combining fire pattern studies difficult (Andison, 2012; Perera et al., 2007). To guarantee the comparability of the fire pattern study results, Andison (2012) proposed a universal spatial language and associated fire pattern metrics that I adopted in this research to define and characterize fire events from pixel mortality maps derived from Landsat data. A detailed explanation of the process is provided in the following sections.

3.2. Spatial language

The spatial language by Andison (2012) converts raw mortality maps into three patch types: ‘disturbed areas’, ‘island remnants’, and ‘matrix remnants’. Disturbed areas and island remnants are both elements of fire mortality maps, and are commonly referred to in studies about vegetation remnants, although rarely similarly defined. Matrix remnants was added by Andison (2012) to capture other areas of influence of a fire that lie beyond the boundaries of disturbed patches, such as corridors between and peninsulas within disturbed patches. The disturbance event boundary was originally generated by Andison (2012) using a 200 m in-and-out buffering algorithm using polygon data. Disturbance events are created as follows. First, all adjacent pixels of the complete mortality class from the raw mortality maps are merged into polygons with eight direction connectivity and assigned to the disturbed class; likewise, connected pixels of the partial mortality class become island remnants. Second, the disturbed and island remnant areas are combined to delineate the boundaries of individual disturbed patches within each fire. Third, disturbed patch boundaries were buffered out 200 m, and any internal holes or donuts filled in. Lastly, the result was buffered back 200 m. The final product defined the outer boundary
of a disturbance event. The new vegetation remnants areas created by this buffering exercise are called matrix remnants. A conceptualization of the process is included in Figure 3.1.

Figure 3.1. Conceptualization of the spatial language and metrics proposed by Andison (2012).
3.3. Fire pattern metrics at event scale

The implementation of HRV typically involves the use of a suite of metrics that represent the spatial distribution of fire patterns at fine to meso-scales on the landscape (Keane et al., 2009). When information from various fire events is combined, the broad-scale patch arrangement within fire events can be analyzed in both temporal and spatial scales to inform management plans (Morgan et al., 2001). Many metrics can be generated to quantify landscape structure of landscape patterns, with the most relevant often depending on the application (Landres et al., 1999). To characterize the amount and arrangement of fire patterns from the discrete patch-fire events Andison (2012) proposed seven fire pattern metrics that have been used to help guide harvesting planning in Alberta and Saskatchewan over the last 10 years (Andison and McCleary, 2014). The seven metrics can be roughly divided into two groups, ‘event’ and ‘within-event’, as described Table 3.1 and briefly below:

- **Event metrics** – As described by Andison (2012) a fire event is the equivalent of a harvesting compartment within which there are often multiple harvesting blocks (or disturbed patches). I evaluated two fire event metrics: event area (EA) and shape index (SI). EA is the total area affected by the fire (in ha) corresponding to the area within the event perimeter, and it is the equivalent of a harvesting event within a compartment. SI measures the complexity of shape of the fire event calculated as the ratio of the event perimeter to that of the simplest possible shape of the same size (i.e. in this case a square given I utilized raster data) (Mcgarigal and Marks, 1994). SI captures the relative compactness of a fire event.

- **Within-event metrics** – These metrics capture the details of the amount and spatial arrangement of the fire effects and are useful as guides for within-fire event residual design. %TR is the total proportion of the area of a fire event that survives in some form, which corresponds to the total area of unharvested vegetation remnants within a compartment. %IR and %MR are the percent of the fire event area covered by island remnants and matrix remnants respectively within a fire event (which adds up to %TR). Number of disturbed patches (NDP), and percentage of largest disturbed patch (%LDP), characterize the number and size variability of disturbed patches respectively. NDP represents the total number of patches per fire event whereas %LDP is the proportion of the event area covered by the largest disturbed patch. The two metrics provide useful information on the relative level of fragmentation within individual fire events.
Table 3.1. Explanation seven spatial fire pattern metrics.

<table>
<thead>
<tr>
<th>Type</th>
<th>Metric [unit]</th>
<th>Acronym</th>
<th>Formula</th>
<th>Reference</th>
<th>Interpretation</th>
<th>Ecological relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event</td>
<td>Event area [ha]</td>
<td>EA</td>
<td>Matrix remnants + island remnants + disturbed areas</td>
<td>Andison (2012)</td>
<td>The total area affected by the fire</td>
<td>Boreal tree species might be evolutionary adapted to specific fire sizes (e.g. reproductive mechanisms) (Delong and Kessler, 2000)</td>
</tr>
<tr>
<td></td>
<td>Shape index [no units]</td>
<td>SI</td>
<td>Total perimeter of the disturbance event / perimeter of a square with area of EA</td>
<td>Andison (2012) and Mcgarigal and Marks (1994)</td>
<td>Measures the complexity of the perimeter by comparing with a standard shape with the same area</td>
<td>Higher edge density tend to moderate microclimate of adjacent burned areas by providing shade, wind protection and propagules (Oliver, 1981; Forman and Gordon, 1981)</td>
</tr>
<tr>
<td>Within-event</td>
<td>Percentage of matrix remnants [%]</td>
<td>%MR</td>
<td>(Total area of matrix remnants / EA) * 100</td>
<td>Andison (2012)</td>
<td>Percentage of residuals physically attached to the surrounding matrix of intact forest</td>
<td>The areas where vegetation was spared might enhance tree regeneration by providing seed source to adjacent burned areas or provide refugia for in-situ recolonization of small mammals with reduced dispersal capabilities (Banks et al., 2011)</td>
</tr>
<tr>
<td></td>
<td>Percentage of island remnants [%]</td>
<td>%IR</td>
<td>(Total area of island remnants / EA) * 100</td>
<td>Andison (2012)</td>
<td>Percentage of residuals lying entirely within disturbed patches</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Percentage of total remnants [%]</td>
<td>%TR</td>
<td>(Total area of island remnants + total area of matrix remnants) / EA) * 100</td>
<td>Andison (2012)</td>
<td>Percentage of vegetation that survives in some form</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of disturbed patches [patches]</td>
<td>NDP</td>
<td>Number of patches resulting of the combination of island remnants and disturbed classes</td>
<td>Andison (2012)</td>
<td>Total number of disturbed patches of the combination of island and disturbed classes per event</td>
<td>Measurement of the fragmentation caused by an event (Eberhart and Woodard, 1987; Turner et al., 1997; Turner and Romme, 1994)</td>
</tr>
<tr>
<td></td>
<td>Percentage of largest disturbed patch [%]</td>
<td>%LPD</td>
<td>(Area of the largest disturbed patch / EA) * 100</td>
<td>Andison (2012)</td>
<td>Size variability of disturbed patches</td>
<td></td>
</tr>
</tbody>
</table>
Chapter 4

4. To what level of detail can a Landsat-derived model be used to predict tree mortality?

4.1. Introduction

Due to recent interest in Historical Range of Variation (HRV)-related requirements from regulatory and certification agencies, the need for historical fire pattern knowledge is ubiquitous across the Canadian boreal forest (Perera et al., 2007).

Fire is both a complex and dynamic process that creates highly variable spatial patterns across events (Lentile et al., 2006; Wotton et al., 2010). Thus, characterization of HRV requires large amounts of site-specific fire pattern data, which can then be used for planning purposes at the landscape scale. In addition, to ensure the comparability of results across various ecological conditions, it is critical to use consistent standardized approaches based on physically quantifiable fire effects (Key, 2006; Lentile et al., 2006). As a result, analysis of HRV requires methods that are cost-effective for mapping fire patterns at landscape scales and allow direct comparisons of results across various ecological conditions.

Most fire pattern studies have been conducted with multispectral Landsat sensor imagery (Chuvieco et al., 2006; Zhu et al., 2012), as Landsat offers the longest running image data archive and free surface reflectance products suitable for time-series analysis. Landsat-derived fire pattern studies generally map burn severity, defined as the degree of ecological change resulting from a fire event (Lentile et al., 2006). Multi-temporal approaches that apply image ratios and image differencing techniques have been developed to detect changes associated with burned vegetation (Eidenshink et al., 2007), which can then be validated against ground-truth estimates. The differenced Normalized Burn Ratio (dNBR) (Key and Benson, 2006), which is an absolute measurement of change between the pre- and post-fire images, and its relativized version (RdNBR) (Miller and Thode, 2007), which is the relative amount of change based on pre-fire reflectance, have become the most widely used spectral indices to assess burn severity in North America (Brewer et al., 2005; Eidenshink et al., 2007; French et al., 2008; Lentile et al., 2006). However, there is evidence that in forested systems dNBR provides more accurate measurement of burn severity than does RdNBR (Brewer et al., 2005; Soverel et al., 2010; Zhu et al., 2006).
Estimating burn severity on the ground tends to be a subjective process, and the process can vary depending on ecological conditions or mapping objectives (Hall et al., 2008; Lentile et al., 2006). Most often the ground-based procedures associated with the Composite Burn Index (CBI) (Key and Benson, 2006) are used, which yield a continuous number as the result of averaging fire impacts on multiple vegetation strata (i.e. substrate, herbs and low shrubs, tall shrubs and saplings, understory trees, and canopy trees) from visual estimates on 30 by 30m plots (Key and Benson, 2006). Correlation of CBI measures and remote sensing spectral values is then compared through regression to gauge the accuracy of estimations (Key, 2006). CBI has the advantage of been very rapid but in turn is very subjective (Lentile et al., 2006).

There is limited literature on burn severity assessments using Landsat-derived dNBR and CBI in the Canadian boreal forest. Hall et al. (2008) studied four fires in the western boreal forest with promising results with a maximum overall $R^2$ of 0.84. Soverel et al. (2011) analyzed ten fires in the western Canadian boreal and montane forest and obtained an overall $R^2$ of 0.69, which substantially varied across fire events from 0.40 to 0.89. French et al. (2008) reviewed 26 studies covering the boreal forest of western Canada and Alaska and found an average accuracy of 73% with large variability (50–95%). These studies all highlight that burn severity results are variable across ecological conditions, although relationships between dNBR and CBI were moderately to highly significant across the boreal forest region. Despite the promising results of satellite burn severity mapping, there are also challenges associated with its application to analyze HRV. Satellite-derived burn severity is difficult to define and quantify and strongly relies on ground truth data for validation, which hinders the comparability of results obtained and applicability to landscape scales. Also, in the literature the majority of studies involved a small number of fires over a limited geographic area, and employed unique combinations of indicators, measurement criteria, spatial definitions, and raw data type, precision and accuracy (Andison and McCleary, 2014). As a result, there are very limited comprehensive and consistent temporal and spatial geodatabases of fire patterns across the boreal forest; which leaves managers with insufficient baseline information to analyze fire patterns for HRV estimates. To augment comparability and coverage of fire pattern studies, it is thus necessary to use measures and techniques that are repeatable and automated across large areas (Key, 2006; Lentile et al., 2006).

Tree mortality is defined as the percentage of crown loss and is a measurable expression of burn severity that is ecologically significant in forested systems and relevant to management (Lentile et al., 2006; Miller and Thode, 2007; Miller and Yool, 2002). As a consequence, tree mortality estimates from aerial photographic-interpretation (API) can be used for calibrating and validating models using Landsat-
derived spectral indices. There are various established methods to derive tree mortality information from remotely-sensed data. Smith et al. (2007) and Lentile et al. (2009) used Landsat-derived variables from spectral mixture analysis (i.e. percentage char, green and brown vegetation) to estimate percentage of tree mortality as acquired with a spectrometer at the plot level. Another source of tree mortality estimates can come from very high spatial and spectral resolution sensor data. For example, API from high resolution photos provides very high spatial resolution fire pattern information (relatively to Landsat sensor imagery) that measures tree mortality. These aerial images can provide information on fire size, type, and spatial arrangement of within-fire vegetation remnants with greater accuracy and precision than any other remote method (Wulder, 1998). Such high spatial resolution data can be used to train and validate models using Landsat-derived spectral indices (as in Wu et al. (2015)), with considerable advantages. First, tree mortality is estimated via a direct measurement of a single variable, rather than a composite index averaged from multiple strata. As a result, maps of tree mortality would give a more concrete basis to map fire patterns with satellite-derived data that would augment the comparability of results across ecological conditions. Second, API can provide spatially continuous data for validation with the potential to cover larger areas and faster than field-based alternatives. Finally, if Landsat-derived spectral indices can be successfully used to map API derived tree mortality, a ‘crosswalk’ could be developed between these two main sources of spatially continuous historical fire pattern data. The crosswalk methodology may be used to leverage the Landsat data archive for fire pattern analysis over more than 40 years. However, the degree to which Landsat-derived spectral indices can be used to generate tree mortality maps of sufficient accuracy and precision for detailed fire pattern analyses is unknown.

In this paper I examine the degree to which Landsat Thematic Mapper (TM) imagery can be used, in combination with other pre- and post-fire variables, to predict classes of tree mortality as defined by API for ten fires occurring from 1983 to 2004 in the western boreal forests of Canada. To do so I use classification trees to create 16 models from a combination of remotely sensed, environmental and forest inventory variables. I conclude with some remarks on the usability of the models according to the level of detail and classification accuracy required for particular applications. The results of this study will be used to assess the capacity to continuous update pan-boreal fire patterns into a comprehensive database providing objective, consistent, and cost-effective results on which to base HRV estimates.
4.2. Study area

I focused on ten fires in the Canadian boreal forest of Alberta and Saskatchewan that burned between 1983 and 2004, for which interpreted tree mortality estimations and both pre- and post-Landsat TM imagery were available (Figure 4.1). The total burned area of all fires covers 14,464 ha in the boreal shield, boreal plains and taiga plains ecozones, encompassing a diversity of conditions from continental to sub-arctic climate and from dense to open-forest, in different forest compositions (Ecological Stratification Working Group, 1996). Fires were skewed towards smaller fires ranging in size from 87 to 6,680 ha. Fire location varied in latitude from 54.4167º to 59.7120º and in longitude from -116.9214º to -102.6000º.

Figure 4.1. Location of the fire sample.
4.3. Data

4.3.1. Interpreted tree mortality estimations

To characterize tree mortality I used vector delineations of percentage crown loss from the HRV database (see section 2.2.1). Ten fires from the database formed the basis of this study based on Landsat TM image availability (see below). For these ten fires post-fire aerial photography were available within three years of the fire event (Table 4.1), reducing possible bias associated with delayed tree mortality.

To allow the delineation of the fire perimeter and to increase the representation of the unburned class, an additional polygon was added to each fire event by buffering out the perimeter 100 m. After empirical tests, I selected 100 m buffer because it represented a convenient trade-off between polygon size (i.e. compared to total area of other classes), and image availability (i.e. the larger the buffer the increased likelihood of the occurrence of snow, shadow or cloud within the area of interest). This buffer polygon was then subdivided to match the average number of polygons per class. Two challenges complicated the comparison of polygons from the HRV database with the Landsat imagery: the minimum mapping unit from HRV database being substantially smaller than that of Landsat (i.e. 0.01 vs 0.09 ha) and second, the HRV database is polygon-based compared to the raster-based Landsat imagery. To guarantee similar minimum mapping units and ensure that the HRV polygons were sufficiently represented by the Landsat data (i.e. the majority of Landsat pixels falling within the polygons), I imposed a minimum polygon size of 0.36 ha (equivalent to four Landsat pixels) on the remainder of the analysis.

4.3.2. Landsat data

The ten fire events were covered by 33 scenes (path/rows) of the Landsat Worldwide Referencing System (WRS-2) (US Geologic Survey GLOVIS website, see http://glovis.usgs.gov/, accessed March 2015). To guarantee sufficient context in selecting pre- and post-fire images, all surface reflectance Landsat TM scenes within ±four years from the fire date were acquired. In total 670 Landsat images were acquired and masked according to the area of interest for each fire (i.e. the fire perimeter buffered by 100 m), in accordance with the coverage of the interpreted tree mortality polygons. The Fmask algorithm, developed by Zhu and Woodcock (2012), was used to discard images with at least one pixel of cloud, cloud shadow or snow within the masked area. Two different spectral indices were calculated: Landsat dNBR and Landsat Tasselled Cap Transformation (TCT) wetness, explained in detail below.
Table 4.1. Detailed information of fire sample.

*Aerial photo date refers to the acquisition date of the post-fire aerial photo that was used to delineate the classes of mortality. Inventory photo date refers to the acquisition date of the pre-fire aerial photo that was used to produce the pre-fire forest inventory data. Fire size refers to the area contained within the fire perimeter. Latitude and longitude is at the centroid of the polygon.*

<table>
<thead>
<tr>
<th>Fire name</th>
<th>Date of ignition</th>
<th>Aerial photo date</th>
<th>Inventory photo date</th>
<th>Ecozone</th>
<th>Province</th>
<th>Fire size (ha)</th>
<th>Latitude (decimal degrees)</th>
<th>Longitude (decimal degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Keane</td>
<td>12-Jul-04</td>
<td>2004</td>
<td>1983</td>
<td>Boreal Shield</td>
<td>Alberta</td>
<td>6,460</td>
<td>58.200054</td>
<td>-110.379312</td>
</tr>
<tr>
<td>Cone</td>
<td>30-Jul-03</td>
<td>2003</td>
<td>1994</td>
<td>Boreal Plains</td>
<td>Alberta</td>
<td>352</td>
<td>57.448882</td>
<td>-115.015387</td>
</tr>
<tr>
<td>Rainbow</td>
<td>29-May-86</td>
<td>1986</td>
<td>1979</td>
<td>Boreal Plains</td>
<td>Saskatchewan</td>
<td>113</td>
<td>54.986654</td>
<td>-107.383691</td>
</tr>
<tr>
<td>Mcarther</td>
<td>31-Jul-84</td>
<td>1986</td>
<td>1971</td>
<td>Boreal Shield</td>
<td>Saskatchewan</td>
<td>84</td>
<td>56.88209</td>
<td>-108.21279</td>
</tr>
<tr>
<td>Overflow</td>
<td>30-Jul-84</td>
<td>1988</td>
<td>1979</td>
<td>Boreal Plains</td>
<td>Saskatchewan</td>
<td>88</td>
<td>53.113478</td>
<td>-102.596376</td>
</tr>
<tr>
<td>Rail</td>
<td>4-Aug-84</td>
<td>1984</td>
<td>1979</td>
<td>Boreal Plains</td>
<td>Saskatchewan</td>
<td>87</td>
<td>54.389557</td>
<td>-106.685556</td>
</tr>
</tbody>
</table>
I used Landsat-derived differenced Normalized Burn Ratio (dNBR) as our main variable to characterize fire effects on tree mortality. dNBR is an absolute measure of change for each pixel that has been widely used and tested for burn severity mapping (Key and Benson, 2006). First, a Normalized Burn Ratio (NBR) (García and Caselles, 1991) is computed by normalizing the difference between the near infrared (NIR) and short-wave infrared (SWIR) bands of Landsat TM sensor imagery. The dNBR (Key and Benson, 2006), is then calculated by subtracting pre- and post-fire images according to the following equations:

\[
NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)}
\]

\[
dNBR = (NBR_{prefire} - NBR_{postfire})
\]

Selecting the acquisition date of the imagery is crucial for dNBR calculations as terrestrial reflectance is highly sensitive to changes associated to delayed mortality and regrowth, phenology and sun elevation angle (Key and Benson, 2006). For each fire, I used the Extended Assessment (EAs) analysis, as is most commonly used for analyzing burn severity (Eidenshink et al., 2007; French et al., 2008; Key and Benson, 2006). The EAs uses a post-fire image acquired at least one year following the fire; and the pre-fire image as soon as possible before the fire, aiming for anniversary dates to reduce mismatches in phenology and sun-elevation (Key and Benson, 2006). The detailed information of the images chosen for the computation can be found in Table 4.2.
Table 4.2. Landsat Thematic Mapper (TM) sensor image selection.

<table>
<thead>
<tr>
<th>Fire name</th>
<th>Path/Row</th>
<th>Fire date</th>
<th>Pre-image date</th>
<th>Post-image date</th>
</tr>
</thead>
</table>
Table 4.3. Predictor variables.

\(dNBR=\) differenced Normalized Burn Ratio; TCT=\textit{tasselled cap} transformation.

<table>
<thead>
<tr>
<th>Data layer</th>
<th>Variable</th>
<th>Objective</th>
<th>Variable type</th>
<th>Range of values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat dNBR</td>
<td>Landsat dNBR</td>
<td>Burn severity index</td>
<td>Continuous</td>
<td>-2000 to +2000</td>
</tr>
<tr>
<td>Landsat TCT</td>
<td>Landsat TCT</td>
<td>Wetness pre-fire</td>
<td>Continuous</td>
<td>-1500 to +2000</td>
</tr>
<tr>
<td>wetness</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>Main tree species</td>
<td>Dominant species</td>
<td>Categorical</td>
<td>Seven classes: \textit{Populus tremuloides, Betula papyrifera, Larix lariciana,}</td>
</tr>
<tr>
<td>inventory data</td>
<td></td>
<td></td>
<td></td>
<td>\textit{Pinus contorta, Picea mariana, Picea glauca, Pinus banksiana}.</td>
</tr>
<tr>
<td></td>
<td>Forest inventory data</td>
<td>Soil moisture regime</td>
<td>Categorical</td>
<td>Three classes: Dry, Mesic, Wet</td>
</tr>
<tr>
<td></td>
<td>Canopy closure</td>
<td>Ground area in percentage covered by a vertical</td>
<td>Categorical</td>
<td>Four classes: 6-30%, 31-50%, 51-70%, 71-100%</td>
</tr>
<tr>
<td></td>
<td>Extent</td>
<td>Area within the perimeter of the fire</td>
<td>Continuous</td>
<td>84 to 6,680 ha</td>
</tr>
<tr>
<td></td>
<td>Season</td>
<td>Seasonality of the fire</td>
<td>Categorical</td>
<td>Two classes: Spring, Summer</td>
</tr>
<tr>
<td></td>
<td>Province</td>
<td>Province</td>
<td>Categorical</td>
<td>Two classes: Saskatchewan, Alberta</td>
</tr>
<tr>
<td></td>
<td>Ecoregion</td>
<td>Ecozone</td>
<td>Categorical</td>
<td>Three classes: Boreal Plains, Boreal Shield West, Taiga Plains</td>
</tr>
<tr>
<td></td>
<td>Random effects</td>
<td>Name of fire. Representing the variables non-</td>
<td>Categorical</td>
<td>Ten classes: Keane, Perry, Cone, Liege, Steephill, Rainbow, Mcarther, Overflow,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>considered in this study that create fire-specific patterns, such as fire</td>
<td></td>
<td>Rail, Elk</td>
</tr>
<tr>
<td></td>
<td></td>
<td>weather.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
I used Tasselled Cap Transformation (TCT) wetness to characterize water content in the pre-fire environment, as there is evidence that is an important factor in conditioning residuals occurrence (Epting et al., 2005; Leduc et al., 2007; Nowak et al., 2002). TCT outputs three components, as linear combinations of Landsat sensor bands: brightness, greenness and wetness (Crist and Cicone, 1984). TCT wetness has been shown in previous studies to be highly correlated with water content and forest structure, while insensitive to topographical variation (Cohen et al., 1995). I calculated TCT wetness for each of pre-fire images selected for calculating Landsat dNBR.

### 4.3.3. Pre-fire forest inventory data variables

I used pre-fire forest inventory data to characterize the structure and composition of pre-existing vegetation due to its impact post-fire mortality patterns as per described in section. The forest inventory variables used to characterise pre-fire conditions included (1) dominant tree species, (2) canopy closure, interpreted as the percentage of ground area covered by the dominant species canopy, and (3) soil moisture regime, representing the available water supply for plant growth, which largely depends on soil type and topography (Table 4.3) (AVIS, 2005; SFVI, 2004). All three variables were only recorded where crown cover was >5%. The three variables from the pre-fire forest inventory data were converted into a 30 m raster to match the resolution of the Landsat TM imagery.

### 4.3.4. Ancillary data variables

Disturbance events often create predictable patterns at landscape scale that reflect similar macro-ecological conditions (Oliver and Larson, 1996). For example Burton et al. (2008) have found that both fire size and fire frequency differences align with major ecological zone boundaries in the boreal forests of Canada and Alaska. To account for such similarities at landscape scale, all of the polygons were attributed with general descriptors of the fire events coming or derived from the HRV database, but that can be found or calculated by using publicly available data such as Canadian National Fire Database (Canadian Forest Service, 2010). These variables include (1) fire extent, (2) season, (3) province and (4) ecoregion. We also included (5) random effects, accounting for other sources of variability that create event-specific fire patterns and were not considered in this study, such as fire weather (Table 4.3).

### 4.4. Methods

#### 4.4.1. Fire event characterization

Each interpreted API tree mortality polygon was used to query the respective data layers: (1) Landsat dNBR, (2) Landsat TCT wetness, (3) pre-fire forest inventory variables (i.e. crown closure, dominant species and soil moisture regime) and (4) ancillary data variables (i.e. fire extent, season, province,
ecoregion and random effects) (Table 4.3). In the case of continuous data the polygon was assigned the average value and for categorical data the dominant class was assigned (e.g. pre-fire forest inventory variables). The polygons entirely having no canopy cover, defined as <5% crown cover, were removed from the analysis. A total of 2,537 polygons across all six tree mortality classes (i.e. 425, 321, 394, 510, 589 and 298 from unburned to complete mortality) were considered for subsequent analysis.

4.4.2. Tree mortality attribution

To model tree mortality, I developed 16 unique combinations of predictor variables and scenarios of mortality classes. Predictor variables were aggregated into four groups; the first group (referred to as D1 hereafter) used Landsat dNBR as a single predictor variable similar to most studies mapping post-fire effects with satellite data (French et al., 2008). The other three groups (referred to as D2, D3, D4, respectively hereafter) added additional variables with increasing complexity; first the ancillary data variables; second, Landsat TCT wetness; and finally, pre-fire forest inventory data variables, as this information is not always available for all fires in the boreal forest (Table 4.4).

I aggregated tree mortality into four groups: first, the full range of classes (six); followed by four, three and two classes, as shown in Table 4.5 (referred to as M6, M4, M3 and M2, respectively hereafter). For the two classes approach I distinguished the unburned class from any degree of mortality. For three and four classes I always considered an unburned and a complete mortality class. Often the high severity class is associated to stand replacing fire (Agee 1998), and Brown and Smith (2000) defined high severity as >80% tree mortality. Thus, I defined the most severe mapping class, complete tree mortality, as the polygons with more than 76% tree mortality, similar to Brewer et al. (2005). I further included a class of partial-mortality effects, or two for the scenario with four classes; where the low-end included the tree mortality range from 1–50% to augment detection capabilities on ephemeral changes using Landsat TM imagery (Table 4.5).

Variables and tree mortality were then combined into 16 unique groups (hereafter D1M6, D1M4, etc). To explore the relationship between the combinations of tree mortality and the Landsat dNBR (a priori our main predictor variable) we used ANOVA, Tukey’s Honest Significant Difference (HSD) test, and box and whisker plots at the level of significance 0.05. In combination, the four statistical tests provide insights into the separability of the various classes for each mortality scenario at both fire and all fires combined levels. This information can then be used to evaluate the suitability of Landsat dNBR as main predictor variable as well as to serve as additional information to interpret the results from the classification trees.
I developed classification models using the Random Forest (RF) package in R (Breiman 2001) for the 16 unique combinations of variables and tree mortality. RF models are decision tree ensembles that produce predictions and insights into data structure. RF models can be used with categorical and continuous variables simultaneously and are less constrained than parametric methods with respect to data distribution. RF models create multiple decision trees (2,000 in this study) using a random subset of data (i.e. ‘in bag’ samples) and random variable selection at each node, yielding results with low prediction accuracy and high variance at tree level. Combining all of these separate predictions by averaging or voting overcomes many of the weaknesses of individual decision trees. The results of the tree ensemble have low spatial correlation, due to random sampling, high prediction accuracy and low variance, due to averaging results from multiple trees. In addition, the random sample selection leaves a data holdout (i.e. ‘out of bag’ samples) which allows the assessment of the relative importance of any predictor by evaluating the reduction in predictive power of the model without the values of a given variable. For accuracy assessment we used the Out-of-the-bag accuracy (OOB) and average class accuracy (ACA). OOB represented the overall percentage correctly classified by the RF model, which has been shown to be a good indicator of overall class predicting power (Breiman, 1996). OOB is sensitive
to the distribution of the data, thus classes with more representation will have more importance in
determine the overall accuracy of the model. To account for data distribution in model accuracy we
used ACA, calculated as the average of the accuracies at class level. Thus, similar OOB and ACA would
imply that the RF model has adequate data distribution. To analyze models at the class level, confusion
matrices were developed. For comparing the relative importance of the variables I used the percentage
increase in mean squared error (MSE), yielded from RF model computation. To ensure an even data
sample, I employed a stratified data sample equaling the size of the less represented class.

4.5. Results

4.5.1. Exploratory analysis

Homogeneity of variance and normality of distribution between Landsat dNBR variable and
combinations of tree mortality were fulfilled in all cases. One-way ANOVA showed significant
differences for each and all fires in M6–M2 (Table 4.6). Tukey’s HSD test only detected significant
differences between all classes for all fires pooled in M6–M2. For single fires the results varied
considerably: M6 presented significant differences for all classes in none of fires; M4 in one fire; M3 in
four but accounting for 91% of total area; and M2 in all ten fires. Graphical depiction of the results
confirmed the results were consistent with the one-way ANOVA and Tukey’s HSD post-hoc analysis,
suggesting significant differences when all fires were pooled for M6 to M2. It was also apparent that
differences between classes increased from M6 to M2 (Figure 4.2). The unburned class was always
significantly different than any other mortality class regardless the number of mortality classes. Mid-
mortality classes of M6 presented a significant overlap, which decreased from M6 to M3.
Table 4.6. Tukey's Honest Significant Difference (HSD) test between Landsat dNBR variable and combinations of tree mortality.

Grey means significant differences at level <0.05. Different letters between classes imply significant differences among all classes at level <0.05. Order of classes is indicated in parenthesis; where ‘1’ always represents the unburned class and the maximum number per a given combination of tree mortality classes corresponds to complete mortality.

<table>
<thead>
<tr>
<th>Location</th>
<th>M6 (2,3,4,5,6,1)</th>
<th>M4 (2,3,4,1)</th>
<th>M3 (2,3,1)</th>
<th>M2 (2,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All fires</td>
<td>&quot;a&quot; &quot;b&quot; &quot;c&quot; &quot;d&quot; &quot;e&quot; &quot;f&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;c&quot; &quot;d&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;c&quot;</td>
<td>&quot;a&quot; &quot;b&quot;</td>
</tr>
<tr>
<td>Cone</td>
<td>&quot;a&quot; &quot;a&quot; &quot;a&quot; &quot;b&quot; &quot;b&quot; &quot;a&quot;</td>
<td>&quot;a&quot; &quot;a&quot; &quot;b&quot; &quot;b&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;b&quot;</td>
</tr>
<tr>
<td>Keane</td>
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<td>&quot;a&quot; &quot;b&quot; &quot;c&quot; &quot;d&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;c&quot;</td>
<td>&quot;a&quot; &quot;b&quot;</td>
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<td>&quot;a&quot; &quot;ab&quot; &quot;bc&quot; &quot;c&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;c&quot;</td>
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<tr>
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<td>&quot;ab&quot; &quot;a&quot; &quot;c&quot; &quot;c&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;a&quot; &quot;b&quot; &quot;b&quot;</td>
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<td>&quot;a&quot; &quot;b&quot;</td>
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<td>&quot;a&quot; &quot;b&quot; &quot;c&quot; &quot;c&quot;</td>
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<td>&quot;a&quot; &quot;b&quot;</td>
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<td>&quot;a&quot; &quot;b&quot; &quot;b&quot;</td>
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<tr>
<td>Mcarther</td>
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<td>&quot;a&quot; &quot;b&quot; &quot;b&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;b&quot;</td>
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<td>&quot;a&quot; &quot;ab&quot; &quot;b&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;b&quot; &quot;b&quot;</td>
<td>&quot;a&quot; &quot;b&quot;</td>
</tr>
</tbody>
</table>
Figure 4.2. Box and whisker plots between the predictor variable Landsat dNBR and the various combinations of tree mortality.

dNBR = differenced Normalized Burn Ratio.
4.5.2. Tree mortality attribution

I obtained maximum ACA and OOB accuracies for the D4 based models. For models D4M6, D4M4, D4M3 and D4M2 ACA was 43%, 57%, 72% and 91% respectively and OOB was 42%, 54%, 66% and 89% respectively (Figure 4.3). In most cases ACA and OOB were similar, which suggests that models were balanced in terms of data distribution among classes. For D1–D4, ACA and OOB increased from M6 to M2 (Figure 4.3). Differences in accuracy between the M6 and M2 based models were very large, ranging from 48–53% ACA. Adding variables to the models (from D1 to D4) always resulted in higher ACA and OOB accuracies for a given set of mortality classes (Figure 4.3). Differences in accuracy between the D1 and D4 models were relatively small and ranged from 14–22% ACA. Especially apparent was the difference between the models D1–D2 accounting for 11–16% ACA; while differences between D2–D3 and D3–D4 were comparatively lower, with 0–5% ACA. Classification accuracy increased from D1 to D4, which suggests an increase in accuracy as more variables were added.
Figure 4.3. Model classification accuracies for the various models.

For accuracy assessment, I used the average class accuracy (ACA) and out-of-the-bag accuracy (OOB). ACA represents the average of the accuracies at class level and OOB is the overall percentage of occurrences correctly classified. Typically, similar ACA and OOB indicate a balanced data distribution across classes.
Only the binary D4M2 model was able to predict all classes accurately (Figure 4.4). For example, D4M4 was more effective at predicting the 76–100% mortality class (59% ACA) but less effective at predicting the 51–75% class (33% ACA); or D4M3 was more effective at predicting 76–100% class (66% ACA) but less effective at predicting the class 1–75% (56% ACA). As expected, accuracy was highest for unburned class (88%–94% ACA); and variable for the mid- and high-mortality classes depending on the combinations of tree mortality.

I also evaluated the relative importance of the variables used in the most accurate models when all variables were combined (i.e. D4M3 and D4M2). In both models Landsat dNBR was the most important variable, followed by Landsat TCT wetness, random effects and main tree species (Figure 4.5). In model D4M3 Landsat dNBR was substantially more important than Landsat TCT wetness (18% vs 10% respectively), followed by random effects and main tree species, with 4% and 3% MSE respectively. Conversely, in D4M2 Landsat dNBR and Landsat TCT wetness had similar importance (15% vs 12%); then random effects and main species followed for some 3% MSE. The relative importance of the remaining variables was relatively similar and low (<2% MSE), though clearly different for the two models. For example in D4M3 the variables soil moisture and province had more prediction power; while in D4M2 province and extent were more important. Both models suggest that canopy closure is one of the two least important variables. The overall results suggest a relative order of importance of the data layers as follows: Landsat dNBR > Landsat TCT wetness > Ancillary data variables > Pre-fire forest inventory variables (Figure 4.5).
Figure 4.4. Confusion matrix for the models that used all available predictor variables (D4).

On the top of each caption is stated the out-of-the-bag accuracy (OOB) and average class accuracy (ACA). OOB represents the overall percentage of occurrences correctly classified and ACA is the average of the accuracies at class level. Typically, similar OOB and ACA indicate a balanced data distribution across classes. Numbers within squares represent the percentage of occurrences falling within a given combination of predicted and observed tree mortality classes. The diagonal from bottom-left to top-right represents the percentage of correct predictions per class.
Figure 4.5. Variable importance for models using all the available predictor variables for three and two classes of mortality (D4M3 and D4M2).

To compare the relative importance of the variables, I used the increase in mean squared error (MSE), yielded by the random forests computation. TCT is tasselled cap transformation.
4.6. **Discussion**

4.6.1. **Exploratory analysis**

The exploratory analysis provides insights on the capabilities of Landsat dNBR for modelling tree mortality at both fire and all fires combined levels. My results revealed a lack of separability in the mid- and high-ranges of mortality classes in the models M6 and M4. However, collapsing classes of tree mortality appeared to overcome these challenges. Specifically, the models M3 and M2 had relatively distinct mortality classes when all fires are combined, while still preserving significant differences between all classes at the fire level for the majority of the fire sample. While in M2 there is clear separability between classes in all cases; in M3 the mid- and high-mortality classes are only significantly different for four of the ten fires, however those four fires account for 91% percent of the sampled area. This suggests that Landsat dNBR is suitable to discern a maximum of three classes of tree mortality while compared with API dataset.

4.6.2. **Classification**

The number of tree mortality classes (Table 4.5) was the most important factor in driving overall model accuracy regardless of the variables used. As expected, models with fewer mortality classes performed best in terms of overall class accuracy. However, the addition of variables was crucial to increasing overall model classification accuracy and reducing variance for a given combination of tree mortality. Accuracies always increased as more variables were added. Differences in accuracy were greatest between the models D1 and D2, which highlight the importance of using complementary variables to Landsat dNBR in overcoming weakness of particular spectral indices (Morgan et al., 2001).

Not surprisingly models with fewer mortality classes and more variables performed better in terms of class level accuracies. The model based on two mortality classes was the most accurate overall (91% ACA) and at predicting single classes (≥88% ACA). However, this is also the least useful model for managers because it lacks information on details. The configuration of post-fire vegetation remnants is intimately related to seed source and nutrient availability, and thus the timing and successional composition of vegetation (Turner and Romme 1994; Oliver and Larson 1996; Agee 1998). Still, a highly accurate two-class model could be used to preliminarily delineate fire perimeters and serve as an input for a subsequent, more precise, modelling approach to map vegetation remnants.

The three-class mortality model was moderately accurate overall (72% ACA) and predicted the unburned class well (93% ACA) and the completely unburned and partially-burned less so (66% and 56% ACA respectively); although, even with lower accuracy levels, a three-class mortality model has
greater utility for resource management. The lower level of accuracy obtained for the partially-burned class may be acceptable for broader-scale applications such as mapping and comparing HRV metrics across whole events, and even at landscape scales to guide harvesting planning (as in Pickell et al. 2013). The models of six and four mortality classes (M6 and M4) were poorer at predicting one or more mortality classes, which implies they are less reliable for mapping tree mortality. The predictions from such models would provide a false sense of precision to forest managers.

There may be several reasons for the difficulty in capturing partial mortality. Partially disturbed areas likely undergo more ephemeral and geographically dispersed changes than completely disturbed areas, resulting in areas generally of smaller size and patchier that are more difficult to map with Landsat TM’s averaged 30 m pixel size (Cocke et al., 2005; Key, 2006; Lentile et al., 2006). Areas of partial mortality may also signify areas of gradual and continual mortality. Changes in delayed mortality or vegetation re-growth as a result of differences between Landsat and API validation could have reduced the classification accuracy in this case.

Further analysis of most accurate models D4M3 and D4M2 allowed us to understand the relevance of different variables at multiple scales of detail. Not surprisingly, Landsat dNBR was the most important variable in all cases. Landsat dNBR was specifically designed to detect changes associated to burned vegetation and was the only variable utilized that considered both pre- and post-fire scenarios. Landsat TCT wetness was consistently selected as the second most important model variable matching findings of Soverel et al. (2011) in fires of the boreal cordillera and plains. The relevance of this variable highlights the importance of pre-fire moisture content in conditioning fire behaviour and, ultimately, patterns of tree mortality for the fires studied. The third most important variable in both models was random effects. Random effects comprised any source of variability that we did not account for in this study that might influence distinct patterns at fire level. The importance of this variable might suggest the need to introduce additional variables that capture environmental or fixed abiotic variables such us indices on fire weather indices, or topography (Ferster et al., 2016). This result also potentially corresponds to the limitations of the Landsat dNBR algorithm to successfully normalize reflectance when pre- and post-fire images were not acquired on anniversary dates. It is also possible that offsets in the position of API and Landsat data due to inherent positional errors, could have masked changes in tree mortality and increased the importance of the variable random effects.

The fourth most important variable found in this study was dominant tree species, which supports findings of other studies suggesting differential fire effects by tree species (Kafka et al., 2001). However,
considering the relatively low importance of this variable, this also suggests that the relative importance of pre-existing vegetation might be of less importance when fire events of variable intensity are pooled together, as extreme fire weather can override the effects of other factors such as vegetation type (sensu Cumming 2001; Rowe and Scootter 1973). The relative importance of the remaining variables differed between D4M3 and D4M2, although their importance was relatively low. Surprisingly, variables such as seasonality or ecoregion were of only marginal importance, in contrast to results by Burton et al. (2008). Fire size had also little importance for determining tree mortality, which was consistent with the findings of Andison and McCleary (2014). However, the relative importance of these variables might have been affected by the relatively small and skewed sample size (i.e. towards the boreal plains and summer fires) analyzed in this study. In terms of the importance of overall data layers, variables coming from pre-fire forest inventory data (such as dominant tree species, canopy closure and soil moisture regime), were the least important in terms of MSE error. Since these data are not always available for all historical fire events, it might be removed without compromising classification accuracy.

Increasing the accuracy of the partial mortality class and testing the proposed approach to cover more fires and larger areas should be priorities for future research. Since spatial resolution is so critical to efficiently map partial-mortality areas, additional research is needed to test and develop methods that allow the mapping at sub-pixel level, such as image fusion techniques of Landsat ETM and ETM+ sensor imagery (e.g. pan-sharpening) (as in Wu et al. 2015) or spectral mixture analysis (as in Smith et al. 2007; Lentile et al. 2009). The inclusion of additional and more detailed predictor variables also might contribute to increase the accuracy of the partial-mortality class. For example fire weather or topographic indices can be incorporated in the modelling process to better characterize the pre- and post-fire environment. Developing more detailed multi-temporal spectral algorithms that combine more than two Landsat bands to detect changes in burned vegetation might also contribute to an overall increase in accuracy for the partial mortality class.

4.7. Conclusions

Many fire ecologists have expressed the need for a translation between burn severity estimates and post-fire effects on vegetation to augment the comparability of the results across ecological conditions, and to allow the modelling of long-term forest dynamics (Brewer et al., 2005; Lentile et al., 2006; Miller and Yool, 2002). Such information is crucial to provide the necessary framework to analyze the Historical Range of Variation of fire across the boreal forest, in ultimately supporting management decisions with objective and ecologically relevant fire pattern information. My research has shown that high spatial
resolution aerial photo-interpreted data can be used to train and validate classification tree models to
cost-effectively map measures of tree mortality in forested ecosystems. Overall, Landsat TM models
were able to predict with moderate accuracy three and two classes of mortality across the ten fires
analyzed in the boreal forest of Alberta and Saskatchewan (72% and 91%, respectively). The model
based on two mortality classes was very accurate at predicting single classes (≥88%), and can be used
to preliminary map fire perimeters. A modelling approach of three mortality classes captured the critical
partial-mortality class of vegetation remnants, and thus is of greater management value, although with
lower predictive power.

In summary, this study presented a novel approach to mapping fire patterns that uses interpreted
estimates of tree mortality from high resolution aerial photography. The method provides quantifiable,
consistent and transferable fire pattern estimates useful to analyze long-term fire pattern dynamics to
support management decisions. The method provides a cost-effective alternative to conventional field
data that can be produced faster, cheaper and cover larger areas in a spatially continuous basis. The
developed cross-walk methodology between conventional aerial-photo interpretation and satellite
imagery can be used to leverage the Landsat data archive for fire pattern analysis across more than 40
years. A pan-boreal geospatial database of tree mortality would be an invaluable tool with which to help
increase our knowledge on HRV patterns across the boreal. More research is warranted to extend the
analysis to include more fires under different ecological conditions and additional and more detailed
variables to better characterize the pre- and post-fire environment.
5. To what level of detail can three-class mortality maps derived from Landsat data be used to predict seven fire patch metrics?

5.1. Introduction

To make an HRV an operational reality in the boreal, forest managers require a suite of disturbance pattern metrics to help them describe and quantify the fire characteristics they wish to emulate (Landres et al., 1999). Fire mortality pattern metrics quantify composition and configuration (Li and Reynolds, 1995). Composition metrics are not spatially explicit and include the amount or proportion of each patch type within disturbances (Mcgarigal and Marks, 1994). These metrics are often used as baseline information to layout emulation templates, and are therefore essential to support harvesting planning that utilizes fire patterns. For example, the fire event area, and the proportional area of vegetation remnants not only capture key patterns of natural fire behaviour, but also inform management planning on the size of the harvest cutblocks or the amount of tree retention (Andison, 2012). Configuration metrics provide spatial context for composition metrics, such as the distribution or spatial relationship of the patches of a given class (Mcgarigal and Marks, 1994). For example, the number and size variability of burned patches and the spatial dispersion of surviving vegetation can be used by managers to define the fragmentation within the harvest compartment. To provide the necessary metrics to implement HRV management approaches requires defendable fire pattern information from detailed and robust tree mortality maps of natural fires (i.e. those with no fire control, and no cultural disturbance activities before and after).

Earth observation satellites such as the Landsat series acquire imagery on a systematic basis globally. The imagery is processed using stringent radiometric and geometric standards suitable for time-series analysis (Wulder et al., 2008) and that have been applied for fire pattern mapping (Chuvieco et al., 2006; Zhu and Woodcock, 2014). However, the calibration of the spectral values acquired by the sensors requires local field data for validation, which has hindered the applicability of the satellite-based approaches to broader scales. The net result of all these challenges is that most studies have either defined detailed disturbance pattern metrics for a small number of fire events (as in Hall et al., 2008; Soverel et al., 2010), or broad metrics of undetermined accuracy over larger areas (as in Burton et al., 2010).
In Chapter 4 I developed a Landsat-based model to predict fire patterns based on three classes of tree mortality: 1) unburned, 2) partial mortality and 3) complete mortality. The method utilized aerial photo-interpreted (API) polygons from very high spatial resolution aerial imagery to train and validate the Landsat models across the boreal plains ecozone with high accuracy at predicting unburned, and complete, mortality classes (93 and 66% respectively), but with relatively poorer accuracy for predicting partial mortality classes (56%). The method shows potential for generating accurate mortality maps to calculate detailed HRV metrics across the entire Canadian boreal forest. However, the approach only focused on analyzing theoretical model performance and did not compare the degree to which relevant fire pattern metrics are accurately predicted relative to those derived from API methods.

In this Chapter I assess the suitability of utilising a Landsat-based model of tree mortality to capture seven of the more commonly referenced HRV metrics calculated over 14 fires in the boreal forests of Alberta and Saskatchewan, Canada. For those instances where the metrics derived from the Landsat-based approach may differ significantly from those from the API approach, I hypothesize that the accuracy will be influenced by various environmental and fire pattern characteristics.

5.2. Study area

The primary data for this research are 14 fires that occurred from 1984 to 2006 in Alberta and Saskatchewan, Canada, covering a total area of 15,464 ha. The majority of the fires occurred in the Boreal Plains ecozone (N = 8), with the remainder (N = 6) distributed across the Boreal Shield, Montane Cordillera, Taiga Shield and Taiga Plains ecozones (Figure 5.1).
Figure 5.1. Location of the fires in the sample.

The triangles represent the centroid of the fires in the sample and are accompanied by the corresponding fire names. In bold letters are represented the various ecozones that encompass the fires in the sample.
5.3. Data

Two data sources are used to generate post-fire mortality patterns for this study: (1) aerial photographic interpretation (API) (see section 2.2.1), which served as main data source with which to compare; and (2) Landsat imagery (see section 2.2.2), which was used to calculate multiple predictor variables to estimate tree mortality.

5.3.1. Generalized API mortality map data

Due to differences in spatial and radiometric resolution and methods, and data types (i.e. polygon vs. pixel) employed to derive the tree mortality data (Morgan et al., 2010), it is expected that Landsat derived tree mortality classes would be less precise than those captured from API. In Chapter 4 I investigated a number of API derived mortality class combinations using Landsat methods and concluded that three classes are optimal: an unburned class (0% tree mortality), a partial mortality class (1–75% tree mortality), and a complete mortality class (>75% tree mortality). For this study, I changed the complete mortality class to >94% to better match the effect of clear-cut harvesting. An additional 400 m buffer polygon was added to the perimeter of each fire event and assigned to the unburned class. To guarantee the comparability across data types I rasterized the API polygons to match the spatial resolution of Landsat, where each pixel was assigned the majority mortality class in terms of area-coverage. The information pertaining the aerial imagery used in the API process along with the fire characteristics is included in Table 5.1.
Table 5.1. Fire sample information.

Aerial photo date is the elapsed time between the fire report and the acquisition date. Ecozone corresponds to: BP = boreal plains; TS: taiga shield; BS = boreal shield; TP = taiga plains; MC = montane cordillera. Province corresponds to: AB = Alberta; SK = Saskatchewan. Latitude and longitude is to the centroid of the fire event.

<table>
<thead>
<tr>
<th>Fire name</th>
<th>Date reported</th>
<th>Aerial photo date</th>
<th>Ecozone</th>
<th>Province</th>
<th>Fire size (ha)</th>
<th>Latitude (decimal degrees)</th>
<th>Longitude (decimal degrees)</th>
</tr>
</thead>
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<td>Levellers</td>
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<td>57.98410</td>
<td>-119.78200</td>
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<tr>
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<td>TS</td>
<td>AB</td>
<td>32</td>
<td>58.97275</td>
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</tr>
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<td>TS</td>
<td>AB</td>
<td>32</td>
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</tr>
<tr>
<td>Perry</td>
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<td>weeks</td>
<td>TP</td>
<td>AB</td>
<td>326</td>
<td>59.71200</td>
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<td>BP</td>
<td>AB</td>
<td>410</td>
<td>57.4650</td>
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<td>AB</td>
<td>237</td>
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<td>AB</td>
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<td>BP</td>
<td>AB</td>
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<td>57.94102</td>
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<td>56.90000</td>
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<td>Rail</td>
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<td>BP</td>
<td>SK</td>
<td>95</td>
<td>54.41667</td>
<td>-106.66667</td>
</tr>
</tbody>
</table>

15,464
5.3.2. Landsat derived mortality

5.3.2.1. Image pre-processing

Landsat pre- and post-fire image composites were computed to estimate tree mortality for comparison to the API method. To select the suitable imagery we followed the Extended Assessment (EAs) proposed by Key and Benson (2006) as it better portrays long-term ecological consequences by accounting for delayed tree mortality. I used images from up to two years prior to the fire occurrence for the pre-fire composite, and between one and two years after the fire event for the post-fire composite. All available Landsat TM images for the months June, July and August from the area of each fire were processed to surface reflectance products and downloaded from Center Science Processing Architecture (ESPA) On Demand Interface (US Geologic Survey ESPA website, see https://espa.cr.usgs.gov/, accessed July 2016). Each image was masked according to the polygons defined from API (including the 400 m buffer) and pixels removed with cloud, shadow or snow by utilizing the Fmask algorithm developed by Zhu and Woodcock (2012). I also utilized the Fmask algorithm to discard pixels adjacent to clouds or shadows (5 Landsat pixels (30 m)) or with haze (>150 atmospheric opacity).

While most noise was removed from the Landsat imagery by using the procedures described above, undetected clouds, smoke or haze from single date cloud detection (Zhu and Woodcock, 2012) can lead to a false detection of change. To select representative pixels for the pre and post-fire image composites I used a median compositing approach to produce seamless cloud free composites as it is robust against outliers (White et al., 2014), can be directly applied to the filtered image stacks and, unlike the spectral trend analysis algorithms (as in Hermosilla et al. (2016) or Kennedy et al. (2010)), can be computed over shorter temporal windows to help reduce data volumes and processing times.

5.3.2.2. Segmentation

In addition to the information at the pixel level I also created objects at various scales to represent the hierarchical nature of fire patterns and provide spatial context for the classification analysis (Morgan and Gergel, 2010). I utilized the mean-shift algorithm implemented in Orfeo Toolbox (Christophe et al., 2008) with the differenced Normalized Burn Ratio (dNBR) (Key and Benson, 2006) to create segments at various levels of detail (see section 5.3.2.3). Mean-shift clustering is a general non-parametric clustering algorithm first introduced by Fukunaga and Hostetler (1975) and popular in computer vision for satellite image segmentation. The approach requires two main inputs: a spatial radius and range value. The spatial radius is the distance in pixels to be utilized for the search window. The range value is the maximum radiometric distance in the multispectral space. For each pixel the mean-shift algorithm...
calculates a vector with the pixels within the spatial range whose value is within the range value in radiometric units. The method iteratively shifts the center of window to the pixel suggested by the vector until it finds a local maximum of density. All the initial pixels that converged to the same local maxima are considered to be members of the same cluster. For the two segmentations I defined the spatial ranges as 50 and 100 and the spatial radius was set to five pixels.

5.3.2.3. Calculating spectral indices

I calculated multiple multi-temporal spectral metrics utilizing the pre- and post-fire composites. Landsat-derived dNBR was the main variable used to characterize fire effects on vegetation as it has been widely used and tested for burn severity mapping (Eidenshink et al., 2007). I also utilized the differenced version of the near and short-wave infrared Landsat bands (i.e. 4, 5 and 7 in Landsat TM) (dBand4, dBand5 and dBand7) as they are the most sensitive to changes in vegetation condition (Bastarrika et al., 2011); and the Tasseled Cap Transformation (TCT) wetness component (Crist and Cicone, 1984) which is highly correlated with water content and forest structure, but insensitive to topographical variation (Cohen et al., 1995). I also utilized the land cover class derived from the Earth Observation for Sustainable Development of Forests (EOSD) forest cover map (Wulder et al., 2007) and topographic information derived from the Shuttle Radar Topography Mission (SRTM) 1 arc second global product, such as aspect, slope angle and terrain roughness, which calculated as the difference in meters between the value of a cell and the mean value of its eight surrounding cells (Wilson et al., 2007). Lastly, I incorporated the size of each segment (see section 5.3.2.2) in number of pixels and calculated a summary of the independent variables at each of the two segmentation levels, which was then added to pixel level information. The summaries at the segment-level were calculated as follows. For continuous variables (e.g. dNBR) I calculated the mean and standard deviation of the pixels falling within each segment. For categorical variables (e.g. EOSD land cover classes) I calculated the majority class and its proportion.

5.3.2.4. Classification

Random forests (RF) (Breiman, 2001) models build in R (R Development Core Team, 2011) were utilized to predict tree mortality maps for all fires in the sample using as an explanatory variable the tree mortality class (defined in section 2.2.1.2) and as predictor variables the spectral indices calculated in section 2.2.2.3 (dBand4, dBand5, dBand7, dNBR, TCT wetness, EOSD land cover class, aspect, slope angle and terrain roughness). RF models are decision tree ensembles that produce predictions and insights into data structure (Cutler et al., 2007). For this study, I built 14 RF models of 100 trees, one per fire, utilizing the reminder of fires in the sample as training data for each. To ensure an even data sample
across the three tree mortality classes, I employed a stratified data sample at the tree level equalling the size of the least represented class (Chen et al., 2004).

5.3.3. **Fire patch definitions**

I transformed the three-class mortality maps derived from Landsat and API into discrete fire-patch disturbance events using the spatial language proposed by Andison (2012) and that I described in section 3.2. An example of a comparison of the two different data types is included in Figure 5.2.

5.3.4. **Calculating landscape metrics**

Using the disturbance events created from both API and Landsat, I calculated seven metrics that have been used to help guide harvesting planning in Alberta and Saskatchewan over the last 10 years (Andison and McCleary, 2014). The metrics were previously described in section 3.3.
Figure 5.2. Detail of comparison of disturbance events derived from aerial photo interpretation and Landsat for the fire Keane.
5.4. Methods

The analysis involved two stages. First, I computed and compared the results of all seven pattern metrics for Landsat and API. Second, I examined if the effect of a number of key environmental variables and fire patterns could help explain any significant deviations between the two metric estimates. A detailed description of the two steps is included below.

5.4.1. Comparing pattern indicators

The seven pattern indicators were computed for both each individual fire event and all fire events combined. I then compared the results from the two data sources through relative scores calculated as follows. For the variables expressed in proportions (i.e. %IR, %TR, %MR and %LDP) or number of patches (i.e. NDP) I calculated the absolute difference between the Landsat and API estimates. For those variables expressed in area or length units (i.e. EA and SI) we calculated relative differences in percentages. I then applied various statistical tests to the scores.

For all fires combined I calculated the absolute difference between values, where close agreement corresponded to a deviation of less than 5%; moderate between 5% and 20%; and poor for deviations larger than 20%. At the single fire event level I calculated the interquartile range (IQR) and the median values. I categorized IQR in three groups: low dispersion for IQR was anything up to 10%; moderate between 10% and 20%; and high larger than 20%. In the case of the median values, ‘centered’ corresponded to absolute deviations of less than 5%; and ‘under’ or ‘over’ estimation to deviations of more than 5% under or over respectively.

In addition to the relative scores, I compared for single fire events the raw predicted vs. observed metrics to assess whether their population mean ranks differ. For that I utilized to two complementary non-parametric analysis: the two-tailed Kolmogorov-Smirnov (KS) and the two-tailed Wilcoxon Rank Sum (WX) tests at the level of significance 0.05.

5.4.2. Environmental and fire pattern analysis

I expected that particular environmental and fire pattern characteristics will alter the size, complexity and arrangement of the fire effects, making them more or less readily detected with a Landsat approach. To account for that, I tested if the environmental and fire pattern characteristics of single fire events influenced the accuracy of a Landsat approach to predict each of the seven patch metrics (relative scores as described in 5.4.1). I included variables characterizing fire weather conditions (represented by
the drought code index from the Canadian Wildfire Behaviour Prediction system (Girardin and Wotton, 2009a) and the season of burning represented by the Julian day), topographic complexity (represented by the terrain roughness according to Wilson et al. (2007), slope angle and elevation), the dominant land cover class derived from the EOSD forest cover map (Wulder et al., 2007), and fire pattern characteristics derived from the API (represented by the fire size and degree of fire patchiness) (Table 5.2). To understand the relative effect of these environmental variables on metric accuracy I used linear regression models using the relative scores as described in 5.4.1 as the dependent variable and a level of significance of 0.05.
Table 5.2. Explanation of the environmental variables assessed.

EOSD stands for Earth Observation for Sustainable Development of Forests forest cover map. API stands for aerial photo-interpretation.

<table>
<thead>
<tr>
<th>Variable class</th>
<th>Variable name</th>
<th>Explanation</th>
<th>Calculation [units]</th>
<th>Reference data</th>
<th>Reference formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought Code (DC)</td>
<td>Fire weather</td>
<td>Drought Code (DC) is a numeric rating of the average moisture content of deep, compact organic layers.</td>
<td>DC of the centroid of the fire event calculated for the month and year of the fire occurrence</td>
<td>(Wang et al., 2016)</td>
<td>(Girardin and Wotton, 2009a)</td>
</tr>
<tr>
<td>Julian day</td>
<td>Fire weather</td>
<td>Julian day of the fire event occurrence</td>
<td>Julian day of the fire event occurrence</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Terrain roughness</td>
<td>Topography</td>
<td>Terrain roughness is the difference between the maximum and the minimum value of a cell and its 8 surrounding cells.</td>
<td>Average value in m of the roughness of all pixels within the fire event</td>
<td>(Wilson et al., 2007)</td>
<td>(Wilson et al., 2007)</td>
</tr>
<tr>
<td>Slope</td>
<td>Topography</td>
<td>A number that describes both the direction and the steepness of the line.</td>
<td>Average value of the slope angle in degrees of all pixels within the fire event.</td>
<td>Shuttle Radar Topography Mission (SRTM) 1 arc second product (Farr et al., 2007)</td>
<td>-</td>
</tr>
<tr>
<td>Elevation</td>
<td>Topography</td>
<td>Total height above sea level</td>
<td>Average value of the elevation in m of all pixels within the fire event</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Land cover EOSD</td>
<td>Land cover</td>
<td>Land cover type</td>
<td>Predominant EOSD class</td>
<td>(Wulder et al., 2007)</td>
<td>-</td>
</tr>
<tr>
<td>Fire size</td>
<td>Fire patterns</td>
<td>Size of the area affected by a fire event as delineated in API</td>
<td>Size of the fire event in ha</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Percentage island remnants</td>
<td>Fire patterns</td>
<td>Percentage of islands remnants</td>
<td>(Area of islands remnants API / area completely disturbed API) * 100 [%]</td>
<td>API database (Andison, 2012)</td>
<td>-</td>
</tr>
<tr>
<td>Number of island remnant patches per ha</td>
<td>Fire patterns</td>
<td>Number of island remnant patches / fire size</td>
<td>Number of island remnant patches per ha [patches/ha]</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
5.5. Results

5.5.1. HRV metrics

Initial results revealed that the fire Perry had an unusually high level of disagreement between the API and the Landsat derived metrics involving residual levels (e.g. IR +39% and TR +40%) (Figure 5.3). The comparison between the original tree mortality polygons from API and the Landsat derived mortality revealed that these highly biased results reflect a misclassification of a large proportion of the area with complete mortality as partial mortality by the Landsat model. This was the result of the comparatively faster regrowth experienced by a majority non-treed vegetation (i.e. wetland shrub in a 60% of its total area according to the EOSD land cover) compared with areas dominated by treed-vegetation cover (i.e. the reminder of the fires). This skewed the final results and thus was eliminated from the summary statistics at the fire level. The accuracy of the fire pattern metrics at the single fire scale is presented in Figure 5.3 and the results of the KS and WX tests in (Table 5.3).

<table>
<thead>
<tr>
<th>EA</th>
<th>SI</th>
<th>%IR</th>
<th>%TR</th>
<th>%MR</th>
<th>NDP</th>
<th>%LDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>KS</td>
<td>0.64</td>
<td>0.92</td>
<td>0.91</td>
<td>0.87</td>
<td>0.04</td>
<td>0.70</td>
</tr>
<tr>
<td>WX</td>
<td>0.57</td>
<td>0.67</td>
<td>0.99</td>
<td>0.99</td>
<td>0.15</td>
<td>0.92</td>
</tr>
</tbody>
</table>

*Table 5.3. P-values from the Kolmogorov Smirnov (KS) and Wilcoxon Rank Sum (WX) tests analyses.*
The accuracy is expressed in relative scores between predicted and actual values. EA stands for event area; SI for shape index; %TR for percentage of total remnants; %IR for percentage of island remnants; %MR for percentage of matrix remnants; NDP for number of disturbed patches; and %LDP for percentage of the largest disturbed patch.

Figure 5.3. Accuracy of the fire pattern metrics at the single fire scale.
5.5.1.1. **Event scale metrics**

EA was predicted in close agreement when all fires were combined (i.e. -1%). At the single fire event level the results were centered (i.e. median of +4%) and presented low dispersion (i.e. IQR of 7%). However, the model highly over predicted EA on three fires: Abraham, Flett and Steephill (i.e. +34%, +24% and +23%, respectively). SI was also predicted in close agreement for all fires combined (i.e. +3%). At the single fire event level the results for SI were centered (i.e. median of -3%) and with low dispersion (i.e. IQR of 6%). The KS and WX tests found no significant differences between the Landsat and API methods at predicting either EA or SI (Table 5.3).

5.5.1.2. **Within-event metrics**

%TR was predicted with complete agreement overall (i.e. 0%). However, %IR was moderately under predicted by the Landsat method (i.e. -6%) and %MR was moderately over predicted by the same amount (i.e. +6%). At the event-scale the results for the three metrics were all centered (i.e. median of -3%, -1% and -5% respectively for %TR, %IR and %MR). The dispersion of results was moderate for %TR (i.e. IQR of 11%) and low for %IR and %MR (i.e. IQR of 8% and 3% respectively). The Landsat approach tended to over predict %MR for the three largest fires, namely: Keane, Levellers and Cone (i.e. +6%, +8% and +5% respectively) (see Figure 5.3). NDP was overall highly over-predicted by the Landsat method (i.e. +59 patches). However, the individual fire results suggest that this overall bias was largely the impact of the two largest fires, Levellers (+21 patches) and Keane (+30 patches) (Figure 5.3). %LDP was overall very closely approximated (i.e. -4%) and the single fire event results for %LDP were centered (i.e. median of +1) and with low variability (i.e. IQR of 8%). The KS and Wilcoxon tests found no significant differences between the Landsat and API methods at predicting %IR, %TR, %MR or %LDP (Table 5.3). NDP was the only one of these indicators that presented significant differences (Table 5.3).

5.5.2. **Environmental and fire pattern factors affecting the prediction**

The accuracy of predicting some of the pattern metrics was conditioned by various environmental and fire pattern variables. Of the event scale metrics, I found EA was over-predicted in high slope angles or rough terrain (p-values of 0.01 and 0.02 respectively), but only because of the influence of a single fire. Both %IR and %TR were both over-predicted under high drought conditions (p-values of 0.01 and 0.01 respectively). Finally, %MR, SI, NDP and %LDP were significantly influenced by the fire size (p-values of 0.04, 0.02, 0.00 and 0.01). %MR, SI and NDP tended to be over predicted and %LDP under-predicted as fire size increased (see Figure 5.4).
Figure 5.4. Results of the linear model regression for the metrics influenced by environmental factors.

The Y axis represents the relative scores between predicted and actual values for a given metric. The metrics are: EA corresponds to the event area in ha; SI is shape index and has no units; %TR, %IR and %MR are the percentage of total remnants, island and matrix remnants respectively; NDP is the number of disturbed patches; and %LDP is the percentage of total area of the largest disturbed patch. The X axis represents each of the environmental and fire pattern variables that showed significant correlation for a given metric in the ANOVA analysis at 0.05 significance. The variables are described as follows: slope is the average value of the slope angle in degrees; roughness is the average value in m of the difference between the maximum and the minimum value of a cell and its eight surrounding cells of all pixels within the fire event; size is the total fire event area in ha as per defined by aerial photo-interpretation and drought corresponds to the drought code that is a numeric rating of the average moisture content of deep, compact organic layers at the centroid of the fire event.
5.6. Discussion

5.6.1. HRV metrics

5.6.1.1. Event scale metrics

For all fires combined, the two event-scale metrics were predicted with a high degree of accuracy by the Landsat model. This suggests that the outer perimeter of the event being accurately identified by the Landsat model. However, for three out of the 14 fires the EA was considerably over-predicted. The Abraham fire appears to be biased due to poorer manual API delineation as the fire perimeter suggested by the true-color Landsat closely approximated the Landsat delineation. It is possible that such bias was caused by topographic complexity as Abraham presented the highest terrain roughness (34 m vs. a sample mean value of 11 m) and elevation (1,551 m vs. a sample mean value of 598 m) of all fires in the sample. This is supported with findings of Verbyla et al. (2008) which concluded that variation in topography affected Landsat surface reflectance and thus spectral indices such as Landsat dNBR regardless of the vegetation cover or level of tree mortality. For Flett and Steephill fires, the over-prediction appears to be a systematic imagery classification error along the fire boundary.

5.6.1.2. Within-event metrics

The Landsat model predicted overall residual levels (%TR) with very high accuracy, although the details of where and how vegetation are arranged in space were less well predicted. Island remnants were moderately under-predicted, matrix remnants moderately over-predicted, number of disturbed patches highly over-predicted, and the size of the largest patch slightly under-predicted. I propose that taken together, these results suggest that the model is successfully identifying the total amount of vegetation remnants within events, but is miss-classifying some (6%) of the island remnants as matrix remnants. To illustrate our hypothesis of how the Landsat model differs from the API model, consider the examples of fire event patterns shown in Figure 5.5 for a theoretical event.
Figure 5.5. Conceptual Landsat model performance.
The top image shows the results of the API process, and the bottom one from our calibrated Landsat model. The size, shape, and total area of remnants (combination of matrix and island remnants) are in this case identical. However, the Landsat model in this example misclassifies some of the partially burned areas as unburned. Note also that this misclassification error results in reduced the area in (spatially discrete) island remnants, increased area the amount of area in matrix remnants, a higher number of (spatially discrete) disturbed patches (in red), and a decrease in the proportional area of the largest disturbed patch. The fact that the proportional area of the largest disturbed patch was only slightly under-estimated by the Landsat model suggests that these misclassification errors were more likely to split either smaller disturbed patches, or small pieces of large disturbed patches, both of which are more likely to occur near the edges of fire events. This is in agreement with findings by Harper et al. (2004) who suggested that in boreal forest ecosystems most of the partially disturbed areas of a fire are within 50 m of the perimeter. This is exactly what our results in this study suggest, and is consistent with the challenge of capturing partial mortality with Landsat data.

Partially disturbed areas tend to represent more dispersed, fine-scale burn patterns as a result of mixed fire effects (Turner and Romme, 1994) and capturing the is a known source of inaccuracy with an averaged 30 m Landsat pixel (e.g. Miller and Yool (2002)). Partially disturbed areas present more ephemeral fire effects and have less distinctive spectral signatures than areas of high mortality (Pereira et al., 1999), which could result in confusing the signature of such pixels with unburned areas. Partially disturbed areas are also more likely to undergo delayed tree mortality (Angers et al., 2011) which also means partially disturbed areas are more likely to be confused with unburned areas when imagery is obtained very soon after the fire. It is also possible that partial mortality of non-forested areas poses a particularly unique spectral signature that has not yet been captured. Recall that the dominant vegetation type for the Perry fire, which was eliminated from the summary data of single fires, was non-treed wetlands. Such areas are likely to experience a faster regrowth compared with areas dominated by trees making it more difficult to discriminate mortality with the Landsat data. This is particularly true of tree species that only regenerate by seed, such as the coniferous tree species that dominate the area of study. To accurately identify burn patterns in non-treed areas of the boreal forest using Landsat imagery may require further study to define a unique set of methods and rules. Lastly, it is also possible that some areas of partial mortality were classified as disturbed due to differences in canopy coverage that would create a comparable spectral response (Pereira et al., 1999). For example, areas with sparser tree coverage that experienced complete mortality might have a similar spectral signature to those that
had denser pre-fire vegetation but lower levels of mortality, increasing thus the chances of confusion between the two classes.

5.6.2. **Environmental and fire pattern factors affecting the prediction**

5.6.2.1. **Event scale metrics**

I found significant correlations between environmental and fire pattern variables and the accuracy at predicting various patch metrics. SI was moderately over predicted for bigger fires. In section 5.6.1 I discussed that a Landsat approach over-predicts the number of disturbed patches for larger fires mostly near the fire boundary, where partial mortality is more likely occur and thus larger tracts can be misclassified as unburned. Under these circumstances it is possible that multiple disturbed patches could not be connected through the matrix, because they were more than 400 m apart (twice the buffer distance used to calculate the matrix remnants). That will create a less compact event than the one seen in the original API data, increasing the overall edge ratio and thus resulting in the over prediction of SI.

5.6.2.2. **Within-event scale metrics**

Both %IR and %TR were significantly influenced by the drought code (DC) index. %IR and %TR for fires that occurred under drier conditions (higher DC values) was over predicted. Extreme fire weather has an overarching role in determining residual patterns in the Canadian boreal forest (e.g. Johnson et al. (1998)) but I found no correlation between the metrics %TR and %IR and the amount and dispersion of vegetation remnants (i.e. number of islands and percentage of vegetation remnants). It is possible that the relationship between the accuracy at predicting vegetation remnants and DC is related with the way I map tree mortality: the percentage of crown mortality in forested areas. This means that a tree crown that retained dead needles (brown) will be classified by the photo-interpreter as complete mortality, similar to a tree with complete needle consumption or where the bole was almost totally consumed. However, the three cases present substantially different spectral signatures as seen by Landsat, particularly in the near infrared portion of the spectrum, which favour the confusion between the partial and unburned classes. For example, trees that retained dead needles have comparatively higher values in the near infrared part of the spectrum than trees where needles were consumed, which reduces dNBR values and makes more likely the confusion with the partial mortality class. Fires that burn under drier conditions tend to reach higher intensities and are likely to cause increased mortality via horizontal heat transfer (killing the crowns but without causing crown loss). Here is where the confusion between partial and unburned classes is maximized, causing the over-prediction we see. It is also worth noting that changes in DC did not necessarily correspond with seasonal effects, as shown by the lack of
correlation between Julian day and the metrics analyzed. This suggests that DC is a more powerful predictor of fire mortality patterns than is seasonality.

I found that both NDP and %LDP were significantly influenced by the fire size. Both the number of disturbed patches and the proportional area of the largest disturbed patch are directly related to the event size. Andison and McCleary (2014) suggest that NDP increases dramatically with event size. As the number of artificial disturbed patches captured by the Landsat model increases, the size of the largest disturbed patch (%LDP) will logically decline. As discussed above, one possible explanation for this deviation is that partially disturbed patches (which would otherwise be classified as island remnants) are being classified as undisturbed remnants within the event (or matrix remnants). In other words, larger events are more likely to have a larger number of disturbed patches, the vast majority of which are small, and close to the edge.

5.7. Conclusions

Regulatory and certification agencies need historical fire pattern information across the Canadian boreal forest to support natural disturbance-based management strategies. Fire managers require standardized protocols and more cost-effective methods to derive the quantitative metrics needed to inform management plans. In this paper I have assessed the suitability of utilising a Landsat-based model of tree mortality to capture seven key historical range of variability (HRV) metrics as derived from aerial photo-interpretation (API) calculated over 14 fires in the boreal forests of Alberta and Saskatchewan, Canada. The Landsat method provides a cost-effective alternative to conventional field data or API as that can be produced more quickly and less expensively to cover larger areas on a spatially continuous basis. Further, the unambiguous spatial pattern proposed by Andison (2012), and that I here adopted, guaranteed comparable and repeatable results.

Overall, the Landsat-derived method closely approximated most of the seven pattern metrics tested both at the regional scale of all fires combined and also for the more local scale of single fire events. The two event-scale metrics, the total fire event area and its perimeter complexity, were predicted with very high levels of accuracy which preludes that the outer perimeter of the fire event is being accurately identified. If anything, the event-scale metric predictions could only be reinforced by utilizing associated models based on event size. Within-fire event metrics, or the details of the amount and spatial arrangement of the fire patterns, presented more diverse results. The percentage of total vegetation remnants was predicted with very high accuracy as was the percentage of the largest disturbed patch. Other metrics, such as the percentage of island remnants, matrix remnants or number
of disturbed patches, were less accurate, however the biases were moderate and predictable in direction, and as a result are still valuable from a practical perspective. For example the proportion of island remnants can still be used to inform management plans after compensating for the moderate under prediction observed with the Landsat approach. In the views of the results, the inclusion of drought code information is likely to increase overall accuracy of predicting the details of vegetation remnants.

More broadly, there is an increasingly need to characterize detailed fire patterns in a comprehensive and universal way across the Canadian boreal forest to support disturbance-based management approaches. In this study I have demonstrated that a cost-effective method to derive detailed fire pattern metrics using freely available Landsat imagery produces comparable results to conventional approaches based on manual interpretation of aerial photographs. These results suggest that if applied more broadly to more fires a national fire database on fire behavior may be possible. The individual fire pattern results for hundreds of fires across the boreal forest, when summarised will provide significant quantitative information to locally characterize fire patterns and insights into drivers of fire patterns across this large forested region.
Chapter 6

6. Can a Landsat-derived model be used to generate a sufficiently large sample size as to detect differences in fire patterns within and across sub-regions of the boreal plains ecozone?

6.1. Introduction

Despite the availability and potential of open-access and free Landsat data (Woodcock et al., 2008), there have been limited studies that captured the detailed vegetation remnants and/or partial mortality with reasonable accuracy across the Canadian boreal forest. Given the applied nature of the fire mortality pattern information to forest management, regulatory, and certification agencies, incomplete or inaccurate fire pattern estimates are not defendable, and thus of limited value. Further, all of the available studies differ in their methods, data, and spatial language (Andison, 2012), which makes difficult for managers to understand and compare fire patterns across large areas. Thus there is an increasing need to characterize detailed spatial patterns of fire in a systematic and comprehensive way across the broader expanse of the boreal forest. This information can then be used to quantify how fire pattern metrics vary among and within pre-defined ecological zonations (e.g. Parisien et al. (2004)), to define areas where fire patterns are relatively homogeneous (Boulanguer et al., 2012), or to better understand the relationship between fire pattern metrics and various environmental variables (Morgan et al., 2001). If broad scale patterns are found to exist, they would increase the robustness of statistic inferences across the broader expanse of the Canadian boreal forest in support to management efforts.

In Chapter 5 I developed a Landsat-based model to cost-effectively generate seven fire event characteristics based on a three-class mortality map (unburned, partial mortality and complete mortality) coupled with the spatial language proposed by Andison (2012). The method utilizes aerial photo-interpreted (API) polygons of mortality covering 14 fires across the boreal plains ecozone, Canada, to train and validate a random forest classifier (Breiman, 2001) to the area of study. Once calibrated, this model can be used to produce mortality maps for other fires using predictor variables derived from Landsat and ancillary data. The model requires (1) a buffered perimeter to identify the Landsat scenes covering the area of study and, (2) the year of fire occurrence to determine the dates of the pre- and post-fire images needed for the analysis. Overall the Landsat method produced
comparable results to those observed from API, both at the regional scale of all fires combined and at the scale of single fire events. The technique captured the outer perimeter and the total amount of vegetation residuals with high accuracy, although misclassified a small portion (6%) of the partially burned areas as unburned (see Chapter 5). The ability to use freely and widely available Landsat to capture fire patterns at accuracy levels similar to that of API makes this technique well suited for capturing and comparing detailed mortality patterns of hundreds of wildfires across vast areas, and thus potentially a valuable new tools for both researchers and forest managers. However the degree to which this approach can be successfully applied across large areas remains untested.

In this paper I explore the capacity of a recently developed standardized fire mapping approach developed in Chapter 5 using Landsat data and the spatial language by Andison (2012), to characterize, summarize and compare fire mortality patterns in the boreal plains ecozone of Canada. It is important to note that to calibrate the detection model applied to these fires was an entirely separate analytical step that was described in Chapter 5. My hypothesis is that Landsat-based approach can be used to capture and compare fire patterns to a sufficient degree of accuracy and completion across the boreal biome to support management efforts. The results will not only allow the collection of quantitative fire pattern information on an unprecedented scale, but also new insights into the most appropriate scales to characterize spatial fire patterns to support disturbance-based management approaches and a broad range of associated research studies. I also discuss the big data processing decisions and related outcomes for large area mapping of hundreds of fires over the region.

6.2. Study area

The fires sample was distributed across the boreal plains ecozone (Figure 6.1). See section 2.1. for more details.
Figure 6.1. Fire sample across the boreal plains ecozone.
6.3. Data

Two data sources are used for this study: (1) aerial photographic interpretation (API) (see section 2.2.1), which served as main data source to calibrate the Landsat models; and (2) Landsat data (see section 2.2.2), which was used to estimate tree mortality.

6.4. Methods

The developed method is summarized in Figure 6.2 and briefly described below. First, from existing fire history databases I selected all available fires larger than 100 ha which occurred within the boreal plains (BP) from 1985-2014 (section 3.1.) and downloaded, pre-processed and merged the Landsat imagery into seamless cloud-free surface-reflectance composites (section 3.2.). Next, for each fire I produced a three-class mortality map using a random forest classifier previously trained with manually interpreted polygons of tree mortality from aerial imagery and multi-temporal spectral indices calculated from the Landsat composites and ancillary data (section 3.3.). Based upon the pixel mortality predictions for each fire, I then calculated discrete patch-disturbance events based on the spatial language by Andison (2012) (section 3.4.) and derived seven fire pattern metrics of interest for managers (section 3.5.). Next, I screened out the predictions that were not consistent with the reference perimeters from the fire databases (section 3.6.). Finally, I pooled the results from all fires and analyzed the variability of the fire pattern metrics across the full fire sample and the ecoregions within (section 3.7.). A description of each step is given below.
Figure 6.2. Analysis workflow.
6.4.1. Sample selection from fire databases

As reference data for this study I captured as many previously identified historical fires as possible from the boreal plains ecozone that occurred between 1985 and 2014 that were at least 100 ha in size. I sampled from three publically available sources (1) the federal Canadian fire and (2) provincial fire databases, as well as (3) fire events with perimeters derived from the High Resolution Forest Change (HRFC) for Canada product (White et al., 2017). This initial screening process yielded 1,147 fires across 5.3 Mha. From each fire I retained the perimeter and the fire year.

6.4.2. Image selection and processing

6.4.2.1. Landsat image scene selection

For each fire that met the above criteria, I used fire year and perimeter (which included a 20 km buffer to allow for mapping errors) to select the corresponding pre and post-fire Landsat images. The pre-fire temporal window was between one to six years prior to the fire. Lengthening the pre-fire temporal window minimized the chances of gap occurrence (mostly due to cloud coverage) while still representing a relatively static picture of low productivity boreal ecosystems. The post-fire temporal window included images from one to two years after the fire, which aligns well with the extended assessment (EAs) proposed by Key and Benson (2006). EAs better portrays the long-term ecological effects of fire accounting for delayed tree mortality and secondary mortality agents (Key and Benson, 2006), and has been most often used in burn severity mapping of forested and shrub systems (Eidenshink et al., 2007; French et al., 2008). Candidate Landsat imagery included LT-1 corrected-products from Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI) from the United States Geological Survey (USGS) archive over all fires within the defined pre and post-fire windows. I selected a 130 day window from each fire event (from mid-May to mid-September) to maximize the number of Landsat images while avoiding images before vegetation green-up or after vegetation senescence, reducing probability of snow presence, and minimizing the chances of classification errors associated to low-sun elevation angles late in the fire season (Verbyla et al., 2008). To reduce the processing times, I removed scenes with more than 80% cloud cover estimation from the Fmask layer (Zhu and Woodcock, 2012) included in the image metadata. All candidate images were sent to the USGS ESPA platform (http://espa.cr.usgs.gov) to be processed to surface reflectance products and downloaded.
6.4.2.2. Filtering and stacking

From all the Landsat ESPA layers I retained the red, near (NIR) and short-wave infrared (SWIR) bands since they are the most responsive to changes in vegetation condition (i.e. 3, 4, 5 and 7 in Landsat TM/ETM+; and 4, 5, 6 and 7 for OLI) (Pereira et al., 1999); and the water mask of water from the Fmask layer. I also utilized the Fmask to mask out pixels flagged as cloud or near cloud (distance < 150 m), as well as cloud shadows and haze (atmospheric opacity < 200).

6.4.2.3. Median compositing

While most noise was removed from the Landsat imagery by using the procedures described above, undetected clouds, smoke or haze from single date cloud detection (Zhu and Woodcock, 2012) can lead to a false detection of change. To select representative pixels for the pre and post-fire image composites I used a median compositing approach to produce seamless cloud free composites as it is robust against outliers (White et al., 2014), can be directly applied to the filtered image stacks and, unlike the spectral trend analysis algorithms (as in Hermosilla et al. (2016) or Kennedy et al. (2010)), can be computed over shorter temporal windows to help reduce data volumes and processing times. I also created a water layer mask with the pixels classified as water by the Fmask in more than 60% of the total valid observations, similar to methods of Hermosilla et al. (2016).

6.4.3. Predict three-class pixel mortality maps

To produce tree mortality maps for single fires I utilized a Random Forest (RF) classifier (Breiman, 2001) previously trained with aerial-photo interpreted polygons for 14 fires across the boreal plains ecozone and a suite of explanatory variables to characterize the spectral response of fire effects (see Chapter 5). Tree mortality was defined as the percentage of crown mortality of overstory vegetation and/or consumption of lesser vegetation, and was classified into three classes: unburned = 0-5%, partial mortality = 6-94%, and complete mortality = >94. The explanatory variables for the RF classifier included the difference in the green, near-infrared (NIR) and shortwave infrared (SWIR) Landsat bands (i.e. 3, 4, 5 and 7 in Landsat TM/ETM+), the differenced Normalized Burn Ratio (dNBR) (Key and Benson, 2006) that is based on the NBR by García and Caselles (1991) and responsive to changes in live vegetation (NIR), moisture content, mineral soil exposure, char and ash occurrence (SWIR) (Miller and Thode, 2007) that is highly correlated to changes in canopy cover (Mccarley et al., 2017); and the differenced Normalized Difference Vegetation Index (dNDVI) (Rouse et al., 1974) to improve the characterization of forest structure and photosynthetic activity (Bolton et al., 2015). In addition I included an assessment of pre-fire vegetation condition through the pre-fire NBR and NDVI, the land cover class from the Earth
Observation for Sustainable Development of Forests (EOSD) product (Wulder et al., 2007); as well as topographic information derived from the Shuttle Radar Topography Mission (SRTM) 1 arc second global product, which included aspect, slope angle and terrain roughness, calculated as the difference in meters between the value of a cell and the mean value of its eight surrounding cells (Wilson et al., 2007).

To provide spatial context for the classification (Morgan and Gergel, 2010), I summarized the pixel-level explanatory variables by segments and incorporated them as additional explanatory variables to the RF classifier. To do this the mean-shift algorithm implemented in the Orfeo Toolbox (Christophe et al., 2008) was used on the dNBR values (Key and Benson, 2006). The approach requires two inputs: a spatial radius and a range value. The spatial radius is the distance in pixels to be utilized for the search window. The range value is the maximum radiometric distance in the multispectral space. For each pixel the mean-shift algorithm calculates a vector with the pixels within the spatial range whose value is within the radiometric range. The method iteratively shifts the center of window to the pixel suggested by the vector until it finds a local maximum of density. All the initial pixels that converged to the same local maxima are considered to be members of the same cluster. For the segmentation I utilized a spatial range of 50 pixels and a spatial radius of five pixels.

6.4.4. Calculate fire-patch disturbance events

Pixel-level mortality maps were converted into discrete fire-patch disturbance events using the spatial language of Andison (2012) described in section 3.2. Lastly, water pixels were masked from the disturbance event. For the purpose of this study we only retained the disturbance events intersecting with the reference perimeter from the fire databases. Figure 6.3 shows an example of the complete process, from the image mosaics to defining the disturbance events.
The top thumbnail represents the difference between pre and post fire composites, where the red channel corresponds to the difference in Landsat near-infrared band (4 in TM and 5 in OLI), the green channel to the difference in the shortwave-infrared 1 band (5 in TM and 6 in OLI) and the blue channel the difference in the shortwave-infrared 2 band (7 in TM and OLI). The middle thumbnail represents the three class mortality map from the random forest classifier. The bottom figure corresponds to the disturbance event by Andison (2012).
6.4.5. Derive seven fire pattern metrics
For each disturbance event I calculated seven fire pattern metrics as per described in section 3.3.

6.4.6. Secondary screening
The last data processing step was to filter out fire events that were not consistent with the fire perimeters utilized for reference, to avoid possible biases during the spatial pattern analysis. A secondary screening process consisted of a sequence of automated quality control steps followed by a visual evaluation of the results. First, I removed the fire events for which the mortality maps presented more than 5% of data gaps in the mortality prediction within or near (1 km) the perimeters suggested by the fire databases. Second, I removed the fire events that were not detected (i.e. all unburned pixels from the mortality maps) or covered less than 30% of the area suggested by the reference perimeters. Finally, through visual inspection I discarded the disturbance events that included adjacent contemporaneous fire events or with signs of anthropogenic activity (harvesting cutblocks).

6.4.7. Spatial pattern analysis
To explore the variability in fire patterns I pooled the results from single events and summarized and compared the seven pattern metrics using a combination of box-and-whisker plots and spyder plots calculated on median values. Spyder plots show the relative values for a single data point given an arbitrary number of variables, and are useful to highlight similarities or differences in the fire pattern metrics among the ecoregions. To guarantee sufficient data representation, I did not consider the ecoregions with less than 30 fires. To test for differences in fire pattern metrics I compared the cumulative distributions functions of each metric across all possible pair-wise combinations through the non-parametric two-tailed Wilcoxon Rank Sum (WX) and the Kolmogorov-Smirnov (KS) tests at the p < 0.01 significance. The KS test was used as a goodness-of-fit test to compare the shape of the distribution while the WX also assessed differences of central tendency (median). To increase the robustness of the results, I only considered as significantly different the cases when both tests indicated significant differences.

6.5. Results
6.5.1. Image selection and processing
In total, I retrieved information from 1,147 fire events covering 5.3 Mha. I extracted imagery from an area equivalent to 82 unique Landsat scenes (i.e., path and row combinations) and a total of 18,148 pre and post-fire images. On average a pre-fire pixel had 21 Landsat observations in the 6 years prior to the fire,
of which 9 were usable after filtering for noise and cloud (Figure 6.4). The closest pre-fire observation occurred an average of 41 days from the opening of the acquisition window, or 323 days before the fire (Figure 6.5). In contrast, a post-fire pixel had an average of 8 Landsat observations over the two year observation window, of which an average of three were usable after filtering out potentially noisy pixels (Figure 6.4). The closest post-fire observation was acquired an average of 104 days after the acquisition window opened, or 386 days after the fire event (assuming that each fire occurred on the 1st of August). The median value selected for the post-fire window across all fire events was on average 230 days after the window opened (126 days since the first acquisition), or 512 days from the fire date (Figure 6.5). The median value selected for the pre-fire composite was acquired in average 772 days since the opening of the pre-fire window (731 days from the closest acquisition), or an average of 1,137 days before the fire.
Figure 6.4. Number of observations per pixel for the image compositing averaged by individual fires.

Figure 6.5. Time difference (days) for the image compositing averaged by individual fires.

'Median' corresponds the distance in days between the selected median pixel and a hypothetical fire occurring the 1st of August of the fire year reported in the fire history databases. 'Closest' is the nearest observation in days from a hypothetical fire occurring the 1st of August of the fire year.
6.5.2. Secondary screening

From the 1,147 fires analyzed 507 (44%) adhered to the secondary screening criteria (Figure 6.6). Of the 640 fires that were discarded at this step, 195 (17%) presented data gaps within the post-fire image composites making calculation of spatial landscape metrics impossible; 264 (23%) covered less than 30% of the reference perimeter area; 113 (10%) included adjacent/overlapping fire events; and 68 (7%) included anthropogenic disturbances (most often harvest cutblocks). The final sample included 507 fires ranging in size from 36 to 269,360 ha and covering 2,535,561 hectares.

![Figure 6.6. Summary of the screening process.](image)
6.5.3. Spatial pattern analysis

6.5.3.1. Overall

EA ranged from 36 to 269,360 ha. The median event area (EA) of the fire sample was 475 ha, compared to a mean of 5,001 ha indicating that fire size is highly positively skewed (Figure 6.7). In fact, the 9% of fires greater than 10,000 ha represent 75% of the area burned in all fires in the sample. The mean shape index (SI) was 2.09, and 1.68 at the median, ranging from 1.03 to 12.23. The mean number of disturbed patches (NDP) was 52, with a median of 8, and a range from 1 to 3,117. However, both the NDP and the SI co-varied directly with fire size, where the number of disturbed patches ranged between averages of 7 and 421, and the shape index between 1.6 and 5, for fires smaller than 1,000 and 421 and 5.0 for fires greater than 10,000 ha. The percentage of the largest disturbed patch (%LDP) averaged 60% and was 63% at the median, with a range from 8% to 96%. The total remnants (%TR), island remnants (%IR), and matrix remnants (%MR) had means of 39%, 15% and 24%, respectively; and medians of 37%, 13% and 23%, respectively. %TR ranged from 5% to 91%, %IR from 1 to 56% and %MR from 3% to 59%.
Figure 6.7. Summary boxplots of the comparison between ecoregions.

‘ALL’ stands for all fires combined.
6.5.3.2.  Ecoregions comparison

I found significant differences in fire patterns for four of the seven metrics in four ecoregion pairs (Figure 6.8). The %MR of the Mid-Boreal Uplands (MBU) were significantly lower than those from the Western Alberta Upland (WAU), Slave River Lowland (SRL) or Wabasca Lowland (WL) ecoregions. In addition, the %TR of the MBU were significantly lower than those from the WAU or SRL ecoregions. The fires in MBU had significantly lower island remnants (%IR) than those from SRL and significantly larger event area (EA) than those in WAU. I also observed large differences in the median values through the spyder plots (Figure 6.8) that did not translate into significant differences as captured by the Kolmogorov-Smirnov (KS) and Wilcoxon Rank Sum (WX) analyses. An example is the comparatively larger size of the fires in SRL relative to other ecoregions (Figure 6.8). This suggests that some of these differences may be the result of differences in the population shape that are not necessarily associated with shifts in median values. Some of the least represented ecoregions might not show significant differences due to lack of statistical power as a result of small sample sizes and the conservative 0.01 significance values I used.

The spyder plots grouped by ecoregion (Figure 6.9) highlighted unique combinations of fire pattern metrics suggesting the existence of unique ‘signatures’ of burning patterns in the areas of study. Two groups of fire patterns were particularly easily differentiated. The SRL group had much larger fires (+Event Area (EA)), with more complex shapes (+Shape Index (SI)); a higher amount of disturbed patches (+Number of Disturbed Patches (NDP)) but a relatively small largest patch area (-Percentage of Largest Disturbed Patch (%LDP)) relative to other regions. The SRL region also had a higher amount of vegetation residuals than the other ecoregions (+Percentage of Total Remnants (%TR), +Percentage of Island Remnants (IR) and +Percentage of Matrix Remnants (%MR)). In contrast, fires in the WL region were smaller, had more regular shapes (-SI), fewer disturbed patches (-NDP), a larger largest disturbed patch (+%LDP), and less residual vegetation (-%IR and -%MR). The rest of ecoregions presented more complex, and less distinctive fire pattern characteristics. MBL was characterized by smaller-sized fires (-EA), above-average fire event complexity (+SI), few disturbed patches (-NDP) with no clear dominant patch in terms of total area (-%LDP), and a below average amount of residuals (-%IR and -%MR). MBU had close to average size and complexity (~EA and ~SI), below average number of disturbed patches (-NDP), a higher dominance of the largest disturbed patch (+%LDP) and much smaller level of all types of residuals (~%IR and ~%MR). Lastly, CHL had very large fires (+EA) that are simply shaped (-SI), with an average amount of disturbed patches, one large dominant disturbed patch (+LDP), and an average amount of overall residuals (~%IR and ~%MR). WAU had very small fires (-EA) with simple shapes (-SI), a smaller than average amount of disturbed patches (-NDP) and a relatively small dominant disturbed
patch (-%LDP). The amount of island remnants in the WAU was average (~%IR), although it had the highest amount of matrix remnants (+%MR).

Figure 6.8 Spyder plot grouped by fire pattern metric and significant differences in the cumulative distribution functions by ecoregion pairs.

The spyder plots are calculated using the median of each metric. The maximum and minimum values for each metric correspond to the maximum and minimum ecoregion values for each metric. EA is event area; SI is the shape index; %TR is the percentage of remnant islands; %IR is the percentage of island remnants; %MR is the percentage of matrix remnants; NDP is the number of disturbed patches; and %LDP is the percentage of the total event area (EA) of the largest disturbed patch. ‘ALL’ stands for all fires combined; MBU for Mid-Boreal Uplands; WL for Wabasca Lowland; MBL for Mid-Boreal Lowlands; SRL for Slave River Lowlands; WAU for Western Alberta Uplands; and CHU for Clear Hills Uplands.
Figure 6.9. Spyder plots grouped by ecoregion.

The spyder plots are calculated using the median of each metric. The maximum and minimum values for each metric correspond to the maximum and minimum ecoregion values for each metric. EA is event area; SI is the shape index; %TR is the percentage of remnant islands; %IR is the percentage of island remnants; %MR is the percentage of matrix remnants; NDP is the number of disturbed patches; and %LDP is the proportion of the total event area (EA) of the largest disturbed patch.
6.6. **Discussion**

6.6.1. **Image selection, processing, and secondary screening**

One of the advantages of using Landsat data to capture fire patterns is access to significantly more fires across a greater area – relative to an approach based on aerial photo-interpretation (API). The results from 507 fires in our dataset certainly suggest that this is true. Extrapolating from the effort required to assemble the 129 fire database in the western boreal (from Andison and McCleary (2014)), it would take years, and several millions of dollars to build a database of more than 500 fires using aerial photos.

Having said that, one of the limitations of the method proposed here is the ineligibility of a substantial number of fires. The primary limitation of any method that uses Landsat data is that it is limited to capturing fire patterns post-1985 – as Landsat TM imagery was only systematically collected after 1984 (White and Wulder, 2014). This potentially creates a temporal bias since it eliminates as much as 50 years of otherwise available fire history, depending on the location. The pre-1985 period is relevant because it not only includes significantly different climate patterns, but also most the only pre-suppression fire data for the southern boreal. This is a serious limitation for studies with the goal of creating benchmarks for forest management. For studies further north where fire control is either more recent, or has not yet occurred, this is not an issue (e.g. Burton et al. (2008)).

Of the 1,147 fires from the fire databases that occurred after 1985 and were larger than 100 ha in size, 17% were discarded as a result of data gaps. To increase the amount of available pixels after the filtering, the distance used to discard pixels near clouds could be decreased, or the tolerance to eliminate haze increased. It is not recommended to further extend the acquisition window because it can cause variability in Landsat spectral reflectance, in particular dNBR values, due to changes in phenology and sun elevation in northern regions (Verbyla et al., 2008).

Another 23% of the fires were eliminated because the fire perimeters from the fire databases did not overlap sufficiently with the fire perimeter detected using the Landsat-based approach. There are two possible reasons for this error. First, the historical fire databases fail to accurately capture the outer boundaries of some historical wildfires due to errors in spatial location and/or date of fire occurrence. If true, this could be a serious limitation for any spatial analyses that includes pre-fire conditions, topographic features, or fuel-type, and may be worth further investigation. A second possible reason for the significant difference in fire boundary delineation is the presence of wetlands. By comparing those fires with EOSD land cover product (Wulder et al., 2007) I observed that many of these fires were dominated by non-treed wetlands and presented strong negative dNBR signals suggesting greener and
moister post-fire scenarios indicative of vegetation regrowth (Pereira et al., 1999). This ‘wetter’ post-fire scenario was also identified by Jones et al. (2013) as a challenge for mapping fire pattern in wetlands in the Everglades of Florida. The authors hypothesized that fire affected patch soils and elevation leading to higher water tables. The results suggest that it is difficult to capture changes over areas that regenerate quickly after fire using this method, as imagery of the fire year is not utilized. To maximize the quality of the results using this framework I suggest using the EOSD product to discard fires dominated by those vegetation types. Unfortunately, this creates a biased sample. Methods such as proposed by Hermosilla et al. (2016) that identify and characterize the NBR magnitude drop after disturbance based on imagery from the fire year might be more suitable to capture burned areas in non-treed wetlands. My experience also suggests that those parts of fires that burn in wetlands are readily identified by manual interpretation through differentiating standing dead trees with an understory of lush green vegetation.

Lastly, fires were also deemed ineligible because they included overlapping neighbouring fires (10%) or cultural features (7%) that inflated the perimeters and thus biased the fire pattern metrics. The overlapping fires must have occurred by the end of the pre-fire window (after the median value selected) or during the post-fire window but on a different year. The challenge in this case is differentiating the patterns from a single fire event in time and space. This is an unavoidable challenge, and applies equally to API sampling. Similarly, the choice of fire size threshold (100 ha minimum in this case) is subjective, and thus also a universal filter regardless of the method used. To resolve this challenge a means of defining the fire perimeter prior to the analysis is necessary. This could be undertaken in an automated way as an integrated part of the process through spectral trend analysis as in Hermosilla et al. (2016); or manually through visual interpretation of dNBR values for single fires as in Monitoring Trends in Burn Severity project (MTBS) in USA (Eidenshink et al., 2007).

### 6.6.2. Spatial pattern analysis

#### 6.6.2.1. Overall

The event sample was skewed towards smaller events, although most of the area burned was the result of infrequent events larger than 10,000 ha. This is consistent with findings from other studies focusing on larger areas of study and time frames using historical database data (e.g. Stocks et al., 2002), which suggests that my sample is consistent with the historical fire-size distribution.

In terms of general burn patterns, the two fire pattern metrics that varied by event size – the number of disturbed patches and the event shape – have been noted by others. The idea that larger fires have
more complex shapes than smaller ones is not new and has been reported in multiple studies based on various data sources and methods for the same study area (Andison and McCleary, 2014; Burton et al., 2008; Eberhart and Woodard, 1987; Parisien et al., 2006). However, while my averaged shape values were similar to these other studies I found considerably higher values for the larger fires. The more convoluted perimeters obtained from the pixel-based mortality maps were likely the result of an increased presence of peninsulas and bays compared to the more generalized shapes coming from the aerial photo-interpretation process. These differences highlight the need to characterize detailed fire patterns using standardized methods and a consistent spatial language (sensu Andison (2012)).

The increase in the number of disturbed patches with event size was also identified by Andison and McCleary (2014), which was the only other study to report this particular metric. I found that fire events had a dominant disturbance patch covering 40-80% (2nd and 3rd quartiles) of total event area, which almost exactly matches the pattern noted by Andison and McCleary (2014).

With regards to the amount of vegetation remnants, the 37% reported in this manuscript is close to the 41% calculated by Andison and McCleary (2014) for the same area using the same spatial language and aerial photo-interpretation. It is also within the 20-40% reported by Soverel et al. (2010) for fires in western boreal Canada. Our results are however substantially higher than the 3-15% of Delong and Tanner (1996) in northeastern British Columbia, which I attribute to spatial language differences. Their definition of ‘vegetation remnants’ (averaging 9%) was the equivalent of our ‘island remnants’, which in this study averaged 13%. The vast majority of the remaining 28% difference exists in remnant area reflects the inclusion of matrix remnants, for which Delong and Tanner (1996) did not account.

6.6.2.2. Ecoregions comparison

The comparison between ecoregions revealed differences in fire metrics that suggest differences in dominant weather patterns, topography, and vegetation patterns that affect fire behaviour (Ryan, 2002). The most telling result was the higher amount of vegetation remnants in wildfires of the Mid-Boreal Uplands (MBU) compared to those of both the Western Alberta Upland (WAU) and Slave River Lowland (SRL). The differences between the MBU and the SRL are logically consistent with differences in moisture content, the physical arrangement of the fuels, climate and topography. The MBU has a larger proportion of flammable fuel types compared to SRL and less fragmentation (Parisien et al., 2004). SRL has colder temperatures, sparser vegetation and a comparatively higher amount of peatlands, fens and bogs than MBU (Ecological Stratification Working Group, 1996). Although the SRL is dominated by more flammable conifer fuel-types, it is distributed sparsely in exposed, waterlogged or non-productive
areas that reduces fuel continuity and overall fuel loads, which in turn decreases overall fire intensity and increases the chances of residual formation (e.g. Harper et al., 2004). The fact that fire is less likely to burn in wetlands areas or with high moisture regime, creating pockets of remnants (Araya et al., 2016; Epting et al., 2005; Leduc et al., 2007; Nowak et al., 2002) further supports this hypothesis.

Similarly, the differences between MBU and WAU are consistent with changes in topography that control the soil moisture regime and the fuel accumulation. The southern part of the WAU ecoregion (where most fires are) extends into the Rocky mountain foothills, and is dominated by linear ridges with strong local relief. Local topography is known to influence fire behaviour and residual formation. For example, slope changes and ridges have been associated with fire boundaries (Holsinger et al., 2016) and strong topographic variation is known to control fuel accumulation and moisture, which ultimately increases the chances of vegetation remnant formation (Kane et al., 2015; Krawchuk et al., 2016).

Details aside, the ecoregion differences noted here strongly suggest that fire signature patterns are in fact linked to broad differences in vegetation, topography, and climate patterns. The ability to capture and understand the specifics of such patterns is a key to not just fire behaviour prediction, but a better representation of pre-industrial conditions for harvest pattern emulation efforts. Lastly, the results also suggest that assuming that fire pattern signatures translate from one ecological zone to the next would be inadvisable.

6.7. Conclusions

Understanding pre-industrial fire patterns, in particular analyzed vegetation remnant patterns and/or partial mortality, has become both a research and forest management priority in Canada and beyond (Perera and Buse, 2014). Over the last two decades, we have learned just how challenging it is to create this knowledge in a defendable manner. Importantly, we have learned that natural wildfire patterns have a very high level of natural variability (e.g. Andison and McCleary (2014) and Parisien et al. (2006)), which makes studies with small sample sizes, limited geographic scope, or biased data interesting, but not particularly valuable. Free and open access to the Landsat archive has enabled the detection and delineation of an unprecedented number of fire events across the boreal forest (White et al., 2017; Wulder and Coops, 2014), and thus has potential to help unify a growing collection of fire pattern data into comprehensive databases. However, to-date Landsat-based studies on boreal fire patterns are either inaccurate or incomplete and they all differ in their methods, data, sample size, and spatial language (sensu Andison (2012)). On the other hand, while fire mortality maps generated from aerial photo-interpretation are highly accurate and precise, the cost is very high, and it can only be done in
areas where sufficient coverage of aerial photos exists (Morgan et al., 2010). In all, this makes it difficult for managers and other researchers alike to interpret fire patterns over large areas. What is needed is a universal combination of methods and spatial language that can be applied to generate a large enough sample size – of sufficient accuracy – to differentiate the signature of within zone fire patterns from those between zones.

My contribution to this challenge was to test the ability of Landsat imagery to capture and compare fire patterns using a repeatable, consistent and cost-effective approach to a sufficient degree of accuracy and completion across the boreal biome. The proposed framework represents an example of what that may look like. The framework utilises a recently developed fire mapping approach in Chapter 5 that consist of supervised random forest classification of freely available Landsat data and tree mortality polygons from aerial photo-interpretation to produce three-class mortality maps, which, after aggregated in discrete events using the spatial language proposed by Andison (2012), are used to calculate seven key fire pattern metrics. The framework requires basic reference information from fire databases: (1) a reference perimeter, to define the area of interest for each fire; and (2) the year of fire occurrence, to determine the pre and post-fire images needed for the analysis. I demonstrated this methodological framework by mapping and characterizing key fire patterns characteristics for 507 events across the boreal plains ecozone.

Clearly, Landsat imagery is an invaluable resource for mapping boreal wildfires using the proposed framework. Despite of the rigorous screening process, I was able to include over 500 fires in the sample – far in excess of any other study to date for the study area. The results suggest that there is indeed value in capturing and comparing fire pattern signatures between and within broad ecological zones. Summaries from this demonstration generated a significant amount of new information on the fire pattern signature of various ecoregions of the boreal plains ecozone that is critically required by managers. The comparison between ecoregions revealed differences in fire metrics, which in turn suggested various climate, topography, and/ or vegetation ecosystem drivers.

Despite the many virtues of Landsat data and the methods as described here, this study revealed two critical limitations. First, given our understanding of the strong link between fire climate and burning patterns (e.g. Wotton et al. (2010) and Fauria and Johnson (2008)), limiting fire pattern data to 1985 and beyond almost certainly compromises our ability to capture the full range of fire patterns. This also introduces a strong fire control bias of the forest management areas. Second, this study revealed a potential key weakness of Landsat data as regards identifying fire patterns in wetlands. The spectral
signature of vegetation regrowth in such areas is difficult to identify by anything other than subjective means via photo interpretation. It is also important to note that applying the methods described in this paper to another major ecological region requires aerial photo-interpreted data for calibration.

Overall, the results suggest that my original hypothesis that the Landsat data archive can be used to accurately and universally provide precise historical fire patterns is partially, but not entirely proven to be true. If the goal is to create highly defendable fire pattern results across and between areas of the boreal forest, clearly some combination of Landsat and aerial photo-based data and methods are required.
Chapter 7

7. What are the relative roles of disturbance history, climate, vegetation, and topography and their complex interplay on resulting fire patterns across boreal plains?

7.1. Introduction

Spatial tree mortality patterns caused by fire are the result of a range of local and regional conditions at multiple spatial and temporal scales (Turner and Romme, 1994; Wotton et al., 2010). In the boreal forests of Canada this results in highly variable fire spatial patterns within and among regions (e.g. Andison and McCleary, 2014; Burton et al., 2008; Parisien et al., 2004). In theory, describing the three components of the fire environment — fuels, topography and weather — provides a framework to predict fire spatial patterns (Agee, 1998). Drivers of fire spatial patterns can be classified into either bottom-up or top-down controls. Vegetation and topography are bottom-up controls that influence fuel abundance, connectedness and combustibility, which in turn determines the spread of individual fires and spatial burning patterns (Ryan, 2002). Another important bottom-up control is disturbance history, since previously burned areas are less likely to experience subsequent fires until the amount and connectedness of combustibles has had time to mature (Parks et al., 2017; van Wagendonk et al., 2001). Top-down controls, such as weather and climate, control fire occurrence and spatial burning patterns at regional scales (Agee, 1998). Weather influences fire occurrence at the stand level over periods of hours to days (Ryan, 2002). Climate exerts controls over vegetation productivity (i.e., fuels), the average conditions for burning, and the distribution, type, and quantity of flammable vegetation (Meyn et al. 2007; Krawchuk et al., 2009).

Although fire spatial patterns are controlled by a number of factors, the impact of climate is paramount because of its influence during infrequent extreme fire years that account for the majority of the area burned across the Canadian boreal forest (Wotton et al., 2010). Current evidence suggests that climate change could increase future fire mortality patterns and thus alter forest succession pathways (Flannigan et al., 2003; Wotton and Flannigan, 2017; Young et al., 2017). These effects have already been observed in the boreal forest such as changes to species composition (e.g. Johnstone et al. (2010)), tree age structure (e.g. Stralberg et al. (2018)), and biodiversity (e.g. Kofinas et al. (2010)). Thus, it is critical
that we improve our understanding of the controls on fire spatial patterns. Of particular interest is to better understand when, and why, fire vegetation remnants occur as their amount and spatial configuration are important for the resilience of boreal systems (Drever et al., 2006). In the heterogeneous forests of the Canadian boreal, this requires extensive and detailed (1) fire pattern information at a sufficient degree of consistency and accuracy, and (2) environmental data to characterize the dominant controls of fire behaviour.

Multiple studies have quantified and compared spatial fire pattern attributes associated to fire perimeters and environmental conditions preceding, during, and post fires across large areas of the Canadian boreal forest (e.g. Burton et al. (2008); Mansuy et al. (2014, 2010); Parisien et al. (2006)). However, to-date only few studies have examined those relationships based on the more detailed patterns of mortality within fire events (Araya et al., 2016; Ferster et al., 2016; Whitman et al., 2018). The number of fires analyzed in these studies was small (<50) due to the demanding data calibration and validation requirements when creating high resolution multi-class mortality maps. For example, Ferster et al. (2016) examined detailed mortality patterns across 37 western Canadian boreal forest fires using aerially-interpreted polygons of morality against pre-fire vegetation, topography, and fire weather. They found lower mortality occurred where fuel continuity was low and when fires burned during non-drought conditions. Araya et al. (2016) investigated the occurrence of residual vegetation within 11 boreal wildfire events in Canada by considering variation in land cover, natural fire breaks and topographic variables and found proximity to wetlands was the most important factor for variation in burn severity. Likewise, Whitman et al. (2018) compared remotely sensed burn severity maps for six large fires in the northwestern boreal forest against multiple biotic and abiotic controls of fire behaviour. The results suggested that the different levels of severity were adequately predicted using a combination of pre-fire forest characteristics and topo-edaphic variables. The authors however, did not observe any significant effects of fire weather on the observed fire patterns. Combined, the findings from these studies provided much needed insights to fire managers on fire-weather/climate relationships over broad areas of the Canadian boreal and to forest managers on the response and resilience of boreal forests to the impacts of fire.

To-date, no study that I am aware of, has examined relationships between the spatial arrangements of fire mortality levels, including fire vegetation remnants, and top-down (weather and/or climate) and bottom-up (topographical and vegetation structure) controls on fire behaviour based on a large fire sample size. As a result, the link between the variability in spatial mortality patterns and the actual environmental conditions when they occur is not well understood. A more complete understanding of
the influence of environmental variables on fire spatial patterns in general, and vegetation remnants in particular, is required by managers to better understand the main drivers that are historically responsible of maintaining ecosystem function across the broader expanse of the boreal forest (Pickell et al., 2013).

The overall objective of this study is to examine interactions between the spatial fire patterns and multiple environmental controls based on a large fire sample size, as follows. First, I identify and describe the three principal dimensions of variability in spatial fire patterns. Second, I quantify the predictability of each dimension given a suite of multiple top-down (monthly climate) and bottom-up (topography, fuels, natural barriers and disturbance history) environmental controls. Third, I quantify the relative importance and interactions between the environmental controls on fire patterns. I conclude with some remarks about hypothesized shifts in fire patterns under a climate change scenario. To accomplish these objectives, I leverage the recent availability of a comprehensive Landsat-derived fire pattern dataset that describes six fire pattern metrics for the Canadian boreal plains ecozone covering 507 fires and 2.5Mha (see Chapter 6). This dataset is unique in that it includes information about the fire vegetation remnants through a range of metrics that quantify the amount and spatial arrangement of fire mortality levels. The proposed framework of analysis allowed us to characterize the predictability of fire spatial patterns across a broad range of environmental conditions to provide important insights for fire management, conservation planning, and climate change adaptation.

7.2. Study Area

The fire sample was distributed across the boreal plains ecozone as per described in section 6.2. See section 2.1. for more details.
7.3. Data

7.3.1. Independent variables – six fire pattern metrics

To represent observed fire patterns I utilized a Landsat-derived dataset with seven fire pattern metrics for 507 fires that burned 2.5 Mha across the boreal plains ecozone (see Chapter 6). This dataset represents to-date the most comprehensive database of spatial fire patterns in Canada that includes information about fire vegetation remnants for the study area. The dataset includes the year of fire occurrence retrieved from either national and provincial databases or the High Resolution Forest Change (HRFC) for Canada product (White et al., 2017). In Chapter 5 I trained a random forest classifier (Breiman, 2001) using multi-temporal Landsat spectral (such as the differenced Normalized Burn Ratio (dNBR) by Key and Benson (2006)) and ancillary indices (land cover and topography) with aerial photo-interpreted (API) polygon of mortality for a subset of fires across the ecozone. Three classes of mortality were defined based on percentage of crown loss or lesser vegetation consumption attributable to the most recent fire: unburned = 0-5%, partial mortality = 6-94%, and complete mortality >= 94%. Once calibrated, the random forest classifier was applied in Chapter 6 to map 507 fires that were previously identified in either national and provincial fire atlases or the HRFC product.

The seven spatial pattern metrics describing fire were initially proposed by Andison (2012) to represent key characteristics and can be broadly classified as ‘event’, if they describe characteristics only based on the fire perimeter (size and complexity), or ‘within-event’, if they describe the amount and spatial arrangement of the mortality classes within the fire perimeter. Within-event metrics include three metrics that describe the amount of unburnt vegetation remnants as well as number of patches and the percentage of the largest disturbed patch with respect to the total event area characterized by the number and size variability of disturbed patches respectively (see section 3.3).
Each fire pattern metric was calculated based on the three-class pixel mortality maps derived from Landsat imagery that were then transformed into discrete fire-patch disturbance events (see section 3.2). Lastly, water pixels were masked from the disturbance event. Figure 7.1 shows an example of the complete process, from deriving the spectral indices to defining the disturbance events.

For this study I modified a number of the original fire pattern metrics used in Chapter 6. I normalized the number of disturbed patches (NDP) and the complexity of the perimeter (SI) to the fire size (EA) to remove their dependency from fire size and allow comparison across a range of fire event sizes. The new normalized variables are called NDPn and SIn, respectively.

### 7.3.2. **Predictor variables – environmental data**

To characterize the predictability of the six fire pattern metrics, I used a suite of environmental variables that included top-down (monthly climate) and bottom-up (topography, pre-fire land cover, and disturbance history) controls on fire behaviour (Table 7.1). A detailed description of each is included in the following sections.
Figure 7.1. Process to derive a disturbance event.

The top thumbnail represents the difference between pre- and post-fire composites, where the red channel is the difference in Landsat NIR band (4 in TM and 5 in OLI), the green channel is the difference in the SWIR 1 band (5 in TM and 6 in OLI), and the blue channel is the difference in the SWIR 2 band (7 in TM and OLI). The middle thumbnail represents the three-class mortality map from the RF classifier. The bottom figure corresponds to the disturbance event by Andison (2012).
Table 7.1. Explanatory environmental variables.

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Metric [unit]</th>
<th>Acronym</th>
<th>Description</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly climate</td>
<td>Top-down</td>
<td>August Monthly Drought Code (MDC)</td>
<td>MDCAug</td>
<td>August MDC</td>
<td>Captures summer drought peak – potential for fire intensity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May MDC</td>
<td>MDCMay</td>
<td>May MDC</td>
<td>Captures spring drought peak – potential for fire intensity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>August overwintered MDC</td>
<td>MDCAug&lt;sub&gt;o/w&lt;/sub&gt;</td>
<td>August overwintered MDC</td>
<td>Captures summer drought peak but includes moisture depletion during winter – potential for fire intensity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May overwintered MDC</td>
<td>MDCMay&lt;sub&gt;o/w&lt;/sub&gt;</td>
<td>May overwintered MDC</td>
<td>Captures spring drought peak but includes moisture depletion during winter – potential for fire intensity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Majority class [fuel]</td>
<td>MC</td>
<td>Majority class</td>
<td>Most important fuel type</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Majority class [fuel]</td>
<td>%MC</td>
<td>% Area covered by majority class</td>
<td>Homogeneity in fuel types</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Wetlands [soft barrier]</td>
<td>%We</td>
<td>% Wetlands</td>
<td>Amount of natural breaks</td>
</tr>
<tr>
<td></td>
<td>Bottom-up</td>
<td>% Non-treed wetlands [soft barrier]</td>
<td>%NTWe</td>
<td>% Non-treed wetlands</td>
<td>Amount of natural breaks</td>
</tr>
<tr>
<td>Pre-fire land cover (fuels</td>
<td>Bottom-up</td>
<td>% Water [hard barrier]</td>
<td>%Wa</td>
<td>% Water</td>
<td>Amount of natural breaks</td>
</tr>
<tr>
<td>and barriers)</td>
<td></td>
<td>% Forest [fuel]</td>
<td>%Fo</td>
<td>% Forest</td>
<td>Potential for severe fires</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Conifer forest [fuel]</td>
<td>%CFo</td>
<td>% Conifer forest</td>
<td>Potential for severe fires (more flammable fuels)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Conifer forest to total forest [fuel]</td>
<td>RCFo</td>
<td>% Conifer forest to total forest</td>
<td>Potential for severe fires (more flammable fuels)</td>
</tr>
<tr>
<td>Disturbance history</td>
<td>Bottom-up</td>
<td>% Young forest</td>
<td>PER</td>
<td>% of area burned before the fire from 1985</td>
<td>Release of build-up fuels</td>
</tr>
<tr>
<td>Topography</td>
<td>Bottom-up</td>
<td>Terrain roughness</td>
<td>ROU</td>
<td>Average terrain roughness</td>
<td>Complexity of the terrain</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Elevation</td>
<td>ELE</td>
<td>Average terrain elevation</td>
<td>Forest type and effect on fire regime</td>
</tr>
</tbody>
</table>
7.3.2.1. Monthly climate

I quantified climate conditions using the Monthly Drought Code (MDC) (Girardin and Wotton 2009), a monthly derivative of the daily Drought Code (DC) from the Canadian Forest Fire Weather Index (FWI) System (Van Wagner, 1987). The FWI has been routinely used by fire managers across Canada for the past 30 years and provides six output indices representing fuel moisture (Fraser et al., 2017) and fire behavior potential (Wang et al., 2017). DC is a daily index of moisture stored in the deep compact organics in the soil and large woody fuels and, consequently, a good indicator of potential for extreme fire behaviour (Girardin and Wotton, 2009) and has been used with success in the boreal forest (Girardin et al., 2009). The DC conventionally requires time-series of complete daily weather temperature and precipitation data during the fire season (Van Wagner, 1987), which are not available for large portions of the boreal forest (Girardin and Wotton, 2009). As a result, I used MDC as an approximation to daily DC that still captures moisture trends in deep organic layers (Girardin and Wotton, 2009) and has been used with success in other studies (Bergeron et al., 2010; Girardin et al., 2009; Marchal et al., 2017). To obtain monthly temperature and precipitation data I utilized ClimateNA (version v5.50) (Wang et al., 2016), which provides ready-to-use interpolated monthly temperature and precipitation for each fire given a centroid’s elevation, longitude and latitude.

I calculated the MDC for May and August of the fire year as representative of spring and summer drought conditions, respectively. I did not use the MDC of the fire month because the precise fire dates were not available for all fires in the sample. The MDC was calculated in two ways. First, I calculated MDC without overwintering per Girardin and Wotton (2009). MDC was reset every year to a value of 15 at the start of the fire season (May 1st) following the assumption of saturating overwinter precipitation (>200mm from November to March) (Lawson and Armitage, 2008). Second, I calculated MDC with an earlier start to the fire season (April 1st), and taking into account the effect of winter moisture depletion and moderate soil drainage capacity to capture spring drought conditions that commonly result in relatively early fires in the boreal plains ecozone (Pickell et al., 2017; Wilkinson et al., 2017).

7.3.2.2. Pre-fire land cover

Pre-fire land cover variables were used to characterize the type and arrangement of fuels using a 12-class Landsat-derived Disturbance-Informed Annual Land Cover Classification produced by Hermosilla et al., (2018) for the years 1985 to 2017. For each fire, I extracted land cover of the previous fire year within the fire perimeter to obtain the majority land cover class and its percentage, and the percentages of water, forest, coniferous forest, ratio of coniferous forest to total forest, non-treed wetlands, and wetlands (see Table 7.1).
7.3.2.3. Disturbance history

I characterized previous disturbance events (from the beginning of the Landsat TM data record, 1984) to the time of the fire at each fire location using the percentage of area burned within the perimeter prior to the fire from the High Resolution Forest Change (HRFC) product produced by White et al. (2017). The HRFC is a pixel-based dataset that includes both the year of change and the attributed change type (either insect, harvest or fire) based on time-series analysis of Landsat data between 1985 and 2014.

7.3.2.4. Topography

I characterized the effect of topography on local moisture conditions, accumulation of fuels and heat transfer (Bennett et al., 2010) through two metrics by intersecting the global 30 m digital elevation model Shuttle radar mission (SRTM) 1 arc second product with the fire perimeter. The average terrain roughness was calculated as the difference in elevation (m) between a cell and the maximum value among its eight nearest cells and the mean elevation (see Table 7.1).

7.4. Methods

I quantified the relationships between the observed fire pattern metrics and environmental variables in three stages. First, I reduced fire pattern metrics into three principal components and described each based on the most important fire pattern metrics. Second, I assessed the relationship between each component and a suite of environmental explanatory drivers using random forest regression tree models. I then discussed the predictive power of the models and the relative importance of the various explanatory variables. A more detailed description of each step is included below.

7.4.1. Exploratory analysis

I first used exploratory statistical tools to compare the relations across the six fire pattern metrics. Exploratory analysis involved a combination of Pearson correlation tests and box-and-whisker plots. Correlation tests were evaluated based on absolute correlations and their associated p-values utilizing the R package ‘PerformanceAnalytics’. I considered absolute correlation values >0.8 as high, between 0.5 and 0.8 as moderate, and <0.5 as low. Box-and-whisker plots were performed for significant relationships at p < 0.05.

7.4.2. Principal components analysis

PCA was used to simplify the six fire pattern metrics into three dimensions that explained most of the variance. Prior to conducting principal components analysis (PCA), I scaled and centered each of the fire pattern metrics using the ‘caret’ package in R, following recommendations by Lemay and Temesgen.
(2005). Then I evaluated and described the three components based on the relative importance of the original six fire pattern metrics. For that I retrieved the ranking of variable importance based on out of the bag sample (Breiman, 1996) from a random forest model using each principal component as the independent variable and the six fire pattern metrics as dependent variables. I only described the variables that increased the mean squared error of the model by ≥ 70%.

To examine the variability of fire patterns across the area of study I created spatially explicit maps for each principal component. I also created a summary plot on the relative dominance of each component based on seven discrete classes.

### 7.4.3. Predictability of fire patterns

I built random forest regression models to predict each of the three components using the environmental variables in two ways. First, I created models for all fires combined and evaluated the percentage of variance explained and the variable importance, which is useful to understand overall pattern predictability and relative importance of the environmental controls. I also used the same data to build and plot a single decision tree using the 'rpart' package to provide additional insights into the hierarchical structure of the explanatory variables selected (e.g. Gavish et al. (2018)). For example, variables higher in the tree explain more of the variance between observations, and therefore represent their hierarchical importance; while lower branches represent more localized or interactive processes that distinguish group membership at a more subtle level (Amatulli et al., 2006).

### 7.5. Results

#### 7.5.1. Exploratory analysis

**7.5.1.1. The boxplot**

The six fire pattern metrics revealed high variability (and Figure 7.2). The metrics with the smallest standard deviation (SD) and most narrow interquartile range (IQR) were those describing vegetation remnants, namely the shape index (SIn), the number of disturbed patches (NDPn) and the percentage of the largest disturbed patch (%LDP). Variables characterizing remnant patterns were less variable overall, where the percentage of total remnants (%TR) had the highest variability and ranged from 5.3% to 91.1%. The percentage of island remnants (%IR) and matrix remnants (%MR) had comparable variability in terms of SD, IQR and range.
Table 7.2. Summary of six fire pattern metrics.

SD is the standard deviation and IQR the interquartile range.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>IQR</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sln</td>
<td>57.7</td>
<td>59.5</td>
<td>19.4</td>
<td>29.1</td>
<td>8.2 to 96.7</td>
</tr>
<tr>
<td>%IR</td>
<td>14.6</td>
<td>13.2</td>
<td>8.5</td>
<td>11.2</td>
<td>0.1 to 56.2</td>
</tr>
<tr>
<td>%TR</td>
<td>38.5</td>
<td>37.1</td>
<td>14</td>
<td>19.1</td>
<td>5.3 to 91.1</td>
</tr>
<tr>
<td>%MR</td>
<td>23.9</td>
<td>22.7</td>
<td>11.2</td>
<td>16</td>
<td>3.4 to 59.2</td>
</tr>
<tr>
<td>NDPn</td>
<td>23</td>
<td>12.5</td>
<td>27.4</td>
<td>29.2</td>
<td>0 to 100</td>
</tr>
<tr>
<td>%LDP</td>
<td>60.5</td>
<td>63.5</td>
<td>22.5</td>
<td>38.8</td>
<td>8.1 to 96.1</td>
</tr>
</tbody>
</table>

Figure 7.2. Overlaid violin and notched box-and-whisker plots.
7.5.1.2. The correlation plot

In terms of vegetation remnants, I found that the percentage of total remnants (%TR) was highly correlated with the percentage of matrix remnants (%MR), but only moderately correlated with the percentage of island remnants (%IR). Likewise, the percentage of the largest disturbed patch (%LDP) was highly inversely correlated to %MR, but only moderately inversely correlated to %TR. I also found moderate correlations between the shape index (Sln) and the number of disturbed patches (NDPn); and low correlations between the NDPn and the %LDP.

![Scatterplot matrix, with histograms, kernel density overlays, absolute correlations, and significance asterisks (0.05, 0.01, 0.001). %LDP is the percentage of the largest disturbed patch; Sln is the normalized shape index; %IR is the amount of island remnants; %TR is the amount of total remnants; MR is the amount of matrix remnants; NDPn is the normalized number of disturbed patches.](image-url)

Figure 7.3. Pearson correlation tests after normalization.
7.5.2. **Principal components analysis**

The first three principal components explained 91% of the total variance in the six fire pattern metrics representing 49%, 22% and 20% for the first, second and third components, respectively. The representation of the first and second components is included in Figure 7.4, along with the variable loadings (variable importance in vector form).

The first component (PC1) indicates ‘patchiness’, or the spatial heterogeneity in the burned patches, principally determined by the number of disturbed patches (NDPn), the percentage of total remnants (%TR) and the percentage of the largest disturbed patch (%LDP) (Figure 7.5). An increase in ‘patchiness’ translated into more and smaller patches (-NDPn), an increased amount of total vegetation remnants (+%TR) and a smaller percentage of the largest disturbed patch (-%LDP). The second component (PC2) indicates ‘compactness’, or the complexity of the perimeter, principally determined by the shape index (SIn), the percentage of total remnants (%TR) that infills the gaps between and within disturbed patches, and the number of disturbed patches (NDPn) that controls the amount of peninsulas, corridors and bays of the final perimeter. An increase in ‘compactness’ translated into more regular perimeters (+SIn), an increased amount of total vegetation remnants (+%TR) and less and larger patches (+NDPn). The third component (PC3) indicates ‘residualness’, or the amount of fire vegetation remnants within the burned patches, and corresponds to the percentage of island remnants (%IR), or the vegetation remnants that fall entirely within disturbed patches. An increase in ‘residualness’ translated into a higher percentage of island remnants (+%IR).

The maps representing the spatial variability of each principal component (Figure 7.6) revealed a high level of variability in all cases without identifiable regional patterns. The summary map representing the relative dominance of each component was highly variable as well, and had no apparent regional patterns. It is important to note that all seven classes of dominance were well represented across all 507 fires.
Figure 7.4. PCA analysis.

PC1 is in the X axis and PC2 in the Y axis. The loadings (red) are included along with the label of the fire pattern metric that they represent where %LDP is the percentage of the largest disturbed patch; SIn is the normalized shape index; %IR is the amount of island remnants; %TR is the amount of total remnants; %MR is the amount of matrix remnants; NDPn is the normalized number of disturbed patches.

Figure 7.5. Variable importance for the three first principal component based on a random forest model.
Figure 7.6. Variability of the three dimensions of fire patterns.

Each component was stretched from the 5% to the 95% quartile and re-scaled from 0 to 255. The thumbnail with all fires combined was the result of plotting the three channels (PC1, PC2 and PC3) at the same time to the nearest of seven discrete colors included in the legend. In the bottom-right thumbnail the dominance of first, second or third components was represented by red, green and blue, respectively. The co-dominance of two components was the result of combining the colors associated to each, which resulted in either magenta, cyan or yellow. If none of the three components dominated the other, then we assigned a white color.
7.5.3. Predictability of fire patterns

7.5.3.1. Overall model

The most important environmental controls predicting ‘patchiness’ (PC1) were from pre-fire land cover (Figure 7.7). These controls described the amount of fuel (the proportion of forest and the proportion of the dominant class); the fuel types (the proportion of conifer forest and their ratio with respect to total forest); and the amount of fire breaks (the percentage of wetlands and water).

For ‘compactness’ (PC2) the most important controls were a combination disturbance history, land cover and climate factors. Specifically, the percentage of young forest was the most important control, by a factor of two. Next, the most important controls were land cover via the amount of fire breaks (percentage of wetlands and water), followed by climate representing long term summer drought (Monthly Drought Code with and without overwintering).

For ‘residualness’ (PC3) the most important controls were a combination of the disturbance history, topography and land cover, with marginal contributions from climate. The two most important controls by far, and with comparable importance, were the percentage of young forest and mean elevation. These were followed in importance by the land cover describing the amount of flammable fuels (the percentage of conifer forest and the percentage of conifer forest to total forest) and the amount of soft fire breaks (non-treed wetlands); and finally by climate through the overwintered drought for the months of August and May.

Figure 7.7. Variance explained and most important variables using random forest models.

The shapes represent the different data types (rhomboid = land cover; circle = climate data; square = disturbance history; triangle = topography.)
7.5.3.2. Single decision trees

Individual decision trees provided insights into the hierarchical structure of the drivers and of more localized interactive processes that were not directly observable from the overall importance of the random forest model. For example, in the case of ‘patchiness’ (PC1), areas covered by forest almost entirely (> 84%), which accounts for 12% of the number of fires, always resulted in very low ‘patchiness’ (Figure 7.8). Areas with sparser forest were somewhat more variable. Overall, ‘patchiness’ was more variable in less densely forested areas (< 84%), dominated by coniferous or wetland-treed vegetation, with low percentage of water (< 28%) at moderate to high elevations (≥ 270m), which accounted for 62% of total number of fires. This subset of fires presented localized but important variations in ‘patchiness’ closer to the leaves due to variation in overwintered drought, which was not evident from the variable importance rankings derived from random forest (Figure 7.7). Specifically, fires were first divided by overwintered summer drought (≥ 194), which accounted for 43% of fires, then twice split by overwintered spring drought: first ≥ 90, for 35% of the fires, and then by ≥ 123, for 24% of the fires. In all cases more droughty conditions resulted in a decrease in ‘patchiness’. The overwintered spring drought (≥ 57) was also an important source of variability for ‘patchiness’ in less flammable fuel types (i.e. broadleaf, herbs, mixedwood, shrublands and wetlands) that represented 17% of all fires.
Figure 7.8. PC1, or 'patchiness', decision tree.

The minimum bucket size was 20. The numbers below indicate the PC values represented from white (low values, low patchiness) to dark red (high values, high patchiness). The percentage represents the proportion of fire falling on the respective value.
Overall the fires with lower ‘compactness’ (PC2) were those with some percentage of young forest (> 0.008%) (Figure 7.9). Fires with no young forest presented high variation. I found the highest level of variability for ‘compactness’ in areas with no young forest (< 0.008%), experiencing summer drought (≥ 166) and that had a predominant majority land cover class (≥ 36%). This subset represented a 58% of the total number of fires. The largest subsequent data split responded to the majority land cover class including all cover types but for broadleaf, shrubland and wetland-treed vegetation and accounting for the 54% of fires. The existence of water through low threshold percentages (i.e. 3.5%, 1.5% and 0.5%) was critical to determine significant variation in ‘compactness’ in a more interactive process closer to the leaves. In all cases, the existence of water resulted in less compact fires. Less droughty conditions (< 166) resulted overall in more compact burns, although not always.
Figure 7.9. PC2, or 'compactness', decision tree.

The minimum bucket size was 20. The numbers below indicate the PC values represented from white (low values, low compactness) to dark green (high values, high compactness). The percentage represents the amount of fires falling on the respective value.
Likewise, ‘residualness’, was first split by the percentage recently burned area and then by either the amount of non-treed wetlands or the overwintered spring drought (Figure 7.10). Overall ‘residualness’ was highly variable across the various biotic and abiotic conditions. I found the highest proportion of the data in ‘residualness’ in fires with no previous burned area (< 0.008%), experiencing summer drought (≥ 166) and with presence of non-treed wetlands (≥ 0.5%). This subset represented 53% of the total number of fires (Figure 7.10). For this subset of fires, the interactions were complex and involved a combination of topographic (mean elevation), and land cover controls describing the amount of fire breaks (% water) or fuels (% forest, % conifer forest and % conifer forest to total forest). In this case, there were multiple instances where land cover controls were selected closer to the nodes, which contrasts the results found in PC1 where climate variables were most important, or with PC2 where fire breaks were most important. Overwintered spring drought (≥ 135) was locally important to separate ‘residualness’ in more localized interactions closer to the leaves; for example, in areas that were not previously burned (< 0.008%), or non-treed wetlands (< 0.5%) and where the forest was conifer-dominated (≥ 42%). The thresholds selected for spring overwintered drought were relatively similar despite their different locations in the decision tree (125 and 135, respectively).
Figure 7.10. PC3, or ‘residualness’, decision tree.

The minimum bucket size was 20. The numbers below indicate the PC values represented from white (low values, low residualness) to dark blue (high values, high residualness). The percentage represents the proportion of fire falling on the respective value.
7.6. **Discussion**

7.6.1. **Three principal dimensions of variability in spatial fire patterns**

Fire spatial patterns were highly variable across the Boreal Plains ecozone, but the patterns were explained by environmental variables representing both bottom-up and top-down controls. I found high variability in all six fire spatial pattern metrics representing mortality patterns for the boreal plains ecozone. This result is consistent with the highly variable patterns found in other studies over the same area (Andison and McCleary, 2014; Parisien et al., 2004) and across the broader expanse of the boreal forest (Parisien et al., 2006). This high variability in fire patterns is in turn indicative of the complexity of the processes involved in fire spatial patterns at multiple spatial and temporal scales. The high variability of observed fire spatial patterns combined with the lack of regional patterns suggests that the inter-annual variation in climate patterns and fuel characteristics control the majority of variation in fire spatial patterns for the boreal plains ecozone.

In Chapter 6, the spatial language proposed by Andison (2012) allowed me to quantify key fire spatial pattern characteristics through many different metrics in ways that did not exist before. However, to summarize, analyze and extract fire pattern knowledge from many fire spatial pattern metrics across large areas is challenging and requires the use of more sophisticated analytical methods. Through principal component analysis, I identified three primary characteristics of fire spatial patterns that could be explained by environmental variables: ‘compactness’, ‘patchiness’ and ‘residualness’. ‘Compactness’ describes the number, shape, and spatial arrangement of the burned patches that form the fire perimeter. Generally speaking, a higher amount of dispersed patches will form less compact events since the matrix remnants will not completely infill the gaps (>200m apart) or it will create a significant amount of peninsulas and bays that also increase overall fire perimeter complexity (Andison, 2012).

‘Patchiness’ and ‘residualness’ are very closely linked as they both represent the variability of mortality patterns within the area of influence of a fire. In particular, ‘patchiness’, describes the number and size variability of the burned patches within the fire perimeter. Patchier fires are those that have a large amount of matrix remnants and a large number of disturbed patches that are spatially dispersed and with less dominance of the largest disturbed patch. The amount of matrix remnants is the percentage of residuals physically attached to the surrounding matrix of intact forest but still part of the general area of influence of a fire (Burton et al., 2008). ‘Residualness’ was the most detailed (fine-resolution) fire attribute as it represents the variability of island remnant survival patterns within the disturbed patches. Among the three components identified, ‘patchiness’ captured more than twice the amount of variance.
than ‘compactness’ or ‘residualness’. This result suggests that the majority of variance in fire patterns was related to the number and size variability of the burned patches, which confirms previous research by Andison and McCleary (2014).

7.6.2. Predictability of the three dimensions of spatial fire patterns

Overall the amount of total variance explained by the models combining all fires for all three components (‘patchiness’, ‘compactness’ and ‘residualness’) was generally low (< 17%), which is to be expected given the high variability of ecological conditions covered in the fire database. This lack of predictive power is likely due to fire patterns being inherently complex, partly because ignition and spread depend strongly on local weather conditions that change rapidly (i.e. daily or hourly) (Wotton et al., 2010) and which I did not account for in this study. In fact, Wang et al. (2014) provided evidence that the majority of fire spread occurs over extreme fire weather conditions creating mega-fires. Furthermore, extreme fire weather can override topographic or fuel effects in boreal forests (Rowe and Scootter, 1973), which makes it challenging to establish causal relationships between the observed patterns and each of the components of the fire environment. It is also possible that summarizing the topographic and land cover data to the percentages of fire perimeter area led to a loss of detail (as per compared with pixel-based calculations).

7.6.3. Relative importance and interactions between the environmental controls

7.6.3.1. Compactness

In terms of variable importance, the most important explanatory variables predicting each of the three fire characteristics were substantially different (Figure 7.11). For example, the most important variables for predicting ‘compactness’ were a combination of the disturbance history, land cover and climate. In particular, the percentage of young forest was the most important predictor, though the relatively low threshold (i.e. ≥0.008%) indicates that it was occurrence and not the amount of area affected that was important for the model. Overall, the fires with lower ‘compactness’ had some percentage of young forest, while fires with no recent fire presented high variation depending on other variables. The presence of young forest resulting from recent fires within the Landsat time series (1984-present) indicates a release of built-up fuels leading to a decrease the overall fire intensity, which acts as a barrier for fire spread under non-droughty conditions (Parks et al., 2017; Wang et al., 2014). The young forest will in turn increase the chances of vegetation remnant formation and thus result in more heterogeneous and patchy fires with more complex perimeters (Harvey et al., 2016).
The amount of water bodies were also important in predicting ‘compactness’ generally in combination with other variables. In all cases the existence of water resulted in less compact burns. The low percentage of water selected by the model (3.5%, 1.5% and 0.5%) suggests that the presence/absence of water is more important than its quantity. The considerably low water threshold could also reflect the need for additional variables to characterize the environmental context in more detail such as the configuration of water bodies or the structure and types of surroundings fuel.

I found the highest variation for ‘compactness’ in areas experiencing summer drought as a function of the amount and type of fuels. The break selected for summer drought (166) may be compared to the threshold identified by fire managers in Canada separating low MDC values (<200) from higher values indicating moderate to high droughts (Girardin and Wotton, 2009). I propose that under higher drought conditions, fires would more likely burn over broader areas, increasing the chances of affecting different fuel arrangements thereby creating less compact patterns. In contrast, under low drought conditions area(s) burned would be considerably smaller, likely affecting less diverse fuels, and as a consequence we would expect fires to be more compact.

Finally, other studies have also suggested that an increase in fire size increases the complexity of the perimeter as fires burn in a patchier way (Delong and Tanner, 1996; Eberhart and Woodard, 1987; Kafka et al., 2001). As fires spread to larger extents, there is an increased chance of encountering natural barriers (Eberhart and Woodard, 1987), fuel discontinuity (Kafka et al., 2001) or changes in moisture content (Epting et al., 2005). However, I could not test this hypothesis because we did not have a sufficiently representative sample size.

7.6.3.2. Patchiness
The most important variables predicting ‘patchiness’, or the number and variability of the burned patches within the fire perimeter, came from the land cover with important but local contributions from interacting climate variables. In particular, the most important variables described the amount and type of forest cover within the event and the amount of natural fire breaks (% water) or less flammable fuel types under non-droughty conditions (% non-treed wetlands) (Erni et al., 2017).

First, areas covered by forest almost entirely (> 84% of total area) always resulted in very low ‘patchiness’. Less densely forested areas generally dominated by coniferous or wetland-treed vegetation were highly variable as a function of the amount of natural breaks, topography and climate. The fact that spatial variation in fuels (i.e. land cover type) influences fire spread, the intensity and thus the resulting patterns at broad scales is well-established in the literature. In fact, many studies have
found that structure and composition of pre-existing vegetation conditioned the ‘patchiness’ of fires at broad scales (Cumming, 2001; Kafka et al., 2001; Leduc et al., 2007). For example, Kafka et al. (2001) suggested that the relative importance of forest cover varied as a function of site conditions and stand age, even under extreme fire weather conditions.

Similar to what occurred for ‘compactness’, a small percentage of water (0.5%) split more than half the fires for ‘patchiness’ which suggest that the presence/absence of water is more important than its quantity. Again, another possibility is that the model requires additional variables to either characterize the configuration of the patches of water, or some contextual information such as the type and amount of fuels in the surroundings.

Insights from the single decision trees revealed key insights with respect to the role of topography and droughty conditions on ‘patchiness’. Generally speaking, lower elevations (< 270m) resulted in more variable ‘patchiness’ in response to drought, where droughty years resulted in less patchier burns. Furthermore, areas with non-treed wetlands resulted in patchier burns under non-droughty conditions in summer as fuels were not dry enough, resulting in a more disperse burn mosaic with more and smaller burned patches. Combined the results suggest that a subtle elevation gain was important as a means to separate areas with and without wetlands that could either act as fire barriers during wetter years but as fire ‘wicks’ in droughty conditions thus inducing variability in ‘patchiness’.

Localized but important variations in ‘patchiness’ closer to the leaves due to variation in overwintered drought. Drought was determined by multiple thresholds associated to the spring and summer overwintered drought code. The fact that the most important climate variables were those calculated with overwintering supports the importance of drought carried over from the previous season as a factor for predicting fire occurrence in western Canadian forests. Moreover, the combination of spring and summer drought to determine overall ‘patchiness’ may be indicative of the need for detailed fire-weather conditions preceding and during the fire to assess seasonality effects.

7.6.3.3. Residualness

The most important variables predicting ‘residualness’, or the amount of island remnants within the burned patches, were a combination of the disturbance history, topography and land cover, with local contributions from climate, specifically spring drought. Overall ‘residualness’ was highly variable across the various biotic and abiotic conditions and it was difficult to extract general rules of thumb.
As per described in ‘compactness’, the percentage of young forest was the most important predictor with the same relatively low threshold (i.e. ≥0.008%) that suggests that it was occurrence and not the amount of area affected that was important for the model. In all cases, fires with some percentage of young forest resulted in a decrease in ‘residualness’. This aligns well with results by Beverly and Martell (2003) in northwestern Ontario after a prescribed surface fire that found that Pinus strobus trees with a smaller diameter than 1.3 m resulted in complete mortality, while the mortality decreased with increasing tree diameter from 1.3 m.

Many of the relationships with ‘residualness’ found here have been already been discussed before in ‘compactness’, while others have been noted in other studies. For example, increased chances of fire vegetation remnant formation have been associated with certain fuel types and percent land cover variables (Madoui et al., 2010), topography (Krawchuk et al., 2016) and fire weather (Birch et al., 2015; Krawchuk et al., 2016; Madoui et al., 2010). My results suggest that the proximity and amount of non-treed wetlands and water increased the abundance of vegetation remnants, as fires tend to avoid areas with a high moisture regime thereby creating pockets of fire vegetation remnants in their surroundings (Eberhart and Woodard, 1987; Madoui et al., 2010).

Mean elevation was another important control of ‘residualness’ discussed previously in the context of ‘compactness’. In this case, areas with low elevation (mean elevation < 672m) had more and different controls associated to the amount and type of available fuels than their counterparts at higher elevations. I hypothesized that mean elevation in this case is a surrogate for historically wetter conditions found at higher elevations within the area of study. These patterns were likely the result of increased precipitation due to orographic uplift across the Rocky Mountains and are portrayed by the mean historical monthly drought code for the month of July and the years from 1901 to 2002 calculated by Girardin and Wotton (2009). Because those areas are generally wetter, the amount and types of fuels become more important under extreme fire-weather conditions whereas areas at lower elevations are drier and can burn under less extreme conditions. At these lower elevations, fuel characteristics tend to determine what burns, thus conditioning the amount of residuals.

My results also suggest that overwintered spring drought was important as it acted in concert with land cover and topography to separate ‘residualness’ in either dense and conifer dominated forest or areas that underwent previous disturbance. For example, for the 15% of fires with recent burns, about half required droughty conditions in May to ignite and resulted in high amount of residuals. It is possible that spring drought controls the formation of fire vegetation remnants through the timing of spring on-
set leaf growth (Pickell et al., 2017) and/or the availability of wetlands to a fire. The complex interaction between detailed fire patterns and the various environmental controls of fire behaviour portrayed the complex interactions required to predict fire patterns at fine scales.

<table>
<thead>
<tr>
<th>Single attributes</th>
<th>Collective attributes</th>
<th>Controls</th>
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<tbody>
<tr>
<td>Number of disturbed patches</td>
<td>Patchiness</td>
<td>Amount and type of fuels</td>
</tr>
<tr>
<td>% of total remnants</td>
<td></td>
<td>Fire breaks</td>
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<tr>
<td>% of the largest disturbed patch</td>
<td></td>
<td>Fire breaks</td>
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<tr>
<td>Shape index</td>
<td>Compactness</td>
<td>Previous disturbance</td>
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<td>% of total remnants</td>
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<td>Summer drought</td>
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<tr>
<td>Number of disturbed patches</td>
<td></td>
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<tr>
<td>% of island remnants</td>
<td>Residualness</td>
<td>Previous disturbance</td>
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<tr>
<td></td>
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<td>Topography</td>
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<tr>
<td></td>
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<td>Amount and type of fuels</td>
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Figure 7.11. Summary of the results.

Icons created by Joan Teixeira, Irene, Zdenek, Jason D'Amato, Harold Weaver from the Noir Project.
7.6.4. Implications under a changing climate

I expect that under a changing climate the temperatures are going to increase and the fire seasons are going to be longer (Flannigan et al., 2003). Forested areas are unlikely to experience drastic changes in the next years but frequency of the fires is likely to increase and so the amount of spring and summer droughts (e.g. Young et al. (2017)). ‘Patchiness’ is not likely to change since it is almost solely driven by land cover. However, the effect of summer drought and winter moisture depletion on more localized areas of dense forest and complex terrain can result in an overall reduction in ‘patchiness’. ‘Compactness’ is likely to experience a high deviation in terms of fire patterns with respect to the historical baseline since it is largely driven by disturbance history and summer drought. In particular, an increase in drier areas is going to in turn increase the variability in ‘compactness’ as a function of the proportion of water, homogeneity of land cover types, arrangements, and amount of available fuels. ‘Residualness’ is likely to vary only modestly as it is not strongly driven by climate. However, it is also going to be affected by more frequent fires and an increase in the amount of previously disturbed areas. This is going to be particularly evident in flatter areas with different amounts and types of fuels. More localized areas dominated by dense conifer-dominated forest may also experience decreases in the level of ‘residualness’ due to spring drought.

7.6.5. Limitations and future directions

There are some limitations to the strength of conclusions which can be drawn from this work. For example, I did not account for precise fire dates which limited our ability to assess the effects of seasonality on fire patterns and may also introduce bias in the environmental thresholds selected. To address this limitation, future research could include information about the ignitions as well as more detailed daily weather indices which impact fire spread and behaviour. Such information could increase the overall predictive power of the statistical models. However, the low density of weather stations in northern Canada, coupled with the highly variable local weather patterns, may also introduce bias in models for fires lacking adjacent weather stations. Moreover, the inclusion of additional variables to characterize the configuration of water bodies and surrounding fuel types and amount, would likely provide an enhanced understanding of the role of water bodies in controlling fire patterns. Future research into controls of spatial fire patterns would also benefit from including more detailed fire pattern metrics such as the size, variability and spatial distribution of the vegetation remnants, for which I did not account. More sophisticated methods to simplify, summarize and analyze the variability of fire patterns across large areas (such as the one proposed here using principal components analyses) is also recommended. Finally, further research is warranted to test the transferability of the results in the
eastern boreal forest using different independent datasets. The comparison of the results would serve to test the validity of the findings discussed here, as well as provide additional insights into the main drivers of fire pattern variability in regions with substantially different environmental and anthropogenic conditions.

7.7. Conclusions

Understanding spatial patterns created by fire, particularly vegetation remnants, as well as their associated environmental conditions, has become both a research and forest management priority in Canada. In this study I leveraged a comprehensive Landsat-derived fire pattern dataset for the Canadian Boreal Plains ecozone to-date to analyze the link between observed fire spatial patterns and multiple top-down (monthly climate) and bottom-up (topography, vegetation structure and disturbance history) controls. I identified three main dimensions of fire patterns which simplify interpretation of the results. ‘Compactness’, or the complexity of the perimeter; ‘patchiness’, or the spatial heterogeneity in the burned patches, and ‘residualness’, or the amount of fire vegetation remnants within the burned patches. My results provided further insights into the relative role of environmental controls on fire regimes in the boreal forests of western Canada. Even though the metrics I used were more detailed than those of previous studies, my results support previous findings that fuel arrangement and types lead to different fire patterns and that the potential for prolonged droughts is a major control on fire patterns across the Canadian boreal forest. The complex interaction between detailed fire patterns and the various environmental controls of fire behaviour portrayed the complex interactions required to predict fire patterns at fine scales.
Chapter 8

8. Conclusions

8.1. Research innovations

Concerns about the long-term sustainability of the Canadian boreal forest call for more holistic and robust management methods. Emulation-based approaches that use knowledge of pre-industrial patterns have been proposed to guide harvesting planning and prescribed and managed burning planning. In particular, it has been suggested that forest management patterns should be modelled after the Historical Range of Variation (HRV) (Attiwill, 1994; Hunter, 1993; Johnson et al., 1998), where HRV is defined as the variability of ecological conditions experienced by a fairly intact ecosystem, for a given time period and extent (Landres et al., 1999). Because fires are an integral part of boreal systems (Brandt et al., 2013), most regulatory and certification agencies in Canada now require forest management plans to include some level of historical fire pattern approximation (Perera and Buse, 2014), such as guidelines for stand structure retention (e.g. OMNR, 2001; FSC, 2001). To make HRV an operational reality in the Canadian boreal forest requires defining and characterizing the spatial fire patterns at fine to meso-scales across large and remote areas.

Characterization of spatial fire patterns requires thematic maps of tree mortality, which are most commonly derived from remotely-sensed imagery, either from satellites (Coops et al., 2018) or aerial photos (Andison, 2012). Further, to guarantee the comparability of results, it is critical to use a consistent spatial language that defines the area of influence of a fire and the different patch-types within. Many metrics can be generated to describe and quantify key fire characteristics for single events (Landres et al., 1999). When multiple fires from a representative fire sample are combined, the spatial and temporal variability of spatial fire patterns can be analyzed at landscape patterns (Morgan et al., 2001).

However, up until now, current methods to map and study spatial fire patterns are neither cost-effective nor repeatable, leaving researchers and managers alike with insufficient information to interpret fire patterns across large areas. Firstly, current methods to map fire patterns are not cost-effective over large areas. While fire mortality maps generated from aerial photo-interpretation are highly accurate and precise, the cost is high, and it can only be undertaken in areas where sufficient coverage of aerial photos exists (Morgan et al., 2010).
Landsat imagery have a large area coverage (185 km wide swath for single scenes) and moderate spatial resolution (30 m) that is well suited to capture changes in tree condition at the stand level across landscape scales (White et al., 2014).

Free and open access to the Landsat archive provides systematically acquired, large area coverage imagery (185 km wide swath for single scenes) of moderate spatial resolution (30 m) that has potential to capture the spatial variation in tree mortality at the stand level for an unprecedented number of fire events across the boreal forest (White et al., 2017; Wulder and Coops, 2014). However, to-date Landsat-based studies on boreal fire patterns are either not accurate enough, do not include partial mortality (which I believe to be a critical part of historic patterns) and/or are based on a very small number of fires as a result of relying on very expensive and subjective Composite Burn Index (CBI) field data for validation (Key and Benson, 2006). Secondly, there is little agreement on the spatial language and methods to define, observe and examine spatial fire patterns across large areas which makes comparing and combining results difficult. Consistent data, methods, and spatial language are needed to generate sufficient sample sizes to assess spatial pattern. Also essential are novel tools to study the variability of fire patterns and their response to biotic and abiotic controls.

The main objective of this dissertation is to develop, test and demonstrate the value of a novel framework to help improve our understanding of historical fire patterns across the Canadian boreal forest. The research presented herein advances in our understanding of the variability and causality of spatial fire patterns across large remote boreal regions addressing both scientific and management communities. Major contributions from this research include three main research themes:

- **Theme 1: ‘model development’** – I re-imagined how to capture and describe spatial fire patterns across large and remote areas of the boreal forest through an innovative and cost-effective framework that combines Landsat satellite data, polygons of mortality from aerial photo-interpretation and a consistent spatial language and metrics to capture key fire characteristics.
- **Theme 2: ‘model testing’** – I demonstrated how this new framework can be extrapolated to other landscapes not in the original formulation area. In particular, I produced a fire pattern database comprising 507 new fires and 2.5 Mha – far in excess of any other study to date for the same area and created summaries of the results.
- **Theme 3: ‘model demonstration’** – Through analysis I showed how the data generated could be used in combination with new tools and methods to reveal new layers of research possibilities and
interesting patterns of fire mortality that was not previously possible. This allowed me to (1) characterize and assess differences in fire pattern signatures between pre-defined ecological zonations, and (2) characterize the interactions between spatial fire patterns and biotic and abiotic environmental controls.

Below I provide a summary of the three main research themes undertaken in this thesis, which were briefly described above, and describe how each of these goals have been addressed.

8.2. **Theme 1: ‘model development’**

With 38.5 Mha of forest and 11% of the total tree volume (Canadian Forest Service, 2013), the boreal plains is the third largest ecozone in Canada (Canadian Forest Service, 2013) and of critical importance ecologically and in the economy. Fire is the most prevalent natural disturbance agent in the Canadian boreal forest with highly variable fire return intervals ranging between 30-300 years (Parisien et al., 2006) and spatial fire patterns responding to regional differences in climate, vegetation and anthropogenic activity (Parisien et al., 2004). Sustainable forest management and enhancements to existing fire management policies and practices require a thorough understanding of the spatial fire patterns created and maintained by fire.

The study of variation in spatial fire patterns requires a comprehensive coverage of thematic maps of mortality and a consistent spatial language to identify the area of influence of the fire and the single elements or patches of areas with relatively homogeneous fire effects. Free and open access to the Landsat image archive (Wulder et al., 2008) represents an unique opportunity to map fire patterns across large areas inexpensively, and thus can help to develop a suite of comprehensive and transferable metrics on fire patterns to be derived and compared across regions. Despite the availability and potential of Landsat data, the reliance of current calibration methods which require expensive and arguably inadequate CBI field data (Key and Benson, 2006; Kolden et al., 2016) for validation have hindered the applicability of these methods to larger scales and resulted in Landsat based studies typically covering a small number of fires and over a limited geographic area. Moreover, the lack of standardized methods and spatial language makes difficult to compare and interpret the results over larger areas. In all, the lack of spatially explicit data makes difficult or impossible to study spatial fire patterns over both small areas (because managers cannot be sure that small studies captured the variability of fire patterns) and larger areas (because the data, methods and assumptions from different studies are not comparable). What is needed is a universal combination of data sources, methods and
spatial language that can be applied to generate a large enough sample size – of sufficient accuracy – to study spatial fire patterns across the broader expanse of the boreal forest.

My contribution to this challenge was to develop, test, and demonstrate the value of a novel and more accurate and cost-effective method to produce mortality maps coupled with the spatial language and fire pattern metrics proposed by Andison (2012). This first theme was addressed in two phases. First, I assessed the accuracy and data requirements of multiple Landsat spectral models calibrated to tree mortality polygons derived aerial photo-interpretation (API) to predict mortality at multiple levels of detail (Chapter 4); and second, I assessed the accuracy of a single, three-class Landsat spectral model to predict fire patch-metrics for single fires after applying a consistent spatial language to the raw pixel mortality maps (Chapter 5). A more detailed description of these two phases is included below.

In phase (i) I conceptualized and tested a novel, more cost-effective, method to produce mortality maps that relies on aerial photo-interpreted (API) polygons for calibration and a random forest algorithm (RF) for prediction. There are several advantages to using polygons of tree mortality instead of field plot CBI data to map fire patterns. First, in forested systems, Landsat spectral indices are highly correlated to fire effects on overstory vegetation (Fraser et al., 2017; Lentile et al., 2006; Miller and Thode, 2007) and less so with the obscured sub-canopy effects (Cocke et al., 2005). Second, API can provide a cheaper and quicker alternative to producing validation data for burn severity studies, which will help in cost-effectively covering larger areas. Third, polygons of tree mortality are spatially continuous rather than plot-based, which better capture the variability of fire effects across the fire event. Lastly, tree mortality is estimated via a direct interpretation of changes in colors (contrast) and texture on high resolution aerial images, rather than a composite index aggregating fire effects on multiple strata. As a result, tree mortality from API provides a more concrete basis to map fire patterns with satellite-derived data that can augment the comparability of results across ecological conditions and be more useful for managers.

I also explored a machine learning algorithm to predict tree mortality, RF, which, I believe, presents three advantages with respect to conventional simple regression models. First, RF can utilize several predictor variables of multiple data types to predict fire effects, as opposed to a single continuous variable in conventional regression models. RF also computes a variable importance factor (Breiman, 1996), which can be used to determine which variables from Landsat or ancillary data were essential in the prediction of mortality in each case. Second, RF can handle complex interactions between variables in a hierarchical fashion, as well as non-linear relationships, which are typical of fire effects but difficult
to capture with conventional regression models. Third, RF is non-parametric, removing the need for assumptions about data normality resulting in a more flexible model.

Key insights from Chapter 4 suggest that at the most, three classes of mortality (unburned, partial and complete mortality), can be predicted with fair accuracy using a Landsat spectral model. In terms of the importance of overall data layers, variables derived from pre-fire forest inventory data (such as dominant tree species, canopy closure and soil moisture regime) hold little predictive power, likely due to their coarse spatial resolution compared to the fire patterns observed. Because these data are not always available for all historical fire events, I concluded that they may be removed without compromising classification accuracy.

In phase (ii), which corresponds to Chapter 5, I combined a novel cost-effective method to predict tree mortality maps derived with the spatial language and associated metrics to describe the amount and spatial arrangement of mortality patterns by Andison (2012). Specifically, I utilized seven key fire pattern metrics proposed in Andison (2012) which can be derived from the three-class Landsat spectral model. Overall I found very close correspondence for the two event-scale metrics: the total area affected by fire and the complexity of the perimeter. The more detailed within-fire event metrics presented more varied results and were somewhat less precise. For example, the total amount of remnants or the largest disturbed patch were accurately captured. Other indices such as the number of disturbed patches or total amount of island remnants presented moderate systematic biases, but still might be serviceable given that the biases were predictable in direction.

In total, these results suggest that if applied more broadly to more fires a national fire database on fire behaviour may be possible. The individual fire pattern results for hundreds of fires across the boreal forest, when summarised will provide significant quantitative information to locally characterize fire patterns and insights into the controls of fire pattern across this large forested region.

### 8.3. Theme 2: ‘model testing’

The opportunity to couple the previously developed and calibrated Landsat spectral model (Chapter 5) with the ability to use freely and widely available Landsat makes the technique described in Theme 1 well suited for capturing and comparing detailed mortality patterns of hundreds of fires across vast areas. This in turn has the potential to generate valuable fire pattern data and new tools for analysis for both researchers and forest managers interested in studying fire regimes. However, the degree to which this approach can be successfully extrapolated to other landscapes not in the original formulation area remains untested. The second goal of my thesis is a demonstration of how this new framework can be
extrapolated to other landscapes. I also discuss the big data processing decisions and related outcomes for large area mapping of hundreds of fires across the boreal plains ecozone of western Canada. I addressed this in Chapter 6 via generating a significant amount of fire pattern data for the area of study and summarizing the patterns observed for the multiple sub-regions within. For this I applied the previously calibrated Landsat spectral model hundreds of fires within the boreal plain ecozone. To select the pre- and post-fire Landsat imagery necessary to compute the bi-temporal change detection I utilized, as reference data, the areas and years where fires burned for the length of the Landsat archive (1985 to 2015) within the boreal plains ecozone that I obtained from publicly available national, provincial and other fire atlases. With 507 fires over 2.5 Mha mapped, this study represents the most comprehensive fire pattern database of mortality patterns (including partial mortality and/or information of vegetation remnants) in Canada, far in excess of the western boreal Canadian fire dataset of 129 fires (Andison and McCleary, 2014). Extrapolating from the effort required to assemble the 129 fire database in the western boreal (from Andison and McCleary (2014)), it would take years, and several millions of dollars to build a database of more than 500 fires using aerial photos. Further, through summary boxplots of the seven fire pattern metrics, I illustrated the historical range of variability in fire patterns within and among ecoregions, which can assist managers to take more informed decisions. This new comprehensive fire pattern database provides more complete fire pattern information to undertake a detailed study of spatial fire patterns over the area of study. For example it can be used to quantify how fire pattern metrics vary among and within pre-defined ecological zonations (e.g. Parisien et al. (2004)), to define areas were fire regimes are relatively homogeneous (Boulanger et al., 2012), or to better understand the relationship between fire pattern metrics and various environmental variables (Morgan et al., 2001).

Key insights from Chapter 6 revealed that one of the limitations of the method proposed here is the ineligibility of a substantial number of fires that were removed in the screening phase. This included the presence of overlapping and contemporary neighbouring fires that and of cultural features that were combined to the target fire event biasing the spatial pattern metrics; and also, of areas dominated by non-treed wetlands, whose spectral signature of vegetation regrowth after fire was systematically misclassified as unburned.

In summary, the significant amount of fire pattern data generated and the associated methods to summarize fire patterns across the sub-regions demonstrated the potential of the method and provided useful insights into characterizing spatial fire patterns across large areas of the boreal forest inexpensively. This research also highlighted the importance and challenges associated to the big data
processing of Landsat data and the need for a screening phase to guarantee data quality. In particular, it provided useful new quantitative information for managers interested in guiding harvesting planning using fire patterns as a benchmark. Also, I found some evidence of the variation of spatial patterns across regions, which suggests that assuming that fire pattern signatures translate from one ecological zone to the next would be inadvisable. The results presented here call for a more detailed analysis of the relative roles and the complex interplay of the various biotic and abiotic controls on fire patterns across this vast area of study.

8.4. Theme 3: ‘model demonstration’

Understanding the spatial patterns created by natural fires, in particular regarding fire vegetation remnants, and the environmental conditions when they occur, has become both a research and forest management priority in Canada (Perera and Buse, 2014). However, because of the lack of available spatially explicit data, until now there has been little examination of the variability in spatial fire patterns and their interaction with main biotic and abiotic controls over a large area. In the third and last theme of this research I showed how the data generated in Chapter 6 could be used in combination with new tools and methods to help reveal an entirely new layer of research possibilities and interesting patterns that was not previously possible. This was accomplished in two steps.

First, in Chapter 6 I characterized and assessed differences in fire pattern signatures between pre-defined geographical divisions across the boreal plains. For that I developed and applied tools to summarize and compare unique fire patterns signatures for sub-regions within the boreal plains ecozone. I utilized two different statistical tests to compare the shape and median of the cumulative distribution functions across all pairs of ecoregions, which highlighted mostly differences in the amount of vegetation remnants in four ecoregion pairs. The ecoregion differences noted here strongly suggest that fire signature patterns are in fact linked to broad differences in vegetation, topography and climate patterns, which in turn suggests that it will be inadvisable to assume that fire pattern signatures translate from one ecological zone to the next. Moreover, the results suggested the existence of unique ‘signatures’ of burning patterns in the areas of study that helped me to differentiate two broad groups in terms of spatial fire patterns.

Second, in Chapter 7 I assessed the relative importance and complex interplay of abiotic and abiotic environmental controls on resulting post-fire patterns. For that I leveraged the recent available comprehensive Landsat-derived fire pattern dataset for the Canadian boreal plains ecozone, covering 507 fires (Chapter 6) to undertake a comparison between observed fire patterns and multiple top-down
(monthly climate) and bottom-up (topography, vegetation structure and disturbance history) controls on fire behaviour. Across this large number of fires I identified three dimensions of fire patterns that describe the variability in fire patterns: ‘compactness’, or the complexity of the perimeter; ‘patchiness’, or the spatial heterogeneity in the burned patches, and ‘residualness’, or the amount of fire vegetation remnants within the burned patches. Via applying a combination of decision trees algorithms I determined that the three dimensions of fire patterns were affected differentially by the multiple controls. For example, I found that ‘patchiness’, or the spatial heterogeneity in the burned patches, was mostly conditioned by the land cover through variables characterizing the type and connectedness of the fuels. However, summer and winter drought were locally important in less densely forested areas with complex topography. ‘Compactness’, or the complexity of the perimeter, responded to a combination of the disturbance history, land cover (via the amount of fire breaks) and summer drought. Drier areas presented overall a more variable ‘compactness’ as a function of the proportion of water, homogeneity of land cover types and amount of flammable fuels. ‘Residualness’, or the amount of fire vegetation remnants within the burned patches, was a function of the disturbance history, topography and land cover. Flatter areas presented the most variable patterns, in response to changes in the amount and types of fuel. Spring drought was of localized importance in dense conifer-dominated forest. This research is innovative as it utilized novel approaches to summarize and quantify fire patterns across large areas.

In summary, findings from this research demonstrate the value of utilizing an integrated suite of new tools and methods to summarize and extract general fire patterns across large areas in support management decisions across the Canadian boreal forest. Key insights from this research offer an enhanced understanding of the variability of spatial fire patterns across and within regions as well as of the hierarchical interactions between resulting fire patterns and environmental controls that are critically required to support management decisions and anticipate responses to a changing climate.

### 8.5. Implications for management

As discussed in the introduction, forest managers in Canada have been strongly encouraged to adopt an ecosystem-based management approach to harvesting based on the Historical Range of Variation (HRV), where HRV is defined as the variability of ecological conditions experienced by a fairly intact ecosystem, for a given time period and extent (Landres et al., 1999). A key requirement for the implementation of such approaches is to define and characterize spatial fire patterns (Boulanger et al. 2013). In particular, to quantify the variability of fire patterns as well as the abiotic and biotic drivers
across large areas of the boreal forest. In this thesis I made several advancements relevant to management that are summarized below:

- First, as part of the data analysis I derived information from 507 fires covering 2.5 Mha across the boreal plains ecozone. The fire areas ranged from 36 - 269,360 ha, although this was highly skewed towards very large infrequent fire events > 10,000 ha. The number of patches and the complexity of the perimeter were co-variant with fire size, with as many as 3,000 patches per fire. Fires consisted of a dominant patch covering from 8% - 96% of the total fire area, with the majority having a dominate patch 40 - 80% of the total area. On average 37% of the perimeter area corresponded to unburned or partially burned vegetation remnants, but again this result was highly variable from 5% - 91% of the total area. The percentage of matrix remnants was more important than the percentage of island remnants in determining the percentage of total remnants. In addition a greater amount of matrix remnants generally implied elevated fragmentation within the fire perimeter due to more disturbed patches. Similarly, the percentage of the largest disturbed patch generally decreased as the number of disturbed patches increased.

- Second, I determined that, at a minimum, harvesting management approaches that aim to approximate natural fire patterns should incorporate knowledge of three fire pattern dimensions: ‘patchiness’, or the number and size variability of the burned patches within the fire perimeter; ‘compactness’, or the number, shape, and spatial arrangement of the burned patches that form the fire perimeter; and ‘residualness’, or the variability of island remnant survival patterns within the disturbed patches. Generally, patchier fires were those with a larger amount of matrix remnants, more disturbed patches that are spatially dispersed, and smaller contribution of the largest disturbed patch to the total area. More compact fires corresponded to fires with less and larger patches that had a low level of dispersion and a regular perimeter. Lastly, an increase in residual patches was associated with a higher proportion of the vegetation remnants occurring within the disturbed patches.

- Using these three dimensions as a general guide I found that ‘patchiness’ is mostly conditioned by the land cover which is a surrogate for type and connectedness of the fuels. In addition, however, summer and winter drought can be locally important in less densely forested areas with complex topography. ‘Compactness’ responded to a combination of the disturbance history, land cover (via the amount of fire breaks) and summer drought. Drier areas presented overall more variable compactness as a function of the proportion of water, homogeneity of land cover type and thus the amount of flammable fuels. ‘Residualness’ was also a function of the disturbance history,
topography and land cover. Flatter areas shown the most variable patterns, in response to changes in the amount and types of fuel. Spring drought was of localized importance in dense conifer-dominated forest.

- Lastly, high variability in all six fire pattern metrics demonstrated the pyro-diversity of fire patterns in the Canadian boreal forest. This high variability in fire patterns is in turn indicative of the complexity of the processes involved in fire pattern formation at multiple spatial and temporal scales. Differences between ecoregions strongly suggests that fire patterns are linked to broad differences in vegetation, topography and climate patterns. This implies that assuming simple translations of fire pattern information between ecoregions is inadvisable, and that additional in-situ fire pattern information needs to be acquired for each new region before characterizing the variability in fire patterns.

8.6. Research limitations

While meeting my three goals, this work does have some limitations which are discussed in detail below:

- First, given our understanding of the strong link between climate and burning patterns (Fauria and Johnson, 2008; Wotton et al., 2010), limiting fire pattern data only back to 1985 compromises the ability to capture the full temporal range of fire patterns. This also introduces a strong fire control bias in forest management areas where fire control has been in effect since the 1980’s, since suppressed fires are likely to result in smaller and less severe fires that those without suppression.

- The second limitation is a weakness of Landsat spectral model with regards identifying fire patterns over areas that regenerate quickly after fire using this method, as imagery of the fire year is not utilized. This was particularly evident over non-treed wetlands where post-fire images covering burned areas suggested a greener and moister indicative of vegetation regrowth. The spectral signature of vegetation regrowth in wetlands is difficult to identify by anything other than subjective means via photo-interpretation. Thus, to maximize the quality of the results using this framework I suggest using the annual land cover maps produced by Hermosilla et al. (2018) to discard fires dominated by this vegetation types. Unfortunately, this created a biased sample.

- It is also important to note that applying the methods described in this paper to another major ecological region requires aerial photo-interpreted data for calibration. Thus, a third limitation of this study is that the approach still requires a sample of fire mortality maps generated from aerial photos, for both calibration and validation. However, the number of fires required to capture the variability of fire patterns is still less that what would be required using plot data.
Fourth, through this research I determined that at most three classes of mortality can be separated using a Landsat spectral model. This represents a broad range of mortality (6-94% of tree mortality) and clearly limits our availability to understand fire vegetation remnants in detail. Further research in Chapter 5 suggests that the method misclassified a small portion (6%) of the partially burned areas as unburned areas which created a moderate bias on some of the fire pattern metrics utilized.

Fifth and finally, the proposed model relies on a reference perimeter and year of burn as it is based on a bi-temporal change detection algorithm. To resolve this challenge a means of defining the fire perimeter and the fire year prior to the analysis is necessary. This could be undertaken in an automated way as an integrated part of the process through spectral trend analysis as in Hermosilla et al. (2016); or manually through visual interpretation of dNBR values for single fires as in Monitoring Trends in Burn Severity project (MTBS) in USA (Eidenshink et al., 2007).

8.7. Directions for future research

I recommend that future work be focussed in three areas:

- A pan-boreal geospatial database of mortality patterns and associated fire pattern metrics would be an invaluable tool with which to help increase our knowledge on fire regimes across the boreal forest. Towards that, more research is warranted to extend the analysis to include more fires under different ecological conditions and additional fire pattern metrics to better characterise the spatial pattern of mortality created by fire.

- Another direction for future research focussed on testing more cost-effective sources for data for calibration of the Landsat-derived models. This could include the potential of unmanned aerial vehicles (UAVs) to provide cost-effective data for validating and calibrating Landsat-derived models across large areas (Fraser et al., 2017). In particular to assess the viability of a more complex measurement of mortality that also incorporates the residual vegetation structure via using a photogrammetric point cloud to calibrate spatially explicit Landsat mortality maps.

- The last recommendation is to test the transferability of the proposed methodology in Chapter 7 to the eastern boreal forest based on a different and independent dataset. Such comparison will serve to test the validity of the hypotheses posed as well as to provide additional insights into the main drivers of fire pattern variability in regions with substantially different environmental and anthropogenic conditions.
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